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Conditioning on What? Heterogeneous Contributions and Conditional Cooperation

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Abstract

We experimentally investigate how different information about others' individual contributions affects people's willingness to cooperate in a one-shot linear public goods game. We find that when information about individual contributions is provided, contributions are generally higher than when only average information is available. This effect is particularly strong when others' individual contributions are relatively homogeneous. When both types of information are provided, this effect is moderated. In the case of individual feedback we find the willingness to contribute to be higher the lower the variation in others' contributions, but with pronounced heterogeneity in individuals' reactions. While the majority of people are mainly guided by others' average contributions, more people follow the bad example of a low contributor than the good example of a high contributor. Overall, we provide evidence that information (and lack thereof) about others' individual contributions affects people's willingness to cooperate in systematic ways.

Keywords

Conditional cooperation; Information; Heterogeneity; Public goods; Experiments

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1 Introduction

What makes people cooperate? Understanding the determinants of behavior in social dilemmas is important for numerous economic interactions, ranging from team work in

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organizations to multilateral treaties among nations. In this type of situation, contributions to public goods (or consumption of common pool resources) typically differ across individuals. Yet, there is surprisingly little conclusive evidence on how information (and lack thereof) about heterogeneity in others' individual contributions affects people's *willingness to cooperate* within groups. Most previous empirical studies either exclusively studied reactions to average behavior, or looked at repeated interactions which are likely to be biased by strategic considerations. In addition, from a theoretical perspective there seems to be no unanimous guidance as models of other-regarding preferences make different behavioral predictions about how people react to heterogeneity in others' individual contributions (see Section 3).

In this study, we provide clean experimental evidence on how different information – *aggregated, disaggregated, or both* – about others' heterogeneous contributions affects subjects' willingness to cooperate in a linear public goods game. We contribute to the previous literature in two respects: First, to rule out potential confounds due to strategic concerns from repeated interaction, we conduct a *one-shot experiment*. To control for different beliefs about others' behavior, following Fischbacher et al. (2001, henceforth FGF), we apply a variant of the *strategy method* (Selten, 1967) which allows us to elicit people's general attitude toward cooperation and classify them into different cooperation 'types' (see also Fischbacher and Gächter, 2010, for more recent evidence). Second, in contrast to FGF and replications of their experiment (see Chaudhuri, 2011, for a review), we not only study reactions towards average behavior but also examine how people react when confronted with heterogeneity in others' individual contribution behavior. In particular, we ask which, if any, contribution of the other group members is most influential in determining own willingness to cooperate? Are people more inclined to follow a bad example of an uncooperative group member, do they match a good example of a high contributor, or do they just go along with the average?

These are important questions as examples of heterogeneous contributions to a common good are ubiquitous in social and economic life. Think of the Kyoto Protocol designed to reduce emissions of greenhouse gases. While most industrialized countries have signed the protocol, other countries continue to abstain from signing the treaty, thus free riding on the efforts of others. Likewise, think of municipalities publicizing households' heterogeneous electricity consumption and recycling rates. Or, imagine a team context in which, for example, an academic working on a joint paper faces one free riding and another highly dedicated co-author.

Insight from these questions suggests what kind of information can facilitate cooperation when institutions have some discretion about information policy, for example in the case of fund-raising or charitable giving. It may also give guidance about which contribution a policy maker should try to increase in order to best enhance further cooperation. This might be relevant in the case of teamwork or international treaties where a leader can try to motivate single group members to increase their contribution.

Our experimental design comprises three between-subjects treatments in which we systematically vary others' individual contributions and the information subjects receive. In

our baseline treatment (*AVG*), we replicate FGF and provide subjects only with information about others' average contribution behavior. In this treatment, if subjects wanted to match a certain contribution or were concerned about the composition of the average, they would have to form beliefs about the distribution of individual contributions. In our second treatment (*IND-AVG*), we remove this lack of knowledge by additionally providing information about others' individual contributions. In this case, subjects can condition their behavior on both individual and average others' contributions. Finally, in our third treatment (*IND*) we remove the aggregated feedback and only provide information about others' individual contributions.

Although information about average behavior is still available implicitly in *IND*, this treatment allows us to explore whether explicitly providing average information on top of individual information has a focal effect moderating reactions to variation in others' individual contributions.

