Three Essays on Nonprofit Supply Management

by

Chao Wu

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Graduate Supervisory Committee:

Mahyar Eftekhar, Chair
Thomas Kull
Joline Uichanco
Yimin Wang

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ABSTRACT

Nonprofit operations management has gained increasing attention from both academia and policymakers. While the literature has focused on monetary donations, it is important to recognize that individuals also support charity organizations through volunteering and in-kind gifts. This dissertation examines the role of in-kind donations in supporting the operations of Nonprofit organizations. It is divided into three pieces: the first two investigate the relationship between individuals' time and monetary donations, and their implications for Nonprofit operations, while the last part centers on individuals' goods donations.

The first chapter explores a fundamental question: Do volunteering activities discourage or encourage donations? While some research suggests that people view their time and financial contributions as substitutes, others believe that they should be complementary. Two controlled online experiments indicate that volunteering improves subsequent monetary donations and that, as greater effort is required, people tend to reduce their donations. These results highlight the importance of considering both the labor and financial contributions of volunteers and creating volunteer projects with an appropriate level of effort.

The second chapter is about how to manage volunteers, taking into account how volunteers can be unpredictable, heterogeneous, and even donate money. The results challenge conventional knowledge in volunteer management, highlighting the need to integrate the management of volunteers and donors. Volunteers are not only suppliers of labor, but also consumers of volunteering activities. Moreover, enhancing the job efficiency of volunteers may also hinder the performance of charities.

Last, the donation of goods is a vital form of supply for charities, which can be resold to generate additional revenue. However, not all in-kind gifts are useful, and unwanted donations can place a financial strain on charitable organizations. Despite this, nonprofits may hesitate to reject undesired donations for fear of discouraging future support. In response, I employ behavioral interventions to encourage donors to voluntarily increase the quality of their gifts.

To my amazing and ever-supportive fiancée, Yujin, who's been there for me with all the ups and downs through my pursuit of the Ph.D.; To my wonderful mom and dad, whose unwavering belief in me and constant encouragement have been the driving force behind my accomplishment. And last but not least, to my fluffy companion, Phoenix, who's kept me busy and away from my laptop. Without her, this dissertation would have another chapter.

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Chapter 1

DOES VOLUNTEERING CROWD OUT DONATIONS? EVIDENCE FROM ONLINE EXPERIMENTS

1.1 Introduction

Volunteering in the United States has had a rising contribution to economics in recent years. In 2017, 64.4 million Americans (i.e., 25.1% of adults) provided a total of 8.8 billion hours of volunteer services to charities, corresponding to $195 billion worth of labor, as compared to 2008, when individuals provided an estimated 8 billion hours or $144.7 billion worth of labor (NCCS 2020). However, charities face multiple concerns. First, while volunteers are producers of social welfare, they are customers of an especial volunteering experience. Much research has centered on what motivates individuals to start volunteering, but it is easy to turn off volunteers with poor design of volunteer tasks (Omoto and Snyder 1995; Millette and Gagne 2008). Although the literature on work design in commercial settings has received significant attention (Griffin 1991; Humphrey *et al.* 2007), it is not clear how to design volunteer work that increases volunteers' contribution. Second, charities are cautioned against investing on their volunteering programs because volunteers are considered unreliable source of labor supply (Ata *et al.* 2019), and providing volunteering opportunities to potential donors is assumed to decrease their subsequent monetary donations (Brown *et al.* 2019). Volunteering is assumed to crowd out monetary donation because, from the perspective of standard economic theory, time is considered a limited resource with an opportunity cost, and individuals expend their resources (i.e., time and money) to maximize their utility (Meier 2006). Since volunteering and donating contribute to the same set of utilities, one may expect less monetary donations from those who have already devoted their time to a charity (Reed *et al.* 2007). Despite significant research to understand whether individuals prefer to donate time or money, there has been a theoretical ambiguity in the relationship between the two (Andreoni 2006) that casts doubt on whether charitable organizations should offer volunteer opportunities. This paper has two goals. First, it explores the causal relationship between volunteered time and money. Unveiling this relationship provides insights to develop effective workforce management policies in charitable settings. Second, it sheds further light on how to design volunteer tasks. Despite its importance, this topic has not received much attention from operations management perspective, and so we benefit from the existing literature of economics and psychology to build our theoretical assumptions.

In particular, we address two research questions through two consequential experiments. First, we explore the causal relationship between volunteering and a subsequent monetary donation. To design a real and meaningful volunteer task, we collaborated with a local charity, the Society of St. Vincent de Paul Phoenix (SVdP; www.stvincentdepaul.net/), and ran the experiments online through the Prolific platform. Our results demonstrate that volunteering significantly increases both the likelihood and the amount of an individual's monetary donations by 15% and 21%, respectively. Results of experiment 1 reveal that participants who spend more time on the volunteering task, on average, make more monetary donations. Consequently, our second question centers on the relationship between a volunteer's level of effort and their subsequent donation decisions. We define effort as a subject's conscious exertion of power (mental and/or physical activity) to accomplish a task (Eisenberger 1992). Our results show a decreasing trend between participants' level of volunteering effort and their subsequent donations. This is in contrary to Olivola and Shafir (2013) that show that individuals that anticipate more effort in a fundraising event will donate more than those who expect an effortless campaign.

This study is a *causal explanation* research that does not aim to discuss the mechanisms behind this causal relationship.[1] Nevertheless, we find that the causal relationship between

[1]Experimentation is used for causal description that is to describe the consequences that are associated to purposefully varying a treatment, or causal explanation that is to find the conditions where the causal relationship holds (Cook *et al.* 2002).

volunteering and donation cannot be explained by a single mechanism. Although we find that volunteering increases the chance and amount of donation, combining the results of our two experiments, we observe a general concave relationship between individuals' volunteering effort and their donation. We observe that as individuals' volunteering efforts increase from zero to some degree, their subsequent donations increase. This trend can be justified by *moral consistency*. However, when volunteers spend enough effort in their tasks, the marginal utility of giving decreases. This decreasing trend can be attributed to the presence of *moral licensing*. Furthermore, comparing donations obtained from participants who were assigned a defined task vs. those who were given more autonomy, we found that volunteering tasks with more flexibility were likely lead to more donations.

This paper contributes to the theory and practice of philanthropic management in several ways. First, the conventional wisdom indicates that volunteering programs are costly (e.g., charities require to spend additional resources to train and manage volunteers) that discourages charities to develop and expand volunteering programs. For example, a cross-country survey shows that only 60% of nonprofits have volunteers involved, and among those with volunteers, 73% have less than ten volunteers (Huysentruyt *et al.* 2016). Previous studies, such as Liu and Aaker (2008) and Olivola and Shafir (2013), inform that those who *think* of donating time first will be more likely to donate money as well but were not able to conclude whether an actual volunteer experience causally influences donations. Using a real volunteering task, we show that offering volunteer opportunities increases the likelihood and amount of a person's monetary donations. Given the significant volunteering rate in the United States (Dietz and Grimm Jr 2018), our findings suggest that volunteering could help charities increase available resources, particularly when compared with fundraising events, which typically cost a charity 5-25% of its donation income (Andreoni and Payne 2003, 2011).

Second, this study demonstrates that this causal relationship exists even in the absence of in-person experience. From a theoretical perspective, this finding challenges the notion of mechanisms such as *social norm* (Martin and Randal 2008), *personal connection* (Chen and Li 2009; Kessler and Milkman 2018), and *social signaling* (Ariely *et al.* 2009) as the main drivers of monetary donations among individuals. This result has practical values, too; Virtual volunteering is a solution, with significant benefits in terms of scalability, for charities whose volunteering events are constrained by their space and workforce. Currently, despite growing interest among individuals in virtual volunteering, charities hesitate to offer virtual volunteering opportunities due to the cost of developing virtual volunteering capacity (Liu *et al.* 2016), and that virtual volunteering is assumed to be impotent in building emotional connections with individuals (Humbad 2021). For example, while due to the Covid-19 pandemic, in the fall of 2020, two-thirds of volunteers have decreased or stopped contributing to charities (Njapa 2022), a survey shows that only less than one-third of nonprofits consider virtual volunteering even facing the pandemic (VolunteerMatch 2020). Our results, however, suggest that developing the infrastructure and programs for virtual volunteering would not only spare charities much of the cost of fundraising events but also reach more volunteers and potential donors.

