ISSN 1178-2293 (Online)

University of Otago
Economics Discussion Papers
No. 2102

JANUARY 2021

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Nathan W. Chan, Stephen Knowles, Ronald Peeters, Leonard Wolk

Address for correspondence:

Ronald Peeters
Department of Economics
University of Otago
PO Box 56
Dunedin
NEW ZEALAND
Email: ronald.peeters@otago.ac.nz
Telephone: 64 3 479 8731

Cost-(in)effective public good provision: An experimental exploration*

Nathan W. Chan† Stephen Knowles‡ Ronald Peeters§ Leonard Wolk¶

Abstract

This paper investigates the determinants of cost-(in)effective giving to public goods. We conduct a pre-registered experiment to elucidate how factors at the institutional and individual levels shape individual contributions and the cost-effectiveness of those contributions in a novel public good game. In particular, we examine the role of consequential uncertainty over the value of public good contributions (institutional level) as well as individual characteristics like risk and ambiguity attitudes, giving type, and demographics (individual level). We find that consequential uncertainty tends to reduce overall contributions, but not the cost-effectiveness of those contributions. Meanwhile, cost-effectiveness varies by giving type—which is a novel result that is consistent with hypotheses we generate from theory—but other individual characteristics have little influence on contributions or cost-effectiveness. Our work has important positive and normative implications for charitable giving and public good provision in the real world, and it is particularly germane to emerging online crowdfunding and patronage platforms that confront users with a multitude of competing opportunities for giving.

Keywords: Risk, ambiguity, cost-effectiveness, public goods, charity

JEL classification codes: H41, C92, D81, C72, D70

*We acknowledge the assistance of Dawnelle Clyne and Khoa Trinh in the lead up to the experiments and thank Murat Genç, Dennis Wesselbaum and the participants of the New Zealand Micro Study Group meeting 2020 for their helpful comments. This research was funded by a University of Otago Research Grant (ORG-0119-0320).

†Resource Economics, University of Massachusetts Amherst, Amherst MA, USA; nchan@umass.edu.

‡Department of Economics, University of Otago, Dunedin, New Zealand; stephen.knowles@otago.ac.nz.

§Department of Economics, University of Otago, Dunedin, New Zealand; ronald.peeters@otago.ac.nz.

¶Department of Finance, Vrije Universiteit Amsterdam, The Netherlands; l.wolk@vu.nl.

1 Introduction

Individuals engage with myriad public goods in their daily lives, ranging from environmental quality to human services to public spaces and public art, and they may contribute to these various causes through monetary donations, in-kind gifts, and volunteerism. This diverse landscape presents private citizens with a rich choice set for public good contributions, but it also creates challenges for coordination and cost-effective allocation of resources. Given vast heterogeneity in public goods and technologies for augmenting public goods, there is latitude for misallocation of resources across causes (Chan and Wolk, 2020). These issues have become even more pronounced in recent times, as online crowdfunding and patronage platforms offer a growing menu of public good possibilities to a rapidly expanding base of contributors.

In this paper, we investigate the determinants of cost-(in)effective contributions to public goods, exploring factors at both the institutional and individual levels. At the institutional level, we examine whether patterns of giving are influenced by consequential uncertainty over the value of public good contributions. At the individual level, we consider risk and ambiguity attitudes, giving type as elicited through a charitable giving task, and common demographic covariates. To understand these relationships, we model behavior in a public good game that accounts for heterogeneity in giving types and social preferences. We derive from this model testable predictions that flow transparently from microfoundations, and we proceed to test these hypotheses in a pre-registered online experiment.

Our experimental design builds on that of Chan and Wolk (2020), which features a set of four simultaneous public good contribution decisions with different marginal per capita returns (MPCRs). Importantly, this multiple public good environment makes possible cost-ineffective contributions, as subjects may contribute at low MPCRs without exhausting all contribution possibilities at high MPCRs. We extend this framework to examine how individual and institutional factors affect contribution amounts and the cost-effectiveness of those contributions. In particular, we construct two treatments in which the MPCR of each public good is a random variable with known bounds. Importantly, bounds are non-overlapping across the four public goods, allowing us to construct a clean and novel measure of cost-ineffectiveness to test our hypotheses. In one treatment, the distributions for these random variables are known (Risky treatment), while in another treatment the distributions are unknown (Ambiguity treatment); we compare these treatments to each other and to a control treatment in which MPCRs are certain (Certain treatment). We also include an array of additional tasks to elicit individual characteristics, allowing us to investigate the relationship between cost-ineffectiveness and demographics, risk and ambiguity attitudes, risk literacy, giving types, and attentiveness.

We conduct a series of parametric and non-parametric tests to compare contribution behavior across treatments and across individuals. First, focusing on contribution levels, we find that individual characteristics have little predictive power for individual contributions. However, we do see differences in contributions across treatments, indicating that consequential uncertainty may influence overall giving behavior. In particular, we see that total contributions are lower in Risky relative to Certain, which suggests that the presence of risk may dampen overall giving. Total contributions in Ambiguity are between these two extremes and are not statistically distinguishable from either.

Turning to our measure of cost-ineffectiveness, we find that (the nature of) uncertainty has no detectable impact on the cost-effectiveness of contributions. Likewise, cost-effectiveness does not vary with the vast majority of individual characteristics that we elicited, including demographics, risk and ambiguity attitudes, risk literacy, and attentiveness. However, we *do* find interesting differences in cost-effectiveness across our four giving types, as classified through subjects' actions in a separate charitable giving task: non-donors, pure warm-glow givers, pure altruists, and impure altruists. Here, we find that non-givers contribute in a more cost-*effective* manner than pure warm-glow givers and impure altruists. Individuals with warm-glow motives are most inclined to contribute in a cost-*ineffective* manner, and these effects are especially pronounced in the Ambiguity environment. These findings are robust for within- and between-subjects analyses, and they are also robust to alternative classifications rules for giving type.

Our experimental results provide important insights for the broader world. Individuals have always had many avenues for augmenting public goods, e.g., when facing multiple charitable causes. These choice sets continue to expand with modern crowdfunding and patronage platforms, making room for inefficient allocation of resources across public goods. Inefficiency may arise from individual or institutional factors, and understanding the influence of these different factors is crucial to improving public good provision. In many cases, there may be uncertainty about the productivity of different public good investments. For example, how well do investments in civic crowdfunding projects (e.g., urban greenspaces, public art installations, etc.) enhance social cohesion? How well do individual actions (e.g., wearing face masks, minimizing social contact) help blunt the spread of infectious diseases? Our experimental results shed light on such settings, revealing that uncertainty in productivity of public good investments affects overall contribution levels, but not the cost-effectiveness of allocations across technologies.

There are also important questions about how public good contributions differ along dimensions of individual heterogeneity. What types of individuals are most generous in public good provision, and which are most likely to contribute in cost-(in)effective ways? We find that, by and large, individual characteristics have little bearing on contribution levels. However, an individual's giving type—i.e., whether they are a non-giver, warm-glow giver, pure altruist, or impure altruist—does influence the efficacy of contributions. This finding accords with predictions from theory, although we are the first, to our knowledge, to document this empirically. Overall, our work provides novel and timely insights into both positive and normative aspects of public good provision.

Our work advances several distinct lines of inquiry in the economics of public good provision and charitable giving.

In focusing on efficiency, our work ties in with discussions spurred by the Effective Altruism movement. Effective Altruists urge donors to give to charities that generate the greatest benefit per dollar donated. This idea has been a topic of substantial interest among philosophers and ethicists (Singer, 2015; MacAskill, 2016), but it also has natural intersections with efficiency and cost-effectiveness concerns long articulated by economists (List, 2011; Karlan and Wood, 2017). These principles have also gained traction outside of academia, e.g., in the form of organizations like Charity Navigator and GiveWell, which seek to quantify the social impact of dollars donated across charities and causes.

Yet, in spite of clear economic and ethical rationales for effective altruism, many individuals still appear unresponsive or inattentive to the effectiveness of their charitable efforts. Evidence from laboratory and field experiments shows that most donors do not increase their donations when provided with information about the effectiveness of the charity (Clark et al., 2018; Karlan and Wood, 2017). Metzger and Günther (2019) show that many participants in laboratory experiments are unwilling to purchase, even for a minimal fee, information on the efficiency of the charity they have been asked to donate to.[1] Instead, these participants show greater interest in purchasing information about the people that the charity will help, suggesting that efficiency is not a top priority. Along similar lines, Berman et al. (2018) report that, for most participants, emotional attachment to a charitable cause is more important than the effectiveness of the charity, which may explain why few people behave as effective altruists. Genç et al. (2020) show via a choice experiment that most donors place significantly greater weight on where a donation is spent (preferring it to be spent closer to home), while assigning less importance to the effectiveness of the donation or the needs of the recipient. In short, there is robust evidence that many donors show little interest in the efficiency of the charities to which they are donating.

We explore how this (in)attention to cost-effectiveness may relate to institutional and individual factors. Our investigation into individual characteristics contributes to a broader literature on how contribution behaviors differ across motivations for giving. An influential body of theory within economics separates motives for giving into two main types: pure altruists and warm-glow givers (Warr, 1982; Andreoni, 1989, 1990; Ribar and Wilhelm, 2002; Yildirim, 2014). Pure altruists derive utility from the total amount of the charitable good provided. To a pure altruist, her donation and the donations of others are perfect substitutes, leading to crowding out of charitable donations (Warr, 1982). In contrast, a warm-glow giver derives utility from the act of giving itself, thus removing the scope for crowding out (Andreoni, 1989, 1990). A third category, impure altruists, comprises individuals who earn

[1] Gangadharan and Nemes (2009) report a similar finding in the context of a public good game: when there is an unknown probability that the private account and/or public account will not be paid out, most participants choose not to pay a small fee to find out what this unknown probability is.

utility both from own donations and total donations. It is often assumed that warm-glow givers are more prone to inefficient donations than pure altruists (Singer, 2015), a result that follows clearly from theory. However, to our knowledge, there is no direct empirical evidence supporting this claim. For example, Null (2011) separates donors into different types by *assuming* those who donate inefficiently must be warm-glow givers (after ruling out risk aversion). Similarly, Karlan and Wood (2017) report that some participants increase donations when presented with information on the effectiveness of donations, but many participants do not. They posit that the latter group may include warm-glow givers, but their experimental design does not allow them to ascertain this. Against this backdrop, our work provides an important contribution by demonstrating a direct link between giving type and cost-effective public good provision.

Individuals have a wide array of opportunities to contribute to public goods and charitable causes, so an implicit concern raised in all of the aforementioned studies is that donors may misallocate their resources toward less worthy causes. A number of recent studies have tackled this issue of multiple public goods directly. Much of the work in this realm focuses on coordination of donors across public goods. Corazzini et al. (2015) show that coordination problems can be eliminated by making one public good focal by offering better payoffs. Earlier work by Cherry and Dickinson (2008) similarly finds that subjects successfully coordinate on the option with highest social returns when faced with multiple public goods, even when the level of social returns is endogenous to aggregate contributions. Interestingly, when comparing a setting with multiple homogeneous public goods to an equivalent setting with a single public good, they report greater contributions in the former than the latter, suggesting the importance of framing. Bernasconi et al. (2009) also investigate this "unpacking" effect and similarly find improvements in contribution levels in the unpacked case. Similar to the above papers, Blackwell and McKee (2003) construct an environment with global and local public goods. They find that when the two goods provide equal societal returns, subjects donate more to the local public good; however, when social returns are higher for the global cause, subjects give more to the global public good—in spite of it generating smaller private returns.