To investigate the effects of variation in others' individual contributions on people's willingness to cooperate, in *IND* and *IND-AVG*, we systematically vary the composition of a given average contribution. For example, in one case an average of 5 is given by individual contributions of 5/5/5, while in another case individual contributions are 0/5/10. By comparing two such cases, we can examine whether people react to variation or whether they are mainly concerned about average behavior only.

Our main finding shows that compared to the *AVG* treatment, subjects exhibit a significantly higher willingness to cooperate when only information about others' individual contributions is provided (*IND*). This effect is particularly strong when others' individual contributions are relatively homogeneous, and less pronounced when they differ a lot. Explicitly announcing the average on top of others' individual contributions (*IND-AVG*) has a moderating effect leading to lower contributions than in *IND* but still higher contributions than in *AVG*.

When information about individual contributions is provided (*IND* and *IND-AVG*), we find, *ceteris paribus*, that the willingness to contribute is on average the lower the higher the variation in the other group members' contributions.¹ This suggests that subjects do in fact care about the composition of the average contribution, an observation that could not be captured by the original design of FGF. At the individual level, however, we find pronounced heterogeneity in how 'conditional cooperators' react to variation in others' contributions. While the majority of 'conditional cooperators' are mainly guided by others' average contribution, we also find a considerable fraction of 'conditional cooperators' who react strongly to the minimum and maximum contribution of others. In line with the results from the aggregate analysis, we find the distribution of types to be skewed towards those who focus on the minimum.

When comparing the *IND* and *IND-AVG* treatment we find evidence that explicitly announcing the average contribution in addition to individual contributions induces subjects

¹This result is in line with previous evidence on social interaction effects (Gächter and Thöni, 2005), showing that cooperation is easier to sustain among like-minded people with similar cooperative preferences.

to condition their contributions more strongly on the average or median contribution and less strongly on the maximum. The reaction towards the minimum, in contrast, stays similar. This indicates that providing average information on top of individual information induces a self-serving bias, i.e., the moderating effect only operates downwards but not upwards.

Related to our study, some previous papers have analyzed the effects of different information regimes on cooperation in public goods games. In contrast to us, all of these studies focus on the dynamic effects of information in repeated interactions and, overall, report rather mixed results. While Sell and Wilson (1991) find higher cooperation rates under individual compared to aggregate contribution feedback, Carpenter (2004) reports an effect in the opposite direction, while Croson (2001) and Bigoni and Suetens (2012) find no significant differences across these two feedback conditions.² We differ from these studies by applying a one-shot game which rules out possible confounds due to strategic considerations. Because we use the strategy method rather than a direct-response experiment, we can further draw inference about people's general willingness to cooperate without any distortion due to beliefs. In addition, this allows us to observe responses in nodes of the game that are rarely reached by actual play.

There are two further related studies looking at the effect of heterogeneity in others' individual contributions on cooperation. Using data from a repeated public goods game, Croson (2007) finds that the median contribution of others in the previous period is a better predictor of subjects' contributions in the next round than either the minimum or the maximum of others. However, because in her game subjects interact repeatedly - again - her results might partially be driven by strategic considerations. Cheung (2013), who developed his design independently of ours, also employs the strategy method to study how individuals' willingness to contribute responds to variation in others' contributions. Unlike us, he only considers a situation in which information about individual contributions is given (our *IND* treatment), and applies a reduced public goods game with only three players and four possible contribution levels. Because we apply an often employed parameterization of the public goods game (groups of four, $MPCR=0.4$, contribution levels between 0 and 20), our results are more likely to be comparable to the results from previous public goods experiments. Furthermore, because compared to Cheung we also have a richer dataset (more observations per individual), we can extend his findings by looking more closely at individual heterogeneity in reactions towards variation in others' contributions.

Our paper proceeds as follows. The next section describes the experimental design and procedures. In section 3, we discuss behavioral predictions based on different models of other-regarding preferences. The experimental results are presented and discussed in section 4. Section 5 concludes.

²See also Vesterlund (2003) and Irlenbusch and Rilke (2012) for further studies looking at the effects of information on public goods provision.

