Public good production in heterogeneous groups: An experimental analysis on the relation between external return and information*

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Abstract

In this article, we study voluntary contributions of heterogeneous groups to a public good in an experiment. Members of the same group have either low or high external marginal returns. We vary the level of information about the heterogeneity and about a contributor's type between groups. While controlling for the net costs of contributions, we find that the level of information determines how types in heterogeneous groups vary in their contributions. When the type of a contributor can be identified, types with high returns contribute more, otherwise the effect disappears or even reverses with low types contributing more than high types. This result provides evidence for the so-called "poisoning-of-the-well" effect and demonstrates how it interacts with the information structure of the environment. Without any information about heterogeneity, there is no difference in contributions by types.

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Keywords: Public goods; Voluntary contribution mechanism; Heterogeneity in marginal per capita returns; Internal and external return; Information on types and type specific contributions; Poisoning-of-the-well

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1 Introduction

Heterogeneity in general affects cooperation in many ways. Team members who contribute to joint projects differ, for instance, in their talents, skills, and qualifications. In some cases, heterogeneous abilities are even necessary to achieve a common goal (Papps et al. (2011)) or to be more productive (Hamilton et al. (2003)). Although members in heterogeneous groups might be motivated to contribute to a joint project because of concerns for social returns (e.g., Andreoni (1988 and 1990)) and conditional cooperation (e.g., Fischbacher et al. (2003), Gächter (2007)), the channel through which heterogeneity among group members affects individual contributions to a joint project is not clear, as the heterogeneity affects not only the returns, but also the costs of cooperation. In a group with heterogeneous abilities,[1] normative conflicts may arise as social preferences themselves could be influenced by the perception of heterogeneity, namely how individuals perceive their ability and that of others.

Role dependent preferences (as documented by Goeree et al. (2002), Gächter and Riedl (2005) and Bellemare et al. (2008)) can lead to conflicting views on what contribution norm should apply in heterogeneous groups, as an example of the Bonn orchestra illustrates. In this context, the rehearsal time before the performance can be interpreted as the net contribution of each musician to the joint project, the performances in front of the public. This net contribution varies amongst musicians. Soloists spend less time rehearsing with the whole group compared to violinists while receiving the same pay, thus earning a higher relative pay per joint rehearsal time. The management of the Bonn orchestra justified the difference in the relative pay between violinists and soloists with the excellence of soloists and their vital contribution to the joint project. The management referred to the high pressure soloists face when performing and refused to adjust the pay according to the rehearsal time. Violinists disagreed strongly and made a complaint.[2] While violinists considered equal remuneration of each musician's nominal work hours as fair, management and soloists seemed to favor remuneration according to the effective contributions to the joint project, the latter accounting for other factors such as responsibility, stress, etc. This dispute in the Bonn orchestra illustrates that conflicting views on fair contributions are likely to emerge in groups with heterogeneous abilities and plural values (Konow (2000), Konow (2003), Cappelen et al. (2007)).

This example fits the standard conflict in public goods experiments, where contributions increase the public good by more than what each member contributed. Contributions are costly and the

[1] In this paper, the term "*ability*" refers to the external return of a contribution. The external return indicates by how much a group member's contribution increases the public good. Other scholars have referred to the external return also as "productivity" (Tan (2008)) or "capacity" (Kölle (2015)).

[2] The case was eventually settled with hiring part-time student violinists for some rehearsals to fill in for the overworked violinists (Klassik News, March 24, 2004 and Kölner Stadt-Anzeiger, July 16, 2004).

returns of the joint project are shared equally among all group members, providing incentives to free ride. This trade-off represents the social dilemma situation. In other words, contributing to the joint project is socially efficient but not in the interest of the individual member. It becomes a source of normative conflicts as multiple contribution norms may arise (Kingsley (2016) and Nikiforakis et al. (2012)). Conflicting norms may even intensify when persons differ in their ability to contribute to the public good, as in our example. Two factors that influence voluntary contributions, and thus may exacerbate or mitigate such conflicts, are the efficiency of contributions and information about others and their behavior.

In this article, we examine the relationship between information and heterogeneous abilities to increase a public good. Thereby, we bridge two strands of public goods research. The first studies the effect of returns on contributions, and the second is looking at how information conditions affect contributions. The challenges we are confronted with in order to understand the effect of ability on the contribution to public goods are threefold: first, the literature on groups with heterogeneous marginal per capita returns does not control for the net costs of contributions. A higher marginal return makes contributions more efficient and might trigger efficiency concerns or altruistic preferences. However, a high return also decreases the net costs of contributions to the public good rendering contributions more affordable, a consequence that has been overlooked so far in the literature that studies heterogeneity in returns from public goods. Second, the literature on internal and external returns focuses exclusively on homogeneous groups. This literature cannot address how individuals react when group members differ in their return rates. And third, the literature on returns and the literature that explicitly studies the effect of information on public goods focuses only on situations where all group members' return rates are common knowledge. The literature on information in public goods experiments has studied the effects of reporting individual or aggregate contribution levels, but has not considered different types of contributors or varied the information about contributions of different types.

Our experimental design improves on these points. We vary the individual ability within groups while controlling for the costs of contributing. This allows us to exclude lower net contribution costs as a motive of high ability members to adjust their contributions in a heterogeneous environment. We systematically change the information scenarios under which persons make their contribution decisions, which allows us to better study conflicting social norms of contributing to the public good. Thus, the novel contribution of this study to the literature is twofold. It is the first to isolate the effect of external returns on contributions from the net costs of contributing in heterogeneous groups. And, it presents the first analysis on how information on peers' abilities affects contributions. In brief, this is to the best of our knowledge the first study to investigate the effect of the ability to increase the public good and the effect of information on cooperation in heterogeneous groups in a systematic way.

Our results can be summarized as follows. We find that in the absence of information about heterogeneity in the ability to increase the public good, contributions of both ability types are identical. When heterogeneity is known to be present, but contributions cannot be linked to the contributors' types, group members with lower external returns tend to contribute more than those with higher returns. When, additionally, contributions can be linked to the contributors' types, individuals with a higher external returns tend to contribute more than those with lower returns. Given our results, we can attribute the positive relation between marginal per capita return and contributions reported in the literature at least partly to the external return and conclude that the relation persists even when controlling for the net costs of contribution. However, the positive relation of contributions and the external return holds only as long as there is common knowledge about external returns and the contributor's type. As soon as both or only one part of information is lacking, this relation breaks down. Without any information about the existence of heterogeneity, persons with different returns make the same nominal contributions, i.e., ensure that they have the same contribution costs. When individuals know about the heterogeneity, but cannot link contributions to a specific type, low types contribute more than high types, while the inverse behavior is observed, i.e., high types contribute more than low, when contributions can be linked to the types. This behavioral pattern resembles what Fisher et al. (1995) presented as puzzle and named the "poisoning-of-the-well."[3] The results of our study suggest that this effect is closely related to the information structure of the environment. In addition, our results provide empirical support for a conjecture by Ledyard (1995, p.159-160) that contributions to joint projects in heterogeneous groups are very likely to be influenced by the information about heterogeneity. Our results indeed show that type specific contribution behavior is not stimulated by heterogeneity per se – as would be suggested by efficiency concerns or altruism–, but by heterogeneity in interaction with information.

The remainder of the article is organized as follows. Section 2 summarizes related research and places the current study in the literature. Section 3 describes the experimental design and the procedure and gives a descriptive overview of the data. We introduce our empirical model of individual contribution behavior in section 4. Our results are presented in section 5 and discussed and summarized in

[3]Fisher et al. (1995) introduced the term "poisoning-of-the-well" to refer to persons who are better off due to their high marginal per capita returns ("the well"), but who contribute less in heterogeneous groups than in homogeneous groups that consist only of their own type. We discuss the relation to our results further in section 6.
"Poisoning-of-the-well" resembles the rhetoric expression "poisoning the well," the latter referring to the action of deliberately presenting adverse information about a person with the aim to discredit this person. Whether the resemblance was intended by Fisher et al. (1995) is not clear, however, even though the meaning of both expressions is very distinct, they refer to deliberate negative actions.

section 6, highlighting our contribution to the literature. We conclude in section 7.

2 Literature

In this section, we summarize related results from the (linear) public goods literature and position our paper. Thereby, we focus on two aspects of public goods: returns and information setting. For comprehensive surveys on public goods in experimental economics beyond this subset of the literature see Ledyard (1995) and Camerer (2003).

2.1 Returns from public goods

The effect of public good returns on contributions is of constant interest and has been investigated extensively. Thereby, returns of public goods have many dimensions that can vary between groups or across members within a group. Whatever the focus of interest, linear public goods are all structured in a similar way. Public goods experiments usually study behavior of groups with 3 to 10 members. Each group member has a monetary endowment w and can contribute to the public good that will be shared equally amongst its members. For instance, if member i contributes c_i to the public good, i receives the return $\mathbf{G}_i$ generated by the public good. What i does not contribute, i.e., the difference between i's endowment (w) and contribution (c_i), stays in a private account. The marginal return from the private account is usually normalized to one.[4] This general structure can be summarized as follows:

$$\pi_i = w - c_i + \mathbf{G}_i \tag{1}$$

The literature varies the way the return from the public good $\mathbf{G}_i$ is modeled. The most general representation of $\mathbf{G}_i$, that nests several models in the literature, is

$$\mathbf{G}_i = \iota_i c_i + \mu_i \sum_{\forall j \neq i} \epsilon_j c_j \tag{2}$$

and is presented in line (1) of Table 2. In this general version, the contribution of member i has several effects. First, member i benefits from the own contribution to the public good by $\iota_i \cdot c_i$, also referred to as "internal return", usually with $0 < \iota_i < 1$. The marginal net cost of member i contributing to the public good $(1 - \iota_i)$ is larger than zero, because of ι_i being smaller than one,

[4]We concentrate on returns from the public good and, for simplicity, we ignore that the marginal return of investments in the private account might differ between members. For research that has looked into the effect of varying returns to private and public accounts see Palfrey and Prisbrey (1997).

which provides the monetary incentive for free-riding. Second, i's contribution generates a surplus for other group members, the "external return." Vice versa, others' contributions generate external returns for i, denoted by $\epsilon_j, \forall j \neq i$ for each unit contributed by member j. We interpret the external return as "ability," which is similar to other interpretations of ϵ, such as "productivity" (Tan (2008)) or "capacity to contribute" (Kölle (2015)). Ability determines the effective contribution ($\epsilon_j \cdot c_j$) by which member j's contribution increases the public good. Contributions of persons with higher ability thus increase the public good more effectively. For example, to achieve the same effective contributions regardless of ability, members with high ability will have to contribute less than members with low ability ($\epsilon_h \cdot c_h = \epsilon_l \cdot c_l$ with $\epsilon_h > \epsilon_l \rightarrow c_h < c_l$). Another example constitutes that the same nominal contributions lead to higher effective contributions by persons with higher ability ($c_h = c_l$ with $\epsilon_h > \epsilon_l \rightarrow \epsilon_h \cdot c_h > \epsilon_l \cdot c_l$).

