Altruistic Bluffing: An Experiment on Indirect Signalling

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Abstract

People are often motivated to act in a way that sends a favourable signal about their character. This paper proposes a separation of signalling into its direct and indirect components: an observed behaviour can influence a person's image directly when the behaviour itself is image-relevant, and it can influence a person's image indirectly by changing people's beliefs about an unobserved, image-relevant behaviour. In an experiment on charitable giving, we show that individuals engage in indirect signalling to make an "altruistic bluff": donors engage in an image-irrelevant behaviour (donating to many charities) to change observers' beliefs about an unobserved, image-relevant behaviour (donating large amounts). This bluff works, as it leads observers to form beliefs that are positively biased.

Keywords: Signalling, Observability, Charitable Giving, Altruism
JEL: C91, D01, D64, D91

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1 Introduction

As social beings, humans are heavily influenced by how others perceive and evaluate them (Fiske, 2018). From an early age, we learn that how we behave matters for whether other people think of us as friendly or unfriendly, honest or deceitful, and intelligent or stupid. We learn that the impression we make – our public image – matters for our interactions with others throughout our education, at the workplace, and in our social lives. And we learn that conforming with social norms will often help us get along with other people. This social motivation has many positive effects because the desire to improve our public image can prompt us to act prosocially (Bénabou and Tirole, 2006; Andreoni and Bernheim, 2009). Thus, when individuals are observed, they often become more cooperative (Samek and Sheremeta, 2014), volunteer more (Linardi and McConnell, 2011), and increase donations (Lacetera and Macis, 2010; Karlan and McConnell, 2014). Yet, such studies only focus on one behaviour (e.g. donated amounts) and its related character trait (e.g. altruism).

Far less attention has been paid to the empirically relevant case where individuals engage in more than one behaviour and care about the joint image they obtain from all their behaviours. If in those cases not all behaviours are observed, signalling may take two forms (as illustrated in Figure 1): an observed behaviour can influence a person's image *directly* if the behaviour itself is image-relevant, and it can influence a person's image *indirectly* by changing people's beliefs about an unobserved, image-relevant behaviour.

For example, an employee might frequently stay at their desk during lunch breaks or until late in the evening. This can influence the employee's image in two ways: if the co-workers care about time spent in the office *per se*, it may influence the employee's image *directly*. In addition, spending more time in the office may change the co-workers' beliefs about the unobserved effort of the employee. Such image effects that take place through beliefs about unobserved behaviour is what we refer to as *indirect* signalling. Importantly, because effort is unobserved, some individuals may send manipulative, indirect signals: for example, the employee might sit extra hours by their desk to improve their image and chance of promotion, but in fact use the time to send personal e-mails or read articles unrelated to work (cf. pseudo-commitment strategies, Rothlin and Werder, 2007). Another example is when students carry textbooks and highlighters and sit in the front row in class. While this may influence their image in itself (direct), it may also influence their image by changing beliefs about how much unobserved effort they put into their studies (indirect). Consequently, teachers might reward the "first-row students" even if some of these students do not in fact put any effort into studying outside of class. A third example is when citizens show their social engagement through charity stickers on cars or "vanity" license plates, e.g. labelling themselves as "voluntary firefighters"

(Carpenter and Myers, 2010). Such signals may improve a person's image in itself (direct), but it may also influence their image by changing beliefs about unobserved donations or volunteering (indirect). Yet, as we show in this study, publicly demonstrating support for a cause might not in fact translate into devoting significant resources to it.

The notion of indirect signalling provides new insights compared to the traditional signalling model from Spence (1973). First, it implies that image concerns may play a larger role than is often acknowledged: people might not care about employees staying late in the office, students sitting in the front row in class, or citizens putting charity stickers on cars *per se*. Yet, even behaviours that are in themselves unimportant may be driven by image concerns if observers expect them to be correlated with unobserved behaviours such as working, studying, or volunteering, which can be informative of a person's type.[1] Second, such indirect signalling opens the door for deception: as we show in this paper, individuals may strategically change the observed behaviour to give others a wrong belief about e.g. how much they work, study, or volunteer, thereby inflating their positive reputation. Third, we further show that one can avoid deception from indirect signalling not only by removing the chance to send a signal (as in the canonical signalling model), but also by requiring individuals to send signals about *all* relevant behaviours. Because indirect signalling works through changing beliefs about unobserved behaviour, making all behaviours observable shuts down this signalling channel.

In this paper, we study indirect signalling through the case of charitable giving, as previous research has demonstrated that social motivation greatly influences donations to charity (e.g. Agerström et al., 2016; Krupka and Croson, 2016; House, 2018). Notably, donations involve two related, but distinct decisions: (i) how much to donate, and (ii) what charities to donate to. Often, the decisions are not both observable. When the charities are observed but not the amounts, then donors may use this strategically in an attempt to inflate their reputation. For example, donors may want to publicly show that they give to multiple charities, e.g. through social media posts or when talking to friends, to make others infer that they donated large amounts. Such indirect signalling could lead to biased beliefs among observers, who mistakenly think that giving to many charities implies giving large amounts, and it would be wasteful, as a larger number of donations imply greater processing costs.[2] To investigate

[1] This is in contrast to Spence's (1973) view on signalling, where education is directly informative about a person's type. Indirect signalling would occur if the employer expects education to be correlated with another, potentially observable behaviour (e.g. having lived abroad), which in turn would make the employer infer something about a person's type (e.g. being cross-culturally competent).

[2] In the field, donors often give to several charities, which is wasteful as a large part of the processing costs are independent of the size of the donation (Ahmed et al., 2016; Bloom, 2016). These processing costs stem from transaction costs as well as labour costs from accounting tasks such as maintaining records of donations, issuing receipts, reporting back to donors and the government, etc. While the costs are larger for donations via traditional channels (mail, cheque, etc.), Ahmed et al. (2016) show that even a donation made by credit card often costs more than USD 2 to process. These processing costs are modest for any one donation, but large

whether indirect signalling plays a role in the context of charitable giving, we ask in this paper: how do individuals adapt their giving behaviour to different levels of observability?

To address this research question, we build a conceptual framework and provide experimental evidence on whether image concerns can have negative effects when individuals use indirect signals to manipulate their public image. Participants decide under different levels of observability (i) how much to donate to charity and (ii) how many charities to give to.[3] We mimic charitable giving in the field by providing a wide range of charities across different causes and by including fixed transaction costs for each additional charity participants give to. As such, donors' public image may be influenced by (i) how altruistic they are, and (ii) how efficiency-minded they are. To see whether people respond to transaction costs in giving to multiple charities, we compare treatments with and without transaction costs (*NoCost* vs. *Private*). With transaction costs, we then compare treatments with different levels of observability to test for indirect signalling. In the treatments with observability, donors are informed that spectators will judge them after observing their decision(s) by assigning non-monetary (dis)approval points. In *PublicN*, spectators observe what charities a donor has given to, but not the donated amounts. This partial observability allows for indirect signalling, as donors may signal how much they donated by means of how many charities they donated to. This is similar to field situations where charities enable donors to signal that they donated by social media posts, badges, cards, or other small gifts, which often do not specify the donated amount. Finally, in *PublicNAmount* donors are informed that the spectators will also observe the amounts donated to each charity, thereby removing the possibility for indirect signalling. Comparing *PublicN* to *Private* (*PublicNAmount*) sheds light on the extent of indirect signalling with no (full) observability as benchmark.

We derive three key results from our study: first, we find that donors decrease the number of charities they give to when each donation comes with a fixed transaction cost. This suggests that spreading donations among different charities is perceived as a costly signal. Second, we find that the extent to which donors are observed influences how many charities they give to. Specifically, a considerable share of donors engages in wasteful, indirect signalling when spectators only observe which charities they donate to. They do so because they (correctly) anticipate that spectators infer greater total donations from a larger number of charities. With such partial observability, donors can improve their image by engaging in an "altruistic bluff",

in the aggregate as 160 million donors on average give to 4.3 charities every year in the US alone (Blackbaud Institute, 2018; YouGov (Oana Dumitru), 2022). Many charities have responded to the loss that comes from donors spreading their donations among too many charities by introducing a minimum amount for donations (e.g. Earth Island Institute).

[3]While the participants decide what charities they donate to, we show in Section 5.3 that indirect signalling in the current experiment takes place through *how many* charities donors give to rather than *what* charities.

in which they give tiny donations to many charities in order to signal that they are altruistic. Importantly, such altruistic bluffing works, as spectators evaluate those donors more positively who give to several charities. But when spectators also see the donated amounts, donors do not inflate the number of charities they give to, as altruistic bluffing is no longer possible. Third, looking at the total amounts donated, we find no differences between the treatments. We discuss potential reasons for the lack of an effect, including that the demand for a good image is price sensitive: the price of improving one's image is higher when donations are also observed, as donors can then no longer improve their image by making several tiny donations.

This study makes two important contributions to the literature. The primary contribution of this paper is to show empirically that individuals engage in wasteful indirect signalling to improve their public image. In its standard form, signalling behaviour directly influences beliefs about a person's type (Spence, 1973). Theoretical studies have extended this framework to multidimensional signalling games, where individuals engage in multiple behaviours to send signals about multiple unobserved characteristics (e.g. Quinzii and Rochet, 1985; Engers, 1987). Yet, existing empirical papers focus only on image concerns for one behaviour, showing e.g. that image concerns can make individuals behave more prosocially (Freeman, 1997; Batson, 1998). In the case of charitable giving, individuals also tend to be influenced by others' views and behaviour, as social norms have been shown to affect donations (Croson and Shang, 2008; Bicchieri and Xiao, 2009; Shang and Croson, 2009; Krupka and Weber, 2013; Drouvelis and Marx, 2021). In this study, we propose a distinction between direct and indirect signalling. By doing so, we show how signalling may also occur for behaviours that are not relevant for reputation per se if the observed behaviours correlate with relevant unobserved behaviours. Some individuals even use indirect signals strategically to (successfully) inflate their own reputation even though doing so is wasteful and increases transaction costs.

A second contribution of this paper relates to the literature on charitable giving, as we study how donors decide how many charities to give to. Most studies within this literature focus on the donated amounts (Andreoni and Payne, 2013; Saeri et al., 2022), and some studies examine how this varies with an exogenous change in the number of recipients (Bolton et al., 1998; Andreoni, 2007; Soyer and Hogarth, 2011; Chiang and Hsu, 2019). Relatedly, other studies examine competition between charities and whether giving to one charity crowds out donations to others (e.g. Reinstein, 2011; Corazzini et al., 2015; Meer, 2017; Gee and Meer, 2019). More recently, Fehérová et al. (2022) and Yeganloo et al. (2024) study how autonomy in deciding how many charities to give to influences the donated amounts. In this paper, we examine the choice to spread one's donations and find that donors have an intrinsic preference for spreading donations across multiple charities. As we discuss in Section 5, this is primarily

driven by a preference for giving to charities across different topics.

Because increasing the number of charities involves processing costs, the paper is also related to the increased focused on the efficiency of charities (Singer, 2009; Null, 2011; Exley, 2020) and the role of overhead costs (Gregory and Howard, 2009; Gneezy et al., 2014). In particular, we address a source of efficiency loss that charities face but which has received little attention in the literature: the increased processing costs that stem from donors spreading their donations to multiple charities (see Footnote 2). Our study shows that donors take such processing costs into account by reducing the number of charities they give to, but most donors still prefer to spread their donations to some extent.

This paper proceeds as follows: Section 2 presents a conceptual framework that explains how indirect signalling may occur when an individual engages in multiple behaviours. In Section 3, we detail the experimental design and our hypotheses. We present the main results and mechanisms in Section 4 and discuss further results in Section 5, including how the spectators respond to the signals of donors, how responsiveness to treatments correlates with relevant psychological traits, and what other motives donors may have for spreading their donations. The Online Supplement includes further results, tables, and figures.

2 Conceptual Framework

In the following, we explain how indirect signalling may occur in situations where individuals engage in more than one behaviour simultaneously. Our notation is general, as the idea of indirect signalling is general, but we use the frame of charitable giving to reflect the experiment presented in Section 3.

2.1 Setting

Consider an individual i who makes two decisions, a and b ($a \in A \subset \mathbb{R}$, $b \in B \subset \mathbb{R}$). To tie the model to our experiment, we consider a to be total donations to charities, and b to be the number of charities one donates to.[4] When deciding on a and b, we follow Bénabou and Tirole (2006) and assume that individuals have both extrinsic, intrinsic, and reputational motives. We denote by $x(a, b)$ the individual's monetary payoff from the combination of a and b, with both actions weakly reducing payoff ($x'_a \leq 0, x'_b \leq 0$; $x''_{aa} = 0, x''_{bb} = 0$), e.g. by giving to charity. We assume that both actions involve cognitive costs $C(a, b)$, $C'_a, C'_b > 0$, which are convex ($C''_{aa} \geq 0$, $C''_{bb} \geq 0$) and separable ($C''_{ab} = 0$). Such costs could for example be the effort

[4] For the examples provided in the Introduction, a could e.g. be 'working hard' or 'effort in studying', and b 'the act of staying late in the office' or 'always bringing one's books and sitting in the front of the classroom'.

required to decide how much and to what charities to give to (Huck and Rasul, 2010; Knowles and Servátka, 2015).

We represent the psychological benefits of the joint decision (a, b) by the function $g(a, b, \alpha, \beta)$, where α and β are sensitivities towards the two behaviours. The sensitivities are drawn independently from a continuous and bounded distribution f with support over both positive and negative values. Individuals know their own sensitivities, but they need to infer others' sensitivities from their decisions (as explained below). We assume that individual i receives psychological benefits from both a and b ($g'_a, g'_b \geq 0$), that the marginal benefits from a and b are decreasing ($g''_{aa}, g''_{bb} < 0$), and that the marginal benefits are increasing in the sensitivities ($g''_{a\alpha}, g''_{b\beta} > 0$, which is the standard single-crossing condition). In the case of charitable giving, this means that individual i receives utility from giving to charity (from pure or impure altruism, Andreoni, 1989, 1990; Crumpler and Grossman, 2008) and from giving to more charities (Sharps and Schroeder, 2019; Schmitz, 2021). Because spreading donations to more charities is inefficient in our experiment, we expect β to be inversely correlated with concerns for efficiency.

Finally, individual i may care about their reputation $R(a, b)$, which we model as the beliefs that spectators have about α and β. Specifically, the spectators infer α and β from the information set Ω, which could entail either full observability ($\Omega = \{a, b\}$), partial observability ($\Omega = \{a\}$ or $\Omega = \{b\}$), or nothing ($\Omega = \{\varnothing\}$). In sum, the individual receives the following utility:

$$U(a, b) = x(a, b) + g(a, b, \alpha, \beta) - C(a, b) + \gamma_a E(\alpha|\Omega) + \gamma_b E(\beta|\Omega), \tag{1}$$

where $R(a, b) \equiv \gamma_a E(\alpha|\Omega) + \gamma_b E(\beta|\Omega)$, and γ_a and γ_b are sensitivities towards the reputations for α and β, respectively. Note that this formulation is general and also encompasses situations where individual i does not care about their reputation for a specific sensitivity (in which case $\gamma_a = 0$ or $\gamma_b = 0$).

The individual decides on (a, b) by maximising Equation 1 with respect to a and b. This yields the following first-order conditions that implicitly characterise the optimal levels a^* and b^*:

$$g'_a + r_a = C'_a - x'_a \tag{2}$$

$$g'_b + r_b = C'_b - x'_b \tag{3}$$

where $r_a \equiv \gamma_a \frac{\partial E[\alpha|\Omega]}{\partial a} + \gamma_b \frac{\partial E[\beta|\Omega]}{\partial a}$, and $r_b \equiv \gamma_a \frac{\partial E[\alpha|\Omega]}{\partial b} + \gamma_b \frac{\partial E[\beta|\Omega]}{\partial b}$ are the partial effect of a and b on $R(a, b)$.

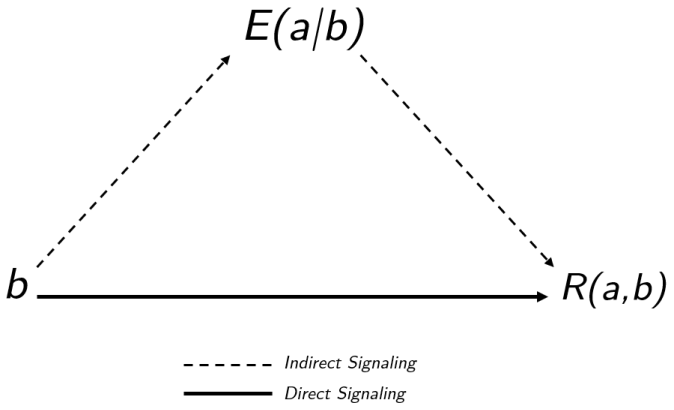
2.2 Effect of Observability

In the following, we provide intuition based on the conceptual framework. We discuss further details in Appendix A.1 and refer the reader to the seminal work of Quinzii and Rochet (1985) and Engers (1987) for comprehensive models of multidimensional signalling.

In the case of no observability ($\Omega = \{\varnothing\}$), we assume that behaviour does not influence reputation ($r_a = r_b = 0$). Individual i chooses the optimal levels of a and b to equate the marginal psychological benefits (g'_a and g'_b) with the marginal monetary and cognitive costs ($C'_a - x'_a$ and $C'_b - x'_b$, respectively). Then, an increase in α (β) leads to an increase in a (b). In the example of charitable giving, this means that people who are more altruistic give greater amounts to charity, and people who care more about spreading donations between charities give to more charities. The interplay between α (β) and b (a) depends on the sign of g''_{ab}, and this is less straight-forward to determine ex ante, as we discuss in Appendix A.1.

When choices are observed ($\Omega = \{a, b\}$), the sign of r_a and r_b will determine how observability influences the optimal levels of a and b compared to the case of no observability. For simplicity, we restrict our attention to pure-strategy Perfect Bayesian equilibria, and we assume that, ceteris paribus, there is a monotonic, increasing relationship between α (β) and a (b), which is anticipated by the spectators, as beliefs are accurate in equilibrium. In the context of charitable giving, these assumptions imply that, holding all other things equal, people who are more altruistic give more to charity, and people who care more about spreading donations between charities give to more charities.

Figure 1: Indirect Signalling



Notes: the figure illustrates how two decisions, a and b, influence an individual's reputation, $R(a, b)$. The figure shows the case where the spectator only observes b and forms beliefs about a conditional on b, $E(a|b)$. This means that b can influence $R(a, b)$ *directly* if the behaviour itself is image-relevant (bold line), and it can influence $R(a, b)$ *indirectly* if b affects $E(a|b)$, and $E(a|b)$ affects $R(a, b)$ (dashed line).

In the case of full observability ($\Omega = \{a, b\}$), a and b may influence reputation in two ways. Observing a influences beliefs about α, but it may also influence beliefs about β, depending on the sign of g''_{ab} (and vice-versa for b). Intuitively, if $g''_{ab} > 0$, an individual may decide on a high level of a both due to a high α and a high b. Thus, a high a and a low b send a stronger signal about α than a high a and a high b. The sign of r_a and r_b will then depend on the relative concerns for the reputation of α (γ_a) and β (γ_b). In the case of charitable giving, previous studies show that individuals are more concerned about *how much* donors give than *how* they give (Berman et al., 2018), implying that $\gamma_a > \gamma_b$. Then, $r_a > 0$, meaning that giving greater amounts provides a better reputation, while the sign of r_b is ambiguous.

In the case of partial observability ($\Omega = \{a\}$ or $\Omega = \{b\}$), we distinguish between *direct signalling* and *indirect signalling*. In the case where only b is observed (as in our experiment), direct signalling comes from the effect that b has on $R(a, b)$ from b itself, and indirect signalling is the effect that b has on $R(a, b)$ via the beliefs about a (illustrated in Figure 1). In other words, whereas direct signalling occurs when a decision influences the beliefs about a person's type (e.g. as in Spence, 1973), indirect signalling occurs when a decision influences the beliefs about a person's unobserved decisions, and these beliefs in turn affect the beliefs about a person's type. Such indirect signalling is not present with full observability, as the spectators then also observe a. With partial observability, on the contrary, the indirect channel may matter greatly: if $g''_{ab} > 0$, a greater b correlates with a greater a, which in turn predicts a greater α (and vice-versa for $g''_{ab} < 0$). For the example of charitable giving, this means that spectators who see a larger number of charities would infer that the total donations are greater and therefore believe that the person is more altruistic. Thus, in contrast to the case of full observability, $r_b > 0$ could occur even if neither donors nor spectators care about b per se. For charitable giving, this implies that even if neither donors nor the spectators care about the number of charities donors give to, observing the number of charities may influence donor behaviour if (i) donors care about their reputation from the (expected) amounts they donate, and (ii) there is a common belief that donors who give to many charities tend to donate more. Under partial observability, the beliefs about the relation between a and b will therefore be of great importance, and we measure these both for the spectators (first-order beliefs) and donors (second-order beliefs) in the experiment.

3 Experimental Design

We conduct an experiment to examine how individuals adapt their giving behaviour to different levels of observability. The experiment consists of four parts and a survey (see Figure 2). First,

one group of participants ('dictators' or 'donors') make decisions about how much to donate and how many charities to donate to. In different treatments, dictators make their decisions under either no, partial, or full observability. Second, we measure social norms for the donation decisions by eliciting normative and empirical expectations. Third, we elicit participants' beliefs about donated amounts in the treatment with partial observability. Fourth, a second group of participants ('spectators') provide non-monetary (dis)approval points to the dictators based on what they observe. Finally, participants complete a survey. In all treatments, we make sure that participants understand the donation decision, the transaction costs, and the level of observability with a series of control questions that all must answer correctly in order to continue with the experiment. The full set of instructions are available online and can be accessed here: https://doi.org/10.17605/OSF.IO/PMB56.