2 Experimental Design and Procedures

2.1 The Basic Setup

In our experiment we apply a standard one-shot linear public goods game. Subjects are randomly matched into groups of four and each subject is endowed with 20 tokens which she can either (partly or fully) keep or contribute to a joint project. The payoff function for each individual i is given by:

$$\pi_i = 20 - c_i + 0.4 \sum_{j=1}^4 c_j,$$

where the amount of public good provision is equal to the sum of contributions of all group members. If subjects are only interested in maximizing their own monetary payoff, the dominant strategy for each subject i is to free-ride completely, i.e., $c_i = 0$ for all i . However, as marginal social benefits exceed marginal private costs, social welfare is maximized when all group members contribute their whole endowment. Hence, we have a typical social dilemma situation in which individual and group interests are at odds.

Within this basic setting, we elicit people's general attitude towards cooperation by allowing subjects to state their contributions conditional on the contribution decisions of others. Following the design of FGF, each subject is asked to make two types of decisions: an *unconditional contribution* and a *conditional contribution*. The unconditional contribution is a single decision in which subjects choose how many of their 20 tokens they want to contribute to the public good. For the conditional contribution, we apply a variant of the "strategy method" (Selten, 1967). In a series of decisions, subjects have to indicate how much they want to contribute given specific public goods contributions by the other group members. Like in FGF, to ensure incentive compatibility at the end of the experiment a random mechanism determines for each individual which of the two decisions – the *conditional* or the *unconditional contribution* – becomes payoff-relevant. Therefore, in each group, for three randomly selected subjects the *unconditional contribution* is used. For the fourth subject, the *conditional contribution* corresponding to the other three group members' unconditional contributions applies.

2.2 Treatments

Our experimental design comprises three between-subjects treatments in which we systematically vary others' individual contributions and the information subjects receive about it (see Table 1 for an overview).

In the first treatment (*AVG*), only information about others' average behavior is provided, i.e., participants are shown a table in which they are asked to state their conditional contributions for each of the 21 possible values of (rounded) average contributions by the other three group members (compare the original paper by FGF). Hence, in this treatment, if subjects want to match a certain contribution of any of the other group members or are concerned about the composition of the average, they have to form beliefs about the distribution of individual contributions

In our second treatment (*IND-AVG*), we remove this lack of knowledge by additionally providing information about others' individual contributions. This means that in this treatment, when stating their conditional contributions subjects are shown the complete vector of others' individual contributions as well as the corresponding average contribution. This allows us to investigate how subjects condition their contributions depending on the specific composition of individual contributions in the group. To operationalize this, we apply the so-called *Conditional Information Lottery* design that has been previously used and validated by Bardsley (2000) and Bardsley and Sausgruber (2005). In total, subjects are confronted with 36 tasks displayed in a contribution table. There are 35 fictitious tasks chosen by the experimenters and 1 real task determined by the actual unconditional contributions of the subject's group members.³ Subjects are told that all but one task are fictitious and that only the real task will affect earnings. Importantly, participants do not know ex-ante which task is the real one and thus have an incentive to treat each task as being payoff relevant.

The fictitious tasks are chosen such that (i) subjects cannot easily figure out which task contains the real unconditional contributions of their group members, and (ii) they exhibit sufficient variation to investigate the effects of heterogeneous contribution behavior on the willingness to cooperate. To ensure (i) we fit the distribution of contributions used in these tasks to a typical one-shot public good experiment with the same parameters that was run as a pilot.⁴ To achieve (ii) we implement several cases which have the same average but differ in the composition of individual contributions. For example, while in one case an average of 5 is given by individual contributions of 5/5/5, in another case the same average results from individual contributions of 0/5/10. For an overview of all 35 fictitious tasks see Table A1 in the Appendix.

Finally, our third treatment (*IND*) is identical to *IND-AVG* treatment except for the fact that we remove the aggregated feedback and only provide information about others' individual contributions. The comparison between the two treatments allows us to examine whether providing average information on top of individual information moderates the effect of variation in others' individual contributions. Although subjects in *IND* could, in principle, easily calculate the average contribution of others as well, it is not clear whether they indeed do engage in such reasoning. Social psychologists, for example, have argued that people sometimes act as *cognitive misers* who rely on cognitive shortcuts and who do not use all information available (Fiske and Taylor, 1991). Furthermore, from a methodological point of view this treatment allows us to vary only one dimension at a time going from *AVG* to *IND-AVG* to *IND*.