However, by how much i benefits from others' contributions depends not only on the effective contributions of other members, but also on how much member i values the public good times the share it receives from the public good, denoted by μ_i with usually $0 < \mu_i < 1$. The combination of the own valuation for the public good, μ_i, and the ability of others to increase the public good, ϵ_j, constitutes the "external individual return" from the public good for member i, with usually $1/N < \mu_i \cdot \epsilon_j < 1, \forall j \neq i$, and with N denoting the number of group members with whom i shares the return of the public good.

Several researchers studied the effect of returns from public goods on contributions. We will present these studies now in order, explain in detail how they vary one or more of the three parameters, ι, μ and ϵ, and the restrictions they impose on these parameters. Table 1 summarizes this discussion.

In a standard public goods game, presented in line (2) of Table 1, all members have the same ability to increase the public good, meaning the same external return $\epsilon_i = \epsilon_j = \epsilon$, and the same valuation for the public good $\mu_i = \mu_j = \mu$, with an internal return for i being equal to $\iota = \mu\epsilon$. The term $\mu\epsilon$ is referred to in the literature as "marginal per-capita return" (hereafter MPCR) and indicates the marginal return from contributing one monetary unit to the public good relative to the marginal return of keeping the money in the private account, the latter is normalized to one. The marginal net cost of contributing to the public good is the same for each member ($1 - \mu\epsilon$). Isaac and Walker (1988) use this standard version of the public good and vary the MPCR in order to study its effect on contributions. They compare homogeneous groups with high MPCR to those with low MPCR. One main result of this study and others is that groups with higher MPCR have a higher propensity to contribute. This finding squares with persons having concerns for efficiency in other contexts (e.g., in dictator games (Engelmann and Strobel (2004), Andreoni and Miller (2002)) and is robust across

	Individual return $\mathbf{G}_i$ from the public good	Restrictions	Examples
(1)	$\iota_i c_i + \mu_i \sum_{\forall j \neq i} \epsilon_j c_j$		general representation
(2)	$\mu\epsilon \sum_{\forall j} c_j$	$\mu_i = \mu;\ \epsilon_j = \epsilon;\ \iota_i = \mu\epsilon$	IW88 (Standard game)
(3)	$\mu_i\epsilon \sum_{\forall j} c_j$	$\epsilon_j = \epsilon;\ \iota_i = \mu_i\epsilon$	FISW95, PP97, RR13, FST14, R16
(4)	$\mu \sum_{\forall j} \epsilon_j c_j$	$\mu_i = \mu;\ \iota_i = \mu\epsilon_i$	T08
(5)	$\mu_i \sum_{\forall j} \epsilon_j c_j$	$\iota_i = \mu_i\epsilon_i$	K15
(6)	$\iota c_i + \mu\epsilon \sum_{\forall j \neq i} c_j$	$\iota_i = \iota;\ \mu_i = \mu;\ \epsilon_j = \epsilon$	GG89, CDP92, PIB01, GHL02
(7)	$\mu \sum_{\forall j \neq i} \epsilon_j c_j$	$\iota_i = 0;\ \mu_i = \mu$	this experiment

Table 1: Structures of the individual return function of the public good ($\mathbf{G}_i$) used in the literature as nested forms of the general representation in line (1).
The return function $\mathbf{G}_i$ enters the payoff of individual i (π_i) in linear public goods experiments when contributing c_i of the own endowment w: $\pi_i = w - c_i + \mathbf{G}_i$.
Notation: "j" denotes all members of a group including i if not otherwise stated. The term "$\epsilon_j \cdot c_j$" denotes the effective contribution to the public good of each member's nominal contribution "c_j," with "ϵ_j" indicating the external return of each member to the joint project. The individual valuation for the public good "μ_i" defines how much i values the sum of others' effective contributions. The internal return "ι" describes what i receives from his/her own contribution c_i to the public good.
Notes on Examples: CDP92=Carter, Drainville and Poulin (1992), FST14=Fischbacher, Schudy, and Tessier (2014), FISW95=Fischer, Isaac, Schatzberg and Walker (1995), GG89=Goetze and Galderisi (1989), GHL02=Goeree, Holt and Laury (2002), IW88=Isaac and Walker (1988), K15=Kölle (2015), PIB01=Packard, Isaac and Bial (2001), PP97=Palfrey and Prisbrey (1997), RR13=Reuben and Riedl (2013), R16=Robbett (2016), T08=Tan (2008).

studies with different MPCR and group sizes.

Introducing heterogeneity within groups, Fisher et al. (1995), Fischbacher et al. (2014), Palfrey and Prisbrey (1997), Reuben and Riedl (2013), and Robbett (2016) study behavior of groups comprised of members with different MPCR. The return function of these studies (summarized in line (3)) has the same effective contributions for each group member $\epsilon_i = \epsilon$, but varies the valuation for the public good (μ_i). Tan (2008), on the other hand, varies the effective contributions of group members to the public good ϵ_i, but keeps the valuation for the public good constant, $\mu_i = \mu$ as shown in line (4). In these previous studies, it is not possible to separately study the effect of μ_i or ϵ_i, as they only look at their joint effect. Kölle (2015), however, varies both aspects of the return function and allows for heterogeneity in both, the valuation i has for the public good, μ_i, and i's ability to increase the public good, ϵ_i, as shown in line (5). Some of the studies that compare behavior of heterogeneous groups to that of homogeneous groups, report homogeneous groups with high returns to contribute more than groups with low returns, which is in line with the findings of Isaac and Walker (1988).[5] In addition,

[5]Some of those studies (Tan (2008), Reuben and Riedl (2013), Kölle (2015) and Robbett (2016)) are interested in punishment behavior in heterogeneous groups, the effects of which we ignore here as this aspect is not the focus of the current study.

these studies observe that in heterogeneous groups, members with high ability contribute more than those with low ability. Finally, Kölle (2015) observes that groups with heterogeneous abilities (ϵ_i) contribute more on average than those with heterogeneous valuations (μ_i). These differences are driven by low valuation types who reduce their contributions to less than half of the amount of high valuation types. However, when members differ in their ability to contribute, low ability types contribute more than double compared to low valuation types, but still slightly less than high ability types. Given this empirical evidence, one might conclude that individuals react positively to an increase in the MPCR.

The drawback of these studies is that it is impossible to identify whether the motivation to increase contributions originates from higher returns or from lower costs of contributing. This identification problem arises because internal and external returns are perfectly correlated, i.e., a higher MPCR ($\mu_i\epsilon_i$) directly implies lower marginal net costs of contributing (1-$\mu_i\epsilon_i$). In our experimental design, we aim at solving this identification problem and investigate the effect of returns in heterogeneous groups isolated from the costs of contribution. To achieve this goal, we build on the public goods literature that varies independently the internal and external returns and is summarized in line (6) of Table 1. Contrary to the literature presented so far, this stream of research makes a precise distinction between the "internal return" and the "external return" from the public good. Yet, the existing studies examine the separate effect of internal and external returns only in homogeneous groups, where all members have the same internal and the same external return ($\iota_i = \iota;\ \mu_i = \mu;\ \epsilon_i = \epsilon$).

Goetze and Galderisi (1989) and Carter et al. (1992) compare groups that have either low or high internal and low or high external returns in a 2x2 between-subjects design. Both studies find larger contributions when external returns are high, suggesting that subjects react positively to the return of the public good even when it only benefits others. Carter et al. (1992) find this effect to be present in the last 5 periods of the experiment at a significance level of 0.01 but to have disappeared in the last period.[6] Packard et al. (2001) partly replicate Carter et al. (1992) and report that even when internal returns are zero, behavior follows the general qualitative pattern in standard public goods of substantial contributions in the first rounds followed by a decay in later rounds. They also find that initial contributions of groups whose members have zero internal and non-zero external returns are the same as those of groups with the same (non-zero) internal and external returns. However, the contributions decay faster and contribution levels in the final rounds are significantly lower for groups with zero internal return.

These three experiments employed low and high returns of similar magnitude across experiments

[6] Conditional on external returns, contributions are higher when internal returns are higher, although only Carter et al. (1992) find this effect to be significant.

– around 0.3 and 0.8 (and 0 for the internal return in Packard et al. (2001)) in a between-subjects design with groups comprising four members. Subjects interacted only once, either in a one-shot experiment or with rematching groups every period in all experiments, with the exception of Packard et al. (2001), where the group composition remained the same for 10 periods. Finally, Goeree et al. (2002) study one-shot within-subjects designs with 12 treatments combining internal returns similar to previous studies (either 0.4 and 0.8) but a wider range of external returns (0.4, 0.8, 1.2, and 2.4) and groups with 2 and 4 members. They confirm earlier results that subjects react to an increase of the external return by contributing more. To sum up, these four studies provide evidence that persons in homogeneous groups react positively to external returns, even when internal returns are low – even as low as zero.

The current article bridges the two branches of literature – (i) group heterogeneity in MPCR and (ii) separating internal from external returns in homogeneous groups – by looking at heterogeneity in external returns *within* groups. We keep the internal return constant for all group members and vary only the external return that the contribution of a member generates for others, as shown in line (7) of Table 1. Thus, different members in the same group vary in their external returns ($\epsilon_i \neq \epsilon_j$), but have the same internal return ($\iota_i = \iota = 0$). The important point of our design is that the internal return is kept constant for all members which implies the same net costs of contributions. This design allows us to isolate the effect of ability on contributions from that on own well-being in heterogeneous groups. Importantly, it eliminates the confound of lower net costs for high ability types present in previous studies and elucidates the driving force of contribution behavior in a heterogeneous public goods environment.

Coming back to our orchestra example from the introduction, we can draw some links to our design. If soloists and violinists participate in as many rehearsals and are paid the same for each performance regardless of the time actually spent in rehearsals, their internal return of contributing is the same as well as are their marginal net costs of rehearsal time. In reality, however, soloists did not participate in as many rehearsal as violinists. They received the same pay for fewer hours of rehearsing, compared to violinists. This relatively higher salary created tensions with the violinists, even though management thought it to be justified because of the more effective contribution of the soloists. The orchestra management argued that soloists are more vital for a performance. Actually, whereas violinists took the point of equal net contribution costs as argument for demanding the same pay per hour of rehearsal time, management questioned this assumption and brought into consideration that net costs of soloists might be higher than that of violinists, due to, for example, higher stress and thus needed compensation.

2.2 Information settings in public goods

External returns may affect contributions via the own preferences that arise solely as reaction to changed incentives (e.g., efficiency concerns, altruism) or via more complex reflection taking own and others' incentives and contributions into account. As a consequence, information might very likely affect the channel through which heterogeneity in external returns affects contribution behavior. Therefore, in our study, we vary the information group members have about the return rates of others to generate insight in contribution behavior in heterogeneous groups. Up to this point in time, little is known about the effect that information has on contributions in public goods experiments. A few studies exist that vary the aggregation level of the information that group members receive after each round on others' contributions (Sell and Wilson (1991), Croson and Marks (1998), Andreoni and Petrie (2004)).[7] Complementary, Marks and Croson (1999) look at the information about the distribution of valuations for the public good in groups whose members vary in their valuations.