We build on this tradition by implementing an experiment with multiple public goods, but we highlight a different aspect of the problem. Extending the design of Chan and Wolk (2020), we eliminate the scope for coordination problems, thus allowing sharper focus on individual allocations as the locus of inefficiency. In this way, our experiment more directly addresses issues raised by effective altruists, who express concerns about individuals' willingness to allocate funds to inferior causes. Although our work bears similarities to Chan and Wolk (2020), it is distinct. Whereas Chan and Wolk (2020) provide a proof-of-concept for this experimental design and shed light on framing effects induced by the choice sets, we provide deeper insight into policy relevant determinants of cost-ineffectiveness. We show how the propensity for cost-(in)effective donations may be influenced by individual characteristics and the broader information environment.

Our findings on the provision of inferior public goods also shed light on the industrial organization of charities. In particular, how do less efficient and less impactful charities survive in the market? We find that warm-glow givers and impure altruists often spread their contributions across causes, including inferior ones that might not otherwise survive under effective altruism. This pattern of behavior can uphold otherwise unproductive charities, with accompanying implications for efficiency of charity markets and social welfare.

Incorporating uncertainty has been a topic of interest in the public good games literature. However, while a number of papers study risk in public good games (see, e.g., Dickinson (1998), Gangadharan and Nemes (2009), Théroude and Zylbersztejn (2020)), few study ambiguity. Levati and Morone (2013) and Björk et al. (2016) are among the few to examine both risk and ambiguity, and they do not find significant differences in contribution behavior in situations involving risky, ambiguous, or deterministic MPCRs for single public good settings. According to the latter, there is also no interaction between strategic uncertainty and natural uncertainty. They find that cooperative attitudes and beliefs about group members' contributions are unaffected by natural uncertainty. Even so, focus has remained on settings with single public goods, which does not allow for studying cost-effectiveness. Our work thus provides novel insights into the interplay between cost-effectiveness and the overarching information environment.

The remainder of the paper proceeds as follows. Section 2 provides theoretical background and hypotheses for our public good game. Section 3 outlines specific parameters used in our experimental treatments and describes details of the experiment. We discuss results in Section 4, while Section 5 concludes.

2 Theory

Let there be n players and m public goods with prices normalized to unity. Following Chan and Wolk (2020), each player i has budget w_j^i to allocate to public good j: $x_j^i \in [0, w_j^i]$. The marginal per capita return (MPCR) of public good j is denoted γ_j. That is, player i's contribution to public good j, x_j^i, produces a benefit of $\gamma_j \cdot x_j^i$ to all players $k = 1, \ldots, n$.

Departing from Chan and Wolk (2020), let the MPCRs be subject to risk: $\gamma_j \sim F_j$. Let $\widetilde{\gamma}_j = \int_{\gamma_j} \gamma_j \, \mathrm{d}F_j$ and public goods be ordered such that $\widetilde{\gamma}_1 < \ldots < \widetilde{\gamma}_m$. Finally, let the support of γ_j be $(\underline{\gamma}_j, \overline{\gamma}_j)$.[2]

Defining utility over total payoffs, the expected utility of player i is given by

$$\int_{\gamma_1} \cdots \int_{\gamma_m} u^i \big(\sum_{j=1}^{m} \left[(w_j^i - x_j^i) + \gamma_j \cdot (x_j^i + X_j^{-i}) \right] \big) \, \mathrm{d}F_m \cdots \mathrm{d}F_1,$$

[2]To maintain focus on interesting cases in which there is a social dilemma, we constrain the support of each F_j is within $(\frac{1}{n}, 1)$.

where $X_j^{-i} = \sum_{k \neq i} x_j^k$. Rewriting this expression as

$$\int_{\gamma_1} \cdots \int_{\gamma_m} u^i \Big(\sum_{j=1}^{m} \big[\, w_j^i - (1-\gamma_j) \cdot x_j^i + \gamma_j \cdot X_j^{-i} \,\big] \Big) \, \mathrm{d}F_m \cdots \mathrm{d}F_1,$$

we see that both the effective cost $1 - \gamma_j$ and the effective benefit γ_j are subject to risk.

How might cost-effectiveness of contributions vary across individuals? We first consider risk attitudes. If a player is risk neutral, we derive the same condition as Chan and Wolk (2020) for the cost-effective allocation of resources. That is, if $x_j^i > 0$, then cost-effectiveness requires that $x_\ell^i = w_\ell^i$ for all $\ell > j$. Clearly, this holds in an example where $u^i(\pi) = \pi$. In this case, the above expression is equal to

$$\int_{\gamma_1} \cdots \int_{\gamma_m} \sum_{j=1}^{m} \big[\, w_j^i - (1-\gamma_j) \cdot x_j^i + \gamma_j \cdot X_j^{-i} \,\big] \, \mathrm{d}F_m \cdots \mathrm{d}F_1$$

$$= \sum_{j=1}^{m} [w_j^i - (1-\widetilde{\gamma}_j) \cdot x_j^i + \widetilde{\gamma}_j \cdot X_j^{-i}\,].$$

and, under cost-effectiveness, $x_j^i > 0$ only if $x_\ell^i = w_\ell^i$ for all $\ell > j$; otherwise, this player can increase her utility by shifting resources from x_j^i to x_ℓ^i.

Alternatively, if player i is risk averse (e.g., $u^i(\pi) = \pi^\alpha$ with $\alpha \in (0,1)$), this is not obvious. The reason is that payoffs may depend on player i's beliefs about the contributions of others (i.e., X_j^{-i} for all $j = 1, \ldots, m$). For instance, if i expects all others to contribute fully to public good m ($x_m^k = w_m^k$) and nothing to the other public goods ($x_j^k = 0$ for $j < m$), player i may decide to contribute a positive amount to public good $m-1$ instead of m to mitigate risk. However, this possibility only arises when γ_m and γ_{m-1} have overlapping supports, so that γ_{m-1} may be realized at a higher value than γ_m. To rule out this possibility, we focus on cases with non-overlapping supports.

Assumption 1. *$\underline{\gamma}_\ell > \overline{\gamma}_j$ for all $\ell > j$.*

Proposition 1. *For all risk types, $x_j^i > 0$ implies $x_\ell^i = w_\ell^i$ for all $\ell > j$.*

This proposition states that individuals, regardless of risk or ambiguity attitudes, should contribute in a cost-effective manner. That is, one should not contribute to a public good j until exhausting all possibilities to contribute to higher-MPCR public goods $\ell > j$.

We now consider the role of giving type. We consider four giving types as defined by Gangadharan et al. (2018) and Gandullia et al. (2020): non-donors, pure altruists, warm-glow givers, and impure altruists. The latter three types may contribute to public goods, but for different reasons. Above, we assumed that players' utilities are defined over total payoffs to allow for more parsimonious exposition of risk types. Here, we consider richer preference structures to elucidate differences across giving types.

Pure altruists may contribute because they derive utility from the aggregate level of public good provision, e.g.,

$$u^i\Bigg(\underbrace{\sum_{j=1}^{m}\left[w_j^i - x_j^i\right]}_{\text{numeraire}}, \underbrace{\sum_{j=1}^{m}\gamma_j\left[x_j^i + X_j^{-i}\right]}_{\text{public good}}\Bigg). \tag{1}$$

Such behavior would also be consistent with a preference for efficiency, and there is evidence from prior public good experiments that (some) subjects behave in such a way (Goeree et al., 2002).

However, there is also evidence from public good experiments of warm-glow givers who instead derive utility from their own act of giving (Andreoni, 1993). These individuals may value contributions to each public good separately, e.g.,

$$u^i\Bigg(\underbrace{\sum_{j=1}^{m}\left[w_j^i - x_j^i\right]}_{\text{numeraire}}, \underbrace{x_1^i, ..., x_m^i}_{\substack{\text{contributions}\\ \text{to each } m}}\Bigg), \tag{2}$$

or they may derive utility from the total amount they have contributed across all m public goods, e.g.,

$$u^i\Bigg(\underbrace{\sum_{j=1}^{m}\left[w_j^i - x_j^i\right]}_{\text{numeraire}}, \underbrace{\sum_{j=1}^{m}x_j^i}_{\text{total contributed}}\Bigg). \tag{3}$$

Impure altruists combine both warm-glow and altruistic motives. Importantly, these differences in preference structures across giving types have implications for cost-(in)effective giving. A pure altruist has no reason to contribute cost-ineffectively to the public good, as doing so will reduce the total amount of the public good provided. On the other hand, a warm-glow giver may contribute cost-ineffectively. If there are diminishing marginal warm glow benefits for each specific public good in (2), then a warm-glow giver may spread their contributions across public goods in a cost-ineffective manner. Indeed, this is an underlying assumption of Null (2011). However, even a warm-glow giver who values total contributions over all public goods could act similarly. In this case, contributions to $m-1$ and m are perfect substitutes in (3), and the individual will be indifferent between contributing to one cause or the other, which can beget a cost-ineffective allocation across causes.

As a result, we expect more cost-effective contributions among pure altruists and more cost-ineffective contributions among warm-glow givers, with impure altruists falling between these two poles. We summarize these insights in the following proposition:

Proposition 2. *Pure altruists will contribute in a cost-effective manner. Impure altruists will contribute less cost-effectively than pure altruists, and warm-glow givers will contribute even less cost-effectively than impure altruists.*

3 Experimental design

We conduct an experiment with $n = 3$ players and $m = 4$ public goods. For each public good, players have an endowment of $w_j^i = 10$ points available that they can contribute to public good j. We implement three treatments with differing marginal per capita returns (MPCR), γ_j, for each public good:

Treatment Certain. The values of the four MPCRs are *certain*:

$$\gamma_1 = 0.475 \quad \gamma_2 = 0.625 \quad \gamma_3 = 0.775 \quad \gamma_4 = 0.925.$$

Treatment Risky. The values of the four MPCRs are subject to *risk*:

$$\gamma_1 \sim \text{Un}(0.40, 0.55) \quad \gamma_2 \sim \text{Un}(0.55, 0.70) \quad \gamma_3 \sim \text{Un}(0.70, 0.85) \quad \gamma_4 \sim \text{Un}(0.85, 1.00).$$

Treatment Ambiguity. The values of the four MPCRs are subject to *ambiguity*:

$$\gamma_1 \in (0.40, 0.55) \quad \gamma_2 \in (0.55, 0.70) \quad \gamma_3 \in (0.70, 0.85) \quad \gamma_4 \in (0.85, 1.00).$$

In all three treatments there is a clear ranking in the four MPCRs ($\gamma_4 > \gamma_3 > \gamma_2 > \gamma_1$). Thus, our null hypothesis is that players' contributions are cost-effective in all treatments (regardless of their beliefs about the other two players' choices).