³When the real task is identical to one of the 35 fictitious tasks, we add another fictitious task so that no task shows up twice. The restriction to a manageable set of selected cases is necessary as the the number of all possible combination of other players' contributions amounts to 1771, which makes it hardly feasible to let subjects decide for each possible contribution level. Note that this approach is different to the one of Cheung (2013) who instead restricts the number of players to three and the possible contribution levels to 0, 2, 4, and 6 which, in turn, allows him to include all possible combinations of others' contributions.

⁴After the experiment we asked subjects for their incentivized beliefs about which case is the actual combination of contributions. Our results reveal that each case was selected at least once and only 10 out of 256 (3.9%) participants guessed the actual combination correctly, which is not significantly different from random luck ($1/36 = 2.78\%$; binominal test: $p = 0.252$).

2.3 Procedures

The experiment was conducted at the Cologne Laboratory for Economic Research (CLER). We used the experimental software z-Tree (Fischbacher, 2007) and recruited student participants from the University of Cologne with the online recruiting software ORSEE (Greiner, 2004). In total, we ran twelve experimental sessions with 32 participants each. Thus, we had 384 subjects, 128 per treatment. At the beginning of each session, participants were randomly assigned to cubicles in the lab. After taking seats, subjects had to read the instructions explaining the public goods problem, the incentives, and the rules of the game. After that, participants had to answer several control questions to make sure that they understood the game. Only after all participants had answered all questions correctly, the experiment started. At the end of each session, subjects were asked to fill in a short questionnaire on their motivation and demographic data. Afterwards, they were informed about the decisions of their group members and about their payoffs. Finally, participants were privately paid their individual earnings in cash. On average, participants earned €14.50 and all sessions lasted for approximately one hour.

3 Behavioral Predictions

In the following, we discuss the predictions of different theories of other-regarding preferences on how heterogeneous contribution behavior of others could influence people's willingness to cooperate. All three models we discuss are consistent with free riding, but make different predictions for 'conditional cooperators'. For more formal considerations supporting our lines of reasoning we refer the reader to the Appendix.⁵

According to the model of Fehr and Schmidt (1999; henceforth FS-model), individuals suffer both from advantageous and disadvantageous inequality, with the latter looming at least as large as the former. Individuals with such preferences are willing to contribute to the public good if others do so as well provided that the benefit of reducing the costs of (advantageous) inequity outweighs the monetary costs of contributing. Given the payoff structure of our experiment and the assumptions of the FS-model, this condition can only be fulfilled if the own contribution is equal or lower than the lowest contributions of others, i.e., no player wants to be worse off than the richest of the other group members.⁶

In contrast, the model of Bolton and Ockenfels (2000; henceforth BO-model) assumes that individuals suffer from inequity when their own payoff differs from the *average* payoff. Because the average does not vary with the specific composition of others' contributions, in our context the BO-model predicts no effect of disclosing heterogeneous individual contribution behavior of others.

Finally, the model by Charness and Rabin (2002; henceforth CR-model) assumes that people are concerned about efficiency and that they care about the group member with the lowest payoff (maximin). Because in the public goods game, the lowest payoff belongs to the group member contributing the most, this model can explain why individuals might be willing to

⁵The intention of our experiment is to analyze reactions to the composition of others' contributions. We do not aim at contesting the different models (see e.g., Engelmann and Strobel, 2004).

⁶See also Sugden's principle of reciprocity (1984) which is related.

contribute up to the maximum contribution of others when being provided with this information.⁷

Taken together, when holding constant the average contribution of others, an increased spread of others' individual contributions may have a negative (FS-model), a positive (CR-model), or no effect (BO-model) on people's willingness to contribute.

4 Results

We divide our analysis in two parts. First, we compare contribution behavior across the three treatments to analyze how different information about others' contributions influences people's willingness to cooperate. Second, we investigate behavior in the *IND* and *IND-AVG* treatment more closely to identify behavioral patterns depending on the composition of others' individual contributions.⁸

