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Heterogeneous productivity in voluntary public good provision: An experimental analysis

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Heterogeneous Productivity in Voluntary Public Good Provision: An Experimental Analysis

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March 2011

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ABSTRACT

Heterogeneous Productivity in Voluntary Public Good Provision: An Experimental Analysis*

This article experimentally examines voluntary contributions when group members' marginal returns to the public good vary. The experiment implements two marginal return types, low and high, and uses the information that members have about the heterogeneity to identify the applied contribution norm. If agents are aware of the heterogeneity, contributions increase in general. However, high types contribute more than low types when contributions can be linked to the type of the donor but contribute less otherwise. Low types, on the other hand, contribute more than high types when group members are aware of the heterogeneity but contributions cannot be linked to types. Our results underline the importance of the information structure when persons with different abilities contribute to a joint project, as in the context of teamwork or charitable giving.

JEL Classification: C9, H41

Keywords: public goods, voluntary contribution mechanism, heterogeneity, information, norms

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1 Introduction

People who contribute to public goods or to common projects are, generally speaking, not alike. They differ, for instance, in their talents, skills, and qualifications. In some cases, heterogeneous abilities are even necessary to achieve a common goal. Naturally, the question arises of how group heterogeneity affects contributions to joint projects. This article examines the voluntary contribution behavior of individuals with heterogeneous abilities using laboratory experiments.

Differences in individual capacities within a group, e.g., between citizens in a society or team members, might stimulate voluntary contributions from those whose special abilities are desperately needed. For instance, after the devastating Kobe earthquake in Japan in 1995, local transportation systems in the town of Kobe were paralyzed. Bicycling became a vital means of transportation. The serious problem then became that many bicycles broke and were left unrepaired due to a lack of the necessary equipment and expertise to fix the damage. To help the people in Kobe, a number of bicycle enthusiasts from all over Japan came to Kobe voluntarily and offered much-needed assistance with repairing the broken bicycles.

On the other hand, heterogeneous abilities can become an obstacle when soliciting effort to accomplish common projects, as exemplified by the legal dispute among musicians in the Beethoven Orchestra in Bonn. The musicians cooperating to perform a common musical program are heterogeneous with respect to many factors, including the instruments they play, the (number of) notes they play during a given piece of music, and the amount of time they must spend practicing in joint rehearsals before a performance. However, under the unionized contracts of orchestra musicians in Germany, all orchestra members are guaranteed equal payment regardless of the particular instrument they play. In March 2004, the violinists of the Beethoven Orchestra demanded higher pay on the grounds that they have to rehearse more than musicians playing other instruments.[1] The other musicians, particularly soloists, argued that they were subject to more pressure than the violinists, so receiving the same pay for less rehearsal time seemed to be

[1]The request was mainly based on the opportunity cost argument, namely that the additional free time that other musicians enjoy can be used to augment their monthly wages by teaching or performing elsewhere.

justified.[2]

The above examples capture two general considerations relevant to the voluntary contribution behavior of individuals with heterogeneous abilities. On one hand, heterogeneity between group members might evoke different contribution norms. On the other hand, the appropriate contribution norm may depend on the context in which the heterogeneity is perceived. In the case of the Kobe earthquake, the norm called for help from persons who were knowledgable about bicycle repair. The conflicting views between soloists and violinists in the Bonn orchestra suggest that violinists consider equal remuneration of nominal work hours to be an appropriate norm, while soloists seem to favor remuneration according to effective contribution, which takes into account other factors (responsibility, stress, etc.). What kind of norm is considered appropriate thus depends on the circumstances and is an empirical question.

The experimental literature has studied extensively contribution norms and behavior in the context of voluntary contribution mechanisms for homogeneous groups (see Ledyard, 1995, for a survey). In a classical linear voluntary contribution mechanism, group members receive an endowment from which they can invest in a group project with an outcome that is shared equally amongst all members at the end of the project. The marginal return for each member of one unit contributed to the group project by any member is what the literature has termed the marginal per capita return. To assess the effect of this marginal return on contributions, some studies compare homogeneous groups that differ in their marginal returns (e.g., Isaac and Walker, 1998). One main result of these studies is that groups with higher marginal returns have an increased propensity to contribute. This finding seems to be robust across studies and for different marginal returns and numbers of group members.

Only a few studies have examined heterogeneous groups in which members vary in their marginal returns.[3] Fisher et al. (1995) and Tan (2008) compare the type specific behavior of heterogeneous groups consisting of

[2]The case was eventually settled with a compromise in which part-time student violinists were hired for some rehearsals to fill in for the overworked violinists (see Klassik News, March 29, 2004 on klassik.com).

[3]Other experimental studies have focused on alternative sources of heterogeneity, for example, wealth (e.g., Buckley and Croson, 2006, and Chan et al., 1996,) or marginal benefits (e.g., Palfrey and Prisbrey, 1997, and Bagnoli and Mckee, 1991).

members with high and low marginal returns to that of homogeneous groups. Within heterogeneous groups, both studies find that individuals whose contributions have higher marginal returns to the public good tend to have a higher propensity to contribute than do members of the same group with lower marginal returns. These results seem to suggest that efficiency concerns prevail in controlled laboratory studies. However, in these studies, the contributor benefits from his or her own contribution; hence, contributions of high types are not only more efficient but also less costly for the donor. High types might therefore contribute more because of two factors: they can better advance the joint project and their costs of contribution are low.

The present study investigates the effect of the first of these two factors on contributions, which we will refer to as "productivity." The literature on distributive justice has suggested different fair contribution and sharing rules (Konow, 2003). Based on this literature, we motivate three plausible social norms, namely *an equal nominal contribution, an equal effective contribution,* and *an efficient contribution norm*, that we examine experimentally.

To do so, first we introduce heterogeneity by allowing the marginal returns of individual contributions to vary between two types, a low and a high productivity type, in a standard linear voluntary contribution mechanism while maintaining symmetry of costs among group members. Second, we vary the level of information about heterogeneity in three different treatments. In the baseline treatment, group members are informed about their own marginal returns as well as about individual nominal contributions of others. In the other two treatments, participants are additionally informed about the marginal returns of the other productivity type. Furthermore, in the third treatment, participants also know which productivity type made a particular contribution. This design allows us to control the extent to which individuals know about heterogeneity, and hence, it provides restrictions on the contribution norms that can be applied. In this way we aim to discriminate between different contribution norms and to examine the joint effect of a heterogeneous environment and information on voluntary contributions.