Third, the existing literature of workforce management primarily focuses on developing effective staffing policies while considering elastic demand (Villarreal *et al.* 2015) and random supply (Kesavan *et al.* 2014), all in commercial contexts. The nascent literature of workforce management in charitable settings centers merely on volunteers' labor value. For example, Sampson (2006) uses goal programming on volunteer assignments to minimize the total cost of labor shortage, over-utilization of labor, and volunteer preference on tasks. Ata *et al.* (2019) consider volunteer show-up uncertainty in a dynamic queuing model to derive optimal staffing policy, and Urrea *et al.* (2019) study heterogeneity in volunteers by considering the difference in volunteer experience level and analyzing the operational performances of charities. None of these studies considers that volunteers will make a monetary donation, and so the optimal workload is limited to maximize volunteers' labor value. Results of this study suggest considering a new facet of volunteer–charity relationship while designing volunteer workforce management.

Finally, most charities do not follow any guideline to design volunteer tasks, and develop volunteer programs in order to meet their labor demand (Johnson 2022; Federal Emergency Management Agency 2013). Stated differently, volunteer tasks are developed similar to how jobs are designed for paid staff; Recent surveys reveal volunteers' complaint that "volunteering is becoming too much like paid work" (McGarvey *et al.* 2019). This practice, however, ignores that volunteering is also an opportunity for charities to further engage with their donors. On the other hand, the existing literature related to work design mainly focuses on paid labors in the commercial setting, and aims to enhance employees' job experience and satisfaction (Fried and Ferris 1987; Grant and Parker 2009). Therefore, despite the value of this line of research for charity volunteer management, they are not tailored to specific nature of charity settings. Our study aims to fulfill this gap in the work design literature on how to develop a volunteering service that maximizes participants' future monetary donations.

In this regard, our study offers two critical insights. First, it demonstrates a concave relationship between an actual volunteering effort and the value it generates for individuals. To our knowledge, Olivola and Shafir (2013) is the only study that centers the effort–value relationship in charitable settings. They find that volunteers who *imagine* a more effortful task increase their subsequent donations, yet, this does not unveil whether the effort-value relationship holds in an actual setting. Second, a survey analysis from 399 charities shows that volunteering task characteristics are critical factors for the effectiveness of volunteer management (Studer 2016) while the existing literature has paid little attention to the characteristics of the volunteer task (Pajo and Lee 2011). Results of this study offer insights how to design volunteering tasks. Our results show that too much work might leave them exhausted and reduce their future support. In addition, volunteering task with less autonomy will reduce the future donations from volunteers. This behavior is also aligned with the work design literature, which concludes that employees are less motivated when job lacks autonomy (Grant and Parker 2009). This finding will guide charities to design meaningful, manageable tasks that give volunteers a positive experience and optimize the time and donations charities receive. This finding is particularly useful because, for example, SVdP data shows that the charity has two types of volunteers; *Formal* volunteers are dedicated and long-term committed individuals who serve the charity regularly. Nevertheless, *episodic* volunteers form the majority of SVdP volunteers, who visit the charity less often and irregularly. The number of formal volunteers has been sharply decreasing over the past few years, and episodic volunteers form the majority of charities' volunteers (Macduff *et al.* 2004; Cnaan *et al.* 2022). SVdP data shows that about 50% of their volunteers visit the charity only once. It therefore is critical for charities like SVdP to maximize these volunteers' contribution.

1.2 Theoretical Background

While time and money are, to some extent, exchangeable (DeVoe and Pfeffer 2007), they differ in their value and nature (Okada and Hoch 2004; Zauberman and G. 2005; Liu and Aaker 2008) and so generate a different level of utility (Reed *et al.* 2007). Consequently, mounting research focuses on the relationship between an individual's choice to volunteer and donate monetary gifts.[2] For instance, Brown *et al.* (2019) argue that individuals gener-

[2]For example, in the context of *image motivation* (i.e., also known as identity mechanism or social esteem that relates to an individual's decisions motivated by others' perceptions about his/her behavior (Ariely *et al.* 2009).) Ellingsen and Johannesson (2009) and Carpenter and Myers (2010) show that giving time increased an individual's utility more than giving money because volunteering had a *better* signaling effect. A major line of the existing literature centers on a debate as to whether individuals consider their time donation as a *substitute* for their monetary donation (Duncan 1999; Bekkers 2010; Feldman 2010), or as a *complement* (Brown and Lankford 1992; Apinunmahakul *et al.* 2009; Cappellari *et al.* 2011). Theoretical research argues that this relationship should be substitutive. For example, Duncan (1999) considers both altruism and warm-glow utility to assert that time and money donations are perfectly substitutive in an equilibrium. Andreoni (2006) argues that two forms of charitable givings should logically form a substitution relationship because time is a limited resource with an opportunity cost (Meier 2006). Empirical studies present a mixed view. Feldman (2010) finds a substitution effect by capturing the tax benefits changes based

ate more warm-glow utility from volunteering than donating a comparable amount of money, and so caution charities against providing volunteer opportunities to potential donors as volunteering crowds out monetary donations. However, Lilley and Slonim (2014) show that pure altruism leads to substitution and crowd-out effects, but not warm-glow utility, which results in less substitution between volunteerism and donations. In exploring the causal impact of fundraising requests on volunteers, Yeomans and Al-Ubaydli (2018) find that the fundraising ask increased contributions from long-term volunteers and decreased engagement from new volunteers. In this paper, we do not consider individuals' choice to donate money vs. time. Therefore, we limit our focus to the causal relationship between volunteering and donation since this perspective has received little attention in previous charity literature.

1.2.1 Volunteering and Subsequent Donation

Volunteering is assumed to foster individuals' trust and enhance their perception of the charity's missions and/or the critical social causes to support (Feldman 2010), which are vital factors influencing donation decisions (Parsa *et al.* 2022). Liu and Aaker (2008) explain the positive impact of volunteering on donation using the theory of *construct activation and accessibility*. In this theory, money and time are social constructs that activate different goals: thinking about money activates goals of economic utility while thinking about time triggers goals of emotional well-being (Brendl *et al.* 2003). Moreover, volunteering reduces the psychological distance between the volunteer and the cause the charity supports because spending time is essentially a personal action (Olivola and Liu 2009). Therefore, a time-

on survey data between 1996 and 1999; however, she confirms that the net effect becomes complementary when considering other effects, such as intrinsic motivation (i.e., relates to an individual's internal rewards for acting in the interest of others' well-being such as pure altruism or any form of pro-social preferences, (Bernheim 1986; Andreoni 1988; Meier 2006; Ariely *et al.* 2009).) and identification with a charity's mission. The complementary effect is also confirmed in other studies, such as Brown and Lankford (1992) and Bryant *et al.* (2003), which find that volunteering and donating have a complementary relationship at the household level.

ask (volunteering request) evokes emotions associated with helping others and brings the charity's mission closer to the individuals' sense of self. A money-ask, however, activates an individual's rational mindset, evoking a value-maximizing goal that diminishes the emotional implications to consider the economic utility of giving money to a charity. Examining the causal effect of volunteering and monetary donation, Liu and Aaker (2008) found that individuals were more likely to give money when asked to volunteer first. Consequently, they conclude that people are more generous when they are primed with a notion (e.g., volunteering) that personally engages them in a cause.

A second theory to explain why an individual's volunteering leads to her subsequent donation is the *endowment effect*, which refers to the increased value people place on an object that they own (Thaler 1980; Furche and Johnstone 2006). In a famous experiment by Kahneman *et al.* (1990), subjects were divided into sellers and choosers. The sellers were given a pen and told that it was theirs to keep unless they chose to sell it. Choosers were told that they did not yet own a pen but would have the option to receive one. All participants then indicated their willingness to sell or buy the pen at each possible price. The sellers showed a significantly higher willingness to pay than the choosers. The sellers' higher valuation of an object is due to the *psychological ownership* that is established through three routes: experience of control, intimate knowledge, and investment of oneself on the target (Pierce *et al.* 2001, 2003; Norton *et al.* 2012). Norton *et al.* (2012) demonstrate that investment of oneself will significantly increase the valuation of products. Volunteering can facilitate psychological ownership of the charity through these channels since volunteers invest their time and effort, learn about the charity and its mission, and experience how their contributions can make a difference.

