When Does Less Information Translate into More Giving to Public Goods? *

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Abstract

This paper theoretically and experimentally investigates the impact of information provision on voluntary contributions to a linear public good with an uncertain marginal per-capita return (MPCR). Uninformed donors make contribution decisions based only on the expected MPCR (i.e. the prior distribution), while informed donors observe the realized MPCR before contributing. The theoretical analysis predicts that the impact of information on average contributions crucially depends on the generosity level of the population, modeled as a stochastic change in the pro-social preferences. In particular, a less generous population increases contributions substantially in response to good news of higher than expected MPCR and reduces contributions relatively little in response to bad news of lower than expected MPCR. The opposite is true for a more generous population. Thus, the theory predicts that information provision increases (reduces) average contributions when the population is less (more) generous. This prediction finds strong support in a two-stage lab experiment. The first stage measures subjects' generosity in the public good game using an online experiment. The resulting measure is used to create more and less generous groups in the public good lab experiment, which varies the information provided to these groups in the lab. The findings are in line with the theoretical predictions, suggesting that targeted information provision to less generous groups may be more beneficial for public good contributions than uniform information provision.

JEL Classifications: H41, C72, C90.

Keywords: information provision, linear public good game, other-regarding preferences, lab experiment.

1 Introduction

Private voluntary contributions have been increasingly viewed as a vital source of funding for public goods. For example, DonorsChoose, a fundraising platform for public school projects, has quickly gained popularity since its inception in 2000 and has raised close to $640 million up-to-date.[1,2] Other crowdfunding platforms that fundraise for public projects include Public Good[3], Razoo[4], and Pledge Music[5]. Interestingly, while the non-profit sector is growing, with the number of non-profits surpassing 1.5 million, recent evidence suggests that individual donors are often poorly informed when making contributions. According to 2015 Camber Collective survey about private charitable giving in the U.S., "49% of donors don't know how nonprofits use their money".[6] Such lack of information may have a significant impact on giving since existing lab experiments suggest that donors care about the use of their money, with more valuable projects receiving higher contributions (see Ledyard, 1995, and Cooper and Kagel, 2016).

This paper uses a linear public good framework to theoretically and experimentally investigate the impact of more information about the marginal per-capita return (MPCR) of the public good on total contributions. In particular, it compares two information environments (treatments) corresponding to informed and uninformed donor populations (subject groups). An uninformed population (subject group) only observes the prior distribution of the MPCR and thus makes a contribution decision based on the expected MPCR. An informed population (subject group) observes the realized MPCR prior to contributing. By studying how donors respond to good news of higher than expected MPCR and bad news of lower than expected MPCR, we can determine whether information provision is on average beneficial or harmful for giving.

Interestingly, our theoretical analysis and experimental findings reveal that the relative response to good and bad news crucially depends on the generosity level of the population, which reflects the strength of donors' pro-social motivations for giving. We find that a less generous population increases contributions substantially in response to good news and reduces contributions relatively little in response to bad news. The opposite is true for a more generous population that exhibits a stronger response to bad news than good news. As a result, we find that information provision is beneficial for giving in a less generous donor population, but harmful in a more generous donor population.

To glean more insight into this differential response to good and bad news, it is instructive to

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[1]For more information, visit `https://www.donorschoose.org/about`.

[2]According to Charity Navigator, the overall contributions to education related causes in the US amounted to $59.77 billion in 2016. For more information, see `https://www.charitynavigator.org/index.cfm?bay=content.view&cpid=42`.

[3]`www.publicgood.com`

[4]`www.razoo.com`

[5]`https://www.pledgemusic.com/`

[6]See `http://www.cambercollective.com/moneyforgood/`

discuss how donors' preferences impact the equilibrium contribution behavior in our theoretical model. We follow a growing literature that depicts agents as having other-regarding preferences (e.g. Rabin, 1993; Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000; Charness and Rabin, 2002; Falk and Fischbacher, 2006; Arifovic and Ledyard, 2012). Such preferences are partially motivated by existing experimental findings revealing that, while it is payoff maximizing to contribute nothing to the public good and socially optimal to contribute the entire endowment, most contributions in the lab are in-between these two extremes (Ledyard, 1995; and Cooper and Kagel, 2016). To capture this behavior, we follow Arifovic and Ledyard (2012) by modeling agents as having pro-social concerns, represented by agents' preference for higher average payoff in the population, and also having fairness concerns, represented by agents' dis-utility from obtaining lower than the average payoff. We refer to agents with stronger pro-social preferences as more generous since they have higher propensity to contribute.

The above preference specification gives rise to an equilibrium giving behavior by each agent that can be classified into one of three types based on their own generosity level: 1) selfish giving of 0 for low generosity; 2) generous giving of the entire endowment for high generosity; 3) conditional cooperative giving, matching the average expected contributions in the population, for moderate generosity. The individual generosity level is private information to each agent and thus the expected equilibrium giving takes into account the distribution of the pro-social preferences in the population. Quite intuitively, for a fixed MPCR, the expected equilibrium giving increases with the likelihood of generous giving and decreases with the likelihood of selfish giving.

Besides the distribution of the pro-social preferences, the equilibrium giving function is also affected by the MPCR. As the MPCR increases, the marginal cost of giving goes down while the social benefit goes up. This reduces the incentives for selfish giving in favor of cooperative and generous giving. As a result, the equilibrium giving function is increasing in the MPCR. Interestingly, the rate of increase is not constant, but instead it features increasing returns to MPCR when the MPCR is low (i.e. the expected giving function is convex in the MPCR for low values) and diminishing returns when the MPCR is high (i.e. the expected giving function is concave in the MPCR for high values). This is because at low MPCR, selfish giving dominates and an increase in the marginal return has a significant impact of incentivizing agents away from selfish to conditional and generous giving. This impact of increasing the MPCR eventually diminishes as the likelihood of selfish giving decreases substantially at high values of the MPCR.

The shape of the equilibrium giving function is instrumental in evaluating the impact of information provision. While a convex giving function tends to generate a greater response to good news and a weaker response to bad news, the opposite is true for a concave giving function. Interestingly, we find that a more generous population reaches diminishing returns faster, and thus exhibits a wider concave region. This is because more generous agents are also more easily induced to give

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and contribute significant amounts even at lower values of the MPCR. As a result, a more generous population is less responsive to good news and more responsive to bad news. The opposite is true for a less generous population, which features increasing returns for a wider range of the MPCR and thus is more responsive to good news than bad news. Consequently, the average informed giving is higher than the uninformed giving for a less generous population, while the opposite holds for a more generous population.

This novel finding of our model gives rise to testable hypotheses, which we experimentally investigate in the lab. Since our theoretical model suggests that the generosity level of the population plays a vital role in how agents respond to information, a defining feature of our experimental design is controlling for the generosity level of the sessions. We accomplish this by running our experiment in two stages. First, we conduct an online experiment to elicit subjects' generosity levels in the public good game prior to the lab experiment. Using this data, we create more and less generous groups in the lab, and inform the subjects about the generosity level of their session by using a neutral language. In the lab, subjects play a repeated one-shot linear public good game in groups of three with uncertain MPCR (either high (0.60) or low (0.40) with equal probability). There are two information treatments. In the Known MPCR treatment, subjects observe the randomly chosen MPCR before they make their contribution decisions. In the Unknown MPCR treatment, they are only informed about the distribution of the MPCR, and asked to make their contributions without observing which MPCR is chosen.

The experimental findings are in line with the theoretical predictions. In the more generous sessions, the average contributions in the Unknown MPCR treatment are not statistically different than the average contributions in the Known MPCR treatment under good news (MPCR of 0.60), but are statistically higher than the average contributions under bad news (MPCR of 0.40). Thus, on average, information reduces contributions to the public good in the relatively more generous sessions. The opposite is true for the less generous sessions: the average contributions in the Unknown MPCR treatment are not statistically different than the average contributions under bad news, but are statistically lower than the average contributions under good news. Thus, information is on average good for giving in the less generous sessions.

Our findings suggest that targeted information provision may be a successful strategy for increasing public good contributions. In particular, the model and the experimental results reveal that less generous donors are more responsive to good news about the returns from the public good. Thus, focusing on better informing these donors, who are often overlooked in fundraising campaigns, may be a more fruitful strategy than uniform information provision. In the next section, we briefly discuss how our findings contribute to the existing literature on public good provision.

2   Related Literature

This paper connects two research strands that investigate two important factors that impact public good provision and cooperation: 1) information, and 2) the social preference composition of groups.

2.1   Information

Much of the earlier literature on public good provision assumes that donors operate under complete and perfect information (Ledyard, 1995; Andreoni and Payne, 2013; Vesterlund, 2016). In reality, however, information is often limited, which has given rise to a more recent trend of studying public good provision under incomplete and imperfect information.

On the theoretical front, there is sparse literature that studies public good provision under incomplete information about the public good value. In particular, in the context of discrete public goods, Menezes at. al. (2001), Laussel and Palfrey (2003), and Barbieri and Malueg (2008, 2010) introduce private information about donors' heterogeneous valuations of the public good, while Krasteva and Yildirim (2013) endogenize the choice of information acquisition and find that more information about one's own value improves giving. In contrast, our current setting features a public good with homogeneous returns and finds that more information about the return is not always beneficial.

Our paper is also related to the literature that studies the use of indirect signaling channels to transmit information to donors. In particular, Vesterlund (2003), Andreoni (2006), and Krasteva and Saboury (2019) study how the size and the form of a leadership gift by a large donor impacts other donors' beliefs about the quality of a public good.[7] In a similar vein, Lange et al. (2017) study how a fundraiser may impact donors' beliefs by including a gift with the solicitation request. While these existing models are interested in the ability of different indirect channels to inform donors, our primary focus is on the direct impact of information provision on donors' willingness to contribute to public projects.

Our model and experimental set-up is cast as a continuous linear public good with an uncertain MPCR. In this respect, it is closest to the experimental literature that considers limited information about the returns. Although some of this literature focuses on information about others' valuation and/or endowment by incorporating heterogeneity in the public good environment (e.g. Marks and Croson 1999; Chan et al. 1999), most of the focus has been on the impact of *uncertainty* about the MPCR. In particular, Gangadharan and Nemes (2009), Levati et al. (2009), Fischbacher et al. (2014), Stoddard (2015), Boulu-Reshef et al. (2017), Butera and List (2017) and Théroude and Zylbersztejn (2017) study how increasing the *riskiness* of the returns, in terms of a mean preserving

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[7]In addition, Potters et al. (2005, 2007) experimentally investigate information revelation through leadership giving.

spread, affects contributions. For example, Levati et al. (2009) compare the contributions to a linear public good with a certain return α to the contributions with an uncertain return that may take either high $(\alpha + a)$ or low $(\alpha - a)$ value with equal probability.[8] Since both scenarios feature the same expected return α, the focus of the comparison is on the response to risk rather than the impact of good and bad news. In contrast, we are interested in how donors respond to good and bad news about the MPCR, which more closely represents the impact of information provision. To the best of our knowledge, our paper is the first to investigate public good contributions in this environment.

It is worth highlighting that our work is also related to a growing literature that studies the impact of variety of information (such as cost-to-donation ratio, recipients' or non-profits' characteristics, other donors' giving, and so on) on donations to non-profits and individual recipients outside the lab (e.g. Eckel et al., 2007; Shang and Croson, 2009; Fong and Oberholzer-Gee, 2011; Null, 2011; Butera and Horn, 2017; Karlan and Wood, 2017; Brown et al., 2017; Exley 2016, 2017; Portillo and Stinn, 2018; Metzger and Günther, 2019). These studies vary in the degree to which donors benefit from the non-profit's services, from donations to public radio (Shang and Croson, 2009) to donations that benefit an anonymous third party (Fong and Oberholzer-Gee, 2011). Prosocial considerations are likely a stronger determining motive for giving in the latter since donors are not direct beneficiaries.

Perhaps due to the significant variability in the nature of the provided information and the likely motives behind donors' contributions, the findings in the above studies are mixed. For instance, Fong and Oberholzer-Gee (2011) consider a dictator game setting with real-welfare recipients and find that information about the recipient is mostly used to withhold contributions from less preferred recipient types and thus information leads to an overall decline in aggregate transfers. Metzger and Günther (2019) focus on donations to NGOs that implement education projects for children and young adults in poor countries and find that the average donations increase in response to information about the recipient type and decrease in response to information about administrative costs. Butera and Horn (2017) allow donors to choose from a large list of real charities with different missions and observe that response to program effectiveness depends on whether this information is provided privately or publicly. The benefit of our induced value public good experiment is that we are able to control both for the information that donors posses as well as the strength of the pro-social preferences in the population. Our findings suggests that the impact of information depends crucially on the pro-social preferences of donors, with information being less advantageous in the presence of more pro-social donors. This insight can be used in future field experiments to investigate how information provision about program effectiveness may differentially impact

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[8]Although the findings are mixed, Levati and Morone (2013) and Stoddard (2017) show that the parameterization of the public good game can play an important role in determining the direction of this effect.

fundraising by non-profits that vary in the direct benefits they provide to their donors and the composition of their donor base.

2.2 Social Preferences Composition of Groups

The second strand of related literature studies social preferences (i.e. other-regarding preferences) for giving. This literature has established that people have different motivations for giving and they can be classified into different types based on these motivations (see the following surveys: Camerer, 2003; Fehr and Schmidt, 2006; Cooper and Kagel, 2016). While some people are selfish and do not give anything, others are conditional cooperators whose contributions depend on what others give (e.g. Brandts and Schram, 2001; Fischbacher et al., 2001; Kurzban and Houser, 2005).

