Sponsor Preferences and Persuasion in Child Sponsorship Programs

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This is a work-in-progress for the master's degree thesis at the University of Chicago.
I will upload future versions to: `https://github.com/jtschoi/Projects`.

Abstract

While few studies underline the positive impact of child sponsorship programs (CSP), the literature on how to maximize sponsorship is almost non-existent. This paper addresses this issue by (i) introducing a model of potential sponsor (PS) preferences inspired by Bénabou and Tirole (2006) and (ii) providing an information-design interpretation of CSP sponsor-recipient match environments by using the Bayesian persuasion model in Kamenica and Gentzkow (2011). The study also conducts reduced-form analyses using data from Compassion International to bolster the said model of PS preferences. Future objectives include structural estimation of PS utility function and, using the said estimation, finding the optimal signal using the principles of Bayesian persuasion.

1 Introduction

As non-governmental child sponsorship organizations (henceforth CSO) are continuing to expand their operations around the world, more children – both domestic and international – are receiving sponsorship through direct matches with sponsors, who often are economically better-off than their beneficiaries. For instance, Compassion International (2018), have exceeded 1,800,000 in the number of directly-sponsored children in 2018; World Vision reports that their sponsorship program reaches out to approximately 3,800,000 globally (Huber 2019). Studies investigating the said programs' effectiveness are profoundly few, but they commonly underline the positive impacts of the child sponsorship programs (henceforth CSP) to the lives of recipients. Wydick et al. (2013), for example, use a dataset of approximately 10,000 individuals across six countries – part of whom were supported through Compassion International – to conclude that sponsorship has increased the recipients' years of education, school completion rates, and employment outcomes as adults (pp. 418-430). An earlier study by Kremer et al. (2003) also provides evidence for the positive impact of CSP, although the program under scrutiny specifically targeted schools.

Despite the said few discoveries highlighting the positive results of CSP for the sponsorship recipients, there are even fewer items in the literature studying how the sponsor-recipient matches are created, and how they can be maximized. There are two dimensions to this hardly-inspected set of problems. The first is identifying sponsors' preferences over recipient characteristics, as some attributes may hinder or promote the selection of potential recipients (henceforth PR) by potential sponsors (henceforth PS). This problem perhaps owes in part to the lack of public data surveying the motives behind the PS's participation in CSP. Another aspect is to analyze whether the current signal structure of delivering PR information to the PS is optimal in terms of maximizing sponsorship.[1] While this is a complicated standalone question, note that one should account for the PS preferences as well in order to more thoroughly assess the optimality of the said structure.

This paper aims to provide answers to the said dimensions in the following manner. Firstly, the study introduces a model of PS preferences over PR characteristics by modifying that of prosocial behavior in Bénabou and Tirole (2006). As in the said paper, I also consider reputational concerns of the PS. For tractability, this study reduces the PR characteristics entering the PS's utility function into two: "urgency" and "instability." The study also provides an interpretation of the CSP sponsor-recipient match environment (henceforth match environment) using the framework of Bayesian persuasion (Kamenica and Gentzkow 2011). I designate the Sender and the Receiver of signals to be the CSO and the (representative) PS, respectively. By combining the two steps of identifying PS preferences and setting up a Bayesian persuasion model, it is possible to analyze whether any persuasion is beneficial and, if so, what the optimal signal is.

Furthermore, this study employs an empirical analysis of the Compassion International dataset of 9,518 matched and unmatched children collected via web-scraping. The said analysis entails reduced-form strategies of survival analysis and regression discontinuity design (henceforth RDD) as well as structural estimation of the PS's utility function. Using the former approach, I find evidence for the urgency-instability framework of PS preferences previously mentioned. The study conducts the latter method to examine whether repu-

[1] Another extension for optimality in this dialogue is maximizing the "social welfare" of the CSP environment by jointly considering maximal sponsorship and the PS utility.

tational concerns of the PS are well-founded and to use the estimated utility function for finding optimal signals according to the Bayesian persuasion environment. I will follow Keane et al. (2011) and Evans and Viscusi (1991) for the said structural estimation.

2 Economic Framework

2.1 Model of Potential Sponsor Preference

Existing studies have suggested that PS make sponsorship decisions based on reasons such as improving oneself through charitable actions and religious beliefs (Rabbitts 2014). However, the literature is almost devoid of the discussion about why some PR might be selected over others. Rabbitts (2014) introduces a story of sponsor for Kindu Trust, who has chosen a recipient about the age of their granddaughter, suggesting that there is some degree of homophily at work (pp. 287-288); however, there is only anecdotal evidence. To address this issue, I develop a model of the (representative) PS's preference over PR types, which is heavily inspired by Bénabou and Tirole (2006) (henceforth BT). The study also follows calculations in Carpenter and Myers (2010) (henceforth CM), in which the said paper makes use of the model in BT.

Let $\Omega \subseteq \mathbb{R}^2$ be the compact space of *overall* PR types. That is, $\omega \in \Omega$ represents the *overall* state of the PR that the *representative* PS can observe. The study will later explore the interpretation of $\omega \in \Omega$ as the type of an individual PR, where multiple (yet i.i.d.) PS are making sponsorship decisions for individual PR.

I will typically denote an element of Ω as $(\theta, t) \in \Omega$, which is composed of two parts: i) how urgently a PR needs (material) assistance (henceforth *urgency*, and denoted by θ), and ii) how unstable an environment a PR is living in (henceforth *instability*, and denoted by t). PS is altruistic in the sense that he or she wants to help the neediest or those with higher θ.[2] At the same time, this altruism is limited as the PS prefers to spend his or her sponsorship on the PR that are in stable environments where actual positive changes could occur. For instance, the PS may feel that his or her donation is not going to affect the livelihoods of those in regions suffering from ongoing wars, corrupt governments, or life-threatening epidemics.[3]

Together with the above specifications, the PS chooses an action $a \in A = [0, \bar{a}]$, where $\bar{a} \in \mathbb{R}_{++}$ is an arbitrary positive number. The said action refers to the degree of sponsorship for the PR. This choice of action produces the "direct payoff" from sponsorship at level a for a type-(θ, t) PR, which is as follows:

$$(r_1\theta - r_2 t)a - C(a) \tag{1}$$

where $C(a)$ represents the cost of sponsorship at level a.[4] The parameters $r_1 \in \mathbb{R}$ and $r_2 \in \mathbb{R}$ represent how much the PS pays attention to the urgency and instability of the PR, respectively. If $r_1, r_2 \geq 0$, this would

[2] Despite this characterization, the study admits that one may interpret θ as the degree of homophily between the PS and the PR, as in the anecdotal evidence of Rabbitts (2014). However, the study does find evidence for PS's preference over PR urgency in Section 3.

[3] The said concern over PR instability is somewhat related to the discussion of outcome-oriented philanthropy in Brest (2012), where "donors seek to achieve clearly defined goals" (p.42).

[4] I note that in this setup, there is not much distinction between pure and impure altruism (e.g., as in Andreoni 1990) or between benefit from public goods and that from private goods. This simplification is to allow one to focus on PR characteristics.

support the interpretation of urgency and instability as previously elaborated; that is, the direct payoff is greater when helping a more destitute child (higher θ) and when helping a child with a greater probability of being helped by the sponsorship (lower t). Combined, (r_1, r_2) can be understood as the type of PS. Following BT and CM, this study assumes that r_1 and r_2 are jointly-normally distributed, so that

$$\begin{pmatrix} r_1 \\ r_2 \end{pmatrix} \sim \mathcal{N}(\bar{r}, \Sigma) \quad \text{where} \quad \bar{r} = \begin{pmatrix} \bar{r}_1 \\ \bar{r}_2 \end{pmatrix}, \quad \Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix} \tag{1'}$$

and further supposes that the PS's peers know of the joint distribution of r_1 and r_2.

In addition to this direct benefit, the study assumes that PS may be concerned about his or her reputation, which has to do with the values of r_1 and r_2 perceived by his or her peers (e.g., friends or colleagues who do not engage in CSP). The said peers cannot directly observe r_1 and r_2, but do know the joint distribution of (r_1, r_2) as previously mentioned and are able to form expectations based on the PS's choice of a. Together with this, I assume that the peers are unable to observe the type of PR (or its distribution, as discussed in short). Again following BT, I assume that the "reputational payoff," denoted $R(a; r_1, r_2)$ is linear in the said conditional expectations. I write this as follows:

$$R(a; x, b_1, b_2) = x\big(b_1\mathbb{E}[r_1|a] - b_2\mathbb{E}[r_2|a]\big) \tag{2}$$

where $x \in [0, 1]$ denotes the visibility, from the peers' viewpoint, of the PR's action. In addition, $b_1 \geq 0$ and $b_2 \geq 0$ denote how much the PS cares about being considered caring about the urgency and instability of the PR. For the sake of simplicity, let $\beta_1 \equiv xb_1$ and $\beta_2 \equiv xb_2$ denote how much weight is given to each component of reputational payoff; then, one may write $R(a; x, b_1, b_2) \equiv R(a; \beta_1, \beta_2)$.[5]

Aggregating the direct and reputational payoffs, I now write the utility function of the representative PR, $U(\cdot)$, as follows:

$$U(a, \theta, t) = (r_1\theta - r_2 t)a - C(a) + \beta_1\mathbb{E}[r_1|a] - \beta_2\mathbb{E}[r_2|a] \tag{3}$$

However, in the discussion of Bayesian persuasion to follow, the PS does not directly see the underlying types of the PR (or, equivalently, states of the world). Rather, he or she observes the signal realization $s \in S$ together with some signal π which gives rise to a posterior belief of PR types, denoted by $\mu_s \in \Delta\Omega$. Let $a^*(\mu, r_1, r_2)$ denote the optimal action of the type-(r_1, r_2) PS when faced with the interim problem of observing $\mu \in \Delta\Omega$. One may express this as follows:

$$a^*(\mu, r_1, r_2) \in A^*(\mu, r_1, r_2) \equiv \operatorname*{arg\,max}_{a \in A} \; \mathbb{E}_{(\theta,t)\sim\mu}\big[(r_1\theta - r_2 t)a - C(a) - \beta_1\mathbb{E}[r_1|a] - \beta_2\mathbb{E}[r_2|a]\big]. \tag{4}$$

Following BT, let $C(a) = \frac{k}{2}a^2$ with $k > 0$. With the assumption that $R(a; \beta_1, \beta_2)$ is differentiable in a, one

[5] The simplication of considering x together with b_1 (so that $\beta_1 \equiv xb_1$) will also be useful in the structural estimation setting as x and b_1 cannot be estimated separately. Similar logic follows for x and b_2.