The third reason to support the positive impact of volunteering is *pro-social behavior*, which refers to behavior that benefits other people. Volunteering establishes an identity signaling effect on individuals; people act pro-socially, at least partially, to signal to themselves and others that they are moral individuals (Bénabou and Tirole 2006; Ariely *et al.*

2009). An individual's moral identity (e.g., moral values, goals, and concerns) is central to self-understanding (Blasi 1993), which motivates her to behave consistently with her moral notions (Bénabou and Tirole 2011; Gawronski and Strack 2012; Jennings *et al.* 2015). Individuals who have behaved pro-socially seem to retain their *moral consistency* by making more charitable givings (i.e., higher amount of donations) (Shang and Croson 2009; Heger and Slonim 2022). Shang and Croson (2009) found that those who experienced social pressure to give more in the past also gave more in the future. In a two-stage lab experiment, Heger and Slonim (2022) first used a default recommended donation amount as a nudging mechanism to increase participants' donation. Those who were exposed to high default donations in the first stage donated more in both stages compared to those who were initially exposed to low default donations. Moreover, Gneezy *et al.* (2012) showed that people were more likely to hold to their moral identities when their recent pro-social behavior was costly. They argue that people interpret costly actions as a signal of their moral identity while costless actions produce weaker identity. Similarly, adding a new cause to support, such as disaster relief, did not cannibalize people's existing causes (Bergdoll *et al.* 2019; Deryugina and Marx 2021).

However, pro-social behavior could also lead to *moral licensing* for some individuals, which could explain a negative impact of volunteering on donations. Moral licensing refers to the situation that one who has done something good recently may feel *licensed* to act *less* morally later (Merritt *et al.* 2010). Research shows evidence for inter-temporal substitution, in which individuals substitute between their first and second donations to a charity (Cairns and Slonim 2011; Leliveld and Risselada 2017). From this perspective, individuals may feel licensed to shirk future monetary donations when they have already volunteered.

1.2.2 Volunteering Effort and Subsequent Donation

Effort refers to any mental or physical activity that mediates between how well one can potentially perform to meet some goal (such as completing a task) and how well they actually perform (Eisenberger 1992; Shenhav *et al.* 2017; Inzlicht *et al.* 2018). Effort is costly; between equally rewarding options, individuals choose the one that requires less work or effort (Hull 1943; Frederick 2005; Kool *et al.* 2010), because effort can cause feelings of fatigue, frustration, stress and anxiety (Inzlicht and Al-Khindi 2012; Saunders *et al.* 2015; Elkins-Brown *et al.* 2016). Individuals typically prefer to accept fewer rewards to avoid effort (Apps *et al.* 2015). Neoclassic economics theories propose that individuals tend to avoid effortful tasks (Frederick 2005), and value an object less if it demands more effort (Kaufman 1999). For instance, if a longer travel time is required for a consumer to receive a product, her utility declines, so she values the product less than she would if she could obtain it effortlessly. However, psychological studies show that individuals feel happier and like objects and outcomes more when they are obtained through effort (Aronson and Mills 1959; Festinger 1962; Van Boven and Gilovich 2003). People adjust their attitudes towards the object to justify the effort they already applied. Norton *et al.* (2012) illustrated what they call the IKEA effect, where products that involved individuals' effort were preferred over identical products made by others.

A number of contradicting theories have posited a positive or negative effect of effort on donation. Olivola and Liu (2009) use the *martyrdom effect* to explain why some of the most successful fundraising campaigns involve painful or effortful activities such as charity marathons and fire-walks. Based on this phenomenon, the prospect of effort escalates an individual's motivation to participate in and contribute to an activity supporting a cause they care about. Second, assuming that a positive impact of volunteering on donation can be explained by endowment effect, one could expect that additional volunteering effort further increases the monetary donation that one will make. This is because, based on the endowment effect, individuals who invest more of themselves in the target feel a stronger sense of psychological ownership (Pierce *et al.* 2001), which in turn increases their valuation of the target (Furche and Johnstone 2006). Individuals who invest more time and effort in volunteering may value the charity more, and donate more. Therefore, endowment effect might explain why more involvement in a charity's mission leads to individuals' larger amount of donation; Why running or biking tens of miles would lead to more donations. However, the moral licensing effect assumes that individuals accumulate *moral credits* and use them to offset negative behavior later (Jordan *et al.* 2011). Volunteers who expended more effort (and so collected more moral credits), would donate less in the future than those who had acquired fewer moral credits through past effort. Consequently, individuals who have invested more of themselves in charitable giving expect less marginal utility from additional donations, and so make fewer subsequent donations. Overall, it is reasonable to assume that *some* effortful volunteering tasks can increase a person's valuation of a charity, and hence donations. However, it is unlikely that effort monotonically increases the value as the willingness to exert more effort decreases when more effort is applied (Inzlicht *et al.* 2014). Stated differently, people are willing to expend effort up to a limit, and any goal that demands effort beyond that limit might be devalued (Brehm and Self 1989; Richter *et al.* 2016).

1.3 Experiment 1: Volunteering and Donation

1.3.1 Charity and Task Selection

We designed our experiment in collaboration with a local charity, the Society of Saint Vincent de Paul Phoenix (SVdP). SVdP is a large nonprofit organization headquartered in St. Louis, Missouri that assists homeless and low-income families with free services such as medical and dental clinics, meals, clothes, and housing. During the COVID-19 pandemic, SVdP developed several virtual volunteering tasks including a task to make a "sweet dreams" card. The goal of creating these cards was to show love and respect to the guests who stay overnight in SVdP's shelters. Each individual's pillow has a card and mint left on it for their overnight stay. We chose this task for our experiment because it provided volunteers an opportunity to connect with the community through a service that could feasibly be completed through an online platform that helps us measure the time participants spent to complete a task.

1.3.2 Design and Implementation

We recruited participants through the Prolific platform. To ensure that participants had experience with performing online tasks and a good reputation on Prolific, we recruited only individuals who had successfully completed at least 100 submissions and had an approval rate of at least 95%. We also restricted the participants to those located in the U.S. who were at least 18 years old. The task was visible only to those who met the criteria. The description of this experiment was purposely generic; we stated only that it included a set of online tasks and survey questions, indicated the expected time to finish (i.e., 15-20 minutes), and stated the amount of compensation for completing the task (i.e., $4.50).

At the outset, all subjects were provided a short consent form that explained the general purpose of the study, the overall process and estimated duration of the experiment, and that they would receive $3 upon completing the task, and an additional $1.50 bonus at the end of the experiment. All participants were informed that they could leave at any time. Next, they read a short note about SVdP that included general information about its services, and the number of clients it serves. This stage controls for the salience and context effects.

This experiment follows a between-subject design with two treatment conditions. Participants were randomly assigned to one of the two groups: *Volunteer* and *Task*. Participants in the *Volunteer* group were directed to complete the sweet dreams card task for SVdP. Instructions and optional templates were provided. To assure participants make the card by themselves (instead of uploading other greeting cards they could find online without any inputs), we asked them to include the words “Saint Vincent de Paul” or “SVdP” on their cards. We also provided two optional blank templates with the SVdP logo in the bottom right corner. Although the participants received some optional templates, they were allowed to use any text or pictures they wanted.

Since art-making can improve people’s moods (De Petrillo and Winner 2005; Dalebroux *et al.* 2008) and thus encourage pro-social behaviors (Cavanaugh *et al.* 2015), we included a treatment group that received the same online drawing task but for a different purpose.

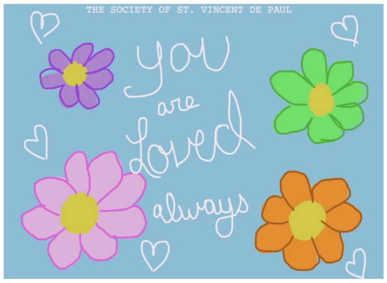


Figure 1.1: Examples of Finished Cards in Experiment 1

Participants of the *Task* group were instructed to create a card for themselves and were notified that the purpose of this task was to assess the artistic quality of virtual painting. Upon completion, participants of the *Volunteer* and *Task* groups submitted their products by uploading their files.

The last stage included two pages of survey questions. On the first, we collected demographic information (e.g., age, gender, education, and household income). Questions were presented in random order to avoid any order effects. After responding to the questions, participants received a $1.50 bonus, and were asked if they would like to donate some of the bonus to SVdP. Using a bonus as the source for donation decisions is common in experimental studies (Leliveld and Risselada 2017; Nook *et al.* 2016). Participants could choose to donate any amount, from 0 to $1.50, with a default of zero donation. We collected additional control information on the second page, asking e.g., if the participant was familiar with SVdP prior to this experiment. On the debrief page, participants received the completion code to enter in the Prolific platform to receive their compensation. Due to restrictions on our institution's grants, we are not allowed to make donations directly to other organizations. Therefore, regardless of the participants' choices, they were paid the full bonus, received a "thank you" note, and were notified that their donations could not be accepted due to the authors' institution's policy.