Groups consist of individuals with different social preferences (i.e. types). The existing literature mainly focuses on how the group composition changes the level of cooperation and finds that the composition of social preference types in groups matters in achieving and maintaining high levels of cooperation (e.g. Burlando and Guala, 2005; Gächter and Thöni, 2005; Page et al., 2005; Gunnthorsdottir et al., 2007; Gächter, 2007; Ones and Putterman, 2007; de Oliveira et al., 2015). One common finding in this literature is that contributions are higher in homogeneous groups with members who are more generous. Moreover, the existence of one selfish person in the group is enough to harm the groups' ability to cooperate (de Oliveira et al., 2015). We contribute to this research strand by studying the impact of information across two populations (subject groups) with different levels of generosity.

The rest of the paper is organized as follows: Section 3 introduces the theoretical model, and derives the testable hypotheses; Section 4 describes the experimental design that we use to test these hypotheses; Section 5 presents the results from the laboratory experiment; and Section 6 concludes.

3 Theory and Hypotheses

The linear public good environment consists of groups of $N \geq 2$ agents. Each agent i is endowed with wealth W and chooses an amount g_i to allocate to a public good that benefits everyone in their group equally. The monetary payoff of agent i is

$$M_i = W - g_i + v \sum_{k=1}^{N} g_k$$

where $v \in (\frac{1}{N}, 1)$ denotes the marginal per-capita return (MPCR) of the public good. Clearly, the payoff maximizing strategy is $g_i = 0$ and the socially optimal strategy is $g_i = W$. Therefore, in the absence of other-regarding preferences, the unique Nash equilibrium is for all agents to contribute zero.

Since the above equilibrium behavior is a drastic departure from the existing experimental evidence (see Ledyard, 1995), the literature has considered the possibility of other-regarding preferences, which feature a concern not only for one's own payoff, but also for others' payoffs both in absolute and relative terms (e.g. Rabin, 1993; Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000; Charness and Rabin, 2002; Falk and Fischbacher, 2006; Arifovic and Ledyard, 2012). In particular, Arifovic and Ledyard (2012) stipulate the following utility function for agent i:

$$u_i(M_i, \overline{M}) = M_i + \beta_i \overline{M} - \gamma_i \max\{\overline{M} - M_i, 0\} \tag{1}$$

where $\overline{M} = \frac{1}{N} \sum_{k=1}^{N} M_k$ is the average earnings in the game. The agent-specific parameter β_i captures i's pro-social motives for giving, which we refer to as the individual i's generosity level.[9] Such motives are necessary to induce positive contributions. The parameter γ_i captures i's inequality aversion, which generates disutility whenever i's earnings fall below the average.

The utility representation in eq. (1) is closely related to alternative utility specifications proposed by Fehr and Schmidt (1999) and Charness and Rabin (2002). In fact, Arifovic and Ledyard (2012) show that eq. (1) is a linear transformation of these alternative specifications, apart from ignoring possible payoff effect from punishing non-cooperative behavior in a repeated setting.[10] Our analysis focuses on Arifovic and Ledyard's specification since it yields a convenient representation of the agent's optimal contribution as a function of the average expected giving, $\overline{g}$. Such representation is both intuitive and provides a straightforward way of deriving the equilibrium expected giving $\overline{g}(v)$ as a function of the MPCR. To see this, note that eq. (1) can be re-written as:

$$u_i(g_i, \overline{g}) = W - g_i + vN\overline{g} + \beta_i \left(W - \overline{g} + vN\overline{g}\right) - \gamma_i \max\{g_i - \overline{g}, 0\} \tag{2}$$

where $\overline{g} = \frac{1}{N} \sum_{k=1}^{N} g_k$. Maximizing (2) with respect of g_i gives rise to the following best response function:

$$g_i = \begin{cases} 0 & \text{if} & \beta_i \leq \beta_1(v) \\ \overline{g} & \text{if} & \beta_i \in [\beta_1(v), \beta_2(v, \gamma_i)] \\ W & \text{if} & \beta_i \geq \beta_2(v, \gamma_i) \end{cases} \tag{3}$$

where

$$\beta_1(v) = \frac{N(1-v)}{Nv - 1}, \beta_2(v, \gamma_i) = \frac{N(1-v)}{Nv - 1} + \gamma_i \frac{N-1}{Nv - 1}.$$

Eq. (3) reveals three types of contribution behavior: selfish giving of 0 for low β_i, unconditional generous giving of W for high β_i, and conditional cooperative giving of $\overline{g}$ for intermediate

[9]In Arifovic and Ledyard's paper, this term is referred to as the level of altruism. Due to different definitions of altruism in the economics and psychology literature, we opt to avoid confusion by referring to β_i as the individual's generosity.

[10]Refer to Section 2.2.2 in Arifovic and Ledyard (2012) for a detailed discussion about the relationship between these well-known utility specifications. In particular, the linear multiplier that converts the utility specification given by Fehr and Schmidt (1999) to eq. (1) depends on the group size N, which is fixed in our analysis. Thus, these two specification should give rise to the same equilibrium behavior.

β_i.[11] Given this best response function, the expected equilibrium giving must satisfy the following equation:

$$\overline{g}(v) = \Pr(\beta_i \geq \beta_2(v, \gamma_i))W + \Pr(\beta \in [\beta_1(v), \beta_2(v, \gamma_i)])\overline{g}(v). \tag{4}$$

Eq. (4) states that the equilibrium expected giving is simply the weighted average giving of the generous agents, who give all their endowment, and the conditional contributors, who match the expected average giving in the population. Re-arranging terms, we can re-write eq. (4) as

$$\overline{g}(v) = \frac{1}{1 + \frac{\Pr(\beta \leq \beta_1(v))}{\Pr(\beta \geq \beta_2(v, \gamma_i))}}W \tag{5}$$

Thus, the expected equilibrium giving depends on the relative likelihood of the payoff maximizing (selfish) giving and socially optimum (generous) giving, i.e. $R(v) = \frac{\Pr(\beta \leq \beta_1(v))}{\Pr(\beta \geq \beta_2(v, \gamma_i))}$. As expected, the average giving is decreasing in the relative likelihood of selfish giving (i.e. $R(v)$) since it causes the conditional contributors to adopt more pessimistic beliefs about the average giving in the population.

To determine how the expected equilibrium giving varies with the MPCR, v, we need to take into account the distribution of other-regarding preferences since it affects the relative likelihood of selfish giving, $R(v)$. In particular, in order to focus attention on the comparative statics with respect to the population's generosity level, we simplify the model by letting $\gamma_i = \gamma$ be identical across the population.[12] Furthermore, we model the pro-social preferences in the population as distributed according to an exponential distribution $\beta_i \sim Exp(1/\lambda)$ where higher λ represents a (stochastically) more generous population.[13] This specification allows us to conduct comparative statics with respect to the generosity level of the population, captured succinctly by the parameter λ.

Given the expected equilibrium giving function and the distribution of pro-social preferences in the population, the following lemma describes how the expected giving varies with the MPCR, v, and the population's generosity level λ.

Lemma 1 $\overline{g}(v)$ *is increasing in* $v \in \left(\frac{1}{N}, 1\right)$ *with* $\lim_{v \to \frac{1}{N}} \overline{g}(v) = 0$ *and* $\lim_{v \to 1} \overline{g}(v) = W$. *Moreover, there exists a unique* $\tilde{v}(\lambda) \in \left(\frac{1}{N}, 1\right]$ *with the following properties:*

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[11] Fischbacher et al. (2001) find evidence of these types of contribution behavior in the lab, with a third of subjects conforming to the Nash equilibrium prediction and another half behaving as conditional cooperators. Eq. (3) reveals that this contribution behavior depends not only on the agent's individual characteristics captured by (β_i, γ_i), but also on the MPCR.

[12] The results in this section readily generalize to a stochastic inequality aversion parameter γ_i as long as γ_i and β_i are independently distributed.

[13] The use of a distribution function with infinite support ensures that the expected giving is always interior to the endowment and reaches the extreme values of 0 and W only in the limit when $v \to \frac{1}{N}$ and $v \to 1$, respectively. In addition, the exponential distribution provides a tractable way of varying the strength of the pro-social preferences of the population by changing the parameter λ. It is also worth noting that our analysis generalizes to other common distributions on $\mathbb{R}^+$, which include the χ^2 and the *Gamma* distributions. The proof of this is available upon request.

1) $\overline{g}''(v) > 0$ *for* $v < \tilde{v}(\lambda)$ *and* $\overline{g}''(v) < 0$ *for* $v > \tilde{v}(\lambda)$;

2) $\tilde{v}(\lambda)$ *is decreasing in* λ *with* $\lim_{\lambda \to 0} \tilde{v}(\lambda) = 1$ *and* $\lim_{\lambda \to \infty} \tilde{v}(\lambda) = \frac{1}{N}$.

The formal proof of Lemma 1 is relegated to Appendix A. Intuitively, it reveals that the equilibrium giving is increasing in the MPCR since higher v increases the net social benefit of giving, captured by $Nv - 1$, and decreases the individual cost of giving, captured by $1 - v$. Moreover, the equilibrium expected giving approaches zero as the net social benefit of giving becomes negligible (i.e. $v \to \frac{1}{N}$) and it approaches W as the marginal cost of giving becomes negligible (i.e. $v \to 1$).

Interestingly, the first property reveals that the marginal benefit of increasing the MPCR is non-monotone and tends to diminish at higher values of the MPCR. In particular, the average giving $\overline{g}(v)$ exhibits increasing returns to MPCR for low values ($v < \tilde{v}(\lambda)$), but diminishing returns for high values ($v > \tilde{v}(\lambda)$). To grasp the intuition behind this dynamics, note that for low values (i.e. $v < \tilde{v}(\lambda)$), there is a significant number of agents who do not contribute. Thus, raising the MPCR in this case has an increasing marginal impact as it shifts a growing number of agents away from selfish to conditional and generous giving. However, this impact of increasing the MPCR eventually levels off as the number of selfish agents dwindles. Consequently, for high values of the MPCR ($v > \tilde{v}(\lambda)$), the marginal impact of further increasing the MPCR is diminishing as it induces a smaller number of agents to move away from selfish giving.

The second property further reveals that a more generous population, characterized by a larger λ, reaches diminishing returns to MPCR faster, i.e $\tilde{v}(\lambda)$ is decreasing in λ. The reason is that for a more generous population, composed of individuals with relatively high β_i, inducing most agents to give requires only a modest increase in the MPCR. The opposite is true for a less generous population, in which significant portion of agents require a large increase in the MPCR in order to contribute.

Figure 1 illustrates a numerical example for two different values of λ (low and high generosity levels) and provides visual support for Lemma 1. It is evident from Figure 1 that $\overline{g}(v)$ is increasing in v for both generosity levels. While $\overline{g}(v)$ is convex at low values of v, it is concave at high values. Moreover, a more generous population (Figure 1a) reaches diminishing returns of higher MPCR faster as illustrated by the fact that it is concave for a wider region of v (i.e. $\tilde{v}(16) < \tilde{v}(6)$).

The shape of the giving function described by Lemma 1 has an important implication for the impact of information provision. To see this, suppose that, as in the experimental design in Section 4, the MPCR (v) is drawn from a discrete distribution with $v = \{v_L, v_H\}$, where $\frac{1}{N} < v_L < v_H < 1$, and $\Pr(v = v_r) = p_r$ for $r = \{L, H\}$.[14] In the absence of information, the agent's giving ($\overline{g}_U$) is based on the expected MPCR, $E[v]$. In contrast, an informed agent gives based on the realized

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[14]To ease the exposition, we present the theoretical results using a two-point distribution for the MPCR since it corresponds to our experimental design in Section 4, but the theoretical results extend to any arbitrary non-degenerate distribution of the MPCR.
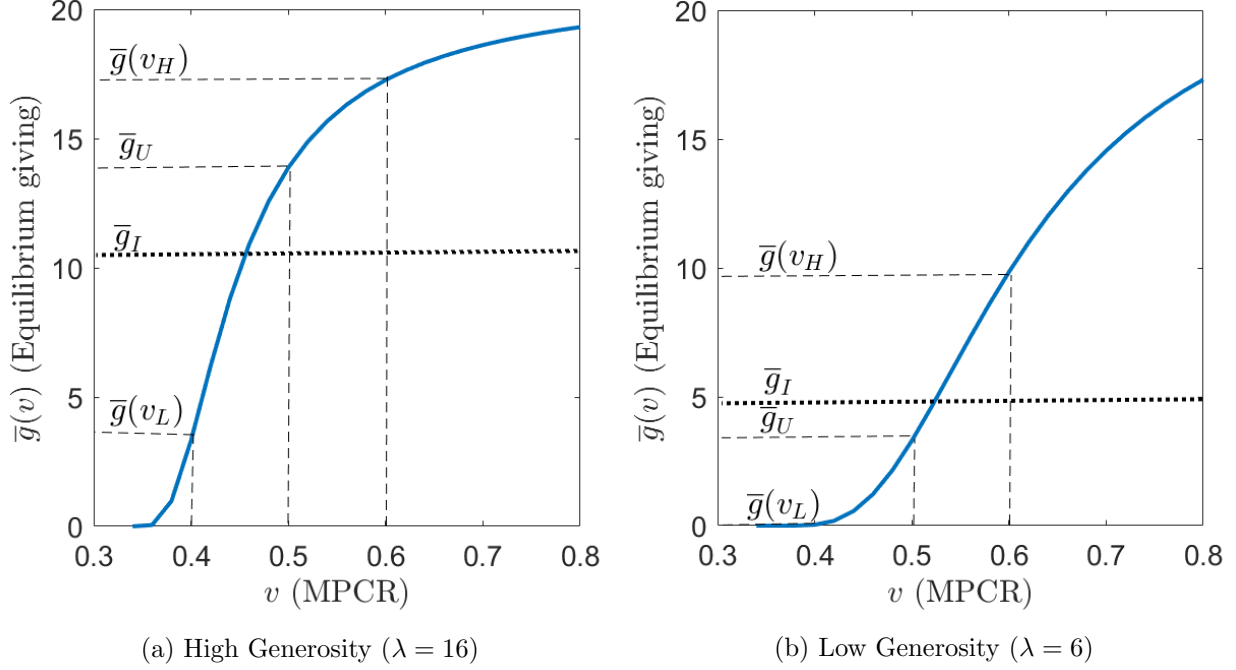
(a) High Generosity ($\lambda = 16$)　　　　　(b) Low Generosity ($\lambda = 6$)

Figure 1: Informed and uninformed giving for $\gamma = 4$, $v_L = 0.4$, $v_H = 0.6$, and $p_L = 0.5$

MPCR, v, and thus the expected informed giving ($\bar{g}_I$) is the weighed average contributions under a high and a low MPCR.

$$\bar{g}_U = \bar{g}(E[v]); \quad \bar{g}_I = p_L \bar{g}(v_L) + p_H \bar{g}(v_H) \tag{6}$$

Clearly, information can either decrease giving by revealing low value v_L (bad news), or increase giving by revealing high value v_H (good news). The relative magnitude of the response to good and bad news depends of the shape of the giving function described by Lemma 1 and illustrated in Figure 1. In particular, Figure 1a) illustrates the case of a generous population for which the giving function is mostly in the concave region. It is evident from the figure that the expected equilibrium giving responds more to bad news than good news, i.e. $|\bar{g}_U - \bar{g}(v_L)| > |\bar{g}_U - \bar{g}(v_H)|$. Consequently, when the population is rather generous, information is on average bad for giving, i.e. $\bar{g}_U > \bar{g}_I$. The opposite is true for a more selfish population that is likely to feature a convex giving function for a wider range of v. Thus, as Figure 1b) illustrates, the response to good news in this case is larger than the response to bad news (i.e. $|\bar{g}_U - \bar{g}(v_H)| > |\bar{g}_U - \bar{g}(v_L)|$), causing information to be on average beneficial for giving (i.e. $\bar{g}_I > \bar{g}_U$). The following Proposition formalizes this dynamics.