Our findings can be summarized as follows: When individuals are made aware of the heterogeneity in productivity, the average propensity to contribute increases. However, the information structure evokes different relative contribution patterns between types, resulting in contribution norms

that vary with the information group members have. The less information is available, the more equal contribution norms prevail; the more information is available, the more efficient contribution norms take over. The information about heterogeneity affects contribution behavior differently depending on the productivity type. Public information about heterogeneity in productivity within a group increases individual contributions almost exclusively for low types, who contribute more than high types, whereas the latter do not change their contribution behavior compared to the no information benchmark. However, more detailed feedback information on the contributor's type induces high types to contribute more and, at the same time, low types to lower their contributions.

The remainder of the article is organized as follows. Section 2 introduces the voluntary contribution mechanism and section 3 presents different motives to contribute. Section 4 describes the experimental design, presents the behavioral predictions explaining how varying the information about heterogeneity across treatments allows us to identify different contribution motives and gives a brief overview of our data. Section 5 presents our empirical model of individual contribution behavior and the results of the analysis. Section 6 discusses our results in the light of the literature and section 7 concludes.

2 The linear voluntary contribution mechanism

In order to introduce heterogeneity in the economic environment, we augment the standard linear model of the voluntary contribution mechanism (VCM). First, we introduce a productivity factor for each group member to reflect heterogeneity in individuals' ability to produce the public good. The joint project in a group with n members can be written as:

$$G = \sum_{j=1}^{n} (p_j y_j)$$

where y_j is an individual's nominal contribution to the group project and p_j denotes the individual's productivity. Each group member has either high or low productivity, i.e., $p_j \in \{p^H, p^L\}$ for all $j \in \{1, \ldots, n\}$. We will refer to individuals with high productivity as H-types, and those with low productivity as L-types. Any unit contributed to the joint project is efficient

but units of H-types progress the group project further, i.e., $1 < p^L < p^H$. The effective contribution of each group member to the joint project therefore depends on two factors: the individual nominal contribution (y_j) and the individual productivity (p_j). We consider a group that is composed of an equal number of H-types and L-types.

Second, we ensure identical pecuniary incentives to contribute across all group members as follows: the payoff of individual i from the public good is independent of i's contribution. In other words, each individual does not benefit from his or her own contribution but receives a share of the output generated by the contributions of only the other group members. Additionally, the contribution of one other member with different productivity is excluded from the public good pool, so that each subject benefits from a public good pool provided by a balanced number of individuals of both productivity types. The payoff of an individual i with an endowment w resulting from the interaction in a group with n members can be written as

$$\pi_i = w - y_i + G_i. \tag{1}$$

Each group member benefits from the amount allocated to the own account $(w - y_i)$ and the returns G_i from the joint project, where

$$\begin{aligned} G_i &= \frac{1}{n-2} \sum_{j \neq \{i,k\}} (p_j y_j), \; p_i \neq p_k, \text{ and } i, j, k \in \{1, \; \ldots \; , n\} \\ \text{and } G &= \sum_{j=1}^{n} (p_j y_j) = \sum_{i=1}^{n} G_i. \end{aligned}$$

The following are the novel features of our model. First, unlike in the standard VCM, group members are excluded from the returns generated by their own contributions. This is necessary because, otherwise, H-types not only advance the joint project more but also benefit from their own contributions more than L-types do, resulting in two motivations to give: higher efficiency and lower costs of contributing. Excluding members from benefiting from their own contribution keeps contribution costs constant across types and prevents the described confound.

Second, group members nevertheless face a symmetrical payoff structure: every individual benefits only from contributions of an equal number of both productivity types. Hence, both productivity types are equally accounted

for in everyone's payoff function. For example, consider a group composed of six members; three H-types and three L-types. An L-type individual i's payoff from the public good is derived as 1/4 of the sum of the contributions by the two other L-types and two randomly selected H-types. Consequently, by excluding the contributions of the individual him- or herself and of one member of the opposite type, we maintain the symmetry of individual payoff functions.

3 Contribution motives

In this section we review different motives to contribute to public goods. Efficiency requires that total surplus be maximized when each group member invests his or her whole endowment in the group project because $\partial \sum \pi_k / \partial y_i = -1 + p_i > 0$. However, from an individual point of view, there is a strong incentive not to contribute to the joint project because the marginal benefit of contributing one point is -1, i.e., $\partial \pi_i / \partial y_i = -1$. A number of empirical and experimental studies on social dilemma problems suggest different individual motivations that can help to overcome such an incentive to free-ride and to arrive at equilibria that lie in between those two extreme cases.

First, suppose individuals are concerned not only with advancing their own income but also with increasing others' payoff. Those persons might be motivated by either altruism or concerns for social efficiency. We approximate the utility function of such a person by

$$U_i = \pi_i + R_i(\pi_{-i})$$

where $R_i(\pi_{-i})$ is a linear, continuous, increasing and twice differentiable function that captures an individual's concern for others' payoff.

One unit contributed by group member i increases the public good, hence, the total payoff of the other group members by p_i, because

$$\frac{\partial G}{\partial y_i} = \frac{\partial G_{-i}}{\partial y_i} = \frac{\partial \pi_{-i}}{\partial y_i} = p_i.$$

From this it follows that group member i will contribute to the public good as long as his marginal utility gain is sufficiently high so that it satisfies the

following first-order condition,

$$\frac{\partial U_i}{\partial y_i} = -1 + \frac{\partial R_i(\pi_{-i})}{\partial \pi_{-i}} p_i \geq 0,$$

implying

$$\frac{\partial R_i(\pi_{-i})}{\partial \pi_{-i}} \geq \frac{1}{p_i}. \tag{2}$$

Therefore, when individuals are altruistic or concerned about social efficiency, their marginal utility in others' payoff is either constant or decreasing, and if H-types and L-types are randomly drawn from the same population of altruists and their level of altruism is independent from their productivity type, H-types will, on average, contribute more than L-types. This means, even if the function R_i varies across the population, condition (2) is easier to satisfy for H-types than for L-types because of $1 < p^L < p^H$. Being concerned about what is socially optimal can be a norm based on the understanding that "people often seek to maximize surplus, sometimes at a personal cost, and that this goal is regarded as 'fair'." (Konow, 2003, p.1205). We will refer to this norm hereafter as the *efficient contribution norm*.