Sell and Wilson (1991) find that information on individual contributions of other group members increases average contributions – compared to providing information on aggregate contributions, or no information at all – and suggest that such behavior can partly be explained by the fact that trigger strategies and positive reinforcement can be better applied when information on individual contributions is available. These strategies can only be applied when group members interact repeatedly, thus with a partner matching protocol, where the same group members interact over several periods, but not with stranger matching, where group composition changes after every period. Supporting evidence for such behavior is reported in Cox and Stoddard (2015) who find more extreme behavior in a partner matching compared to stranger matching when information on individual behavior is available instead of aggregate contributions. Andreoni and Petrie (2004) and Croson and Marks (1998) find significantly larger contributions when – in addition to providing information on individual contributions of other group members – individual contributors can be identified, either by a digital photograph or by subject ID numbers. Marks and Croson (1999) study threshold public goods games with three levels of information that group members have about the valuations of others.[8] Their results suggest that without information on individual contributions of other group members, information on heterogeneous valuations of the public good does not alter the aggregate level of contributions.

In contrast to this literature, we investigate the effect of various levels of information in a systematic way. More precisely, we look at three conditions in which we vary the information group members have

[7] In the field, Ayres et al. (2012) look at the effect of information about energy usage of peers on energy consumption. They report high energy consumers to reduce their consumption after learning about others' consumption.

[8] In all conditions, subjects only knew whether the sum of all contributions was above the threshold, in which case the public good was provided. Otherwise, every contributor was reimbursed his or her contribution.

about the heterogeneity of the external returns in the group, but always provide information about individual (nominal) contributions of others. In the baseline treatment, group members are informed about their own internal and external return as well as individual nominal contributions of others in the previous periods. In the other two treatments, participants are additionally informed about the internal and external returns of other group members. Furthermore, only in the third treatment, participants are informed about which type made a particular contribution. This design allows us to control the level of information about heterogeneity in the external return and to systematically examine how the structure of information affects voluntary contributions in a heterogeneous environment.

3 The experiment

The experiment was designed to uncover the effect of the external return on contributions to public goods in heterogeneous groups. We exploit the variation in the information about the heterogeneity that group members have to isolate the social norms applied in heterogeneous environments. We explain the payoff function in more detail in section 3.1. Each group faces one of three information conditions about the external returns in the group, which we present in section 3.2 below.

3.1 Payoff function

In the experiment, each of the n group members has to decide how to divide the personal endowment w between a private account and a group account. Each unit that a member i allocates to the private account generates a return of one, and each unit that i contributes to the public good c_i generates an *internal return* from the public good of ι for i. Thus, the net costs for i of contributing a unit to the public good are $1-\iota$. But i's contribution also generates an external return for other group members. And vice versa, i benefits from the external returns generated by other group members' contributions to the public good. Thereby, we distinguish between the *external return* ϵ_j that indicates by how much a unit contributed by member j increases the public good for others, and the *external individual return* $\mu\epsilon_j$, that refers to how much i (and others except j) benefit from another group member's contribution. There are two external return types with equal representation of each type in the group: a low ability type (ϵ_L), hereafter referred to as L-types, and a high ability type (ϵ_H), hereafter referred to as H-type. The payoff function of group member i can be summarized as follows:

$$\pi_i = w - c_i + \iota c_i + \mu \sum_{\forall j \neq i,k}^{n} \epsilon_j c_j$$
$$\text{with } \epsilon \in \{\epsilon_H, \epsilon_L\}, H \in \{1, \ldots, n/2\}, L \in \{n/2+1, \ldots, n\}, \epsilon_i \neq \epsilon_k; i, k \in \{1, \ldots, n\}$$

As pointed out in section 2.1, in standard public goods experiments, internal returns equal external individual returns and are referred to as marginal per capita return (hereafter referred to as $MPCR = \iota_i = \mu \cdot \epsilon_i$). Heterogeneity in MPCR introduces also heterogeneity in the costs of contributing to the public good. For example, one unit contributed by a person with a high MPCR increases the public good more than a one unit contribution from a person with a low MPCR as $MPCR_H > MPCR_L$. At the same time, the net costs of the same effective contribution to the public good is lower for a person with a high MPCR compared to a person with a low MPCR ($1 - MPCR_H < 1 - MPCR_L$). These two simultaneous effects of heterogeneity in MPCR make it difficult to identify whether persons with high returns contribute more because they increase the public good more effectively or because their costs are lower. The separation of MPCR in internal and external return enables us to introduce variation in the ability to contribute to the public good via the external return while keeping the internal return and thus the costs of contribution constant across types.[9]

It is important to notice, however, that keeping the internal returns constant across types, but allowing each member to benefit from the contributions of all other group members would lead to an asymmetric payoff structure, as each member always benefits from contributions of fewer members of the own type, and more members of the other type.[10] Kölle (2015) emphasizes the importance of symmetry in the payoff function in public goods games when every member contributes the same net amount of tokens, which would not be the case in our experiment when a member benefits from all other members' contributions. As we want contributions not to be influenced by an asymmetric payoff function but solely by the change in the external return, we exclude the contributions of a person with an opposite type such that every member benefits from the contributions of an equal number of both types. Thus, we assure a symmetric payoff structure in our experiment. In addition, we set the internal return to zero $\iota = 0$ for all members in all groups.[11]

[9]In fact, Carter et al. (1992) and Goeree et al. (2002) have shown in the case of homogeneous groups that contributions are sensitive to both, external and internal returns. We concentrate solely on the effect of external returns, i.e., contributions benefiting only others, and vary those marginal benefits within groups while we keep private costs via the private benefits of contributing constant across individuals.

[10]If all members contributed the same nominal amount in our experiment, then H-types would have lower payoffs, as they benefit from contributions by less H-types, whereas L-types would receive a larger return from the public good, as they benefit from the external return of one more H-type's contribution. Consider a group composed of six members; three L-types and three H-types. While all would benefit the same from their own contribution when the internal return is the same across types, in addition, H-types would benefit from contributions of three L-types and only two H-types, in contrast to L-types who would benefit from contributions of two L-types and three H-types. As the marginal contribution of H-type members increases the public good by more than that of L-types, L-types receive a larger return from the public good.

[11]Surely, this feature creates a discrepancy between our design and the orchestra example. As explained before, we make this design choice purely in order to isolate the effect of ability on increasing the public good from the net costs of contributing. Packard et al. (2001) also studied such boundary case with $\iota = 0$ in homogeneous groups. As internal returns were zero, they interpreted contributions as purely altruistic and reciprocal because they exclusively benefit others. Packard et al. (2001) emphasize the importance of such boundary designs, which are not necessarily meant

These considerations explain the particularity of how we set up the payoff function and calculated external returns. The sum of the effective contributions to the public good from other group members, $\sum_{\forall j \neq i,k} \epsilon_j c_j$, restricts i to benefit from contributions of $n-2$ members. The two members from whose contribution i is excluded are, first, the member i itself, because of an internal return of zero and, second, another member k with a type opposite to that of i ($\epsilon_i \neq \epsilon_k$), because of the symmetry of the payoff function. Restricting the benefits to contributions from fewer members but the same number of L-types and H-types ensures symmetry of the payoff structure for the returns from the public good across members.

In the experiment, there are $n = 6$ group members, three members per type. The external returns are $\epsilon_L = 1.33$ for L-types and $\epsilon_H = 3.99$ for H-types. All members have the same valuation and benefit from effective contributions of four other group members ($\mu = 1/4$) (excluding themselves and another randomly selected group member with an opposite type). Therefore, external individual returns for a nominal contribution of L-types and H-types are $\mu\epsilon_L = 0.3325$ and $\mu\epsilon_H = 0.9975$, respectively. These external individual returns are comparable to those employed by the other experiments reviewed in section 2.1, which lay in the range between 0.3 and 2.4.

3.2 Information treatments

A group member stays the same type and interacts in the same group repeatedly over 15 periods. After each period, all group members' individual nominal contributions to the project are revealed anonymously to the whole group. Our treatment variable, the level of information, varies in two ways: first, subjects either do or do not receive information on the distribution of types within the group, and second, the feedback information about the nominal contributions of all group members does or does not identify contributors by their type. We study the following information scenarios that are summarized in the top part of Table 2.

In the *No-info* treatment, subjects know their own type, i.e., they are informed about their own external return, but not the distribution of external return types within their group.[12] In the *Part-info* and *Full-info* treatments, the distribution of types is explicitly stated in the instructions. Additionally,

to replicate 100% of a real world situation, rather to isolate and focus on particular factors of interest. Nevertheless, Packard et al. (2001) provide a real world example with zero internal returns of public good contributions: They figure a homeowner who cleans up parts of her garden that is in sight of her neighbors, but not in her own, implying internal returns of zero for cleaning up this part of her garden. However, if everybody cleans also these spots of the garden that are not visible to the owner but to their neighbors, everybody in the neighborhood will be better off.

[12] The instructions never used the word "ability" or "external return" and left open the possibility that differences in the external return between group members may exist. While this approach implies loosing some control over group members' beliefs concerning other members' types, it implements the *No-info* treatment, our benchmark treatment, in a way that is as close as possible to the other two treatments.

Information about …	*Treatments (between-subjects design)*		
	No-Info	*Part-Info*	*Full-Info*
… external returns	Own type	Own type *and* distribution of external returns in group	
… type of contributors	*without* identification of contributor's type		*with* identification of contributor's type
Descriptive Statistics: contributions			
Mean	0.42	0.54	0.56
	(0.25)	(0.28)	(0.29)
Mean L-type	0.42	0.59	0.50
	(0.22)	(0.28)	(0.28)
Mean H-type	0.43	0.50	0.62
	(0.28)	(0.27)	(0.28)
Periods	15	15	15
N subjects	54	54	54
Total Nobs	810	810	810

Table 2: Summary of experimental design and descriptive statistics (mean contributions of both types and by type - all as proportion of endowment, standard deviations in parenthesis, number of periods, number of subjects, and total number of observations.)

the feedback information in the *Full-info* treatment allows subjects to link an individual nominal contribution to the contributor's type. In sum, the three treatments gradually change the level of information about the heterogeneity in the external return within the group and whether the type of an individual contributor is known or not.

3.3 Experimental procedure

The computerized experiment (zTree, Fischbacher, 2007) took place at the laboratory of the Max Planck Institute of Economics in Jena, Germany. A total of 162 undergraduate students (54 per information treatment) from Jena University were recruited using an online recrutement system (ORSEE, Greiner, 2004). Participants were on average 24 years old and 43% of them were men. In order to capture some of the individual heterogeneity amongst participants that might influence the behavior in the experiment, participants completed a standard personality questionnaire after the experiment, resulting in a personality index for each participant.[13] The personality index of our participants ranges

[13]We administered the revised version of the Sixteen Personality Factor Questionnaire (Cattell et al., 1993) in its official German version by Schneewind and Graf (1998). In particular, our personality index is derived from the individual score in the global personality scale that captures conscientiousness or self-control. This personality index reflects several

from one to nine with a mean value of 4.35.