As a first step, we follow a similar approach as FGF and group subjects depending on their conditional contributions into three different contribution types: 'conditional cooperators' who contribute more to the public good the more others contribute, 'free riders' who never contribute a positive amount irrespective of what others do, and 'others' who display more complicated patterns.⁹ The results from this categorization reveal that across treatments we find a similar fraction of 'conditional cooperators' (*AVG*: 67%, *IND-AVG*: 60%, *IND*: 56%; $\chi^2(2) = 3.74$, $p = 0.154$)¹⁰, a similar fraction of 'free riders' (*AVG*: 22%, *IND-AVG*: 16%, *IND*: 20%; $\chi^2(2) = 1.29$, $p = 0.524$), but a significantly different fraction of 'others' (*AVG*: 11%, *IND-AVG*: 24%, *IND*: 24%; $\chi^2(2) = 9.05$, $p = 0.01$). Since we are interested in systematic reactions to variation in others' individual contributions, in the following, we concentrate on the behavior of 'conditional cooperators' only. Also note that 'conditional cooperators' constitute the largest fraction in each of the three treatments.

4.1 Effects of Individual vs. Average Information on Conditional Cooperators

We start our analysis by pair-wise comparing contribution behavior of 'conditional cooperators' in *IND-AVG* and *IND* with the corresponding cases in *AVG* that have the same (rounded) average of the other group members' contributions. Among all 35 comparisons, 19 reach statistical significance using a non-parametric Kruskal-Wallis-test ($p < 0.1$). When having a closer look at these cases, it turns out that treatment differences are particularly strong when others' individual contributions are relatively uniform and less pronounced when they differ a lot. This can be illustrated by comparing the standard deviation of others' individual contributions¹¹ between the cases yielding significant and insignificant treatment comparisons, respectively. While the former have an average standard deviation of 3.3, for

⁷If the concerns for efficiency are sufficiently strong, the CR-model can even explain full contributions to the public good irrespective of others' behavior. However, previous evidence suggests that there are only very few people who contribute unconditionally to increase overall welfare.

⁸In the following it is important to keep in mind that the presented results are based on our selection of the 35 cases. While we have no indications that this selection affects our findings in any systematic way, it should be mentioned that it might not be immediately clear whether our results generalize to the complete set of possible cases.

⁹See the Appendix for an exact description of our classification strategy.

¹⁰All reported statistical tests in this paper are two-sided if not stated otherwise.

¹¹Throughout the paper we will use the standard deviation in others' individual contributions as a simple measure for contribution heterogeneity. Very similar results are obtained, however, using alternative measures such as the range or the variance.

the latter it is 5.7. These results are mainly driven by differences between *IND* and *AVG*, i.e., when either only individual or only average information is provided. When both types of information are given, this effect of variance is moderated, leading to intermediate contributions (compare Table A1 in the Appendix). We summarize this finding in our first observation:

Observation 1: *If others' individual contributions are relatively uniform, this has a positive effect on cooperation compared to presenting only the average contribution. If individual contributions vary a lot, contributions are similar under both information regimes. When both types of information are provided, this effect is moderated.*

This result is further supported by a regression analysis. Table 2 shows results from a random effects regression with own conditional contributions as the dependent variable and average contribution of the other group members as the independent variable. To isolate the effects of the three information regimes, we use the *IND-AVG* treatment as the reference group and include dummy variables for *IND* (removing average information) and *AVG* (removing individual information), respectively, and interact them with the average others' contributions.

The results reveal that 'conditional cooperators' contribute on average 0.86 tokens for each token of the others' average contribution when both types of information are available. If only average information is available, this decreases to 0.77 tokens (-12%), which is significantly less (Wald-test, $p < 0.001$). In contrast, if only individual information is available, contributions per-token of others' average contribution amount to 0.84 tokens which is not significantly different from *IND-AVG* ($p = 0.186$), but significantly higher than in *AVG* (Wald-test, $p < 0.001$). Furthermore, we also observe a significant level effect between *IND* and *IND-AVG* (Wald-test, $p = 0.037$), but not between *IND* and *AVG* (Wald-test, $p = 0.243$) or *IND-AVG* and *AVG* (Wald-test, $p = 0.167$).

Taken together, these results indicate that compared to the situation in which both types of information are given, removing average information leads to generally higher contributions, whereas removing individual information has a negative effect on conditional contributions. To further investigate what drives these results, in the following we study in more detail to what extent individual information about others' individual contributions affects subjects' willingness to cooperate.