Second, when group members observe nominal contributions of others (y_j), norms concerning equity may play a role in determining individual levels of contribution to a public good. The proportionality principle is often used as a measure of equity (see Konow, 2003 for a more general discussion of justice theories). This principle suggests that an individual's benefit from a joint project should be in proportion to the degree to which a person contributed to the project. Because in VCMs benefits from public goods are shared equally among group members, according to the proportionality principle, all individuals are expected to contribute equally. When group members differ in their productivity, equity depends on the way individual contributions are evaluated. Thereby, contributions might be evaluated with reference either to nominal units of endowment contributed (y_i) or to their 'effective' impact on the joint project ($p_i y_i$). Hereafter we will refer to these norms as the *equal nominal contribution norm* and the *equal effective contribution norm*, respectively.

It is important to note that if the reference point of the proportionality principle is nominal contributions, then group members' knowledge about

heterogeneity in the group will have no influence on contribution behavior. On the other hand, effective contributions can only be used as a reference point when there is sufficient information about heterogeneity in a population. Therefore, the intensity with which different reference points of the proportionality principle can come into play depends on the level of information that group members have about the productivity of others.

We vary the information groups have about the productivity of their members to investigate if behavior is shaped by efficiency concerns or proportional fairness and, for the latter case, which reference point is used. For instance, if persons act according to a contribution norm that has nominal contribution levels as a reference point, H-types and L-types would make the same nominal contributions regardless of whether members are aware of differences in productivity within their group. Similarly, behavior should not change with the level of information when group members are only concerned about altruism or efficiency. In this case, H-types would contribute more on average than L-types regardless of the information they possess about the difference in productivity.

If individuals make their contribution decisions according to a contribution norm with reference to effective contributions, however, such norms cannot come into play without sufficient information about the heterogeneity within the group. In this case, contribution behavior will differ depending on whether the information about heterogeneity in productivity is public. More precisely, without information, the reference point remains that of equal nominal contributions, whereas when information about heterogeneity is public, L-types will contribute (nominally) more than H-types, resulting in equal effective contributions of both types.

4 The experiment

4.1 Experimental design

In light of the different contribution motives, what norm is adopted in heterogeneous environments is -a priori- not clear. Therefore, we need to rely on empirical evidence to study the norms that are prevalent in heterogeneous environments. To provide such empirical evidence, we conducted a public good experiment. In the experiment, members of a group had to decide how to divide their private endowment between a private account and a group

project. The nominal contributions of each member to the group project were public information. The treatment variable in our experiment, the level of information, is varied in two ways: first, subjects either do or do not receive precise information on the distribution of productivity types within the group, and second, the feedback information about the contributions of all group members does or does not reveal each contributor's type.

In particular, we study three treatments with the following information scenarios. In the *No-info* treatment, group members know their own productivity, but not the distribution of types within their group. In the *Part-info* and *Full-info* treatments, the distribution of types is explicitly stated in the instructions. Additionally, the feedback information in the *Full-info* treatment allows members to link an individual contribution to the contributor's type. In sum, the three treatments gradually change the level of information about the heterogeneity in the population and contributions by different types.

Each information treatment comprised nine groups. Each group consisted of six members, three H-types with $p^H = 3.99$ and three L-types with $p^L = 1.33$, who interacted with each other in the same group over 15 periods (partner matching).[4] A group member remained either a H-type or a L-type throughout the whole experiment. At the beginning of every period, each group member was endowed with w =17 points and had to decide how many of them (y_i) to invest in a joint project and how many to keep ($w - y_i$). After all group members had made their decisions, individual payoffs were computed according to the VCM (as presented in equation 1), and group members were informed about their payoffs. Additionally, a table was displayed containing the history of contributions by each group member in all previous periods. In the *Full-info* treatment, this table also displayed the type of each contributor. The order of individual contributions in the history table was randomized so that contributions could not be attributed to a specific group member.

[4]The two productivity values were chosen with respect to the parameters used in previous research on heterogenous marginal per capita returns (MPCR). For instance, the two MPCRs used in Fisher et al. (1995) were 0.3 and 0.75, implying that a one-unit contribution by a low (high) MPCR type generates 1.2 (3) units of public goods in groups with four members. Therefore, the MPCR values used in Fisher et al. (1995) are comparable to the productivity factors of 1.33 and 3.99 used in our design.

4.2 Behavioral predictions

In light of the norms discussed in section 3 and our experimental design, we derive the following predictions about the behavior in the experiment.

(i) *Efficient contributions norm*:
If individuals are concerned about others' payoff and social efficiency, both types will contribute to the joint project, with H-types contributing on average more than L-types. The level of information that group members have about the heterogeneity in productivity within the group, will have no influence on contribution levels ($0 < y^L < y^H$ in all treatments).

(ii) *Equal nominal contributions norm*:
If individuals follow the proportionality principle with nominal contributions as a reference point, group members will contribute the same amounts regardless of their type and whether they are aware of the heterogeneity in productivity within the group ($y_i = y_k, \forall i \neq k$ in all treatments).

(iii) *Equal effective contributions norm*:
If individuals follow the proportionality principle with effective contributions as a reference point, both types will make the same nominal contributions when there is no information about heterogeneity ($y_i = y_k, \forall i \neq k$ in the *No-info* treatment). However, when individuals are informed about the heterogeneity in productivity in the group, L-types will contribute more than H-types resulting in equal effective contributions to the joint project by H-types and L-types (if i is a L-type and k is a H-type, $p^L y_i = p^H y_k$ implies $y_i > y_k$ in the *Part-info* and *Full-info* treatments).