Upon arrival and random seating in the lab, subjects received written instructions.[14] Once all subjects had finished studying the instructions, they answered some control questions to check their understanding of the interaction in the experiment. After the questions had been correctly answered by everyone, the experiment started. All group members decided about their contribution to the public good, after which the computer calculated individual payoffs and informed group members about their payoffs. Additionally, a history table was displayed containing the list of nominal contributions by each group member in all previous periods. The order of individual contributions in the history table was randomized so that contributions could not be attributed to a specific group member.[15] In the *Full-info* treatment, the history table also displayed the type of each contributor.

At the end of a session, subjects received their payoff from the experiment and a show-up fee of 2.5 Euros in cash. Experimental earnings were counted in points and exchanged for Euros, with 80 points corresponding to 1 Euro. Subjects earned on average 5.7 Euros for the 15 rounds, which lasted on average 30 minutes.[16]

3.4 Descriptive Statistics

In total, we observe 2,430 contribution decisions for the whole experiment, breaking down into 3 treatments with 9 groups per treatment, each with 6 members who decide in every of the 15 periods how much to contribute to the joint project. The bottom part of Table 2 reports the mean of the average individual contributions over 15 periods as a proportion of the endowment. Across the treatments, participants contribute about 50 percent of their endowment. The average contributions in the treatments *Part-info* and *Full-info* appear to be slightly higher than that in the *No-info* treatment.[17] Mean contributions by type appear to be similar for both types in the *No-info* treatment (L-type: 0.42, H-type: 0.43, Signed ranks test: p-value = 0.51), but appear to differ for the other two treatments.

traits that are associated with the tendency to rely on rules and socially accepted behavior (Conn and Rieke, 1994). The index is expressed in sten-scores that can range from one to ten. Sten values are derived from comparing test scores to the results of a norm population. The average (expected) sten-value in the German population is 5.5 with a standard deviation of 2, whereby higher sten-values indicate higher awareness and personal reliance on societal norms and rules.

[14] A presents a translation of the original German instructions.

[15] Participants were informed that they benefit from contributions of "four other group members" (*No-info* treatment) and "two of each type" (*Part-info* and *Full-info* treatment), but they were not informed about which of the displayed nominal contributions they benefited from. Therefore, in the *Part-info* treatment, it was hardly possible to infer the type of the contributor from displayed nominal contributions, or, similarly, to deduce in the *No-info* treatment that there were different types.

[16] Each session consisted of two phases each lasting 15 periods. In the second phase, groups were confronted with one of the two other treatments in order to study path dependency of contribution behavior. In this article, we consider only the first phase. Average earnings for the whole experiment (including both phases) were about 11 Euros.

[17] Ranksum tests comparing contributions of *Part-info* and *No-info*, and those in *Full-info* and *No-info* result in p-values of 0.23 and 0.20, respectively.

Aggregated average contributions of L-types are higher in the *Part-info* treatment and lower in the *Full-info* treatment compared to those of H-types.[18]

The dynamics in the experiment are shown in Figure 1. The upper panel plots the average contribution as a share of the endowment by treatment across the 15 periods. In all three treatments, the average contribution generally decreases over the course of the experiment, with a stronger decay towards the end. There are noticeable differences across the treatments in how contribution behavior evolves over time. In the *No-info* treatment, the general trend of contributions is downward sloping, a behavior that is in line with observations in other public goods experiments. In contrast, in the other two treatments with information about heterogeneity, average contributions seem to increase initially before following the general trend of decay. The lower panel of Figure 1 shows the average contribution as a share of the endowment by types across the 15 periods, separately for each treatment. Again, contributions of the two types appear to be similar in the *No-info* treatment. In Part-Info, *L-types* contribute slightly more than *H-types* in nearly every round, while in *Full-info* the pattern is reversed.[19] In the following, we estimate an empirical model of contribution behavior that allows us to exploit the information at the individual level.

4 Empirical model of contribution behavior

In this section, we present a random effects Tobit model in order to quantify the effect of information and external return on contribution behavior over time while controlling for individual heterogeneity. The choice of the empirical model is guided by the dynamic nature of the data and the fact that contributions are bounded below and on top. Our model allows individual contributions to depend not only on the treatment variables, but also on observable and unobservable personal characteristics as well as time. This way, we are able to provide statistical evidence of how information about heterogeneity affects behavior and to gain more insight on how individual contributions evolve over time.

In our model, we describe the share that individual i contributes from his or her own endowment

[18] Aggregation of contributions per group leaves us with 9 observations per treatment and allows us to perform standard non-parametric tests. Wilcoxon signed ranks tests that account for the dependencies of types within groups, however, cannot reject the null hypothesis that types make the same contributions at conventional levels of significance ($p = 0.11$ in *Part-info* treatment and $p = 0.26$ in *Full-info* treatment). The lack of significant variation in the analysis of aggregated data is not surprising. Though necessary for appropriate non-parametric testing, aggregation neglects information contained in individual data. It is very likely that information exerts its effect through dynamic interaction over time.

[19] B includes supplementary analyses of the group average contributions of the three treatments for each period (Table 4) and of the group average contributions by type for each period in each treatment (Table 5).

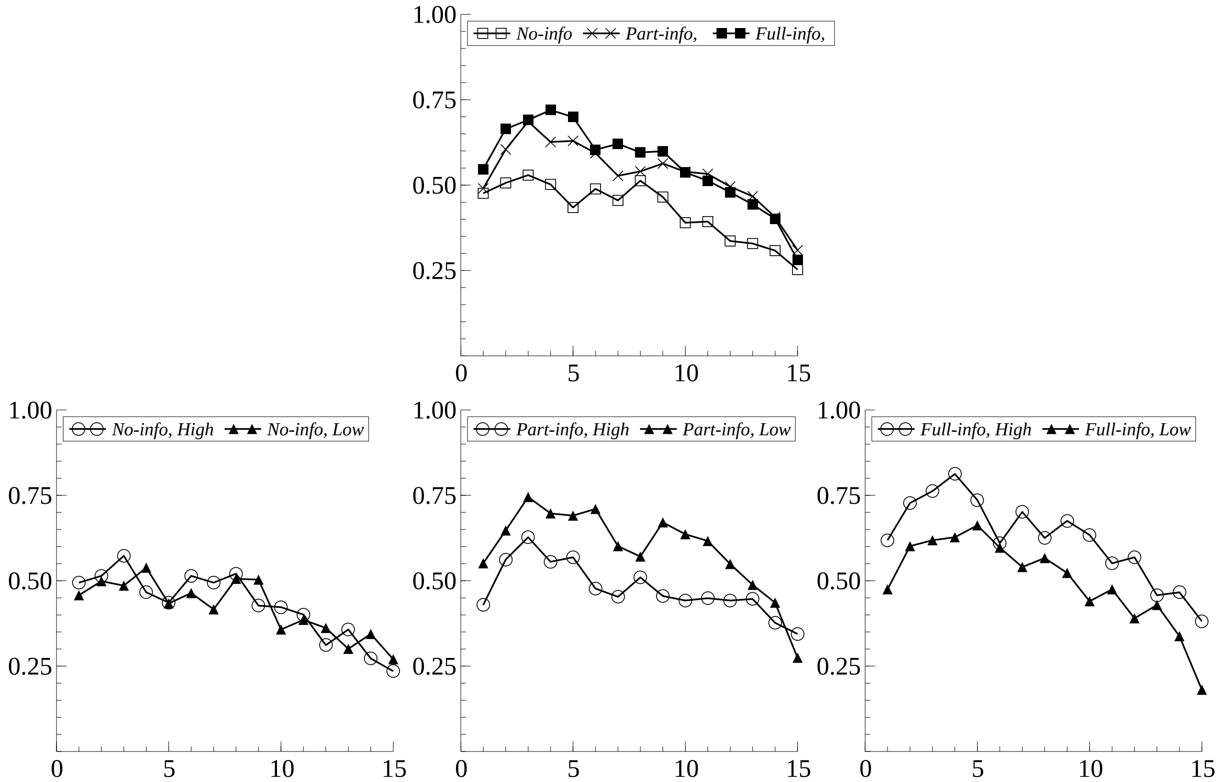

Figure 1: Upper panel: Average nominal contributions as share of the endowment for the three treatments (*No-info*, *Part-info* and *Full-info*) Lower panels: Average nominal contributions as share of the endowment for the external return types (*High*- and *Low*-types)

in period t, $y^{\star}_{it}$, as a function:

$$y^{\star}_{it} \quad = \quad \gamma_0 + \gamma_1 \textit{Part-info}_i + \gamma_2 \textit{Full-info}_i + \mathbf{h}_i \omega + f(t) + \mathbf{x}_i \beta + u_{it} \tag{3}$$

where γ_0 indicates the basic contribution level. We capture the influence of different levels of information about heterogeneity in the external return by treatment dummies, with the *No-info* treatment as a baseline. Parameter γ_1 measures the influence of information about heterogeneity and γ_2 measures the effect when external return can be additionally linked to specific contributions. $\textit{Part-info}_i$ ($\textit{Full-info}_i$) are dummy variables indicating the treatment in which i participated. The vector $\mathbf{h}$ contains a dummy variable for the type ($High_i = 1$ if i is a H-type and zero otherwise) and interaction terms of the type with the treatments. The parameter vector ω measures the effect of types across treatments. We control for time trends by including $f(t)$, a function of time. The vector $\mathbf{x}_i$ represents individual observable characteristics (age, gender, personality index). Their influence on contributions is captured by the parameter vector β. Idiosyncratic errors, u_{it}, are assumed to be independent of type and other individual characteristics in $\mathbf{x}_i$.

Given the design of the experiment, individual contributions to the joint project are doubly censored, first at the lowest contribution level of 0 units and second at the highest contribution level of 17 units, the endowment in each period.[20] As we define our variable of interest, the contribution to the public good as a share of the endowment, censoring is between 0 and 1. We therefore use a standard regression doubly censored Tobit model to estimate the relation for the latent proportions $y^{\star}_{it}$ that a group member i contributed (c_i/w) described in model (3) with

$$y_{it} \begin{cases} = 0 & \text{if } y^{\star}_{it} \leq 0, \\ = y^{\star}_{it} & \text{if } 0 < y^{\star}_{it} < 1, \\ = 1 & \text{if } y^{\star}_{it} \geq 1. \end{cases} \tag{4}$$

We estimate four specifications of the model in equation (3).[21] The first specification includes only treatment dummies for the different information conditions. The second looks only at the two types. The last two specifications control for both treatments, types, and their interaction. All specifications include the same set of background characteristics. The first three specifications model the time trend non-parametrically by including dummy variables for each period ($f(t) = \delta_t 1_t$ with 1_t being an indicator function for period t, for $t > 1$ and $f(1) = 0$). We find an inverse-U relation between time and the contributions to the joint project. Therefore, in the last specification, we model the time trend as a quadratic polynomial that includes interaction effects with types and the three information conditions:[22]

$$f(t) = \tau_{10} \cdot t + \tau_{20} \cdot t^2 + \mathit{Interaction}(t, \mathit{High}_i, \mathit{Part\text{-}info}_i, \mathit{Full\text{-}info}_i). \tag{5}$$

Parameterizing the time as quadratic polynomial allows us to account for both linear and non-linear effects of time as well as to include interactions with the different information conditions while minimizing the loss of degrees of freedom.