Proposition 1 *There exist generosity levels $0 < \lambda_1 \leq \lambda_2 < \infty$ such that the expected informed giving exceeds the uninformed giving for $\lambda \leq \lambda_1$, while the uninformed giving exceeds the expected informed giving for $\lambda \geq \lambda_2$.*

The proof of Proposition 1 follows immediately from the Jensen's inequality and is relegated to Appendix A. The proposition states that while informed giving exceeds uninformed giving for a less generous population, information is detrimental for giving if the population is more generous. As discussed above, the key driver for this dynamics is that a less generous population is more responsive to good news than bad news, while the opposite is true for a more generous population.

Lemma 1 and Proposition 1 provide testable hypotheses that we investigate by using a lab experiment described in Section 4. In particular, our experimental design aims to test the following hypotheses.

Hypothesis 1 *In a less generous population, the agents' average response to good news is higher than their response to bad news. As a result, the informed giving, on average, is higher than the uninformed giving.*

Hypothesis 2 *In a more generous population, the agents' average response to good news is lower than their response to bad news. As a result, the informed giving, on average, is lower than the uninformed giving.*

The above hypotheses imply that providing more information about the value of the public good should on average be beneficial for provision if the population is less generous, but detrimental for provision if the population is more generous. In the next section, we describe the experimental design used to test these two hypotheses in the lab.

4 Experimental Design

In order to test our hypotheses, we need to control for the level of generosity in each session. We do so by conducting the experiment in two stages.[15] In Stage 1, we measure the subjects' generosity level in the public good game by using an online experiment. One to two weeks later, using the information obtained from Stage 1, we invite some of them to the lab to participate in the second stage of the experiment.

Our experiment is a 2x2 between subjects design[16]: *Less Generous* vs. *More Generous* and *Known MPCR* vs. *Unknown MPCR*. Using the data collected in Stage 1, we create relatively more and less generous sessions in the lab. More specifically, we only invite subjects who were classified as relatively less generous to the *Less Generous* treatment; and we only invite subjects who were classified as relatively more generous to the *More Generous* treatment.

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[15]This aspect of our design is inspired by and similar to Burlando and Guala (2005), Gächter and Thöni (2005), and de Oliveira et al. (2015).

[16]We run the *Known MPCR* and the *Unknown MPCR* treatments within subjects. Although subjects know that the experiment has two parts, they do not know anything about the second part when they play the first part. We only report the data from the first treatment played since the behavior in the first treatment contaminated the data from the second treatment (i.e. ordering effect).

Please indicate how many tokens (if any) you would like to contribute, for each possible average tokens contributed by other two group members:

	Your Contribution
if others' average contribution is 0 tokens	
if others' average contribution is 1 tokens	
if others' average contribution is 2 tokens	
. . .	
if others' average contribution is 20 tokens	

Figure 2: Conditional Contribution Table

In Stage 2, subjects come to the lab to participate in a linear public good game described in Section 3. Subjects are placed in groups of three and play a one-shot linear public good game with an uncertain MPCR, which takes values of 0.4 or 0.6 with equal probability. They play the game for 10 rounds with random rematching. In the *Unknown MPCR* treatment, subjects make a contribution decision without knowing which MPCR will be used for that round. However, the subjects know that each realization of the MPCR is equally likely. In the *Known MPCR* treatment, subjects are informed about the realized MPCR for that round when they make their decisions. We pay subjects for one of the rounds picked at random at the end of the experiment. Finally, they fill out a survey. Below, we provide detailed information about each stage of the experimental design.

Stage 1: First, invitees receive an invitation email to participate in an incentivized online experiment with a possibility of being invited to an experiment in our lab. The online experiment, programmed in Qualtrics, consists of the Fischbacher et al. (2001) (henceforth FGF) conditional contribution game.[17] In this game, each subject is endowed with 20 tokens (1 token=$0.40), assigned to a group consisting of two other members, and asked to play a linear public good game with an MPCR of 0.50. Each subject makes two decisions: Decision 1 and Decision 2. In Decision 1, subjects state how many of their tokens, if any, they would like to contribute to a group project (unconditional contribution) that benefits everyone in their group equally. Next, in Decision 2, they fill out a conditional contribution table (see Figure 2). In this table, they indicate how many tokens they would like to contribute to the group project *conditional* on the other group members' average contribution in Decision 1. For example, they state how much they would like to contribute if the other group members contributed 0 tokens on average in Decision 1, how much they would like to contribute if others contributed 1 token on average in Decision 1, and so on. Thus, in Decision 2, subjects make a total of 21 conditional contribution decisions.

After all subjects have participated in the online experiment, we randomly construct groups

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[17]The instructions for the online experiment can be found in Appendix E.

of three. Next, for each group, we randomly pick two group members for which Decision 1 will be implemented. We implement Decision 2 for the other group member. In other words, we randomly determine which of the two group members' unconditional contribution decisions will be implemented. Depending on the average unconditional contribution made by these two group members, we implement the other group member's conditional contribution as indicated in her conditional contribution table. Then, we calculate the earnings accordingly. The payments for the online experiment are delivered by Venmo, Paypal or cash. In order to avoid any potential contamination that may be created by the outcome of this stage, the subjects are not informed about the outcome and receive their payments for the online experiment only after Stage 2 is conducted.

The FGF conditional contribution game described above is a good way to measure the generosity level (β_i) of the subjects in the public good game. It is commonly used in the literature (with over 2,000 citations) to classify subjects into types in the public good game: selfish (or free-riders who contribute zero), conditional cooperator (subjects whose contributions depend on the others' average contribution) and pro-social (or full cooperators who contribute everything).[18] As described in Section 3, each subject's type is determined by their level of generosity, β_i. Those with a relatively low β_i are selfish, those with a high β_i are pro-social and others with a β_i somewhere in between are conditional cooperators. Since one of our goals is to create more and less generous groups in the lab, we calculate a measure for each subject by using the data collected from the conditional contribution game in Stage 1. More specifically, for each subject we calculate the following parameter that works as a proxy for the subject's level of generosity (i.e. β_i):

$$\hat{\beta}_i = \frac{\sum_{j=0}^{20}(g_j^i - j)}{\sum_{j=0}^{20} j}, \tag{7}$$

where g_j^i is subject i's stated conditional contribution in Decision 2 for an average contribution by others, $j = 0, 1..., 20$. If a subject is selfish, who always contributes zero independent of the others' giving, then her $\hat{\beta}_i$ is equal to -1. If a subject is pro-social, who always contributes all of her endowment independent of the others' giving, her $\hat{\beta}_i$ is equal to $+1$. If a subject is a perfect conditional cooperator, who perfectly matches the others' average contributions, then her $\hat{\beta}_i$ is equal to 0. Overall, a subject of higher generosity tends to contribute a larger amount for any average contribution level of the other group members, resulting in a higher $\hat{\beta}_i$.

Next, we rank all the subjects based on their $\hat{\beta}_i$ and divide them into two equally populated samples using the median. This gives us two samples, one below the median and one above the median. The first sample includes selfish subjects as well as (weak) conditional cooperators, thus it is relatively less generous. The second sample is relatively more generous since it includes pro-

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[18]Boosey et al. (2019) shows the validity of this procedure to explain behavior in public good games. Also see Thöni and Volk (2018) that review 17 replication studies of FGF and show that the FGF findings are stable.
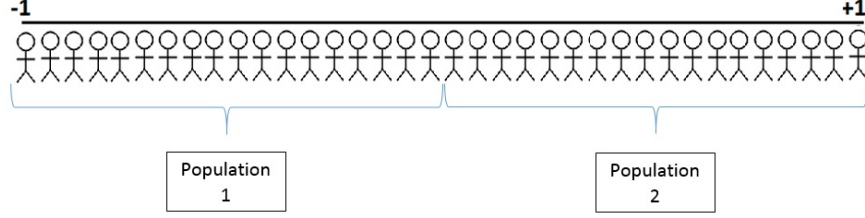
Figure 3: Providing Info About the Session's Generosity Level

social subjects who contributed everything as well as (pro-social) conditional cooperators. More information on the distribution of types in our experiment is provided in Section 5. Next, we use these two samples to control for the generosity level in the public good game in the lab as explained below.

Stage 2: After dividing the subjects into two equally populated samples, we invite them to participate in the second stage in the Economic Research Lab at Texas A&M University.

Subjects play a one-shot linear public good game in groups of three for ten rounds in the lab. The groups in each round are constructed randomly (stranger matching design). In each round, subjects start out with 20 tokens (1 token =$0.50) in their individual accounts and are asked to decide how many of these 20 tokens, if any, they would like to contribute to a group project (g_i). The monetary payoff function for this game is as follows:

$$M_i = 20 - g_i + v \sum_{k=1}^{3} g_k$$

The MPCR (v) of the public good is either 0.40 with 0.5 probability or 0.60 with 0.5 probability, which is determined randomly and independently for each group in each round.[19] In the *Unknown MPCR* treatment, subjects make their contribution decision about the public good without knowing which MPCR is selected for that round, but they know that it is either 0.40 or 0.60 with equal probability. In the *Known MPCR* treatment, subjects are informed about the randomly chosen MPCR for that round and then are asked to make their contribution decisions about the public good. In both treatments, at the end of each round subjects receive feedback about their earnings, other group members' average contribution, and the randomly determined MPCR in the round.

In the *Less Generous* (*More Generous*) treatment, we only invite subjects whose $\hat{\beta}_i$ was below (above) the median. This is how we control for the level of generosity in each session. At the end of the instructions[20], before the experiment starts, we remind subjects about their participation in the online experiment and provide them with information about the level of generosity in their session. Using a neutral language, we explain how a measure (i.e. $\hat{\beta}_i$) was created using their

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[19]The independent draw of the MPCR on the round and the group level eliminates any potential effect coming from the order of the MPCR.

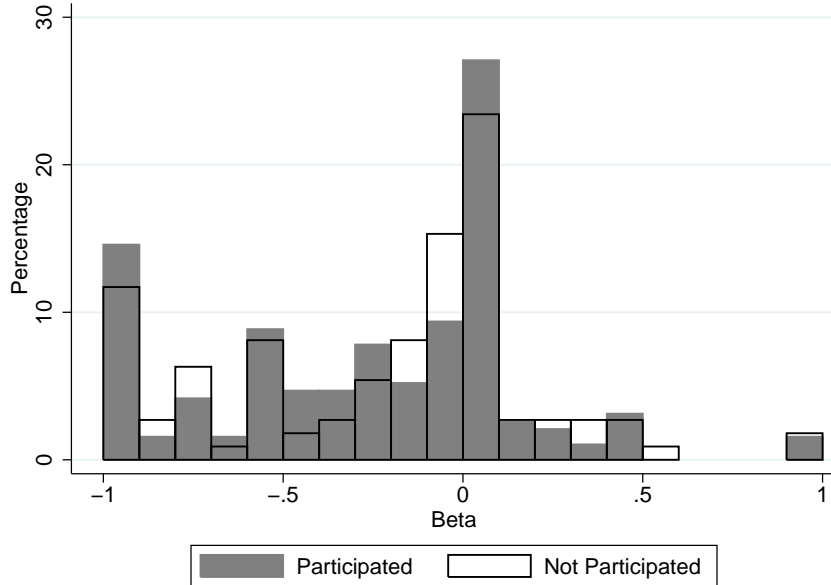[20]Instructions used in the lab experiment can be found in Appendix D.

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Figure 4: Distribution of $\hat{\beta}_i$

responses in the online experiment, how this measure should be interpreted (i.e. the higher the measure for a participant, the higher that participant's contributions), and how it was used to rank everyone as shown in Figure 3. In the *Less Generous* (*More Generous*) treatment, we tell subjects that participants from Population 1 (2) were invited to that session.

5   Results

Six experimental sessions were conducted in the Economic Research Lab at Texas A&M University in April 2017. Subjects were recruited through ORSEE (Greiner, 2004), and the lab experiment was coded in z-Tree (Fischbacher, 2007). The average earnings were \$9.85 in the first stage and \$21 in the second stage (including a show up fee of \$8 in the second stage).

A total of 360 subjects participated in the online experiment and 44 of these preferred not to be invited to the lab experiment. From the remaining group, we excluded 13 as their behavior in the online experiment seemed random. The final pool of subjects for Stage 2 was 303, and 111 of those also participated in the second stage.