In order to conform to a norm with efficient or effective contributions as possible reference points, group members need to compare themselves to their peers, and especially to peers of their own and the other type. Detailed information on contributors' types supports coordination of type specific contribution norms. It might not be possible to establish and maintain type specific contribution norms when types cannot be identified. Whereas the *Part-info* treatment only informs group members about the presence of heterogeneity, the *Full-info* treatment allows group members to link others' contribution behavior to their types. Therefore, even though different contribution norms might come into play with public knowledge about heterogeneity, coordination on these norms might be more easily established in the *Full-info* treatment and we expect behavior in the *Part-info* treatment to be amplified in the *Full-info* treatment. Table 1 summarizes the different

Treatment	Contribution motive		
	efficient	equal	
		nominal	effective
No-info	$y_H > y_L$	$y_H = y_L$	$y_H = y_L$
Part-info	$y_H > y_L$	$y_H = y_L$	$y_H < y_L$
Full-info	$y_H > y_L$	$y_H = y_L$	$y_H < y_L$

Table 1: Predictions (i), (ii), and (iii)

qualitative predictions.

4.3 Experimental procedure

The experiment was computerized and conducted in eight sessions with a total of 162 undergraduate students (54 per treatment) from Jena University at the laboratory of the Max Planck Institute of Economics in Jena, Germany. Recruitment was performed with the help of an online system (ORSEE, Greiner, 2003), and the experiment was executed using the software zTree (Fischbacher, 2007).

Prior to the beginning of the first period and after the exposition of the instructions, subjects were asked once to state a contribution norm and to predict the average contribution of others. 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.[5] This questionnaire allows us to capture an individual personality trait that reflects the tendency to rely on rules and norms (Conn and Rieke, 1994). A sample copy of the instructions is included in Appendix A.

At the end of each 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.[6]

[5] We used the official German translation of the revised version of the Sixteen Personality Factor Questionnaire (Cattell et al., 1993) translated by Schneewind and Graf (1998).

[6] Each session consists of two phases of group interactions lasting 15 periods in each period. In the second phase, groups were confronted with another treatment that will ultimately allow us to study path dependency of norms. In this article we consider only the first phase. Average earnings for the whole experiment (including both phases) were

4.4 Descriptive Statistics

Table 2 summarizes background characteristics of our participants. Participants are on average 24 years old, 43 percent of them are male. The individual index on norm-reliance is derived from a normalization of the test scores and results in so-called sten-values that can range from one to ten,[7] whereby higher sten-values indicate stronger reliance on norms. The norm-reliance scores of our participants range between one and nine with a mean value of 4.35.

Variable	Mean (s.d.)	Description
Age	23.7 (3.69)	Actual age in years
Gender	0.43 (0.49)	Gender of the participant, Male = 1, Female = 0
Personality index	4.35 (1.68)	Measure of norm reliance between 1 and 10

Table 2: Participants' characteristics (N=162)

An individual made a contribution decision in each of 15 periods resulting in a total of 2,430 contribution decisions (810 per treatment). Table 3 reports the mean of the average individual contributions over 15 periods as a proportion of their endowment. Across the treatments, participants contributed about 50 percent of their endowment. The average contributions in the treatments *Part-info* and *Full-info* appear slightly higher than that in the *No-info* treatment. Table 3 also reports mean contributions by type. They appear similar for both types in the *No-info* treatment, but differ for the other two treatments. 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.

Figure 1 plots the average contribution as a proportion of the endowment by treatment across 15 periods. In all three treatments, the average contribution globally decreases over the course of the experiment, with a

about 11 Euros.

[7]These values are derived from a normalization of the test scores and measured in sten-scores for the norm population. The average (expected) sten value in the population is 5.5 with a standard deviation of 2.

Treatment	All Mean (s.d.)	L-type Mean (s.d.)	H-type Mean (s.d.)
No-info (N = 54)	0.42	0.42	0.43
	(0.25)	(0.22)	(0.28)
Part-info (N = 54)	0.54	0.59	0.50
	(0.28)	(0.28)	(0.27)
Full-info (N = 54)	0.56	0.50	0.62
	(0.29)	(0.28)	(0.28)
All (N = 162)	0.51	–	–
	(0.28)	–	–

Table 3: Average contribution as a proportion of the endowment

quicker decay towards the end. There are noticeable differences across the treatments in how contribution behavior evolves over time. In the *No-info* treatment, contributions continuously decrease over time in conformity with other public good 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.

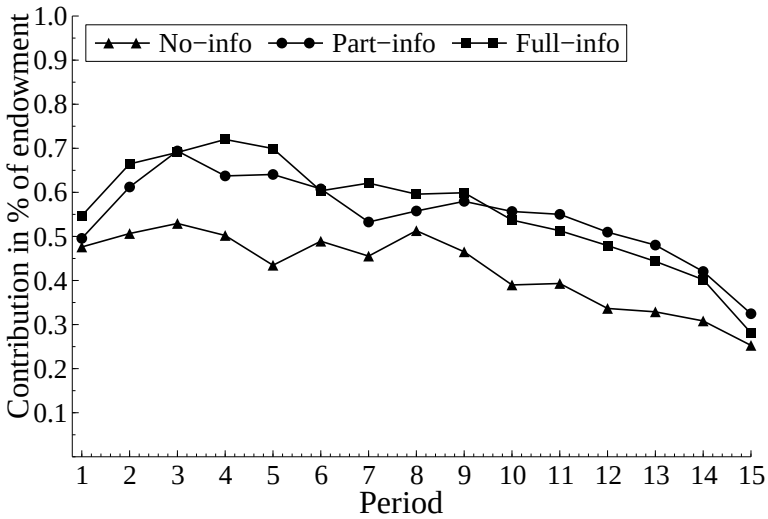

Figure 1: Average nominal contributions as a proportion of the endowment for the three treatments (*No-info*, *Part-info* and *Full-info*)