[20] In fact, 23% and 21% of all contribution decisions are at the upper and lower limits, respectively.

[21] We thank Charles Bellemare for providing his tobit model OX code.

[22] The detailed time function is given by:

$$\begin{aligned} f(t) &= \tau_{10} \cdot t + \tau_{11} \cdot t \cdot \mathit{Part\text{-}info}_i + \tau_{12} \cdot t \cdot \mathit{Full\text{-}info}_i \\ &+ \tau_{13} \cdot t \cdot \mathit{High}_i + \tau_{14} \cdot t \cdot \mathit{High}_i \cdot \mathit{Part\text{-}info}_i + \tau_{15} \cdot t \cdot \mathit{High}_i \cdot \mathit{Full\text{-}info}_i \\ &+ \tau_{20} \cdot t^2 + \tau_{21} \cdot t^2 \cdot \mathit{Part\text{-}info}_i + \tau_{22} \cdot t^2 \cdot \mathit{Full\text{-}info}_i \\ &+ \tau_{23} \cdot t^2 \cdot \mathit{High}_i + \tau_{24} \cdot t^2 \cdot \mathit{High}_i \cdot \mathit{Part\text{-}info}_i + \tau_{25} \cdot t^2 \cdot \mathit{High}_i \cdot \mathit{Full\text{-}info}_i \end{aligned}$$

5 Results

In this section, we present the estimation results of the four specifications introduced above. Specification (1) estimates the effect of the information conditions on contributions without controlling for the type. Specification (2) complements these results and estimates only the effect of types. Specification (3) controls for both, information conditions and types as well as their interaction. Specification (4) models the time trend as a quadratic polynomial, instead of using time dummies as did the Specifications (1) to (3), and adds interaction effects with the treatment variables and time. Furthermore, we present in this section the marginal effects of type and information on contributions. We also investigate whether and how types react differently to the distinct levels of information.

5.1 Parameter estimates

Parameter estimates of the main variables are presented in Table 3 and parameter estimates for the time trend of Specifications (1) to (3) in Table 6 in C. Specification (1) indicates that contributions are significantly smaller in the *No-info* treatment than in the other two treatments. However, there seems to be no difference in contributions between the two treatments with more information. Specification (2) singles out the effect of the external return on contributions, which is positive. However, even though the effect is significantly different from zero, it is rather small.

The estimated parameters of Specification (3) indicate that information about heterogeneity has a significantly positive impact on contributions ($\gamma_1, \gamma_2 > 0$).[23] Whereas the general propensity to contribute with little information (γ_0) and the increase to contribute with partial information (γ_1) remain almost of the same magnitude as in Specification (1), the increase of nominal contributions in the *Full-info* treatment is now only half of the increase in the *Part-info* treatment. Controlling for information reveals that the positive effect of external returns on contributions comes exclusively from the *Full-info* treatment environment.

The three specifications control for background characteristics and for the time trend with period dummies. We find that women tend to make significantly lower contributions ($\beta_2 < 0$) and that age and the personality index have significant but relatively small negative effects on contributions. All effects are significant at $p = 2.5\%$ or less. The influence of background characteristics on contributions is robust across specifications. The period dummy coefficients reveal an inverse U-shaped time trend,

[23] In the *Full-info* treatment, this increase is almost exclusively driven by the H-type ($\gamma_2 < \omega_2$). In the *No-info* treatment, H-types contribute significantly less than their L-type peers ($\omega_0 < 0$), but the size of the effect is relatively small and there is practically no difference in this respect when looking at the *Part-info* treatment (ω_1 not significantly different from zero).

indicating an increase in contribution levels until period three and a strong decrease over the last three periods of the experiment. Specifications (1) and (2) are nested in Specification (3). The loglikelihood values of the three models indicate that the model of Specification (3) fits much better our experimental observations.[24]

Specification (4) models the time trend as a quadratic polynomial, as in equation (5), allowing us to control for more interaction effects while minimizing the loss in degrees of freedom. The unobserved heterogeneity in Specifications (1) and (2) is about twice the size of the one in the other two Specifications (3) and (4), where we control separately for the influence of information and external return as well as their interaction and time effects. However, Specification (4) still seems to fit better our experimental observations than Specification (3). The Akaike Information Criterion (AIC) (Akaike (1974)) allows us to compare the goodness-of-fit between the two specifications: the AIC of Specification (3) is 66391.4 and the AIC of Specification (4) is 66353.4. Thus, the relative likelihood of Specification (3) is very low compared to Specification (4).[25,26] We continue to work with the latter.

Specification (4) has the advantage of controlling for the interaction of the time trend and the information conditions. The results reveal that the effect of information materializes largely through dynamic interactions over time and that this effect varies by type. More precisely, information about heterogeneity has a non-linear effect on individual contributions of both types. Instead of the standard monotonic decay, contributions increase before they diminish ($\tau_{11}, \tau_{12} > 0$ and $\tau_{21}, \tau_{22} < 0$). Moreover, additional information counterbalances the declining trend for contributions of H-types ($\tau_{24}, \tau_{25} > 0$). These parameter estimates are not individually significant. In order to test whether their joint effect is significant and to assess the global picture of these individual interactions, we compute expected contributions and calculate marginal effects using our estimated parameters.

5.2 Marginal effects on contributions

In this section, we present the marginal effects estimations based on the parameter estimates from Specification (4). The details of how we computed the marginal effects are presented in D.

[24] Loglikelihood ratio tests: Specification (1) vs (3): $p = 0.00$, Specification (2) vs (3): $p = 0.00$.

[25] The relative likelihood of Specification (3) is $\exp((66353.4 - 66391.4)/2) = 0.00056 \cdot 10^{-5}$.

[26] In section 5.2, we present our marginal effects analysis of Specification (4). Additionally, we present the marginal effects based on Specification (3) in E. A comparison of the marginal effects predictions of both specifications with the empirical observations confirms also visually a better fit of Specification (4) with the data.

		Specification 1		Specification 2		Specification 3		Specification 4	
Variable	Parameter	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
Constant	γ_0	0.86	9.69	1.02	10.77	0.84	8.95	0.93	5.93
Part-info	γ_1	0.20	16.89			0.21	12.30	0.09	0.43
Full-info	γ_2	0.24	21.72			0.10	5.96	0.02	0.12
H-type	ω_0			0.05	4.33	-0.04	-2.42	-0.03	-0.12
H-type *Part-info*	ω_1					-0.01	-0.50	0.04	0.12
H-type *Full-info*	ω_2					0.29	12.80	0.33	1.20
linear term of the Time trend	τ_{10}							0.01	0.28
Part-info	τ_{11}							0.06	1.02
Full-info	τ_{12}							0.05	0.89
H-type	τ_{13}							0.01	0.14
H-type *Part-info*	τ_{14}							-0.07	-0.76
H-type *Full-info*	τ_{15}							-0.03	-0.39
quadratic term of the Time trend	τ_{20}							-0.00	-0.86
Part-info	τ_{21}							-0.00	-1.25
Full-info	τ_{22}							-0.00	-1.17
H-type	τ_{23}							-0.00	-0.29
H-type *Part-info*	τ_{24}							0.00	1.11
H-type *Full-info*	τ_{25}							0.00	0.55
Age	β_1	-0.01	-5.35	-0.01	-6.64	-0.01	-4.85	-0.01	-4.84
Gender	β_2	-0.25	-22.83	-0.24	-21.01	-0.24	-19.91	-0.24	-19.84
Personality index	β_3	-0.03	-10.56	-0.03	-10.29	-0.03	-9.24	-0.03	-9.28
Time dummies		Yes		Yes		Yes		No	
Number of Observations		2430		2430		2430		2430	
Number of Parameters		21		19		23		21	
	σ_ϵ	-1.07	-63.5	-1.03	-61.38	0.58	62.54	0.58	64.14
Log-Likelihood value		-33431		-33931		-33173		-33156	

Table 3: Estimation results for nominal contribution behavior (dependent variable: nominal contribution as a share of the endowment).

External return

The upper panels in Figure 2 show the predicted average nominal contributions as a share of the endowment for H- and L-types in each treatment, while the lower panels present the marginal effect of being an H-type compared to an L-type, i.e., having an impact on the public good that is three times larger, with 95% confidence bounds. The upper left panel in Figure 2 depicts the *No-info* treatment.

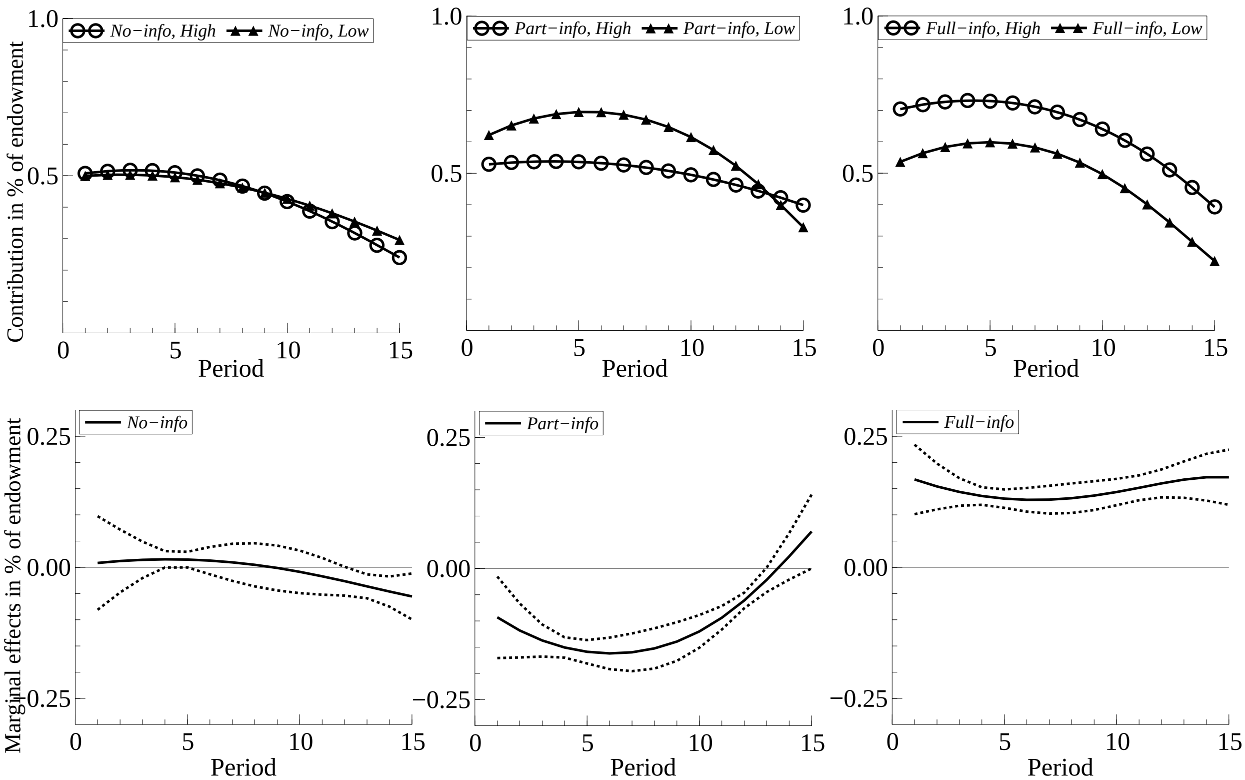

Figure 2: Upper panels: Predicted average contributions (as a share of the endowment) over time for each treatment and type.
Lower panels: Marginal effects of external return types on contributions for each treatment. (The graphs project the difference in relative nominal contributions between H-types and L-types with 95% confidence bounds.)