1.3.3 Results and Discussion

In total, we received 866 responses, with 417 submissions for the *Task* group, and 449 submissions for the *Volunteer* group. On average, participants in the *Task* and *Volunteer* groups spent 13.4 (SE=0.447) and 14.5 (SE=0.506) minutes, respectively.

Withdrawal of subjects from research studies is a common challenge in online experiments that requires careful analysis to ensure that no confounding variables were introduced to the treatments. Otherwise, the causal inference assumptions, such as Stable Unit Treatment Value Assumption, will be violated. Table 1.1 includes the breakdown of the withdrawals in each stage by group. About one third of the withdrawals occurred at the first stage where both groups received the same information, and so we do not further investigate the reasons why these participants withdrew from the study. However, during the painting stage, 97 and 103 participants withdrew from the experiment in the *Task* and *Volunteer* groups, respectively.

A possible explanation for the withdrawals is that participants withdrew because they felt underpaid for their time. However, we incentivized participants with a well above average payment (i.e., $13.5 per hour payment compared with Prolific $6 per hour payment requirement), and participants in each group are blind to other treatment conditions. Hence, regardless of the painting task, all participants were incentivized to complete the study. Therefore, we followed up with these 200 participants in a post-experiment survey, and asked why they withdrew from the study. Of 177 responses (88.5%), 37.9% of participants withdrew because they did not have enough time to complete the task at that moment, though they indicated that they were interested in finishing it later, and 57.6% indicated that they started the experiment with inappropriate device (e.g., tablet or smartphone) that did not allow them to draw. While Prolific allows participants to contribute to an experiment via mobile, tablet, or computer, our experiment required them to use computers (to complete the online painting task). A few indicated that they encountered with hardware issues although they were using a computer.[3] These participants, however, indicated that they would finish the drawing, should they have proper equipment. Last, 4.5% of participants withdrew the study for other reasons, some of whom withdrew the study for altruistic reasons; They believed that "the money should be going to the homeless people, not to people making cards for them." We did not re-invite the withdrawn participants to finish the study later because they had already received partial treatment before withdrawing from the study. Hence, inviting them for the repetitive study would create additional confounding factors.

Finally, we follow the instruction suggested by Dumville *et al.* (2006) to address the attrition concern; Table 1.2 compares the distribution of participants characteristics among each treatment groups and those who withdrew the study. We do not find any statistically significant differences in any of the participants' characteristics.

The uneven group size is also partially due to the simple randomization method (i.e., participants had equal chance of receiving one of the two treatments). Due to randomization, the total number of participants in the *Task* group is 570 and 611 in the *Volunteer* group. Alternative randomization methods such as block or adaptive randomization can potentially "force" an even group size (Cook *et al.* 2002). However, these methods are either infeasible in our setting or could lead to additional confounding factors.[4] Therefore, we follow the instruction by Schulz and Grimes (2002) and use simple randomization in our study.

Table 1.2 includes the balance of demographic information across three groups, descrip-

[3]For instance, a participant indicated that they were using "a different and older model laptop" at that time and "it was too difficult to make a decent drawing using my laptop's track-pad."

[4]For example, a randomized block design requires researchers to recruit the participants first and assign treatment with equal group size. On the Prolific platform, participants are completing studies for monetary incentives, and we cannot hold all participants until they start the experiment. Adaptive randomization adjusts the treatment assignment probability if the initial randomization does not produce the desired ratio in each condition (Rosenberger 1999). However, this may lead to additional bias: the *Task* or *Volunteer* groups will have more participants who started late.

Table 1.1: Withdrawal Break Down by Stage

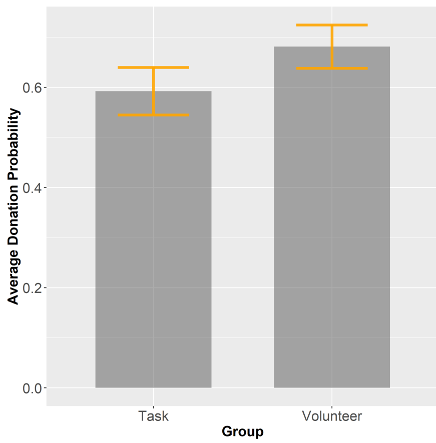
	Stage 1 (Background)	Stage 2 (Drawing)
Task (153)	56	97
Volunteer (162)	59	103

Table 1.2: Characteristics of Participants in the Task, Volunteer, and Withdrawal groups. Values are Percentages (Numbers).

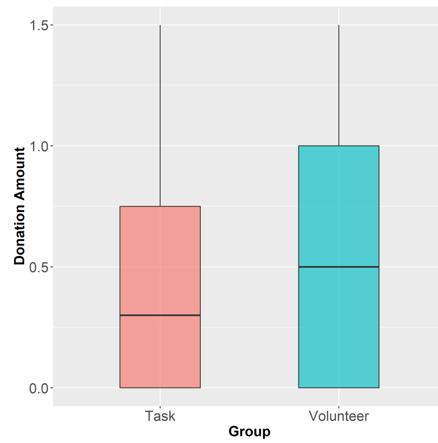
		Task (N = 417)	Volunteer (N = 449)	Withdrawal (Task) (N = 86)	Withdrawal (Volunteer) (N = 91)
Gender	Female	47.72 (199)	51.00 (229)	48.84 (42)	50.55 (46)
Age	18-30	37.89 (158)	40.53 (182)	38.37 (33)	38.46 (35)
	31-40	30.94 (129)	30.07 (135)	27.91 (24)	28.57 (26)
	41+	30.94 (129)	28.95 (130)	31.40 (27)	31.87 (29)
Income	<$50,000	35.01 (146)	39.20 (176)	36.05 (31)	37.36 (34)
	$50,001-$100,000	40.29 (168)	34.52 (155)	40.70 (35)	39.56 (36)
	>$100,001	22.78 (95)	24.94 (112)	22.09 (19)	21.98 (20)
Education	<= Associate	34.29 (143)	37.86 (170)	33.72 (29)	36.26 (33)
	Bachelor's	42.21 (176)	41.65 (187)	41.86 (36)	42.86 (39)
	>= Master	23.26 (97)	20.04 (90)	22.09 (19)	18.68 (17)
Familiarity	None	71.94 (300)	71.27 (320)	74.42 (64)	71.43 (65)

Note: some columns may not add up to 100% because a few participants chose "Prefer not to choose."

tive statistics, and the proportion test across the three groups. Overall, there is no significant difference across all control variables (i.e., demographic variables). A typical concern in online experiments is that participants' main goal to complete a task is the compensation they will receive and so are less likely to respond to the treatment. For example, Goenka and Van Osselaer (2019) found that 38.5% of the participants do not allocate any bonus to donations. In the context of our study, this flooring effect (e.g., observations concentrated on zero donations) decreases the power, which makes it more challenging to detect any effect. Despite this limitation, our results are statistically significant.



(a) Average Donation Probability with 95% confidence interval



(b) Donation Amount Comparison across two Groups

Figure 1.2: Amount and Probability of Donation across the two Groups

Our analysis of the primary outcome of the donation decision revealed two main results. Figure 1.2a shows the likelihood of donations across the two groups. About 68.15% of the *Volunteer* group donated (SE=0.022) as compared to 59.23% of the *Task* group (SE=0.024). This difference is statistically significant at $p = 0.008$. It is worth indicating that all p-values are obtained from a two-sample Wilcoxon rank-sum (Mann-Whitney) test against the null hypothesis of equal means. Moreover, while 19.8% in the *Volunteer* group donated all their bonus, 14.6% of participants in the *Task* group donated all their bonus. We further compared the distributions with Kolmogorov-Smirnov Test. The difference between *Volunteer* and *Task* groups is statistically significant at $p = 0.024$. (Robustness tests are presented in the Appendix.)

Result 1 *Participants in the* Volunteer *group were more likely donate compared to those in the* Task *group.*

Second, on average, the *Volunteer* group donated \$0.587 (SE=0.027) while the *Task* group donated \$0.485 (SE=0.026) (Figure 1.2b). The pairwise Wilcoxon comparisons between *Task* and *Volunteer* yielded statistically and economically relevant difference with

20.9% ($p = 0.007$) increase in average donations.