On Tuesday 25 August 2020, we invited up to 216 potential participants (18–65 yrs, fluent in English) via Prolific to participate in a "decision-making experiment". In total, 201 participants both accepted the consent form and completed all tasks. All these participants visited all three treatments and completed four public good tasks in each treatment, but the order in which they visited the three treatments was subject to individual randomization. After completing the experimental treatments, subjects completed a sequence of short individual tasks in which we elicited gender, age, giving type (Gangadharan et al., 2018; Gandullia et al., 2020), risk attitude (Eckel and Grossman, 2002, 2008), ambiguity attitude (Baillon et al., 2018), attention level (Frederick, 2005; Sirota and Juanchich, 2018), and risk literacy (Cokely et al., 2012). We offer brief descriptions of these tasks in the next section and provide full details in Appendix A.

Groups were formed as soon as a triple of participants completed the full suite of tasks. The three players within a group were paid according to the same randomly drawn treatment (although players may have visited those treatments in a different sequence) and received feedback on their final earnings.[3] On average, participants earned £8.04 (£4.00 participation

[3]To compute the MPCRs for the Ambiguity treatment, we draw for each public good j two values a_j and b_j from a uniform distribution, using the clocktime at which the first participant entered the group as the seed. Next, for each public good j, the MPCR γ_j is the random draw from the $\beta(a_j, b_j)$ distribution, scaled to the respective MPCR interval.

fee; £2.62 for the main treatment; £1.43 in the short individual tasks) for on average 23 minutes of their time.

Prior to data collection, ethical approval was obtained from Vrije University School of Business and Economics Research Ethics Review Board (reference code SBE6/9/2020kwk350) and University of Otago's Human Ethics Committee (reference code D20/183). Moreover, this study was pre-registered in advance on 18 August 2020 in the AEA RCT Registry under the unique identifying number "AEARCTR-0006304".

The experiment was programmed using oTree (Chen et al., 2016). Screenshots are available in Appendix C.

4 Results

4.1 Descriptive statistics

Our post-experimental questionnaire included survey questions for basic demographic variables (gender and age) and a series of tasks to elicit each participant's giving type, risk attitude, ambiguity attitude, risk literacy, and attentiveness. We summarize these tasks here briefly and provide additional details on each in the appendix.

For giving type, we use a two-stage charitable giving task, following the design of Gangadharan et al. (2018) as implemented by Gandullia et al. (2020). Based on the donations made in each stage of this task, we classify each participant as a non-donor, a pure warm-glow donor, a pure altruist, or an impure altruist.[4] To elicit risk attitudes, we use the lottery menu described by Eckel and Grossman (2002, 2008), and we use the method of Baillon et al. (2018) to elicit ambiguity attitudes. We normalize both scales so that they range from 0 to 1, with low values indicating risk/ambiguity aversion and high values indicating risk/ambiguity loving attitudes. Attentiveness was measured with a cognitive reflection test (CRT) (Frederick, 2005) using the multiple choice format described by Sirota and Juanchich (2018). We use the four questions from the Berlin Numeracy Test of Cokely et al. (2012) to measure risk literacy. Both attentiveness and risk literacy are encoded as the fraction of correct answers given to these survey questions.

Table 1 presents participant characteristics based on the post-experimental questionnaire. We show statistics for each treatment sequence and for the full sample; as described above, we use the following abbreviations: Certain (C), Risky (R), and Ambiguity (A). There are no major differences across the different sequences.

We now turn to participant behavior in the experiment. Table 2 presents average contribution levels across the four different public goods, by treatment environment, and by sequence.

[4] We show in our robustness checks that our giving type results are robust to marginal changes in the classification criteria.

		gender			giving type							
Seq	N	male	female	age	none	p.w-g	p.alt	i.alt	risk	amb	crt	r.lit
CRA	27	55.5%	44.4%	25.3	0.0%	11.1%	3.7%	85.2%	0.40	0.51	0.43	0.29
CAR	34	44.1%	55.9%	25.6	8.8%	17.6%	5.9%	67.6%	0.28	0.47	0.42	0.37
RCA	26	61.5%	38.5%	26.4	7.7%	19.2%	7.7%	65.4%	0.51	0.54	0.36	0.30
RAC	44	59.1%	40.9%	26.3	11.4%	15.9%	13.6%	59.9%	0.48	0.47	0.52	0.34
ACR	36	55.6%	44.4%	26.3	5.6%	13.9%	8.3%	72.2%	0.43	0.48	0.35	0.32
ARC	34	61.8%	39.2%	25.5	0.0%	14.7%	8.8%	76.5%	0.43	0.47	0.39	0.33
Total	201	56.2%	43.8%	25.9	6.0%	15.4%	8.5%	70.1%	0.42	0.49	0.42	0.33

Table 1: Participant characteristics. Treatment sequences use the following abbreviations: Certain (C), Risky (R), and Ambiguity (A). Giving types are non-donors (none), pure warm-glow givers (p.w-g), pure altruists (p.alt), and impure altruists (i.alt). The columns for risk, amb, crt, and r.lit provide information on risk attitude, ambiguity attitude, attentiveness, and risk literacy, respectively.

	Certain				Risky				Ambiguity			
Seq	PG 1	PG 2	PG 3	PG 4	PG 1	PG 2	PG 3	PG 4	PG 1	PG 2	PG 3	PG 4
CRA	4.74	5.26	6.37	6.78	5.15	5.41	5.85	7.00	4.85	5.52	5.63	6.67
CAR	4.18	4.79	5.68	7.12	3.79	4.82	5.62	7.15	4.12	4.65	5.79	7.12
RCA	4.54	4.88	5.46	6.35	3.58	4.04	4.62	6.15	4.46	4.50	5.23	6.42
RAC	3.07	4.00	5.20	6.82	2.93	3.75	5.07	6.57	2.86	3.89	5.16	6.59
ACR	4.25	5.06	6.33	7.08	4.00	4.94	6.06	7.17	4.14	5.19	6.14	7.61
ARC	3.59	3.94	4.97	6.35	3.62	4.15	5.09	5.94	3.35	4.06	4.97	6.21
Total	3.97	4.60	5.64	6.77	3.77	4.47	5.39	6.67	3.86	4.58	5.48	6.79

Table 2: Summary statistics for contribution levels.

Comparing across sequences, we find that participants who started with the risky public goods contribute significantly less to the first three risky public goods and to the first two ambiguous public goods compared to those who started with the certain public goods (p-values from multivariate ANOVA tests: $p = .009$, $p = .009$, $p = .099$, $p = .035$, $p = .052$). We find that those in the RCA and RAC sequences contribute significantly less in the risky environment and in the ambiguous environment than those who started with the certain public goods ($p = .016$, $p = .094$), indicating that there may be order effects. In subsequent analysis, we will focus on between-subject comparisons based on participants' contributions in their first task to remove the impact of order effects.[5] However, we note that our primary findings continue to hold in within-subject analyses on the full sample, as described in Appendix B.

[5]The average response times for the first multiple public good games task that participants face are 102 (Certain), 106 (Risky) and 139 (Ambiguity) seconds. Although the response time for Ambiguity are substantially above those for Certain and Risky, a Kruskal-Wallis test does not reject the null hypothesis of equality across the three different first tasks ($p = .166$).

4.2 Contribution behavior

Table 3 shows contribution behavior in the first task, with contributions for each public good and total contributions by treatment. We find that subjects are responsive to MPCR, with average contributions increasing in MPCR in all treatments (Wilcoxon tests result in p-values below .001 for all three comparisons between consecutive PGs in all three treatments).

Treatment	N	PG 1	PG 2	PG 3	PG 4	Total
Certain	61	4.4262	5.0000	5.9836	6.9672	22.3771
Risky	70	3.1714	3.8571	4.9000	6.4143	18.3429
Ambiguity	70	3.7571	4.6429	5.5714	6.9286	20.9000

Table 3: Contributions across treatments.

What other factors influence contributions? At the institutional level, we find that contributions vary by information environment. In particular, contributions are lower in Risky than in Certain. We see this for total contributions ($p = .016$) and also for contributions to the first three public goods ($p = .007$, $p = .015$, $p = .028$); contributions to PG 4 are not significantly different for these two treatments ($p = .238$). Conclusions for the Ambiguity environment are less clear-cut. Total contributions in Ambiguity lie between between Risky and Certain but are statistically indistinguishable from either of these treatments ($p > .11$). For each public good, contributions are not different between Certain and Ambiguity ($p > .15$), nor are they different between Risky and Ambiguity ($p = .082$ for PG 2; $p > .15$ for the others).[6]

To analyze the role of individual characteristics, we regress total contributions on individual characteristics and present the results in Table 4. Interestingly, we find that none of the individual characteristics is predictive of total contributions. Perhaps most notable is our result with respect to risk attitude, particularly because several of our treatments feature consequential uncertainty. Yet, across treatments with and without uncertainty, we do not find evidence that risk attitude is correlated with public good contributions. This null result is consistent with Gangadharan and Nemes (2009), who find no correlation between risk aversion and contributions to public goods. Our result stands in contrast to Jones and Rachlin (2009) and Jing and Cheo (2013), who find that risk averse participants tend to contribute less to public goods. We likewise do not find that ambiguity attitude or risk literacy are predictive of public good contributions.

4.3 Cost-effectiveness

We have shown how total contributions differ across treatments. Might the cost-effectiveness of those contributions also differ? We previously showed that contributions increase in MPCR. However, individuals may still contribute in a cost-ineffective manner if they contribute posi-

[6]We use the convention of calling estimates significant when $p < .05$. However, we will provide explicit p-values for all $p \in (.05, .10)$ throughout for transparency.

Characteristic	Certain	Risky	Ambiguity	All
Constant	6.0576	23.2928***	25.5060***	19.2903***
Gender	0.1138	0.2914	−2.4241	−1.0713
Age	0.2468	−0.1317	0.0372	0.0357
Giving type				
pure warm-glow	−0.8906	−3.7705	−5.9983	−3.2546
pure altruist	3.6746	−2.1545	−3.7749	−0.9453
impure altruist	4.1622	−0.5370	−6.0386	0.0207
Risk attitude	6.0955	1.6755	4.8083	2.2567
Ambiguity attitude	−2.7803	−5.6125	−1.8393	−3.8123
Attention level (CRT)	7.1448**	1.0609	0.0284	2.3808
Risk literacy	8.7953	3.1361	0.7134	3.8909
Observations	60	70	68	198

Table 4: Total contributions. * 10%; ** 5%; *** 1%. Observations do not include those for which questionnaire data is incomplete.

tive amounts to multiple public goods without exhausting contribution opportunities for the highest MPCR ones. In this section we investigate individuals' cost-(in)effectiveness in giving.

We define cost-ineffectiveness as

$$CI(x^i) \;=\; \textstyle\sum_{j=2}^{m} \min\big\{ \sum_{\ell=1}^{j-1} x^i_\ell \;;\; \sum_{\ell=j}^{m} (w^i_\ell - x^i_\ell)\big\},$$

where $w^i_\ell = 10$ and $m = 4$ in our experiment. The minimum value for $CI(x^i)$ is 0 (no ineffectiveness) and the maximum is 40, obtained with the allocation $(10, 10, 0, 0)$.