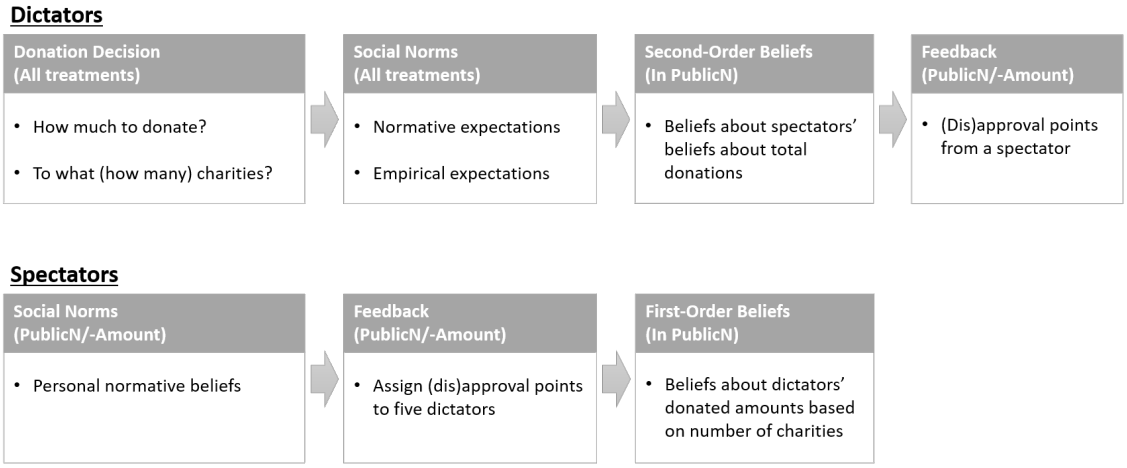
3.1 Donation Decision

Setting. The main part of our experiment is a modified dictator game, in which dictators choose (i) how much of EUR 100 they want to donate to charities or keep for themselves and (ii) how many charities they want to give to. Here, we use the large nominal stakes of EUR 100 to make it meaningful for donors to distribute the money to several causes. Participants are informed that 10 dictators are randomly chosen and their donation decisions implemented (for validation of the random payment procedure, see e.g. Bolle, 1990; Cox et al., 2008; Charness et al., 2016; Clot et al., 2018).

When making their decisions, participants see a list of 49 charities divided into the following seven topics: Health, Rights, Environment, Development Aid, Youth and Children, Security, and Women Advocacy. Specifically, they see the list of seven topics, and clicking on any topic will show the seven charities within that topic. If donors click on a charity, they see two sentences that describe the activities of the charity as well as a small picture that represents the topic. A graphical illustration and the description of all charities are provided in the instructions available online. With the comprehensive list of 49 possible charities, we aim to induce an impression of an overwhelming number of possible targets for donations, reflecting how donors may feel about selecting charities in the field. To preclude order effects, we present the different topics in random order, and we randomise the appearance of the charities under each topic.

All 49 charities have received a top rating in the CharityWatch efficiency ranking, and we inform participants about this to mitigate that donors give to multiple charities in order to reduce the risk of their donations being spent inefficiently.

Figure 2: Timeline of the Experiment



Treatments. In a between-subjects design, we divide participants into four treatments (see Table 1). First, we test in two treatments without observation whether individuals care about the costs of donating to many charities. Specifically, dictators in the *NoCost* treatment are informed that the entire amount that they donate will be received by the respective charities. In contrast, dictators in the *Private* treatment are informed that they have to pay a transaction cost of EUR 1 for each additional charity they give to (reflecting the fixed costs of donating in the field, cf. Footnote 2).[5] Comparing giving behaviour between *NoCost* and *Private* sheds light on the influence of transaction costs. Notably, if dictators do not adapt their behaviour to transaction costs, it would reduce the scope for the dictators to send signals by spreading their donations, as mimicking the 'desirable type' would be similar to cheap talk.

Second, we introduce two further treatments with observation to examine how individuals adapt their giving behaviour to different levels of observability. Both observed treatments include transaction costs (of which observers are also informed), so the benchmark without observation is the *Private* treatment. In the *PublicN* treatment, dictators are informed prior to their allocation decision that two spectators will judge them after observing what charities they give to and that the spectators will learn their last name (Charness and Gneezy, 2008; see Samek and Sheremeta, 2014, Regner and Riener, 2017, and Fromell et al., 2020, for similar manipulations).[6] The spectators observe the list of charities that dictators give to and evaluates the decisions by sending feedback through non-monetary (dis)approval points (similar

[5]To avoid having differential transaction costs when effectuating the payments to the charities, we covered the actual transaction costs of the charities.

[6]As our focus is on dictator behaviour, we decided to recruit more dictators to allow for a sufficiently large statistical power for the main comparisons. We therefore have each spectator observe five dictators, and pairs of spectators evaluate the same five dictators.

to e.g. Deffains et al., 2019), which we describe further in Section 3.4. In the *PublicNAmount* treatment, spectators additionally observe the amounts donated to each charity. Comparing *Private*, *PublicN*, and *PublicNAmount* sheds light on how the level of observability causally influences behaviour when an individual makes two decisions simultaneously.

Table 1: Treatment Overview

Treatments	Costs	Observed
NoCost	-	-
Private	1€ per charity	-
PublicN	1€ per charity	Charities
PublicNAmount	1€ per charity	Charities & Donated Amounts

3.2 Social Norm Elicitation

We further examine the role of social motivation by eliciting social norms, which are informative of what behaviours individuals think are socially desirable. To measure social norms directly, we first recruit a separate sample ('social norm raters') and present them with the decisions of the dictators. Each social norm eliciter only sees the decisions in one of the four treatments, and we ask them how much they think a person *ought* to give and to how many charities. By using a separate sample rather than the dictators to elicit these 'personal normative beliefs' (Bicchieri, 2017), we reduce biases in these responses that would occur e.g. from self-justification.

In the main study, we then elicit the normative and empirical expectations of the dictators for both the total donations and the number of charities donated to. Specifically, after making their own choices, dictators are asked what they think the median responses among the social norm raters are (normative expectations), and dictators are asked what they think the median decision among dictators is (empirical expectations).[7] This belief elicitation is incentivised: we draw at random either the questions related to normative or empirical expectations, and participants receive EUR 0.5 if they correctly guess the number of charities and the amount donated (with a margin of error of ± EUR 3).

After the questions related to normative and empirical expectations, dictators state their beliefs about how much they think dictators on average donated to each of the seven topics. These belief elicitations are incentivised, as one topic is drawn at random, and dictators earn EUR 0.5 if their guess is correct (± EUR 3). These questions shed light on a possible coordination problem in giving, to which we return in Section 5.3.

[7]Prior to this page in the experiment, all participants read an explanation of what a median is, see examples from sets of numbers, and show in a control question that they are able to find the median in a series of numbers.

3.3 Second-Order Beliefs

As explained in Section 2, the case of partial observability (*PublicN*) allows for indirect signalling. Yet, the direction of the indirect signalling effect depends on the (expected) relation between the two behaviours. To shed light on this, we ask dictators (spectators) in *PublicN* about their second-order (first-order) beliefs about the total donations based on the observed number of charities. Specifically, we ask spectators to guess the total amount donated by the dictator based on the number of charities they donates to. This question is incentivised as we randomly draw one guess for each spectator, and the spectator additionally earns EUR 0.5 if they correctly guess the amount donated (± EUR 3). We then elicit second-order beliefs from the dictators by asking them to state what the first-order beliefs of the spectators are. This question comes as a surprise to not influence the previous decision, and it is incentivised as the dictator may additionally earn EUR 0.5 if they correctly guess the beliefs of the spectators (± EUR 3). The elicitation of first- and second-order beliefs provides a test for whether dictators expect that their decision about how many charities to donate to influences the spectators' beliefs about total donations.

3.4 Feedback

After participants answer questions related to social norms, spectators in *PublicN* and *PublicNAmount* observe the decisions by the dictators and evaluate them on a 6-point scale. We use the German high school grading system, which is a 6-point scale ranging from "very good" to "insufficient". This is a grading system that is well-known to all participants and therefore used in other experiments with German samples (e.g. Barrett and Dannenberg, 2016). For ease of interpretation, we recode the variable ex post such that a higher rating is more favourable.

3.5 Survey

At the end of the experiment, participants answer demographic questions about their gender, age, field of study, and how many hours they have volunteered in the past year. We then elicit several measures to explore factors beyond our conceptual framework that may influence the dictators' decisions. First, participants answer a question about their general risk preferences (Dohmen et al., 2011). Second, participants rate on a 5-point Likert scale how important they think supporting each of the seven topics is. Third, they answer two questions about their preferences for spreading donations.[8] Fourth, they answer the 10-item Self-Importance

[8] One concern is whether the treatments influence participants' responses to the questions about preferences for spreading donations (cf. post-treatment bias, Montgomery et al., 2018). Yet, we find no differences across treatments for these questions, risk preferences, the Self-Importance of Moral Identity scale, nor the average

of Moral Identity scale (Aquino et al., 2002), which measures the degree to which a person wants to possess moral qualities (Internalisation) and the degree to which a person wants to communicate being moral to others (Symbolisation). We standardise responses to all the attitudinal controls as proportions of maximum possible (POMP) scores, ranging between zero and one, to enable an easy interpretation despite using different scale lengths (Cohen et al., 1999; Mellenbergh, 2019).[9]

3.6 Procedure

The experiment was conducted between March and May 2023 as an online experiment of the experimental laboratory of the University of Hamburg. We recruited a total of 826 individuals, of whom 804 completed the experiment. Of these, 585 were dictators, 132 were spectators, and 87 were social norm raters. We oversampled the number of dictators in *Private*, *PublicN*, and *PublicNAmount* (168-170) compared to *NoCost* (77) to ensure sufficient power for the contrasts between different levels of observability. With this sample size, we expected based on power simulations to have a power of .8 to detect a difference in the number of charities of 1 and in total donations of EUR 6.5 (see Online Supplement S.1). Yet, one spectator and 10 dictators in *PublicN* fail to provide consistent answers to the questions about first- and second-order beliefs, respectively, leaving us with a main sample of 793 individuals.[10] In the main sample, 36 percent were male, and the mean age was 26 years. We provide further sample characteristics and summary statistics in Tables S.8 and S.9.

For completing the study, dictators (social norm raters and spectators) received a show-up fee of EUR 4.5 (3) in addition to the payment for the incentivised belief elicitation questions and the payment to the 10 randomly selected dictators.[11] The median earnings of the experiment were EUR 4.5, and the median completion time was 21 minutes.

3.7 Hypotheses

Drawing on our conceptual framework, we now explain our pre-registered hypotheses about how transaction costs and observability influence giving behaviour. First, we compare *NoCost*

perceived importance of the seven topics (Kruskal-Wallis test, all $p's > .208$, cf. Online Supplement S.2).

[9]We use POMP scores rather than standardised (z) scores, as the responses to the 'spread for efficiency' question and the Internalisation subscale are skewed (test for skewness: $p = .045$ and $p < .001$, D'Agostino and Belanger, 1990; Royston, 1991). Such skewness can make the z scores misleading (Cohen et al., 1999).

[10]The first and second-order belief elicitations provide an additional comprehension check. For example, if a spectator observes (no) donations to a charity, then believing that total donations are (not) zero suggests that the spectator did not understand the task. In Online Supplement S.3, we show that our results are also robust to including stricter, non-preregistered sample restrictions.

[11]We adjusted the participation fee from EUR 3 to EUR 4.5 after the first two sessions to account for the fact that the experiment lasted slightly longer than in the pilot. We show in Online Supplement S.3 that our results are robust to controlling for this change.

and *Private* to shed light on the role of transaction costs. To document that transaction costs matter is an important first step, as it is necessary for interpreting the later results of observability as costly signalling rather than e.g. cheap talk.

Previous research indicates that many people have a preference for giving to multiple charities even if some charities are more effective than others (Sharps and Schroeder, 2019; Schmitz, 2021). Yet, other studies demonstrate that people care about their donations not being wasteful, e.g. by avoiding paying too much for administration (Meer, 2014; Portillo and Stinn, 2018). Similarly, another study shows that donors shift towards donating more to highly productive charities, but that this substitution is weaker when charities are more different (Ek, 2017). This suggests a trade-off between giving to multiple charities and giving in an efficient manner. Such a trade-off has not yet been studied in a setting where donors decide how many charities to give to when increasing the number of charities involves an efficiency loss (in the form of transaction costs). Yet, if the trade-off exists, we expect dictators to give to fewer charities when each donation involves transaction costs, leading to our first hypothesis:

Hypothesis 1 (Efficiency) *Dictators on average give to more charities in* NoCost *than in* Private*.*

We then turn to the effects of observability. Importantly, we expect indirect signalling to influence behaviour differently depending on the (expected) correlation between the two decisions (which in our conceptual framework is given by the sign of g''_{ab}, see Section 2). In the pre-registration, we therefore conditioned the direction of the following hypotheses on the expected correlation between the two decisions. Looking at the first- and second-order beliefs that we elicit in the *PublicN* treatment, we find that spectators believe that dictators who donated to more charities donated larger amounts (repeated measures correlation $r_{rm} = .602$, $p < .001$), and dictators anticipate this relation (Pearson's $r = .404$, $p < .001$). This suggests that $g''_{ab} > 0$, and we use this to formulate the following hypotheses.

With $g''_{ab} > 0$, increasing the number of charities in *PublicN* has two effects (as explained in Section 2): it influences reputation from observing a greater b (direct effect), and it influences reputation through the spectator beliefs about total amounts (indirect effect). If individuals are more concerned about *how much* donors give than *how* they give (Berman et al., 2018), then the indirect effect should outweigh the direct effect, leading to an increase in the number of charities that dictators donate to in *PublicN*. In contrast, the comparison between *Private* and *PublicNAmount* is not clear ex ante. On the one hand, dictators may be motivated to decrease b in *PublicNAmount* to make their giving a greater signal about a. On the other hand, as explained below, we expect total donations to be greater in *PublicNAmount* than in *Private*. With $g''_{ab} > 0$, this should make dictators in *PublicNAmount* increase the number of

charities they give to compared to *Private*. Due to these opposite effects, we do not include a hypothesis comparing the number of charities in *Private* and *PublicNAmount*. Thus, we arrive at our second hypothesis:

Hypothesis 2 (Number of Charities)

1. *The average number of charities participants give to is greater in* PublicN *than in* Private.
2. *The average number of charities participants give to is greater in* PublicN *than in* PublicNAmount.

We expect total donations to be greater in *PublicNAmount* than in *PublicN* and *Private* because when donations are observed, giving more is a signal of greater altruism ($\frac{\partial E(\alpha|\Omega=\{a,b\})}{\partial a} > 0$). Furthermore, for $g''_{ab} > 0$, total donations should be greater in *PublicN* than in *Private*. This is because b is greater in *PublicN* (cf. Hypothesis 2), which leads g'_a to be greater in *PublicN* than in *Private*, which in turn increases total donations. Our hypothesis regarding total donations is therefore as follows:

Hypothesis 3 (Total Donations)

1. *On average, participants donate more in* PublicNAmount *than in* PublicN.
2. *On average, participants donate more in* PublicNAmount *than in* Private.
3. *On average, participants donate more in* PublicN *than in* Private.

4 Analysis

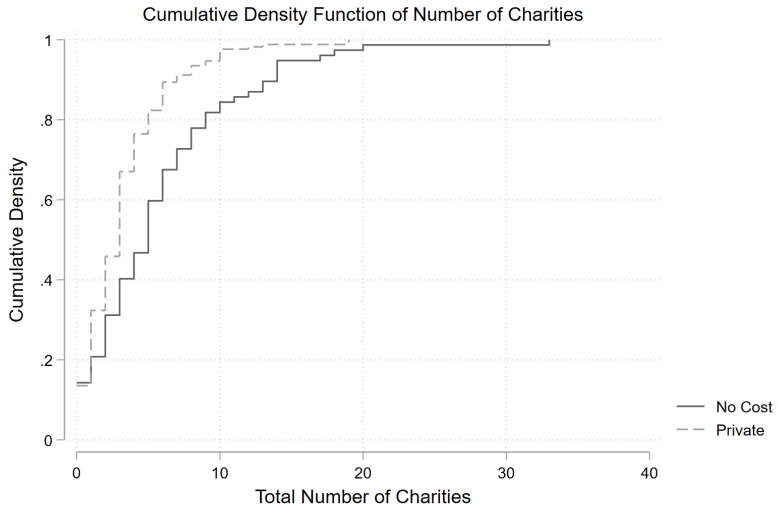
We now present the results on how participants respond to the inclusion of transaction costs and to the (partial or full) observation by spectators. In doing so, we follow the pre-analysis plan exactly, as we estimate "regressions with (i) no controls, (ii) demographic controls (age, gender, field of study, and hours of volunteering the past year), and (iii) controls also for attitudes (two questions on preferences for diversification, internalisation, and symbolisation)." Our preferred specification is (iii), as adding the relevant control variables increases the efficiency and statistical power of our analysis. In Online Supplement S.3, we show that our results are robust to using different operationalisations of the control variables. We also show that all significant results in this section are at least marginally statistically significant when we control for the family-wise error rate (FWER) or the false-discovery rate (FDR). Table A.1 provides descriptive statistics, Figure A.1 shows the distribution of total donations, and Figures A.2 and A.3 show how donations were allocated across topics and charities.

4.1 H1: Donors Respond to Transaction Costs

The first hypothesis states that donors should respond to transaction costs by reducing the number of charities they give to. This result is crucial for studying signalling: if transaction costs do *not* matter for the donors, then changing the number of charities one donates to would be similar to cheap talk. To test H1, we pre-registered to use negative binomial regressions, as the number of charities is count data (i.e. non-negative integers). We show in Online Supplement S.3.2 that negative binomial regressions are preferable to Poisson regressions and zero-inflated negative binomial regressions, but that our results are robust to using these instead.

Comparing *NoCost* and *Private*, we do find that donors respond to transaction costs: donors in *NoCost* on average give to 5.82 charities, whereas they only give to 3.27 charities on average in *Private* (see Figure 3). Table 2 documents that this difference is statistically significant for all levels of controls (all $p's < .001$). The table reports the results in the form of incidence rate ratios (irr). The irr is .59, which means that the average number of charities donated to in *Private* is .59 times the average number of charities in *NoCost*. Because this is significantly lower than 1, it implies that the average number of charities is lower in *Private* than in *NoCost*. Alternatively, holding all control variables at their means, the predicted number of charities donated to in *NoCost* is 5.19, and the predicted value for *Private* is 3.05.

Figure 3: Total Charities in NoCost vs. Private



Notes: the figure presents the cumulative density function (or empirical distribution function) of the dictators' decision about how many charities to give to, shown separately for *Private* and *NoCost*.

Table 2: Transaction Costs and the Number of Charities (H1)

	(1)	(2)	(3)
Private	0.56***	0.55***	0.59***
	(0.07)	(0.07)	(0.07)
Demographic Controls	No	Yes	Yes
Attitudinal Controls	No	No	Yes
Observations	247	247	247

Notes: negative binomial regressions with the number of charities as the dependent variable. The demographic controls are age, gender, field of study, and volunteering. The attitudinal controls are preferences for spreading donations (two questions) and the two subscales of the Self-Importance of Moral Identity scale. The corresponding table with all coefficients is Table S.10. Coefficients are incidence rate ratios.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Online Supplement S.4.1, we show that adding transaction costs has no effect on the number of dictators who donate (extensive margin), but it decreases to how many charities dictators donate conditional on them giving (intensive margin). We sum up the results on H1 as follows:

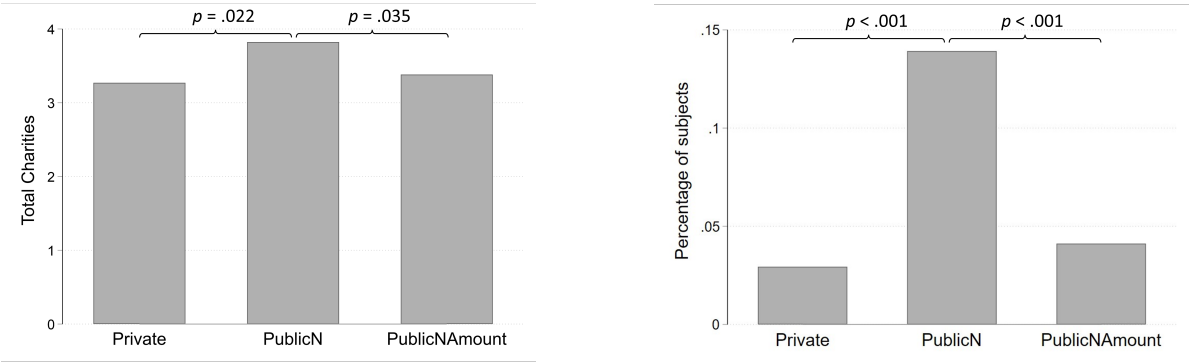
Result 1 *Individuals give to fewer charities when they have to pay transaction costs for each charity they give to. This effect is driven by a change in donation behaviour among the individuals who give (intensive margin) and not by the number of individuals who give (extensive margin).*

4.2 H2: Partial Observability Affects the Number of Charities

The second hypothesis states that donors give to more charities when spectators only observe what charities they give to. As the outcome is again the number of charities (i.e. count data), we use the same analysis strategy as for H1.

PublicN vs. Private. Comparing *PublicN* and *Private*, we indeed find that donors on average give to more charities when spectators only observe what charities donors give to (3.82, *PublicN*) than when there is no observation (3.27, *Private*), cf. Figure 4a. Looking at negative binomial regressions, this effect is statistically significant ($p = .022$, cf. Table 3). The incidence rate ratio is 1.21, and this implies that the average number of charities donated to in *PublicN* is 1.21 times the average number of charities in *Private*. Because this is significantly greater than 1, it implies that the average number of charities is larger in *PublicN* than in *Private*. Alternatively, one could examine the predicted values in the two treatments when holding all control variables at their means. Here, we find a predicted average number of charities of 3.68 in *PublicN*, which is significantly larger than the 3.04 in *Private*. With the

Figure 4: Donations to Charities and Observability



(a) Average Number of Charities

(b) Donors Making Small Donations

Notes: Figure (a) shows the average number of charities that dictators donate to by treatment. p-values are obtained from negative binomial regressions with all control variables. Figure (b) shows the percentage of donors who make donations that are smaller than EUR 3 by treatment, and the treatment effects are robust to different definitions of "small donations" of EUR 1, 2, 3, or 4. p-values are obtained from logit regressions with all control variables.

transaction cost of EUR 1 per donation, this corresponds to an increase in total transaction costs of 17 percent.

The treatment difference is driven by a change in the extensive rather than the intensive margin. That is, adding partial observability leads more participants to donate to at least one charity, but it does not change the average number of charities donors give to conditional on positive donations. Thus, we find that while 86 percent of donors give to charity in *Private*, this number increases to 96 percent in *PublicN*.[12] This difference is statistically significant for all levels of control (logit regressions, all $p's < .003$). In contrast, we find no difference in the number of charities that donors give to conditional on positive donations (negative binomial regressions, all $p's > .339$).