Figure 2 visualizes the evolution of average contribution behavior by

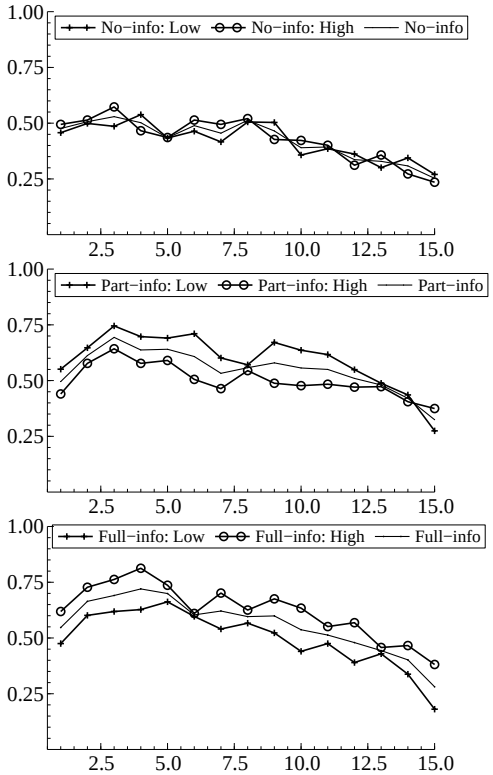

Figure 2: Average nominal contributions as a proportion of the endowment by treatment and productivity type

treatment and by productivity type over time. We also notice patterns in contribution behavior between types across the treatments similar to those of the aggregate average contributions presented in Table 3. In the *No-info* treatment, there is no apparent difference in contributions between the two types, while in the *Part-info* treatment L-types appear to contribute more than H-types. These observations are consistent with the behavior predicted by an *equal effective contribution norm*. However, in the *Full-info* treatment, the pattern of the *Part-info* treatment seems to reverse: H-types contribute more than L-types suggesting behavior motivated by an *efficient contribution norm*.

5 Empirical model of contribution behavior and results

In this section we present a dynamic model in order to quantify the effects identified visually in the previous section and to test whether they are significant while controlling for individual heterogeneity. The choice for the empirical model is guided by the dynamic nature of the data and the fact that contributions are bounded below and on top. This allows us to provide statistical evidence of how individual contribution behavior evolves in line with plausible contribution norms and how information about heterogeneity affects individual contribution behavior over time.

We describe the proportion that individual i contributes from his or her own endowment in period t, $y^{\star}_{it}$, as the function:

$$y^{\star}_{it} = \gamma + \omega High + f(t) + x_i\beta + \epsilon_{it} \tag{3}$$

Where γ indicates the basic contribution level, ω captures the effect of productivity, with the dummy variable $High$ being equal to one if i is a H-type and zero otherwise. We control for time trends by including $f(t)$, a function of time. The vector x_i represents the individual observable characteristics of age, gender, and norm-reliance. Their influence on contributions is captured by the parameter β. Idiosyncratic errors, ϵ_{it}, are assumed to be independent of productivity and other individual characteristics in x_i.

The influence of information is captured by treatment dummies. The complete model, including treatment dummies, with the *No-info* treatment as a baseline is given by:

$$\begin{aligned} y^{\star}_{it} &= \gamma_0 + \gamma_1 \textit{Part-info} + \gamma_2 \textit{Full-info} \\ &+ \omega_0 High + \omega_1 High \cdot \textit{Part-info} + \omega_2 High \cdot \textit{Full-info} \\ &+ f(t) + x_i\beta + \epsilon_{it} \end{aligned} \tag{4}$$

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 period endowment.[8] We therefore use a standard regression doubly censored Tobit model

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

to estimate the relation for the latent contribution proportions $y_{it}^{\star}$ described in model (4) with

$$y_{it} \begin{cases} = & 0 \quad \text{if } y_{it}^{\star} \leq 0, \\ = & y_{it}^{\star} \quad \text{if } 0 < y_{it}^{\star} < 1, \\ = & 1 \quad \text{if } y_{it}^{\star} \geq 1. \end{cases} \tag{5}$$

Baseline: specification 1

We estimate two specifications of the model in equation (4). Both specifications include the same set of background characteristics, but vary in the way time effects are modeled. In specification 1, the time trend is modeled 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 $f(1) = 0$). The main estimation results are reported in Table 4.

The first thing to note from the results of specification 1 is that group members invest a positive amount of their endowment ($\gamma_0 > 0$ with $p = 0.000$) in the group project. Further, information about heterogeneity has a positive impact on contributions (γ_1, γ_2 and $\omega_2 > 0$ with $p = 0.000$). In the *Full-info* treatment, this increase is almost exclusively driven by the more productive type ($\gamma_2 = 0.100 < \omega_2 = 0.293$). In the other two treatments (*No-info* and *Part-info*), H-types contribute significantly less compared to their L-type colleagues, but this effect is relatively small ($\omega_0 = -0.044, p = 0.024$ and $\omega_1 = -0.012, p = 0.623$). The period dummy coefficients reveal a non-linear time trend, indicating an increase in contribution levels until period 6 and a strong decrease over the last third of the experiment (after period 12). Finally, we find that women tend to make significantly smaller contributions ($\beta_2 = -0.239$ with $p = 0.000$) and that age and norm-reliance have significant but relatively small negative influences on contributions.

The time dummies (with estimates presented in Table 5) indicate an inverse-U relation: Contributions increase the first 3 periods before following a relatively steady decline.

		Specification 1		Specification 2	
Variable	Parameter	Coefficient	T-value	Coefficient	T-value
Constant	γ_0	0.843	8.953	0.934	5.925
Part-info	γ_1	0.210	12.299	0.086	0.428
Full-info	γ_2	0.100	5.955	0.024	0.122
H-type	ω_0	-0.044	-2.422	-0.026	-0.119
H-type *Part-info*	ω_1	-0.012	-0.498	0.037	0.124
H-type *Full-info*	ω_2	0.293	12.801	0.329	1.197
linear Time trend	τ_{10}			0.013	0.276
Part-info	τ_{11}			0.062	1.024
Full-info	τ_{12}			0.054	0.892
H-type	τ_{13}			0.009	0.141
H-type *Part-info*	τ_{14}			-0.070	-0.761
H-type *Full-info*	τ_{15}			-0.033	-0.393
quadratic Time trend	τ_{20}			-0.002	-0.862
Part-info	τ_{21}			-0.005	-1.245
Full-info	τ_{22}			-0.004	-1.166
H-type	τ_{23}			-0.001	-0.286
H-type *Part-info*	τ_{24}			0.006	1.111
H-type *Full-info*	τ_{25}			0.003	0.547
Background characteristics		Yes		Yes	
Time dummies		Yes		No	
Number of Observations		2430		2430	
Number of Parameters		23		21	
	σ_ϵ	0.584	62.539	0.584	64.139
Log-Likelihood value		-33172.7		-33155.7	

Table 4: Estimation results for nominal contribution behavior (dependent variable: proportion that an individual contributes from his or her initial endowment).