may write the first-order condition (FOC) as follows:

$$ka = r_1\mathbb{E}_\mu[\theta] - r_2\mathbb{E}_\mu[t] + \frac{\partial R(a;\beta_1,\beta_2)}{\partial a} \tag{5}$$

$$\Leftrightarrow \quad r_1\mathbb{E}_\mu[\theta] - r_2\mathbb{E}_\mu[t] = ka - \beta_1\frac{\partial\mathbb{E}[r_1|a]}{\partial a} + \beta_2\frac{\partial\mathbb{E}[r_2|a]}{\partial a} \tag{5'}$$

and $a = a^*(\mu)$ will solve the expressions (5) and (5'). Notice that in (5'), the right-hand side of the equation is a function of a, whereas the left-hand side is a function of r_1 and r_2 which were assumed to be jointly normal. Then, at the interim optimum, one may write:

$$\mathbb{E}[r_1|a] = \mathbb{E}\big[r_1|r_1\mathbb{E}_\mu[\theta] - r_2\mathbb{E}_\mu[t]\big] \quad \text{and} \quad \mathbb{E}[r_2|a] = \mathbb{E}\big[r_2|r_1\mathbb{E}_\mu[\theta] - r_2\mathbb{E}_\mu[t]\big] \tag{6}$$

where $r_1\mathbb{E}_\mu[\theta] - r_2\mathbb{E}_\mu[t]$ is jointly normal with r_1 and r_2. Similar arguments for deriving the expression (6) are made in BT. Following CM, let $\sigma_{r_1,(r_1\mathbb{E}_\mu[\theta]-r_2\mathbb{E}_\mu[t])}$ and $\sigma_{r_2,(r_1\mathbb{E}_\mu[\theta]-r_2\mathbb{E}_\mu[t])}$ denote the covariance between r_1 and $r_1\mathbb{E}_\mu[\theta] - r_2\mathbb{E}_\mu[t]$ and that between r_2 and $r_1\mathbb{E}_\mu[\theta] - r_2\mathbb{E}_\mu[t]$, respectively. Also, let $\sigma^2_{r_1\mathbb{E}_\mu[\theta]-r_2\mathbb{E}_\mu[t]}$ denote the variance of $r_1\mathbb{E}_\mu[\theta] - r_2\mathbb{E}_\mu[t]$.[6] For the ease of notations, let us also define

$$\rho_1(\mu) \equiv \frac{\sigma_{r_1,(r_1\mathbb{E}_\mu[\theta]-r_2\mathbb{E}_\mu[t])}}{\sigma^2_{r_1\mathbb{E}_\mu[\theta]-r_2\mathbb{E}_\mu[t]}} \quad \text{and} \quad \rho_2(\mu) \equiv \frac{\sigma_{r_2,(r_1\mathbb{E}_\mu[\theta]-r_2\mathbb{E}_\mu[t])}}{\sigma^2_{r_1\mathbb{E}_\mu[\theta]-r_2\mathbb{E}_\mu[t]}}.$$

Then, with the notations developed above, one may write:

$$\begin{aligned} &\mathbb{E}[r_1|a] = \mathbb{E}[r_1|r_1\mathbb{E}_\mu[\theta] - r_2\mathbb{E}_\mu[t]] = \bar{r}_1 + \rho_1(r_1\mathbb{E}_\mu[\theta] - r_2\mathbb{E}_\mu[t] - r_2 - \bar{r}_1\mathbb{E}_\mu[\theta] + \bar{r}_2\mathbb{E}_\mu[t]) \\ \Leftrightarrow \quad &\mathbb{E}[r_1|a] = \bar{r}_1 + \rho_1(\mu)\Big\{ka - \beta_1\frac{\partial\mathbb{E}[r_1|a]}{\partial a} + \beta_2\frac{\partial\mathbb{E}[r_2|a]}{\partial a} - (\bar{r}_1\mathbb{E}_\mu[\theta] - \bar{r}_2\mathbb{E}_\mu[t])\Big\} \end{aligned} \tag{7-1}$$

and similarly, one may also derive:

$$\mathbb{E}[r_2|a] = \bar{r}_2 + \rho_2(\mu)\Big\{ka - \beta_1\frac{\partial\mathbb{E}[r_1|a]}{\partial a} + \beta_2\frac{\partial\mathbb{E}[r_2|a]}{\partial a} - (\bar{r}_1\mathbb{E}_\mu[\theta] - \bar{r}_2\mathbb{E}_\mu[t])\Big\} \tag{7-2}$$

where (7-1) and (7-2) together yield a system of differential equations. The said system yields the solutions in (8-1) and (8-2), where I follow BT and CM to assume that the constant terms are 0:

$$\mathbb{E}[r_1|a] = \bar{r}_1 + \rho_1(\mu)\Big\{ka - k(\beta_1\rho_1(\mu) - \beta_2\rho_2(\mu)) - (\bar{r}_1\mathbb{E}_\mu[\theta] - \bar{r}_2\mathbb{E}_\mu[t])\Big\} \tag{8-1}$$

$$\mathbb{E}[r_2|a] = \bar{r}_2 + \rho_2(\mu)\Big\{ka - k(\beta_1\rho_1(\mu) - \beta_2\rho_2(\mu)) - (\bar{r}_1\mathbb{E}_\mu[\theta] - \bar{r}_2\mathbb{E}_\mu[t])\Big\} \tag{8-2}$$

Notice that

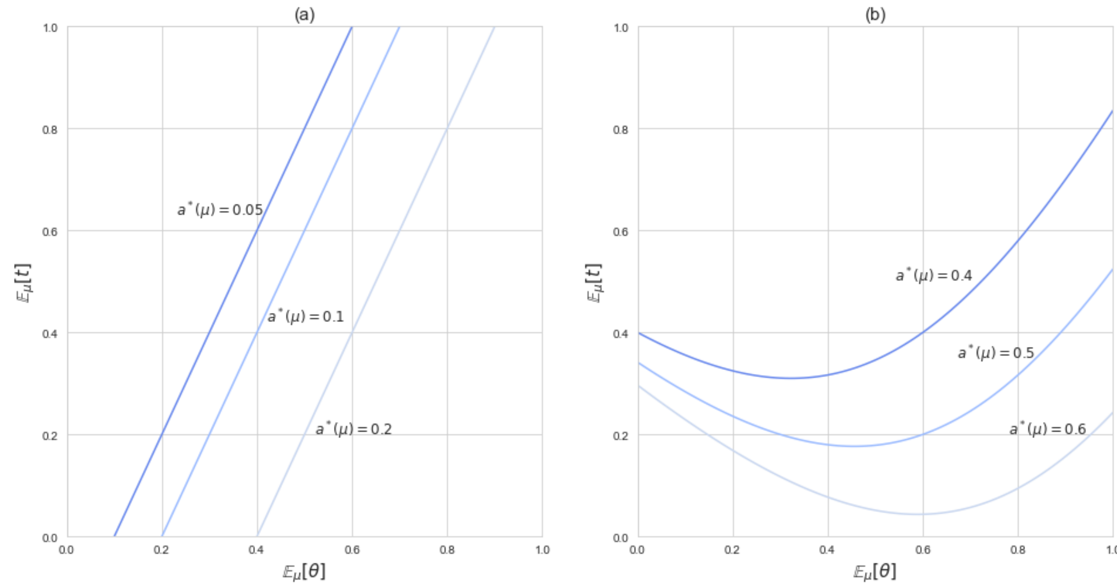
$$\frac{\partial\mathbb{E}[r_1|a]}{\partial a} = k\rho_1(\mu) \quad \text{and} \quad \frac{\partial\mathbb{E}[r_2|a]}{\partial a} = k\rho_2(\mu).$$

Inserting these expressions in (5') and re-organizing with $a = a^*(\mu)$, I yield the following expression for the interim optimal solution:

$$a^*(\mu, r_1, r_2) = \frac{1}{k}\big(r_1\mathbb{E}_\mu[\theta] - r_2\mathbb{E}_\mu[t]\big) + \big\{\beta_1\rho_1(\mu) - \beta_2\rho_2(\mu)\big\} \tag{5''}$$

[6] Note that via calculation, $\sigma^2_{r_1\,\mathbb{E}_\mu[\theta]-r_2\,\mathbb{E}_\mu[t]} = (\mathbb{E}_\mu[\theta])^2\sigma_1^2 + (\mathbb{E}_\mu[t])^2\sigma_2^2 - 2\,\mathbb{E}_\mu[\theta]\,\mathbb{E}_\mu[t]\sigma_{12}$. Similarly, $\sigma_{r_1,(r_1\mathbb{E}_\mu[\theta]-r_2\mathbb{E}_\mu[t])} = \mathbb{E}_\mu[\theta]\sigma_1^2 - \mathbb{E}_\mu[t]\sigma_{12}$ and $\sigma_{r_2,(r_1\mathbb{E}_\mu[\theta]-r_2\mathbb{E}_\mu[t])} = \mathbb{E}_\mu[\theta]\sigma_{12} - \mathbb{E}_\mu[t]\sigma_2^2$.

Figure 1: Iso-action $(a^*(\mu, r_1, r_2))$ Curves, With or Without Reputational Concerns



NOTE: I abuse the notation to write $a^*(\mu, 1, 0.5)$ as $a^*(\mu)$ in the panels. Panel (a) shows the isoaction curves when $\beta_1 = \beta_2 = 0$; that is, when there is no reputational concern. Panel (b) shows those when $\beta_1 = \beta_2 = 0.1$; this is therefore an example of when there are reputational concerns. Only displaying $(\mathbb{E}_\mu[t], \mathbb{E}_\mu[\theta]) \in [0, 1]^2$; in both cases, $\sigma_1^2 = \sigma_2^2 = 0.1$, σ_{12}, $k = 2$, $r_1 = 1$, and $r_2 = 0.5$.

where, using the expression for ρ_1 and ρ_2 this may further be expanded as:

$$a^*(\mu, r_1, r_2) = \frac{1}{k}\big(r_1 \mathbb{E}_\mu[\theta] - r_2 \mathbb{E}_\mu[t]\big) + \frac{(\beta_1\sigma_1^2 - \beta_2\sigma_{12})\,\mathbb{E}_\mu[\theta] + (\beta_2\sigma_2^2 - \beta_1\sigma_{12})\,\mathbb{E}_\mu[t]}{(\mathbb{E}_\mu[\theta])^2\sigma_1^2 + (\mathbb{E}_\mu[t])^2\sigma_2^2 - 2\,\mathbb{E}_\mu[\theta]\,\mathbb{E}_\mu[t]\sigma_{12}}. \tag{5*}$$

Without reputational concerns (i.e., $\beta_1 = \beta_2 = 0$), the expression in (5”) has a direct interpretation: if $r_1, r_2 \geq 0$, higher actions are chosen when the average urgency ($\mathbb{E}_\mu[\theta]$) is higher and the average instability ($\mathbb{E}_\mu[t]$) is lower. This also illustrated in panel (a) of Figure 1. With reputational concerns in the model, however, the direction in which optimal action moves according to changes in average urgency and instability (which are caused by changes in μ) is dependent on Σ, the variance-covariance matrix of (r_1, r_2), and also (β_1, β_2). This ambiguity is captured in the expression in (5*) as well as panel (b) of Figure 1. As seen from the said panel, there are regions of $(\mathbb{E}_\mu[\theta], \mathbb{E}_\mu[t])$ that, despite increasing direct payoffs through decreasing average instability and increasing average urgency.

2.2 Model of Bayesian Persuasion

This paper interprets the CSP environment as a Bayesian persuasion problem, following the seminal work of Kamenica and Gentzkow (2011) (henceforth KG). Specifically, I consider a single-Sender, single-Receiver environment where the former refers the CSO and the latter the representative PS. In order to facilitate a match, a CSO uploads information about the PR onto its official website, from which the PS can select whom to sponsor (or to not be matched at all). However, as the Sender in persuasion, the CSO is not necessarily bound to tell the information about the PR as is.[7] Rather, the organization designs a signal, which is a mapping from the set of PR types to distributions of signal realizations (e.g., the description about the PR seen on CSO websites).