PublicN vs. PublicNAmount. The data also suggest that donors give to more charities in *PublicN* (3.82) than in *PublicNAmount* (3.38), cf. Figure 4a. While this difference fails to reach statistical significance without any control variables ($p = .136$), it becomes statistically significant in our preferred specification, where demographic and attitudinal controls increase the efficiency of the estimate without notably changing the incidence rate ratio (irr, $p = .035$,

[12]The share of participants who donate some of the EUR 100 endowment seems relatively high; yet, many participants donate rather small amounts, such that 21-24 percent of donors in our study give at most 10 percent of their endowment. The high share of individuals donating is likely influenced by the endowment being unearned rather than earned (Hoffman et al., 1994, 1996; Lefgren et al., 2016) and the recipients being charities rather than other participants (Cartwright and Thompson, 2022; Livingston and Rasulmukhamedov, 2023). In fact, these two factors may interact in leading to even higher donations (Umer et al., 2022). Yet, because these factors are held constant across treatments, they are unlikely to affect the main treatment comparisons.

cf. Table 3). The irr is 1.17, and this implies that the average number of charities donated to in *PublicN* is 1.17 times the average number of charities in *PublicNAmount*. This translates into predicted values at the mean of all control variables of 3.62 in *PublicN* and 3.09 in *PublicNAmount*, corresponding to an increase in total transaction costs of 15 percent.

Again, the treatment difference is driven by a change in the extensive rather than the intensive margin. Whereas 85 percent of donors in *PublicNAmount* donate to charitiy, this number increases significantly to 96 percent in *PublicN* (logit regressions, all $p's < .001$). We find no difference in the number of charities that donors give to conditional on positive donations (negative binomial regressions, all $p's > .624$). We summarise the results as follows:

Result 2 *Dictators give to more charities when spectators only observe the number of charities donated to (partial observability) compared to situations of no or full observability.*

Table 3: Observability and the Number of Charities (H2)

	PublicN vs. Private			**PublicN vs. PublicNAmount**		
	(1)	(2)	(3)	(4)	(5)	(6)
PublicN	1.17*	1.20**	1.21**	1.13	1.14	1.17**
	(0.10)	(0.11)	(0.10)	(0.09)	(0.10)	(0.09)
Demographics	No	Yes	Yes	No	Yes	Yes
Attitudes	No	No	Yes	No	No	Yes
Observations	328	328	328	328	328	328

Notes: negative binomial regressions with the number of charities as the dependent variable. The demographic controls are age, gender, field of study, and volunteering. The attitudinal controls are preferences for spreading donations (two questions) and the two subscales of the Self-Importance of Moral Identity scale. The corresponding table with all coefficients is Table S.11. Coefficients are incidence rate ratios.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Mechanism. As demonstrated above, our data suggest that adding image concerns to the donation decision has an effect primarily by inducing donations from the dictators who would otherwise not have donated. In terms of our conceptual framework, this implies that introducing reputational concerns, $R(a, b)$, is important for changing the behaviour of donors whose intrinsic motivation, g, was not large enough to induce giving on its own. If the results are truly driven by dictators trying to manipulate their public image, we would expect that such dictators give strategically to improve their reputation at the lowest possible costs. Dictators in *PublicN* achieve this by making many small donations, as spectators only see the number of charities and not the amounts donated. In an exploratory analysis, we do find this type of "bluffing" in charitable giving especially among dictators in *PublicN*. As seen in Figure 4b, the

share of dictators making donations less than EUR 3 is significantly greater in *PublicN* than in both *Private* and *PublicNAmount* (logit: both $p's < .001$).[13] The 14 percent of dictators in *PublicN* who give donations less than EUR 3 make on average 3.6 such donations. This suggests a mechanism for Result 2: when spectators only observe what charities a donor has given to but not the donated amounts, some individuals use this strategically by making many tiny donations.

4.3 H3: Observability Does Not Influence Donated Amounts

The third hypothesis relates to how observability affects the amounts that dictators donate. To test this, we use tobit regressions, as the total donations are censored data between 0 and 100 (with the upper limit depending on how many charities dictators choose to donate to). For robustness, we also consider the nonparametric Mann-Whitney U-test (henceforth MWU-test, Wilcoxon, 1945; Mann and Whitney, 1947) or the semiparametric Symmetrically Censored Least Squares estimator (henceforth SCLS test Powell, 1986).

PublicNAmount vs. PublicN. H3.1 states that dictators should donate more on average in *PublicNAmount* than in *PublicN*. Yet, we find little difference with average donations of EUR 45.23 in *PublicNAmount* and EUR 44.64 in *PublicN*. Testing for differences in tobit regressions, we find no statistically significant difference regardless of the level of controls (all $p's > .615$, cf. Table 4). We also find no statistically significant difference using the MWU-test ($p = .985$) and the SCLS estimator ($p = .774$).

PublicNAmount vs. Private. H3.2 states that dictators should donate more on average in *PublicNAmount* than in *Private*. Yet, while dictators donate slightly more in *PublicNAmount* (EUR 45.23) than in *Private* (EUR 40.22), this difference is not statistically significant for any level of control (tobit, all $p's > .219$, cf. Table 4). The difference is also not statistically significant in any robustness test (MWU: $p = .180$, SCLS: $p = .146$).

PublicN vs. Private. Finally, H3.3 states that dictators donate more on average in *PublicN* than in *Private*. While donors give slightly more in *PublicN* (EUR 44.64) than in *Private* (EUR 40.22), this is not statistically significant (tobit: all $p's > .117$ cf. Table 4, MWU: $p = .216$, SCLS: $p = .220$). We summarise the results in this section as follows:

[13] As this is an exploratory analysis, we determined the cut-off for how large a "small donation" is a posteriori. The effect is significant for the *Private* vs. *PublicN* comparison for cut-offs in the range (0,4); for the *PublicN* vs. *PublicNAmount* comparison, it is significant for cut-offs in the range (0,11).

Result 3 *The total amounts that dictators give to charity are not affected by neither full nor partial observation by the spectators.*

Table 4: Observability and Total Donations (H3)

PublicNAmount vs. PublicN			
PublicNAmount	-1.17	-1.58	-1.90
	(3.91)	(3.93)	(3.78)
Demographic Controls	No	Yes	Yes
Attitudinal Controls	No	No	Yes
Observations	328	328	328
PublicNAmount vs. Private			
PublicNAmount	4.84	3.83	2.79
	(3.93)	(4.01)	(3.92)
Demographic Controls	No	Yes	Yes
Attitudinal Controls	No	No	Yes
Observations	340	340	340
PublicN vs. Private			
PublicN	5.94	5.15	4.34
	(3.78)	(3.80)	(3.73)
Demographic Controls	No	Yes	Yes
Attitudinal Controls	No	No	Yes
Observations	328	328	328

Notes: tobit regressions with total donations as the dependent variable. The demographic controls are age, gender, field of study, and volunteering. The attitudinal controls are preferences for spreading donations (two questions) and the two subscales of the Self-Importance of Moral Identity scale. The corresponding tables with all coefficients are Tables S.12-S.14. Coefficients are average partial effects, robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Mechanism. In this section, we have shown that the level of observability did not significantly influence the total donations made by the dictators. This somewhat contradicts a literature demonstrating that people tend to donate more when they are observed (e.g. Lacetera and Macis, 2010; Karlan and McConnell, 2014). Yet, Bradley et al. (2018) document in a meta-analysis that effects of observation tend to be largest in in-person experiments, whereas we run an online experiment with a standard university lab sample. One reason to expect a smaller effect in an online study is the "online disinhibition effect" (Joinson, 1998, 2003; Suler, 2004; Lapidot-Lefler and Barak, 2012). This theory builds on social psychology and the notion of "inhibition", which occurs when people constrain their behaviour due to worries about public evaluation, anxiety about social situations, or other reasons for self-consciousness (Zimbardo, 1977). Already Joinson (1998) noted that on the Internet, one could see disinhibition

stemming from a "reduction in concerns for self-presentation and the judgement of others" (p. 44). We aimed at reducing such feeling of anonymity in the current experiment by showing the dictators' names to the spectators. Yet, we speculate that dictators still put less value on reputational concerns in our setting compared to in-person lab experiments. In terms of our conceptual framework, this implies that the costs of giving ($-x'_a$) may be too large compared to the reputational concerns (γ_a).

Another reason for the lack of significant effects on donated amounts could be that dictators anticipate that while giving increases evaluations, it does so with a decreasing effect. That is, while donors may increase donations from e.g. EUR 20 to 40 and see an increase in their evaluations, increasing donations from e.g. EUR 80 to 100 has almost no effect on evaluations (discussed in Section 5.1).

These explanations – online disinhibition and the decreasing effect of donations on evaluations – suggest that the perceived reputational benefits of donating larger amounts may be limited. But why, then, do we observe individuals who send wasteful, indirect signals to strategically manipulate their public image by increasing the number of charities they give to (cf. Section 4.2)? One notable difference is that the cost of manipulating one's signal in *PublicN* is much lower: a dictator may engage in "bluffing" and send a signal by donating e.g. only EUR 1 to a charity. In contrast, spectators in *PublicNAmount* call the dictators' bluff, as they see also the amounts donated. Therefore, it is much more costly for dictators to manipulate their public image in *PublicNAmount* than in *PublicN*. If demand for a favourable image is price sensitive, we speculate that such a cost-benefit explanation can reconcile the different results for H2 and H3.

5 General Discussion

In the preceding section, we demonstrated that (i) dictators change their giving behaviour when there are transaction costs, (ii) dictators give to more charities when spectators observe only the number of charities that they give to, (iii) some individuals strategically give many tiny donations ("bluffing") to manipulate their public image, and (iv) dictators do not change the total amounts they donate depending on the level of observability. In the following, we first explore whether bluffing works by examining spectator evaluations. We then show that giving to more charities when only the number of charities is observed correlates with a disposition to communicate being moral to others. Finally, we explore other reasons than signalling for giving to multiple charities.

In Online Supplement S.4, we discuss gender differences and show that (i) women tend

to give to more charities and that this is explained by differences in preferences for spreading donations as well as differences in self-importance of moral identity, (ii) women tend to give larger amounts, and (iii) men are more responsive to the *PublicN* treatment. We further discuss the social norms related to the two giving decisions, documenting i.a. that even with transaction costs, there is a normative expectation that donors ought to give to more than one charity. We also discuss that experimenter demand effects are unlikely to influence the results of the experiment.

5.1 Spectator Responses – Bluffing Works

In the following, we explore how spectator evaluations depend on the total donations of the dictator and the number of charities that the dictator donates to. We report here the results of OLS regressions and show in Online Supplement S.5.2 that the results are robust to using instead ordered logit regressions. We cluster on the level of the pair of spectators evaluating the same five dictators.[14] First, we analyse spectator evaluations in *PublicNAmount*. Here, spectators observe both donations and charities, and this allows us to examine what matters for the spectators in their evaluations. Second, we examine spectator evaluations in *PublicN*, and we show that spectator evaluations are influenced via their first-order beliefs about the total donations.

PublicNAmount: What Do Spectators Value? We first examine spectator evaluations in *PublicNAmount*. Including both observed donations and observed charities in the regression yields a highly significant effect of observed donations ($\beta = .034$, $p < .001$), whereas the effect of observed charities is not statistically significant ($\beta = .048$, $p = .229$).[15] The magnitudes and significance are unaffected by the level of control (cf. Table S.15). The result has the interpretation that going from no donations to the maximum possible donations improves evaluations by 3.24 on a 6-point scale.

From the spectator evaluations, we also see that while giving more leads to an improved evaluation, it does so at a decreasing rate (see Figure S.4). To formally test for such non-linearity, we include squared terms of total donations and total charities in the regression. We find that the relation between total donations and spectator evaluations is indeed nonlinear: across all levels of control, the squared total donations is negative and highly significant (all $p's < .001$, cf. Table S.16), and the linear term remains positive and highly significant

[14] Our results are robust to instead clustering on the level of the individual spectator, and the results are robust to adding spectator-fixed effects.

[15] The data do not allow us to separate the effect of the observed number of charities from the observed number of topics that a donor gives to, as these are highly correlated ($r = .847$, Spearman's $\rho = .945$, $p < .001$).

($\beta = .080$, all $p's < .001$). On the contrary, neither total charities nor the square of total charities is statistically significant. The interpretation of the nonlinearity in total donations is that changing one's total donations from e.g. EUR 10 to 20 is associated with an improved average evaluation of .66, whereas an increase from e.g. EUR 70 to 80 is only associated with an improved average rating of .09.

One potential concern with the above regressions is the strong correlation between total donations and total charities in *PublicNAmount*. Specifically, the Pearson's r between total donations and total charities is .531 ($p < .001$, Spearman's $\rho = .587$, $p < .001$), and such collinearity may reduce our ability to statistically detect how each of the two variables is associated with spectator evaluations. To mitigate this problem, we examine the two variables separately: specifically, we first conduct three OLS regressions of evaluations on total donations, holding the number of charities within $\{1, 2\}$, $\{3, 4\}$, and $\{5, 6\}$, respectively. In all three intervals, the coefficient on total donations is statistically significant (all $p's < .014$, cf. Table S.17), and the average coefficient is $\beta = .025$. That is, holding charities almost constant, every additional euro donated on average leads to an approved evaluation of .025 on a 6-point scale (shown visually in Figure S.5). Second, we conduct six regressions of evaluations on total charities, holding the total donations within the intervals $[10, 24]$, $[25, 39]$, $[40, 54]$, $[55, 69]$, $[70, 84]$, and $[85, 100]$, respectively. We find no positive, statistically significant relation in any of the intervals (cf. Table S.18), and the average coefficient is $\beta = -.015$ (shown visually in Figure S.6). That is, holding donations within narrow bounds, we overall find no effect of total charities on evaluations.

In sum, we find that under full observability, spectators do not respond to the number of charities that dictators donate to. In contrast, spectators give better evaluations to dictators who donate larger amounts, although at a decreasing rate.

PublicN: The Effect of Bluffing. We next look at spectator evaluations in *PublicN*. Estimating an OLS regression with only the observed charities, we now find a positive and significant effect of increasing total charities on spectator evaluations ($\beta = .145$, $p = .006$), and this is unaffected by the level of control (cf. Table S.19). Hence, increasing the number of charities one donates to leads to an improved evaluation. Testing for nonlinearities as before, we also here see a decreasing effect: the coefficient on the squared term is negative and statistically significant for all levels of controls (all $p's < .001$, cf. Table S.20), and allowing for the nonlinearity increases the coefficient on observed charities to $\beta = .649$ (all $p's < .001$). The interpretation of this nonlinearity is that increasing the number of charities from e.g. 1 to 3 is associated with an improved evaluation of .958, whereas increasing the number of charities

from e.g. 5 to 7 is only associated with an improved evaluation of .245.[16]

Yet, a closer look at the data indicates that while spectators in *PublicN* approve of dictators who give to more charities, they do so because they believe the dictators have given larger amounts and not because of the number of charities per se. We find a strong, positive correlation between the number of charities dictators give to and the first-order beliefs of the spectators about how much the dictators donated (repeated measures correlation $r_{rm} = .602$, $p's < .001$). That is, spectators correctly anticipate a positive relation between total donations and the number of charities, but they overestimate this relation compared to the actual Pearson's $r = .347$ in *PublicN*. In a regression of spectator evaluation on both the number of charities and the spectators' first-order beliefs about donations, we find that the effect of observed charities diminishes substantially and loses its statistical significance ($\beta = .034$, $p = .440$), whereas the effect of first-order beliefs is highly significant ($\beta = .023$, $p < .001$, cf. Table S.19). This is corroborated by a mediation analysis: the effect from the number of charities to evaluations goes solely through first-order beliefs as a mediator ($p < .001$), while the direct effect is insignificant ($p = .111$, cf. 'indirect-only mediation', Zhao et al., 2010). In sum, these results confirm the finding above, namely that spectators award dictators who donate large amounts, but they care less about the number of charities, i.e. how the amounts are donated.

5.2 Behaviour Correlates with Self-Importance of Moral Identity

To further shed light on the extent to which donor behaviour is strategic, we compare participants' behaviour with their answers to the Self-Importance of Moral Identity scale (Aquino et al., 2002). This scale measures how important moral identity is for a person's self-definition, defining morality as the combined set of the following traits: caring, compassionate, fair, kind, generous, helpful, hardworking, honest, and friendly. Of the 10 items in the SIMI scale, five measure the degree to which a person wants to possess moral qualities (Internalisation), and five items measure the degree to which a person believes that their actions communicate being moral to others (Symbolisation).

We find that dictators with an above-median score in Internalisation tend to donate more than dictators with a below-median score (tobit, $p < .001$, cf. Table S.28). The size of the effect is such that having an above-median Internalisation score predicts an increase in total donations of EUR 13. Opposingly, we find no significant correlation between Symbolisation and total donations ($p = .664$). These results mirror those of Hansson et al. (2022), who find

[16] As with *PublicNAmount*, we are not able to separate the effect of the number of charities from the number of topics, as the two are highly correlated ($r = .842$, Spearman's $\rho = .904$).

that Internalisation but not Symbolisation predicts greater donations to charity. Yet, looking at the number of charities donors give to, the pattern is reversed: we find no significant correlation with scores on Internalisation (negative binomial regression, $p = .196$, cf. Table S.29), but Symbolisation is a highly significant predictor ($p = .001$). The interpretation of this effect is that having an above-median Symbolisation score predicts an increase in the number of charities of 25 percent. Interestingly, of the treatments where giving to multiple charities involves transaction costs, only the association in *PublicN* reaches statistical significance ($p = .016$). These results suggest that the two decisions, total donations and the number of charities, tap into distinct psychological constructs.

In sum, we find that total donations is related to the desire to posses moral qualities, but the number of charities donors give to – especially in *PublicN* – is related to communicating being moral to others. This supports the notion that many donors in *PublicN* strategically attempt to improve their reputation.

5.3 Why Do Donors Spread Donations?

In Section 4, we demonstrated that donors respond to transaction costs and reputational benefits of giving to more charities. Yet, a general result is that dictators are willing to pay additional transaction costs in order to donate to more than one charity, also when there is no observation. We explore further reasons for why donors may have a preference for donating to more than one charity in this section.

Preference for Diversification. In our study, we found that dictators tend to diversify donations across different charities. While this may relate to a more general diversification bias in decision-making (Read and Loewenstein, 1995; Fox et al., 2005; Baron and Szymanska, 2011) even when this is inefficient (Null, 2011), we also find that the tendency to diversify donations correlates with self-reported preferences for diversification. Specifically, we ask all participants to rate their agreement with the statements "It is important to spread one's donations to reduce the risk that a particular charity will miss out" and "It is important to spread one's donations to reduce the risk that donations will be spent inefficiently".[17] In all treatments and in the total sample, we find that agreement with the statement that a particular charity should not miss out strongly predicts giving to more charities (negative binomial regressions, all $p's < .044$, cf. Table S.25). The interpretation for all treatments combined is that going from 'Completely Disagree' to 'Completely Agree' leads to an increase of 143 percent in the

[17] As noted in Section 3, we sought to make it clear to all participants that giving to multiple charities is inefficient in our setting, so we informed them that all charities had been picked from a list of highly efficient charities. Yet, we included this question in case participants may e.g. doubt the validity of such charity ratings.

number of charities a dictator donates to. Opposingly, agreement with the statement that spreading reduces the risk of inefficiency is always insignificant (all $p's > .115$).[18]

A Preference for Multiple Topics. Another possible reason for giving to multiple charities is that it enables donors to support different topics. Specifically, charities that operate under similar causes are closer to being substitutes, and one may speculate that donors would be less willing to pay additional transaction costs for donating to different but interchangeable charities (e.g. Berman et al., 2018). If this is true in our setting, it would imply that donors who give to more charities choose these from different rather than from the same topic. This is indeed what we find (see Figure S.3).

No Coordination Problem. Another reason for donating to different charities is that dictators may wish to donate to the charities/topics that receive few donations from others. Viewed jointly for all dictators, the giving decision would in this respect be a coordination game, where dictators seek to coordinate on giving in such a way that all the charities/topics that the dictators find important receive donations. Intuitively, if all dictators bundle their giving into a single donation to increase efficiency, there is an increased risk that some of the causes that the dictators deem worthy do not receive funding. This gives rise to strategic uncertainty, and dictators may diversify their donations to reduce this uncertainty.

To test whether dictators view the giving decision as a coordination problem, we use the participants' beliefs about the mean donations to each of the seven topics. Specifically, if participants seek to give to topics that others do not give to, we should see a negative relation between the share a donor allocates to a topic and how much the dictator believes that others give to the topic. Yet, we find the opposite effect: looking only at the dictators who donate positive amounts, we find for all seven topics a positive relation between the share of donations a person allocates to the topic and the expected share of others' donations accruing to the topic (Spearman's $\rho \in [.208; .402]$, all $p's < .001$, cf. Figure S.7). This suggests that dictators do not view the giving decision as a coordination problem; rather, the data are in line with a false-consensus effect (Ross et al., 1977), where dictators believe that there is a consensus to support exactly the topics they find most deserving.

Strategic Choice of Charities? Observability could also change donation behaviour by making dictators give to those charities or topics that they believe spectators find important

[18] One problem with correlating the number of charities with responses to the statements is that agreement with the two statements is highly correlated (Pearson's $r = .455$, $p < .001$). Yet, regressing the total number of charities on the responses separately, we find that the coefficient on 'spreading such that a charity does not miss out' is significantly greater than the coefficient on 'spreading to reduce inefficiency' (Wald test, $p < .001$).

rather than donating to the topics they themselves find important. In other words, observability may change 'what' charities are being donated to in addition to 'how many' charities.

A first test of this channel is to see whether dictators prefer to give to different topics when they are observed compared to when they are not observed. A visual examination suggests that there is no difference in the relative donations made to each topic across the treatments (donated amounts in Figure S.8; number of charities in Figure S.9). This impression is confirmed statistically: in 21 pairwise treatment comparisons (with and without controls), we only find one statistically significant comparison; donors in *PublicNAmount* allocate less of their total donations to the topic of health (fractional regression, $p = .048$).