(Other parameter estimates are presented in Table 5, Appendix C.)

Time and treatment interaction effects: specification 2

In a second specification, we model the time trend as a quadratic function, that captures the nonlinear relation of contributions and time found for specification 1, including interaction effects with productivity and information:[9]

$$f(t) = \tau_{10} \cdot t + \tau_{20} \cdot t^2 + Interaction(t, High, \textit{Part-info}, \textit{Full-info}). \quad (6)$$

This allows us to account for both non-linear effects of periods and interactions with the different treatments while minimizing the loss of degrees of freedom. Estimation results are presented in Table 4.

Specification 2 reveals that the effect of treatment variables materializes largely through dynamic interactions over the periods. More precisely, information about heterogeneity has a non-linear effect on individual contributions of both productivity types. Instead of the standard monotonic decay, they increase before they diminish (as captured by the positive coefficients τ_{11} and τ_{12} and the negative coefficients τ_{21} and τ_{22}). Moreover, the positive coefficients τ_{24} and τ_{25} suggest that additional information counterbalances the declining trend for contributions of H-types. These parameters are not individually significant. In order to test whether their joint effect is significant and to assess the global picture of those individual interactions, we compute expected contributions and calculate marginal effects using our estimated parameters.[10] The results are presented in Figure 3. The upper panels in Figure 3 present predicted average nominal contributions as a proportion of the endowment for H- and L-types in each treatment, while the lower panels show the marginal effects of productivity on contributions with 95% confidence bounds.

The upper left panel in Figure 3 depicts the *No-info* treatment. It suggests that in the absence of information about heterogeneity both types make the same nominal contributions and exhibit a similar monotonic de-

[9]The detailed time function is given by:

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

[10]Details of the estimation procedure of the marginal effects are included in Appendix B.

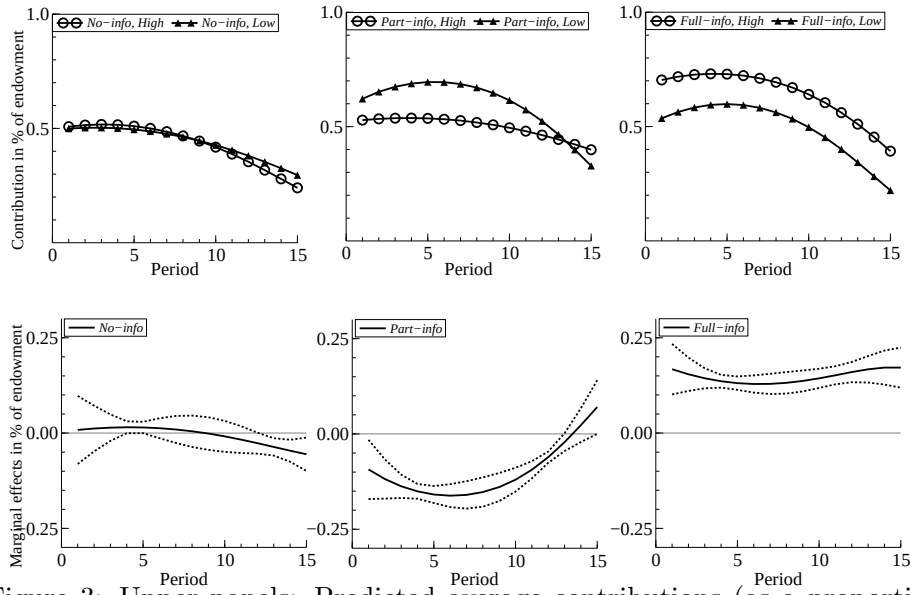

Figure 3: Upper panels: Predicted average contributions (as a proportion of the initial endowment) over time for each treatment and type.
Lower panels: Marginal effects of productivity on contributions for each treatment. (The graphs project the difference in relative nominal contributions between H-types and L-types.)

cay of their individual contributions. The marginal effects analysis for this case, presented in the lower left panel, confirms this observation. We cannot reject the null hypothesis of no effect throughout periods 1 to 12.

The other four panels illustrate the case for the treatments with more information. In contrast to the *No-info* treatment, we find here that contributions of both types are not monotonically declining but rather parabolic, depicting the tendency for average contributions to increase initially before following the standard pattern of decay. Furthermore, from the lower middle and lower right panels, we learn that contribution behavior differs significantly between the two types and also between the *Part-info* and the *Full-info* treatments indicating the extent to which types respond differently to the information about heterogeneity.

The upper and lower middle panels illustrate behavior in the *Part-info* treatment. There, the predicted average contribution of L-types is between 5% and 10% of their endowments higher than that of H-types. In summary, the *No-info* treatment allowed us to discriminate between equal and efficient contribution motives, whereby we find support for equal contribu-

tion motives. However, in the *No-info* treatment we could not discriminate whether equal contribution motives rely on equal nominal or effective contributions. As discussed in section 4.2 the *Part-info* treatment was designed to discriminate between those two equal-contribution motives. The results of the latter treatment, support our findings of equal contribution motives in the *No-info* treatment, and suggest equal effective contribution motives.

According to our prediction, we expect behavior in the *Full-info* treatment to reconfirm the finding from the *Part-info* treatment because in the former coordination is facilitated by informing group members additionally about a contributor's type. Contrary to this conjecture, contribution behavior between H- and L-types seems to be reversed. The predicted contributions and marginal effects for the *Full-info* treatment, illustrated in the upper and lower right panels, indicate that when contributions can be linked to the type of the contributor, H-types give significantly more than L-types. The lower right panel indicates that this difference comprises around 15% of the endowment and remains constant over time as contributions of both types follow the same time trend.

