MACS 30250 Literature Review Assignment

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1 Literature Review

The motivation behind trying to understand the factors that may promote or hinder recipient-sponsor matches in a child sponsorship program (CSP hereafter) or to make a better prediction of the said matches is essentially to help create a better system in which more recipients can benefit from CSP. In addition, it is to extend the literature on CSP from an economic standpoint, which is currently very scarce in spite of the huge volume of active sponsorship (Wydick et al. 2013).

From an economist's point of view, the problem at hand boils down to a piece in a market design problem where the goal is to maximize the "social welfare" within this relatively-small economy of sponsors and recipients. As Roth (2002) has argued, in a market design problem, "experimental and computational economics are natural complements to game theory" (p. 1342). And as such, this section will highlight relevant literature not only in the field of microeconomics but also covering computational methods applicable to the research question.

One way to understand the "market economy" of CSP is to interpret a match between sponsorship recipients and sponsors as a durable commodity with psychic benefits (as the programs do not give off observable material benefits) that incur maintenance costs (as they typically last longer than a one-shot donation). The demand-side of this economy is the potential sponsors (PS hereafter) who pay a pecuniary price to acquire and sustain the said commodity, and the supply-side are the potential sponsorship recipients (PR hereafter). While it is true that the Compassion dataset gathered by the author only contains information from the PR, it would nonetheless be crucial to identify the intent behind the PS engaging in CSP; they are the ultimate decision-makers, "making or breaking" a successful match in CSP.[1]

[1]This interpretation of CSP as a market economy has been inspired by papers such as Becker and Lewis (1973) and Hansen and Hansen (2006), which focus not on CSP, but on fertility and child adoption, respectively. For a more general discussion on the market for charity, reference can be made to List (2011).

More generally, it would be important to understand why people devote themselves to charitable causes from an economic standpoint. Work by Andreoni (1989) introduces the "warm-glow model of giving," in which the author argues that the motivation behind giving is not simply to complete a common objective (such as working towards providing a public good) but is also driven by the givers' own utility that is less related to the said common objective and is more personal to oneself – something that is described as the "warm glow." Because of this, the author describes this type of altruism with personal sentiments attached as "impure altruism" (pp. 1450-1455). This theory has garnered empirical support through efforts including experimental approaches by Andreoni and Miller (2002) and Harbaugh et al. (2007), which attempt to encompass altruism in the frameworks of economics and neuroscience.

In the sense that altruism is "impure" and includes one's own satisfaction, CSP can be understood as programs that strengthen the "warm glow" side of charity programs. By providing a match between sponsors and recipients, the PS can expect to have a more intimate understanding of how one's donation affects the PR. This component of CSP is especially important to note as some recent studies have shown favorable evidence towards the positive impact of CSP on the years of schooling during childhood and adult income of the recipients (Wydick et al. 2013, 2017). The PS, after having processed such information, may be able to reinforce their return from warm glow as the contribution they made have less uncertainty in positively impacting the recipients' lives.

Due to the relative lack of studies focusing on individual matches in CSP, I borrow insight from studies on child adoption programs. Such programs share similar mechanism with CSP in that there are two parties, the potential adoptive parents (analogous to the PS) and the biological parents or foster cares (analogous to the PR). Yet unlike the PR who are not the ultimate decision-makers and have to accept any sponsorship offer they receive, the biological parents and foster cares can hold onto the adoption requests they get and select the best among them (and reject all others). In this sense, child adoption resembles that of a deferred acceptance mechanism in which the potential adoptive parents make proposals, and the CSP signaling games in which the PR have private information and tries to optimize the message sent to the PS to promote successful matches.[2] In addition, even if the mechanism behind the two can be considered similar, it should also be noted that the intent behind participants in each type of program may differ greatly.

[2]For a more general discussion of deferred acceptance algorithm and signaling games, I refer to Roth (2008) and Gibbons (1997), respectively.

With the cautions above in mind, however, Baccara et al. (2014) present compelling results about the preferences and characteristics of adoptive parents in America. According to the authors, adoptive finalization costs – which can be considered as a part of barrier to entry in adoption – significantly (and negatively) impact adoption applications of potential adoptive parents. In addition, certain ethnicities and gender (white and hispanic, and female) are favored over others (African American and male) and gay and lesbian couples are correlated more strongly with greater numbers of applications in comparison to heterosexual couples (pp. 148-155). While the results from this paper are not directly applicable, it can be inferred that certain PR characteristics will appeal more strongly to the PS than others, further buttressing the purpose of conducting the research at hand.

While much attention was directed towards the PS, understanding the PR is an equally important piece in the puzzle for successful matches in CSP. Wydick et al. (2013, 2017) document that there are roughly 9 million children who are receiving sponsorship across more than 100 nations around the world, and the number is expected to be even larger when considering for the PR who have not been matched yet (pp. 401-402). Further examination into the detailed statistics of the PR information that was gathered from Compassion International will be conducted in the Data section, with comparison to the past Compassion statistics present in Wydick et al. (2017).