A second test of whether observability changes 'what' charities dictators give to is to examine how important the topics are, to which the dictators donate. Recall from Section 3 that our survey asks all participants to rate how important they think each topic is (see Appendix S.2 for evidence that there is no post-treatment bias for these questions). Computing the relative importance rating for each topic, we consider the case where dictators give to topics to which they assign a weight less than 1/7; that is, donations to topics that dictators think are less important than the average topic. If we found that dictators in *PublicN* are more likely to give to topics they find relatively unimportant, it could suggest that the dictators sought to give in a way that the spectator would appreciate. Yet, we find no difference in the likelihood that dictators donate to topics they consider relatively unimportant (Fisher's exact tests: *PublicN* vs. *Private*, $p = .359$; *PublicN* vs. *PublicNAmount*, $p = .434$).

In sum, we find no evidence that the dictators are strategically changing which charities or topics they give to when observed.

6 Conclusion

In this paper, we provide empirical evidence that individuals engage in indirect signalling to improve their public image. In the context of charitable giving, we first show that donors care about transaction costs: they reduce the number of charities they give to when each donation is costly. Yet, when donors are observed and evaluated only based on what charities they give to, they (correctly) anticipate that spectators will infer greater donated amounts from a larger number of charities. A considerable share of donors uses this strategically and engage in a wasteful "altruistic bluff", whereby they make multiple tiny donations to signal that they have given large amounts and are thus altruistic. Such bluffing is not possible when spectators also observe total donations, and donors give to fewer charities when total donations are also observed. We also show that the altruistic bluff is effective: when spectators only see what

charities a donor has given to, they infer that giving to more charities imply giving larger amounts and therefore evaluate the donor more positively.

To explain these results, it is important to separate signalling into its direct and indirect components. With this distinction, it becomes evident that signalling can also occur for behaviours that bear no reputational effects per se if the observed behaviours correlate with relevant unobserved behaviours. Some individuals use indirect signalling to deceive others: the observable behaviour – in our case the number of charities donated to – can be strategically used to distort beliefs about unobserved behaviour. This dynamic is not confined to charitable giving and is likely to arise whenever one can easily change visible actions to influence others' beliefs about harder-to-observe actions. For example, job seekers may invest excessively in obtaining public certifications to signal competence and too little in developing substantive, yet less visible, skills. Politicians may devote too much money and time to marketing and frequent social media posts to signal political action, even if this comes at the expense of developing and implementing well-founded policies. And organisations that seek to appear inclusive may invest excessively in the sheer number of visible diversity programmes, even if fewer initiatives of higher quality would improve the organisational culture more. In each case, the focus on an easily observed behaviour as an indirect signal of less visible behaviour leads to a misallocation of resources, distorted beliefs among observers, and reduced overall efficiency. Our study offers potential ways to mitigate such wasteful indirect signalling: if possible, one may seek to remove the observed signal (as in our *Private* treatment) or make the relevant behaviour observed (as in *PublicNAmount*).

Yet, our study also has some limitations that are important for interpreting our results. First, our study draws on only one sample, and it is not clear how the results generalise to other samples or cultures. Notably, because we consider indirect signalling, populations may behave differently not only due to different preferences for a certain behaviour, but also due to different correlations between observed and unobserved behaviours.

Second, our study uses an online lab setting, in which donors signal to anonymous spectators. It is probable that the incentives for signalling are greater in field settings that involve face-to-face interaction and long-run reputation-building. In addition, our setting exogenously imposes a level of observability on the participants. This is interesting from a practical perspective, as e.g. organisations may decide the extent to which workers are monitored, and charities or companies may allow their customers to send signals of different informational value after donations or purchases. In other domains, however, individuals self-select into different degrees of observability, e.g. by choosing what to tell friends or what to post on social media. Because such self-selection increases the scope for manipulating one's public image, it

could be that it reduces the signalling value of observed behaviours. An interesting avenue for future research is therefore to examine how selection into different levels of observability occurs and how such selection influences the credibility of the signals being sent.

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A Appendix

A.1 Conceptual Framework

In this section, we provide further details about the analysis of the conceptual framework presented in Section 2.

Benchmark: No Observability ($\Omega = \{\varnothing\}$). As explained in Section 2, we assume that unobserved behaviour does not influence reputation; that is, if $\Omega = \{\varnothing\}$, then $r_a = r_b = 0$. Then, the optimal decisions are implicitly defined by $g'_a = C'_a - x'_a$ and $g'_b = C'_b - x'_b$. Due to the concavity of g and convexity of $C - x$, this leads to a positive relation between α (β) and a (b). How b (a) is associated with α (β) depends on the sign of g''_{ab}. In the case of charitable giving, spreading one's donations across many charities is inefficient (cf. Footnote 2), and we therefore assume that β is inversely related to efficiency concerns. Yet, there is mixed evidence on the relation between efficiency and donations (Karlan and Wood, 2017): for example, Butera and Horn (2020) find that many donors give less when the charities are efficient, as giving to efficient charities allows donors to save money while maintaining a high charitable output ($g''_{ab} > 0$). In contrast, Metzger and Günther (2019) find that information about aid effectiveness increases donations for high-impact projects and decreases donations for low-impact projects ($g''_{ab} < 0$). Without knowing the sign of g''_{ab} a priori, we instead note from Equations 2 and 3 that (i) $g''_{ab} = 0$ implies no effect of α (β) on b (a), (ii) $g''_{ab} > 0$ implies that an increase in α (β) leads to an increase in b (a), and (iii) $g''_{ab} < 0$ implies that an increase in α (β) leads to a decrease in b (a).

Signalling and Indirect Signalling. With observability, we allow for $r_a \neq 0$ and $r_b \neq 0$. As noted in Section 2, we restrict our attention to pure-strategy Perfect Bayesian equilibria, and we assume a monotonic, increasing relationship between α (β) and a (b), which is anticipated by the spectators (i.e. $\frac{\partial E[\alpha|a\in\Omega]}{\partial a} > 0$, $\frac{\partial E[\beta|b\in\Omega]}{\partial b} > 0$).

In the case of full observability ($\Omega = \{a, b\}$), a and b both influence $R(a, b)$ by their positive relations to α and β, respectively. In addition, there may be a relation between α (β) and b (a), depending on the sign of g''_{ab}. Intuitively, if $g''_{ab} > 0$, an individual may decide on a high level of a both due to a high α and a high b. Thus, a high a and a low b send a stronger signal about α than a high a and a high b. That is, $\frac{\partial E[\alpha|\Omega=\{a,b\}]}{\partial b} < 0$ (and likewise $\frac{\partial E[\beta|\Omega=\{a,b\}]}{\partial a} < 0$). The relative concerns for α (γ_a) and β (γ_b) then determines the sign of r_a and r_b. As explained in Section A.1, $\gamma_a > \gamma_b$ is likely to hold in our experiment on charitable giving. Then, $r_a > 0$, meaning that giving greater amounts provides a good reputation, while the sign of r_b is ambiguous and may even be negative if $\gamma_a > -\gamma_b \frac{\partial E[\beta|\Omega=\{a,b\}]}{\partial b} \cdot \left(\frac{\partial E[\alpha|\Omega=\{a,b\}]}{\partial b}\right)^{-1}$.

Naturally, $g''_{ab} < 0$ would lead to the opposite case. If $g''_{ab} = 0$, i.e. if the psychological benefits received from both behaviours are independent, we assume that there is no reputational spill-overs ($\frac{\partial E[\beta|\Omega=\{a,b\}]}{\partial a} = \frac{\partial E[\alpha|\Omega=\{a,b\}]}{\partial b} = 0$), as α and β are drawn independently. In this case, $r_a > 0 \Leftrightarrow \gamma_a > 0$ and $r_b > 0 \Leftrightarrow \gamma_b > 0$ follow from the positive relation between α (β) and a (b).

The case of partial observability ($\Omega = \{a\}$ or $\Omega = \{b\}$) leads us to distinguish between *direct signalling* and *indirect signalling*. As explained in Section 2, indirect signalling is the effect that b has on $R(a, b)$ via the beliefs about a. This channel is not present when the spectators observe a. If $g''_{ab} > 0$, then $\frac{\partial E[a|\Omega=\{b\}]}{\partial b} > 0$, which in turn leads to $\frac{\partial E[\alpha|\Omega=\{b\}]}{\partial b} > 0$. That is, whereas a greater b, ceteris paribus, predicted a smaller α in the case of full observability ($\frac{\partial E[\alpha|\Omega=\{a,b\}]}{\partial b} < 0$), the opposite may thus be true in the case of partial observability.

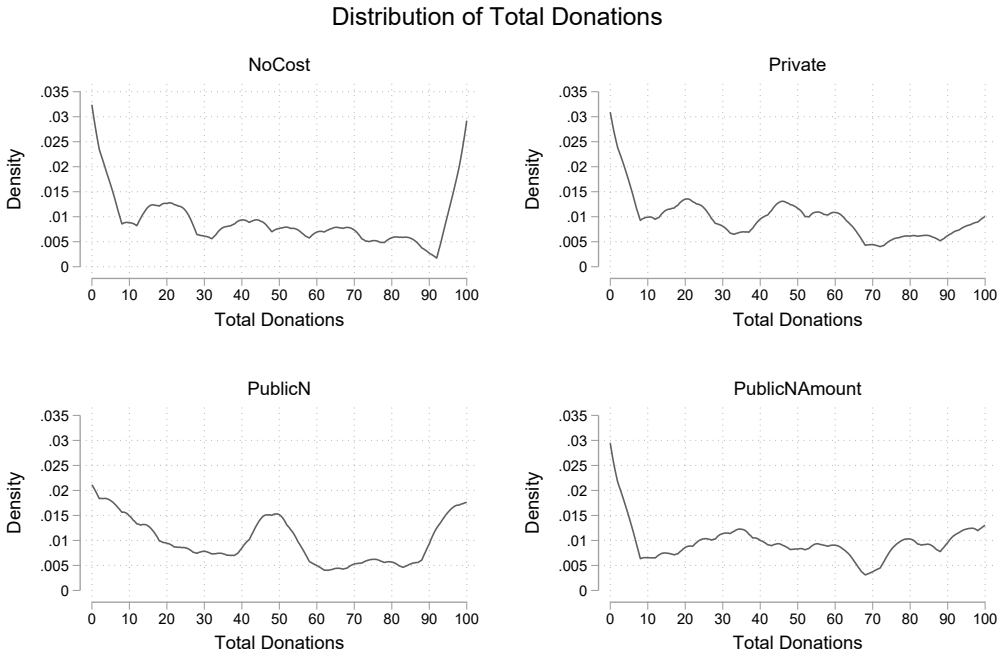
A.2 Tables and Figures

Table A.1: Descriptive Statistics

	NoCost	Private	PublicN	PublicNAmount	Total
Observations (Dictators)	77	170	158	170	575
Donations					
Actual Donations	44.55	40.22	44.64	45.23	43.50
Norm. Exp. Donations	55.35	49.89	52.92	55.05	52.98
Emp. Exp. Donations	41.69	42.66	43.17	42.56	42.64
Charities					
Actual Charities	5.82	3.27	3.82	3.38	3.80
Norm. Exp. Charities	9.60	6.18	4.96	6.59	6.42
Emp. Exp. Charities	7.38	5.65	4.59	4.58	5.27

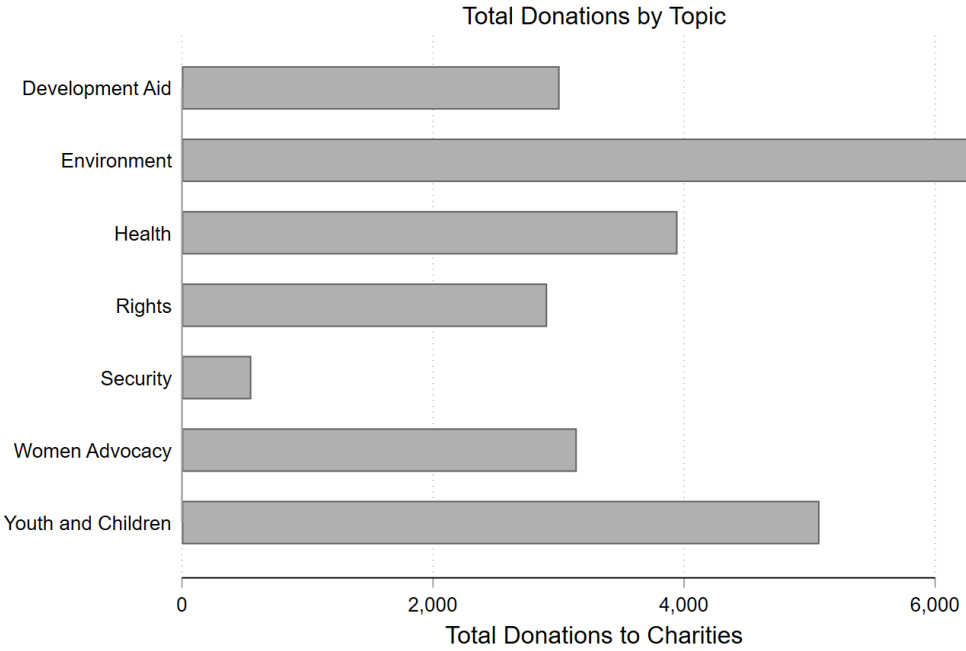
Notes: the table shows average values for each treatment and combining all treatments. Actual Donations and Actual Charities refer to the total donations (excl. transaction costs) and the total number of charities that dictators chose to give to. Norm. (Emp.) Exp. is the normative (empirical) expectations elicited by the dictators after the donation decision. Note that we deliberately randomised fewer dictators into the *NoCost* treatment to obtain more power for the comparisons between levels of observability, cf. the pre-registration. The reason for the lower number of observations in *PublicN* than in *Private* and *PublicNAmount* is that *PublicN* includes an additional control question, cf. Section 3.3.

Figure A.1: Distribution of Total Donations Across Treatments



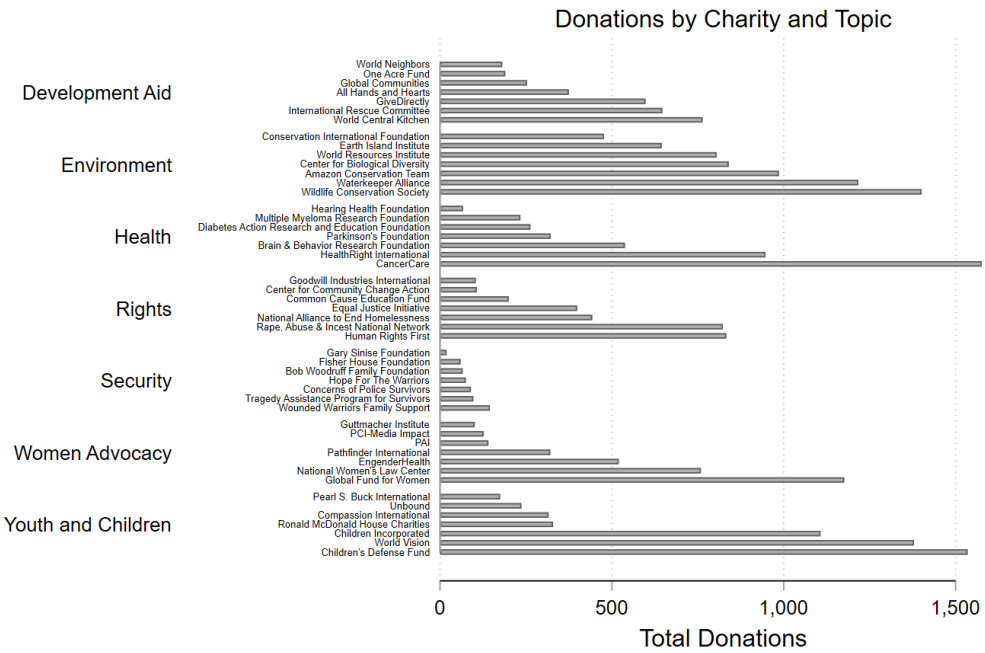
Notes: this figure shows kernel densities of total donations for each treatment, using the Epanechnikov kernel and bandwidth 8.

Figure A.2: Total Donations Across Topics



Notes: this figure shows the total donations to each of the seven topics, pooling all treatments.

Figure A.3: Total Donations Across Charities



Notes: this figure shows the total donations to each charity, grouped by the seven topics. The figure pools donations from all treatments.

Online Supplement

Bluffing in Charitable Giving – An Experiment on Indirect Signalling

Jonas Pilgaard Kaiser & Juliane Koch

31 October 2025

S.1 Power Analysis

We pre-registered that we would aim for 170 dictators in *Private*, *PublicN*, and *PublicNAmount*. This decision was informed by an analysis of statistical power (simulations in Stata, version 17). For comparing dictator decisions about the number of charities to give to, we expected to have a power of 0.8 to detect a minimum treatment difference of approximately 1 charity. To arrive at this result, we assumed that donors would give to an average of 4 charities (similar to the empirical pattern uncovered by Blackbaud Institute (2018)).

For comparing amounts donated between treatments, we run simulations based on giving behaviour in a dictator game by Kaiser (2023), where participants gave on average 37.8 percent of their endowment with a standard deviation of 20.7. Accounting for censoring and using tobit regressions, we expected to have a power of 0.8 to detect a minimum treatment difference of EUR 6.5.

The power simulations are agnostic about the potential explanatory power of the control variables that we use in our analysis. As we do not factor in the efficiency gain from including the control variables, we consider the power estimates to be conservative.

S.2 No Post-Treatment Bias

In this section, we document that there is no evidence of post-treatment bias in the attitudinal variables that we elicit in the survey part of the experiment. Post-treatment bias is a concern that arises when control variables are elicited after the treatment manipulation, as the treatment manipulation could influence the control variables and thereby distort the statistical inference. In the following, we consider possible treatment differences in risk preferences,

answers to the two questions about preferences for spreading donations, answers to the two subscales of the SIMI scale, and the average perceived importance of the seven topics.

We first test for statistical differences when comparing all treatments simultaneously. This has the advantage of reducing the number of tests, thereby reducing the risk of Type I errors. Using the nonparametric Kruskall-Wallis test, we find no statistical differences in any of the aforementioned variables (all $p's > .208$).

Second, we examine all contrasts between treatments in all of the control variables. This analysis has the benefit of capturing differences between treatments in cases where e.g. three of the four treatments are sufficiently similar that the Kruskall-Wallis test does not find overall differences. The disadvantage is that we now conduct six tests for six variables, which implies a potentially inflated Type I error rate. The resulting p-values from Mann-Whintey U-tests are shown in Table S.1. We find no statistically significant differences, but we do find two marginally statistically significant differences. As this is to be expected with 36 tests, we conclude that we find no evidence of post-treatment bias.

Table S.1: Post-Treatment Bias, Pairwise Treatment Comparisons

(a) **Risk Preferences**

	NoCost	Private	PublicN
NoCost	.	.	.
Private	0.235	.	.
PublicN	0.051	0.346	.
PublicNAmount	0.238	0.911	0.431

(b) **Spread for Equality**

	NoCost	Private	PublicN
NoCost	.	.	.
Private	0.358	.	.
PublicN	0.147	0.469	.
PublicNAmount	0.370	0.968	0.431

(c) **Spread for Efficiency**

	NoCost	Private	PublicN
NoCost	.	.	.
Private	0.821	.	.
PublicN	0.302	0.253	.
PublicNAmount	0.619	0.695	0.518

(d) **Internalisation**

	NoCost	Private	PublicN
NoCost	.	.	.
Private	0.464	.	.
PublicN	0.948	0.372	.
PublicNAmount	0.861	0.444	0.888

(e) **Symbolisation**

	NoCost	Private	PublicN
NoCost	.	.	.
Private	0.315	.	.
PublicN	0.594	0.547	.
PublicNAmount	0.059	0.332	0.084

(f) **Perceived Importance**

	NoCost	Private	PublicN
NoCost	.	.	.
Private	0.984	.	.
PublicN	0.201	0.131	.
PublicNAmount	0.217	0.119	0.979

Notes: the tables show p-values for each pairwise comparison between all treatments for the six variables. p-values stem from Mann-Whitney U-tests.

S.3 Robustness

S.3.1 Sample Restrictions

In the main analysis, we included all participants who completed all parts of the experiment and passed all control questions. In the following, we examine the robustness of our results to employing stricter, non-preregistered screeners. First, we exclude participants who provided inconsistent responses to the norm elicitation questions. Here, participants are asked about their beliefs about total donations including transaction costs (when these apply) and their beliefs about the number of charities. In *Private*, *PublicN*, and *PublicNAmount*, the transaction costs of EUR 1 imply that donations should be strictly larger than the number of charities, and we thus exclude 19 participants from the main sample for whom this was not the case. Second, as we run an online experiment, one potential concern is the use of bots in aiding participants. As suggested by Zhang et al. (2022), participants with an odd-numbered screen resolution are potential bots, and this leads to the further exclusion of 20 participants. Third, we exclude participants who answered any control question wrong more times than there were possible multiple choice answers. This can occur since we do not inform participants about what question(s) they get wrong. This leads to the exclusion of further 15 participants. Fourth, we wanted to exclude participants who were flagged by an experimenter in a lab session for needing extensive additional explanation, suffering from technical difficulties, or the like. Yet, while there were seven such participants in our sample, they were all excluded by the previous screeners. Hence, we arrive at a restricted sample of 740 participants.

Across all hypotheses, we find no change in the qualitative conclusions when adding additional sample restrictions. At our preferred level of control (cf. our pre-registration), the incidence ratio for Hypothesis 1 changes from .59 to .61, the incidence ratio for Hypothesis 2.1 changes from 1.21 to 1.18, and the incidence ratio for Hypothesis 2.2 changes from 1.17 to 1.15. For all these cases, the incidence ratios remain statistically significant despite the loss of power from using fewer observations (although the contrast between *PublicN* and *PublicNAmount* now yields $p = .052$). For Hypothesis 3.1, 3.2, and 3.3, the average partial effects change from -1.90, 2.79, and 4.34 to -2.66, 3.10, and 4.24, respectively. In none of these cases do the regressions on the restricted sample yield significant effects.