I formalize the persuasion setting as follows, which very closely follows KG.

States, actions, common prior, and payoffs — Let $\Omega \subseteq \mathbb{R}^2$ be the compact state space (i.e., space of PR types), as specified in the previous subsection. Let $A \subseteq \mathbb{R}_+$ be the set of actions (i.e., sponsorship decisions) available to the PS. I assume that the Sender and the Receiver share a common prior belief $\mu_0 \in \Delta\Omega$. In addition, let S be a finite set of signal realizations, where each element $s \in S$ gives rise to a belief $\mu_s \in \Delta\Omega$. Using this, let signal π be defined as $\pi : \Omega \to \Delta S$.

The Receiver's utility function is denoted $U(a, \theta, t)$ and is elaborated in the expression (3). The Sender's payoff function is denoted $v(a, \theta, t)$, where $a \in A$ and $(\theta, t) \in \Omega$ as before. For simplicity, I assume the following properties for $v(a, \theta, t)$:

$$\begin{aligned} &\text{(Increasing in actions)} \quad v_a(a,\theta,t) > 0 \quad \forall a > 0 \\ &\text{(Increasing utility in urgency and instability)} \quad v_\theta(a,\theta,t) > 0 \quad v_t(a,\theta,t) > 0 \quad \forall a > 0 \end{aligned}$$

That is, the CSO receives greater utility from higher sponsorship decisions (i.e., higher a) of the PS and from assisting those who urgently require assistance or are in unstable environments (i.e., higher θ and t). When compared with the Receiver, notice that instability affect the utility of the Sender and direct benefit of the Receiver in opposite ways.

Timing. — I follow the standard Bayesian persuasion process formalized in KG. This can be re-written as follows, to fit the context of this study:

(i) The Sender (i.e., the CSO) chooses (and commits to) signal $\pi : \Omega \to \Delta S$.

(ii) Nature draws $(\theta, t) \sim \mu_0 \in \Delta\Omega$

(iii) Nature draws signal realization $s \in \pi(\theta, t) \in \Delta S$

(iv) The Receiver (i.e., the PS) observes both π and s, and forms posterior belief $\mu_s \in \Delta\Omega$.

(v) The Receiver chooses action (or sponsorship decision) $a \in A$.

It is important to note that the Sender decides its (optimal) signal π prior to the nature's draw of the state, which makes the setting differ from that of communication games such as that described in Crawford and Sobel (1982). This specification allows the Receiver to simply optimize based on the posterior belief that is formed and removes the strategic element found in the aforementioned communication games.

Optimization. — In the previous subsection, I have explored the optimization problem of the PS as the

[7] For instance, Plan International's website displays health information about the PR, but every child's webpage bears the message that the said child has been healthy and not suffered from any serious illness (Plan International n.d.). While it could be that the organization has uploaded information of those who actually are healthy, there is reasonable doubt that at least a small portion of the PR has past or present records of severe medical conditions. For the types of information revealed by other major organizations, I refer to Table 5 in the Appendix.

Receiver provided that he or she forms posterior belief μ_s after having seen the realization s and signal π together. Therefore, I will focus on the Sender optimization problem.

The benchmark case in KG assumes that the Sender knows perfectly about the preferences of the Receiver. However, in the context of this paper, the Sender (i.e., the CSO) may be unsure about the type of the Receiver (i.e., r_1 and r_2). The Sender may still be cognizant of the joint distribution of (r_1, r_2), just like the peers in the case of reputational concerns. Denoting the distribution of posteriors that arises from signal π given μ_0 as $\langle \pi | \mu_0 \rangle$ and accounting for the Sender's uncertainty of Receiver types, the ex-ante optimization problem of the Sender can be written as:

$$\max_{\pi} \ \mathbb{E}_{\mu_s \sim \langle \pi | \mu_0 \rangle} \Big[\int_{(r_1, r_2)} \mathbb{E}_{(\theta,t) \sim \mu_s} \big[v(a^*(\mu_s, r_1, r_2), \theta, t) \big] \ dF(r_1, r_2) \Big] \tag{6}$$

where $F(r_1, r_2)$ refers to the joint cumulative distribution function of r_1 and r_2. The said function is the joint normal distribution described in (1').

The problem in expression (6) can be difficult to solve as it would require the CSO to choose an element in the set of functions. KG simplify the said problem by the Sender choosing a distribution of posteriors $\tau \in \Delta\Delta\Omega$ that coincide with $\langle \pi | \mu_0 \rangle$. This can be accomplished as for any distribution of posteriors, it is possible to find a signal that induces the said distribution (Gentzkow and Kamenica 2016).

Subsequently, the problem in (6) becomes as follows:

$$\max_{\tau \in \Delta\Delta\Omega} \ \mathbb{E}_{\mu_s \sim \tau} \big[\hat{v}(\mu_s) \big] \quad \text{s.t.} \quad \mathbb{E}_{\mu \sim \tau}[\mu] = \mu_0 \tag{6'}$$

where

$$\hat{v}(\mu_s) \equiv \int_{(r_1, r_2)} \mathbb{E}_{(\theta,t) \sim \mu_s} [v(a^*(\mu_s, r_1, r_2), \theta, t)] \ dF(r_1, r_2). \tag{6"-1}$$

The condition $\mathbb{E}_{\mu \sim \tau}[\mu] = \mu_0$ is referred to as Bayes plausibility, and is implemented for the assumption that the common prior is μ_0. By using the concavification approach elaborated in KG, expression (6') can be written as

$$\max_{\tau \in \Delta\Delta\Omega} \ \mathbb{E}_{\mu_s \sim \tau} \big[V(\mu_s) \big] \quad \text{s.t.} \quad \mathbb{E}_{\mu \sim \tau}[\mu] = \mu_0 \tag{6*}$$

where $V(\mu) \equiv \sup\{z | (\mu, z) \in co(\hat{v})\}$ and V is the concavification or concave closure of $\hat{v}$. It follows from this method that there is gain from persuasion if and only if $\hat{v}(\mu)$ is a convex function in $\mu \in \Delta\Omega$ (KG). Furthermore, in case one assumes that the Sender perfectly knows the Receiver's type (i.e., (r_1, r_2)), one may proceed by setting $\hat{v}(\mu)$ as written below:

$$\hat{v}(\mu_s) = \mathbb{E}_{(\theta,t) \sim \mu_s} [v(a^*(\mu_s, r_1, r_2), \theta, t)] \tag{6"-2}$$

and the rest of the procedure can be followed accordingly. Once the Sender finds an optimal distribution of posteriors τ^*, it is relatively easy to construct the corresponding signal $\pi^* : \Omega \to \Delta S$ using the following equation:

$$\pi^*(s|\theta, t) = \frac{\tau^*(\mu_s) \mu_s(\theta, t)}{\mu_0(\theta, t)} \quad \forall \mu_s \in \text{supp}(\tau^*)$$

and signal realization $s \in S$ induces the posterior $\mu_s \in \Delta\Omega$.

2.3 Motivating Example

With the foundations laid above, I now provide simple example to illustrate how to find a numerical solution to the Sender's optimization problem in the expressions (6') and (6*). For simplicity, I also assume that the Sender perfectly knows about the Receiver's type and that the Receiver does not have any reputational concerns. I abuse the notation so that $a^*(\mu) \equiv a^*(\mu, r_1, r_2)$ and $A^*(\mu) \equiv A^*(\mu, r_1, r_2)$, where (r_1, r_2) is the Receiver's type.

Before delving into the problem, I note that I follow a particular method of solving Bayesian persuasion problems described in Lipnowski and Mathevet (2017) (henceforth LM). I will briefly elaborate LM's strategy to finding a optimal signal structure in Bayesian persuasion settings with finitely many states. The said paper refers to Tardella (2008) and mentions that it is difficult to directly compute the concavification of a function. In light of this, the authors instead find a set of posteriors (called outer points of a posterior cover) in $\Delta\Omega$ whose subset can be the support to the optimal distribution of posteriors. This set is denoted as $\text{out}(\mathbb{C}^*)$ below, where $\mathbb{C}^*$ is the said posterior cover. By Theorem 1 and Proposition 1 in LM, $\text{out}(\mathbb{C}^*)$ can be written as:

$$\begin{aligned}
&\text{out}(\mathbb{C}^*) = \big\{\mu^* \in \Delta\Omega \mid B(\mu^*) = \{\mu^*\}\big\} \\
&\text{s.t. } B(\mu^*) \equiv \{\mu \in \Delta\Omega \mid \text{supp}(\mu) \subseteq \text{supp}(\mu^*) \text{ and } A^*(\mu^*) \subseteq A^*(\mu)\}.
\end{aligned}$$

Notice that by assuming Ω is finite, the set $\text{out}(\mathbb{C}^*)$ is also finite. Therefore, one may write a simple algorithm for the possible combinations of the elements (i.e., posteriors) in $\text{out}(\mathbb{C}^*)$ and find the optimal distribution of posteriors τ^* that solves (6').

Using this characterization of the solution to Bayesian persuasion, consider the following example setup. To allow for a 2D graphical representation, let $\Omega = \{(0.7, 0.4), (0.7, 0.7), (0.4, 0.7)\}$ where each element $(\theta, t) \in \Omega$ is an urgency-instability pair. For the sake of convenience, let let us denote $\omega_1 = (0.7, 0.4)$, $\omega_2 = (0.7, 0.7)$, and $\omega_3 = (0.4, 0.7)$.[8] The prior belief is $\mu_0 \in \Delta\Omega$. Suppose also that $A = \{0.5, 0.35, 0.05\}$. The Receiver's type is $(r_1, r_2) = (1, 0.5)$ and the Sender is fully aware of the said type. The Receiver and the Sender have the following utility functions, respectively:

$$U(a, \theta, t) = (\theta - 0.5t)a - 0.5a^2 \qquad v(a, \theta, t) = \theta t\sqrt{a}$$

and notice that these functional forms agree with the specifications laid out in previous subsections. With this, the Receiver's utility in each state-action pair can be written down as in Table 1.

Given an arbitrary $\mu \in \Delta(\Omega)$, the Receiver chooses an action in $A^*(\mu) \subseteq A$ where

$$A^*(\mu) = \underset{a \in A}{\arg\max}\, \mathbb{E}_{(\theta,t)\sim\mu}\Big[U(a, \theta, t)\Big]$$

[8]Accordingly, let any $\mu \in \Delta(\Omega)$ be denoted as $\mu = (p_1, p_2, p_3)$, where p_i denotes the probability of state ω_i under μ for all $i \in \{1, 2, 3\}$.