The dynamic behavior that we observe in different treatments is very similar between types, with two notable exceptions. In the *No-info* treatment, contributions by H-types decline in the last three periods slightly faster than those made by L-types, leading to a significant but almost negligible difference in contributions between the two types. In the *Part-info* treatment, the general decline in contributions over time is less pronounced for H-types. As a result, in the last three periods, contributions by the two types are no longer significantly different.

A summary of the above observations is in order. On one hand, we find evidence against the *efficient contribution norm*, where individuals are supposed to react solely to their individual productivity parameter. This comes from the findings in the *No-info* and *Part-info* treatments, where contribution behavior instead supports an *equal effective contribution norm*. On the other hand, in the *Full-info* treatment, we observe contribution behavior providing evidence for the *efficient contribution norm*.

Given this mixed evidence, we conclude that individuals do not react solely to their own productivity, nor do equal contribution norms persist in the presence of sufficient information on heterogeneity. Second, efficient contributions emerge when information is provided within a group about in-

dividuals' characteristics and contribution behavior. Third, the information structure affects types differently.

6 Discussion and further results

The present experiment was designed to investigate the impact of productivity isolated from costs of contribution. Therefore, we excluded subjects from the returns of their own contributions. This is quite different from the standard experimental public goods literature, in which a person always benefits from his or her own contribution (see Ledyard, 1995 for a survey). Despite this difference in design, in agreement with findings in this literature, we found positive contributions to the joint project and a common decay in contributions over time.

Closely related to our article are Fisher et al. (1995) and Tan (2008) who study public goods experiments with groups whose members vary in the marginal returns that a contributed unit generates for themselves and others, also referred to as MPCR ("marginal per capita return"). In these experiments, group members receive the marginal returns of their own contributions. As a consequence, contributions of members with high productivity are less costly for the donor. Our experimental design allows us to isolate the effect of productivity on contributions; hence, our results complement the findings of these studies.

In Tan (2008), the same groups of four persons participate in three subsequent treatments. Her second treatment is comparable to our *Full-info* treatment. There, half of the group is assigned a high MPCR (0.9) and the other half a low MPCR (0.3). She finds that members with a high MPCR contribute more than those with a low MPCR, a finding qualitatively similar to our results. In Fisher et al. (1995) two out of four group members have a high MPCR (0.75) and the other two a low MPCR (0.3). The same group members interact in two parts of ten periods each. After the first ten periods, members with a low MPCR are assigned a high MPCR and vice versa. In the first part of the first sessions, Fisher et al. (1995) report behavior that they name "poisoning of the well" because high types contribute less than low types. The difference in contributions between types reversed in the second part, when high types contribute more than low types. These findings resemble the differences we find between our *Part-info* and *Full-info*

treatments. Given our results, we conjecture that their findings occurre due to the differences in information scenarios between the two parts of their experiment. Indeed, participants in their experiments were only implicitly informed about the heterogeneity in the group. They might have anticipated different MPCRs in the first part, but they knew about it for sure in the second part after they had switched types. Our conjecture might find even more support in further observations of Fisher et al. (1995). After recognizing the poisoning of the well effect, in the remaining sessions, Fisher et al. (1995) explicitly reminded participants before the first part of the experiment of the possibility of different private MPCRs. In those later sessions, the poisoning of the well effect disappeared.[11]

The similarity of our results to those of Fisher et al. (1995) and Tan (2008) indicates that the same information structure leads to similar contribution patterns between types regardless of whether they have the same or different contribution costs. The findings in our experiment and the comparison to the literature underline the importance of the information structure. Therefore, in what follows we discuss differences in behavioral responses to information by productivity type.

Reactions of types to information

In order to investigate how both types react to the provision of information about heterogeneity, we compute marginal effects. Results are presented in Figure 4, with marginal effects of information about heterogeneity on the individual contribution behavior of H-types in the upper panels and of L-types in the lower panels.

The upper left corner panel shows the marginal effects of H-types knowing that group members vary in their productivity (*Part-info*) vs. having no information (*No-info*). In the first half of the experiment, H-types in both treatments contributed similarly, but from period 8 onwards, they contributed significantly more in the *Part-info* treatment. This can be explained by the fact that contributions of H-types in the *No-info* treatment exhibited the standard pattern of decay whereas, in the *Part-info* treatment, they remained relatively stable over time. The marginal effects of having

[11] Fisher et al. (1995) write, "This greater occurrence of poisoning type behavior in *only* Year 1 with *only* the high MPCR types in *only* the first five groups remains a mystery to us." (p. 265, Footnote 11)

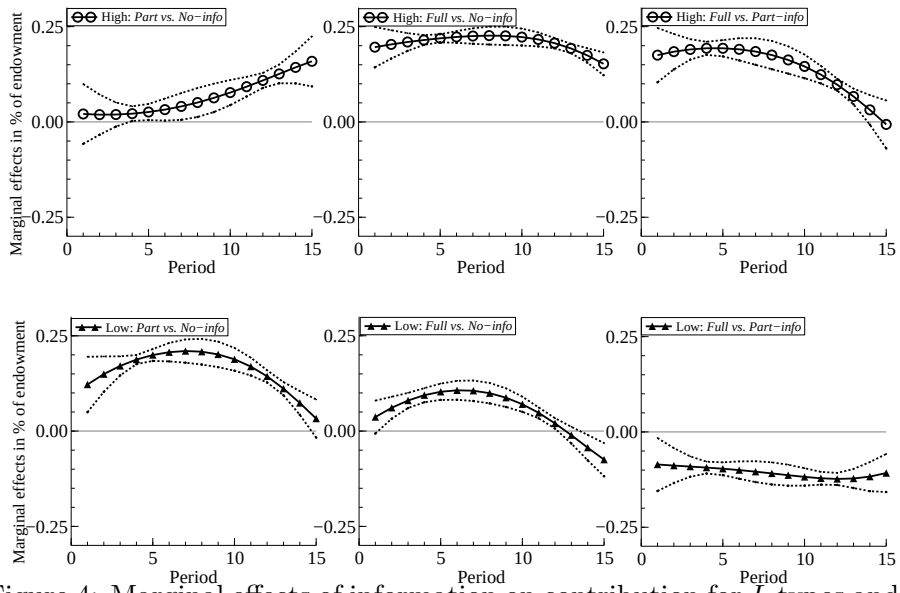

Figure 4: Marginal effects of information on contribution for L-types and H-types. (The graphs project the difference in relative nominal contributions between two treatments.)