S.3.2 Models for Analysing Count Data

Negative Binomial Regression vs. Poisson Regression. The Poisson regression is based on the log-likelihood parameterisation of the Poisson probability distribution, and it assumes among other things that the mean of the distribution is equal to its variance. This

assumption is not necessary for the negative binomial regression, which is based on a Poisson-gamma mixture distribution. The negative binomial regression allows for greater variation of the data (overdispersion) compared to a true Poisson distribution, implying that this is more appropriate when the variance of the count variable is greater than its mean. Thus, while the Poisson model has only one parameter, λ, the negative binomial model has two parameters, λ and α, where α is the overdispersion parameter. In all treatments, we find evidence for overdispersion: in *NoCost*, the average number of charities donated to is 5.82 and the variance is 31.89; in *Private*, the average number of charities donated to is 3.27 and the variance is 9.87; in *PublicN*, the average number of charities donated to is 3.82 and the variance is 7.26; in *PublicNAmount*, the average number of charities donated to is 3.38 and the variance is 7.82. Moreover, in all models for H1 and H2, we find that a likelihood-ratio test rejects that $\alpha = 0$, suggesting that there is overdispersion in our models.

The above results supports our use of the negative binomial regression instead of the Poisson regression as the primary model for testing H1 and H2. Yet, examining robustness by running instead Poisson regressions yield similar results: comparing *NoCost* and *Private* (H1) yields an incidence rate ratio of 1.75 ($p < .001$). Comparing *PublicN* to *Private* (H2.1) yields an incidence rate ratio of 1.20 ($p < .001$), and comparing *PublicN* to *PublicNAmount* (H2.2) yields an incidence rate ratio of 1.17 ($p < .001$).

Negative Binomial Regression vs. Zero-Inflated Negative Binomial Regression. While the negative binomial regression may accommodate a large number of zeros, this would restrict the other predicted outcomes. To predict both a large fraction of zeros and not restrict the other outcomes, one may use a zero-inflated negative binomial regression. This is a mixture model that assumes that the excess zero counts come from a model with a binary outcome (e.g. logit, "excess zeros") and that the remaining counts come from a negative binomial regression ("true zeros", allowing for overdispersion). We think it unlikely that our data provide a case of an excess number of zeros, as 86 percent of donors give to a charity in *NoCost* and *Private*, 96 percent of donors give to a charity in *PublicN*, and 85 percent of donors give to a charity in *PublicNAmount*. This suggests that a zero-inflated model may not be suitable in our case. Trying to estimate zero-inflated negative binomial regressions with maximum likelihood (in Stata version 18) resulted in convergence issues, corroborating that the zero-inflated negative binomial regression is not suitable for our data.

These results support our use of the negative binomial regression instead of a zero-inflated negative binomial regression. Yet, we manage to achieve convergence by (i) transforming our measure of volunteering to a continuous rather than a categorical variable, (ii) dropping

the dummies for the different study areas, and (iii) estimating the logit component of the zero-inflated model without controls. Examining robustness by running instead zero-inflated negative binomial regressions yield similar results: we find an incidence rate ratio of 1.72 when comparing *NoCost* and *Private* (H1, $p < .001$), an incidence rate ratio of 1.20 when comparing *PublicN* and *Private* (H2.1, $p < .001$), an incidence rate ratio of 1.15 when comparing *PublicN* and *PublicNAmount* (H2.2, $p = .062$).

In sum, the data support using a negative binomial regression as the main specification for analysing the number of charities that donors give to. Yet, using instead alternative count data models yields similar results.

S.3.3 Updating the Participation Fee

After starting data collection, we noticed that the experiment lasted slightly longer than in the pilot, implying that we set the participation fee too low for ensuring ethical remuneration of the participants. As a consequence, we raised the participation fee from EUR 3 to EUR 4.5, and participants taking part in the experiment after the first two sessions were aware of the participation fee before starting the experiment.

To ensure that our treatment effects were not influenced by any potential wealth effects from this change of the participation fee, we estimate all our primary specifications when controlling for the level of the participation fee. Importantly, we confirm that all our results were unaffected by this change: we still find significant effects for the number of charities donors give to (H1: $p < .001$; H2.1: $p = .023$; H2.2: $p = .035$), whereas the results for total donations remain statistically insignificant (H3.1: $p = .624$; H3.2: $p = .480$; H3.3: $p = .241$).

S.3.4 Different Operationalisations of Control Variables

Preferences for Spreading Donations. In our main specifications reported in Section 4, we preregistered to control for two variables measuring preferences for diversification. Specifically, the participants rated their agreement with the statements "It is important to spread one's donations to reduce the risk that a particular charity will miss out" and "It is important to spread one's donations to reduce the risk that donations will be spent inefficiently". One issue with using these control variables jointly is, however, that they turned out to be strongly correlated in our data ($r = 0.455$, $p < .001$). If we instead average the responses to the two statements to construct one variable capturing preferences for spreading donations, we find that this strongly predicts how many charities participants give to. Across the tests for H1 and H2, the incidence rate ratio for preferences for spreading donations is between 1.54 and 3.50, all $p's < .050$.

Importantly, our results are unchanged when we change the main specification by replacing the two variables measuring preferences for diversification with their average. Doing so yields significant results for the number of charities participants give to (H1: $p < .001$; H2.1: $p = .021$; H2.2: $p = .038$), while the results for total donations remain statistically insignificant (H3.1: $p = .659$; H3.2: $p = .375$; H3.3: $p = .235$).

Volunteering. In our main specifications reported in Section 4, we control for volunteering as a categorical variable, essentially including a dummy for each possible interval reported by participants. Controlling instead for volunteering as a continuous variable taking on the middle value in each interval does not alter the results: across all tests of our hypotheses, volunteering does not predict neither the number of charities (H1: $p = .830$; H2.1: $p = .307$; H2.2: $p = .109$) nor the total donations (H3.1: $p = .474$; H3.2: $p = .596$; H3.3: $p = .293$). Moreover, our main results for the treatment comparisons remain the same for both the number of charities (H1: $p < .001$; H2.1: $p = .019$; H2.2: $p = .025$) and the total donations (H3.1: $p = .563$; H3.2: $p = .467$; H3.3: $p = .220$).

S.3.5 Correcting for Multiple Hypothesis Testing

We preregistered the six main hypothesis that we tested in Section 4, of which H1 concerns the role of efficiency concerns, H2.1-2 concern (indirect) signalling through the number of charities, and H3.1-3 mainly concern (direct) signalling through the total donations. Testing six rather than one hypothesis implies that our expected overall type I error rate – the probability of finding an effect when there is in fact no effect – is larger than the significance level of .05. We therefore preregistered to also report p-values where we correct for the false discovery rate (FDR) and family-wise error rate (FWER). As we adjust the p-values for multiple hypothesis testing, note that while the type I error rate decreases, the type II error rate – the probability of failing to find an effect when there is in fact an effect – increases.

False Discovery Rate. The FDR is the expected share of detected effects that are false. We control for the FDR using the procedure by Benjamini et al. (2006), which is a linear step-up procedure to obtain multiplicity-adjusted p-values (so-called q-values, see also Anderson, 2008). Controlling the FDR at a level of .05 leads to q-values that imply at least marginal statistical significance for the hypotheses concerning the number of charities (H1: $p = .001$, H2.1: $p = .058$, H2.2: $p = .063$). Unsurprisingly, all results for total donations remain statistically insignificant (all $p's > .226$).

Family-Wise Error Rate The FWER is the probability of falsely rejecting at least one null hypothesis among all hypotheses in a family of tests (all six hypotheses in our case). Controlling the FWER is a more conservative alternative to controlling the FDR, implying that this test involves less statistical power (i.e. a greater risk of a type II error). We control the FWER by the resampling procedure put forth by Westfall and Young (1993), using the *wyoung* package in Stata version 18. This leads to multiplicity-adjusted p-values that suggest that our results related to the number of charities are at least marginally statistically significant (H1: $p < .001$, H2.1: $p = .080$, H2.2: $p = .080$). Again, all results for total donations remain insignificant (all $p's > .4$).

S.4 Discussion

S.4.1 Effect of Transaction Costs

A closer look at the data reveals that the treatment difference is driven by a change on the intensive rather than the extensive margin. That is, we find no effect of transaction costs on the number of dictators who decide to make positive donations. In both *NoCost* and *Private*, 86 percent of dictators donate to charity, and there are no significant differences when adding control variables (logit regression, $p = .995$). Rather, we find a large difference in how many charities dictators give to conditional on them making positive donations. In negative binomial regressions using only the donors who make a positive donation, we find a highly significant treatment difference for all levels of control (irr $= .59$, $p < .001$). Intuitively, holding all control variables at their means, the predicted average number of charities in *NoCost* is 6.19, and the predicted value for *Private* is 3.68.

S.4.2 The Role of Social Norms

As explained in Section 3.2, we elicit normative and empirical expectations from the dictators about both the number of charities and the total donations. In the following, we first present the expectations of the dictators and compare these with the actual decisions made by the dictators.

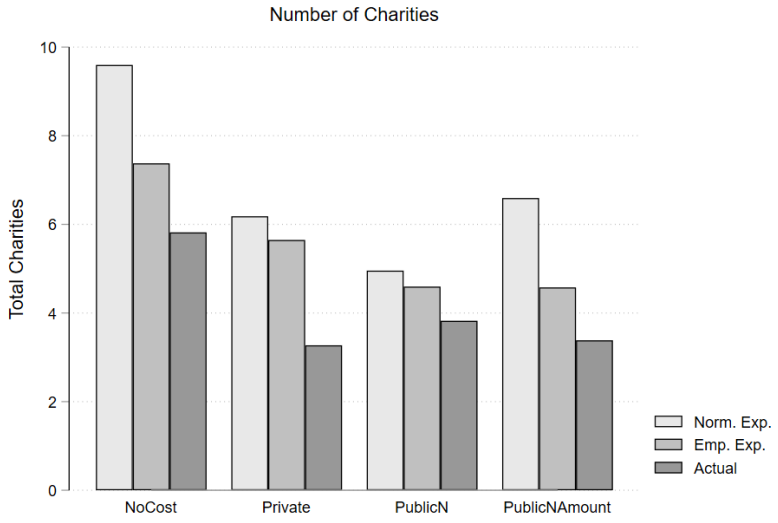
Charities. We first examine the normative and empirical expectations related to the decision about how many charities to give to. As seen in Figure S.1, we find in all treatments that the average normative and empirical expectations are considerably greater than one. That is, dictators on average believe that (i) a separate sample has stated that they believe one ought to give to more than one charity, and (ii) the median dictator gives to more than one charity.

Because giving to only one charity is the most efficient way of giving in our setting, this suggests that dictators on average expect others to assign importance to giving to multiple charities. This corroborates earlier findings in the literature that individuals tend to care more about *giving* than giving *efficiently* (Berman et al., 2018; Metzger and Günther, 2019). In comparing the average decisions made by dictators to their expectations, we use negative binomial regressions while clustering on the level of the dictator. We find that the average decision made by dictators falls short of both the normative and empirical expectations in all treatments (all $p's < .053$).

Yet, comparing normative and empirical expectations between *NoCost* and *Private* shows that both expectations decrease with transaction costs. That is, dictators believe that when there are transaction costs, others state that one ought to give to fewer charities and other donors actually give to fewer charities on average (negative binomial regressions, both $p's < .001$).

In sum, we find that there is a norm of giving to multiple charities, but the average normative and empirical expectations decrease when there are transaction costs.

Figure S.1: Expectations Related to Number of Charities



Notes: the figure presents the average normative and empirical expectations of the number of charities in each treatment and compares this to the actual donation pattern on average.

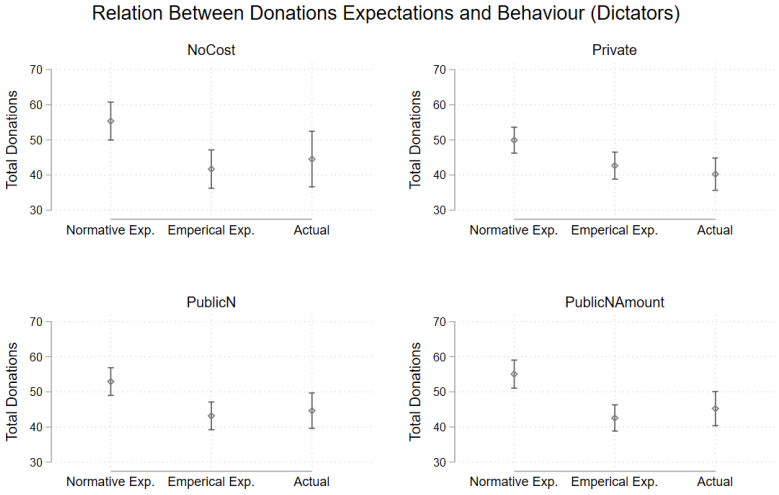
Donations. We next look at the normative and empirical expectations about the total donations. As seen in Figure S.2, dictators in all treatments have normative expectations that exceed both the empirical expectations and actual donations (Wilcoxon signed-rank tests, all

$p's < .017$). Thus, while dictators on average have normative expectations of donations of EUR 50-55 across all treatments, empirical expectations are only EUR 42-43 and actual donations EUR 40-45. In contrast, the average empirical expectations are aligned with the average donations (Wilcoxon signed-rank tests, all $p's > .216$).

Looking instead across treatments, we find in general no differences in normative expectations (MWU-test, $allp's > .370$), but the contrast between *Private* and *PublicNAmount* is marginally statistically significant (MWU-test, $p = .059$). In terms of empirical expectations, we find no difference among any treatments (MWU-test, all $p's > .719$). That is, we find that neither expectation responds to the introduction of transaction costs nor observability.

In sum, we find in all treatments that normative expectations exceed both empirical expectations and average donations. The treatments do not influence any of the two expectations.

Figure S.2: Expectations Related to Donations



Notes: the figure presents average normative and empirical expectations about the total donations in each treatment and compares this to the total donations made by donors on average. The bars display 95 percent confidence intervals.

Spectators. Lastly, we asked spectators in both *PublicN* and *PublicNAmount* about their personal normative beliefs, i.e. how many charities they think dictators ought to give to and how much they think dictators ought to give. For the number of charities, we find median responses in both treatments of 4 and 3, respectively. That is, in both treatments spectators believe that one ought to give to more than 1 charity, suggesting a preference for spreading donations. The answers in the two treatments are not statistically significantly different (negative binomial regression, $p = .671$). With regards to total donations, the median

in both treatments is EUR 55, and answers are not statistically significantly different (MWU-test, $p = .724$).

S.4.3 Gender Differences

In this section, we report gender difference in giving behaviour, i.e. number of charities and total amount, and how this relates to existing literature. Information about preferences for efficiency and equality as well as the Self-Importance of Moral Identity scale allows us to identify underlying mechanisms for such gender differences. Finally, we provide results on differences between men and women as regard the responsiveness to partial observability.

Preferences for Spreading Donations. First, we find that women are more likely to agree to the statement "It is important to spread one's donations to reduce the risk of any organisation coming up short". The interpretation of the coefficient is that men tend to score 0.1 lower in their agreement on a scale from 0 ("Strongly disagree") to 1 ("Strongly agree"), and the difference is statistically significant for all levels of control (OLS regressions, all $p's < .038$, cf. Table S.3). In contrast, we find no gender differences in agreement with the statement "It is important to spread out your donations to reduce the risk that donations will be spent inefficiently" (OLS regressions, all $p's > .358$).

Table S.3: Gender and Preferences for Spreading Donations

	Spread for Efficiency			**Spread for Equality**		
Male	-0.03	-0.02	-0.01	-0.09***	-0.08***	-0.06**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Constant	0.42***	0.25***	0.19	0.48***	0.36***	0.14
	(0.02)	(0.08)	(0.13)	(0.02)	(0.08)	(0.13)
Demographic Controls	No	Yes	Yes	No	Yes	Yes
Attitudinal Controls	No	No	Yes	No	No	Yes
Observations	498	498	498	498	498	498

Notes: OLS regressions with spread preferences as dependent variable, transformed to Proportion of Maximum Possible, and robust standard errors in parentheses. The regressions exclude the NoCost treatment, as this treatment does not involve transaction costs of spreading donations, but results are robust to including this.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Self-Importance of Moral Identity. Second, we find that women score higher on both sub-scales of the 10-item Self-Importance of Moral Identity (SIMI) scale. Specifically, the SIMI scale elicits the degree to which a person wants to possess moral qualities (Internalisation) and the degree to which a person believes that their actions communicate being moral to others

(Symbolisation). For Internalisation, we find that women score 0.04 higher than men on a scale from 0 to 1, and this difference is statistically significant for all levels of control (OLS regressions, all $p's < .014$, cf. Table S.4). For Symbolisation, the difference is 0.08 on a scale from 0 to 1 (OLS regressions, all $p's < .001$, cf. Table S.4). That is, women in general state that morality is more important for their self-identity, and this is true for both their desire to possess moral qualities and to communicate being moral.

Table S.4: Gender and Self-Importance of Moral Identity

	Internalisation			**Symbolisation**		
Male	-0.04***	-0.04***	-0.03**	-0.08***	-0.07***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Constant	0.84***	0.87***	0.85***	0.45***	0.32***	0.26***
	(0.01)	(0.03)	(0.03)	(0.01)	(0.05)	(0.06)
Demographic Controls	No	Yes	Yes	No	Yes	Yes
Attitudinal Controls	No	No	Yes	No	No	Yes
Observations	575	575	575	575	575	575

Notes: OLS regressions with SIMI subscales as dependent variable, transformed to Proportion of Maximum Possible, and robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Differences in Charities and Donations. We now turn to the actual behaviour of men and women in the role of dictators. Here, we find that men tend to give to 16 percent fewer charities (negative binomial regression, $p = .016$), and men on average donate EUR 11.44 less than women (average partial effect, tobit regression, $p < .001$). While both differences remain statistically significant when including demographic controls, only the difference in average donations remain when also including attitudinal controls (average partial effect of EUR 6.45, $p = .044$), whereas the difference in the number of charities becomes statistically insignificant ($p = .494$), cf. Tables S.5 and S.6. This reduction of the estimated difference and statistical significance can be explained by the fact that both preferences for spreading donations, Internalisation, and Symbolisation to some extent predict the donation patterns by the dictators. Hence, the gender differences in attitudes towards spreading donations and the self-importance of morality explain gender differences in the number of charities and partly explains gender differences in total donations.

These results extend previous findings on gender differences in charitable giving. First, Bloom (2016) describes that women in general give to more charities than men when giving is influenced by empathy, and women have been shown to be less concerned about efficiency than men (Croson and Konow, 2009). Our results corroborate these findings and suggest that the gender differences can be explained by (i) the different preferences for giving to multiple

charities out of a fear that some charities might miss out and (ii) how important the moral identity of the genders is.

Table S.5: Gender and the Number of Charities

	(1)	(2)	(3)
Male	0.84**	0.85**	0.95
	(0.06)	(0.06)	(0.07)
Private	0.57***	0.56***	0.59***
	(0.06)	(0.06)	(0.06)
PublicN	0.68***	0.67***	0.70***
	(0.07)	(0.07)	(0.07)
PublicNAmount	0.58***	0.58***	0.59***
	(0.06)	(0.06)	(0.06)
Age		0.99	0.99
		(0.01)	(0.01)
Social Sciences		1.00	0.97
		(0.13)	(0.11)
Humanities		0.97	0.97
		(0.11)	(0.10)
Economics		0.95	0.96
		(0.10)	(0.09)
Medicine		0.77	0.80
		(0.18)	(0.17)
Law		1.11	1.09
		(0.13)	(0.12)
Other Field of Study		1.03	1.04
		(0.12)	(0.11)
1-5 Hours, Volunteering		1.04	0.96
		(0.11)	(0.10)
5-10 Hours, Volunteering		1.14	0.94
		(0.13)	(0.10)
10-20 Hours, Volunteering		0.88	0.77**
		(0.11)	(0.09)
20-30 Hours, Volunteering		1.05	0.86
		(0.15)	(0.11)
More Than 30 Hours, Volunteering		1.02	0.91
		(0.10)	(0.09)
Spread Donations for Equality			2.44***
			(0.29)
Spread Donations for Efficiency			1.00
			(0.12)
Internalisation (SIMI)			1.53*
			(0.38)
Symbolisation (SIMI)			2.10***
			(0.34)
Observations	575	575	575

Notes: negative binomial regressions with the number of charities as the dependent variable. The baseline is a person in the *NoCost* treatment who studies Natural Sciences and does not volunteer (0 Hours). Coefficients are incidence rate ratios.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Responsiveness to Treatments. Finally, we look at how responsive men and women are to the *PublicN* treatment, which allows for indirect signalling. As our study is powered to test for main effects and not interaction effects, we pool all other treatments to increase statistical power. In doing so, we find that women do not respond to the *PublicN* treatment;

Table S.6: Gender and Total Donations

	(1)	(2)	(3)
Male	-11.44***	-10.87***	-6.45**
	(3.20)	(3.25)	(3.19)
Private	-6.38	-5.82	-4.51
	(5.04)	(5.01)	(4.83)
PublicN	0.92	-0.03	0.29
	(5.09)	(5.07)	(4.88)
PublicNAmount	-1.41	-1.88	-1.86
	(5.04)	(5.05)	(4.87)
Age		-0.59**	-0.48*
		(0.29)	(0.28)
Social Sciences		0.45	-1.86
		(5.52)	(5.30)
Humanities		2.87	2.58
		(5.06)	(4.86)
Economics		-3.05	-1.93
		(4.51)	(4.34)
Medicine		-10.53	-13.09
		(9.60)	(9.28)
Law		-8.79*	-9.03*
		(5.14)	(4.93)
Other Field of Study		4.83	5.13
		(5.26)	(5.07)
1-5 Hours, Volunteering		-3.75	-5.27
		(4.69)	(4.54)
5-10 Hours, Volunteering		-2.86	-7.45
		(5.16)	(5.08)
10-20 Hours, Volunteering		-0.69	-2.12
		(5.26)	(5.19)
20-30 Hours, Volunteering		0.31	-5.65
		(6.16)	(6.08)
More Than 30 Hours, Volunteering		4.19	1.97
		(4.22)	(4.30)
Spread Donations for Equality			23.81***
			(5.64)
Spread Donations for Efficiency			-13.77**
			(5.51)
Internalisation (SIMI)			51.76***
			(11.18)
Symbolisation (SIMI)			9.11
			(7.62)
Observations	575	575	575

Notes: Average partial effects from tobit regressions with total donations as dependent variable, robust standard errors in parentheses. The baseline is a person in the *NoCost* treatment who studies Natural Sciences and does not volunteer (0 Hours).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the incidence rate ratio is .92 and statistically indistinguishable from 1 (negative binomial regression, $p = .442$), and this is unaffected by the level of control, cf. Table S.7. In contrast, the incidence rate ratio for men is 1.35, and this difference is marginally statistically significant ($p < .062$) and unaffected by the level of control, cf. Table S.7. This implies that men are more responsive to the *PublicN* treatment than women in increasing the number of charities they give to (although from a lower baseline as shown above).