Result 2 *On average, participants in the* Volunteer *group donate larger amounts compared to those in the* Task *group.*

Finally, focusing on the *Volunteer* group, we considered the impact of individuals' effort to finish the task on their donation. To measure a participant's effort, we used the total time that they spent to complete the task (Wise and Kong 2005; Wise and DeMars 2006). As shown in Table 1.3, there is a larger probability that participants who spent more time in the *Volunteer* group donated, and, on average, they donated a larger amount. (We did not ask about participants' feeling about the cards they created. Yet, we received many feedbacks anonymously indicated that participants who were assigned to *Volunteer* group enjoyed the task.)

Results of experiment 1 illustrate that participants who volunteered for a charity are more likely to donate and, on average, make a larger donation than those who do not volunteer. Our experiment was conducted in an online environment, so participants were less likely to establish a connection with the charity than volunteers in a traditional in-person event who actually visit the charity (Liu *et al.* 2016). However, volunteering itself might build a personal connection with the charity's mission, which is an essential psychological driver of giving (Chen and Li 2009; Kessler and Milkman 2018). As discussed in Olivola and Liu (2009), volunteering reduces the psychological distance between the volunteer and the charity as spending time is a personal action. Results of experiment 1 align with this argument, and support the findings of Liu and Aaker (2008) that volunteering activates a social construct associated with emotional well-being that increases donations.

The positive impact of volunteering effort (i.e., time) on donation suggests that the relationship can be explained by the endowment effect. The investment of time and effort may have established psychological ownership of the charity, which increased their willingness to donate. This relationship can also be explained by the effect of moral consistency. The *Volunteer* group completed a more costly and meaningful task than the *Task* group,

Table 1.3: Relationship between Time and Donation in *Volunteer* Group

	Dependent variable:	
	Donation Amount (*OLS*)	Donation Probability (*probit*)
Duration_mins	0.009^{***}	0.024^{***}
	(0.002)	(0.007)
Constant	0.463^{***}	0.135
	(0.044)	(0.110)
Observations	449	449
R^2	0.026	
Adjusted R^2	0.024	
Log Likelihood		−273.560
Akaike Inf. Crit.		551.120
Residual Std. Error	0.558 (df = 447)	
F Statistic	12.080^{***} (df = 1; 447)	

Note: *10%, **5% and ***1% statistical significance.

which may have primed participant's pro-social identity and motivated more donations to maintain consistency with that identity (Gneezy *et al.* 2012).

All these three theories are further defended by our observation that participants who put more effort (i.e., spent more time) in volunteering donated more. However, the time spent in experiment 1 was self-induced, so the relationship we observed between effort and donation is subject to the self-selection bias. For example, Exley and Terry (2019) designed an experiment to allow participants to self-select into work for charity or themselves, and found that those who chose to work for themselves decreased their effort as their wage increased, while those working for charity did not. In our experiment, participants who spent more time making the card might be those whose intrinsic values led them to care more about the cause (and so donated more). In experiment 2, we used a variation of virtual

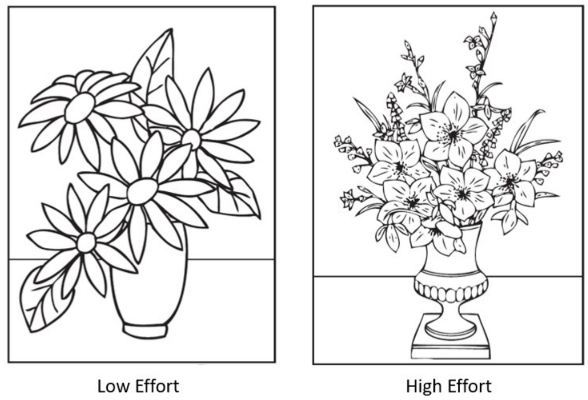


Figure 1.3: Coloring Patterns Used in each Group

volunteering task that randomized different levels of *required* effort among participants to see whether donation size would still correlate with time spent.

1.4 Experiment 2: Volunteering Effort and Donation

The goal of experiment 2 was to explore the relationship between an individual's level of volunteering effort and subsequent donation. As in experiment 1, we recruited participants through Prolific using the same selection criteria. We also added a new filter to exclude those who had participated in experiment 1.

1.4.1 Design and Implementation

Experiment 2 followed the same procedure as experiment 1 except in the virtual volunteering task. Instead of allowing participants to draw their own picture, we followed Mertins and Walter (2021a) example by providing participants with a template to color. Participants could choose any colors, and were able to add additional words and arts to the template. We varied the complexity of the pattern and randomly assigned participants into two groups. Participants of the Low Effort (LE) group were asked to color a simple pattern, and participants of the High Effort (HE) group were asked to color a more complex pattern (Figure 1.3). Before conducting the actual experiment, we ran a pilot test to ensure that the time difference between the two tasks is significant.

Figure 1.4: Examples of Finished Cards in Experiment 2

1.4.2 Results and Discussion

We received 947 submissions from participants who were randomly assigned to one of the two groups with equal probabilities. We received 494 submissions for the *LE* group and 453 submissions for the *HE* group. Table 1.5 includes the distribution of different group attributes. We found no significant difference in the control variables (i.e., social-demographic information and familiarity with the charity) or acceptance rates between the two groups. We also sent a follow-up survey to the 192 participants who withdrew the study in the drawing stage, and received 164 responses (85.4%). Similar to Experiment 1, most participants (96.3%) withdrew because either they did not have enough time (36.6%) or access to proper equipment (59.8%) to complete the experiment. Table 1.5 compares the distribution of participants' characteristics and we do not find any statistical significant differences between the participants who completed vs. those who withdrew the study.

Table 1.4: Withdrawal Break Down by Stage

	Stage 1 (Background)	Stage 2 (Drawing)
LE (162)	60	102
HE (141)	51	90

We measured effort in terms of the time spent to complete a task. Manipulation check showed that our treatment successfully influenced the two groups' time spent on the task.

Table 1.5: Characteristics of Participants in the Low Effort (LE), High Effort (HE), and Returned Groups. Values are Percentages (Numbers).

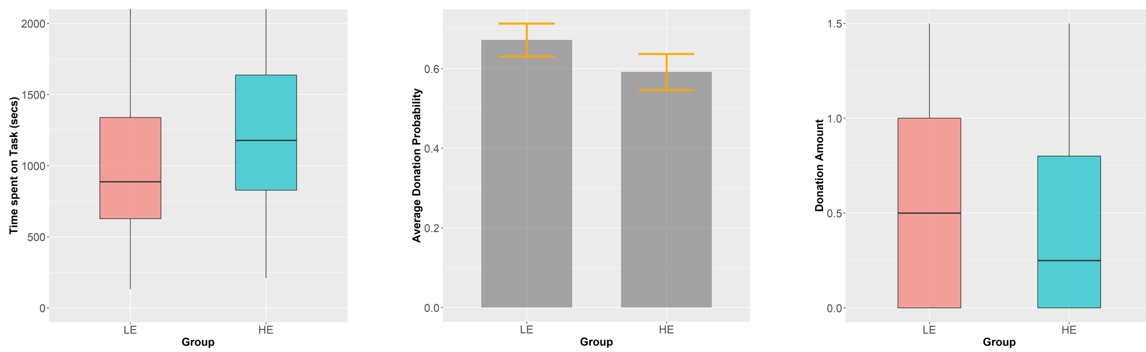
		LE (N = 494)	HE (N = 453)	Returned (LE) (N = 87)	Returned (HE) (N = 77)
Gender	Female	46.56 (230)	46.36 (210)	48.28 (42)	46.75 (36)
Age	18-30	40.89 (202)	44.37 (201)	41.38 (36)	41.56 (32)
	31-40	31.38 (155)	30.24 (137)	32.18 (28)	31.17 (24)
	41+	27.53 (136)	25.39 (115)	26.44 (23)	24.68 (19)
Income	<$50,000	41.09 (203)	45.92 (208)	45.98 (40)	44.16 (34)
	$50,001-$100,000	36.64 (181)	31.57 (143)	34.48 (30)	33.77 (26)
	>$100,001	20.04 (99)	20.31 (92)	19.54 (17)	20.78 (16)
Education	<= Associate	41.09 (203)	44.15 (200)	42.53 (37)	44.16 (34)
	Bachelor's	39.88 (197)	39.74 (180)	39.08 (34)	38.96 (30)
	>= Master	18.83 (93)	15.89 (72)	17.24 (15)	16.88 (13)
Familiarity	None	78.14 (386)	81.68 (370)	79.31 (69)	77.92 (60)

Note: some columns may not add up to 100% because a few participants chose "Prefer not to choose" option.