5.1   Conditional Contribution Game Findings

The attrition rate from Stage 1 to Stage 2 is high since when recruiting for the online experiment, it was impossible to predict whether a subject would be assigned to the *Less Generous* or the *More Generous* treatment sessions. This made it difficult to schedule session times that would be convenient for a large number of subjects. Nevertheless, it is important to confirm that there is no
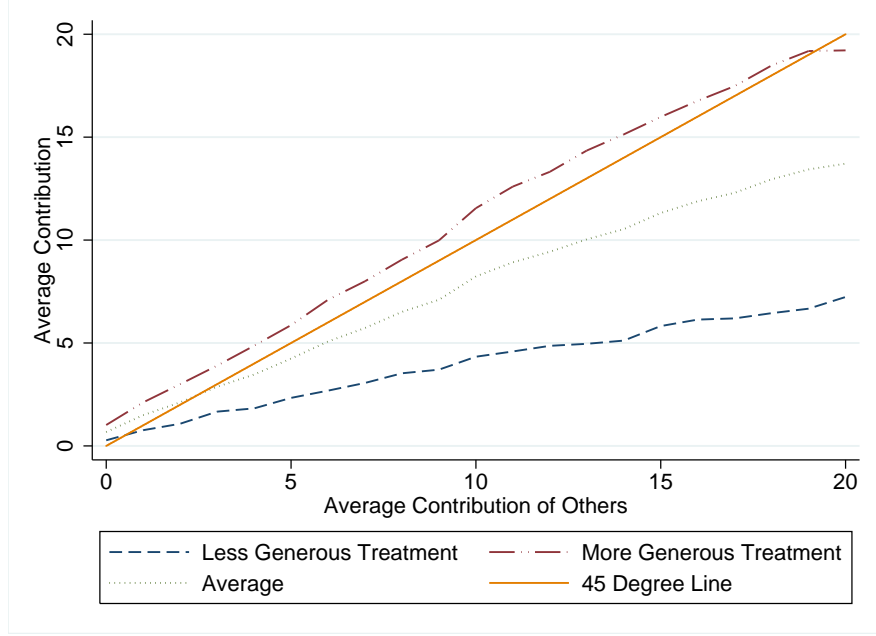
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Figure 5: Average Contributions in Stage 1 for Each Possible Average Contribution of Others

systematic difference in the generosity level of the subjects who participated in both stages versus the ones who participated in the first stage only. For this purpose, we look at Figure 4 that presents the percentage distribution of $\hat{\beta}_i$, as computed using (7), for the 303 participants who were invited to Stage 2 in our experiment. The darker color represents the participants who participated in both stages (111 subjects), whereas the lighter color- the participants who only participated in the first stage (192 subjects). Using the Kolmogorov-Smirnov equality of distributions test, we confirm that the difference between the distribution of $\hat{\beta}_i$ across these two samples is not statistically significant (*p-value* is 0.536).

The mean and median of $\hat{\beta}_i$ from the online experiment are -0.25 and -0.11 respectively. The median is the cut-off point for the *More Generous* and the *Less Generous* sessions. The subjects whose $\hat{\beta}_i$ is below (above) the median are invited to the *Less Generous (More Generous)* treatment sessions. This is the only difference between these two treatments.

Figure 5 illustrates the conditional contribution decisions made in the online experiment (Stage 1) by those who also participated in the lab experiment (Stage 2). A perfect conditional cooperator, who always matches the others' average contribution, would be located on the 45 degree line. If a subject is located above this 45 degree line, it indicates that the subject contributed more than the average for all possible average contributions made by the other group members. In contrast, a subject who contributed less than the average would be located below this line. The average conditional contributions made for each possible contribution level of the others looks very similar to the FGF data. Figure 5 also illustrates the average conditional contributions made by the

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Table 1: Average Contributions Across Treatments

	Unknown MPCR	Known MPCR	
		High MPCR	Low MPCR
Less Generous	3.56 (n=18)	6.67 (n=33)	4.37 (n=33)
More Generous	12.41 (n=24)	12.14 (n=36)	9.24 (n=35)

subjects in the *More Generous* and the *Less Generous* treatments separately. We provide a more detailed information regarding the behavior observed in the FGF game in Appendix B.

5.2   The Impact of Information on Public Good Contributions

In this sub-section, we present the results from Stage 2 of the experiment, where subjects played the public good game in the lab as described in Section 4.

Table 1 presents the average contributions made across treatments, which are computed by taking the average amount of tokens contributed across all ten periods by each subject. In the *Less Generous* treatment, we find that the *Unknown MPCR* contributions are not significantly different from the *Known MPCR* contributions when the MPCR realization is low (unadjusted *p-value* is 0.332, multiplicity adjusted *p-value* is 0.332).[21] However, the *Unknown MPCR* contributions are significantly lower than the *Known MPCR* contributions when the MPCR realization is high (unadjusted *p-value* is 0.005, multiplicity adjusted *p-value* is 0.009). Thus, subjects in the *Less Generous* treatment do not respond much to information when they receive bad news (MPCR of 0.40), but they substantially increase their contributions when they receive good news (MPCR of 0.60). This is in line with Hypothesis 1.

The above observation is also evident from Figure 6 on the left, which shows the average contributions in all ten periods in the *Less Generous* treatment. It reveals that the uninformed contributions follow a similar path over time as the informed average contributions for the low MPCR. However, there is an upward jump in the informed average contributions for the high MPCR. The statement below summarizes this finding.

Result 1: In line with Hypothesis 1, in the *Less Generous* treatment, the average *Known - Low MPCR* contributions are not significantly different from the average *Unknown MPCR* contributions, while the average *Known - High MPCR* contributions are significantly higher than the average *Unknown MPCR* contributions.

In the *More Generous* treatment, we see the opposite trend. Table 1 reveals that the *Unknown*

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[21]Following the multiple hypothesis testing method proposed by List et al. (2019), we report both the unadjusted p-values (Remark 3.1) and the multiplicity adjusted p-values (Theorem 3.1). The Mann-Whitney U test also yields very similar p-values.
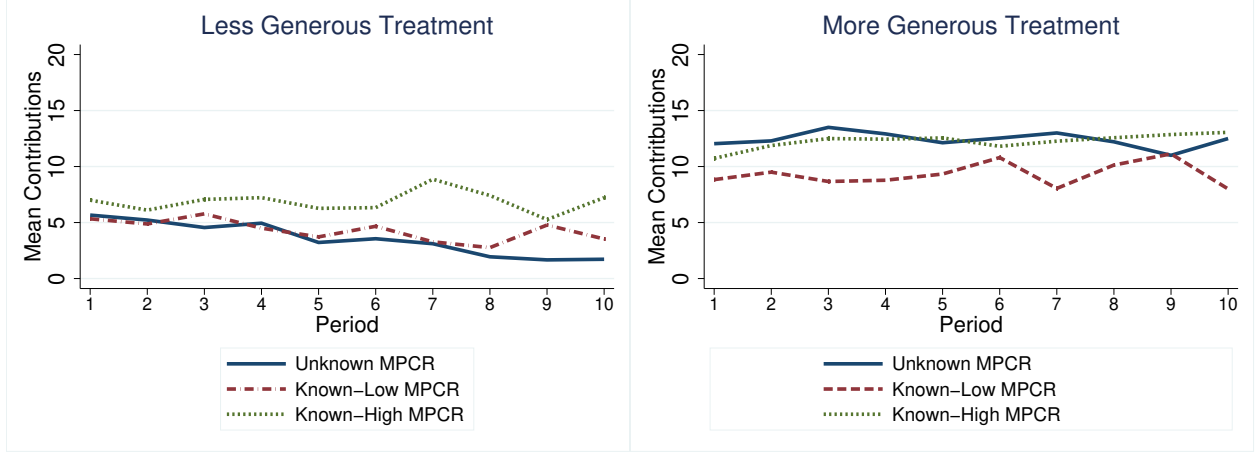
Figure 6: Mean Contributions

MPCR contributions are not statistically different from the *Known MPCR* contributions when the MPCR realization is high (unadjusted *p-value* is 0.837, multiplicity adjusted *p-value* is 0.837), but they are significantly higher than the *Known MPCR* contributions when the MPCR realization is low (unadjusted *p-value* is 0.016, multiplicity adjusted *p-value* is 0.027). Contrary to the *Less Generous* treatment findings, subjects in the *More Generous* treatment do not respond much to good news, but they significantly decrease their contributions upon obtaining bad news. This is also evident in Figure 6 on the right, which shows the average contributions in all ten periods in the *More Generous* treatment. In the *More Generous* treatment, while the average uninformed contributions follow a similar path as the informed average contributions for the high MPCR, there is a decrease in average informed contributions for the low MPCR.

Result 2: In line with Hypothesis 2, in the *More Generous* treatment, the average *Known - Low MPCR* contributions are significantly lower than the average *Unknown MPCR* contributions, while the average *Known - High MPCR* contributions are not significantly different than the average *Unknown MPCR* contributions.

To check the robustness of our findings, we next present the regression results. Since the lowest possible contribution amount is zero tokens and the highest possible contribution amount is 20 tokens, we need to control for a potential censuring. Although a Tobit model is useful in accounting for censoring, it restricts the data by not allowing different motives behind the zero contribution.[22] In other words, the Tobit model does not differentiate between the subjects who are selfish and would always contribute zero independent of the MPCR realization, and those who

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[22]A similar reasoning can also apply to subjects who contribute everything. Since we have only one subject who contributed everything in all periods, we restrict our attention to only selfish types.

Table 2: Double Hurdle Model Regression Results

	Probit	Less Generous Treatment Tobit		More Generous Treatment Tobit	
	(1)	(2)	(3)	(4)	(5)
Less Generous	-0.836*				
	(0.470)				
Known MPCR	0.004	2.332**	0.865	-2.559*	-4.675***
	(0.431)	(1.144)	(1.009)	(1.379)	(1.179)
Known MPCR*High MPCR			3.211***		3.555***
			(0.773)		(0.580)
Lagged Others' Average		0.258***	0.275***	0.149***	0.148***
		(0.074)	(0.071)	(0.046)	(0.054)
Beta		-0.976	-0.816	9.695***	9.709***
		(2.365)	(2.082)	(2.367)	(2.126)
Period		-0.253**	-0.288***	-0.0822	-0.0203
		(0.111)	(0.102)	(0.118)	(0.116)
Constant	2.126***	2.891*	3.150*	11.91***	11.51***
	(0.458)	(1.704)	(1.612)	(1.692)	(1.393)
Observations	111	414	414	531	531

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The robust standard errors clustered at the individual level are in parentheses.
The dependent variable for the Probit model is Contributed which takes the value of 1 if the subject contributed at least once, and otherwise zero. The dependent variable for the panel data Tobit models is Contributions. The number of observations in column 1 is the total number of subjects participated in this study. The numbers of observations in the remaining four columns are the number of decisions made in 9 periods by subjects who contributed at least once across all 10 periods.

contribute zero due to the treatment (e.g. due to receiving bad news). Following Moffatt (2015, Ch 11.), we use a double hurdle model (also see Brown et al., 2017 for another example of using a hurdle model in experimental data).

The double hurdle model treats the probability of being a contributor and the extent of the contribution separately. Thus, by using this model, we can examine the impact of information on the extensive and the intensive margins. The results are reported in Table 2. We first run a Probit model regression using the cross section of all 111 subjects to analyze the factors that impact whether subjects contribute or not (i.e. being a potential contributor or not). The dependent variable in this probit model is Contributed which takes the value of one if the subject contributed a positive amount in any of the ten periods and zero otherwise.[23] The estimates of the first hurdle

[23]As per the suggestion of an anonymous referee, we also run an alternative specification that takes into account the contribution behavior only in the last eight periods when determining whether a subject is a potential contributor. This aims to address a potential concern that, even with a stranger matching design, some selfish subjects could be contributing positive amounts early on in the game in order to induce giving by others (specifically by conditional

are presented in the first column of Table 2. There are a total of six subjects who contributed zero in all ten periods. Being in the *Known MPCR* treatment does not affect the *probability* of contributing to the public good. This implies that information does not impact contributions on the extensive margin. However, being in the *Less Generous* treatment significantly decreases the probability of contributing. This is not surprising given that we created the *Less Generous* vs. *More Generous* treatments based on the subjects' level of generosity measured in Stage 1.

Next, we run a Tobit model for the *Less Generous* and the *More Generous* treatments separately to study the factors that impact contributions *conditional* on contributing at least once (i.e. conditional on being a potential contributor). Thus, we exclude the subjects who failed the first hurdle. In columns (2)-(5), we report the marginal effects of the coefficients on the uncensored latent variable. The second and the third columns are created using the data collected in the *Less Generous* treatment and the last two columns are created using the data collected in the *More Generous* treatment. The dependent variable for all four columns is the contributions to the public good in each round.

The first model in columns 2 and 4 shows the average impact of information on contributions. The variable *Known MPCR* is a dummy variable for the *Known MPCR* treatment sessions. Thus, it takes the value of 1 if the subjects were informed about the realized MPCR for that round before they made their decisions. The model also controls for the following variables: *Lagged Others' Average*, which is the average contributions made by other group members in the previous round; *Beta*, which is $\hat{\beta}_i$ that was computed using the data from the online experiment (i.e. Stage 1); and *Period*, which is simply the time trend. It is evident from columns 2 and 4 that in the *Less Generous* treatment, information about the MPCR has a positive and significant impact on contributions for those who are potential contributors. In contrast, in the *More Generous* treatment, information hurts the average contributions. These observations are summarized below.

Result 3: Consistent with Hypotheses 1 and 2, the overall impact of information about the MPCR is to increase average contributions to the public good in the *Less Generous* treatment and to decrease average contributions in the *More Generous* treatment.