Table S.7: Gender and Responsiveness to PublicN

	(1)	(2)	(3)
Male	0.75***	0.76***	0.86*
	(0.07)	(0.07)	(0.07)
PublicN	0.92	0.91	0.95
	(0.09)	(0.09)	(0.09)
Male × PublicN	1.35*	1.36*	1.33*
	(0.22)	(0.22)	(0.20)
Demographic Controls	No	Yes	Yes
Attitudinal Controls	No	No	Yes
Observations	575	575	575

Notes: negative binomial regressions with the number of charities as the dependent variable. The demographic controls are age, gender, field of study, and volunteering. The attitudinal controls are preferences for spreading donations (two questions) and the two subscales of the Self-Importance of Moral Identity scale. Coefficients are incidence rate ratios.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

S.4.4 1/N Heuristic

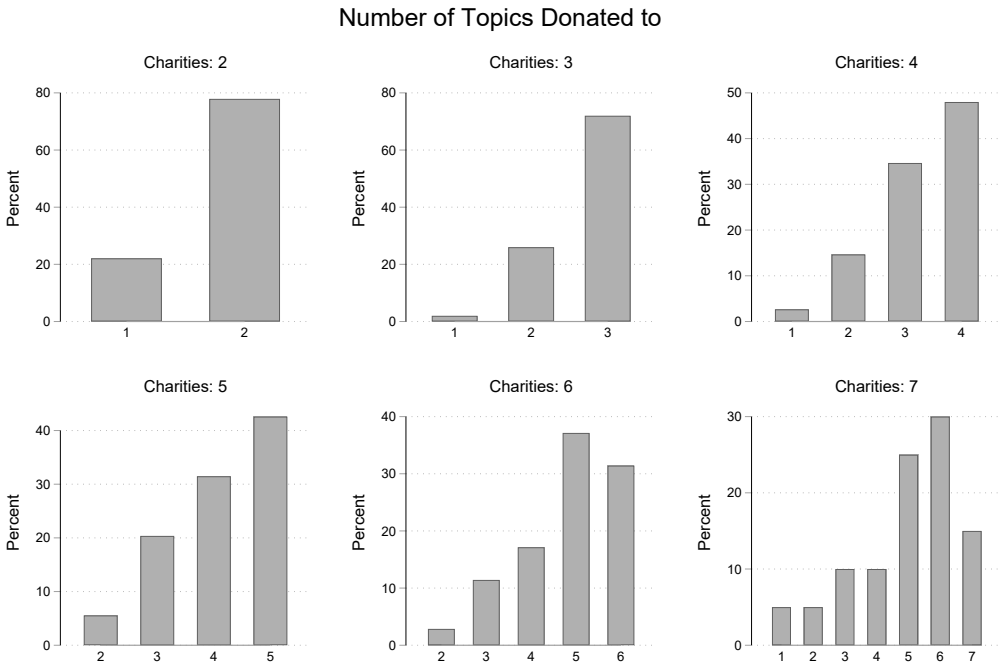
Of the dictators who donate to more than one charity, 42 percent apply a naive form of diversification, in which they give the same share of their donations to each of the charities they donate to (cf. the 1/N heuristic, Benartzi and Thaler, 2001). One might suspect that the tendency to use a 1/N heuristic is lower in *PublicNAmount*, as donors have the opportunity to signal to the spectators what charities are relatively more important. Yet, if anything, the opposite seems to be true: in *PublicNAmount*, 50 percent of dictators who give to more than one charity use the 1/N heuristic; the respective shares for the other treatments is 37-42 percent.

S.4.5 Diversification Across Topics

Figure S.3 pools all treatments and shows the distribution of how many topics dictators gave to, separated by how many charities the dictators donate to (from 2 to 7). For instance, among

the 100 dictators who gave to three charities, 72 picked those charities from three different topics, 26 picked them from two different topics, and the remaining 2 dictators picked them from the same topic. For all dictators who gave to 2-5 charities, picking each charity from its own topic is the mode of the distribution. For the dictators who gave to 6 or 7 charities, the mode is instead to give to one less topic than the number of charities, i.e. 5 or 6, respectively. This suggests that dictators who give to more charities tend to choose these from different topics.

Figure S.3: Donations Spread Across Topics



Notes: this figure pools all treatments and shows the distribution of the number of topics dictators donate to, separated by the number of charities the dictators donated to (from 2 to 7). For instance, the top left graph shows the distribution of the number of topics for the dictators who gave to two charities. Of these dictators, 78 percent donated to two different topics, whereas 22 percent donated to two charities within the same topic.

S.4.6 Experimenter Demand Is Unlikely to Drive the Effects

Experimenter demand effects (EDE) refer to changes in participants' behaviour due to expectations about what the researcher wants or perceives as appropriate behaviour (Orne, 1962; Zizzo, 2010). Although there is only limited evidence of EDE in experimental economics (Camerer, 2015; de Quidt et al., 2019), we address potential concerns of EDE in this section and explain why it is unlikely to influence the qualitative results of this paper.

One possible concern is that the instructions influence how much donors give in the experiment, for example, through the examples and control questions that are provided. Yet, the examples that are provided to explain the task balance high and low donations to avoid such influence. Thus, when reading the rules of the experiment, participants see both an example with donations of 5€ to one charity and total donations of 40€ to three charities. In the control questions, participants are asked about earnings and transaction costs for total donations of 20€, 5€, and 40€ to 2, 1, and 3 charities, respectively. These examples were also constant across treatments. Consequently, the examples avoid providing a strong anchor for the donors. Accordingly, Figure A.1 shows that the size of donations were distributed through the entire range with no strong bunching on a particular amount.

A second possible concern is that highlighting transaction costs could signal to donors that it is better to only give to one charity. In particular, the instructions in all treatments with transaction costs explain that giving to more charities leads to greater transaction costs, thereby reducing the total amount that can be given to the charities. In thus explaining the consequences of transaction costs, donors could perceive that they should not spread donations. Yet, as documented in Table A.1, the average normative expectations for the number of charities to give to in the treatments with transaction costs range between 4.96 and 6.59. This is considerably larger than the average number of charities that donors give to in these treatments (3.27-3.82). Thus, explaining the consequences of the transaction costs did not lead the participants to think of it as inappropriate to spread donations to many charities.

In sum, we consider it unlikely that EDE is driving the qualitative results of this paper. This is supported by further design choices that are often argued to reduce EDE: for example, we use a between-subjects design, in which participants are blind to the other treatments (Charness et al., 2012). Also, the experiment was conducted as an online lab study, which avoids the participants' reliance on us rejecting or accepting their work based on their responses (as is e.g. the case with crowdworking platforms such as Amazon's Mechanical Turk, Mummolo and Peterson, 2019). The online lab format also implied that participants read the instructions on their own and had no face-to-face interaction with the experimenter (Zizzo, 2010). And the experimenters in charge of conducting the online sessions did not know the purpose or hypotheses of the study (de Quidt et al., 2019).

In addition to EDE, note that donors in the observed treatments may be influenced to act based on expectations about what their peers consider appropriate. Specifically, donors are told that two other participants will learn their last names and assess them based on either what charities they donate to ($PublicN$) or what charities they donate to and how much ($PublicNAmount$). This may induce donors to behave in such a way that will increase their

social esteem, for example, by increasing donations to appear altruistic. Importantly, this type of behavioural change based on the expectations and reactions of others is exactly what we aim to study in this paper.

S.5 Further Tables and Figures

S.5.1 Main Analysis

Table S.8: Sample characteristics

	Freq.	Percent
Gender		
Female	511	64.4
Male	282	35.6
Field of Study		
Natural Sciences	190	24.0
Social Sciences	93	11.7
Humanities	115	14.5
Economics	167	21.1
Medicine	22	2.8
Law	110	13.9
Other	96	12.1
Volunteering in the Previous Year		
0 Hours	272	34.3
1-5 Hours	133	16.8
5-10 Hours	96	12.1
10-20 Hours	80	10.1
20-30 Hours	50	6.3
More Than 30 Hours	162	20.4
Total	793	100.0

Table S.9: Summary statistics by Treatment and Role

	NoCost	Private	PublicN	PublicNAmount	Total
Dictators					
Risk preferences	0.46	0.50	0.52	0.49	0.50
Spread Donations for Equality	0.49	0.45	0.43	0.46	0.45
Spread Donations for Efficiency	0.44	0.42	0.39	0.41	0.41
Internalisation	0.83	0.82	0.83	0.83	0.83
Symbolisation	0.39	0.42	0.41	0.44	0.42
Spectators					
Risk preferences	.	.	0.52	0.51	0.52
Spread Donations for Equality	.	.	0.53	0.42	0.48
Spread Donations for Efficiency	.	.	0.47	0.44	0.46
Internalisation	.	.	0.88	0.85	0.87
Symbolisation	.	.	0.40	0.44	0.42
Social Norm Raters					
Risk preferences	0.52	0.43	0.47	0.47	0.47
Spread Donations for Equality	0.47	0.36	0.35	0.44	0.41
Spread Donations for Efficiency	0.36	0.32	0.27	0.35	0.33
Internalisation	0.82	0.85	0.85	0.86	0.84
Symbolisation	0.44	0.39	0.40	0.40	0.41

Notes: the table shows the average values by treatment and role. All variables are standardised as proportions of maximum possible (POMP) scores with 0 (1) being the lowest (highest) possible score. 'Spread Donations for Equality' refers to agreement with the statement "It is important to spread out one's donations to reduce the risk that any specific charity misses out on funds". 'Spread Donations for Efficiency' refers to agreement with the statement "It is important to spread out one's donations to reduce the risk that the donations are used inefficiently". Internalisation and Symbolisation are the subscales of the Self-Importance of Moral Identity scale.

Table S.10: Transaction Costs and the Number of Charities (H1)

	(1)	(2)	(3)
Private	0.56***	0.55***	0.59***
	(0.07)	(0.07)	(0.07)
Age		0.97**	0.98**
		(0.01)	(0.01)
Male		0.79*	0.90
		(0.10)	(0.11)
Social Sciences		0.85	0.83
		(0.18)	(0.16)
Humanities		0.83	0.84
		(0.16)	(0.15)
Economics		0.84	0.86
		(0.15)	(0.14)
Medicine		0.82	0.78
		(0.28)	(0.26)
Law		1.19	1.09
		(0.24)	(0.20)
Other Field of Study		1.04	0.96
		(0.25)	(0.22)
1-5 Hours, Volunteering		1.28	1.28
		(0.24)	(0.22)
5-10 Hours, Volunteering		1.33	1.08
		(0.25)	(0.20)
10-20 Hours, Volunteering		0.99	0.89
		(0.20)	(0.18)
20-30 Hours, Volunteering		1.17	0.91
		(0.27)	(0.20)
More Than 30 Hours, Volunteering		1.27	1.09
		(0.22)	(0.19)
Spread Donations for Equality			2.13***
			(0.45)
Spread Donations for Efficiency			0.76
			(0.15)
Internalisation (SIMI)			2.52**
			(1.13)
Symbolisation (SIMI)			2.56***
			(0.75)
Observations	247	247	247

Notes: negative binomial regressions with the number of charities as the dependent variable. The baseline is a person in the *NoCost* treatment who studies Natural Sciences and does not volunteer (0 Hours). Coefficients are incidence rate ratios.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.11: Observability the Number of Charities (H2)

	PublicN vs. Private			**PublicN vs. PublicNAmount**		
	(1)	(2)	(3)	(4)	(5)	(6)
PublicN	1.17*	1.20**	1.21**	1.13	1.14	1.17**
	(0.10)	(0.11)	(0.10)	(0.09)	(0.10)	(0.09)
Age		0.98**	0.97***		1.01	1.00
		(0.01)	(0.01)		(0.01)	(0.01)
Male		0.98	1.06		0.86	0.98
		(0.09)	(0.09)		(0.08)	(0.08)
Social Sciences		1.23	1.18		1.04	1.01
		(0.19)	(0.17)		(0.16)	(0.14)
Humanities		1.08	1.06		1.05	1.03
		(0.16)	(0.14)		(0.15)	(0.13)
Economics		1.11	1.08		0.99	0.96
		(0.15)	(0.13)		(0.13)	(0.11)
Medicine		0.91	0.93		0.70	0.79
		(0.23)	(0.22)		(0.22)	(0.23)
Law		1.20	1.10		0.99	1.03
		(0.18)	(0.15)		(0.14)	(0.13)
Other Field of Study		1.02	0.98		1.03	1.04
		(0.16)	(0.14)		(0.13)	(0.12)
1-5 Hours, Volunteering		1.02	0.94		0.91	0.80*
		(0.14)	(0.12)		(0.12)	(0.09)
5-10 Hours, Volunteering		1.20	1.03		1.07	0.82
		(0.17)	(0.14)		(0.15)	(0.11)
10-20 Hours, Volunteering		0.93	0.79		0.84	0.68***
		(0.15)	(0.12)		(0.13)	(0.09)
20-30 Hours, Volunteering		1.07	0.86		0.95	0.79
		(0.19)	(0.15)		(0.17)	(0.12)
More Than 30 Hours, Volunteering		1.02	0.92		0.93	0.82*
		(0.13)	(0.11)		(0.10)	(0.08)
Spread Donations for Equality			2.15***			2.60***
			(0.34)			(0.35)
Spread Donations for Efficiency			1.08			1.35**
			(0.17)			(0.18)
Internalisation (SIMI)			1.00			1.17
			(0.31)			(0.33)
Symbolisation (SIMI)			2.12***			1.74***
			(0.45)			(0.34)
Observations	328	328	328	328	328	328

Notes: negative binomial regressions with the number of charities as the dependent variable. The baseline for Specifications (1-3) is a person in the *Private* treatment who studies Natural Sciences and does not volunteer (0 Hours). The baseline for Specifications (4-6) is a person in the *PublicNAmount* treatment who studies Natural Sciences and does not volunteer (0 Hours). Coefficients are incidence rate ratios.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.12: Total Donations, PublicNAmount vs. PublicN (H3.1)

	(1)	(2)	(3)
PublicNAmount	-1.17	-1.58	-1.90
	(3.91)	(3.93)	(3.78)
Age		-0.32	-0.23
		(0.41)	(0.40)
Male		-10.27**	-6.84*
		(4.16)	(4.07)
Social Sciences		8.40	4.62
		(7.25)	(7.02)
Humanities		4.83	3.49
		(6.65)	(6.45)
Economics		-2.74	-2.10
		(5.91)	(5.71)
Medicine		-24.99*	-25.32*
		(13.79)	(13.40)
Law		-9.56	-9.60
		(6.45)	(6.23)
Other Field of Study		1.48	1.16
		(6.16)	(6.00)
1-5 Hours, Volunteering		-4.73	-7.47
		(5.96)	(5.83)
5-10 Hours, Volunteering		0.40	-4.18
		(6.90)	(6.82)
10-20 Hours, Volunteering		-1.50	-2.76
		(6.83)	(6.80)
20-30 Hours, Volunteering		6.70	1.04
		(8.09)	(7.97)
More Than 30 Hours, Volunteering		2.03	0.69
		(5.16)	(5.26)
Spread Donations for Equality			29.04***
			(7.08)
Spread Donations for Efficiency			-12.84*
			(6.98)
Internalisation (SIMI)			38.57***
			(14.22)
Symbolisation (SIMI)			3.01
			(10.00)
Observations	328	328	328

Notes: tobit regressions with total donations as the dependent variable. The baseline is a person in the *PublicN* treatment who studies Natural Sciences and does not volunteer (0 Hours). Coefficients are average partial effects, robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.13: Total Donations, PublicNAmount vs. Private (H3.2)

	(1)	(2)	(3)
PublicNAmount	4.84	3.83	2.79
	(3.93)	(4.01)	(3.92)
Age		-0.59	-0.50
		(0.36)	(0.35)
Male		-9.37**	-4.34
		(4.28)	(4.33)
Social Sciences		2.85	1.01
		(7.73)	(7.55)
Humanities		6.92	6.86
		(6.59)	(6.44)
Economics		5.37	5.75
		(5.80)	(5.66)
Medicine		-4.81	-3.51
		(12.36)	(12.21)
Law		-1.85	-2.55
		(6.70)	(6.53)
Other Field of Study		8.15	9.93
		(7.56)	(7.40)
1-5 Hours, Volunteering		-3.65	-4.78
		(6.04)	(5.96)
5-10 Hours, Volunteering		-0.48	-4.45
		(6.79)	(6.82)
10-20 Hours, Volunteering		0.49	-1.01
		(6.73)	(6.78)
20-30 Hours, Volunteering		4.50	-1.96
		(8.15)	(8.20)
More Than 30 Hours, Volunteering		4.11	1.17
		(5.59)	(5.73)
Spread Donations for Equality			18.86**
			(7.47)
Spread Donations for Efficiency			-11.16
			(7.37)
Internalisation (SIMI)			38.95***
			(14.91)
Symbolisation (SIMI)			14.89
			(9.80)
Observations	340	340	340

Notes: tobit regressions with total donations as the dependent variable. The baseline is a person in the *Private* treatment who studies Natural Sciences and does not volunteer (0 Hours). Coefficients are average partial effects, robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.14: Total Donations, PublicN vs. Private (H3.3)

	(1)	(2)	(3)
PublicN	5.94	5.15	4.34
	(3.78)	(3.80)	(3.73)
Age		-0.98***	-0.90***
		(0.35)	(0.34)
Male		-9.23**	-6.06
		(3.96)	(3.98)
Social Sciences		7.67	5.39
		(6.63)	(6.51)
Humanities		5.16	4.14
		(6.24)	(6.12)
Economics		-2.42	-2.48
		(5.61)	(5.55)
Medicine		0.56	-4.40
		(10.08)	(10.02)
Law		-0.99	-2.82
		(6.45)	(6.33)
Other Field of Study		8.13	6.58
		(6.53)	(6.44)
1-5 Hours, Volunteering		-3.90	-3.65
		(5.78)	(5.73)
5-10 Hours, Volunteering		-3.04	-5.40
		(6.08)	(6.08)
10-20 Hours, Volunteering		1.92	-0.04
		(6.65)	(6.66)
20-30 Hours, Volunteering		-1.07	-4.55
		(7.63)	(7.70)
More Than 30 Hours, Volunteering		6.61	5.73
		(5.29)	(5.51)
Spread Donations for Equality			9.06
			(7.27)
Spread Donations for Efficiency			-6.64
			(7.37)
Internalisation (SIMI)			44.63***
			(14.16)
Symbolisation (SIMI)			5.10
			(9.53)
Observations	328	328	328

Notes: tobit regressions with total donations as the dependent variable. The baseline is a person in the *Private* treatment who studies Natural Sciences and does not volunteer (0 Hours). Coefficients are average partial effects, robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

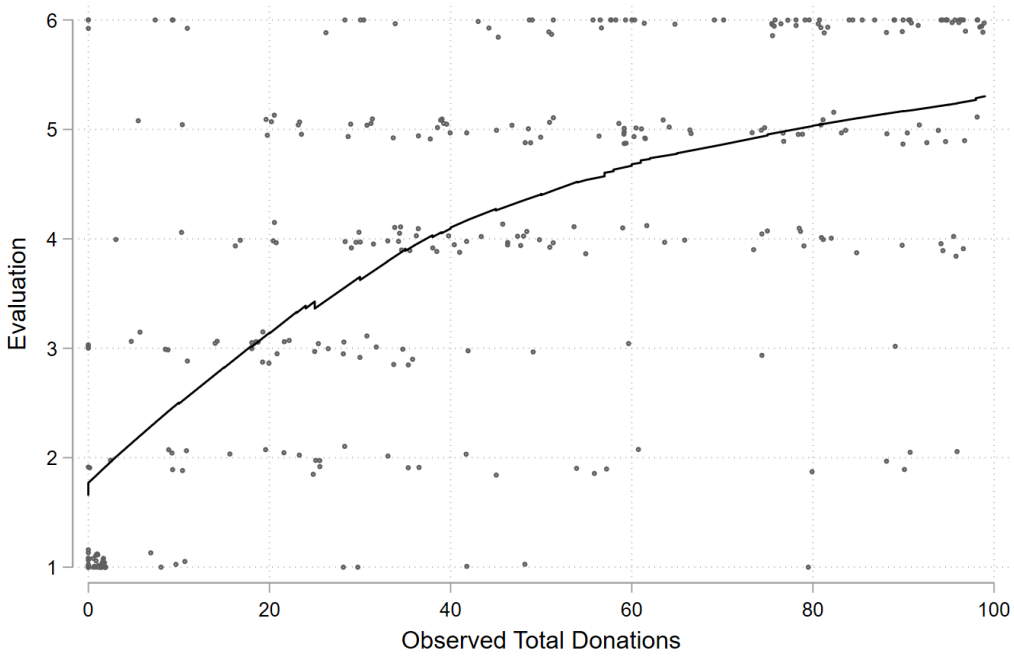
S.5.2 Spectator Evaluations

Table S.15: Spectator Evaluations, PublicNAmount

	(1)	(2)	(3)
Observed Donation	0.03***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)
Observed Charities	0.06	0.05	0.05
	(0.05)	(0.04)	(0.04)
Age		0.03	0.03
		(0.03)	(0.03)
Male		-0.37	-0.38
		(0.23)	(0.26)
Social Sciences		-0.68**	-0.73**
		(0.30)	(0.34)
Humanities		-0.93*	-1.00*
		(0.55)	(0.54)
Economics		-0.54	-0.43
		(0.33)	(0.31)
Medicine		-0.52	-0.69
		(0.46)	(0.60)
Law		-0.09	-0.10
		(0.38)	(0.42)
Other Field of Study		-0.38	-0.40
		(0.33)	(0.33)
1-5 Hours, Volunteering		-0.30	-0.25
		(0.35)	(0.35)
5-10 Hours, Volunteering		0.06	0.08
		(0.30)	(0.29)
10-20 Hours, Volunteering		0.09	0.10
		(0.30)	(0.29)
20-30 Hours, Volunteering		0.95***	0.99**
		(0.35)	(0.37)
More Than 30 Hours, Volunteering		-0.52	-0.52
		(0.40)	(0.38)
Spread Donations for Equality			-0.39
			(0.41)
Spread Donations for Efficiency			-0.21
			(0.46)
Internalisation (SIMI)			0.66
			(1.24)
Symbolisation (SIMI)			-0.14
			(0.61)
Constant	2.27***	2.00**	1.77
	(0.19)	(0.96)	(1.43)
Observations	330	330	330

Notes: OLS regressions with spectator evaluations as the dependent variable. The baseline is a person who studies Natural Sciences and does not volunteer (0 Hours). Standard errors are clustered at the level of pairs of spectators.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure S.4: Diminishing Effect From Total Donations



Notes: locally weighted regression, using Cleveland's (1979) tricube weighting function and bandwidth 0.8.