On average, participants in the *LE* group spent 18.07 (SE=0.489) minutes, and participants in the *HE* group spent 22.37 (SE=0.574) minutes to complete their task. A pairwise comparison was statistically significant at $p \leq 0.001$ level (Figure 1.5a). Our analysis of the primary outcome of the donation decision revealed two main results. First, considering the donation probability, we found a statistically significant difference between the groups, with 59.2% of the *HE* group donating compared to 67.2% of the *LE* group ($p = 0.012$; see Figure 1.5b).

Result 3 *Participants in the* High-effort *group are less likely to donate compared to the participants in the* Low-effort *group.*

Second, on average, the *LE* group donated greater amounts: *LE* participants donated



(a) Time Spent on the Coloring Task (in seconds)

(b) Average Donation Probability with 95% confidence interval

(c) Donation Amount Comparison

Figure 1.5: Time Spent on the Coloring Task, and Donation Amount and Probability Comparison

an average of \$0.579 (SE= 0.026), while *HE* participants donated \$0.502 (SE= 0.027). The donation difference is statistically significant at $p = 0.018$. Moreover, 21.5% of participants in the *LE* group donated the entire bonus (\$1.5) compared to 18.3% in the *HE* group. The proportion test does not result in a conventional significant p-value ($p = 0.261$). Yet, we further compare the distributions with Kolmogorov-Smirnov Test, which shows a significant difference at ($p = 0.059$). (Robustness tests are presented in Appendix A.)

Result 4 *Participants in the* High-effort *group donate less than the participants in the* Low-effort *group.*

As in experiment 1, we estimated the relationship between time spent volunteering and subsequent donation decisions within each group (Table 1.6). In the *LE* group, those who spent more time donated more. This observation is consistent with the results of experiment 1, in which volunteers who spent more time made a larger donation. However, we did not find any significant relationship between the time spent on the task and donation decision in the *HE* group.

Results of experiment 2 suggest that different levels of effort in volunteering influence donation decisions. Specifically, we observed a drop in donations as participants expended more effort that implies that, at least, some degree of crowd-out effects exists in volun-

Table 1.6: Relationship between Time and Donation in the *LE* and *HE* Groups

	Dependent variable:			
	Amount (LE)	Probability (LE)	Amount (HE)	Probability (HE)
Duration_mins	0.007***	0.016***	0.003	0.007
	(0.002)	(0.006)	(0.002)	(0.005)
Constant	0.455***	0.164	0.430***	0.065
	(0.050)	(0.117)	(0.055)	(0.125)
Observations	494	494	453	453
R^2	0.017		0.005	
Adjusted R^2	0.015		0.003	
Log Likelihood		−308.489		−305.197
Akaike Inf. Crit.		620.978		614.394
Residual Std. Error	0.570 (df = 492)		0.564 (df = 451)	
F Statistic	8.477*** (df = 1; 492)		2.204 (df = 1; 451)	

Note: *10%, **5% and ***1% statistical significance.

teering. This observation challenges the assumption that endowment effect explains the results of experiment 1 because if the endowment effect is the primary mechanism for this observation, we would expect an increase in donations when participants expend more time in volunteering. However, experiment 2 provides a contradicting result; those in the HE group donated significantly less than those in the LE group. This finding implies that, at least, some degree of crowd-out effects exists in volunteering. A plausible theory to explain the donation decline in the *HE* group is the moral licensing effect. As participants spent more time creating appealing products, they generated more moral credits to forego the pro-social decision to donate (Sachdeva *et al.* 2009; Jordan *et al.* 2011). Participants in the *HE* group spent 23.8% more time on the volunteering task and may have decreased their subsequent donations feeling they had already expended significant resources (in terms of effort) from their charitable giving budget.

The donation decline seems to contradict the findings in experiment 1, where participants in the *Volunteer* group who spent more time tended to make larger donations, too. This inconsistency could be due to the existing selection bias; participants who chose to spend more time might have already been more altruistic and made more monetary donations. We further tested the relationship between time spent on volunteering and donations within each *LE* and *HE* groups. While the participants in the *LE* group had the same pattern as the *Volunteer* group in experiment 1, those in the *HE* group did not show any considerable trend. This is an intriguing result because if the observation from experiment 1 results from selection bias, then the selection effect caused by this bias should also occur within each group. One explanation is that our sample size was not large enough to observe the relationship. However, in both *Volunteer* and *LE* groups (Tables 1.3 and 1.6), the time variable is significant at $p = 0.01$, which implies that this observation is unlikely due to statistical errors or lack of power. A more plausible explanation is that volunteering effort creates a moral consistency drive until individuals' efforts reach to a certain threshold, then the positive effect as participants exert more effort is cancelled out by crowd-out mechanisms, namely moral licensing.

1.5 General Discussion and Insights

Understanding the relationship between volunteering and monetary donation is important given the notable size of the charitable market (List 2011), the decreasing trend of donations (Philanthropy Panel Study 2021), and the valuable role that charities play in modern life (Pautman 2000). In 2020, charitable giving in the United States exceeded $470 billion, 69% of which came from individuals (Giving USA 2021). While this is a large market, studies show that the percentage of American households that donated to a charity in a given year has significantly declined from 66.2% in 2000 to 49.6% in 2018 (Philanthropy Panel Study 2021), which escalates charities financial instability and risk of failure (West 2004; Calabrese 2013; Battilana and Lee 2014), a challenge that is magnified by an economic decline (Osili *et al.* 2019).

An array of reasons could explain the impact of an individual's volunteering on their subsequent donation. For example, a volunteering event provides social interactions that could increase happiness and thus donation (Harris and Thoresen 2005; Borgonovi 2008). Volunteers might also be motivated to donate as they observe the social impacts of serving those in need or as they observe generosity in others and wish to conform to social norms (Martin and Randal 2008). While it is reasonable to assume that these factors could increase a volunteer's donation, we still observed a positive spillover effect in the absence of these factors. In our online setting, volunteers do not see the impact of their effort, do not interact with each other, nor do they receive any social recognition. Therefore, virtual volunteering that prevents exposure to any social norm provides a unique opportunity to identify the leading mechanisms of donation decisions in the absence of in-person experience.

Based on the results we obtained, we can think of three simultaneous mechanisms that determine either the positive or negative relationship between volunteering and donation. First, similar to Liu and Aaker (2008) and Olivola and Shafir (2013), we conclude that the motivation to donate to a social cause is influenced by the extent to which individuals feel involved in it. As described in Olivola and Liu (2009), volunteering reduces the psychological gap between the volunteer and the charity since spending time is considered a personal action. Second, moral consistency could be a strong reason as to why those who volunteered donated more to the charity. Third, the marginal utility of individuals' contribution declines after a threshold. Once volunteers perceive they have spent *enough*, they decrease their involvement, which can be explained by the moral licensing effect.

When we combined the results of experiments 1 and 2, we found a concave effort-value relationship. Volunteers initially contributed more when they moved from "no volunteering effort" to "some volunteering effort," but then donations declined as the amount of effort increased. Put differently, effort beyond a certain limit is devalued (Brehm and Self 1989; Richter *et al.* 2016). This aligns with existing literature that states willingness to expend effort typically declines as a function of the amount of effort already exerted (Kool and Botvinick 2014). It holds in charitable settings, too.