4.2 Effects of Heterogeneous Individual Contributions on Conditional Cooperators

To test how subjects in *IND* and *IND-AVG* react to the composition of the average contribution, in Table 3 we apply random effects regressions with individual contributions as the dependent variable. As a benchmark, in model (1) we use the average contribution of others, a dummy for *IND-AVG*, and their interaction as independent variables. To verify the importance of variance in the other group members' contributions, in model (2) we include the standard deviation of the individual contributions as a measure of heterogeneity. The results underline that 'conditional cooperators' do not only care about the average of others' contributions, but also about its composition. Ceteris paribus, we find that the more spread

out others' individual contributions, the lower, on average, the willingness to contribute. This constitutes our second observation:

Observation 2: In addition to the expected strong and positive effect of the *average contributions of others*, we find that the higher the variation in others' individual contributions, the lower, on average, the willingness of 'conditional cooperators' to contribute.

Model (2) in Table 3 further shows that the standard deviation of others' contributions affects 'conditional cooperators' similarly in both treatments, but overall they contribute approximately one token less in *IND-AVG* compared to *IND*. To gain a better understanding of why this is the case, in model (3) in Table 3 we decompose the effect of the average into its three components *minimum*, *median*, and *maximum* and assess the relative importance of each of these factors. If all three components were equally important for contribution behavior and the composition of individual contributions was irrelevant, each coefficient would have equal size.

For the *IND* treatment our estimation results reveal that the minimum is significantly more important than the median (Wald-test, $p < 0.001$) and the maximum ($p = 0.006$), and that the maximum is slightly more important than the median ($p = 0.072$). In the *IND-AVG* treatment, the weight of the minimum remains similar relative to *IND*, but the weight of the median and maximum significantly increases and decreases, respectively. As a result, the minimum and median are relatively more important than the maximum (Wald-test, $p < 0.001$ and $p = 0.018$, respectively), but the difference between minimum and median is now insignificant ($p = 0.282$). Thus, increasing the minimum, median, and maximum by one token explains 39%, 28%, and 33%, respectively, of the total effect in *IND*, and 37%, 34%, and 28%, respectively, of the total effect in *IND-AVG*. Also note that the treatment dummy for *IND-AVG* is now insignificant which indicates that apart from the different influences of the median and the maximum, contribution behavior is similar in *IND* and *IND-AVG*.

These results are interesting as they suggest a form of self-serving bias when average information is provided on top of individual information. While it does not mitigate the effect of the minimum, it does effectively weaken the effect of the maximum on the willingness to contribute. Put differently, providing average information indeed seems to have a moderating effect, but only into the direction of self-interest.

Overall, the results from both treatments suggest that 'conditional cooperators' are more inclined to follow the bad example of a low contributor rather than the good example of a high contributor, i.e., increasing the minimum contribution has a stronger effect on enhancing cooperation than increasing the maximum. While so far we have only looked at aggregate effects, in the following we investigate to what extent 'conditional cooperators' differ with respect to how they react to heterogeneity in others' individual contributions. We therefore estimate the following model

$$contribution_i = \beta_{0i} + \beta_{1i} \cdot average + \beta_{2i} \cdot std.deviation + \epsilon_i$$

separately for each individual i (compare model (2) in Table 3). This allows us to sub-classify ‘conditional cooperators’ depending on whether they react positively, negatively, or neutrally to variations in others’ contributions as indicated by a significantly positive, significantly negative, or insignificant β_{2i} coefficient (at the 5% level). We refer to these three types as *high*, *low*, and *average* types, indicating that they tend to align their contributions primarily with the highest, the lowest, or the average contribution of the other group members, respectively.¹²

According to this criterion, we find 25% *low* types, 61% *average* types, and 14% *high* types in *IND*, and 27% *low* types, 66% *average* types, and 7% *high* types in *IND-AVG* (see also Table 4). Hence, while the majority of ‘conditional cooperators’ does not significantly adjust their contributions to the composition of others’ individual contributions, more than one third of the subjects do indeed systematically react to heterogeneity in others’ individual contributions. In line with the overall negative effect at the aggregate level, at the individual level we find that more subjects react negatively rather than positively to the variance in others’ contributions.