The second model in columns 3 and 5 studies the impact of information separately for good and bad news. The variable *Known MPCR*High MPCR* is the interaction term between *Known MPCR* and *High MPCR*. The baseline in columns 3 and 5 is the *Unknown MPCR* treatment. Thus, the coefficient of *Known MPCR* shows the impact of receiving bad news. And, the coefficient of *Known MPCR*High MPCR* shows the impact of receiving good news *relative* to receiving bad

cooperators) in later periods. The estimates from this specification are reported in Table C1 in the appendix and reveal that our findings are robust to this alternative specification.

news. Finally, the impact of receiving good news relative to the *Unknown MPCR* treatment is the summation of the coefficients of *Known MPCR* and *Known MPCR*High MPCR*.

Column 3 reveals that in the *Less Generous* treatment, when subjects find out that the MPCR is low, they do not significantly change their giving behavior relative to being uninformed. In other words, they do not respond to bad news. However, when they are informed and receive good news, they respond to information by significantly increasing their contributions. This provides further supporting evidence for Result 1. As suggested by Hypothesis 1, the relative response to good news is larger than bad news. Thus, overall, information is good for contributions.

In contrast, Column 5 reveals that in the *More Generous* treatment, when subjects find out that the MPCR is low, they significantly decrease their contributions relative to the uninformed contribution levels. When they receive good news of high MPCR, they respond by significantly increasing their contributions relative to receiving bad news. This provides further supporting evidence for Result 2. Furthermore, as suggested by Hypothesis 2, the negative response to bad news is stronger than the positive response to good news. Thus, on average, information hurts contributions significantly on the intensive margin.

Overall, Results 1-3 provide a strong support for the hypotheses emerging from our theoretical model. In particular, our regression analysis reveals that while information does not affect public good contribution on the extensive margin, it impacts contributions on the intensive margin and the sign of this impact depends on the generosity level of the sessions. In the *Less Generous* sessions, subjects contribute more on average when they are informed about the MPCR compared to when they are uninformed. As suggested by our theoretical analysis and supported by the experimental data, this is because their relative response to good news is greater than their response to bad news. Just the opposite is true for the *More Generous* sessions. In these sessions, subjects who are potential contributors give less on average to the public good when they are informed. This is due to their relative response to bad news being stronger than their response to good news.

6 Discussion and Concluding Remarks

The findings of this study have significant implications for fundraising. In particular, they suggest that targeted information provision may be a more fruitful strategy of increasing public good contributions than uniform information provision. While focusing information efforts on a less generous population may seem counter-intuitive at first, our findings suggests that such strategy may in fact increase average giving due to the differential impact of good and bad news on groups with different generosity level. A field experiment could provide a fruitful avenue for further investigation.

There is related research on "moral wiggle room" (Dana et al. 2007), which suggests that donors may strategically avoid information to justify selfish behavior. In a similar vein, donors have been found to use risk (Exley, 2016; Cettolin et al. 2017), ambiguity (Haisley and Weber, 2010; Garcia

et al. 2019), beliefs about others (Di Tella et al. 2015), and performance metrics (Exley, 2017) as an excuse not to give. Thus, it is worth discussing whether information avoidance could provide an alternative explanation for our findings. One difference between this body of research and ours is that these studies mostly use a dictator game environment, in which donors are not direct beneficiaries of the services provided by their contributions. In contrast, our public good framework allows for both personal benefits and pro-social concerns to affect contribution behavior. The most important difference, however, is that subjects in our study are either *exogenously* informed or uninformed, depending on the treatment. Thus, information avoidance as an excuse not to give is an unlikely explanation for our findings. Granted, it is plausible that subjects in the uninformed treatment could use the lack of information as an excuse not to give, despite knowing that each MPCR is equally likely. Although this could provide an alternative explanation for our findings in the less generous sessions, it fails to explain the behavior observed in the more generous sessions, and it is not clear why moral wiggle room may yield different results across treatments. Since it is beyond the scope of this paper, we leave it to future research.

Last but not least, our framework is limited by some factors that warrant further study both theoretically and experimentally. First, since donors themselves may be able to acquire information by conducting research about non-profits prior to contributing, an important direction for future research includes endogenizing the choice of information acquisition by donors. This would allow us to glean further insight about how information acquisition incentives differ across donors. Moreover, donors often have a choice among multiple non-profit organizations that serve related causes. Such competition among non-profits can impact both how donors respond to information about a particular non-profit as well as their willingness to acquire such information. Thus, a valuable extension of our framework is to consider multiple providers of a particular public good with possibly correlated valuations.

In addition, future research could investigate the impact of information when the returns from public good are *heterogeneous* rather than homogeneous since in many instances donors are not equal beneficiaries of the services/goods provided. While our framework features heterogeneity in donors' concern about their own benefit versus the social benefit from the public good provision, allowing for exogenous heterogeneity in the returns would provide a richer environment to study how the type of information (i.e. private versus social returns) is most beneficial for public good provision. It is also often the case that ambiguity about the returns, rather than uncertainty, is impacting donors contributions. Thus, extending our framework to allow for ambiguity can provide further insights into the role of information provision in public good fundraising.

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Appendix A

Proof of Lemma 1.

For the purpose of this proof, note that

$$\frac{\partial \beta_1(v)}{\partial v} = -\frac{N(N-1)}{(Nv-1)^2} < 0 \tag{A-1}$$

and

$$\beta_2(v, \gamma) = (1 + \gamma)\beta_1(v) + \gamma, \tag{A-2}$$

implying that $\frac{\partial \beta_2(v,\gamma)}{\partial v} = (1+\gamma)\frac{\partial \beta_1(v)}{\partial v}$.

To establish that $\bar{g}(v)$ is increasing in v, note by eq. (5) that

$$\bar{g}'(v) = -\bar{g}(v)\frac{R'(v)}{1 + R(v)} \tag{A-3}$$

Moreover, since $\beta_i \sim Exp(1/\lambda)$, $R(v) = \frac{1-e^{-\beta_1(v)/\lambda}}{e^{-\beta_2(v,\gamma)/\lambda}}$. Therefore, differentiating $R(v)$ with respect to v yields

$$
\begin{aligned}
R'(v) &= \frac{1}{\lambda}\frac{\partial \beta_2(v,\gamma)}{\partial v}e^{\beta_2(v,\gamma)/\lambda} - \frac{1}{\lambda}\left[\frac{\partial \beta_2(v,\gamma)}{\partial v} - \frac{\partial \beta_1(v)}{\partial v}\right]e^{(\beta_2(v,\gamma)-\beta_1(v))/\lambda} = \\
&= -\frac{N(N-1)}{(Nv-1)^2}\frac{1}{\lambda}\left[e^{\beta_2(v,\gamma)/\lambda} + \gamma R(v)\right] < 0, \tag{A-4}
\end{aligned}
$$

where the last equality follows from eqs. (A-1) and (**??**). Then, $R'(v) < 0$ and eq. (A-2) immediately implies that $\bar{g}'(v) > 0$.

To show that $\lim_{v\to\frac{1}{N}}\bar{g}(v) = 0$, we need to show that $\lim_{v\to\frac{1}{N}}R(v) = \infty$. Note that $\lim_{v\to\frac{1}{N}}\beta_1(v) = \lim_{v\to\frac{1}{N}}\beta_2(v,\gamma) = \infty$. Therefore, $\lim_{v\to\frac{1}{N}}e^{-\beta_2(v,\gamma)/\lambda} = \lim_{v\to\frac{1}{N}}e^{-\beta_1(v)/\lambda} = 0$, resulting in $\lim_{v\to\frac{1}{N}}R(v) = \infty$. To see that $\lim_{v\to1}\bar{g}(v) = W$ note that $\lim_{v\to1}\beta_1(v) = 0$ and $\lim_{v\to1}\beta_2(v,\gamma) = \gamma$. This implies that $\lim_{v\to1}R(v) = 0$ and $\lim_{v\to1}\bar{g}(v) = W$.

To establish the existence and uniqueness of $\tilde{v}(\lambda)$ and its corresponding properties, we first derive $\bar{g}''(v)$ by differentiating $\bar{g}'(v)$ with respect to v, yielding

$$\bar{g}''(v) = \frac{\bar{g}(v)}{(1 + R(v))}\left[2\frac{[R'(v)]^2}{1 + R(v)} - R''(v)\right]. \tag{A-5}$$

Differentiating eq. (A-3) with respect to v and simplifying yields

$$R''(v) = \frac{N^2(N-1)^2}{\lambda^2(Nv-1)^4}\left[(e^{\beta_2(v,\gamma)/\lambda} + \gamma R(v))\left(\frac{2\lambda(Nv-1)}{(N-1)} + \gamma\right) + (1+\gamma)e^{\beta_2(v,\gamma)/\lambda}\right] > 0. \tag{A-6}$$

Substituting for $R'(v)$ and $R''(v)$ in eq. (A-4) and simplifying results in

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$$\overline{g}''(v) = \frac{\overline{g}(v)}{(1+R(v))} \frac{N^2(N-1)^2}{\lambda^2(Nv-1)^4}[e^{\beta_2(v,\gamma)/\lambda} + \gamma R(v)] \times$$
$$\left[2\frac{e^{\beta_2(v,\gamma)/\lambda} + \gamma R(v)}{1+R(v)} - \frac{(1+\gamma)e^{\beta_2(v,\gamma)/\lambda}}{e^{\beta_2(v,\gamma)/\lambda} + \gamma R(v)} - \frac{2\lambda(Nv-1)}{(N-1)} - \gamma\right].$$

Note that

$$g''(v) \overset{sign}{=} \frac{1}{\lambda}\left[2\frac{e^{\beta_2(v,\gamma)/\lambda} + \gamma R(v)}{1+R(v)} - \frac{(1+\gamma)e^{\beta_2(v,\gamma)/\lambda}}{e^{\beta_2(v,\gamma)/\lambda} + \gamma R(v)} - \frac{2\lambda(Nv-1)}{(N-1)} - \gamma\right] = \Omega(v,\lambda). \quad \text{(A-7)}$$

Substituting for $R(v)$ in the above expression and further simplifying yields

$$\Omega(v,\lambda) = \frac{1}{\lambda}\left[2\frac{1+\gamma(1-e^{-\beta_1(v)/\lambda})}{e^{-\beta_2(v,\gamma)/\lambda} + 1 - e^{-\beta_1(v)/\lambda}} - \frac{1+\gamma}{1+\gamma(1-e^{-\beta_1(v)/\lambda})} - \frac{2\lambda(Nv-1)}{(N-1)} - \gamma\right]. \quad \text{(A-8)}$$

Note that

$$\lim_{v\to\frac{1}{N}}\Omega(v,\lambda) = \frac{1+\gamma}{\lambda} > 0, \quad \text{(A-9)}$$

since $\lim_{v\to\frac{1}{N}}\beta_1(v) = \lim_{v\to\frac{1}{N}}\beta_2(v,\gamma) = \infty$, and

$$\lim_{v\to 1}\Omega(v,\lambda) = \frac{1}{\lambda}\left[2e^{\gamma/\lambda} - 2\lambda - 2\gamma - 1\right] = \Omega^1(\lambda), \quad \text{(A-10)}$$

since $\lim_{v\to 1}\beta_1(v) = 0$ and $\lim_{v\to 1}\beta_2(v,\gamma) = \gamma$. Note that $\lim_{\lambda\to 0}\Omega^1(\lambda) = \infty$ and $\lim_{\lambda\to\infty}\Omega^1(\lambda) = -2$. Moreover, the term in brackets in eq. (A-9) is strictly decreasing in λ, implying the existence a unique $\tilde{\lambda} > 0$ such that $\Omega^1(\tilde{\lambda}) = 0$. For $\lambda > \tilde{\lambda}$, $\Omega^1(\lambda) < 0$ and thus $\lim_{v\to 1}\Omega(v,\lambda) < 0$. Note that $\lim_{v\to\frac{1}{N}}\Omega(v,\lambda) > 0$ and $\lim_{v\to 1}\Omega(v,\lambda) < 0$ together imply the existence of $\tilde{v}(\lambda) \in (\frac{1}{N},1)$ that solves $\Omega(\tilde{v}(\lambda),\lambda) = 0$.