The picture suggests that, in the absence of information about heterogeneity, both types make the same nominal contributions that exhibit a similar monotonic decay. The marginal effects analysis for this case, presented in the lower left panel, confirms this observation. We cannot reject the null hypothesis of no difference between types throughout periods 1 to 12. In the last three periods, though, L-types contribute significantly more, albeit not by very much with around two percentage points.

The other four panels illustrate the case for the treatments with more information. Here, contributions of both types are not monotonically declining but rather parabolic, depicted by the tendency for average contributions to increase initially before following the standard pattern of decay. Moreover, from the lower middle and lower right panels, we learn that contribution behavior differs significantly between types and also between the *Part-info* and the *Full-info* treatments.

The upper and lower middle panels illustrate behavior in the *Part-info* treatment. There, the predicted average contribution of L-types is higher than that of H-types by about 5% to 10% of the endowment. The difference in contribution behavior between H- and L-types is reversed in the *Full-info* treatment, which is illustrated in the upper and lower right panels of Figure 2. When contributions can be linked to the type of the contributor, H-types give significantly more than L-types. The difference amounts to around 15% of the endowment and remains constant over time as contributions of both types follow the same time trend.

Information by type

Providing information about heterogeneity obviously affects contribution behavior of types in different ways. To test the significance of information on contributions separately for both types, we compute marginal effects presented in Figure 3, for H-types in the upper panels and for L-types in the lower panels.

The upper left panel shows that H-types contribute more in the second half of the experiment when they have information about the heterogeneity than in case they do not have this information. When all group members can additionally link contributions to types as shown in the upper right panel, H-types contribute between 10 and 20 percent more of their endowment. However, this effect is decreasing over time, and in the last two periods, contributions no longer differ significantly. Finally, the upper middle panel indicates that H-types' contributions are around 20 percent higher when they have information about heterogeneity and contributions can be linked to types than in case where they have no information. This effect is relatively stable over time.

We find very different marginal effects for L-types, shown in the lower panels of Figure 3. The lower left and middle panels indicate that information on heterogeneity generally increases the contributions of L-types. The effect is about two times stronger when only information about heterogeneity (lower left panel) is available than in the situation where contributions can be linked to the type (lower middle panel). The difference between both effects is significant and visualized in the lower right panel that depicts the difference between the two treatments with partial and full information.

Finally, we repeated the marginal effects analysis using parameter estimates from Specification (3). We present these two figures, Figures 4 and 5, in E together with a third set of figures, Figures 6

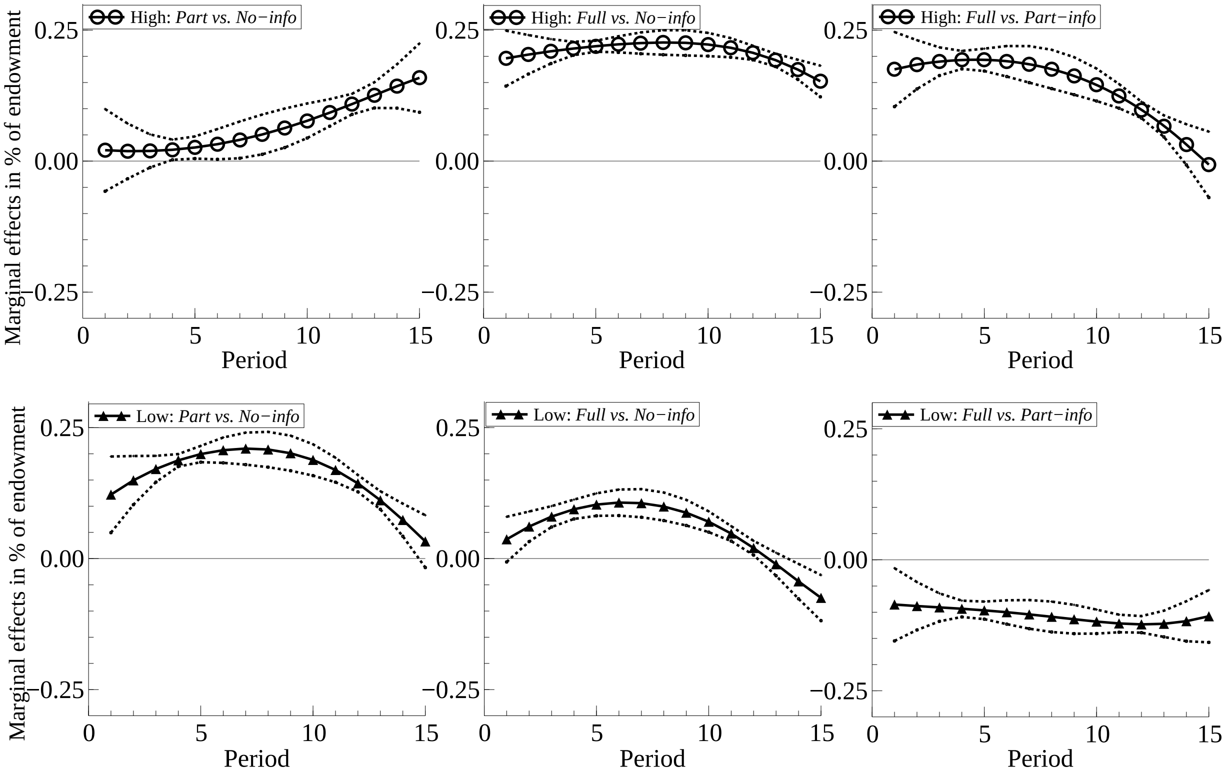

Figure 3: Marginal effects of information on contributions separately for H-types and L-types. (The graphs project the difference in relative nominal contributions between two information scenarios with 95% confidence bounds.)

and 7, in F presenting the same differences based on average data. A comparison of these three sets of figures demonstrates that Specification (4) captures the dynamic evolution of contributions over time much better than Specification (3). These comparisons confirm our choice of Specification (4) as the main model for our analysis and underline the importance of the interaction of time with the treatment variable and the type.

6 Summary of the results and discussion

In this section, we summarize our three main results and discuss them in more detail in light of the existing literature. Our first finding is that *(1) heterogeneity in the ability to provide the public good does not affect nominal contributions when no information on heterogeneity is provided.* Second, we observe that *(2) nominal contributions increase with ability when members are aware of the heterogeneity and contributions can be linked to the ability type.* Yet, we find, third, *(3) nominal contributions to be inversely related to ability, when group members are only aware of the heterogeneity but cannot* *link contributions to the type.*

Our first result in connection with our second indicates that contributions vary by type and information scenario, a finding which expands our knowledge about the effects of return rates in heterogeneous groups in the literature. This literature presumed so far that members of heterogeneous groups react solely to their own marginal per capita return. Such evidence is provided by individual decision experiments on altruism (Andreoni and Miller (2002), Karlan and List (2007)) and public goods experiments with different marginal per capita return between homogeneous groups and within heterogeneous groups (see Section 2.1). These papers demonstrate that individuals react to changes in the efficiency of their contributions. Their findings are qualitatively in line with ours when members have information on the heterogeneity in the group and the contributor's type, which in fact are the information conditions used in the literature. However, if solely altruism or warm glow are driving the behavior in public goods experiments, group members should react exclusively to their external return, i.e., by how much their contributions benefit others, independent of their knowledge about the environment. We find, however, that H-types contribute more in the most transparent information condition. Thus, information about the heterogeneity in the external return is important and drives behavior in such environments. Furthermore, social norms in connection with efficiency concerns are at play rather than altruism alone when members with high external returns make larger contributions.

The findings in this paper are – to the best of our knowledge – the first evidence that group members react to the external returns their peers have and not only to the external returns of their own contributions. In a way, our results push the concept of conditional cooperation (Fischbacher et al. (2003)) a bit further, suggesting that persons have multiple dimensions of conditional cooperation. They not only condition on others' nominal contributions, but also on other factors, in our case ability, in other words, how efficiently contributions affect the joint project. The findings suggest that peer pressure exists on the most able types, when sufficient information is available. This result enhances our understanding of behavior in groups whose members vary in their ability to contribute to a joint project and finds no equivalent in the existing public goods literature.

Our second result states that the positive effect of external returns in heterogeneous groups is grounded in sufficient information on the environment. This result corroborates and extends findings of a strand of the existing public goods literature that is concerned about the effect of returns on contributions. This literature looks exclusively at environments in which group members have full information on contributions and return rates of other members (see section 2.1). One main result of this literature constitutes that individuals react to external and internal returns. Some researchers vary the marginal per capita return for individuals in a group, i.e., internal and external return are the same for an individual but vary between members of a group. Others vary internal and external returns separately and study their variation in homogeneous groups. Our experiment combines both approaches in that we allow internal and external returns to be distinct for individual members of heterogeneous groups. Thereby, we avoid the confounding effect of diverging net contribution costs among heterogeneous group members, which the hitherto literature has neglected. From our second result we can add to the literature the insight that the existing finding of a positive relation between external returns and contributions is in part due to the full information structure employed in these experiments. We can add further that the established finding on the effects of heterogeneous marginal per capita returns is robust to the cost of contribution.

Our third result, probably the most surprising one, indicates that only an environment with rather detailed information induces efficient contributions. Thus, the finding in the previous literature that high ability types contribute more than low types does not always hold and even reverses when less information is provided, i.e., when members are informed about the heterogeneity in the group, but it is not possible to link individual contributions to the ability type. In this case, low ability types contribute significantly more than high types. This evidence, together with the observation that H-types contribute more when information on the contributor's type is available than when it is not, seems to accord with the "poisoning-of-the-well" effect introduced by Fisher et al. (1995).This effect refers to lower contributions of types with high marginal per capita return in heterogeneous groups compared to their contributions in homogeneous groups.[27] Under our different information scenarios, we find that partial information about heterogeneity results in the "poisoning-of-the-well" effect, whereas it is ceased under full information. Hence, we replicate what Fisher et al. (1995) call a "curious phenomenon" that the "poisoning-of-the-well" effect disappeared when the experimenters emphasized more strongly the heterogeneity in the groups to their participants, highlighting themselves the importance of information (p.265, footnote 11). Despite this anecdotal evidence, our study is to the best of our knowledge the first systematic investigation with heterogeneous groups under different information scenarios, hence, the first to report such reversion in contribution patterns by different types of external returns.