This imbalance is illustrated in Figure 1 showing the distribution of individual reactions towards the variance in others’ contributions (as measured by β_{2i}). While in both treatments the majority of observations is around zero, both distributions are clearly left-skewed indicating that more ‘conditional cooperators’ react negatively rather than positively to variation. We summarize our findings in our third observation:

Observation 3: *There is pronounced heterogeneity in how ‘conditional cooperators’ react to the variation in others’ contributions. While the majority is mainly guided by others’ average contribution, a considerable fraction also takes into account the composition of others’ individual contributions. Within the latter group, we find that more people follow the bad example of low contributors rather than the good example of high contributors.*

While observation 3 is true in *IND* and *IND-AVG*, there are also some differences between both treatments. In particular, in Figure 1 in *IND-AVG* we observe a much flatter right-tail and a higher spike at zero compared to the *IND* treatment. In line with the previous results from our aggregate analysis, this suggests that providing additional average information moderates the effect of variation in others’ individual contributions into the direction of self-interest.

In the following, we investigate to what extent the general willingness to cooperate and reactions towards variation in others’ individual contributions correspond with each other. Table 4 shows the average type-specific reactions towards the average and standard deviation of others’ contributions as estimated by the model. Two interesting observations can be made from that. First, Columns 2 and 5 reveal that on average all types react very similarly to the average contribution of others. In fact, a non-parametric Kruskal-Wallis test cannot reject the null hypothesis that coefficients come from the same distribution (*IND* $p = 0.402$;

¹²Note that the three types loosely correspond to the three other-regarding preference models discussed in section 3, i.e., a high type tends to be more in line with CR-model, the low type tends to be more in line with the FS-model, and the average type tends to be more in line with the BO-model.

$IND-AVG$ $p = 0.575$). Furthermore, the correlation between β_{1i} and β_{2i} is also very low and not significantly different from zero (Spearman-rank correlation; IND , $\rho = 0.174$, $p = 0.147$; $IND-AVG$, $\rho = 0.053$, $p = 0.650$). We summarize these findings in our fourth result:

Observation 4: *The general willingness of ‘conditional cooperators’ to contribute, and the way how they react towards heterogeneity in others’ individual contributions are independent factors that both affect contribution behavior.*

Second, while the magnitude of reactions towards the variance appears on average to be relatively low, conditional on being a *low* or *high* type, these reactions can be quite substantial (compare Columns 3 and 6). Holding others’ average contribution constant, increasing the standard deviation of others’ contributions by one unit changes contributions in IND and $IND-AVG$ on average by 0.44 and 0.36 tokens, respectively, which is roughly half of the effect of increasing the average by one unit. For average types, this effect has a mean of zero.¹³

Taken together, while the majority of ‘conditional cooperators’ are mainly guided by the average contribution, others react strongly to variation in individual contributions, especially with a propensity towards self-interest.

5 Discussion and Concluding Remarks

We experimentally investigate how different information about others’ individual contributions affects people’s willingness to cooperate in a one-shot linear public goods game. We find that compared to when only average information is available, providing information about others’ individual contributions has a positive effect on subjects’ willingness to cooperate. This effect is particularly strong when others’ individual contributions are relatively homogeneous and less pronounced when they differ a lot. Explicitly announcing the average on top of individual contributions has a moderating effect leading to intermediate contributions.

When information about individual contributions is provided, on average, we find that the willingness of conditional cooperators to contribute is the lower the more spread out others’ contributions are. At the individual level, however, we find pronounced heterogeneity in how ‘conditional cooperators’ react towards variation in others’ contribution. While the majority is mainly guided by the average contribution, a significant fraction of ‘conditional cooperators’ systematically adjusts their own contribution to the composition of others’ individual contributions. In line with the results from the aggregate analysis, we find more subjects who adjust their contributions downwards rather than upwards when others’ contributions differ a lot. This suggests that ‘conditional cooperators’ are more likely to follow the bad example of an uncooperative group member rather than the good example of a high contributor.

¹³As a robustness check for our classification into *low*, *average*, and *high* types, for each conditional cooperator i we also estimate a model explaining own contribution by the minimum, median, and maximum contributions of others. As expected, *low types* react most to the minimum contribution, *high types* react most to the maximum contribution, and *average types* react fairly equally to all three contributions (compare Table A3 in the Appendix).

This result may provide useful insights into management practices within firms. When constructing teams, for example, forming groups of equal performers is generally preferable because in diverse teams, it is more likely that the negative effect of low performers outweighs any positive effects of the high performers.