To establish the uniqueness of $\tilde{v}(\lambda)$, it suffices to show that $\frac{\partial\Omega(\tilde{v}(\lambda),\lambda)}{\partial v} < 0$. Note that by eq. (A-4), $\Omega(\tilde{v}(\lambda),\lambda) = 0$ can be re-written as

$$\Phi(\tilde{v}(\lambda)) = 2[R'(\tilde{v})]^2 - R''(\tilde{v})(1+R(\tilde{v})) = 0.$$

Thus, $\frac{\partial\Phi(\tilde{v}(\lambda))}{\partial v} < 0$ implies $\frac{\partial\Omega(\tilde{v}(\lambda),\lambda)}{\partial v} < 0$. Differentiating $\Phi(v)$ and evaluating at $\tilde{v}(\lambda)$ results in

$$\frac{\partial\Phi(\tilde{v}(\lambda))}{\partial v} = \frac{R'(\tilde{v})}{R''(\tilde{v})}\left[3[R''(\tilde{v})]^2 - 2R'''(\tilde{v})R'(\tilde{v})\right],$$

where we have taken into account that $1+R(\tilde{v}) = \frac{2[R'(\tilde{v})]^2}{R''(\tilde{v})}$. By eq. (A-3), $R'(\tilde{v}) < 0$ and by eq. (A-5), $R''(\tilde{v}) > 0$. Therefore, $\frac{\partial\Phi(\tilde{v}(\lambda))}{\partial v} < 0$ requires $3[R''(\tilde{v})]^2 - 2R'''(\tilde{v})R'(\tilde{v}) = \zeta(\tilde{v}) > 0$. Somewhat tedious, but straightforward algebra yields:[24]

---

[24] To derive this expression, we have re-written eq. (A-3) as $R'(v) = -\frac{N(N-1)}{(Nv-1)^2}\frac{1}{\lambda}\left[e^{\frac{\beta_2(v)-\beta_1(v)}{\lambda}} + (1+\gamma)R(v)\right]$. Using this expression, we have derived $R''(v)$ and $R'''(v)$, and used the resulting expressions to obtain $\zeta(\tilde{v})$.

$$\zeta(\tilde{v}) = \frac{N^2(N-1)^2}{(N\tilde{v}-1)^4} \times$$

$$\left[\frac{(1+\gamma)^2[R'(\tilde{v})]^2}{\lambda^2} - R'(\tilde{v})e^{\frac{\beta_2(\tilde{v})-\beta_1(\tilde{v})}{\lambda}}\frac{N(N-1)\gamma(4+2\gamma)}{\lambda^3(N\tilde{v}-1)^2} + \frac{3\gamma^2N^2(N-1)^2}{(N\tilde{v}-1)^4\lambda^4}e^{\frac{2(\beta_2(\tilde{v})-\beta_1(\tilde{v}))}{\lambda}}\right]$$

Since $R'(v) < 0$, it follows immediately that $\zeta(\tilde{v}) > 0$ and thus $\frac{\partial\Phi(\tilde{v}(\lambda))}{\partial v} < 0$. This establishes the uniqueness of $\tilde{v}(\lambda)$. To establish property 1), note that by the continuity of $\Omega(v,\lambda)$ in v and eq. (A-8), it follows that $\Omega(v,\lambda) > 0$ for all $v < \tilde{v}(\lambda)$, implying that $\overline{g}''(v) > 0$ for all $v < \tilde{v}(\lambda)$. The uniqness of $\tilde{v}(\lambda)$ also implies that for all $\lambda > \tilde{\lambda}$ (i.e. $\Omega^1(\lambda) < 0$), $\Omega(v,\lambda) < 0$ for all $v > \tilde{v}(\lambda)$. This, in turn, implies that $\overline{g}''(v) < 0$ for all $v > \tilde{v}(\lambda)$.

To establish property 2), note first that the uniqueness of $\tilde{v}(\lambda)$ implies that for $\lambda < \tilde{\lambda}$, $\Omega(v,\lambda) > 0$ for any $v \in \left(\frac{1}{N},1\right)$. Therefore, for $\lambda < \tilde{\lambda}$, $\tilde{v}(\lambda) = 1$. For $\lambda > \tilde{\lambda}$, implicit differentiation of $\Omega(\tilde{v}(\lambda),\lambda) = 0$ results in

$$\tilde{v}'(\lambda) = -\frac{\partial\Omega(\tilde{v}(\lambda),\lambda)/\partial\lambda}{\partial\Omega(\tilde{v}(\lambda),\lambda)/\partial v} \tag{A-11}$$

Recall that $\frac{\partial\Phi(\tilde{v}(\lambda))}{\partial v} < 0$, implies $\frac{\partial\Omega(\tilde{v}(\lambda),\lambda)}{\partial v} < 0$. Thus, it suffices to show that $\frac{\partial\Omega(\tilde{v}(\lambda),\lambda)}{\partial\lambda} < 0$. For this purpose, let $\tilde{\beta}_1(\tilde{v},\lambda) = \frac{\beta_1(\tilde{v})}{\lambda}$, $\tilde{\beta}_2(\tilde{v},\lambda,\gamma) = \frac{\beta_2(\tilde{v},\gamma)}{\lambda}$, and $\omega(\tilde{\beta}_1,\tilde{\beta}_2) = 2\frac{1+\gamma(1-e^{-\tilde{\beta}_1})}{e^{-\tilde{\beta}_2}+1-e^{-\tilde{\beta}_1}} - \frac{1+\gamma}{1+\gamma(1-e^{-\tilde{\beta}_1})}$. Then, $\Omega(\tilde{v},\lambda) = 0$ can be re-written as

$$\Omega(\tilde{v},\lambda) = \frac{1}{\lambda}\left[\omega(\tilde{\beta}_1,\tilde{\beta}_2) - 2\lambda\frac{N\tilde{v}-1}{N-1} - \gamma\right] = 0. \tag{A-12}$$

Differentiating the above expression w.r.t. v yields

$$\frac{\partial\Omega(\tilde{v},\lambda)}{\partial v} = \frac{1}{\lambda^2}\left[\frac{\partial\omega(\tilde{\beta}_1,\tilde{\beta}_2)}{\partial\tilde{\beta}_1}\frac{\partial\beta_1(\tilde{v})}{\partial v} + \frac{\partial\omega(\tilde{\beta}_1,\tilde{\beta}_2)}{\partial\tilde{\beta}_2}\frac{\partial\beta_2(\tilde{v},\gamma)}{\partial v}\right] - \frac{2N}{N-1} =$$

$$= -\frac{1}{\lambda^2}\left[\frac{\partial\omega(\tilde{\beta}_1,\tilde{\beta}_2)}{\partial\tilde{\beta}_1} + \frac{\partial\omega(\tilde{\beta}_1,\tilde{\beta}_2)}{\partial\tilde{\beta}_2}(1+\gamma)\right]\frac{N(N-1)}{(N\tilde{v}-1)^2} - \frac{2N}{N-1} < 0$$

where we have substuted for $\frac{\partial\beta_1(\tilde{v})}{\partial v}$ and $\frac{\partial\beta_2(\tilde{v},\gamma)}{\partial v}$ in the second equation using eqs. (A-1) and (??). The strict inequality follows by our earlier result. Similarly, differentiating $\Omega(\tilde{v},\lambda)$ w.r.t. λ results in

$$\frac{\partial\Omega(\tilde{v},\lambda)}{\partial\lambda} = \frac{1}{\lambda}\left\{\left[-\frac{\partial\omega(\tilde{\beta}_1,\tilde{\beta}_2)}{\partial\tilde{\beta}_1}\frac{\beta_1(\tilde{v})}{\lambda^2} - \frac{\partial\omega(\tilde{\beta}_1,\tilde{\beta}_2)}{\partial\tilde{\beta}_2}\frac{\beta_2(\tilde{v},\gamma)}{\lambda^2}\right] - 2\frac{N\tilde{v}-1}{N-1}\right\} =$$

$$= \frac{1}{\lambda}\left\{-\left[\frac{\partial\omega(\tilde{\beta}_1,\tilde{\beta}_2)}{\partial\tilde{\beta}_1} + \frac{\partial\omega(\tilde{\beta}_1,\tilde{\beta}_2)}{\partial\tilde{\beta}_2}(1+\gamma)\right]\frac{\beta_1(\tilde{v})}{\lambda^2} - \frac{\gamma}{\lambda^2}\frac{\partial\omega(\tilde{\beta}_1,\tilde{\beta}_2)}{\partial\tilde{\beta}_2} - 2\frac{N\tilde{v}-1}{N-1}\right\} =$$

$$= \frac{1}{\lambda}\left\{\frac{(N\tilde{v}-1)(1-\tilde{v})}{N-1}\frac{d\Omega(\tilde{v},\lambda)}{dv} - 2\frac{(N\tilde{v}-1)^2}{(N-1)^2} - \frac{\gamma}{\lambda^2}\frac{\partial\omega(\tilde{\beta}_1,\tilde{\beta}_2)}{\partial\tilde{\beta}_2}\right\}$$

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The first equality follows from $\Omega(\tilde{v}, \lambda) = 0$, the second equality follows from substituting for $\beta_2(\tilde{v}, \gamma)$ from eq. (??) in the first one, and the last equality is derived by substituting for $\beta_1(\tilde{v})$ and re-arranging the terms. It is straightforward to verify that $\frac{\partial \omega(\tilde{\beta}_1, \tilde{\beta}_2)}{\partial \tilde{\beta}_2} > 0$ and thus $\frac{\partial \Omega(\tilde{v}, \lambda)}{\partial v} < 0$ implies that $\frac{\partial \Omega(\tilde{v}, \lambda)}{\partial \lambda} < 0$. Therefore, by eq. (A-10), $\tilde{v}'(\lambda) < 0$ for $\lambda > \tilde{\lambda}$.

Finally, to establish that $\lim_{\lambda \to \infty} \tilde{v}(\lambda) = \frac{1}{N}$, note that eq. (A-7) implies that $\lim_{\lambda \to \infty} \Omega(v, \lambda) = -2\frac{Nv-1}{N-1}$. By definition, $\Omega(\tilde{v}(\lambda), \lambda) = 0$ for $\lambda > \tilde{\lambda}$. Therefore,

$$\lim_{\lambda \to \infty} \Omega(\tilde{v}(\lambda), \lambda) = \lim_{\lambda \to \infty} -2\frac{N\tilde{v}(\lambda) - 1}{N - 1} = 0 \implies \lim_{\lambda \to \infty} \tilde{v}(\lambda) = \frac{1}{N}.$$

This completes the proof. ∎

Proof of Proposition 1.

Given $\frac{1}{N} < v_L < v_H < 1$, by Lemma 1, there exist $\lambda_1 > 0$ be such that $\tilde{v}(\lambda_1) = v_H$ and $\lambda_2 > \lambda_1$ such that $\tilde{v}(\lambda_2) = v_L$. Furthermore, by Lemma 1, $\bar{g}(v)$ is convex for all $v < v_H$ if $\lambda \leq \lambda_1$. Thus, by definition of convexity,

$$p_L \bar{g}(v_L) + p_H \bar{g}(v_H) > \bar{g}(p_L v_L + p_H v_H)$$

Analogously, for $\lambda \geq \lambda_2$, $\bar{g}(v)$ is concave for all $v \geq v_L$, implying the reverse inequality. ∎

Appendix B   Behavioral Types in the Conditional Contribution Game

A total of 360 subjects participated in the first stage of this experiment and played the Fischbacher et al. (2001) conditional contribution game. Using this data, we classify subjects' contribution behavior into the following categories:

- **Conditional Cooperators:** About 73.6% of our subjects (265 subjects) are classified as the conditional cooperative types. Based on their contribution schedule, we further classify them into the following three distinct categories:

    Pro-Social Conditional Cooperators: 11.7% of our subjects (42 subjects) are classified as pro-social conditional cooperators. Their contributions are either equal to or more than the average contributions of others. On average, their contributions lie above the 45 degree line. The Spearman rank correlation coefficients of pro-social conditional cooperators are always positive and highly significant.

    Perfect Conditional Cooperators: 16.9% (61 subjects) are classified as perfect conditional cooperators. These subjects always perfectly match the contributions of others and thus their contributions on average lie exactly on the 45 degree line. Their Spearman rank correlation coefficients are equal to 1 and highly significant.

    Weak Conditional Cooperators: 45% (162 subjects) are classified as weak conditional cooperators. The average contributions made by these subjects lie below the 45 degree line. While these subjects mostly exhibit weakly monotonic and increasing contribution behavior, 6.7% of our subjects (24 subjects) show some slight deviations from the increasing trend. The Spearman rank correlation coefficients of weak conditional cooperators are always positive and highly significant except for one subject whose coefficient is not significant.

- **Free Riders:** 10% (36 subjects) are classified as free-riders or selfish. Independent of the others' average contributions, these subjects never contribute anything.

- **Hump-Shaped Contributors:** About 6.7% (24 subjects) are classified as hump-shaped contributors. These subjects' contributions are increasing in others' average contributions but up to a level (about 10 tokens on average). Beyond this level, their contributions start decreasing as others' average contributions increase.

- **Unconditional Full Cooperators:** 1.7% of our subjects (6 subjects) are classified as unconditional full cooperators. They always contribute all of their endowment independent of others' average contribution.

- **Other:** We classify the remaining 8% (29 subjects) as other. While, 3.9% (14 subjects) exhibits random behavior, about 3.6% (13 subjects) contributed a fixed amount such as 1 or 5 tokens with sometimes slight deviations. Interestingly, the contribution behavior for the 0.5% of subjects (2 subjects) exhibit a reserve hump-shape.

Appendix C

Table C1: Two-part Hurdle Model Regression Results: An Alternative Specification

	Probit	Less Generous Treatment Tobit		More Generous Treatment Tobit	
	(1)	(2)	(3)	(4)	(5)
Less Generous	-0.926***				
	(0.224)				
Known MPCR	-0.107	2.715***	1.191	-2.559*	-4.675***
	(0.272)	(1.018)	(1.146)	(1.379)	(1.179)
Known MPCR*High MPCR			3.294***		3.555***
			(1.009)		(0.580)
Lagged Other's Average		0.258***	0.276***	0.149***	0.148***
		(0.073)	(0.083)	(0.046)	(0.054)
Beta		-0.628	-0.480	9.695***	9.709***
		(1.949)	(1.924)	(2.367)	(2.126)
Period		-0.244**	-0.278**	-0.0822	-0.0203
		(0.122)	(0.113)	(0.118)	(0.116)
Constant	2.186***	3.008**	3.252**	11.91***	11.51***
	(0.224)	(1.485)	(1.565)	(1.692)	(1.393)
Observations	111	405	405	531	531

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The robust standard errors clustered at the individual level are in parentheses.

The dependent variable for the Probit model is Contributed which takes the value of 1 if the subject contributed at least once in the last 8 periods, and otherwise zero. The dependent variable for the panel data Tobit models is Contributions. The number of observations in column 1 is the total number of subjects participated in this study. The numbers of observations in the remaining four columns are the number of decisions made in 9 periods by subjects who contributed at least once in the last 8 periods.

Appendix D   Instructions for the Lab Experiment (Stage 2)

Thank you for participating in our study.

This is an experiment in decision-making. You will earn money based on the decisions that you and others make during this study. Since you could earn a significant amount of money from this study, please pay attention to the instructions.

It is very important that you remain silent and **do not** talk to others. If you have any questions or need assistance, please raise your hand and an experimenter will come to you.

Today, I will be reading the instructions for you. Please follow the instructions as I read them and please **do not** click "NEXT" until I instruct you to do so. We appreciate your cooperation.

Please turn off your electronic devices and put them away. You are **not** allowed to use your electronic devices until the end of the experiment. Please feel free to use the calculator that is provided for you.