Table 1.7: Matched Comparison between Autonomous (i.e., volunteers of Experiment 1) and Defined Groups (i.e., All Participants of Experiment 2)

	Autonomous (260)	Defined (260)
Duration_mins	16.542 (0.684)	16.788 (0.641)
Donation Amount	0.599 (0.035)	0.510 (0.035)
Donation Probability	183 (70.4%)	157 (60.4%)

A side result of our experiment sheds some light on the relationship between the degree of freedom in volunteering tasks and volunteers' subsequent contributions. In particular, autonomy (i.e., being able to choose one's actions from a range of possibilities) is one of the essential innate psychological needs to motivate workers (Ryan and Deci 2000). The *Volunteer* group in experiment 1 had more autonomy than the participants in experiment 2. Therefore, we used coarsened exact matching to match all control variables (income, education, age, gender, and prior familiarity with the charity) and the time spent on the task from experiments 1 and 2. We matched the data between the *Volunteer* group from experiment 1 and all participants in experiment 2. First, we removed all the observations that contained "NA" or "Prefer not to say" in any of the control variables. We dropped 83 observations in this step. Second, we matched the continuous variable "Duration" using quantile method, and applied a one-to-one exact matching for each stratum. Finally, all the unmatched observations are dropped from the analysis. There were 520 results matched from the total $1,396$ observations. Our matching ensures the best possible balance between the two groups; not only do the two groups have exact matching on all the control variables, but also they share almost identical time spent on the task (see Table 1.7). We refer to the *Volunteer* group as the "Autonomous" treatment and both *LE* and *HE* groups as the "Defined" treatment. As shown in Table 1.7, the Autonomous treatment had a significant increase in both donation amount and probability ($p = 0.034$ and $p = 0.021$).

This research is novel in several regards. First, although charitable giving has attracted extensive research, few studies have used actual volunteering tasks (Mertins and Walter

2021a). By assigning an actual volunteering task, we were able to observe more realistic reactions. Second, our findings of a positive volunteering–donating relationship in a virtual volunteering setting provides new insights into means for charities to increase their volunteer labor and donation income. Virtual volunteering would allow charities to reach a large pool of volunteers and potential donors. This is especially important because, in general, running volunteering programs are less costly compared to fundraising campaigns. Moreover, virtual volunteering could prove especially useful to those charities that have limited space and infrastructure to run in-person volunteering events. Third, our results unveil the importance of volunteer management. The majority of volunteers visit a charity irregularly and on a short-term basis (Cnaan *et al.* 2022). Our results indicate that volunteering task design should be considered as a "two-way street," and charities should incorporate the dual identity of volunteers both as labor supply and as customers of volunteering experience. In particular, we suggest that charities (i) assign volunteers a reasonable workload (instead of burning them out), and (ii) design tasks that allow participants to enjoy a level of autonomy. These strategies are more likely to keep volunteers engaged and lead to increased donations.

1.6 Limitations and Future Research

A common concern regarding lab experiments is the external validity of the result. For example, Levitt and List (2007) argue that pro-social behavior can be inconsistent between lab and field settings. First, lab experiments are scrutinized to a higher degree and can cause a demanding effect, which increases the likelihood of charitable behavior in the lab. However, participants work remotely in our setting, and all their data are non-identifiable. Second, the target population and context can differ between lab and field environments. In our experiment, although the participants may be slightly different from the general population as they are online workers, the treatment or the volunteering task is a real task that a charity uses. Third, individuals treat the money differently when they receive it with and without effort (Carlsson *et al.* 2013). Indeed, participants are more generous with windfall earnings than earned endowments in our experiment. Nevertheless, we observed a significant result even with this effect working against our finding. Studies also find that pro-social behaviors in the lab are strongly correlated with the behaviors in the field (Benz and Meier 2008; Franzen and Pointner 2013). In summary, our findings with online participants have strong external validity in practice and theory.

We also acknowledge several limitations in our study that point out future research opportunities. First, participants were not exposed to the traditional in-person volunteering experience. Therefore, we cannot observe the potential impact of social norms on their donation decisions. Second, as demonstrated in Pronin *et al.* (2008) and Huber *et al.* (2011), in addition to the social distance (self vs. other), the temporal distance (now vs. later) is a critical factor in individuals' desire to contribute to a prosocial cause. For example, Huber *et al.* (2011) argue that individuals respond more strongly to the most recent humanitarian crisis. The temporal element is ignored in our study, and perhaps can only be elaborated through a field experiment when a delay between volunteering and donation decision can be designed. Finally, experimental studies are usually designed for *causal description*, which is to describe the consequences attributable to purposefully varying a treatment, or for *causal explanation*, which is to clarify "the mechanisms through which and the conditions under which the causal relationship holds" (Cook *et al.* 2002, p.9). The goal of this study is to describe a causal relationship between a person's volunteering and subsequent donation. Although we used different theoretical views to justify this relationship, future studies may disclose the underlying mechanisms behind this relationship.

Chapter 2

WORKFORCE CONFIGURATION IN CHARITY SETTINGS: A FORWARD-LOOKING APPROACH

2.1 Background

Most charities rely on volunteers who contribute to a wide range of administrative tasks and operations (Whitford and Yates 2002). In 2017, volunteers provided about 6.9 billion hours of services to American charities (AmeriCorps 2017) corresponding to $170 billion worth of labor (Independent Sector 2018). However, volunteers' contributions are not limited to their labor services. A survey shows that 87% of individuals who support charities donate both time and money, and 43% donate money to the same charities where they volunteer (Fidelity Charitable 2014). This points to the dual role of a volunteer: a *producer* of social welfare, as well as a *customer* of the volunteering experience. Thus, the satisfaction of the volunteer-customer during her experience dictates her future involvement with the charity including as future donors (Miller *et al.* 1990; Clary *et al.* 1998; Dwiggins-Beeler *et al.* 2011), and so for the long-term sustainability of a charity, this dual role of a volunteer must be considered when planning the staffing needs. Yet, the common functional structure in charities considers volunteer management and donor management as two separate silos. Specifically, volunteer program managers are responsible for designing volunteering tasks, and recruiting or assigning volunteers, whereas development managers are in charge of fundraising events and donor relations. In this paper, we challenge the conventional charity structure by developing a volunteer management model that explicitly takes into account the dual role of volunteers. To this end, we collaborated with a large charity, the "Society of St. Vincent de Paul of Arizona" (SVdP), and a nonprofit consulting firm, "American Philanthropic," in studying the volunteer staffing problem of social services organizations (e.g., charities).

Contrary to the conventional wisdom indicating that volunteers are always available to charities, they all share similar motivations, complete any given task, and do not impose monetary costs on the host charity, our analysis of SVdP and its data revealed that volunteers are heterogeneous in terms of the strength of their relationship with the charity, their reliability in showing up, and their performance. Volunteers with weak ties with the charity are unreliable at showing up to a volunteering event, are often less effective at performing tasks due to their inexperience and so, are costly sources of labor supply. A volunteer who fails to show up to a "meal packaging" event imposes a shortage cost due to unsatisfied demand, and an obsolescence cost due to the waste of unused raw material (see, e.g., Ata *et al.* 2019).

Volunteers are different from paid workers in the factors that contribute to their job satisfaction. The literature on volunteerism identifies several motivations (e.g., altruistic or social motivations) for an individual to seek out volunteer opportunities. For example, an altruistically motivated volunteer will be unsatisfied if she feels her participation does not contribute meaningfully (Clary *et al.* 1998). This low job satisfaction can potentially lead to her discontinuing a relationship with the charity (Dwiggins-Beeler *et al.* 2011), which is the cost of overstaffing a volunteering event. As another example, some individuals are motivated to volunteer because of the chance to build social networks. For these individuals, their goals are met if the volunteering experience allows them to satisfy their personal or social functions (Marta and Pozzi 2008). Hence, the composition of the volunteering team is crucial for these volunteers. Regardless of the specific motivation, a volunteer that is satisfied with her experience will likely continue ties with the charity, which could eventually develop into a donor relationship (Dwiggins-Beeler *et al.* 2011).

With our work, we develop a volunteer management model that considers the idiosyncratic features of volunteerism and the charity setting. To identify the optimal number of volunteers and team composition for each volunteering event, we propose a distributionally robust optimization model that considers volunteer heterogeneity, turnout uncertainty, and the dual role of volunteers as labor supply and as future donors. In addition, we model the volunteer turnout as random, but only its mean and variance are known to the charity. This choice of a distributionally robust model is motivated by multiple reasons such as low quality and scarcity of data in the charity sector as well as the difficulty of predicting whether or not a volunteer will show up for the scheduled event (e.g., because the charity only observes limited information).