Table S.16: Nonlinearity in Spectator Evaluations, PublicNAmount

	(1)	(2)	(3)
Observed Donation	0.0743***	0.0774***	0.0798***
	(0.0113)	(0.0099)	(0.0090)
(Observed Donation)^2	-0.0004***	-0.0005***	-0.0005***
	(0.0001)	(0.0001)	(0.0001)
(Observed Charities)	0.0503	0.0428	0.0293
	(0.1120)	(0.0970)	(0.0951)
(Observed Charities)^2	-0.0035	-0.0034	-0.0024
	(0.0064)	(0.0062)	(0.0060)
Age		0.0403	0.0379
		(0.0305)	(0.0321)
Male		-0.3891*	-0.3853
		(0.2298)	(0.2523)
Social Sciences		-0.6291*	-0.6863*
		(0.3179)	(0.3554)
Humanities		-0.8982	-0.9901*
		(0.5531)	(0.5459)
Economics		-0.5325	-0.3996
		(0.3285)	(0.3046)
Medicine		-0.3966	-0.6021
		(0.4025)	(0.5458)
Law		0.0246	0.0185
		(0.3691)	(0.4107)
Other Field of Study		-0.5202	-0.5279
		(0.3323)	(0.3251)
1-5 Hours, Volunteering		-0.3343	-0.2695
		(0.3395)	(0.3304)
5-10 Hours, Volunteering		-0.0280	-0.0017
		(0.2922)	(0.2825)
10-20 Hours, Volunteering		-0.0098	0.0001
		(0.2868)	(0.2803)
20-30 Hours, Volunteering		0.8313**	0.8715**
		(0.3362)	(0.3595)
More Than 30 Hours, Volunteering		-0.6498	-0.6344
		(0.4201)	(0.3877)
Spread Donations for Equality			-0.4244
			(0.3935)
Spread Donations for Efficiency			-0.2653
			(0.4712)
Internalisation (SIMI)			0.8966
			(1.1851)
Symbolisation (SIMI)			-0.1524
			(0.5901)
Constant	1.7846***	1.3658	0.9688
	(0.2065)	(0.9688)	(1.3729)
Observations	330	330	330

Notes: OLS regressions with spectator evaluations as the dependent variable. The baseline is a person who studies Natural Sciences and does not volunteer (0 Hours). Standard errors are clustered at the level of pairs of spectators.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.17: Evaluations and Total Donations, PublicNAmount

	(Charities $\in \{1,2\}$)	(Charities $\in \{3,4\}$)	(Charities $\in \{5,6\}$)
Observed Donations	0.03***	0.02***	0.02**
	(0.00)	(0.01)	(0.01)
Constant	2.73***	3.31***	3.29***
	(0.21)	(0.34)	(0.42)
Observations	88	108	50

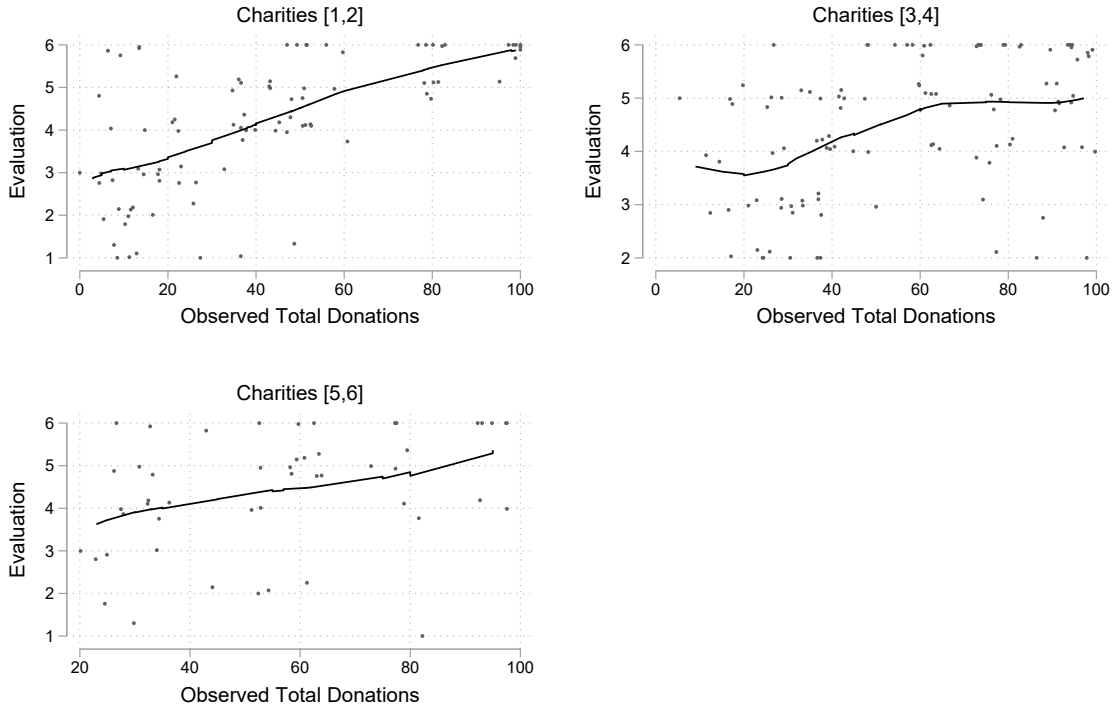
Notes: OLS regressions with spectator evaluations as the dependent variable. Standard errors are clustered at the level of pairs of spectators.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.18: Evaluations and Total Charities, PublicNAmount

	(Donations $\in [10,24]$)	(Donations $\in [25,39]$)	(Donations $\in [40,54]$)
Observed Charities	0.16	0.11	-0.02
	(0.17)	(0.14)	(0.09)
Constant	2.90***	3.35***	4.45***
	(0.42)	(0.60)	(0.33)
Observations	37	55	45
	(Donations $\in [55,69]$)	(Donations $\in [70,84]$)	(Donations $\in [85,100]$)
Observed Charities	-0.32***	-0.04	0.02
	(0.09)	(0.07)	(0.04)
Constant	6.27***	5.17***	5.11***
	(0.39)	(0.30)	(0.32)
Observations	36	41	55

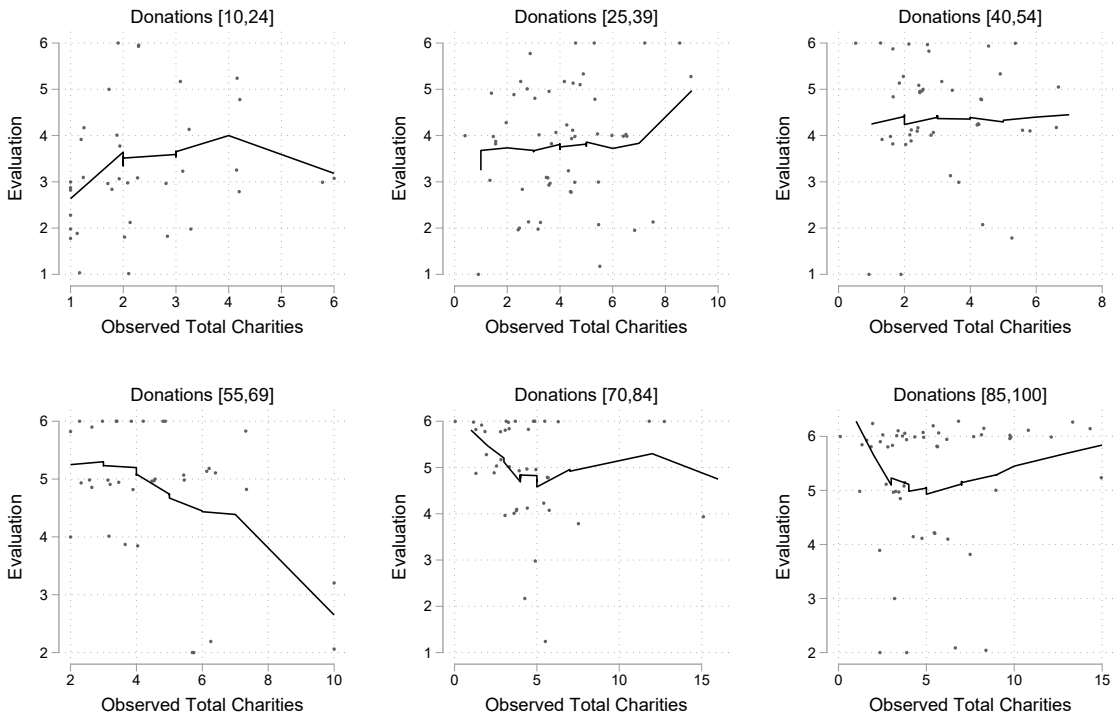
Notes: OLS regressions with spectator evaluations as the dependent variable. Standard errors are clustered at the level of pairs of spectators.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure S.5: Evaluations and Total Donations



Notes: locally weighted regression, using Cleveland's (1979) tricube weighting function and bandwidth 0.8.

Figure S.6: Evaluations and Total Charities



Notes: locally weighted regression, using Cleveland's (1979) tricube weighting function and bandwidth 0.8.

Table S.19: Spectator Evaluations, PublicN

	(1)	(2)	(3)	(4)	(5)	(6)
Observed Charities	0.14***	0.15***	0.15***	0.03	0.02	0.01
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)
FirstOrderBeliefs				0.02***	0.03***	0.03***
				(0.00)	(0.00)	(0.00)
Age		0.01	0.00		0.01	0.01
		(0.02)	(0.02)		(0.02)	(0.02)
Male		-0.09	-0.10		0.08	0.10
		(0.22)	(0.23)		(0.19)	(0.22)
Social Sciences		0.03	-0.05		-0.22	-0.33
		(0.32)	(0.31)		(0.31)	(0.35)
Humanities		0.54**	0.46		0.53**	0.45
		(0.26)	(0.33)		(0.24)	(0.29)
Economics		-0.09	-0.13		0.21	0.22
		(0.27)	(0.28)		(0.28)	(0.29)
Medicine		-0.02	-0.13		-0.37	-0.60
		(0.32)	(0.44)		(0.26)	(0.47)
Law		-0.26	-0.30		0.00	0.01
		(0.22)	(0.22)		(0.28)	(0.22)
Other Field of Study		0.10	0.03		0.13	0.10
		(0.28)	(0.31)		(0.31)	(0.37)
1-5 Hours, Volunteering		-0.17	-0.18		-0.35	-0.38
		(0.24)	(0.25)		(0.25)	(0.24)
5-10 Hours, Volunteering		-0.54**	-0.47*		-0.53**	-0.40*
		(0.26)	(0.28)		(0.21)	(0.23)
10-20 Hours, Volunteering		-0.47	-0.49		-0.87***	-0.84***
		(0.34)	(0.35)		(0.20)	(0.18)
20-30 Hours, Volunteering		0.24	0.20		-0.22	-0.23
		(0.69)	(0.71)		(0.51)	(0.52)
More Than 30 Hours, Volunteering		-0.49	-0.43		-0.64*	-0.54*
		(0.38)	(0.47)		(0.32)	(0.31)
Spread Donations for Equality			-0.26			-0.09
			(0.47)			(0.42)
Spread Donations for Efficiency			0.12			0.23
			(0.41)			(0.36)
Internalisation (SIMI)			0.71			2.03*
			(1.08)			(1.19)
Symbolisation (SIMI)			-0.13			-0.77
			(0.61)			(0.58)
Constant	3.90***	3.88***	3.50***	3.27***	3.09***	1.64
	(0.24)	(0.66)	(0.87)	(0.23)	(0.65)	(1.05)
Observations	321	321	321	321	321	321

Notes: OLS regressions with spectator evaluations as the dependent variable. The baseline is a person who studies Natural Sciences and does not volunteer (0 Hours). Standard errors are clustered at the level of pairs of spectators.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.20: Nonlinearity in Spectator Evaluations, PublicN

	(1)	(2)	(3)
ObservedCharities	0.6487***	0.6464***	0.6574***
	(0.1105)	(0.1139)	(0.1169)
(Observed Charities)^2	-0.0437***	-0.0436***	-0.0446***
	(0.0087)	(0.0089)	(0.0090)
Age		0.0024	-0.0081
		(0.0163)	(0.0216)
Male		0.0128	0.0005
		(0.2111)	(0.2166)
Social Sciences		0.0367	-0.1395
		(0.3028)	(0.2758)
Humanities		0.5645**	0.4745
		(0.2510)	(0.3210)
Economics		-0.2111	-0.3290
		(0.2347)	(0.2420)
Medicine		-0.1484	-0.2616
		(0.2728)	(0.3881)
Law		-0.2256	-0.3079
		(0.2409)	(0.2333)
Other Field of Study		0.0472	-0.0648
		(0.2864)	(0.2913)
1-5 Hours, Volunteering		-0.2469	-0.2551
		(0.2278)	(0.2221)
5-10 Hours, Volunteering		-0.4282*	-0.3437
		(0.2254)	(0.2339)
10-20 Hours, Volunteering		-0.3477	-0.4883
		(0.3234)	(0.3547)
20-30 Hours, Volunteering		0.2286	0.2147
		(0.7532)	(0.7850)
More Than 30 Hours, Volunteering		-0.2982	-0.2300
		(0.3402)	(0.4204)
Spread Donations for Equality			-0.4383
			(0.4710)
Spread Donations for Efficiency			0.4529
			(0.3587)
Internalisation (SIMI)			0.6984
			(0.9707)
Symbolisation (SIMI)			-0.0201
			(0.5824)
Constant	3.0077***	3.0661***	2.8173***
	(0.2861)	(0.6795)	(0.8518)
Observations	321	321	321

Notes: OLS regressions with spectator evaluations as the dependent variable. The baseline is a person who studies Natural Sciences and does not volunteer (0 Hours). Standard errors are clustered at the level of pairs of spectators.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.21: Spectator Evaluations, PublicNAmount, Ordered Logit Regression

	(1)	(2)	(3)
ObservedDonation	0.05***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)
ObservedCharities	0.09	0.08	0.07
	(0.08)	(0.07)	(0.07)
Age		0.07	0.07
		(0.05)	(0.05)
Male		-0.58	-0.57
		(0.37)	(0.41)
Social Sciences		-0.76*	-0.87*
		(0.41)	(0.52)
Humanities		-1.42*	-1.50*
		(0.81)	(0.81)
Economics		-0.65	-0.55
		(0.44)	(0.43)
Medicine		-0.74	-1.08
		(0.69)	(0.93)
Law		0.14	0.11
		(0.60)	(0.69)
Other Field of Study		-0.58	-0.64
		(0.46)	(0.47)
1-5 Hours, Volunteering		-0.46	-0.41
		(0.52)	(0.54)
5-10 Hours, Volunteering		0.03	0.06
		(0.44)	(0.45)
10-20 Hours, Volunteering		0.21	0.24
		(0.46)	(0.45)
20-30 Hours, Volunteering		1.52**	1.57**
		(0.61)	(0.63)
More Than 30 Hours, Volunteering		-0.57	-0.63
		(0.60)	(0.63)
Spread Donations for Equality			-0.64
			(0.65)
Spread Donations for Efficiency			-0.33
			(0.72)
Internalisation (SIMI)			1.07
			(1.86)
Symbolisation (SIMI)			-0.15
			(0.92)
Observations	330	330	330

Notes: ordered logit regressions with spectator evaluations as the dependent variable. The baseline is a person who studies Natural Sciences and does not volunteer (0 Hours). Standard errors are clustered at the level of pairs of spectators.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.22: Spectator Evaluations, PublicNAmount, Marginal Effects From Ordered Logit Regression

	(1)	(2)	(3)
ObservedDonation			
Evaluation=1	-0.0048***	-0.0050***	-0.0051***
	(0.0009)	(0.0008)	(0.0008)
Evaluation=2	-0.0015***	-0.0015***	-0.0016***
	(0.0004)	(0.0004)	(0.0004)
Evaluation=3	-0.0008***	-0.0009***	-0.0009***
	(0.0002)	(0.0002)	(0.0003)
Evaluation=4	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)
Evaluation=5	0.0012***	0.0014***	0.0014***
	(0.0002)	(0.0003)	(0.0002)
Evaluation=6	0.0061***	0.0062***	0.0062***
	(0.0006)	(0.0006)	(0.0006)
ObservedCharities			
Evaluation=1	-0.0097	-0.0075	-0.0070
	(0.0076)	(0.0068)	(0.0067)
Evaluation=2	-0.0029	-0.0023	-0.0022
	(0.0024)	(0.0021)	(0.0021)
Evaluation=3	-0.0017	-0.0014	-0.0013
	(0.0017)	(0.0014)	(0.0014)
Evaluation=4	-0.0003	-0.0002	-0.0001
	(0.0007)	(0.0005)	(0.0004)
Evaluation=5	0.0023	0.0020	0.0019
	(0.0020)	(0.0020)	(0.0019)
Evaluation=6	0.0123	0.0093	0.0087
	(0.0102)	(0.0086)	(0.0085)
Demographics	No	Yes	Yes
Attitudes	No	No	Yes
Observations	330	330	330

Notes: marginal effects from ordered logit regressions with spectator evaluations as the dependent variable. The demographic controls are age, gender, field of study, and volunteering. The attitudinal controls are preferences for spreading donations (two questions) and the two subscales of the Self-Importance of Moral Identity scale. Standard errors are clustered at the level of pairs of spectators.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.23: Spectator Evaluations, PublicN, Ordered Logit Regression

	(1)	(2)	(3)	(4)	(5)	(6)
ObservedCharities	0.17**	0.17**	0.17**	0.05	0.04	0.02
	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)
FirstOrderBeliefs				0.03***	0.03***	0.04***
				(0.00)	(0.01)	(0.01)
Age		0.00	0.01		0.01	0.02
		(0.02)	(0.03)		(0.03)	(0.03)
Male		-0.18	-0.26		0.03	-0.02
		(0.28)	(0.31)		(0.28)	(0.34)
Social Sciences		0.01	-0.15		-0.37	-0.54
		(0.39)	(0.39)		(0.44)	(0.52)
Humanities		0.79**	0.65		0.86**	0.72
		(0.40)	(0.48)		(0.40)	(0.45)
Economics		-0.27	-0.33		0.10	0.15
		(0.35)	(0.38)		(0.39)	(0.42)
Medicine		-0.17	-0.41		-0.62	-1.07
		(0.39)	(0.55)		(0.44)	(0.70)
Law		-0.25	-0.31		0.14	0.16
		(0.30)	(0.33)		(0.45)	(0.35)
Other Field of Study		0.15	0.07		0.24	0.21
		(0.43)	(0.45)		(0.48)	(0.58)
1-5 Hours, Volunteering		-0.43	-0.46		-0.69*	-0.75**
		(0.34)	(0.34)		(0.39)	(0.38)
5-10 Hours, Volunteering		-0.71**	-0.50		-0.78***	-0.54
		(0.33)	(0.37)		(0.28)	(0.33)
10-20 Hours, Volunteering		-0.63	-0.54		-1.20***	-1.04***
		(0.40)	(0.46)		(0.35)	(0.28)
20-30 Hours, Volunteering		0.39	0.43		-0.11	-0.04
		(0.94)	(0.97)		(0.79)	(0.88)
More Than 30 Hours, Volunteering		-0.52	-0.19		-0.81	-0.45
		(0.56)	(0.66)		(0.54)	(0.55)
Spread Donations for Equality			-0.67			-0.35
			(0.68)			(0.68)
Spread Donations for Efficiency			0.13			0.13
			(0.59)			(0.58)
Internalisation (SIMI)			1.69			3.60**
			(1.35)			(1.82)
Symbolisation (SIMI)			-0.77			-1.73*
			(0.80)			(0.92)
Observations	321	321	321	321	321	321

Notes: ordered logit regressions with spectator evaluations as the dependent variable. The baseline is a person who studies Natural Sciences and does not volunteer (0 Hours). Standard errors are clustered at the level of pairs of spectators.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.24: Spectator Evaluations, PublicN, Marginal Effects From Ordered Logit Regression

	(1)	(2)	(3)	(4)	(5)	(6)
ObservedCharities						
Evaluation=1	-0.0152*	-0.0151*	-0.0147*	-0.0040	-0.0032	-0.0013
	(0.0081)	(0.0083)	(0.0084)	(0.0065)	(0.0064)	(0.0062)
Evaluation=2	-0.0025*	-0.0024*	-0.0024*	-0.0007	-0.0005	-0.0002
	(0.0014)	(0.0013)	(0.0013)	(0.0011)	(0.0010)	(0.0010)
Evaluation=3	-0.0110**	-0.0105**	-0.0102**	-0.0027	-0.0020	-0.0008
	(0.0045)	(0.0045)	(0.0046)	(0.0042)	(0.0040)	(0.0039)
Evaluation=4	-0.0112***	-0.0107***	-0.0103**	-0.0022	-0.0018	-0.0007
	(0.0042)	(0.0040)	(0.0041)	(0.0036)	(0.0036)	(0.0034)
Evaluation=5	0.0064	0.0058	0.0056	0.0014	0.0010	0.0004
	(0.0041)	(0.0037)	(0.0037)	(0.0022)	(0.0019)	(0.0019)
Evaluation=6	0.0336**	0.0329**	0.0320**	0.0081	0.0065	0.0027
	(0.0141)	(0.0141)	(0.0143)	(0.0131)	(0.0131)	(0.0125)
FirstOrderBeliefs						
Evaluation=1				-0.0025***	-0.0027***	-0.0030***
				(0.0006)	(0.0006)	(0.0006)
Evaluation=2				-0.0004**	-0.0005**	-0.0005**
				(0.0002)	(0.0002)	(0.0002)
Evaluation=3				-0.0016***	-0.0018***	-0.0019***
				(0.0003)	(0.0003)	(0.0003)
Evaluation=4				-0.0014***	-0.0015***	-0.0017***
				(0.0003)	(0.0003)	(0.0004)
Evaluation=5				0.0009**	0.0009**	0.0010**
				(0.0004)	(0.0004)	(0.0004)
Evaluation=6				0.0050***	0.0056***	0.0061***
				(0.0007)	(0.0007)	(0.0007)
Demographic Controls	No	Yes	Yes	No	Yes	Yes
Attitudinal Controls	No	No	Yes	No	No	Yes
Observations	321	321	321	321	321	321