Table 1: Receiver Utility, Three-State Case

		Actions		
		0.5	0.35	0.05
States	$(0.7, 0.4)$	**0.125**	0.11375	0.02375
	$(0.7, 0.7)$	0.05	**0.06125**	0.01625
	$(0.4, 0.7)$	-0.1	-0.04375	**0.00125**

and after organizing the terms, one may further write

$$\mathbb{E}_{\omega\sim\mu}\Big[u(a,\omega)\Big] = \begin{cases} 0.225\mu(\omega_1) + 0.15\mu(\omega_2) - 0.1 & \text{if } a = 0.5 \\ 0.1575\mu(\omega_1) + 0.105\mu(\omega_2) - 0.04375 & \text{if } a = 0.35 \\ 0.0225\mu(\omega_1) + 0.015\mu(\omega_2) + 0.00125 & \text{if } a = 0.05 \end{cases}$$

Using this, it is possible to derive the set of optimal actions of the Receiver as follows:

$$A^*(\mu) = \begin{cases} \{0.5\} & \text{if } 6\mu(\omega_1) + 4\mu(\omega_2) > 5 \\ \{0.5, 0.35\} & \text{if } 6\mu(\omega_1) + 4\mu(\omega_2) = 5 \\ \{0.35\} & \text{if } 6\mu(\omega_1) + 4\mu(\omega_2) \in (2, 5) \\ \{0.35, 0.05\} & \text{if } 6\mu(\omega_1) + 4\mu(\omega_2) = 2 \\ \{0.05\} & \text{otherwise} \end{cases}$$

where $\mu(\omega_1), \mu(\omega_2) \geq 0$ and $\mu(\omega_1) + \mu(\omega_1) \leq 1$. When there are more than one actions in $A^*(\mu)$ for an arbitrary μ, it is assumed that the Receiver will choose randomly (with equal probabilities) amongst the said actions. Let a-optimal region be informally defined as the subset of $\Delta\Omega$ such that an action $a \in A$ is the optimal response. Then, the a-optimal regions for each $a \in A$ (denoted $\mathbb{C}_a$) can be confirmed in Panel (a) of Figure 2, and a $\hat{v}$-cover is $\mathbb{C}^* = \{\mathbb{C}_{0.5}, \mathbb{C}_{0.35}, \mathbb{C}_{0.05}\}$ (LM, Theorem 1). The set of outer points of $\mathbb{C}^*$, also confirmed in Panel (a) of Figure 2, can be written as follows:

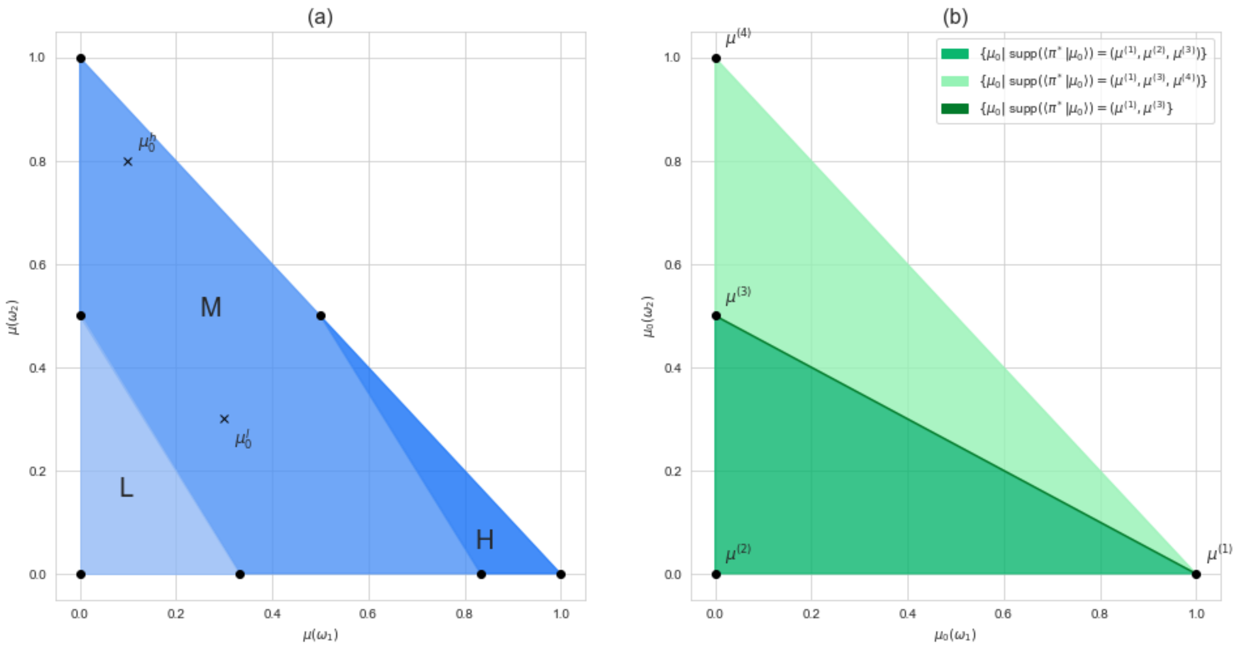
$$\text{out}(\mathbb{C}^*) = \Big\{(1,0,0), \Big(\frac{5}{6}, 0, \frac{1}{6}\Big), (0,0,1), (0.5,0,0.5), (0,1,0), (0.5,0.5,0)\Big\}$$

Now, consider the following three candidates for the common prior belief between the Sender and the Receiver, μ_0^h, μ_0^m, and μ_0^l, where they are any beliefs satisfying the following criteria:

$$\mu_0^h \in \{\mu \in \Delta(\Omega) | \mu(\omega_1) + 2\mu(\omega_2) > 1,\ \mu \text{ is interior}\}$$
$$\mu_0^m \in \{\mu \in \Delta(\Omega) | \mu(\omega_1) + 2\mu(\omega_2) = 1,\ \mu \text{ is interior}\}$$
$$\mu_0^l \in \{\mu \in \Delta(\Omega) | \mu(\omega_1) + 2\mu(\omega_2) < 1,\ \mu \text{ is interior}\}$$

For convenience, let $\mu_0^h = (h_1, h_2, 1 - h_1 - h_2)$, $\mu_0^m = (m_1, m_2, 1 - m_1 - m_2)$, and $\mu_0^l = (l_1, l_2, 1 - l_1 - l_2)$.

Figure 2: a-Optimal Regions and Supports for Optimal Distributions of Posteriors



NOTE: Panel (a) shows the a-optimal regions (denoted **H**, **M**, and **L**, referring to $\mathbb{C}_{0.5}$, $\mathbb{C}_{0.35}$, and $\mathbb{C}_{0.05}$ respectively), outer points of $\{\mathbb{C}_{0.5}, \mathbb{C}_{0.35}, \mathbb{C}_{0.05}\}$ (shown in black, round points), and example priors $\mu_0^l = (0.3, 0.3)$ and $\mu_0^h = (0.8, 0.1)$. Panel (b) shows the regions of priors where a certain set of outer points constitute the support of optimal distribution of posteriors.

Denoting the optimal distribution of posteriors under the prior $p \in \{\mu_0^h, \mu_0^m, \mu_0^l\}$ as $\tau_p \in \Delta\Delta\Omega$, simple calculation reveals that the supports for τ_p are as follows:

$$\begin{aligned} \mathrm{supp}(\tau_{\mu_0^h}) &= \big\{(1,0,0), (0,0.5,0.5), (0,1,0)\big\} \\ \mathrm{supp}(\tau_{\mu_0^m}) &= \big\{(1,0,0), (0,0.5,0.5)\big\} \\ \mathrm{supp}(\tau_{\mu_0^l}) &= \big\{(1,0,0), (0,0.5,0.5), (0,0,1)\big\} \end{aligned}$$

The said supports are also depicted in Panel (b) of Figure 2. Further, to satisfy the Bayes plausibility condition, it must be that the τ_p's have the following probability masses:

$$\tau_{\mu_0^h}(\mu) = \begin{cases} h_1 & \text{if } \mu = (1,0,0) \\ 2(1-h_1-h_2) & \text{if } \mu = (0,0.5,0.5) \\ h_1 + 2h_2 - 1 & \text{if } \mu = (0,1,0) \end{cases} \quad \tau_{\mu_0^l}(\mu) = \begin{cases} l_1 & \text{if } \mu = (1,0,0) \\ 2l_2 & \text{if } \mu = (0,0.5,0.5) \\ 1 - l_1 - 2l_2 & \text{if } \mu = (0,0,1) \end{cases}$$

$$\tau_{\mu_0^m}(\mu) = \begin{cases} m_1 & \text{if } \mu = (1,0,0) \\ 1 - m_1 & \text{if } \mu = (0,0.5,0.5) \end{cases}$$

and the optimal signals compatible with the distributions of posteriors $\tau_{\mu_0^h}$, $\tau_{\mu_0^m}$, and $\tau_{\mu_0^l}$, denoted $\pi_{\mu_0^h}$, $\tau_{\mu_0^m}$ and $\pi_{\mu_0^l}$, are written in Table 2.

From Table 2, one can verify that the optimal design of signals varies with the common prior. However,

Table 2: Optimal Signals with Priors μ_0^h, μ_0^m, and μ_0^l

$\pi_{\mu_0^h}:\Omega\to\Delta(S_h)$			$\pi_{\mu_0^m}:\Omega\to\Delta(S_m)$			$\pi_{\mu_0^l}:\Omega\to\Delta(S_l)$		
ω	$s\in S_h$	$\pi_{\mu_0^h}(s\|\omega)$	ω	$s\in S_m$	$\pi_{\mu_0^m}(s\|\omega)$	ω	$s\in S_l$	$\pi_{\mu_0^l}(s\|\omega)$
(0.7, 0.4)	(1, 0, 0)	1	(0.7, 0.4)	(1, 0, 0)	1	(0.7, 0.4)	(1, 0, 0)	1
(0.7, 0.7)	$\left(0,\frac{1}{2},\frac{1}{2}\right)$	$\frac{1-h_1-h_2}{h_2}$	(0.7, 0.7)	$\left(0,\frac{1}{2},\frac{1}{2}\right)$	1	(0.7, 0.7)	$\left(0,\frac{1}{2},\frac{1}{2}\right)$	1
(0.7, 0.7)	(0, 1, 0)	$\frac{h_1+2h_2-1}{h_2}$	(0.4, 0.7)	$\left(0,\frac{1}{2},\frac{1}{2}\right)$	1	(0.4, 0.7)	$\left(0,\frac{1}{2},\frac{1}{2}\right)$	$\frac{l_2}{1-l_1-l_2}$
(0.4, 0.7)	$\left(0,\frac{1}{2},\frac{1}{2}\right)$	1				(0.4, 0.7)	(0, 0, 1)	$\frac{1-l_1-2l_2}{1-l_1-l_2}$

NOTE: S_h, S_m, and S_l are realization spaces corresponding to signals $\pi_{\mu_0^h}$, $\pi_{\mu_0^m}$ and $\pi_{\mu_0^l}$. For any $k\in\{h,m,l\}$, written beneath $s\in S_k$ are the posteriors (in $\Delta(\Omega)$) that are induced by the signal realizations in S_k, and written beneath $\pi_{\mu_0^k}(s|\omega)$ are the respective probabilities of sending a signal (that induces the posteriors written directly to their left) given the state ω. If a certain $\pi_{\mu_0^k}(s|\omega)$ is equal to 0, the respective information is omitted.

two characteristics are constant regardless of the prior distribution. Firstly, it is optimal for the Sender to design a signal that truthfully reveals the state when $\omega=(0.7,0.4)$. That is, when nature chooses the said state, the Sender is better off by selecting a signal that deterministically raises a truth-revealing realization.[9] It is also of the Sender's interest to *not* raise the said realization in any other states as well, for the sake of Bayes plausibility. This specific state is when the Sender and the Receiver are aligned in their interest due to high urgency and low instability.