You will be paid a show-up fee of $8 for participating in our study today; this will be yours to keep. You will have the opportunity to make more money during the experiment. All of your earnings will be paid to you in cash and in private at the end of the experiment.

The currency used in this experiment is tokens. At the end of the experiment, all of the tokens you have earned will be converted to money at the following rate:

1 Token=$0.50 (1 Token = 50 cents)

Please click NEXT when you are ready.

Next

Instructions

You will be randomly assigned to a group consisting of **three** people. The identity of your group members in this experiment will be kept anonymous and confidential to all participants. Neither before nor after the experimental session will you learn who are/were in your group.

This experiment consists of two sets of 10 rounds, and you will be paid for one round picked at random at the end of the experiment. Right now, nobody knows which round is the paying round. Thus, it is in your best interest to pay equal attention to all rounds.

In each round, each group member has to decide on the allocation of 20 tokens. Each group member starts out with 20 tokens in his/her **private account** in each and every round.

You can leave these 20 tokens in your **private account** or you can contribute them *fully* or *partially* to a **group project** . Each token you do not contribute to the **group project** will automatically remain in your **private account.**

In each round, you will face the same decision. In each round, you will be randomly re-matched with two other participants.

Are there any questions so far?

Please click NEXT when you are ready.

Next

YOUR EARNINGS FROM THE PRIVATE ACCOUNT

You will earn one token for each token you leave in your private account.

Earnings from your private account = 20 - *your contribution to the group project*

For example, if you leave 20 tokens in your private account (and therefore do not contribute to the group project), your earnings from your private account will be 20 tokens. If you leave 6 tokens in your private account (and therefore you contribute 14 tokens to the group project), your earnings from your private account will be 6 tokens.
Only you will earn tokens from *your* private account.

Are there any questions so far?

Please click NEXT when you are ready.

Next

YOUR EARNINGS FROM THE GROUP PROJECT

You as well as your group members can contribute to the group project. The earnings for the group members from the group project will be determined by either of these two formulas:

Formula 1:   Earnings from the group project = (Sum of Contributions X **1.2**) / 3

Formula 2:   Earnings from the group project = (Sum of Contributions X **1.8**) / 3

There is a 50% chance that the earnings from the group project will be calculated by Formula 1. In this case, you and your group members will <u>each</u> earn **(Sum of Contributions X 1.2) / 3** from the project.

There is a 50% chance that the earnings from the group project will be calculated by Formula 2. In this case, you and your group members will <u>each</u> earn **(Sum of Contributions X 1.8) / 3** from the project.

In each round, the computer will randomly determine whether the earnings from the group project will be calculated according to Formula 1 or Formula 2. Right now, nobody knows which formula is going to be used.

We will give you two examples in the following screen. These examples are designed to help you better understand the instructions. They should not be used as a guide for your decisions in the experiment.

Are there any questions so far?

Please click NEXT when you are ready.

Next

EXAMPLES

Example 1:

Suppose that the sum of contributions to the group project made by you and your group members is **27** tokens.

Also, suppose that **Formula 1** is randomly selected.

Then, you and your group members will each earn (27 x **1.2**) / 3 = 32.4 / 3 = 10.8 tokens from the group project.

Are there any questions so far?

Example 2:

Suppose that the sum of contributions to the group project made by you and your group members is **11** tokens.

Also, suppose that **Formula 2** is randomly selected.

Then, you and your group members will each earn (11 x **1.8**) / 3 = 19.8 / 3 = 6.6 tokens from the group project.

Are there any questions so far?

Please click NEXT when you are ready.

Next

TOTAL EARNINGS

Again, there are three participants in each group. This means that you will be matched with two other participants in this sessions. Your total earnings are the **sum** of your earnings from your private account and from the group project:

Total Earnings	=	Earnings From Your Private Account	+	Earnings From the Group Project
		(20 - your contribution to the group project)		With 50% chance: (Sum of Contributions x 1.2) / 3
				With 50% chance: (Sum of Contributions x 1.8) / 3

Are there any questions so far?

Please click NEXT when you are ready.

Next

UNDERSTANDINGS TASK

Before you start making your decisions, we would like you to answer a few questions. These questions are **not** designed to test you; but to help you better understand the experiment. They should **not** be used as a guide for your decisions in the experiment. If you need any help with the questions, please raise your hand and the experimenter will come and help you. You have to answer the questions correctly in order to proceed.

Please click NEXT when you are ready.

Next

QUESTION 1

If you need assistance at any point, please raise your hand.

1. Each group member has 20 tokens in their private accounts. Suppose that nobody contributes anything to the group project.

      a. How many tokens will you earn from your <u>private account</u> ?   `20`

      b. How many tokens will you and your group members each earn from the <u>group project</u> ?   `0`

      c. How many tokens will your <u>total earnings</u> be?   `20`

When you are finished answering the questions, please click NEXT.

`Next`

QUESTION 2

If you need assistance at any point, please raise your hand.

2. Each group member has 20 tokens. Suppose that you contribute 5 tokens to the group project. Your other group members contribute 2 and 9 tokens each to the group project.
Also, suppose that the earnings from the group project will be calculated according to **Formula** 2 (sum of all contributions x **1.8**) / 3.

Please notice that the answers for some questions may not be whole numbers.

      a. How many tokens will you earn from your <u>private account</u> ?   `15`

      b. How many tokens will you and your group members each earn from the <u>group project</u> ?   `9.6`

      c. How many tokens will your <u>total earnings</u> be?   `24.6`

When you are finished answering the questions, please click NEXT.

`Next`

QUESTION 3

If you need assistance at any point, please raise your hand.

3. Each group member has 20 tokens. Suppose that you contribute 5 tokens to the group project. Your other group members contribute 2 and 9 tokens each to the group project.
Also, suppose that the earnings from the group project will be calculated according to **Formula 1** (sum of all contributions x **1.2**) / 3.

Please notice that the answers for some questions may not be whole numbers.

a. How many tokens will you earn from private account ?   `15`

b. How many tokens will you and your group members each earn from the group project ?   `6.4`

c. How many tokens will total earnings be?   `21.4`

When you are finished answering the questions, please click NEXT.

Next

Treatment 1 (Selfish Groups – Informed):

Information about Today's Session

Recently, all of you participated in our online experiment. During this online experiment, you filled out a conditional contribution table and made contribution decisions to a group project that benefited everyone in your group equally.

Using your decisions made in this online experiment, we calculated a measure for each of the participants. This measure ranges between -1 and +1. If a participant's measure is -1, this means that this participant did not contribute anything to the group project no matter what other group members contributed. If a participant's measure is +1, this means that this participant contributed all of their tokens to the group project no matter what other group members contributed. The higher this measure is for one participant, the higher that participant's contributions were.

After we calculated this measure for each of the participants, we ranked everyone based on their measure as shown in the figure below. Then, we divided the participants into two equally sized populations.

For today's session, we only invited participants from Population 1.

Are there any questions so far?

Please click NEXT when you are ready.

Next

FIRST SET OF 10 ROUNDS

The first set of the experiment will last for 10 rounds.

In each round, you will have 20 tokens in your private account and will be asked to make a contribution decision to the group project.

Your total earnings are the **sum** of your earnings from your private account and from the group project:

You will earn 1 token for each token you keep in your private account.

Your earnings from the group project will be:

- Either   (Sum of Contributions x 1.2) / 3   with 50% chance (Formula 1)
- Or   (Sum of Contributions x 1.8) / 3   with 50% chance (Formula 2)

In each round, **only one** of these Formulas will be randomly selected. The randomly selected Formula will be used to calculate the earnings from the group project for that round.

In the first 10 rounds of the experiment, when you make your contribution decision, you will know which formula is going to be used for that round. In other words, when you make your contribution decision, you will know whether Formula 1 or Formula 2 is randomly selected to be used in that round.

In each round, you will be randomly re-matched with two other participants in this session and you will face the same decision. At the end of each round, you will be provided a Round Summary page. On this page, you will receive feedback on your earnings, the formula that was chosen, and your group member's contributions in that round.

Are there any questions so far?

Please click NEXT when you are ready.

Next

INFORMED decision Screen

ROUND 11

You have 20 tokens in your private account. Below, we ask you to make your contribution decision to the group project. Your contribution can be any whole number from 0 to 20.

Please remember that you will be randomly **re-matched** with two other participants in each round.

The randomly selected formula to be used in this round is: **(Sum of Contributions X 1.8) / 3**

How many tokens would you like to contribute to the project? | I |

Please make your decision now and click NEXT when you are ready.

Next

ROUND SUMMARY

Earnings from Private Account: 17 tokens.

Earnings from Group project: 2.80 tokens.
       Other's Average Contribution (rounded up): 2 tokens.
       Sum of Contribution: 7 tokens.
       Formula used: (Sum of Contributions X 1.2) / 3

Your Total Earnings This Round: 19.80 tokens.

Please click NEXT when you are ready.

Next

SECOND SET OF 10 ROUNDS

Again, in each round, you will have 20 tokens in your private account, and you will be asked to make a contribution decision to the group project.

Your total earnings are the **sum** of your earnings from your private account and from the group project:
    You will earn 1 token for each token you keep in your private account.
    Your earnings from the group project will be:
      - Either   (Sum of Contributions x 1.2) / 3   with 50% chance (Formula 1)
      - Or   (Sum of Contributions x 1.8) / 3   with 50% chance (Formula 2)

In each round, **only one** of these Formulas will be randomly selected. The randomly selected Formula will be used to calculate the earnings from the group project for that round.

Different from the previous set of 10 rounds, in this second set of 10 rounds, you will make your contribution decision without knowing which formula is selected for that round. This is the only difference.
Again, in each round, you will face the same decision. Also, in each round, you will be randomly re-matched with two other participants in this session.

Are there any questions so far?

Please click NEXT when you are ready.

Next

Uninformed Decision Screen

ROUND 1

You have 20 tokens in your private account. Below, we ask you to make your contribution decision to the group project. Your contribution can be any whole number from 0 to 20.

Please remember that you will be randomly **re-matched** with two other participants in each round.

How many tokens would you like to contribute to the project?

Please make your decision now and click NEXT when you are ready.

Next

ROUND SUMMARY

Earnings from Private Account: 14 tokens.

Earnings from Group project: 10.40 tokens.
　　　　　Other's Average Contribution (rounded up): 10 tokens.
　　　　　Sum of Contribution: 26 tokens.
　　　　　Formula used: (Sum of Contributions X 1.2) / 3

Your Total Earnings This Round: 24.40 tokens.

Please click NEXT when you are ready.

Next

EARNINGS

Round Chosen for Payment: 8
Earnings (tokens): 21.80 tokens

Earnings (USD): 10.90 tokens
Show-up Fee ($5 +$3): $8
Total Earnings: $18.90

You will receive your payments from the online expeirment within 4 weeks of your participation date.

Please click NEXT when you are ready.

Next

Appendix E   Instructions for the Online Experiment (Stage 1)
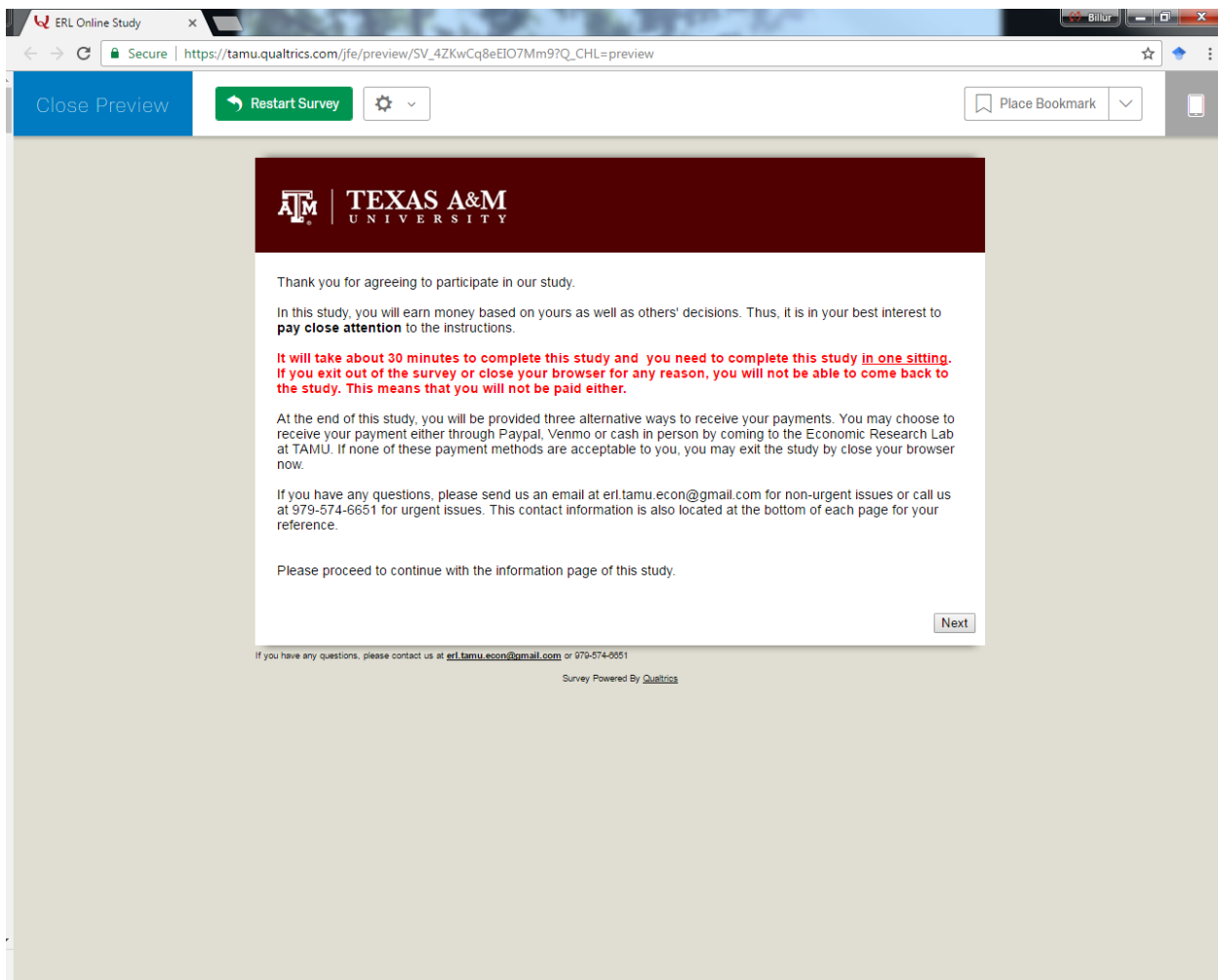
TEXAS A&M
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GENERAL INSTRUCTIONS

Attention: This study contains some questions to ensure that you understand how the game works. You will **not** be able to proceed with the study without answering those questions correctly. Thus, we strongly suggest you to pay very close attention to the instructions and take notes while reading them if necessary.