To understand the intuition behind this measure, consider the example $CI(2, 8, 6, 8) = 10$. First, 2 units can be pushed from the third position to the fourth position. Then, 6 units can be pushed from the second to the third. Lastly, 2 units can be pushed from the first to second. In total, there are 10 pushes that can be made to increase payoffs without increasing expenditures on public goods, resulting in the cost-effective allocation (0,4,10,10). As a second example, $CI(2, 3, 4, 2) = 15$. First, 4 units can be pushed from third to fourth. Second, 3 units can be pushed from second to third, and those 3 units can in turn be pushed from third to fourth. Third, 2 units can be pushed from first to second and from second to third, after which 1 of these can be pushed from third to fourth. In total, there are 15 pushes to arrive at the cost-effective allocation (0,0,1,10).

The maximum possible CI is 0 for someone who does not contribute at all (non-contributors), and also 0 for someone who contributes everything (full-contributors). Hence, only partial contributors can be cost-ineffective. To correct for this we develop a measure of relative cost-ineffectiveness.

Take an individual who contributes $X^i = \sum_{j=1}^{m} x^i_j$ in total. The maximum cost-ineffectiveness is obtained by this amount being contributed to the least effective public goods. This is the allocation $y^i(X^i)$ defined as

$$y^i_j(X^i) \;=\; \max\big\{ \min\big\{X^i - \textstyle\sum_{\ell=1}^{j-1} w^i_\ell \;;\; w^i_j\big\} \;;\; 0\big\}.$$

Now, we can define relative cost-ineffectiveness as

$$RCI(x^i) \;=\; CI(x^i)\,/\,CI(y^i(\textstyle\sum_{j=1}^{m} x^i_j)).$$

This measure is undefined for individuals who cannot contribute cost-ineffectively, i.e., non-contributors and full-contributors. For the two examples above, we obtain $RCI(2,8,6,8) = 10/36 = 0.2778$ and $RCI(2,3,4,2) = 15/31 = 0.4839$.[7] This measure is attractive because it conditions on the total amount contributed, which is endogenous, thus allowing for comparison across subjects.

Figure 1 plots the cumulative distributions of RCI for the three treatments. There are no significant differences across treatments ($p > .35$). Thus, the information environment appears to have little bearing on cost-effectiveness of public good contributions.

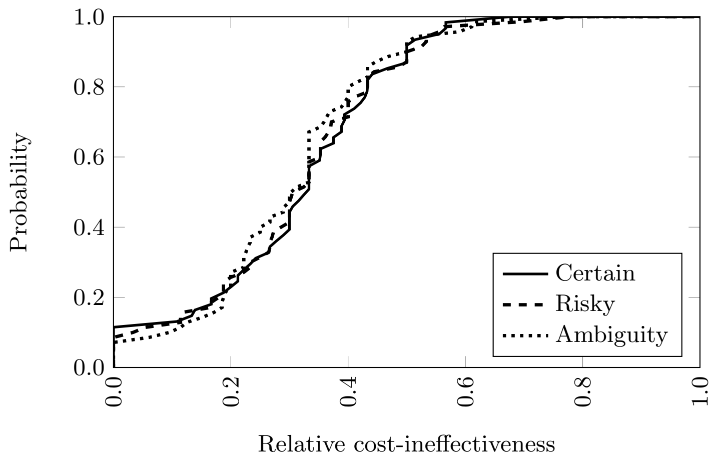

Figure 1: Relative cost ineffectiveness.

We now turn to the role of individual characteristics. Table 5 presents regression results relating RCI to individual characteristics. The most interesting finding is for giving type, for which non-givers are the reference category. Our regression results suggest that warm-glow givers (as assessed by our separate charitable donation task) are more inclined toward cost-*ineffective* contributions than non-givers. This effect is most pronounced under Ambiguity, although it is also observable for Risky; we find no such differences in the Certain environment. Impure altruists also contribute in a more cost-ineffective manner than non-givers, but this appears to be driven primarily by behavior in the Ambiguity environment. Thus, although individual characteristics are not predictive of *total* contributions, as described above, the participant's giving type does influence the cost-effectiveness of contributions. These findings are robust for within- and between-subjects analyses, and they are also robust to alternative

[7] Although these two individuals have the same ranking for both CI and RCI, this need not be the case in general. For example, imagine a third individual with $(1,1,0,0)$. This individual has a lower CI (5) than the other two individuals, but a higher RCI (0.8000).

classifications rules for giving type. Full descriptions and results for these robustness checks are provided in Appendix B.

Characteristic	Certain	Risky	Ambiguity	All
Constant	0.2891**	0.2035*	0.1213	0.2065***
Gender	−0.0337	−0.0027	−0.0510	−0.0309
Age	0.0014	−0.0004	0.0012	0.0008
Giving type				
pure warm-glow	0.1110	0.1485*	0.2135*	0.1371***
pure altruist	−0.0173	0.1443	0.1217	0.0847
impure altruist	0.0746	0.1023	0.2241**	0.1182***
Risk attitude	−0.0324	−0.1015	−0.0269	−0.0588*
Ambiguity attitude	−0.0032	0.1707**	−0.0141	0.0746
Attention level (CRT)	−0.0570	−0.0121	−0.0403	−0.0378
Risk literacy	−0.0048	−0.0092	0.0762	0.0267
Observations	54	67	64	185

Table 5: Relative cost ineffectiveness. * 10%; ** 5%; *** 1%. Observations do not include those that do not contribute to any public good and those that contribute fully to every public good, or other questionnaire data is missing.

These differences can be visualized in Figure 2. We see that there is greater density at low RCI values for non-donors and pure altruists, while for warm-glow givers and impure altruists there is greater density at high RCI values. Average RCI for each giving type is 0.1965 (non-donors), 0.3305 (warm-glow givers), 0.2901 (pure altruists), and 0.3417 (impure altruists). Compared to non-donors, RCI is higher among warm-glow givers (difference is 0.1340; $p = .007$) and impure altruists (difference is 0.1452; $p = .001$). Otherwise, there are no significant differences in pairwise comparisons of RCI across giving types.

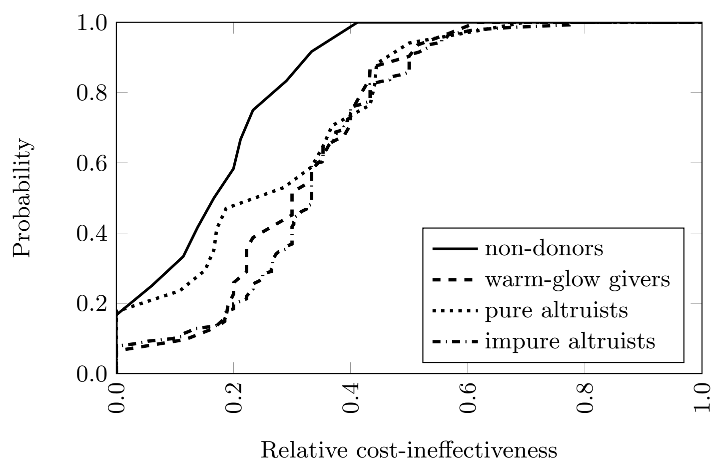

Figure 2: Relative cost ineffectiveness and giving type.

5 Discussion and Conclusion

Our results indicate that the information environment can affect overall contribution behavior, with lower contributions in the Risky setting, but we find little evidence that this institutional factor affects cost-effectiveness of contributions. However, the reverse is true for individual characteristics. Here, we find that individual characteristics have little bearing on total contributions, but that giving type can influence cost-effectiveness. In particular, we find that warm-glow givers and impure altruists are more likely to contribute cost-ineffectively than non-givers.

This latter finding can be rationalized with theory and is consistent with common wisdom concerning warm-glow motives. Indeed, previous literature assumes warm-glow givers are more likely to donate inefficiently than are pure altruists (see, e.g., Null (2011) and Singer (2015)), yet we are not aware of any prior work that directly tests this relationship. Against this backdrop, our results are novel and provide important empirical backing for this commonly held claim. In addition to documenting differences in cost-effectiveness across giving types, we furthermore show that these differences are most pronounced in settings where there may be risk or ambiguity surrounding the value of public good contributions.

More broadly, our experimental work elucidates key factors underlying—or undermining—effective altruism. We shed new light on how the cost-effectiveness of public good provision efforts is influenced by individual characteristics in general and giving types in particular. Moving beyond the individual, we furthermore demonstrate how the information environment can affect the propensity to give. Our results have direct implications for real-world settings, as they suggest that strategies for mitigating uncertainty in the value or efficacy of public goods can help stimulate provision by private actors. Our inquiry into environments with multiple public goods is especially germane given expanding options for public good provision through traditional charities and emerging crowdfunding and patronage platforms.

We can imagine several avenues for future research. First, our theoretical exposition suggests that those with warm-glow motives are more likely to contribute in a cost-ineffective manner. Indeed, we find evidence of this in our experiment, but it is possible that there are other factors that correlate with giving type that drive these between-treatment differences. For example, different giving types may also have different norms or beliefs about how one should allocate resources across different charitable causes. Exploring these possibilities will provide a better understanding of whether giving type, per se, is responsible for our experimental results. A second interesting line of inquiry is to vary whom the individual interacts with in the different public goods. In our experiment, a subject interacts with the same set of group members across all four public goods, but in real-world settings, it is more likely that they will interact with different individuals or networks in each (Bramoullé and Kranton, 2007; Richefort, 2018). Third, there is a need for further inquiry into how giving types are characterized and whether these differ across contexts. In our experiment, we have elicited giving types using a charitable giving task, and we have found that these giving types are correlated with different patterns of behavior in a public good game. Whether giving types are necessarily consistent across these settings remains an open question.

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A Short individual tasks: Description and summary statistics

Giving type

We use the design of Gangadharan et al. (2018) as implemented by Gandullia et al. (2020). Participants are given 20 points and have to decide how many (if any) of these points, g_1, they want to donate to their preferred charity (out of Oxfam, Red Cross, Save the Children, World Wildlife Fund, and Doctors without Borders), knowing that any amount not donated by them will be donated by us (the experimenters), such that the charity organization will always receive a total donation of 20 points. After they have made this decision, they are informed that they have $20 - g_1$ points left, and are given the opportunity to donate any amount, g_2, of these to the charity, knowing that this time no further donation will be made by us, and the charity organization will receive in total $20 + g_2$ points.

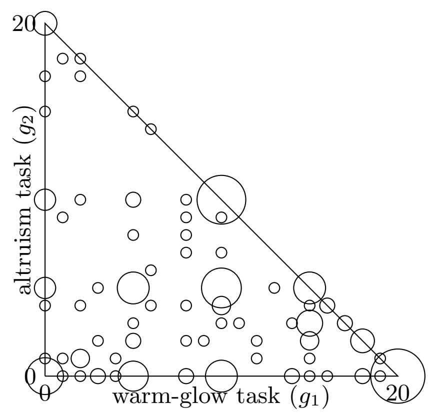


Figure 3: Giving type.