(partial) information (*Part-info*) vs. additional feedback on the type of contributor (*Full-info*) are depicted in the upper right panel. There we find that generally H-types contributed between 10 and 20 percent more of their initial endowment in the *Full-info* treatment than in the *Part-info* treatment. However, in the last two periods, contributions no longer differed significantly. Once again, this can be explained by the fact that contributions of H-types in the *Part-info* treatment do not exhibit the pattern of decay, whereas they do in the *Full-info* treatment. The upper middle panel shows the overall positive and relatively stable effect of around 20 percent on H-types' contributions between no information (*No-info*) and full information (*Full-info*).

We find very different marginal effects for L-types, as shown in the lower panels of Figure 4. The lower left and middle panels present the effect of having (partial) information (*Part-info*) and being fully informed about the type of the contributor (*Full-info*), respectively, compared to having no information about group heterogeneity (*No-info*). The two figures indicate that information on heterogeneity generally increases the contributions of L-types. Whereas contributions were around 15 percent of the endowment

in the *Part-info* treatment, they were only around 5 percent in the *Full-info* treatment. This explains the negative marginal effect on L-types' contributions when comparing the *Full-info* and the *Part-info* treatment, depicted in the lower right panel.

In conclusion, the apparent "poisoning of the well" effect reported by Fisher et al. (1995) and replicated in our study is the joint result of divergent reactions of the two types. When there is (partial) information on heterogeneity, H-types do not contribute less compared to the situation without this information. However, L-types increase their contributions when group members have partial information on the heterogeneity in productivity and, albeit less so, when all group members have full information. Indeed, in the latter information scenario, H-types contribute much more, resulting in the finding of H-types contributing less in the *Part-info* treatment and more than L-types in the *Full-info* treatment. Whether there are particular forces of social pressure in place that emerge from lowering the anonymity of contributors (even though only the type of the contributor is known) that affect L-types and H-types differently is at this point open for discussion and left for further research.

Finally, few and inconclusive studies exist on the effect of information on contributions to VCMs. Andreoni and Petrie (2004) and Croson and Marks (1998) find that revealing information about individual contributions as well as individual characteristics increases individual contributions. Marks and Croson (1999) find that information on heterogeneous valuations of public goods does not significantly alter the aggregate level of contributions. Our results add empirical evidence to this literature. They suggest that more information does not only increase average contributions, but affects contributions of productivity types in heterogeneous groups differently.

7 Conclusions

This article studies the effects of heterogeneity in productivity on voluntary contribution behavior to a joint project using experimental data. We introduce heterogeneity in a standard linear voluntary contribution mechanism by varying the marginal products of individual contributions. In order to separate the effects of productivity from the costs of contribution, group members do not benefit from their own contributions. We use information

as a treatment variable to distinguish between alternative plausible contribution norms. To this end, we gradually increase the level of information about heterogeneity in three treatments to control what subjects know about the heterogeneity.

Our findings outline the importance of the information structure concerning contributions to joint projects with heterogeneous group members, such as teamwork and charitable giving. Our analysis reveals that the information structure evokes different relative contribution patterns for the two types, resulting in contribution norms that vary with information. The less information that is available, the more equal contribution norms prevail; but the more information that is available, the more efficient contribution norms prevail.

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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.

Your payoff from the private account:
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.
Your payoff from the group project:
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.][12] 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.[13]
Please note that four other members of your group benefit from your transfer to the project, but you do not.

One period proceeds as follows:
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.
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

[12]The information in parentheses was **not given** in the *No-info* treatment but was **given** in the *Part-info* and *Full-info* treatments.
[13]This was the factor for H-types. L-types had a factor of 1.33.

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)].[14] 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][24]	
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!

B Marginal effects of information and of productivity 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 productivity on average nominal contributions in the *Full-info* treatment is given by

$$\begin{aligned} \Delta_{i,t}^{HL} &= E(y_{igt}|x_i, t, High = 1, \textit{Part-info} = 0, \textit{Full-info} = 1, c_i) \\ &- E(y_{igt}|x_i, t, High = 0, \textit{Part-info} = 0, \textit{Full-info} = 1, c_i) \end{aligned} \quad (7)$$

for which we calculate the expected contribution levels using the parameter estimates of specification 2 (model in equation (4) and equation 6) to com-

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

pute $y^{\star}_{igt}$. Finally, we apply the censoring rule in equation (5) to obtain y_{igt}. We compute the effect in equation (7) for all individuals who participated in the *Full-info* treatment and for each time period. We average over all individual effects $1/(NT)\sum_{\forall t,i}\Delta^{HL}_{i,t}$ to obtain the total effect. We simulate the variance of the marginal effects, that is used to calculate the t-values, using 100 Halton draws (see Train, 2003 and Judd, 1999).[15]

C Parameter estimates of background characteristics and time trend

		Specification 1		Specification 2	
Variable	Parameter	Coefficient	T-value	Coefficient	T-value
Age	β_1	-0.008	-4.851	-0.008	-4.839
Gender	β_2	-0.239	-19.911	-0.239	-19.840
Norm-reliance	β_3	-0.029	-9.239	-0.029	-9.277
Time dummies	δ_2	0.147	0.933		
	δ_3	0.207	1.509		
	δ_4	0.180	1.364		
	δ_5	0.131	1.084		
	δ_6	0.090	0.790		
	δ_7	0.034	0.301		
	δ_8	0.066	0.524		
	δ_9	0.054	0.458		
	δ_{10}	-0.043	-0.385		
	δ_{11}	-0.048	-0.432		
	δ_{12}	-0.118	-0.973		
	δ_{13}	-0.146	-1.367		
	δ_{14}	-0.225	-2.167		
	δ_{15}	-0.413	-3.808		

Table 5: Parameter estimates of background characteristics and, for specification 1, the time trend

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