Another observation, also invariant to the prior, is that there is always some state $\omega'\in\Omega$ that raises a specific realization that leaves the Receiver wondering whether one is in the state $(0.7,0.7)$ or $(0.4,0.7)$ (with 50% chance each). The exact state that compels the Receiver to contemplate varies with the prior, to satisfy Bayes plausibility. The reason for such a signal realization's inclusion in the optimal signal is that there are regions of Ω where the two parties' interests are misaligned due to higher levels of instability. However, except for the particular case of μ_0^m, there another state $\omega''\in\Omega$ with $\omega''\neq\omega'$ that probabilistically sends a truth-revealing realization. This observation means that even if considering only the states in the regions of Ω where the interests are misaligned, fully uninformative signals to the Receiver can be sub-optimal.

The critical takeaway for the Sender's optimization in this example is that, in situations of partial alignment in interests such as this one, neither full nor no revelation of information is an optimal choice of signaling. While the Receiver is always better off under the full-revelation signal than one that is Sender-optimal, he or she is also better off under the latter than the no-revelation one. Some of the CSO mentioned in Table 5 of the Appendix employ strategies that are akin to the no-revelation case regarding urgency and instability, and I expect Pareto improvement when the said organizations employ Bayesian persuasion. Some organizations, such as Compassion International, do use signal realizations indicating urgency and instability with some variance. In their case, the said groups may benefit from Bayesian persuasion by also considering how finely they want to define the state space (and subsequently, the signal realization space and the common prior).

[9]Here, the truth-revealing realization for some state ω refers to the signal realization leading to a posterior that places a mass of 1 on the said ω.

3 Data and Empirical Framework

3.1 Data

The study conducts empirical analyses involving both reduced-form and structural estimations. The former approach is taken to bolster the argument for the PS' preferences over urgency and instability. The latter is employed as reputational concerns in the model of PS preferences are hard to capture using the former method. Also, by structurally estimating the parameters of the utility function of PS, it will be possible to find the optimal signal structure as described in Subsection 2.2.

For accomplishing the tasks mentioned above, this study has collected individual-level data of 9,518 children from the official website of Compassion International.[10] Among many organizations, I chose Compassion International (henceforth Compassion) as its website provides more individual-level information about the PR. For the types of information presented by other institutions, I again refer to Table 5 in the Appendix. Another practical reason was that Compassion's website had a relatively full list of children available for sponsorship. In contrast, other websites (e.g., that of Save the Children) only showed a few sample individuals through randomization.

I administered data collection daily from April 19, 2019, to May 3, 2019, using web scraping through Python's Selenium module. Each round of collection was made at around 9:00 PM Central Standard Time (CST) for approximately 3 hours, except for the sessions in May due to network-related problems where the processes started at 11:00 PM CST. The first data collection was to curate the characteristics of the PR in the study's sample, which could influence the sponsorship decisions of the PS. Fourteen additional follow-ups were made to check the match/non-match status of each PR. The dataset is right-censored as it has a set window of observation, and the match/non-match statuses of the PR are not visible after the said window.

Table 6 of the Appendix provides the descriptive statistics of most of the available covariates. I separate the table by whether a PR associated with the data was matched within the 14-day window of observation or not. A rudimentary analysis with differences in the means and the corresponding t-statistics, while not entirely conclusive, shows that there is heterogeneity between the two groups separated by match status.

A closer look at the "badge" variables. — Among the covariates, those located in panel D of Table 6 require more attention. They are "urgency" (indicating a PR has waited 180 days or more without a sponsor), "AIDS-affected area," and "vulnerable to exploitation." For simplicity, I will refer to them as "urgency," "AIDS-area," and "exploitability," respectively, and collectively call them "badge variables." These three variables are the more-prominently displayed information, in which the official Compassion website highlights using "badges" or visual indicators right next to the photographs of the PR if applicable. Along with primary information such as the name, birth date, and picture of a PR, these variables are what a PS would first respond to even before clicking on a separate, individual page to acquire information about other PR attributes. I also note that the days of waiting for a sponsor are displayed *only* for the children with urgency badges.[11]

[10] For a more recent list of children waiting for sponsorship, I refer to the following web page: `https://www.compassion.com/sponsor_a_child`.

[11] However, I also note that it is possible to discover an approximate order of days without sponsors for the PR without urgency badges. The said order be can found by setting the display option to "longest waiting" and taking note of the pages

I note that the badge variables correspond well to the urgency-instability framework discussed in Section 2. The urgency variable needs no further explanation; AIDS-area and exploitability map to instability. However, it is not to say that other variables have no contribution to the said urgency-instability framework. For instance, guardian employment status can be an indication of how desperately a PR needs material support. There are also more ambiguous variables, such as the age of PR. As an illustration, younger age might be associated with urgency due to early-childhood development needs, but also with instability because of reasons such as child mortality.

Despite their importance, there are problems associated with the badge variables, especially AIDS-area and exploitability. A more in-depth look at the dataset shows that the Compassion website has coded all PR living in Africa and *only* them as those in AIDS-affected areas. It is true that, on a continent-level inspection, those in Africa are more susceptible to HIV/AIDS. However, this is false on a country- or region-level investigation. For instance, the west-African nation of Burkina Faso has a lower HIV/AIDS prevalence than Haiti (CIA n.d.). Both are nations where portions of the overall sample PR reside in, yet the latter country (being in the Caribbean) is not marked as AIDS-area whereas the former is. Further, for exploitability, the official website does not give any guideline of what constitutes vulnerability to exploitation and what type of exploitation (e.g., labor, sexual) the badge is referring to. Due to these issues, any PS may have misinterpreted the information shown by the said two badges.

3.2 Reduced-form Approaches

This study employs two reduced-form estimation strategies to identify the displayed PR characteristics' impact on yielding sponsorship matches; they are survival analysis and RDD. The former is a suitable choice as the dataset is right-censored; the latter is implemented to assess further the conditional average treatment effect (CATE) of the urgency badge around the cutoff where it begins to be displayed.

Survival analyses. — Survival regressions will be the primary reduced-form strategy that this study employs to understand the relationship between successful matches and the displayed PR characteristics. The critical object of interest in a survival analysis approach is the conditional hazard; it is the probability that an observation is removed (or reaches "death") from the list in the directly subsequent period given that the said observation is on the list (or "alive") and also provided the covariates (Ciuca and Matei 2010). Therefore, conditional hazard directly corresponds to how long it takes for a match to be made (or not made during the survey window) in the CSP environment.

This study explores both parametric and nonparametric survival regressions, following Cox (1972). For the parametric version, I choose to make use of Weibull regression. The nonparametric version is more commonly known as the Cox proportional hazards model (or, simply, Cox regression) (Rodriguez 2010). The two cases differ only by how the baseline hazard function is estimated. In the parametric case, the baseline hazard function assumes a predefined functional form; for instance, Weibull regression sets the said function to be a Weibull function. In the nonparametric case, it is estimated using the data (Rodriguez 2010).

they are shown on.

The paper utilizes both approaches for their complementarity, despite their interpretations not being so different. Parametric survival regressions, due to assuming specific baseline hazard functions, may produce less realistic results accompanied by monotonic conditional hazard functions. Nonparametric versions do not bear this problem but potentially have the problem of overfitting.

Following Rodriguez (2010), I write the continuous-time model of survival regression as follows:

$$\lambda_i(t|X_i) = \lambda_0(t)\ \exp(X_i'\beta)$$

where $\lambda_0(t)$ is the baseline hazard function at time t, X_i' is the vector of covariates for individual i, and $\lambda_i(t|X_i)$ is the conditional hazard function at time t given the said covariates. Because the study does not observe the data in continuous time, one may re-write the above model as follows:

$$\lambda_{ij}(X_i) = \lambda_j\ \exp(X_i'\beta)$$

where j denotes the time interval instead of continuous time, λ_j the baseline hazard function at time interval j, and $\lambda_{ij}(X_\beta')$ the conditional hazard function at time interval j given the covariates X_i of individual i.

For the covariates, this study will primarily consider the treatment variables as the three badge variables (i.e., urgency, AIDS area, and expropriation) with the control variables as age, biological sex, dummy variables for living with father and with mother, continent dummies, guardian employment statuses, educational levels of the PR, and "page" dummies. "Page," unless described otherwise, will henceforth refer to the specific page a PR is displayed on when shown in the order of the longest time waiting.

Regarding the control variables, note that while they are designated as controls to better learn of the effect of the three badge variables, one may interpret some (including guardian employment statuses and age of the PR) as treatments that influence sponsorship matching as well. Further, additional controls, such as average regional monthly income and the number of siblings, will be noted when utilized.

A note on standard errors and multiple hypotheses testing. — The study assumes that there may be structural unobservables at the page level that influence sponsorship matches. For instance, it may be that the PS' attention is restricted to a per-page level, and they may only consider the PR on a specific page to be in their set of alternatives. Per such considerations, the study will use clustered standard errors (SE) at the page level.

Moreover, note that the study regards the PS to be observing multiple PR characteristics at once, and such information is contemporaneously affecting the PS' decision-making. Following this viewpoint, the survival regression strategy described above tests several covariates together for their statistical significance in determining matches. Therefore, I consider multiple hypotheses testing and the corresponding correction for SE. A relatively simple way of implementing the said procedure is to use the Bonferroni correction, which is to test individual hypotheses at the significance level of α/K when the target significance is at α, and there are K hypotheses to test (Dunn 1961).

Regression discontinuity design. — I note that the urgency badge has a dual nature. While being a signal realization to inform the PS about how dire a PR's situation is, it is also an indirect way to show how long the said PR has been on the CSP database waiting for sponsors. This latter part poses a problem in interpreting the sign or statistical significance of the coefficient estimated from survival analysis, as it may highlight the extended exposure to being on the list (and have higher chances of yielding matches). In light of this, the study employs the RDD approach to disentangling the components of the said dual nature. Specifically, it looks at the CATE of urgency badge on match probability at the threshold of it turning on; by doing so, it is possible to estimate the urgency badge's impact on sponsor-recipient matches with less concern for the impact of extended exposure.

This paper uses the fuzzy RDD approach. As previously explained, the said threshold of urgency badge turning on is precisely 180 days after being on the list, and the days of waiting are unobservable to the PS when 180 days have not passed. This inability to pinpoint the days of waiting for the majority of observations prevents the use of sharp RDD.[12] However, the dataset has page information that serves as a proxy for days without sponsorship. As seen from Figure 4 in the Appendix, there is a sharp, monotonic increase of percent showing urgency between the pages three and four; this motivates the use of fuzzy RDD. The probability of being "treated" by the urgency badge does not jump from 0 to 1 (as in the sharp RDD setting), but there still exists a sizeable, discontinuous change in the said probability of treatment at the threshold (i.e., page 3).

I follow Hahn et al. (2001) and use the instrumental-variables version of fuzzy RDD, which can be written as follows:

$$Y_i = \alpha + \gamma \text{urgency}_i + \beta(\text{page}_i - 3) + \delta Z_i(\text{page}_i - 3) + \varepsilon_i$$

where, for individual i, Y_i is the match status (= 1 if matched during the window of observation), urgency_i is the urgency badge variable (= 1 if the said badge is shown), and page_i is the page i was displayed on. urgency_i is instrumented by $Z_i \equiv 1\{\text{page}_i \leq 3\}$. The parameters α, γ, β, and δ are estimated by local linear regression as follows:

$$(\hat{\alpha}, \hat{\tau}, \hat{\beta}, \hat{\delta}) = \underset{\alpha,\tau,\beta,\delta}{\arg\min} \sum_{i=1}^{n} \left(Y_i - \alpha - \tau \texttt{urgency}_i - \delta Z_i(\texttt{page}_i - 3)\right)^2 K_h(\texttt{page}_i - 3)$$

where $K_h(\cdot)$ is the kernel function with bandwidth h. This paper uses triangular kernel with optimal bandwidth h selected by the method of Calonico et al. (2014). For sensitivity analysis of the threshold being page 3, I will also conduct regressions with similar designs using page 2 and page 4 as thresholds.