Notes: marginal effects from ordered logit regressions with spectator evaluations as the dependent variable. The demographic controls are age, gender, field of study, and volunteering. The attitudinal controls are preferences for spreading donations (two questions) and the two subscales of the Self-Importance of Moral Identity scale. Standard errors are clustered at the level of pairs of spectators.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

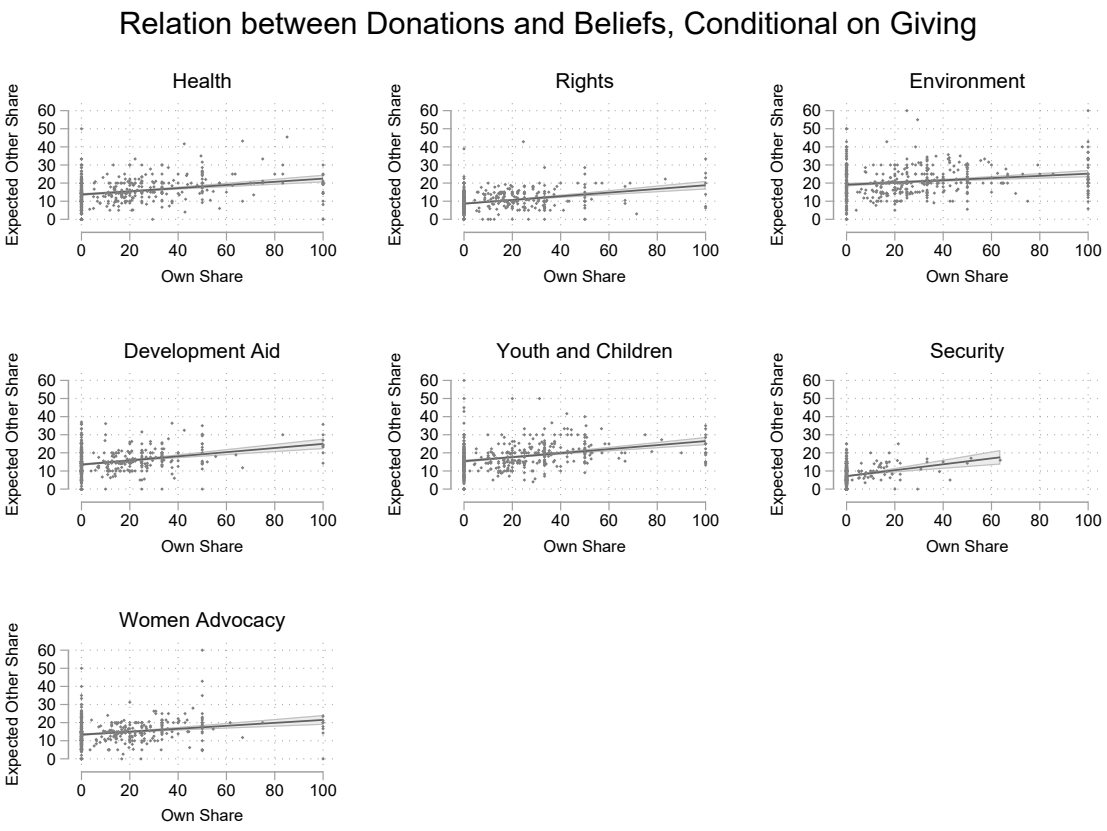
S.5.3 Preferences for Spreading Donations

Table S.25: Preferences for Diversification and the Number of Charities

	NoCost	Private	PublicN	PublicNAmount	All
Spread Donations for Equality	2.28**	2.01***	2.37***	2.85***	2.44***
	(0.93)	(0.52)	(0.45)	(0.59)	(0.29)
Spread Donations for Efficiency	0.77	0.85	1.34	1.33	1.00
	(0.26)	(0.22)	(0.25)	(0.26)	(0.12)
Age	1.01	0.96***	0.99	1.01	0.99
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Male	0.68*	0.96	1.04	0.90	0.95
	(0.15)	(0.14)	(0.11)	(0.12)	(0.07)
Social Sciences	0.58	1.09	1.06	0.99	0.97
	(0.19)	(0.26)	(0.18)	(0.23)	(0.11)
Humanities	0.75	1.03	0.95	1.10	0.97
	(0.22)	(0.23)	(0.16)	(0.21)	(0.10)
Economics	0.76	1.04	1.07	0.92	0.96
	(0.26)	(0.20)	(0.16)	(0.16)	(0.09)
Medicine	0.66	0.98	0.94	0.33	0.80
	(0.55)	(0.35)	(0.27)	(0.35)	(0.17)
Law	0.81	1.37	0.80	1.24	1.09
	(0.27)	(0.31)	(0.14)	(0.23)	(0.12)
Other Field of Study	1.01	0.90	0.99	1.07	1.04
	(0.34)	(0.28)	(0.14)	(0.21)	(0.11)
1-5 Hours, Volunteering	1.41	1.17	0.69**	0.90	0.96
	(0.48)	(0.24)	(0.11)	(0.15)	(0.10)
5-10 Hours, Volunteering	0.76	1.17	0.91	0.80	0.94
	(0.26)	(0.25)	(0.14)	(0.17)	(0.10)
10-20 Hours, Volunteering	0.77	0.96	0.73*	0.70*	0.77**
	(0.28)	(0.22)	(0.13)	(0.14)	(0.09)
20-30 Hours, Volunteering	0.74	1.08	0.69*	0.90	0.86
	(0.26)	(0.29)	(0.14)	(0.21)	(0.11)
More Than 30 Hours, Volunteering	0.82	1.28	0.76**	0.88	0.91
	(0.27)	(0.27)	(0.10)	(0.14)	(0.09)
Internalisation (SIMI)	7.42**	1.21	0.81	1.72	1.53*
	(6.19)	(0.65)	(0.29)	(0.76)	(0.38)
Symbolisation (SIMI)	4.61***	2.00**	2.02***	1.58	2.10***
	(2.71)	(0.66)	(0.54)	(0.45)	(0.34)
NoCost					1.69***
					(0.17)
PublicN					1.19**
					(0.10)
PublicNAmount					0.99
					(0.08)
Observations	77	170	158	170	575

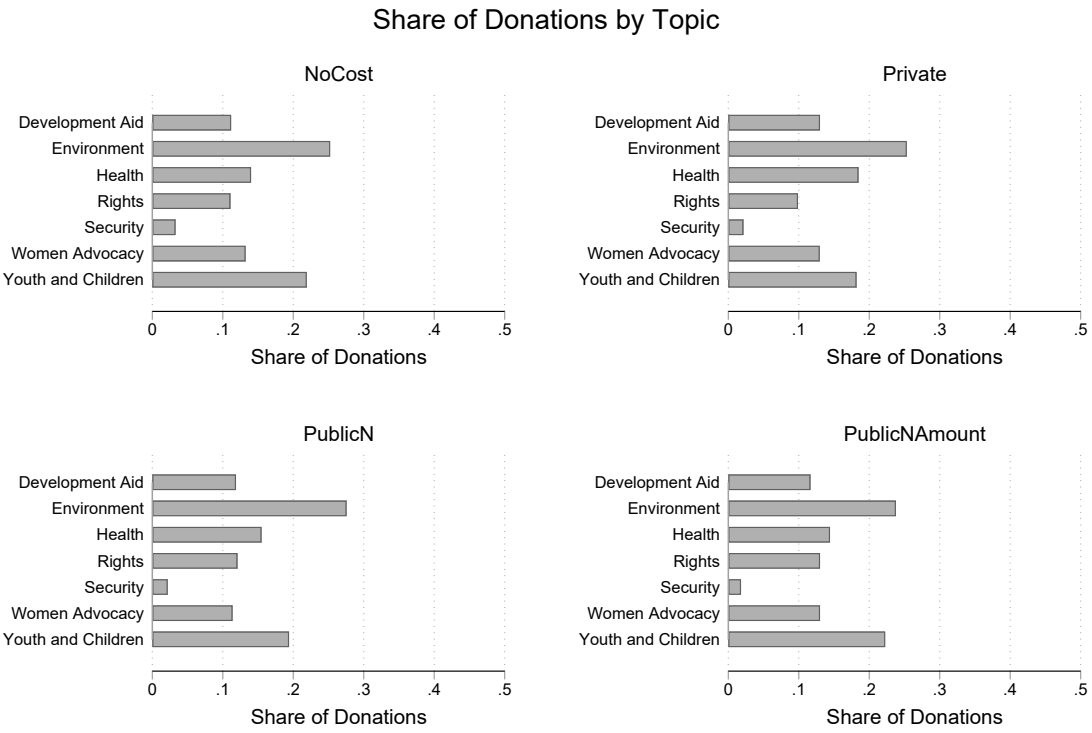
Notes: negative binomial regressions with the number of charities as the dependent variable. The baseline is a person who studies Natural Sciences and does not volunteer (0 Hours). Coefficients are incidence rate ratios.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure S.7: Evaluations and Total Charities



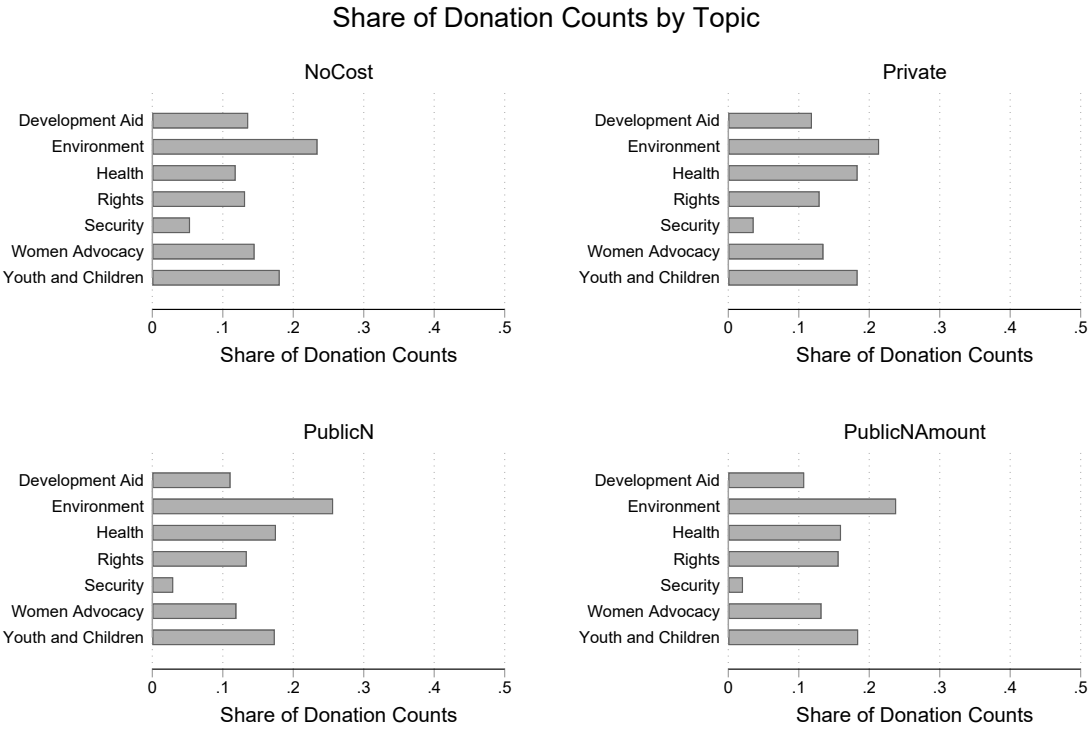
Notes: the figure shows for each of the seven topics the relation between the share of a dictator's donations is allocated to the topic and how much the dictator beliefs that others give on average to the topic. The grey bounds show 95 percent confidence intervals for a linear fit.

Figure S.8: Distributions of Donations by Treatment



Notes: the figure shows for each treatment the share of total donations within that treatment that accrues to each of the seven topics.

Figure S.9: Distributions of Donation Counts by Treatment



Notes: the figure shows for each treatment the share of the number of donations within that treatment that accrues to each of the seven topics.

Table S.26: Number of Topics, Private vs. PublicN

	(1)	(2)	(3)
PublicN	1.25***	1.23***	1.24***
	(0.09)	(0.09)	(0.09)
Age		0.98**	0.98***
		(0.01)	(0.01)
Male		0.95	1.03
		(0.07)	(0.08)
Natural Sciences		1.00	1.00
		(.)	(.)
Social Sciences		1.18	1.13
		(0.15)	(0.14)
Humanities		1.14	1.08
		(0.14)	(0.12)
Economics		1.00	0.98
		(0.11)	(0.11)
Medicine		0.85	0.81
		(0.19)	(0.17)
Law		1.09	1.01
		(0.14)	(0.12)
Other Field of Study		1.19	1.15
		(0.15)	(0.13)
0 Hours		1.00	1.00
		(.)	(.)
1-5 Hours, Volunteering		0.99	0.93
		(0.11)	(0.10)
5-10 Hours, Volunteering		1.10	0.97
		(0.13)	(0.11)
10-20 Hours, Volunteering		1.01	0.88
		(0.13)	(0.11)
20-30 Hours, Volunteering		0.89	0.75*
		(0.14)	(0.11)
More Than 30 Hours, Volunteering		1.01	0.94
		(0.10)	(0.10)
Spread Donations for Equality			1.86***
			(0.25)
Spread Donations for Efficiency			1.00
			(0.14)
Internalisation (SIMI)			1.41
			(0.39)
Symbolisation (SIMI)			1.70***
			(0.31)
Observations	328	328	328

Notes: negative binomial regressions with the number of topics as the dependent variable. The baseline is a person in the *Private* treatment who studies Natural Sciences and does not volunteer (0 Hours). Coefficients are incidence rate ratios. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.27: Number of Topics, PublicN vs. PublicNAmount

	(1)	(2)	(3)
PublicN	1.11	1.11	1.13*
	(0.08)	(0.08)	(0.08)
Age		1.00	1.00
		(0.01)	(0.01)
Male		0.90	1.00
		(0.07)	(0.07)
Social Sciences		1.12	1.07
		(0.14)	(0.13)
Humanities		1.23*	1.18
		(0.14)	(0.13)
Economics		1.02	0.97
		(0.11)	(0.10)
Medicine		0.62	0.67
		(0.19)	(0.20)
Law		0.98	1.00
		(0.12)	(0.12)
Other Field of Study		1.21*	1.19*
		(0.13)	(0.13)
1-5 Hours, Volunteering		0.95	0.85
		(0.10)	(0.09)
5-10 Hours, Volunteering		1.07	0.88
		(0.13)	(0.10)
10-20 Hours, Volunteering		1.02	0.88
		(0.12)	(0.11)
20-30 Hours, Volunteering		1.11	0.93
		(0.16)	(0.13)
More Than 30 Hours, Volunteering		0.98	0.88
		(0.09)	(0.08)
Spread Donations for Equality			2.19***
			(0.27)
Spread Donations for Efficiency			1.17
			(0.14)
Internalisation (SIMI)			1.58*
			(0.42)
Symbolisation (SIMI)			1.52**
			(0.27)
Observations	328	328	328

Notes: negative binomial regressions with the number of topics as the dependent variable. The baseline is a person in the *PublicNAmount* treatment who studies Natural Sciences and does not volunteer (0 Hours). Coefficients are incidence rate ratios.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

S.5.4 Self-Importance of Moral Identity

Table S.28: Self-Importance of Moral Identity and Total Donations

	NoCost	Private	PublicN	PublicNAmount	All
High Internalisation	37.43***	7.77	13.51**	12.09**	12.81***
	(11.02)	(5.90)	(5.85)	(5.85)	(3.18)
High Symbolisation	-5.99	5.97	-0.79	-0.19	1.40
	(10.67)	(5.99)	(5.82)	(5.98)	(3.22)
Male	-22.24**	-5.06	-5.42	-6.07	-6.68**
	(10.22)	(5.93)	(5.53)	(6.22)	(3.20)
Age	-0.11	-1.09**	-1.01*	0.43	-0.51*
	(0.98)	(0.44)	(0.59)	(0.60)	(0.28)
Social Sciences	-29.76*	-2.54	10.48	5.68	-1.73
	(15.25)	(10.01)	(9.09)	(11.28)	(5.34)
Humanities	1.96	4.06	3.38	6.88	1.93
	(14.28)	(8.83)	(8.98)	(9.25)	(4.89)
Economics	-23.20	4.27	-14.49*	4.33	-2.48
	(14.11)	(7.85)	(8.28)	(8.26)	(4.36)
Medicine	-72.39*	8.59	-21.10	-49.91*	-13.41
	(40.15)	(13.73)	(14.81)	(29.00)	(9.34)
Law	-35.59**	5.33	-9.51	-7.20	-8.63*
	(15.48)	(9.42)	(8.51)	(9.02)	(4.97)
Other Field of Study	2.61	18.43	-2.06	1.70	5.03
	(16.25)	(12.07)	(7.66)	(9.68)	(5.09)
1-5 Hours, Volunteering	-0.28	-1.53	-2.26	-10.56	-4.30
	(14.89)	(8.32)	(8.18)	(8.33)	(4.54)
5-10 Hours, Volunteering	-37.75**	-4.75	-7.17	-0.08	-7.13
	(15.71)	(8.81)	(8.60)	(10.73)	(5.10)
10-20 Hours, Volunteering	10.10	3.10	-3.77	-3.55	-1.23
	(16.17)	(9.16)	(9.41)	(9.42)	(5.14)
20-30 Hours, Volunteering	-14.85	-5.56	-3.76	3.14	-2.96
	(16.53)	(10.75)	(10.57)	(11.81)	(6.06)
More Than 30 Hours, Volunteering	17.36	10.56	3.18	-1.01	3.21
	(15.23)	(8.44)	(6.99)	(7.59)	(4.23)
Spread Donations for Equality	47.25**	-0.97	20.75**	38.88***	25.80***
	(19.36)	(10.78)	(10.19)	(10.28)	(5.64)
Spread Donations for Efficiency	-25.30	-3.78	-7.64	-15.44	-13.76**
	(16.02)	(10.95)	(10.34)	(9.65)	(5.50)
NoCost					4.15
					(4.85)
PublicN					4.90
					(3.89)
PublicNAmount					2.71
					(3.84)
Observations	77	170	158	170	575

Notes: tobit regressions with total donations as the dependent variable. High Internalisation (Symbolisation) is a dummy variable taking the value 1 if the participant has an above-median score on the Internalisation (Symbolisation) subscale. The baseline is a person who scores in the bottom half of the Internalisation and Symbolisation subscales of the Self-Importance of Moral Identity scale, who studies Natural Sciences, and who does not volunteer (0 Hours). Coefficients are incidence rate ratios.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.29: Self-Importance of Moral Identity and the Number of Charities

	NoCost	Private	PublicN	PublicNAmount	All
High Internalisation	1.48*	0.97	1.00	1.14	1.09
	(0.34)	(0.14)	(0.11)	(0.14)	(0.08)
High Symbolisation	1.59*	1.18	1.30**	1.11	1.25***
	(0.40)	(0.16)	(0.14)	(0.14)	(0.09)
Male	0.63**	0.92	1.03	0.88	0.93
	(0.15)	(0.14)	(0.11)	(0.12)	(0.07)
Age	1.02	0.96***	0.99	1.01	0.99
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Social Sciences	0.65	1.14	1.03	1.00	0.97
	(0.22)	(0.28)	(0.17)	(0.23)	(0.11)
Humanities	0.72	1.08	0.93	1.04	0.95
	(0.22)	(0.24)	(0.15)	(0.20)	(0.10)
Economics	0.78	1.10	1.07	0.91	0.97
	(0.27)	(0.22)	(0.16)	(0.16)	(0.09)
Medicine	0.57	1.07	0.95	0.29	0.81
	(0.50)	(0.39)	(0.28)	(0.30)	(0.18)
Law	0.82	1.44	0.76	1.20	1.09
	(0.28)	(0.33)	(0.13)	(0.22)	(0.12)
Other Field of Study	1.00	0.95	0.94	1.06	1.02
	(0.35)	(0.30)	(0.14)	(0.21)	(0.11)
1-5 Hours, Volunteering	1.40	1.20	0.71**	0.91	0.99
	(0.49)	(0.24)	(0.11)	(0.15)	(0.10)
5-10 Hours, Volunteering	0.70	1.22	0.95	0.80	0.96
	(0.25)	(0.26)	(0.15)	(0.17)	(0.11)
10-20 Hours, Volunteering	0.84	1.04	0.76	0.72*	0.81*
	(0.33)	(0.24)	(0.14)	(0.14)	(0.09)
20-30 Hours, Volunteering	0.83	1.22	0.70*	0.93	0.91
	(0.31)	(0.32)	(0.14)	(0.22)	(0.12)
More Than 30 Hours, Volunteering	1.03	1.38	0.78*	0.91	0.97
	(0.34)	(0.28)	(0.11)	(0.14)	(0.09)
Spread Donations for Equality	2.58**	2.12***	2.32***	2.88***	2.49***
	(1.12)	(0.55)	(0.44)	(0.60)	(0.30)
Spread Donations for Efficiency	0.75	0.87	1.43*	1.37	1.04
	(0.26)	(0.22)	(0.27)	(0.27)	(0.12)
NoCost					1.65***
					(0.17)
PublicN					1.18*
					(0.10)
PublicNAmount					0.98
					(0.09)
Observations	77	170	158	170	575

Notes: negative binomial regressions with the number of charities as the dependent variable. High Internalisation (Symbolisation) is a dummy variable taking the value 1 if the participant has an above-median score on the Internalisation (Symbolisation) subscale. The baseline is a person who scores in the bottom half of the Internalisation and Symbolisation subscales of the Self-Importance of Moral Identity scale, who studies Natural Sciences, and who does not volunteer (0 Hours). Coefficients are incidence rate ratios.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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