Figure 3 illustrates the choices of the participants, where the volume of the bubbles are proportional to the number of participants making a particular choice. We use the values g_1 and g_2 to determine a participant's giving type as follows:

g_1	g_2	giving type
$= 0$	$= 0$	non-donor or pure selfish
> 0	$= 0$	pure warm-glow giver
$= 0$	> 0	pure altruist
> 0	> 0	impure altruist

The experiments of Gandullia et al. (2020) were conducted via MTurk with 1,062 individuals participating. The resulting distribution over the four giving types was 33%, 20%, 8% and 39% in their study. The distribution resulting from our experiment is 6%, 15%, 8% and 70%. That is, substantially less non-donors and substantially more impure altruists. In our analysis, we use giving type as a categorical variable.

In Appendix B, we consider different thresholds for classifying giving types. Our primary findings are robust to such variations.

Risk attitude

We follow the method introduced by Eckel and Grossman (2002, 2008) and ask participants to choose which lottery they want to play out of a menu of lotteries. All lotteries on the menu yield a high payoff, π_H, or a low payoff, π_L, each with a 50–50 chance, but the values of the high and the low payoff differ across lotteries. In order to obtain more variation in the data, participants in our experiment are given the following menu of 11 lotteries (A–K), and associated CRRA intervals:

lottery		A	B	C	D	E	F	G	H	I	J	K
π_H		10	12	14	16	18	20	22	24	26	28	30
π_L		10	9	8	7	6	5	4	3	2	1	0
CRRA	min	4.91	1.64	1.00	0.72	0.56	0.45	0.37	0.30	0.24	0.16	–
	max	–	4.91	1.64	1.00	0.72	0.56	0.45	0.37	0.30	0.24	0.16

Figure 4 illustrates the choices participants made. In our analysis we take risk as a linear variable and assign the value 0 to the most risk-averse choice (lottery A) and the value 1 to the most risk-loving choice (lottery K).

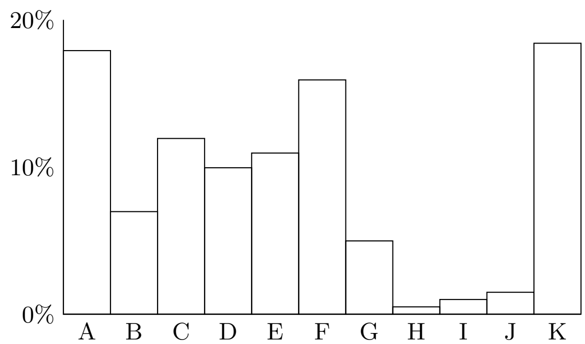


Figure 4: Risk attitude.

Ambiguity attitude

We use the method of Baillon et al. (2018). An urn is filled with red, green and blue balls.[8] Via a stochastic BDM we elicit reservation prices m_r, m_g and m_b for the option on winning (20 points) by drawing a ball of one particular color, and reservation prices m_{-r}, m_{-g} and m_{-b} for the option on winning (20 points) by drawing a ball of one out of two possible colors. Take $\overline{m}_1 = \frac{1}{3}(m_r + m_g + m_b)$ and $\overline{m}_2 = \frac{1}{3}(m_{-r} + m_{-g} + m_{-b})$. Now, $a = 1 - (\overline{m}_1 + \overline{m}_2) \in [-1, 1]$ measures ambiguity attitude. In order to prevent issues related to curvature of utility functions over points, reservation prices are implemented as probabilities to win the 20 points. In order to keep the experiment within time limits, participants are asked to state the reservation for one one-color option and for one two-color option; the exact colors are

[8]We use a method similar to that described in Footnote 3 to design the ambiguous urn.

randomly drawn at the individual level, but always such that for each participant the two colors in the two-color option are complementary to the color in the one-color option.

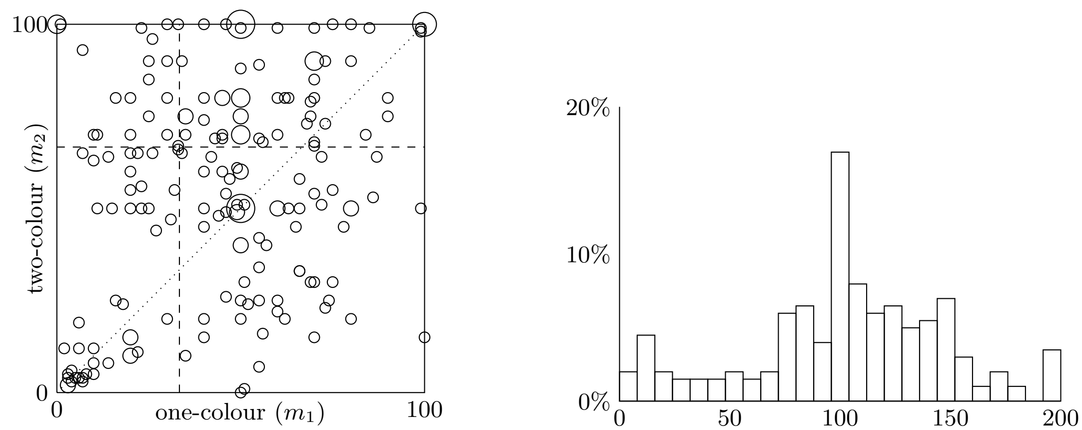


Figure 5: Ambiguity attitude. Left: scatter plot of participants'choices (m_1, m_2); right: distribution of $m_1 + m_2$.

The left panel of Figure 5 shows the participants' choices for m_1 and m_2. The average value of m_1 and m_2 are 45.86 and 57.04. While the average value of m_1 is above the ambiguity neutral value of 1/3, the average value of m_2 is below the ambiguity neutral value of 2/3. Although one-third of the participants reported a value of m_2 below that of m_1, overall the values for m_2 are significantly above those of m_1 (Wilcoxon: $p = .000$). Further, the reported values of m_1 and m_2 correlate significantly (Spearman: $\rho = 0.300$, $p = .000$).

The right panel of the figure shows the distribution of $m_1 + m_2$ that we use to evaluate individuals' ambiguity attitude. Values of $m_1 + m_2$ above 100 indicate ambiguity aversion and those below 100 ambiguity loving. The average value of $m_1 + m_2 = 102.90$ indicates slight ambiguity aversion on average. There are 70 participants (34.82%) with $m_1 + m_2 < 96$, 34 (16.92%) with $m_1 + m_2 \in [96, 104]$, and 97 (48.26%) with $m_1 + m_2 > 104$. In our analysis we encode ambiguity attitude by $1 - \frac{m_1+m_2}{200}$, such that extreme ambiguity-aversion is at 0, ambiguity-neutral is at 1/2 and extreme ambiguity-loving is at 1.

Attention level and risk literacy

To elicit the participants' attention level we use the Cognitive Reflection Test of Frederick (2005), where we follow Sirota and Juanchich (2018) in having participants choose from four possible answers—one of the wrong answers being the intuitive one and one being the correct one. Participants are given 90 seconds to answer the three questions. The percentage of correct answers for the three questions were 38%, 49% and 51%, while the percentage of intuitive answers for each of the three questions were 60%, 37% and 39% inSirota and Juanchich (2018). The respective percentages for our participants are 40%, 49% and 41% for correct answers and 54%, 35% and 38% for intuitive answers—not too different from Sirota and Juanchich (2018). The distribution of participants over the number of correctly answered questions is presented in Figure 6. In our analysis, we incorporate attention level as a linear variable coded as the fraction of correct answers given.

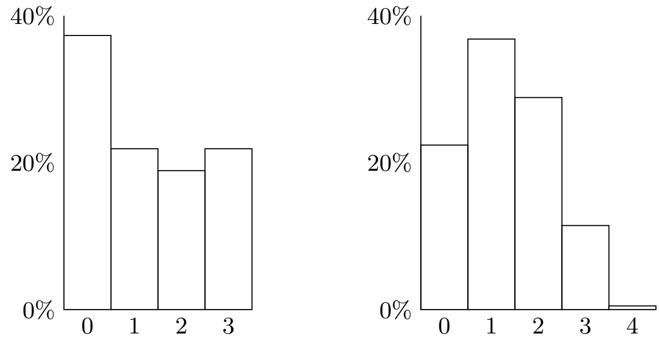


Figure 6: Attention level (left) and risk literacy (right)

We use the four multiple-choice questions from the Berlin Numeracy Test of Cokely et al. (2012) to elicit participants' risk literacy. Participants are given 150 seconds to answer the four questions. The distribution of participants over the number of correctly answered questions is presented in Figure 6. The four individual questions were answered correctly in 54%, 44%, 25%, and 14% of the cases, respectively. In our analysis we incorporate risk literacy as a linear variable encoded via the fraction of correct answers given.

B Robustness

Our primary analysis reveals (i) no correlation between individual characteristics and contribution levels and (ii) a strong relationship between giving type and cost-ineffectiveness. Here, we conduct a series of additional analyses demonstrating the robustness of these results.

B.1 Within-subjects analysis

We restricted our primary analysis to between-subject comparisons based on the first treatment encountered by each subject. This restriction allowed for clean comparisons unconfounded by order effects. We begin by investigating whether our results hold when analyzing the full sample, inclusive of all treatments.

B.1.1 Contribution behavior

Table 6 is the full-sample analog of Table 3, as it presents average amounts contributed to the different public goods and in total for the different treatments. Contributions across public goods are increasing for all treatments (Wilcoxon tests result in p-values below .001 for all three comparisons between consecutive PGs in all three treatments). There are no significant differences in total contributions across treatments (C vs. R: $p = .083$; C vs. A: $p = .768$; R vs. A: $p = .276$). For the individual public goods there are no significant differences between Ambiguity and the other treatments ($p > .23$), but there are between Certain and Risky (PG1: $p = .042$; PG2: $p = .549$; PG3: $p = .508$; PG4: $p = .899$).

Treatment	N	PG 1	PG 2	PG 3	PG 4	Total
Certain	201	3.9701	4.5970	5.6368	6.7711	20.9751
Risky	201	3.7662	4.4726	5.3881	6.6716	20.2985
Ambiguity	201	3.8607	4.5771	5.4826	6.7861	20.7065

Table 6: Contributions across treatments.

Table 7 presents regression results for the relationship between individual characteristics and total contributions for each treatment. Here, we see that none of the individual characteristics elicited in the questionnaire are predictive of total contributions in any of the three treatments, consistent with our findings presented in Table 4.

B.1.2 Cost-effectiveness

Turning to our measure of cost-ineffectiveness, we also find consistent results between our primary analysis and the full-sample analysis. First, we observe that subjects' RCI is not significantly different across treatments (pairwise Wilcoxon tests: $p > .60$).

Table 8 presents regression results revealing that some individual characteristics are predictive of cost-ineffective contribution behavior, with giving type standing out. In particular, pure warm-glow givers and impure altruists tend to have higher RCI, consistent with our

Characteristic	Certain	Risky	Ambiguity
Constant	18.0465***	18.7050***	18.5333***
Gender	−1.0674	0.2156	0.0608
Age	−0.0571	−0.0303	−0.0019
Giving type			
pure warm-glow	0.5450	−2.9193	−1.3420
pure altruist	0.5264	−1.6633	−2.3787
impure altruist	2.4043	−0.0240	−0.1406
Risk attitude	1.4995	1.6895	2.3911
Ambiguity attitude	−1.1956	−3.6911	−2.5452
Attention level (CRT)	3.0917	2.7565	1.7799
Risk literacy	4.0705	3.0337	2.6047
Observations	198	198	198

Table 7: Total contributions. * 10%; ** 5%; *** 1%. Observations do not include those for which questionnaire data is incomplete.

primary findings reported in Table 5. However, unlike in Table 5, we also find that pure altruists have higher RCI in the full sample analysis, although the point estimates remain smaller than for pure warm-glow givers and impure altruists.