Note that because the fuzzy RDD described above utilizes IV, it must satisfy relevance and exclusion restriction. The relevance condition follows from the existence of a threshold for being "treated" with an urgency badge. On the other hand, showing exclusion restriction can be dubious as it may be the case where the page variable itself affects match status. For example, the PS might be negligent of looking at the latter pages in comparison to the earlier ones due to limited time and attention. For example, the PS might be negligent of looking at the pages near the end in comparison to the earlier ones due to limited time and attention. However, because the problem at hand is to estimate the CATE of urgency badge

[12] I note that I also considered the method of assuming a parametric distribution for the days of waiting and fitting the known data points using maximum likelihood estimation. However, because the days of waiting are observed only for the first three pages (approximately only 2% out of the total 140 pages), I deemed that this would be highly inaccurate.

at the threshold, I argue that the page variable would not locally affect the decision-making of a PS. As an illustration, consider a PS browsing a set of PR for sponsorship decisions on page n. While it would be difficult to argue that the said PS would view each page with equal carefulness, it is not unrealistic to assume that he or she may inspect pages $n-1$ to $n+1$ with similar amounts of attention. That is, there is no local direct impact from page numbers to match statuses. This relaxation helps one to apply the exclusion restriction condition.

4 Estimation Results

4.1 Results from Reduced-form Approaches

Survival analyses with Bonferroni corrections. — Presented in Table 3 are the hazard rate estimates (with page-clustered SEs) from both Cox and Weibull regressions. The results across the two methods align well with one another. All of the three badge variables (i.e., urgency, AIDS-area, and exploitability) yield statistically significant results at the 1% level. Note that according to Table 3, urgency is shown to be decreasing match probability. However, this is due to the regressions all using page dummies, which can be considered proxies for urgency. I will examine how urgency affects match probability in the results for RDD, as previously described. I also note that I will use Bonferroni corrections to test whether the variables' statistical significance still holds when examining multiple hypotheses.

Let us further examine the coefficients for AIDS-area and exploitability displayed in Table 3. As the coefficients are hazard rate estimates, those below one mean that they contribute to the increase in survival rates – that is, they would decrease the match probability. AIDS-area and exploitability, which can be argued as signs of instability for PR, do indeed reduce the chance of yielding matches. This discovery bolsters the model of PS preferences elaborated in Section 2. However, I also remark that due to signal realizations for AIDS-area and Africa perfectly overlap (as examined in Section 3), the coefficient on AIDS-area should also account for the impact of a PR being from Africa. It is impossible to disentangle the two differently-labeled but effectively the same variables, given the dataset of this study.

Other points of interest (with statistical significance), while their relationship to the urgency-instability framework of PS preferences is unclear, are as follows. Firstly, a female PR is more likely to yield a match than a male PR, on average. Further, those with only a single guardian being employed are less likely to be matched over those with both guardians employed *and* those with all guardians being unemployed or unconfirmed. Preference for female PR is analogous to that shown for female children in studies of child adoption. In Gravois (2004), the author posits that as a majority of adoptive parents or interested parties are female, there is a tendency for the said adoptive parents to choose children with the same biological sex than to do the otherwise. Baccara et al. (2014) also show that in the case of matching children to adoptive parents, there is a preference for specific ethnicities and genders (African-American and females). Perhaps a similar phenomenon is occurring here, in which there are more female PS than male ones, and they are more willing to adopt female PR; this connects back to the anecdotal evidence in Rabbitts (2014). However, because I have not been able to acquire data on PS demographics, this idea remains to be a hypothesis.

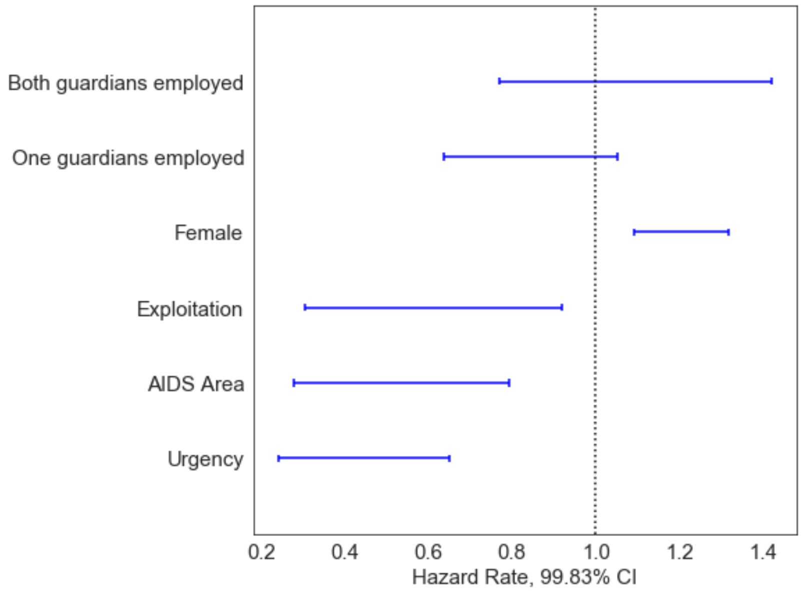
Table 3: Survival Regression Results

	Cox		Weibull	
	(1)	(2)	(3)	(4)
Urgency	0.4450***	0.4460***	0.3901***	0.3959***
	(0.0650)	(0.0621)	(0.0596)	(0.0579)
AIDS-area (Africa)	0.5344***	0.6152***	0.5212***	0.6074***
	(0.0824)	(0.1012)	(0.0899)	(0.1100)
Exploitability	0.6124***	0.6609***	0.5914***	0.6477***
	(0.0981)	(0.1033)	(0.1036)	(0.1105)
Age	1.0355	1.0368	1.0443	1.0454
	(0.0360)	(0.0369)	(0.0394)	(0.0406)
Female	1.2039***	1.2090***	1.2183***	1.2255***
	(0.0362)	(0.0370)	(0.0391)	(0.0403)
Living with mother	1.0268	1.0112	1.0322	1.0147
	(0.0598)	(0.0691)	(0.0632)	(0.0728)
Living with father	1.0111	1.0160	1.0104	1.0162
	(0.0387)	(0.0416)	(0.0410)	(0.0440)
One guardian employed	0.8433**	0.8599**	0.8274**	0.8478**
	(0.0662)	(0.0646)	(0.0708)	(0.0687)
Both guardians employed	1.0954	1.1244	1.0837	1.1201
	(0.1039)	(0.0984)	(0.1105)	(0.1041)
Unenrolled	0.9452	0.9437	0.9389	0.9390
	(0.0794)	(0.0783)	(0.0844)	(0.0834)
Preschool & Kindergarten	0.9672	0.9619	0.9684	0.9601
	(0.0730)	(0.0694)	(0.0786)	(0.0739)
Elementary or Middle	1.0013	1.0004	1.0008	0.9994
	(0.1011)	(0.0984)	(0.1083)	(0.1054)
Regional monthly income		1.0009*		1.0009*
		(0.0005)		(0.0005)
N	9518	9518	9518	9518
Page dummies	Yes	Yes	Yes	Yes
Continent dummies	Yes	Yes	Yes	Yes
Additional controls	No	Yes	No	Yes

NOTE: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$. SE clustered at the page-level in parentheses. Hazard rate estimates reported for all columns, in which the dependent variable is the conditional hazard rate. Columns (1) and (2) report results from Cox regression; (3) and (4) report those from Weibull regression. Values less than 1 indicate reducing the hazard rate (i.e. correlated with longer period of not being matched). Baseline for education is "too young to be in school"; that for guardian employment is "both unemployed or unknown." Page dummies have the baseline of page 1. Continent dummies include Asia, South America, Central America, with the baseline of North America/Caribbean. Additional controls include regional monthly income (scaled to USD), percent of Christians in a country, number of siblings in a family, and living with grandparents. Constant omitted for Weibull regressions.

I also provide a similar (inconclusive yet exploratory) hypothesis about the statistical significance of the conditional hazard of only one guardian employed being less than 1. In the urgency-instability framework, a PS may judge guardian employment as follows: the more guardians a PR has working, the more stable and less urgent he or she is. This assumption in a PS's judgment would mean that, from the model of PS preference developed in Section 2, the direct payoffs from choosing to sponsor a child with only one guardian working is lesser than those from sponsoring children with both or no parents working. This story aligns well with the results in Table 3, but it is not definitive as an additional assumption about the PS is required. Also, it leaves reputational concerns out of the frame, which may have their roles in matching.

Figure 3: Multiple Testing with Bonferroni-Corrected Confidence Intervals



NOTE: Results used to create the confidence intervals are shown in column 1 of Table 3.

Before presenting the robustness under multiple testing, I exhibit the hazard rate functions of Cox and Weibull regressions. Figure 5 of the Appendix plots the graphs of the said functions with analysis time. As opposed to the monotonically increasing hazard function of Weibull regression, that of the Cox regression has a peak at around ten days into analysis time. The monotonic increase of the hazard rate would mean that as a PR waits longer for sponsorship, one becomes increasingly more likely to be matched. However, observations from the data do not fully support this as there is a sizeable amount of PR with extremely long days of waiting. Therefore, the nonparametric Cox regression would a more suitable choice for analysis.

Finally, I present the results of applying Bonferroni correction for multiple testing. I test the hypotheses for statistically significant variables, which are the three badge variables, female, and one guardian being employed. For completeness of guardian employment status, I also consider the variable of both guardians being employed. Following Dunn (1961), testing for the benchmark statistical significance of 1% for all six hypotheses together is roughly the same as testing each hypothesis at the 0.167% level (and constructing 99.83% confidence interval for each). I plot the resulting 99.83% confidence intervals in Figure 3. According to this more stringent judgment of statistical significance, guardian employment status is not an essential factor to determine match probability. The three badge variables and the female variable retain their statistical significance, and their interpretations remain the same.

Fuzzy RDD. — As elaborated in Section 3, estimations using fuzzy RDD around page 3 (and around pages 2 and 4 for sensitivity) are conducted to address concerns regarding the dual nature of the urgency badge. Table 4 shows the results.

I begin by examining the first-stage estimates (in panel B of Table 4), which will gauge how strong the relationship is between the variables page and urgency. The coefficients on the page variable are all shown

Table 4: Results for Fuzzy Regression Discontinuity Design (Using IV)

	Threshold page		
	page 3	page 2	page 4
Panel A. Structural Estimates			
Urgency	0.1067***	−0.0194	−0.2142
	(0.0278)	(0.0469)	(0.3236)
Panel B. First-stage Estimates			
Page	−0.8179***	−0.3412***	−0.2190
	(0.0331)	(0.0570)	(0.1477)
Total N	9518	9518	9518
Left N	109	45	168
Right N	950	666	261
Optimal bandwidth	13.093	9.150	3.445

NOTE: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$. Heteroskedasticity-robust SE in parentheses. Out of the three threshold pages, using page 3 produces the main result; others are used for sensitivity analysis. Dependent variable is binary match status during the window of observation (i.e. $= 1$ if matched in the window). Left and right N refer to the numbers of observations with page less than or equal to the threshold and greater than the threshold used for fitting the local linear regression. Triangle kernel function was used.

to be negative, which means that as the page numbers increase, it is less likely to see the urgency badge. This intermediate result is correct as the pages are in the decreasing order of duration of waiting without sponsorship. I also note that both the magnitude and statistical significance of the coefficient on the page variable are the most considerable for the threshold page of 3. This observation is anticipated, as seen in Figure 4 of the Appendix.