One problem that must duly be noted is the potential conflict of interest between the PR and the CSP organizations. In return for providing "services" such as finding the PS and creating the market for CSP, some CSP organizations require obligations such as religious and faith-based education or continuous communication with the sponsors. This is in no way to imbue negative connotation towards such activities, but to note that some PR may have to pay a greater price to meet the standards of CSP organizations. This particular principal-agent problem has not gathered much attention, while the similar issue between donors and intermediary organizations have been featured in law reviews (Katz 2000, Galle 2010). Therefore, it may be interesting to look at whether certain features that are more well-aligned with the organization's missions (such as being predominantly Christian, as Compassion International is a Christian organization) have significant impact on time it takes to create a successful match.

As there is relatively little attention given to studying CSP, even lesser – or almost nonexistent – focus is given on the application of survival analyses on the matching problem of CSP. Therefore, I will provide a review of the computational methodologies in survival analyses that this paper proposes to apply to the problem. The motivation behind understanding matches in CSP in the language of survival analysis is that the duration or waiting time until a recipient-sponsor match is made can be understood as the time a certain PR "survives" on the list of total PR. In addition, information of the surviving PR is right-censored beyond the window of observation – motivating the use for survival analyses. The first brood of methodologies to be used in this context are the linear models of survival analysis, which can be further branched into parametric (e.g. Weibull regression) and non-parametric survival models (e.g. Cox regression) (Kalbfleisch and Prentice 2002). While having the upper hand in interpretability and causal inference, linear models – especially parametric ones – rely heavily on assumptions such as the monotonicity of hazard functions and tend to underperform in making predictions, in comparison to the non-linear models to be discussed promptly.

With respect to non-linear models (based on machine learning), this paper seeks to focus on survival trees specifically, which is a method that has advantages in prediction and some level of interpretability. In addition to the issues with prediction, another reason to utilize non-linear models is that there are variables from the PR dataset that are difficult to be structurally included in modeling the dependent variable or to "force a specific link between the covariates and the response" (Bou-Hamad, Larocque, and Ben-Ameur 2011, p. 45). Specific to survival trees, Bou-Hamad, Larocque, and Ben-Ameur (2011) document that there are a number of different ways to build a survival (decision) tree, which mostly have to do with choosing a criterion for the binary splitting of the nodes. Such criteria includes comparing Kaplan-Meier statistics, logrank statistics, martingale residuals from null Cox regressions, and more (pp. 47-49).[3] Standard cross-validation and hyperparameter tuning to choose the "best" model can be applied in the context of survival trees as well.

Using the aforementioned economic and computational methods literature as a basis, the paper will subsequently introduce a toy model of signaling in a CSP environment, provide a detailed description of the data collected from Compassion International, and conduct econometric and computational analyses complete with interpretations and predictions.

[3]Notice that these different variants of survival tree primarily rely on retrieving relevant statistics used in the linear survival methods.

2 References

Andreoni, James. 1989. "Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence." *Journal of Political Economy* 97 (6): 1447–1458.

Andreoni, James, and John Miller. 2002. "Giving According to GARP: An Experimental Test to the Consistency of Preferences for Altruism." *Econometrica* 70 (2): 737–753, March.

Becker, Gary S., and H. Gregg Lewis. 1973. "On the Interaction between the Quantity and Quality of Children." *Journal of Political Economy* 81 (2): S279-S288, March-April.

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.

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

Galle, Robert. 2010. "Keep Charity Charitable." *Texas Law Review* 88: 1213-1233.

Gibbons, Robert. 1997. "An Introduction to Applicable Game Theory." *Journal of Economic Perspectives* 11 (1): 127–149, Winter.

Hansen, Mary Eschelbach, and Bradley A. Hansen. 2006. "The Economics of Adoption of Children from Foster Care." *Child Welfare* 85 (3): 559–583.

Harbaugh, William T., Ulrich Mayr, and Daniel Burghart. 2007. "Neural Responses to Taxation and Voluntary Giving Reveal Motives for Charitable Donations." *Science* 316 (5831): 1622-1625, June.

Kalbfleisch, John D., and Ross L. Prentice. 2002. *The Statistical Analysis of Failure Time Data,* Second Edition. Hoboken, NJ: John Wiley.

Katz, Robert A. 2000. "Can Principal-Agent Models Help Explain Charitable Gifts and Organizations?" *Wisconsin Law Review* 1.

List, John A. 2011. "The Market for Charitable Giving." *Journal of Economic Perspectives* 25 (2): 157–180, Spring.

Roth, Alvin E. 2002. "The Economist as Engineer: Game Theory, Experimentation, and Computation as Tools for Design Economics." *Econometrica* 70 (4): 1341–1378, July.

Roth, Alvin E. 2008. "Deferred Acceptance Algorithms: History, Theory, Practice, and Open Questions." *International Journal of Game Theory* 36: 537–569.

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

Wydick, Bruce, Paul Glewwe, and Laine Rutledge. 2017. "Does International Child Sponsorship Pay Off in Adulthood? An International Study of Impacts on Income and Wealth." *World Bank Economic Review* 31 (2): 434–458, June.