In a nutshell, we find an effect of external returns on contributions to joint projects in heterogeneous groups when group members have full information about each other. There is strong evidence in

[27] In Fisher et al. (1995) "the well" are types with a high rate of marginal per capita return, i.e., those with high internal and high external rates of return. They are "well" or "better off" than others as they benefit from their own contribution via the high internal rate of return and have, hence, lower relative costs to contribute compared to low types. The "well" characterizes less precisely high types in our experiment, who have higher external returns but zero internal returns, hence they are "only" more "able" to increase the public good for others, but cannot benefit from their own contribution.

laboratory experiments and field studies that information about others affects contribution to public goods (see section 2.2). In observing homogeneous groups, Andreoni and Petrie (2004) find an increase in contributions when individual contributions can be identified. They suggest that individuals compare their own contributions to some standard that can be established when contributions of others are known. As information is likely to foster social comparisons and to clarify a standard, it is not surprising that individuals react to available information. Such a standard may represent a social norm, but which norm is established in groups with heterogeneous agents is an empirical question, to which our paper provides some evidence.

Our results complement those of Andreoni and Petrie (2004) by adding the aspect of heterogeneity. We find that in heterogeneous groups types react differently to changes in the information about heterogeneity and to changes in the information about the type of the contributor. From the literature on fairness and justice norms one can derive different contribution norms for heterogeneous environments, based either on efficiency or equity (Konow (2003)). By revealing the type-identity of contributors, type specific standards or norms can arise more easily, which gives an idea – at least empirically – of what norm is in place in groups with members who differ in their abilities. Given our results, it seems that the standard emerging in our setting is that of efficient contributions, with high ability types making higher nominal, hence, effective contributions. Our experimental results suggest that efficiency motives emerge with sufficient information and social exposure: when identification of ability is linked to individual contributions, high ability types contribute more compared to a situation when group members are not informed about the heterogeneous abilities in the group.

7 Conclusion

This study explores the relationship between external returns, or the 'ability to increase the value of a joint project for others,' and the level of available information on the return type of all group members in the context of public goods production by groups whose members vary in their external return. Our results not only extend the literature but shed new light on the existing results. We conjecture from our findings that efficient contributions by high ability group members represent a social norm rather than a reaction to increased incentives to contribute. Thus, efficient contributions are more likely in environments with social approval or social pressure, for example when the identity of the contributor is revealed. Whether efficiency is the most desirable norm from the point of view of a policy maker or group members themselves is another important question left for future research.

We conclude by noting that the level of information about heterogeneity is crucial to understand how heterogeneity in groups affects the provision of public goods. We consider our findings important when deciding on the information to be transmitted in teams, for example about the (nominal) performance of individual team members, or when evaluating different disclosure practices of fund raising agencies.

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Appendices

A Instructions

This is a translated version of the German instructions used for the experiment. We provide here the version for H-types in the No-info treatment. Differences between treatments are denoted as comments in the text. Comments by the authors included here as information to the reader but not in the original instructions can be found in square brackets and footnotes.

Welcome to this experiment! These instructions are for your private information. Please read the instruction carefully. Please do not talk to the other participants. If you have any questions, please raise your hand. We will come to you and answer your questions privately.
All amounts are displayed in *Points*. The exchange rate is: 80 points = 1 Euro.
The experiment consists of two phases of 15 periods each. Before each phase, all participants are randomly assigned to groups of six. The group's composition remains the same throughout the experiment.

Detailed Information
You are a member of a group of six. At the beginning of each period, every group member receives 17 points. In every period each group member decides how to split the 17 points. You can transfer points to a private account or to a group project. Your period payoff is the sum of your income from the private account and the income from the group project.

<u>Your payoff from the private account:</u>
For each point you transfer to the private account, you receive a payoff of one point. This means that if you transfer an amount of x points to your private account, your payoff increases by x points. Nobody except you benefits from your private account.
<u>Your payoff from the group project:</u>
The payoff you receive from the project is derived as follows. You receive one quarter of the project's outcome generated by four other members of your group. The project's outcome is the sum of all transfers, whereby each transfer to the project is multiplied by an individual factor[, either 1.33 or 3.99. Two of the four members of your group whose transfers will benefit you have a factor of 1.33, and the other two have a factor of 3.99. Individual factors were randomly assigned to each group member in the beginning of the experiment such that three members were assigned a factor of 1.33 and three were assigned a factor of 3.99. Each member retains the same factor throughout the whole experiment.][28] The payoffs are calculated in the same manner for all six group members.
Each point you transfer to the group project generates 3.99 points.[29]
Please note that four other members of your group benefit from your transfer to the project, but you do not.

<u>One period proceeds as follows:</u>
In each period, you receive 17 points. You decide how many of your 17 points to transfer to your private account and how many to the project. You will make this decision by simply deciding how many points you wish to transfer to the project. The points you transfer to your private account are automatically calculated as the difference of the 17 points and the points you transferred to the project. After every group member has made a decision, the payoff for this period is calculated.

[28] The information between square brackets was **not given** in the *No-info* treatment but was **given** in the *Part-info* and *Full-info* treatments.
[29] This was the factor for H-types. L-types had a factor of 1.33.

At the end of each period, you will receive the following information:

- The number of points that each member in your group transferred to the project (Please note that the numbers of points are listed in random order, i.e. the sequence of transfers is different in each period.)
- Your payoff from the private account
- Your payoff from the project
- Your payoff from the period
- Your total payoff from all previous periods in this phase

Then, the next period will start. In the second period, you will be shown a table (like the one below) with the following information for all previous periods: your transfer to the group project, your payoff in a period, and transfers made by the other 5 members of your group [with the information about their individual factors (H for 3.99 and L for 1.33)].[30] For each period, the transfers of group members are presented in random order, so columns showing the contributions of the other 5 group members will not correspond to the same person for all periods.

	Transfer to the joint project						
	You	Other group members					
		[H]	[H]	[L]	[L]	[L]	
Period		1	2	3	4	5	Payoff
1	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...

In total, you will interact over 15 periods in each phase. You will receive more detailed information on phase 2 after phase 1 ends.
We will ask you to complete a questionnaire after the experiment is completed. At the end of the experiment, your final payoff will be converted into Euros and paid to you immediately. Please remain seated until we call the number of your computer.

Thank you very much for your participation!

[30] Only participants in the *Full-info* treatment received the information allowing them to link a contribution to the contributor's type.

B Group (and type-specific) average contributions in each period

We calculate the averages of group average contributions for each period and test their differences between the information treatments. Table 4 summarizes these results. The joint test of differences in all periods is not significantly different between treatments (*No-* vs *Part-info*, $p-$value: 0.23; *No-* vs *Full-info*, p-value: 0.20; and *Part-* vs *Full-info*, p-value=0.89). There are some differences for some periods; period 2: *No-* vs *Full-info*, p-value=0.07; period 3: *No-* vs *Part-info*, p-value=0.08; period 4:*No-* vs *Full-info*, p-value =0.06; and period 5: *No-* vs *Full-info* p-value=0.04. The last three columns report the p-values of non-parametric tests of these differences that can be interpreted as marginal effects with group averages as independent observations. However, these results need to be taken with caution, as the necessary conditions to conduct non-parametric tests are not satisfied. Period differences are not independent, but very likely to be correlated over time.

	No-info	Part-info	Full-info	p-value of Rank Sum test		
	(T0)	(T1)	(T2)	T0 vs T1	T0 vs T2	T1 vs T2
nr. obs.	9	9	9	18	18	18
Period 1	0.4760	0.4956	0.5468	0.7907	0.2888	0.3299
Period 2	0.5065	0.6122	0.6645	0.2594	0.0701	0.8253
Period 3	0.5294	0.6939	0.6906	0.0848	0.2327	1.0000
Period 4	0.5022	0.6372	0.7200	0.2508	0.0576	0.5074
Period 5	0.4346	0.6405	0.6993	0.1116	0.0420	0.5961
Period 6	0.4891	0.6078	0.6034	0.3311	0.2888	0.8597
Period 7	0.4553	0.5327	0.6209	0.5961	0.1575	0.4797
Period 8	0.5131	0.5577	0.5959	0.8252	0.3536	0.7573
Period 9	0.4651	0.5795	0.5991	0.3301	0.1707	0.9648
Period 10	0.3900	0.5566	0.5370	0.1711	0.2159	0.9296
Period 11	0.3932	0.5501	0.5131	0.2332	0.2332	0.6587
Period 12	0.3366	0.5098	0.4793	0.2330	0.2694	0.8253
Period 13	0.3290	0.4804	0.4434	0.1990	0.3536	0.8597
Period 14	0.3083	0.4205	0.4020	0.3094	0.4011	0.6908
Period 15	0.2527	0.3246	0.2810	0.3770	0.9296	0.4790
All periods	0.4254	0.5466	0.5597	0.2332	0.2004	0.8946

Table 4: The averages of the group average contributions in each period and pairwise tests on differences between information treatments.

Additionally, we calculate the averages of group average contributions for each type and each period and test the differences between types in each information treatment. Table 5 summarizes these results. The joint test of differences between types in all periods is not significant in any treatment (*No-info*, $p-$value: 0.51; *Part-info*, p-value: 0.11; and *Full-info*, p-value=0.26). Columns 4, 7 and 10 report the p-values of non-parametric tests of type differences in each treatment and period. To account for dependencies of *L- types* and *H-types* who interact within each group, we conduct Wilcoxon signed ranks tests. There are some differences in *Part-info* and in *Full-info* for some periods; in *Part-info*: period 4 (p-value=0.08), period 6 (p-value=0.01), and period 10 (p-value =0.05); in *Full-info*: period 4 (p-value=0.10), period 10 (p-value=0.08), period 12 (p-value=0.07), and period 15 (p-value=0.08). However, these results need to be taken with caution, as the necessary conditions to conduct non-parametric tests are not satisfied. Period differences are not independent, but very likely to be correlated over time.