Next, I examine the CATE of urgency on match probability at the designated thresholds. Table 4 presents the results of the structural estimates of the fuzzy RDD. Note that positive values for the coefficients mean that the urgency badge increases the chances of a sponsorship match. The study finds the only positive and the single statistically significant result when using the threshold of page 3. This finding confirms that, despite the worry for the urgency badge's dual nature as previously mentioned, the said variable positively affects match probability at the threshold where it turns on. There may still exist lingering concerns for the urgency badge, as it is challenging to extrapolate a local estimation onto the global setting. However, given that there are 140 pages in total and only three pages show any PR with the urgency badge, extending this effect for additional two pages (i.e., pages 1 and 2) may be justifiable.

5 Future Directions

This study presents a model of PS preferences over PR characteristics that is inspired by the model of prosocial behavior in Bénabou and Tirole. It also provides an interpretation for understanding the CSP sponsor-recipient match environment as an information design problem using the Bayesian persuasion model in Kamenica and Gentzkow (2011). A simple example of how Bayesian persuasion can be beneficial to maximize sponsorship accompanies the said theoretical efforts. Also, the study conducts a reduced-form analysis using the Compassion International dataset and provides evidence for the urgency-instability framework in the model of PS preferences previously mentioned.

The future research direction of this paper is to structurally estimate the PS utility function using the model of PS preferences developed earlier in conjunction with the Compassion International dataset. Further, using the estimated PS utility function, I propose to computationally find the optimal signal structure that befits the dataset of this study. I will follow a modified version of the methods described in Evans and Viscusi (1991) and Keane et al. (2011) to conduct the structural estimation. The objective of the said estimation is as follows. Firstly, it is to account for empirical evidence for or against reputational payoff, which is a component in the model of PS preferences, as it is challenging to verify this component using reduced-form strategies and the current dataset. Secondly, it is to find parameters for the PS utility function that the study can use for calculating the optimal signal structure.

A Appendix

A.1 Appendix Tables

Table 5: Types of Information Revealed by Child Sponsorship Organizations

Organization	$/Month	Types of Information
World Vision	$39	• Basic country-level information • Advanced individual-specific information • Individual health conditions also revealed, but almost all potential recipients indicated as “in satisfactory health” • Basic family-specific information • Short video accompanied
Compassion Int’l	$38	• Basic country- and region-level information • Advanced individual-specific information • Basic family-specific information • Specific badges to indicate vulnerability to AIDS and that to child exploitation, but these are binary (badge or no badge)
Save the Children	$39	• Basic country-level information • Basic individual-specific information with days without a sponsor
ChildFund Int’l	$36	• Advanced individual-level information without days without a sponsor • Basic family-specific information
Plan Int’l	$35	• Basic individual-specific information • Information about the CSO’s operations in the respective country, but no basic country-level information • Detailed information about access to water (e.g., what the main source of water is, how long it takes to reach that source) • Information about the PR’s housing type and how they cook • Individual health conditions also revealed, but in all cases the following message is displayed: “According to the family, (name) has been healthy and not suffered from any serious illness”

NOTE: “Int’l” refers to “International.” “$/Month” refers to the monthly payment amount, in USD, required per child sponsorship in the year 2019. “Basic country-level information” refers to items such as climate, terrain, major diseases, and main diet at a nationwide scale. “Basic region-level information” refers to the same items but at a smaller, regional scale. “Basic individual-specific information” refers to the name, age, country, spoken language, and photos of the children. “Advanced individual-specific information” refers to items such as days of waiting without a sponsor, hobbies, school enrollment status, and family duties of the children in addition to the basic individual-specific information. “Basic family-specific information” refers to items like the status of guardians living with the children, guardians’ employment status, and siblings (if any).

Table 6: Descriptive Statistics by Match Status

	Matched (1)	Not matched (2)	t-statistic (3)
Panel A. Demographics			
Age	4.760	4.587	5.421
Female	47.22	44.77	2.438
Education			
Too young for enrollment	34.70	32.84	1.917
Unenrolled despite of age	13.44	15.33	−2.641
Preschool and kindergarten	33.86	39.00	−5.229
Elementary and middle schools	18.01	12.83	6.952
Panel B. Family Information			
Living with mother	92.57	91.24	2.397
Living with father	69.70	63.59	6.342
Number of siblings	1.558	1.578	−0.638
Guardian employment status			
Both guardians unemployed or unknown	10.07	12.72	−4.090
Only one guardian employed	51.05	53.71	−2.599
Both employed	38.88	33.57	5.383
Panel C. Geographic Information			
Christianity as the dominant religion	66.67	63.38	3.427
Regional average monthly income (USD)	85.847	73.636	7.703
Continent			
Africa	44.29	52.90	−8.589
Asia	10.50	3.91	12.413
South America	20.51	16.43	5.207
North America and Caribbean	9.22	0.05	8.533
Central America	15.49	21.98	−8.361
Panel D. Variables with Specific Badges			
Urgency (during the observation window)	4.62	0.11	14.115
AIDS-affected area	44.29	52.90	−8.589
Vulnerable to exploitation	35.66	43.63	−8.128
N	4132	5386	-

Note: Entries for categorical variables are in percentage terms, and those for continuous variables are averaged by group. Education levels are indicated as those that correspond to the U.S. educational system. The dummy variable "Christianity as the dominant religion" equals to 1 if the corresponding PR's nation has 70% or more population designated as Christians, and is considered as Compassion International is a Christian non-profit organization.

Table 7: Additional Machine Learning Methods Used in the Study

Classifier	Abbrev.	Lin.	HPT Strategy
Linear Discriminant Analysis	LinDA	Y	Shrinkage parameter
k-Nearest Neighbors	KNN	N	k, distance metric
Multilayer Perceptron	MLP	N	Hidden layer size, $l2$, activation fn.
Support Vector Machine	SVM	Y	Kernel, penalty parameter (C)

Note: For linear discriminant analysis, this study uses the least-squares solver. "Lin." refers to whether a method is a linear one or not. HPT and CV refer to hyperparameter tuning and k-folds cross-validation, respectively. "fn." refers to function.

Table 8: Features Used in the Machine Learning Methods

Version Designation	List of Features
Feature-selected	Urgency, age, female, AIDS area, exploitation, mother, father, guardian employment status dummies, continent dummies education status dummies
Whole	All features used in the feature-selected version, and additionally page dummies, country dummies, and language dummies

Table 9: Comparison of Accuracy, Recall for the Matches, and AUC

Method	Accuracy	Recall (= 1)	AUC	Brief HPT Details
Panel A: Whole version				
SDT	0.5823	0.4934	0.6231	Minimum samples per leaf: 8
SRF	0.6811	0.4501	0.7180	Minimum samples per leaf: 5
LinDA	0.6420	0.6751	0.6868	Shrinkage: 0.95
KNN	0.6702	0.5744	0.7087	k: 3, metric: Euclidean
MLP	**0.7361**	**0.6846**	**0.8103**	Hidden layer size: 88, $l2$: 0.6
SVM	0.6966	0.6582	0.7731	Kernel: linear, C: 3.5939
Panel B: Feature-selected version				
SDT	0.6550	0.4633	0.6708	Minimum samples per leaf: 8
SRF	**0.6588**	0.4595	**0.6915**	Minimum samples per leaf: 11
LinDA	0.5840	0.3578	0.5973	Shrinkage: 0.90
KNN	0.6269	0.5113	0.6582	k: 9, metric: Minkowski
MLP	0.6294	**0.5471**	0.6842	Hidden layer size: 23, $l2$: 0.1
SVM	0.5118	0.4218	0.4865	Kernel: sigmoid, C: 1.0081

NOTE: In bold are the maximum values for each column (by panel). The version designation of either "whole" or "feature selected" (abbreviated to FS above) is based on the features used in estimation; the lists for the said features are given in Table 8. Accuracy and Recall (= 1) calculated based on the prediction on the test set. "Recall (= 1)" refers to the ratio of true positives to (true positives + false negatives) for the CSP matches. "AUC" refers to the area under the ROC curve, calculated using the test set.