The result also provides a potential explanation for why when only aggregate information is available, many ‘conditional contributors’ fall short of matching others’ average contributions perfectly. Although we cannot directly test this hypothesis with our data, the behavior we observe in our experiment is at least consistent with the assumption that the lack of information about individual contributions provides subjects with moral “wiggle room” to self-servingly form pessimistic beliefs about others’ minimum contribution which they then try to match. This suggests that even in groups consisting only of ‘conditional cooperators’ it may be difficult to keep contributions on a high level as the presence (in case individual information is available) or the belief (when only average information is available) of a “rotten apple” could give ‘conditional cooperators’ a sufficient reason to justify low own contributions (see Fischbacher and Gächter, 2010, for a similar argument).

Finally, our results might also add to the understanding of previous findings showing that peer-punishment typically stabilizes or even increases contributions. While in public goods games without punishment subjects typically only receive information about average contributions, introducing peer-punishment requires revealing individual contributions (see e.g. Fehr and Gächter, 2000). In the light of our results, this difference in information itself could add to the stabilization of contributions in public goods games with punishment. Additionally, when punishment leads to more equal contribution behavior in subsequent rounds, our results suggest that subjects become inherently more willing to contribute at that level, so that the stabilizing effect is not exclusively due to the threat of punishment.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1. Distribution of individual reactions of conditional cooperators on the variance in others' contributions

Table 1
Overview of our experimental treatments

Treatment	Information about individual contributions	Information about average contributions	# Obs.
<i>IND</i>	Yes	No	128
<i>AVG</i>	No	Yes	128
<i>IND-AVG</i>	Yes	Yes	128

Table 2
Treatment differences in contribution behavior of conditional cooperators

Dependent variable: Own contributions	(1)
avg. others' contribution	0.864 *** (64.16)
AVG * avg. others' contrib.	-0.098 *** (-5.92)
IND * avg. others' contrib.	-0.025 (-1.32)
IND 1 if treatment = IND and 0 otherwise	1.011 * (1.94)
AVG 1 if treatment = AVG and 0 otherwise	0.419 (0.84)
Constant	-0.687 * (-1.90)
<i>N</i>	6986

Notes: The table reports results from random effects regressions. We use data from all 35 cases of conditional cooperators in *IND*, *IND-AVG*, and all 21 cases of conditional cooperators in *AVG*. *z* statistics are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3
Determinants of contribution behavior of conditional cooperators

Dependent variable: Own contributions	(1)	(2)	(3)
avg. others' contribution	0.838 *** (62.31)	0.840 *** (62.58)	
<i>IND-AVG</i> * avg. others' contrib.	0.025 (1.36)	0.026 (1.39)	
STD. DEV.		-0.054 *** (-3.25)	
<i>IND-AVG</i> * STD. DEV.		-0.021 (-0.93)	
MIN			0.333 *** (24.40)
MED			0.239 *** (17.17)
MAX			0.281 *** (21.95)
<i>IND-AVG</i> * MIN			-0.012 (-0.65)
<i>IND-AVG</i> * MED			0.058 *** (2.99)
<i>IND-AVG</i> * MAX			-0.036 ** (-2.01)
<i>IND-AVG</i> dummy 1 if treatment = <i>IND-AVG</i>	-1.011 ** (-2.03)	-0.922 * (-1.82)	-0.762 (-1.50)
Constant	0.324 (0.90)	0.549 (1.50)	0.397 (1.08)
<i>N</i>	5180	5180	5180

Note: The table reports results from random effects regressions. In all specifications we use data from all 35 fictitious cases of conditional cooperators in *IND* and in *IND-AVG*. z statistics are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4
Distribution of types of conditional cooperators and their average reactions to the average and standard deviation of others' contributions

Type	IND treatment			IND-AVG treatment		
	$\bar{\beta}_1$	$\bar{\beta}_2$	# Obs.	$\bar{\beta}_1$	$\bar{\beta}_2$	# Obs.
<i>low</i>	0.81	-0.43	18 [25%]	0.88	-0.36	21 [27%]
<i>average</i>	0.84	-0.01	43 [61%]	0.85	-0.00	51 [66%]
<i>high</i>	0.88	0.44	10 [14%]	0.94	0.36	5 [7%]
<i>All</i>	0.84	-0.05	71	0.86	-0.08	77