Characteristic	Certain	Risky	Ambiguity
Constant	0.2598***	0.1691**	0.1642**
Gender	−0.0294	−0.0197	−0.0209
Age	0.0009	0.0024	0.0020
Giving type			
pure warm-glow	0.1141**	0.1400**	0.1794***
pure altruist	0.0500	0.1073*	0.1181**
impure altruist	0.0832	0.1514***	0.1811***
Risk attitude	−0.0091	0.0003	−0.0612*
Ambiguity attitude	0.0201	0.0301	0.0206
Attention level (CRT)	−0.0745**	−0.0853***	−0.0393
Risk literacy	0.0581	0.0407	0.0101
Observations	185	188	187

Table 8: Relative cost ineffectiveness. * 10%; ** 5%; *** 1%. Observations do not include those that do not contribute to any public good and those that contribute fully to every public good, or other questionnaire data is missing.

B.2 Giving type classification

As discussed in Appendix A, our primary analyses classify subjects into giving types based on the design of Gangadharan et al. (2018). That is, in a separate elicitation, subjects are asked to give g_1 and g_2 in consecutive charitable giving tasks. Then, using the implementation of Gandullia et al. (2020), we classify subjects into giving types according to the rules outlined in the table below. Using these rules, the sample for our main analysis is composed of 6%, 15%, 8% and 70%, respectively, of each giving type.

g_1	g_2	giving type
$= 0$	$= 0$	non-donor or pure selfish
> 0	$= 0$	pure warm-glow giver
$= 0$	> 0	pure altruist
> 0	> 0	impure altruist

However, one may be concerned that any choice of thresholds entails some arbitrariness. One may furthermore worry that our particular thresholds may misclassify pure selfish types, as the thresholds at zero establish a low bar for ascribing prosocial intentions. Therefore, probing the robustness of our results to alternative classification schemes is critical, especially given the prominence of giving type in our findings. In what follows, we (i) vary the thresholds for giving type classifications and (ii) consider a coarser classification that pools all subjects with warm-glow motives. Both variations change our distribution of giving types in a predictable manner, and our main findings remain unchanged under these different classifications.

We begin by considering the following thresholds for giving type:

g_1	g_2	$g_1 + g_2$	giving type
–	–	≤ 2	non-donor or pure selfish
–	≤ 1	> 2	pure warm-glow giver
≤ 1	–	> 2	pure altruist
> 1	> 1	–	impure altruist

These thresholds increase the likelihood that a subject will be classified as a non-donor or pure selfish type, while decreasing the likelihood that one will be classified as an impure altruist. The following table gives the resulting distribution over types, their average total contributions, and relative cost-ineffectiveness:

giving type	N	X	RCI
non-donor	8	19.69	0.2187
pure warm-glow	18	19.75	0.3502
pure altruist	9	20.94	0.2848
impure altruist	65	20.68	0.3399

The overall distribution of giving types remains quite similar to before, with 8%, 18%, 9%, and 65%, respectively, of each type. There is a slight increase in the proportion of non-donors and slight decrease in the proportion of impure altruists under this classification, as predicted.

Our primary findings are unchanged by this alternative classification. There are no significant differences in total contributions across the different giving types (Mann-Whitney: $p > .52$). Pure warm-glow givers and impure altruists contribute more cost-ineffectively than non-donors ($p < .01$), and there are no significant differences across the other categories ($p > .16$).

Table 9 shows that, using this alternative classification for giving type, individual characteristics are still not predictive of total contributions, and giving type remains highly predictive of cost-ineffective contributions.

Characteristic	X	RCI
Constant	17.4637***	0.2166***
Gender	−1.0640	−0.0292
Age	0.0306	0.0010
Giving type		
pure warm-glow	−0.4986	0.1410***
pure altruist	0.4387	0.0720
impure altruist	2.0456	0.1035***
Risk attitude	2.0673	−0.0681**
Ambiguity attitude	−3.6289	0.0775*
Attention level (CRT)	2.5509	−0.0393
Risk literacy	3.9955	0.0314
Observations	198	185

Table 9: Relative cost ineffectiveness. * 10%; ** 5%; *** 1%. Observations do not include those that do not contribute to any public good and those that contribute fully to every public good, or other questionnaire data is missing.

Next, we consider another classification scheme. Here, we create a dummy variable $D_{w\text{-}g}$ with $D_{w\text{-}g} = 1$ if $g_1 > 2$ and 0 otherwise. We consider subjects with value $D_{w\text{-}g} = 1$ to have a strong warm-glow motive, thus pooling pure warm-glow givers and impure altruists into a single group. This table gives the resulting distribution over types, their average total contributions, and relative cost-ineffectiveness:

$D_{w\text{-}g}$	N	X	RCI
0	41	19.24	0.2754
1	160	20.77	0.3406

There are no significant differences in total contributions across the two types ($p = .451$), but they differ significantly in cost-effectiveness ($p = .015$).

Table 10 shows that, using this binary classification of warm-glow motives, individual characteristics are still not predictive of total contributions, and giving type remains highly predictive of cost-ineffective contributions.

Characteristic	X	RCI
Constant	16.7838***	0.2758***
Gender	−1.2252	−0.0264
Age	0.0259	0.0009
$D_{w\text{-}g}$	2.3078	0.0550**
Risk attitude	1.8376	−0.0681**
Ambiguity attitude	−2.7748	0.0713
Attention level (CRT)	2.4912	−0.0365
Risk literacy	4.1970	0.0262
Observations	198	185

Table 10: Relative cost ineffectiveness. * 10%; ** 5%; *** 1%. Observations do not include those that do not contribute to any public good and those that contribute fully to every public good, or other questionnaire data is missing.

C Screenshots

C.1 Information and consent form

Consent Form

You are being invited to participate in this research study being conducted by Nathan W. Chan from the University of Massachusetts Amherst, Stephen Knowles and Ronald Peeters from the University of Otago, and Leonard Wolk from Vrije University Amsterdam. You were selected to participate in this study because you signed up on Prolific.

The general purpose of this research is to better understand group decision making. Participants in this study will be asked to make choices and complete tasks on a computer. If you agree to take part in this study, you will be asked to play a simple online game with two other participants, followed by a survey. We expect this study to take 45 minutes or less to complete.

You will earn 4.00 GBP for completing the study. You will receive an additional 0 to 8.28 GBP based on the choices that you and the other two participants make in the tasks, answers you give in the survey, and on chance.

You and all others taking part in this study will remain anonymous. Your Prolific ID will be used for payment purposes only, and will not be revealed to other participants and it will not be shared with third-parties. When reporting results and sharing data, we will remove individual identifying information so as to maintain confidentiality.

We believe there are no known risks associated with this research study. To the best of our ability, your answers in this study will remain anonymous. However, as with any online-related activity, the risk of a breach of confidentiality is always possible. We will minimize risks by keeping any non-anonymized data encrypted on password-protected computers.

Your participation in this study is completely voluntary and you can withdraw at any time. However, if you quit the study before completing all of the tasks, you will not earn payment for your participation. In this case, data from your decisions will be recorded up to the point that you withdraw. There are no other consequences if you choose to withdraw.

Informed consent is required for any person participating in a University research study. This study has been approved by two Institutional Review Boards for Research With Human Subjects (the University of Otago's Human Ethics Committee and the Vrije University School of Business and Economics Research Ethics Review Board; Reference codes D20/183 and SBE6/9/2020kwk350 respectively).

If you have questions about this project, or if you have a research-related problem, you may contact the researchers, Nathan W. Chan (nchan@umass.edu; +1-413-5455739), Stephen Knowles (stephen.knowles@otago.ac.nz; +64-3-4798350), Ronald Peeters (ronald.peeters@otago.ac.nz; +64-3-4798731), and Leonard Wolk (l.wolk@vu.nl; +31-20-5985262). You can contact them at any time during or after the study ends. If you have any questions concerning your rights as a research subject, you may contact the University of Otago Human Ethics Committee Administrator (Phone: +64-3-4798256; Email: gary.witte@otago.ac.nz), or the Vrije University School of Business and Economics Research Ethics Review Board (Phone: +31 205985667; Email: rerb.feweb@vu.nl)

By clicking "I agree" below you are indicating that you are at least 18 years old, have read and understood this consent form and voluntarily agree to participate in this research study. Please print a copy of this page for your records.

I agree   I do not agree

C.2 Main task

Instructions

You will be assigned to a group with two other participants. Your identity and the identities of the other two group members will remain confidential.

You and your group members will complete three independent tasks, and in each of these tasks you will make four decisions. All group members will receive exactly the same instructions as you.

Task 1	Task 2	Task 3
Decision 1A	Decision 2A	Decision 3A
Decision 1B	Decision 2B	Decision 3B
Decision 1C	Decision 2C	Decision 3C
Decision 1D	Decision 2D	Decision 3D

For each decision, each group member is given a private budget of 10 points and will decide how many of these points to contribute to a group project. Contributions can be any whole number from 0 to 10 points.

All points that the three group members contribute to the group project will be added up, and that total amount will be multiplied by a factor *M*. The resulting amount is the total earnings from the group project. The total earnings from the group project will be split evenly among the three group members. Your personal payoff equals your earnings from the group project, plus the part of your private budget that you did not contribute.

The payoff that you get from each decision is calculated according to the following formula:

$$\mathit{Decision\ Payoff} = \underbrace{\frac{(C_{you} + C_{partner1} + C_{partner2}) \times M}{3}}_{\mathit{Earnings\ from\ group\ project}} + \underbrace{(10 - C_{you})}_{\mathit{Private\ budget\ that\ you\ did\ not\ contribute}}$$

where C_{you} is the amount that you contribute to the group project and $C_{partner1}+C_{partner2}$ is the amount contributed by your other group members.

In each task, you will make four of these decisions, where each decision may have a different value for *M*. Your decision screen will make very clear what this value for *M* is for each decision. Your earnings in a task are the sum of your earnings for each of the four decisions in this task. Therefore:

$$\begin{aligned}
\mathit{Task\ 1\ Earnings} &= \mathit{Decision\ 1A\ Payoff} + \mathit{Decision\ 1B\ Payoff} + \mathit{Decision\ 1C\ Payoff} + \mathit{Decision\ 1D\ Payoff}\\
\mathit{Task\ 2\ Earnings} &= \mathit{Decision\ 2A\ Payoff} + \mathit{Decision\ 2B\ Payoff} + \mathit{Decision\ 2C\ Payoff} + \mathit{Decision\ 2D\ Payoff}\\
\mathit{Task\ 3\ Earnings} &= \mathit{Decision\ 3A\ Payoff} + \mathit{Decision\ 3B\ Payoff} + \mathit{Decision\ 3C\ Payoff} + \mathit{Decision\ 3D\ Payoff}
\end{aligned}$$

The three tasks are very similar, but they provide different information on the values of *M* for each of the four decisions in the task. Make sure you read the information carefully before making your decisions.