The currency used in this study is tokens. At the end of the study, all of the tokens you have earned will be converted to money at the following rate:

1 Token=$0.40 (1 token = 40 cents)

The amount of money that you make in this online study will depend on yours as well as others' decisions .

Please be aware that you are **not** allowed to discuss this study with others.

Feel free to use a calculator if you need.

Next

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GENERAL INSTRUCTIONS

You will be randomly assigned to a group consisting of **three** people. The identity of your group members in this study will be kept anonymous and confidential to all participants.

Each group member starts out with 20 tokens in his/her **private account** and has to decide on the allocation of these 20 tokens. You can leave these 20 tokens in your **private account** or you can contribute them *fully* or *partially* to a **group project**. Each token you do not contribute to the **group project** will automatically remain in your **private account**.

Your total earnings from this study will be the summation of your earnings from your **private account** and the **group project**.

Now, we will explain how your earnings are determined in the following screens.

Next

If you have any questions, please contact us at **erl.tamu.econ@gmail.com** or 979-574-6651

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1. YOUR EARNINGS FROM THE PRIVATE ACCOUNT

You will earn one token for each token you left in your private account.

Earnings from your private account** = 20 – your contribution to the **group project

For example, if you leave 20 tokens in your private account (and therefore do not contribute to the group project), your earnings from your private account will amount to exactly 20 tokens. If you leave 6 tokens in your private account (and therefore you contribute 14 tokens to the group project), your earnings from your private account will be 6 tokens.

No one, except you, will earn anything from your private account.

On the next page, we explain how your earnings from the group project are calculated.

Next

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2. YOUR EARNINGS FROM THE GROUP PROJECT

You as well as your group members can **contribute** to the group project. The contributions by you and your group members will be summed. Then, the earnings for each group member from the group project will be determined by the following formula:

$$\text{Earnings from the Group Project} = \frac{\text{"Sum of Contributions" x (1.5)}}{3}$$

Each group member will **benefit equally** from the group project.

For example, suppose that the sum of tokens contributed to the group project by you and your other two group members is 55 tokens. Then each of you earns (55 x 1.5)/3 = 82.5/3 = 27.5 tokens from the group project.

Next

If you have any questions, please contact us at erl.tamu.econ@gmail.com or 979-574-6651

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<u>**TOTAL EARNINGS**</u>

Your total earnings are the sum of your earnings from your **private account** and from the **group project**:

Total Earnings	**=**	**earnings from your private account**	**+**	**earnings from the group project**
		(20 – your contribution to the group project)		$\dfrac{\text{"sum of contributions" x 1.5}}{3}$

On the following screens, we will ask you to answer a few practice questions.

Next

If you have any questions, please contact us at erl.tamu.econ@gmail.com or 979-574-6651

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TEXAS A&M
U N I V E R S I T Y

UNDERSTANDINGS QUESTIONS (1/2)

To see the instructions, please click here.

Each group member has 20 tokens in their private account. Suppose that nobody contributes anything to the group project.

Your answer for Question 1 is not correct. Since nobody contributed to the group project, this means that you will receive zero tokens from the group project. Thus, your earnings are equal to the tokens that are left in your private account which is 20 tokens.

1. What will your total earnings be?

1

Your answer for Question 2 is not correct. Since nobody contributed to the group project, this means that Group Member 1 will receive zero tokens from the group project. Thus, his/her earnings are equal to the tokens that are left in his/her private account which is 20 tokens.

2. What will Group Member 1's total earnings be?

1

Your answer for Question 3 is not correct. Since nobody contributed to the group project, this means that Group Member 2 will receive zero tokens from the group project. Thus, his/her earnings are equal to the tokens that are left in his/her private account which is 20 tokens.

3. What will Group Member 2's total earnings be?

1

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UNDERSTANDINGS QUESTIONS (2/2)

If you would like to see the instructions that are provided on the previous screens, please click here (opens a pdf file on a new window).

Each group member starts out with 20 tokens in their private account. Suppose that you contribute 6 tokens into the group project. Group Member 1 contributes 0 tokens and Group Member 2 contributes 15 tokens into the group project.

Your answer for Question 4 is not correct. You contributed 6 tokens, Group Member 1 contributed 0 tokens and Group Member 2 contributed 15 tokens. Thus total tokens contributed are: 6+0+15=21

4. What is the total amount of tokens that are contributed to the group project?

| 0 |

Your answer for Question 5 is not correct. Since total tokens contributed to the group project is 21 tokens, each group members receives (21 x 1.5)/ 3 = 10.5 tokens from the group project. Since you left 20-6=14 tokens in your individual account, your total earnings would be 10.5 + 14 = 24.5

5. What will your total earnings be?

| 0 |

Next

If you have any questions, please contact us at erl.tamu.econ@gmail.com (non-urgent issues) or call/text at 979-574-6651 (urgent issues)

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<u>MAKING YOUR DECISIONS</u>

You will make two decisions, which we will refer as "**Decision 1**" and "**Decision 2**".

In **Decision 1**, you will decide how many of the 20 tokens you want to contribute to the group project.

In **Decision 2**, you will fill in a contribution table. We explain how these decisions work on the following screen.

After all participants have made both **Decision 1** and **Decision 2**, we will randomly select one group member to be paid for **Decision 2**. The other two group members will be paid for **Decision 1**. Earnings for the group members will based on these decisions.

When you make your **Decision 1** and **Decision 2**, you do not know whether the random mechanism will select you. You will therefore have to think carefully about both decisions because either one might become relevant for you.

Next

If you have any questions, please contact us at **erl.tamu.econ@gmail.com** or 979-574-6651

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DECISION 1: Description

For **Decision 1**, you will see the following screen:

DECISION 1

Now, we ask you to make your contribution decision for **Decision 1**.

You have 20 tokens in your private account. Below, we ask you to make your contribution decision to the group project. Your contribution could be any whole number from 0 to 20.

Remember:

- You will earn 1 token for each token you keep in your private account.
- Your earnings from the group project will be:

$$\text{Earnings from the Group Project} = \frac{\text{"Sum of Contributions"} \times (1.5)}{3}$$

How many tokens would you like to contribute to the group project?

[   ]

Next

If you have any questions, please contact us at erl.tamu.econ@gmail.com or 979-574-6651

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DECISION 2: Description

In **Decision 2**, you will be asked to fill in a **contribution table** where you indicate how many tokens you want to contribute to the group project for each possible average contribution from your group members (rounded to the next integer) in **Decision 1**. This will be immediately clear to you if you take a look at the following table:

Please indicate how many tokens (if any) you would like to contribute, for each possible average tokens contributed by other two group members:	
	Your Contribution
if others' average contribution is 0 tokens	
if others' average contribution is 1 tokens	
if others' average contribution is 2 tokens	
if others' average contribution is 3 tokens	
if others' average contribution is 4 tokens	
if others' average contribution is 5 tokens	
if others' average contribution is 6 tokens	
if others' average contribution is 7 tokens	
if others' average contribution is 8 tokens	
if others' average contribution is 9 tokens	
if others' average contribution is 10 tokens	
if others' average contribution is 11 tokens	
if others' average contribution is 12 tokens	
if others' average contribution is 13 tokens	
if others' average contribution is 14 tokens	
if others' average contribution is 15 tokens	
if others' average contribution is 16 tokens	
if others' average contribution is 17 tokens	
if others' average contribution is 18 tokens	
if others' average contribution is 19 tokens	
if others' average contribution is 20 tokens	

You simply have to state how many tokens you will contribute to the group project into each input box, conditional on the corresponding average contribution (rounded up) from your group members. You have to make an entry into each input box. For example, you will state how much you would contribute to the group project if your group members' average contribution is 0 tokens, how much you would contribute if your group members' average contribution is 1 token, etc. You can state any whole number from 0 to 20 in each input box.

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DETERMINING THE EARNINGS

After all participants have made both **Decision 1** and **Decision 2,** we will randomly assign groups of 3. Then, we randomly select two group members whose contributions will be based on their decisions in **Decision 1**. This will determine the average contribution of these two group members. Finally, the remaining group member's contribution will be determined based on his/her decisions in the contribution table in **Decision 2**. Earnings for the group members will be based on these decisions.

We provide an example in the following screen. This example is designed to help you better understand the experiment. It should not be used as a guide for your decisions in the experiment.

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EXAMPLE

Suppose that **Decision 1** is the relevant decision for Group Member 1 and Group Member 2. Thus, **Decision 2 (contribution table)** is your relevant decision.

Suppose in **Decision 1**, Group Member 1 contributes 13 tokens and Group Member 2 contributes 5 tokens. This means that the average contributions made by your group members is (13 + 5)/2 = 9 tokens.

Suppose you indicate in your **contribution table in Decision 2** that you would contribute 10 tokens if the other group members' average contribution is 9 tokens.

Sum of contributions to the group project: **13 + 5 + 10 =28** tokens
Each group member earns from the group project: **(28 x 1.5) / 3 = 14** tokens

Your Earnings from your Private Account: **(20 – your contribution) = 20 – 10 = 10** tokens

Your Total Earnings would be:

14 (from the group project**) + 10 (**from the private account**) = 24** tokens

On the following screen, we will ask you to answer a few practice questions.

| Next |

If you have any questions, please contact us at **erl.tamu.econ@gmail.com** or 979-574-6651

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To see the full set of instructions, please click here.

Each group member starts out with 20 tokens in their private account. Suppose that you contribute 6 tokens into the group project. Group Member 1 contributes 0 tokens and Group Member 2 contributes 15 tokens into the group project.

Suppose that **Decision 1** is the relevant decision for Group Member 1 and Group Member 2. Thus, **Decision 2 (contribution table)** is your relevant decision.

Suppose in **Decision 1**, Group Member 1 contributes 6 tokens and Group Member 2 contributes 8 tokens.

Group Member 1 contributed 6 tokens and Group Member 2 contributed 8 tokens. Thus the average contirbutions made by other group members is (6+8)/2 = 14/2 = 7 tokens

1. What is the average contributions made by the other two group members?

| 1 |

Group Members 1 and 2 contributed 6 and 8 tokens. Also, you indicated in your contribution table that you would contribute 5 tokens if the others' average contribution is 7 tokens. This means that the tokens contributed to the group project are: 6 + 8 + 5 = 19 tokens.

Suppose you indicate in your **contribution table** in **Decision 2** that you would contribute 5 tokens if the other group members' average contribution is 7 tokens.

2. What is the total amount of tokens contributed to the group project?

| 1 |

Since you contributed 5 tokens to the group project, you have 20 -5 = 15 tokens left in your private account. This means that you earn 15 tokens from your private account.

3. What are your earnings from your private account?

| 1 |

The total tokens contributed to the group project was 6 + 8 + 5 = 19 tokens. Thus each group member earns (19 * 1.5)/3 = 28.5 / 3 = 9.5 tokens.

4. What are your earnings from the group project?

| 1 |

Your earnings from your private account is 15 tokens. Your earnings from the group project is 9.5 tokens. Thus your total earnings are 15 + 9.5 = 24.5 tokens.

5. What are your total earnings?

| 1 |

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DECISION 1

Now, we ask you to make your contribution decision for **Decision 1**.

You have 20 tokens in your private account. Below, we ask you to make your contribution decision to the group project. Your contribution could be any whole number from 0 to 20.

Remember:

- You will earn 1 token for each token you keep in your private account.

- Your earnings from the group project will be:

$$\text{Earnings from the Group Project} = \frac{\text{"Sum of Contributions" x (1.5)}}{3}$$

How many tokens would you like to contribute to the group project?
(please make sure to use whole numbers only)

[   ]

Next

If you have any questions, please contact us at **erl.tamu.econ@gmail.com** or 979-574-6651

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DECISION 2

Now, we ask you to make your decision for **Decision 2**.

You simply have to state how many tokens you will contribute to the group project into each input box, conditional on the indicated group members' average contribution in Decision 1. You have to make an entry into each input box. *Your contribution could be any whole number from 0 to 20.*

Please enter a valid number.

Please indicate how many tokens (if any) you would like to contribute, for each possible average tokens contributed by other two group members:

	Your Contribution
if others' average contribution is 0 tokens	
if others' average contribution is 1 tokens	
if others' average contribution is 2 tokens	
if others' average contribution is 3 tokens	
if others' average contribution is 4 tokens	
if others' average contribution is 5 tokens	
if others' average contribution is 6 tokens	
if others' average contribution is 7 tokens	
if others' average contribution is 8 tokens	
if others' average contribution is 9 tokens	
if others' average contribution is 10 tokens	
if others' average contribution is 11 tokens	
if others' average contribution is 12 tokens	
if others' average contribution is 13 tokens	
if others' average contribution is 14 tokens	
if others' average contribution is 15 tokens	
if others' average contribution is 16 tokens	
if others' average contribution is 17 tokens	
if others' average contribution is 18 tokens	
if others' average contribution is 19 tokens	
if others' average contribution is 20 tokens	

Next

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