A.2 Appendix Figures

Figure 4: Percent of Showing Urgency by Pages

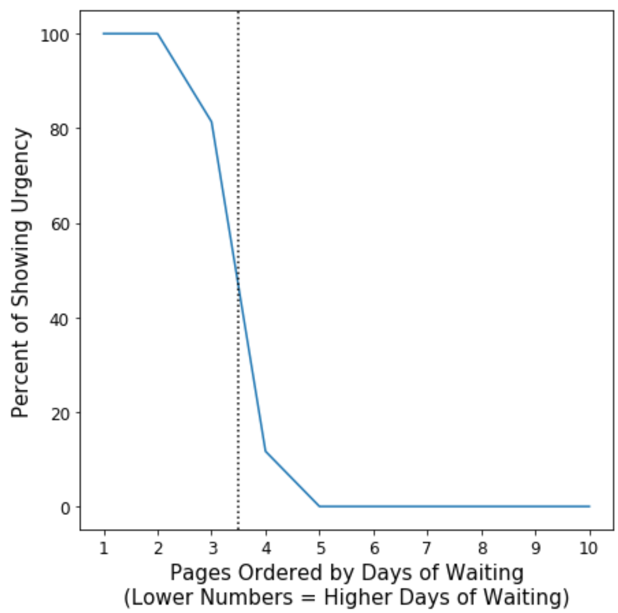
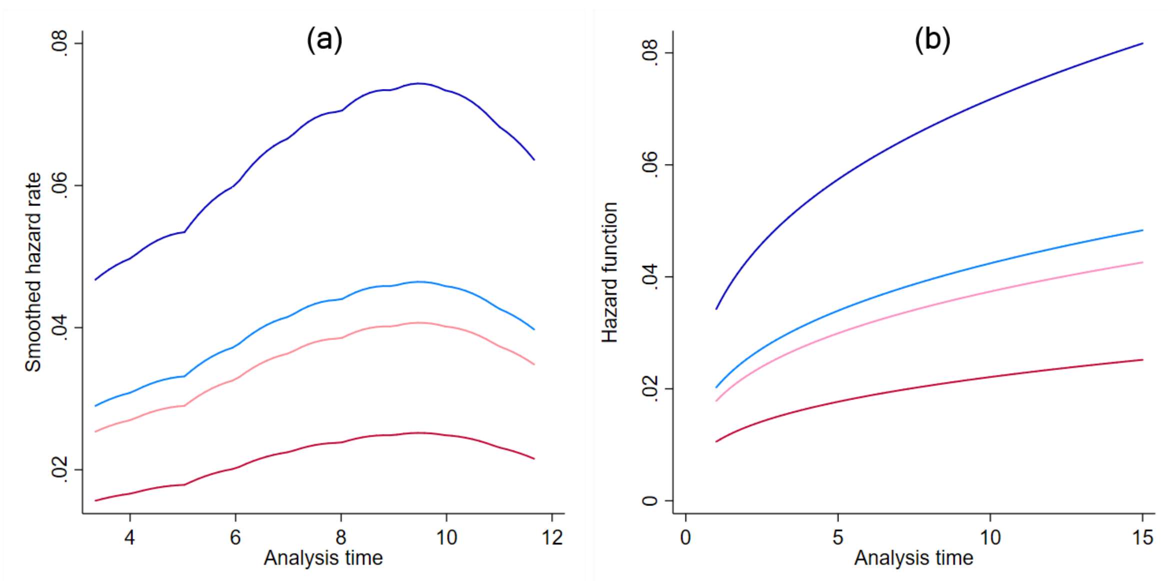
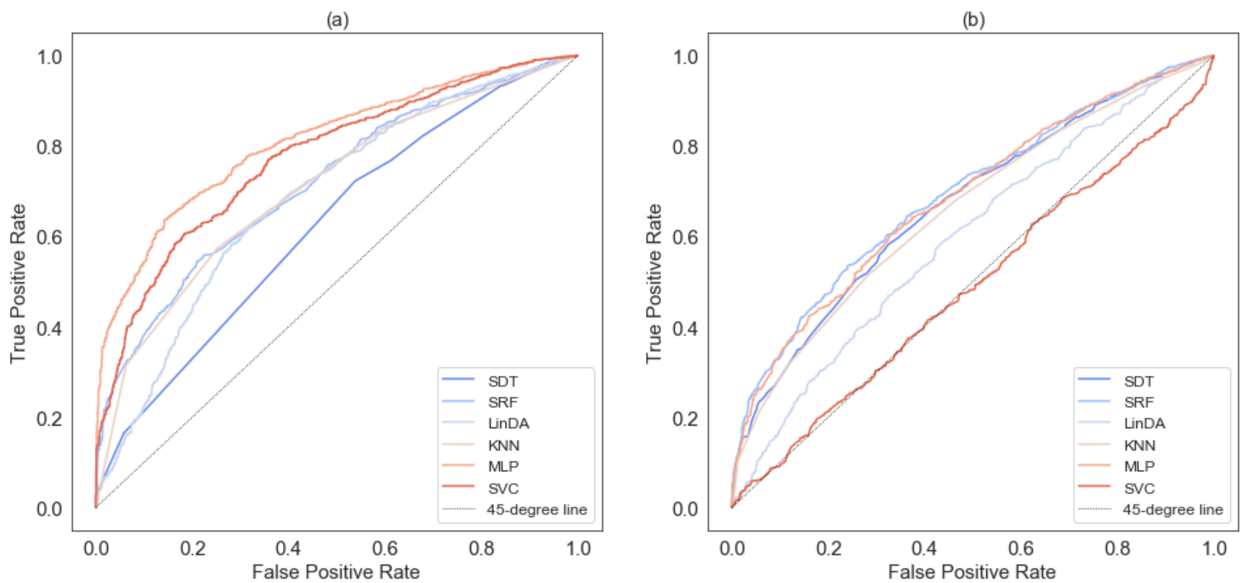


Figure 5: Hazard Rate Comparison of Cox and Weibull Regressions



NOTE: Panels (a) and (b) each refer to smoothed hazard rate and hazard calculated from Cox and Weibull regressions. From top to bottom in both panels, the lines correspond to neither under exploitability nor in AIDS-area, under exploitability but not in AIDS-area, not under exploitability but in AIDS-area, and finally under both.

Figure 6: Receiver Operatoring Characteristic (ROC) Curves for Various Methods



NOTE: Panels (a) and (b) each refer to the "whole" and "feature-selected" versions, respectively. Table 8 lists the features used in each version. SDT, SRF, LinDA, KNN, MLP, and SVC each refer to survival decision tree, survival random forest, linear discriminant analysis, k-nearest neighbors, multilayer perceptron, and support vector machine classifier, respectively.

A.3 Machine Learning Extensions

In place of finding optimal signals, one may instead be interested in predicting, among the PR, who has higher match probability. By doing so, a CSO may be able to create separate programs for those classified as less likely to be matched. I note that this method does not guarantee increased overall sponsorship as it would be equivalent to creating an entirely new mechanism. Also, there has to be some assurance that match predictions are reasonably accurate. In this additional subsection, I will therefore explore whether the said predictions can be made with tractable machine learning methods at high accuracy.

Methods. — Following Kuhn (2014) and Bou-Hamad et al. (2011), it is possible to show that decision trees and random forests are natural extensions to survival analyses described in Section 3. Based on this observation, I will refer to the decision tree and random forest methods using information gain as a splitting criterion as survival decision tree (henceforth SDT) and survival random forest (henceforth SRF), respectively. I will consider the simple problem of classifying whether a PR is alive (i.e., does not match) during the window of observation or the said PR fails (ie., does match) at some point.

This study will also consider additional methods described in Table 7 in Subsection A.1 to compare the prediction results using metrics such as accuracy and recall on the matches. I also plot the receiver operating characteristic (ROC) curve and analyze the areas under the ROC curves (AUC). The study has selected the methods in Table 3 to maintain some balance between linear and non-linear methods. Also, it employs hyperparameter tuning (henceforth HPT) via grid search or random search methods and k-folds cross-validation when applicable. Finally, the study considers some degree of feature selection. Accordingly, I conduct two versions of each method: “whole” (i.e., not using feature selection) and “feature-selected.” Table 8 in Subsection A.1 lists the features used for each of the said versions.

Prediction results. — Table 9 in Subsection A.1 compares accuracy, recall, and AUC among the various machine learning methods that the study uses. The ROC curves are displayed in Table 6 of Subsection A.2. It is noticeable that, in general, the whole versions outclass the feature selected ones. SDT and SRF are exceptions where feature selection increases accuracy for the former and recall for the latter.

In the whole version case, the multi-layer perceptron (MLP) method shows outstanding performance in all of the metrics I use for comparison. On the other hand, SRF works well when there are fewer features used except for recall, where MLP once again dominates other methods. The combined results suggest that future studies should use more advanced machine learning techniques such as MLP to produce predictions. However, it is difficult to say that the prediction results are highly accurate and can be reliably used to create separate programs for those less likely to be matched. Therefore, this study suggests, in the pursuit of maximum sponsorship, the use of information design through Bayesian persuasion over methods relying solely on machine learning predictions.

B References

Andreoni, James. 1990. "Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving." *Economic Journal* 100 (401): 464-477, June.

Baccara, Mariagiovanna, Allan Collard-Wexler, Leonardo Felli, and Leeat Yariv. 2014. "Child-Adoption Matching: Preferences for Gender and Race." *American Economic Journal: Applied Economics* 6 (3): 133-158.

Bénabou, Roland, and Jean Tirole. 2006. "Incentives and Prosocial Behavior." *American Economic Review* 96 (5): 1652–1678.

Bou-Hamad, Imad, Denis Larocque, and Hatem Ben-Ameur. 2011. "A Review of Survival Trees." *Statistics Surveys* 5: 44-71.

Brest, Paul. 2012. "A Decade of Outcome-Oriented Philanthropy." *Stanford Social Innovation Review*: 42–47, Spring.

Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik. 2014. "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs." *Econometrica*, 82 (6): 2295-2326, November.

Carpenter, Jeffrey, and Caitlin Knowles Myers. 2010. "Why Volunteer? Evidence on the Role of Altruism, Image, and Incentives." *Journal of Public Economics* 94: 911-920.

Central Intelligence Agency. n.d. "Country Comparison: HIV/AIDS Adult Prevalence Rate." `https://www.cia.gov/library/publications/resources/the-world-factbook/fields/363rank.html`.

Ciuca, Vasilica, and Monica Matei. 2010. "Survival Analysis for the Unemployment Duration." *Proceedings of the 5th WSEAS International Conference on Economy and Management Transformation* 1: 354-359.

Compassion International. 2018. "Annual Report 2017-2018." `https://www.compassion.com/multimedia/2018-annual-report-compassion-international.pdf`

Cox, David R. 1972. "Survival Analysis for the Unemployment Duration." *Journal of the Royal Statistical Society, Series B (Methodological)* 34 (2): 187-220.

Crawford, Vincent P., and Joel Sobel. 1982. "Strategic Information Transmission." *Econometrica* 50 (6): 1431-1451.

Dunn, Olive Jean. 1961. "Multiple Comparisons Among Means." *Journal of the American Statistical Association* 56 (293): 52-64, March.

Evans, William N., and W. Kip Viscusi. 1991. "Estimation of State-Dependent Utility Functions Using Survey Data." *Review of Economics and Statistics* 73 (1): 94-104, February.

Gentzkow, Matthew, and Emir Kamenica. 2016. "A Rothschild-Stiglitz Approach to Bayesian Persuasion." *American Economic Review: Papers & Proceedings* 106 (5): 597-601.

Gravois, John. 2004. "Why Do Adoptive Parents Prefer Girls?" *Slate*, January 14. `https://slate.com/news-and-politics/2004/01/why-do-adoptive-parents-prefer-girls.html`

Hahn, Jinyong, Petra Todd, and Wilbert Van der Klaauw. 2001. "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design." *Econometrica*, 69 (1): 201-209, January.

Huber, Chris. 2019. "Facts about How Child Sponsorship Works," March 7. `https://www.worldvision.org/sponsorship-news-stories/facts-about-how-child-sponsorship-works`

Kamenica, Emir, and Matthew Gentzkow. 2011. "Bayesian Persuasion." *American Economic Review* 101 (6): 2590-2615.

Keane, Michael P., Petra E. Todd, and Kenneth I. Wolpin. 2011. "The Structural Estimation of Behavioral Models: Discrete Choice Dynamic Programming Methods and Applications." In *Handbook of Labor Economics* 4a, edited by Orley Ashenfelter and David Card. North Holland: Elsevier, 331-461.

Kremer, Michael, Sylvie Moulin, and Robert Namunyu. 2003. "Decentralization: A Cautionary Tale." *Poverty Action Lab Paper* 10, April 15.

Kuhn, Ben. 2014. "Decision Tree for Survival Analysis," November.
`https://www.benkuhn.net/survival-trees`

Lipnowski, Elliot, and Laurent Mathevet. 2017. "Simplifying Bayesian Persuasion." Unpublished.
`http://www.laurentmathevet.com/wp-content/uploads/2017/03/BPCover.pdf`

Rabbitts, Frances. 2014. "Give and Take? Child Sponsors and the Ethics of Giving." In *Child Sponsorship: Exploring Pathways to a Brighter Future*, edited by Brad Watson and Matthew Clarke. New York: Palgrave Macmillan, 280-296.

Rodriguez, Germán. 2010. "Survival Models." *Lecture Notes on Generalized Linear Models*, September.
`https://data.princeton.edu/wws509/notes`.

Tardella, Fabio. 2008. "On the Existence of Polyhedral Convex Envelopes." In *Frontiers in Global Optimization*, edited by Christodoulos A. Floudas and Panos N. Pardalos. Boston: Kluwer, 149-188.

Wydick, Bruce, Paul Glewwe, and Laine Rutledge. 2013. "Does International Child Sponsorship Work? A Six-Country Study of Impacts on Adult Life Outcomes." *Journal of Political Economy* 121 (2): 393-436.