At the end of the experiment you (and your other group members) will be paid for one of the three tasks. A computer will randomly select the task for which you will be paid. Each task is equally likely to be selected, and all group members will be paid for the same task.

All earnings are in points, and you will be paid 0.04 GBP for each point. In addition, you will receive a participation fee of 4 GBP. All relevant payment information will be provided to you on the final screen that will be shown after you have completed a questionnaire. Your earnings will only be paid out if you have completed all tasks and the questionnaire.

Click the next button once you fully understand the instructions. We expect the experiment to take approximately 35 minutes from here.

Next

Control questions

Please answer the following questions.

You will be paid your earnings from one task, which will be chosen at random.

◯ False ◯ True

You will be paid for one of the four decisions in a randomly chosen task.

◯ False ◯ True

For each task, you will have a total of 10 points to allocate over the four group projects.

◯ False ◯ True

Suppose you contribute 6 points to the group project, partner 1 contributes 2 points to the group project and partner 2 contributes 7 to the group project. Further, suppose that the total contributions are multiplied by the factor M=2. What is your total payoff from this decision?

Next

Short summary

- You will be in a group with two other participants.
- You and your partners will complete three tasks.
- In each task, you have to make four decisions.
- For each decision, there is a group project, and all group members have a budget of 10 points that they can contribute to that group project.
- Contributions to the group project by you and your partners are multiplied by a value M, and the total is divided equally among you and your partners. Hence, your payoff for a decision is given by

$$\textit{Decision Payoff} = \underbrace{\frac{(C_{you} + C_{partner1} + C_{partner2}) \times M}{3}}_{\textit{Earnings from group project}} + \underbrace{(10 - C_{you})}_{\textit{Private budget that you did not contribute}}$$

- You will be paid for one out of the three tasks, which will be chosen at random. You will be paid for all four decisions in that task.

Task 1

You have four decisions to make. For each decision, you have a budget of 10 points.

In the boxes below, please state how many of your points you would like to contribute to the respective group project. You can contribute any whole number value from 0 to 10 points.

The value of *M* is different for the four group projects. **For each group project, the minimum and maximum values of *M* are given. Each value of *M* within the specified range is equally likely.** However, for each group project, you and your partners will have the same value for *M*.

Decision 1A. All points contributed by you and your partners to the group project will be multiplied by a value *M* that is between 1.20 and 1.65.
How many of your 10 points will you contribute to the group project?

Decision 1B. All points contributed by you and your partners to the group project will be multiplied by a value *M* that is between 1.65 and 2.10.
How many of your 10 points will you contribute to the group project?

Decision 1C. All points contributed by you and your partners to the group project will be multiplied by a value *M* that is between 2.10 and 2.55.
How many of your 10 points will you contribute to the group project?

Decision 1D. All points contributed by you and your partners to the group project will be multiplied by a value *M* that is between 2.55 and 3.00.
How many of your 10 points will you contribute to the group project?

Next

Short summary

- You will be in a group with two other participants.
- You and your partners will complete three tasks.
- In each task, you have to make four decisions.
- For each decision, there is a group project, and all group members have a budget of 10 points that they can contribute to that group project.
- Contributions to the group project by you and your partners are multiplied by a value M, and the total is divided equally among you and your partners. Hence, your payoff for a decision is given by

$$Decision\ Payoff \quad = \quad \underbrace{\frac{(C_{you} + C_{partner1} + C_{partner2}) \times M}{3}}_{Earnings\ from\ group\ project} \quad + \quad \underbrace{(10 - C_{you})}_{Private\ budget\ that\ you\ did\ not\ contribute}$$

- You will be paid for one out of the three tasks, which will be chosen at random. You will be paid for all four decisions in that task.

Task 2

You have four decisions to make. For each decision, you have a budget of 10 points.

In the boxes below, please state how many of your points you would like to contribute to the respective group project. You can contribute any whole number value from 0 to 10 points.

The value of *M* is different for the four group projects. **For each group project, the minimum and maximum values of *M* are given, and the exact value for *M* will be determined by a complicated random process. Therefore, we do not know the likelihood of each value of *M* within the range provided.** However, for each group project, you and your partners will have the same value for *M*.

Decision 2A. All points contributed by you and your partners to the group project will be multiplied by a value *M* that is between 1.20 and 1.65.
How many of your 10 points will you contribute to the group project?

Decision 2B. All points contributed by you and your partners to the group project will be multiplied by a value *M* that is between 1.65 and 2.10.
How many of your 10 points will you contribute to the group project?

Decision 2C. All points contributed by you and your partners to the group project will be multiplied by a value *M* that is between 2.10 and 2.55.
How many of your 10 points will you contribute to the group project?

Decision 2D. All points contributed by you and your partners to the group project will be multiplied by a value *M* that is between 2.55 and 3.00.
How many of your 10 points will you contribute to the group project?

Next

Short summary

- You will be in a group with two other participants.
- You and your partners will complete three tasks.
- In each task, you have to make four decisions.
- For each decision, there is a group project, and all group members have a budget of 10 points that they can contribute to that group project.
- Contributions to the group project by you and your partners are multiplied by a value M, and the total is divided equally among you and your partners. Hence, your payoff for a decision is given by

$$Decision\ Payoff = \underbrace{\frac{(C_{you} + C_{partner1} + C_{partner2}) \times M}{3}}_{Earnings\ from\ group\ project} + \underbrace{(10 - C_{you})}_{Private\ budget\ that\ you\ did\ not\ contribute}$$

- You will be paid for one out of the three tasks, which will be chosen at random. You will be paid for all four decisions in that task.

Task 3

You have four decisions to make. For each decision, you have a budget of 10 points.

In the boxes below, please state how many of your points you would like to contribute to the respective group project. You can contribute any whole number value from 0 to 10 points.

The value of *M* is different for the four group projects. However, for each group project, you and your partners will have the same value for *M*.

Decision 3A. All points contributed by you and your partners to the group project will be multiplied by the value *M*=1.425. How many of your 10 points will you contribute to the group project?

Decision 3B. All points contributed by you and your partners to the group project will be multiplied by the value *M*=1.875. How many of your 10 points will you contribute to the group project?

Decision 3C. All points contributed by you and your partners to the group project will be multiplied by the value *M*=2.325. How many of your 10 points will you contribute to the group project?

Decision 3D. All points contributed by you and your partners to the group project will be multiplied by the value *M*=2.775. How many of your 10 points will you contribute to the group project?

Next

Short summary

- You will be in a group with two other participants.
- You and your partners will complete three tasks.
- In each task, you have to make four decisions.
- For each decision, there is a group project, and all group members have a budget of 10 points that they can contribute to that group project.
- Contributions to the group project by you and your partners are multiplied by a value M, and the total is divided equally among you and your partners. Hence, your payoff for a decision is given by

$$\textit{Decision Payoff} \;=\; \underbrace{\frac{(C_{you} + C_{partner1} + C_{partner2}) \times M}{3}}_{\textit{Earnings from group project}} \;+\; \underbrace{(10 - C_{you})}_{\textit{Private budget that you did not contribute}}$$

- You will be paid for one out of the three tasks, which will be chosen at random. You will be paid for all four decisions in that task.

C.3 Questionnaire

Questionnaire

You have now completed the main tasks of this experiment.

We now ask that you complete a short questionnaire.

The questionnaire consists of six parts.

Parts 1, 3, 5 and 6 are each presented on one screen; Part 2 is presented over three screens; and Part 4 over four screens. Hence, you will see ten screens in total.

In Parts 2 through 6 you can earn additional points, and hence make additional earnings.

While there is no fixed amount of time given for the first four parts, the last two parts will have a time limit. You will be given 1 minute to complete Part 5 and 2 minutes to complete Part 6.

We expect this questionnaire to take about 15 minutes in total.

Next

C.3.1 Demographics

Questionnaire: Part 1 of 6

What is your gender?

◯Male

◯Female

◯Diverse

◯Prefer not to say

What is your age? (Type a 0 if you do not want to say):

Next

C.3.2 Giving type

Questionnaire - Part 2 of 6 (1/3)

Which of the following five charity organisations do you support the most?

- ◯ Oxfam
- ◯ Red Cross
- ◯ Save the Children
- ◯ WWF
- ◯ Doctors without Borders

Charity	**Brief summary**
Oxfam	Invests privately raised funds and technical expertise in local organizations around the world that hold promise in their efforts to help the poor move out of poverty; committed to long term relationships in search of lasting solutions to hunger, poverty, and social inequities.
Red Cross	Offers blood donation information and services, disaster relief, many helpful educational classes, as well as HIV/AIDS support groups.
Save the Children	Promotes children's rights, provides relief and helps support children in developing countries.
WWF	World Wildlife Fund addresses global environmental issues.
Doctors without Borders	Doctors and nurses volunteer to provide urgent medical care in some 70 countries to civilian victims of war and disasters, regardless of race, religion, or politics.

Next

Questionnaire - Part 2 of 6 (2/3)

You are given 20 points. You can choose to donate any amount from 0 to the entire 20 points to *Doctors without Borders*. We will also make a 20 points donation to *Doctors without Borders*, but will reduce our donation by the amount you choose to donate. Therefore, the amount *Doctors without Borders* will receive will be exactly 20 points, regardless of what you donate. However, how much of the 20 points is donated by you, and how much is donated by us, is up to you.

How much, if anything, do you choose to donate?

Next

Questionnaire - Part 2 of 6 (3/3)

You just have donated 2 points, and have 18 points left. You can choose to donate any amount from 0 to the entire 18 points to *Doctors without Borders*. This time, however, we will NOT make any additional donation to *Doctors without Borders*. In total, *Doctors without Borders* will receive 20 points from the previous task plus however much you decide to donate now.

How much, if anything, do you choose to donate?

Next

C.3.3 Risk attitude

Questionnaire - Part 3 of 6

The table below presents 11 lotteries: Lottery A through Lottery K. Each lottery has a 50% chance of paying you Payoff 1 and a 50% chance of paying you Payoff 2.

	Lottery										
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**
Payoff 1	10	12	14	16	18	20	22	24	26	28	30
Payoff 2	10	9	8	7	6	5	4	3	2	1	0
Note: Payoffs are denoted in points.											

You can choose one lottery to play. Which lottery do you choose?

- ◯Lottery A
- ◯Lottery B
- ◯Lottery C
- ◯Lottery D
- ◯Lottery E
- ◯Lottery F
- ◯Lottery G
- ◯Lottery H
- ◯Lottery I
- ◯Lottery J
- ◯Lottery K

Next

C.3.4 Ambiguity attitude

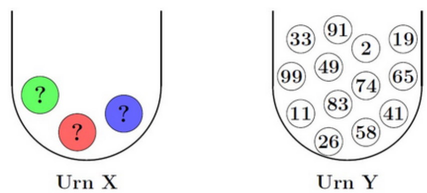
Questionnaire - Part 4 of 6 (1/4)

Instructions

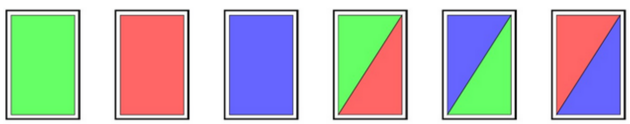
You will have the opportunity to earn 20 points in this task. Please read the following instructions carefully to understand the task.