	No-info			Part-info			Full-info		
	L-type	H-type	p-value	L-type	H-type	p-value	L-type	H-type	p-value
nr. obs.	9	9	18	9	9	18	9	9	18
Period 1	0.4575	0.4946	0.9528	0.5512	0.4401	0.1386	0.4749	0.6187	0.1094
Period 2	0.4989	0.5142	0.9527	0.6471	0.5773	0.3424	0.6013	0.7277	0.4413
Period 3	0.4858	0.5730	0.8121	0.7451	0.6427	0.1229	0.6187	0.7625	0.4733
Period 4	0.5381	0.4662	0.4413	0.6972	0.5773	0.0858	0.6275	0.8126	0.0966
Period 5	0.4336	0.4357	0.8111	0.6906	0.5904	0.2596	0.6623	0.7364	0.6347
Period 6	0.4641	0.5142	0.6773	0.7102	0.5054	0.0152	0.5969	0.6100	0.9055
Period 7	0.4161	0.4946	0.6784	0.6013	0.4641	0.8580	0.5403	0.7015	0.2135
Period 8	0.5054	0.5207	1.0000	0.5708	0.5447	0.7649	0.5664	0.6253	0.6347
Period 9	0.5033	0.4270	0.4764	0.6710	0.4880	0.1232	0.5229	0.6754	0.3743
Period 10	0.3573	0.4227	0.5533	0.6362	0.4771	0.0504	0.4401	0.6340	0.0847
Period 11	0.3856	0.4009	0.9528	0.6166	0.4837	0.1097	0.4749	0.5512	0.5940
Period 12	0.3617	0.3115	0.4413	0.5490	0.4706	0.3139	0.3900	0.5686	0.0661
Period 13	0.3007	0.3573	0.7671	0.4880	0.4728	0.6784	0.4292	0.4575	0.9055
Period 14	0.3442	0.2723	0.4768	0.4357	0.4052	0.5529	0.3377	0.4662	0.1917
Period 15	0.2702	0.2353	0.4061	0.2745	0.3747	0.3139	0.1808	0.3813	0.0858
All periods	0.4215	0.4293	0.5147	0.5923	0.5009	0.1097	0.4976	0.6219	0.2604

Table 5: The averages of the group average contributions by external return type in each period and tests on differences between types for each treatment.

C Estimation results of period dummy variables of Specifications (1), (2) and (3)

		Specification 1		Specification 2		Specification 3	
Variable	Parameter	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
Time dummies	δ_2	0.15	0.92	0.15	0.88	0.15	0.93
	δ_3	0.20	1.49	0.20	1.42	0.21	1.51
	δ_4	0.18	1.40	0.18	1.31	0.18	1.36
	δ_5	0.13	1.08	0.13	1.03	0.13	1.08
	δ_6	0.09	0.77	0.09	0.73	0.09	0.79
	δ_7	0.03	0.30	0.03	0.28	0.03	0.30
	δ_8	0.07	0.52	0.07	0.49	0.07	0.52
	δ_9	0.05	0.45	0.05	0.43	0.05	0.46
	δ_{10}	-0.04	-0.39	-0.04	-0.37	-0.04	-0.39
	δ_{11}	-0.05	-0.44	-0.05	-0.43	-0.05	-0.43
	δ_{12}	-0.12	-0.97	-0.12	-0.93	-0.12	-0.97
	δ_{13}	-0.15	-1.38	-0.15	-1.33	-0.15	-1.37
	δ_{14}	-0.23	-2.18	-0.23	-2.12	-0.23	-2.17
	δ_{15}	-0.41	-3.78	-0.42	-3.66	-0.41	-3.81

Table 6: Parameter estimates of the time trend in Specifications 1, 2, and 3.

D Marginal effects of information and of ability types

We calculate marginal effects as the difference between the expected proportion of contribution for two realizations of a variable of interest. For example, the effect of ability on average nominal contributions in the *Full-info* treatment is given by

$$\begin{aligned} \Delta_{i,t}^{HL} &= E(y_{igt}|x_i, t, High = 1, \textit{Part-info} = 0, \textit{Full-info} = 1) \\ &- E(y_{igt}|x_i, t, High = 0, \textit{Part-info} = 0, \textit{Full-info} = 1) \end{aligned} \quad (6)$$

for which we calculate the expected contribution levels using the parameter estimates of Specification (4) (model in equation (3) and equation (5)) to compute $y^{\star}_{igt}$. Finally, we apply the censoring rule in equation (4) to obtain y_{igt}. We compute the effect in equation (6) for all individuals who participated in the *Full-info* treatment and for each time period. We average over all individual effects $1/(NT)\sum_{\forall t,i} \Delta_{i,t}^{HL}$ to obtain the total effect. We simulate the variance of the marginal effects, that is used to calculate the t-values, using 100 Hamilton draws (see Train (2003) and Judd (1999)).[31]

[31] We discard the first 50 draws of a sequence, using draws 51-150.

E Replication of Figures 2 and 3 based on Specification (3)

The two figures below replicate the marginal effects analysis of Figures 2 and 3 for Specification (3). Whereas average contributions are relatively well captured by Specification (3), the predicted marginal effects based on Specification (3) do not capture very well the non-linearity present in the empirical differences between types as shown in Figures 6 and 7 in F.

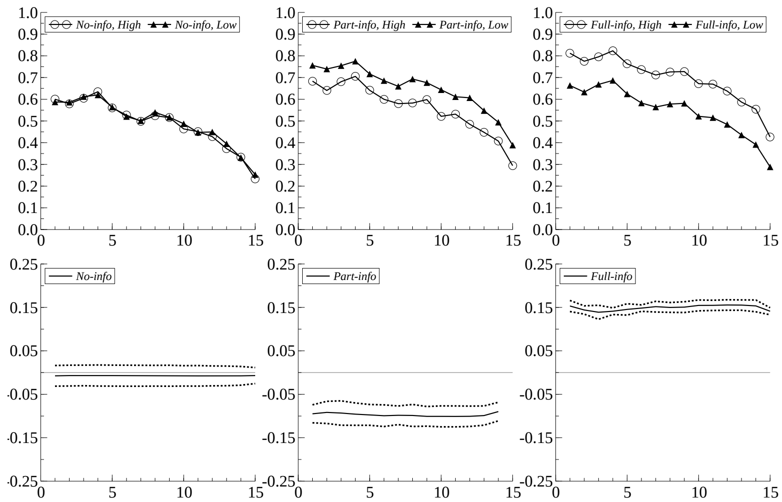

Figure 4: Upper panels: Predicted average contributions (as a share of the endowment) over time for each treatment and type.
Lower panels: Marginal effects of external return types on contributions for each treatment. (The graphs project the difference in relative nominal contributions between H-types and L-types with 95% confidence bounds.)

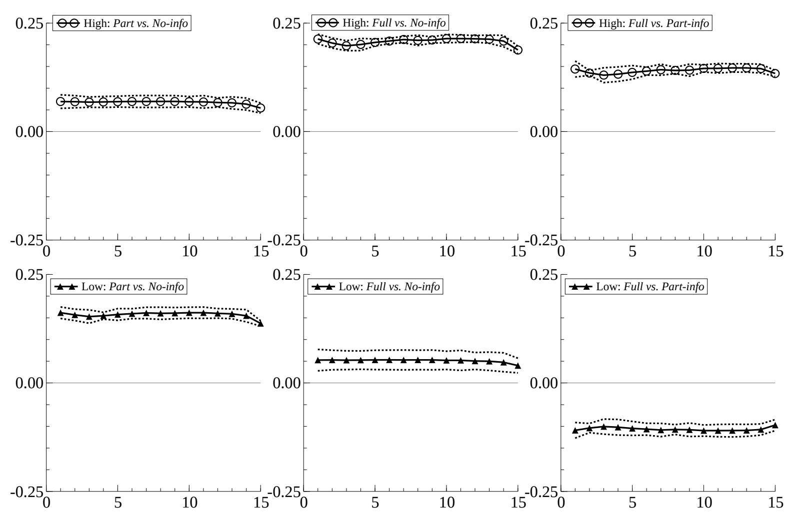

Figure 5: Marginal effects of information on contributions separately for H-types and L-types. (The graphs project the difference in relative nominal contributions between two information scenarios with 95% confidence bounds.

F Replication of Figures 2 and 3 with empirical data

The two figures below (6 and 7) present average group contributions separately by type and information treatments as well as differences between these treatment groups and types over time. Thus they replicate with empirical data the marginal effects predictions of Figures 2 and 3 in the text (p. 22 and p. 24), and 4 and 5 in E.

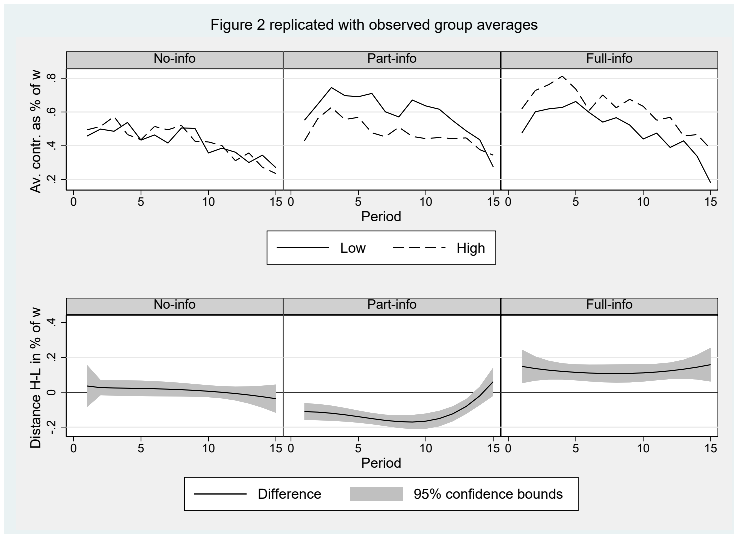

Figure 6: Observed average contributions (as a share of the endowment) over time for each treatment and type (top panels) and differences between types (bottom panels) with 95% confidence bounds.

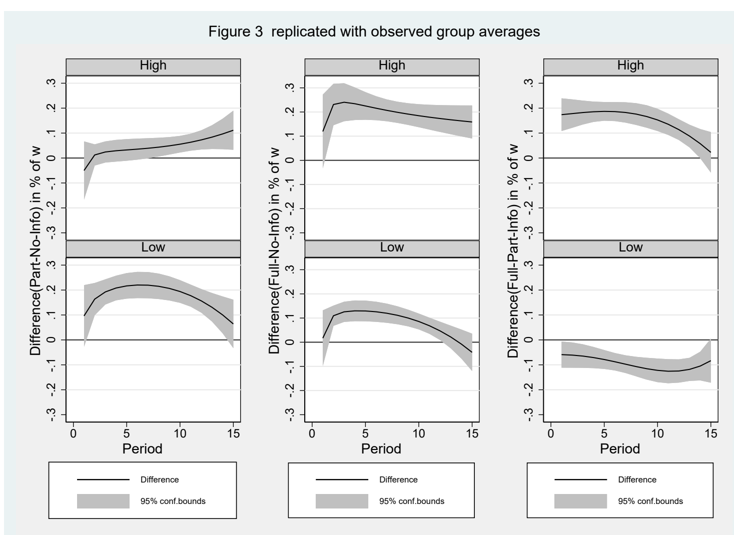

Figure 7: Observed differences in average contributions (as share of the endowment) separately for H-types and L-types. (The graphs project the difference in relative nominal contributions between two information scenarios with 95% confidence bounds.)