There are two urns.

- **Urn X** is filled with 100 balls. Each ball is either green, red, or blue. However, it is not known how many balls of each colour are in this urn.
- **Urn Y** is filled with 101 balls. The balls are numbered from 0 to 100. There is a single ball for each number.



You will be given one of six possible cards. Cards are either one colour (green, red, or blue) or two colours (green/red, blue/green, or red/blue).



The six possible cards

You are asked to **provide a number (N)** between 0 and 100.

After you have provided your number, the computer will draw a ball from Urn Y. Then, there are two possible outcomes depending on the number (N) that you provided and the number (#) on the ball drawn from Urn Y:

- **Outcome 1:** The number (#) on the ball drawn from Urn Y is lower than the number (N) you provided. *In this case, your card will determine whether you win or not.* The computer will draw a coloured ball from Urn X. You will win 20 points if the colour of the ball drawn from Urn X matches the colour (or one of the two colours) on your card. Otherwise, you will earn nothing.
- **Outcome 2:** The number (#) on the ball drawn from Urn Y is larger than or equal to the number (N) you provided. *In this case, neither your card nor Urn X is relevant for whether you win or not.* The computer will draw a second ball from Urn Y. You will win if the number on this ball is less than the number (#) on the first ball. Therefore, the percentage chance that you will win the 20 points is equal to the number (#) on the ball that was first drawn from Urn Y. Note that this chance to win (#) is larger than or equal to the number you provided (N).

In this task, you will make this decision twice. The same two urns will be used for both decisions, and all balls will be returned to the urns between decisions. The only thing that differs between the two decisions is the colour(s) of the card that you receive. You will be paid for one of the two decisions. The computer will randomly select the decision for which you will be paid; each decision is equally likely to be selected.

Next

Short summary

- Urn X is filled with 100 balls. Each ball is either green, red, or blue, but it is not known how many balls of each colour are in this urn.
- Urn Y is filled with 101 balls. The balls are numbered from 0 to 100.

Questionnaire - Part 4 of 6 (2/4)

Please answer the following questions.

The higher your choice of (N), the more likely that your winnings will be determined by the colour of your card and the colour of the ball drawn from Urn X.

◯ False ◯ True

Suppose the number (N) you provide is 63 and the ball drawn from Urn Y has number 15 on it. The chance that you will win 20 points is for sure equal to 15%.

◯ False ◯ True

Suppose the number (N) you provide is 15 and the ball drawn from Urn Y has number 63 on it. The chance that you will win 20 points is equal to 63%.

◯ False ◯ True

Next

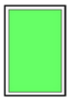
Short summary

- Urn X is filled with 100 balls. Each ball is either green, red, or blue, but it is not known how many balls of each colour are in this urn.
- Urn Y is filled with 101 balls. The balls are numbered from 0 to 100.
- There are two possible outcomes depending on the number (N) that you provided and the number (#) on the ball drawn from Urn Y:
  - Outcome 1: The number (#) on the ball drawn from Urn Y is lower than the number (N) you provided. You will win 20 points if the randomly drawn ball from Urn X matches the colour (or one of the two colours) on your card.
  - Outcome 2: The number (#) on the ball drawn from Urn Y is larger than or equal to the number (N) you provided. The percentage chance that you will win the 20 points is equal to the number (#) on the ball that was drawn from Urn Y.

Questionnaire - Part 4 of 6 (3/4)

Decision 1:

You have a **green** card.



What number (N) do you choose?

Next

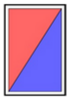
Short summary

- Urn X is filled with 100 balls. Each ball is either green, red, or blue, but it is not known how many balls of each colour are in this urn.
- Urn Y is filled with 101 balls. The balls are numbered from 0 to 100.
- There are two possible outcomes depending on the number (N) that you provided and the number (#) on the ball drawn from Urn Y:
    - Outcome 1: The number (#) on the ball drawn from Urn Y is <u>lower than</u> the number (N) you provided. You will win 20 points if the randomly drawn ball from Urn X matches the colour (or one of the two colours) on your card.
    - Outcome 2: The number (#) on the ball drawn from Urn Y is <u>larger than or equal to</u> the number (N) you provided. The percentage chance that you will win the 20 points is equal to the number (#) on the ball that was drawn from Urn Y.

Questionnaire - Part 4 of 6 (4/4)

Decision 2:

You have a **red and blue** card.



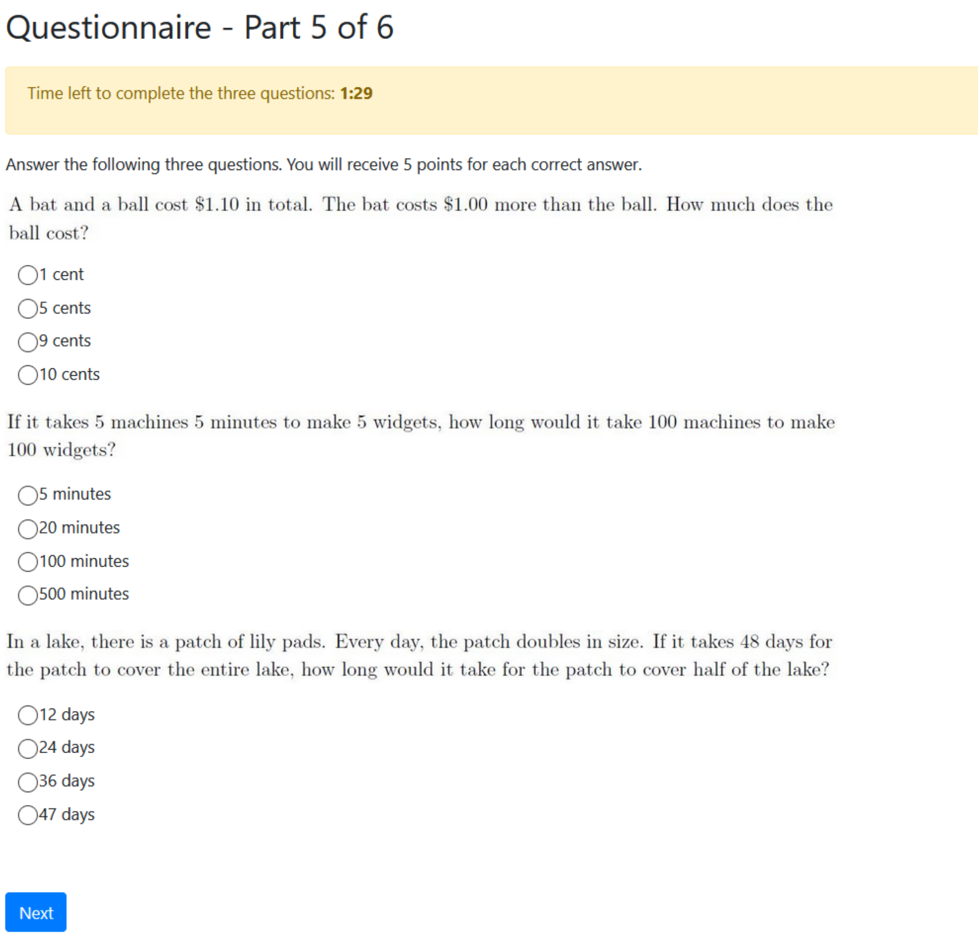
What number (N) do you choose?

Next

Short summary

- Urn X is filled with 100 balls. Each ball is either green, red, or blue, but it is not known how many balls of each colour are in this urn.
- Urn Y is filled with 101 balls. The balls are numbered from 0 to 100.
- There are two possible outcomes depending on the number (N) that you provided and the number (#) on the ball drawn from Urn Y:
  - Outcome 1: The number (#) on the ball drawn from Urn Y is lower than the number (N) you provided. You will win 20 points if the randomly drawn ball from Urn X matches the colour (or one of the two colours) on your card.
  - Outcome 2: The number (#) on the ball drawn from Urn Y is larger than or equal to the number (N) you provided. The percentage chance that you will win the 20 points is equal to the number (#) on the ball that was drawn from Urn Y.

C.3.5 Attention level and risk literacy



Questionnaire - Part 6 of 6

Time left to complete the four questions: **2:29**

Answer the following four questions. You will receive 5 points for each correct answer.

Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five-sided die show an odd number (1, 3 or 5)?

- ◯5 out of 50 throws
- ◯25 out of 50 throws
- ◯30 out of 50 throws
- ◯None of the above

Out of 1,000 people in a small town 500 are members of a choir. Out of these 500 members in the choir 100 are men. Out of the 500 inhabitants that are not in the choir 300 are men. What is the probability that a random drawn man is a member of the choir?

- ◯10%
- ◯25%
- ◯40%
- ◯None of the above

Imagine we are throwing a loaded die (6 sides). The probability that the die shows a 6 is twice as high as the probability of each of the other numbers. On average, out of these 70 throws, about how many times would the die show the number 6?

- ◯20 out of 70 throws
- ◯23 out of 70 throws
- ◯35 out of 70 throws
- ◯None of the above

In a forest 20% of mushrooms are red, 50% brown and 30% white. A red mushroom is poisonous with a probability of 20%. A mushroom that is not red is poisonous with a probability of 5%. What is the probability that a poisonous mushroom in the forest is red?

- ◯4%
- ◯20%
- ◯50%
- ◯None of the above

Next

C.4 Waiting and feedback screens

Please wait ...

Please wait while your other group members finalize their decisions. As soon as everyone is ready, you will automatically be redirected to the next screen. This can take a few minutes.

If you think that you have waited on this screen for too long, you can try to **refresh** the page by either pressing the refresh button in your web-browser or the F5 button on your keyboard.

If you are still on this page after refreshing, then we are still waiting for your other group members to finalize their decisions.

Feedback

On the following screen you will receive feedback from your choices in the individual and group tasks. Your final payoff will also be displayed. Click on the button below to proceed.

Next

Feedback screen

Below we detail the points that you have collected during your participation.

Group task

You participated in three group tasks. The task selected for payment is: **Task 3**

The table below shows a breakdown of your payoff for each decision within the selected group task.

Decision	You kept	Total group contribution	M	Your share of group points	Your payoff
A	9.00 points	3.00 points	1.425	1.43 points	10.43 points
B	9.00 points	3.00 points	1.875	1.88 points	10.88 points
C	9.00 points	3.00 points	2.325	2.33 points	11.33 points
D	9.00 points	3.00 points	2.775	2.78 points	11.78 points

Your total payoff for all group tasks equals **44.40 points**.

Questionnaire

Item	Your payoff
Amount not donated to charity	15.00 points
Lottery outcome	4.00 points
Urns and the colored cards	0.00 points
Calculation tasks	0.00 points

Your total payoff for the individual tasks equals **19.00 points**.

Your total earnings

Your total payoff for all group and individual tasks together equals **63.40 points**. This is equal to **2.54 British Pounds** and will be paid in addition to the 4.00 GBP you receive for completing the study.

Thank you for your participation. **Click 'Next' to finalize your participation.**

Next