At a high level, this paper contributes to the nascent literature of volunteer management that offers insightful lessons about the relationship between volunteers' time and monetary donations (Brown *et al.* 2019), how to increase volunteers' motivations (Gage III and Thapa 2012), and volunteer retention (Dwiggins-Beeler *et al.* 2011), and suggests matching policies between a volunteer's preferences and the opportunities offered to her (Brudney and Meijs 2009; Manshadi and Rodilitz 2022). More specifically, our paper contributes to the line of work centering on volunteer labor staffing; Gordon and Erkut (2004) adopt integer programming to develop a scheduling model, without explicitly considering the shortage cost of volunteers. Sampson (2006) differentiates volunteer labor assignment from commercial labor assignment, mainly in terms of cost structures, and adopts goal programming to minimize the total cost of labor shortage, over-utilization of labor, and volunteer-task mismatch cost. Falasca and Zobel (2012) extend the proposed setting in Sampson (2006), and develop a multi-objective optimization model to assign humanitarian volunteers to different tasks in multiple work locations, assuming that the labor cost is non-trivial. In the same context of humanitarian relief, Lassiter *et al.* (2015) use robust optimization approach to handle the uncertainty in task demand and provide managers a flexible framework for a dynamic allocation of volunteers. Ata *et al.* (2019) consider a problem of volunteering staffing when supply and demand are uncertain, and considering the differences in volunteers' experience and its impact on their performances, Urrea *et al.* (2019) show that a cluster of volunteers with the same experience level outperforms those with mixed experience levels.

Labor no-show is also an issue in commercial workforce management problems (e.g., in retail and in call centers). Employee absenteeism leads to understaffing that undermines store execution, customer satisfaction, and sales (Fisher *et al.* 2006). For example, Fisher *et al.* (2021) use random labor no-show as an exogenous shock to measure the effectiveness of staffing level in retail context. A proposed solution is to rely on *flexible* labor sources such as part-time temporary workers (Kesavan *et al.* 2014; Kamalahmadi *et al.* 2021). However, having too many flexible workers can also decrease retailers' sales (Kesavan *et al.* 2014). In a field experiment, Kesavan *et al.* (2022) find that stable scheduling, in contrast to the on-call shifts, results in both a decrease in labor cost and also an increase in sales, due to the increased employees' effort and reduced turnout uncertainty. Similarly in the volunteering settings, flexible labor policies may not succeed because unlike paid workers motivated by monetary incentives, volunteers contribute their time to gain an *experience to serve* (Dwiggins-Beeler *et al.* 2011). As producers of social good, volunteers are less likely to respond to "on-call" shifts, and would not appreciate if charities treat them as *back-up labors.* Further, as practitioners informed us, the nature of a volunteering event is different from services in commercial settings. Volunteering events are usually scheduled for short shifts (e.g., three hours), and labor shortage will only be realized close to the start of the event when it is too late to call back-up volunteers. There are other differences, too. In commercial settings, the objective of workforce management is to cover the demand while minimizing labor costs (Mason *et al.* 1998) while there is no such labor costs for volunteers (Sampson 2006). In commercial settings, employees are not the decision-makers as they are scheduled. However, in nonprofit settings, volunteers' availability plays a critical role (Sampson 2006).

Our study is different from the existing literature. First, we validate our key assumptions using a quintessential charity's volunteering and donation data, interviews with experts in a nonprofit consulting firm, and well-grounded literature in both social psychology and behavioral economics. Second, we develop an optimization model that balances understaffing and overstaffing costs, explicitly connects individuals' time and monetary donation, and builds this relationship into the charity's objective. The model only requires simple estimates of the mean and variance of volunteer turnout, but its solution is guaranteed to be robust against all possible distributions. Moreover, our closed-form analysis provides simple guidance for volunteer managers and can be easily implemented in an Excel spreadsheet to schedule their volunteering events. To improve the level of granularity, we incorporate the heterogeneity of volunteers and consider all the operational constraints, and derive interpretable decision tree models for various volunteer tasks.

Our results challenge the common functional structure in charities that considers volunteer management and donor management as two separate functions. We suggest that instead of managing their volunteers and donors in separate silos, charities need to consider volunteers as potential donors and manage the volunteer pool by considering their future support. Our numerical experiments demonstrate that SVdP can lose as much as 35% of total labor and donation value when only considering volunteers' labor contribution.

Furthermore, through comparing different models, we show that the role of volunteers changes as a charity takes future donations into account. Under conventional volunteer planning that ignores future donations, the very reliable volunteers with strong ties to the charity are preferred when staffing an event, and only in the case of labor shortage will the less reliable volunteers be used. Under our model that considers volunteers as future donors, the less reliable volunteers can be preferred. This can occur when the less reliable volunteers place a premium on volunteering, and this premium results in an increase in monetary donation that exceeds the expected labor loss caused by their unreliability. Our model's closed-form expression for the optimal staffing plan allows us to derive insights on process improvements for the charity. We find that it is always beneficial for the charity to reduce the volunteers' turnout uncertainty. This can be achieved, for example, by sending customized messages that emphasize the importance of the task that increases the value-based dimension of volunteers' psychological contract (Vantilborgh *et al.* 2012). Moreover, while intuition tells us that increasing the work efficiency of the reliable volunteers (through training programs) should be beneficial, this is surprisingly not always the case. This nuance is because, with more efficient volunteers, the charity will require fewer volunteers to staff an event, resulting in a lower monetary donation due to fewer volunteers benefiting from the activity. Hence, any training programs must be accompanied with a redesign of the volunteering event to ensure that there are sufficient tasks to accommodate a similar sized volunteer pool.

2.2 Practice

This section summarizes key characteristics of volunteer management in practice and justifies our modeling approach and assumptions.

2.2.1 The Society of St. Vincent de Paul

With 800,000 members in 153 countries across six continents, the Society of St. Vincent de Paul is an international humanitarian organization serving more than 30 million people globally. Their services include feeding, clothing, housing, and healing individuals. With a volunteer-to-staff ratio of 16 to 1, SVdP has nearly 100,000 trained volunteers across 4,400 communities in the U.S. that together provided 12.6 million hours of volunteer services during 2017. Its largest division in the U.S. is located in Phoenix, Arizona, where it serves homeless and low-income families with services such as free medical and dental clinics, food warehouses, transition, and housing. Currently, SVdP Phoenix has about 300 regular employees, over 2,500 active and associate members, and more than 6,000 volunteers. In 2019, SVdP used more than 705,400 volunteer hours and provided 2.6 million meals to people in need.

(a) Pizza Friday

(b) Dining Rooms

Figure 2.1: Examples for the Most Frequent Volunteering Tasks

2.2.2 Types of Volunteers, and Volunteering at SVdP

To begin volunteering at SVdP, individuals need to sign up online or through the phone and choose their preferred program(s) and availability based on the volunteering job location. Although there is no actual interview or in-depth screening for the majority of volunteers,[1] an optional orientation is periodically provided, during which volunteers learn more information about different volunteering opportunities.[2] After gathering the list of volunteers, their preferred jobs, and availability, the program managers plan upcoming events and determine the number of required volunteers for each job. Volunteer managers then invite individuals for volunteering tasks. With this process in place, SVdP may not encounter a typical volunteer–task matching problem. After completing the first job, volunteers who wish to return to SVdP need to contact the volunteer coordinator and submit their availability. Before the COVID-19 pandemic, volunteers could sign up for up to one year in advance of volunteering events.

Using SVdP's archival data, we categorize volunteers into two groups: *formal* and

[1]Screening process is completely different for professional medical volunteers.

[2]Before the COVID-19 pandemic, SVdP offered 44 types of volunteering jobs.

episodic. Formal (or benevolent) volunteers are dedicated and long-term committed individuals who share a deep concern about a particular cause and are loyal to the charity, work similarly as paid staff, show up on scheduled dates, and serve the charity regularly. However, the number of formal volunteers available to SVdP is limited, and studies show that the pool of formal volunteers has been shrinking nationwide (Brudney and Meijs 2009). Episodic volunteers form the majority of SVdP volunteers, who visit the charity less often and irregularly. They are only available at a specific period and seek out volunteering tasks that are short-term and flexible. (See Table 2.1 for a comparison of the two volunteer types.) While SVdP managers prefer to hire formal volunteers who are reliable and experienced, there is only a limited number of formal volunteers. Hence, to have enough volunteers to complete a task, managers would invite episodic volunteers. Although increasing in numbers (Macduff 2005), episodic volunteers impose some *volatility*. Sometimes they may not show up on the scheduled date, and sometimes they may bring additional *spontaneous* volunteers whom SVdP did not anticipate.

According to SVdP, the likelihood of an episodic volunteer's no-show is, on average, about 30%. Most absentees either do not alert the coordinators or notify them too late such that finding a replacement is unlikely. Therefore, understaffing of volunteering jobs is a severe challenge resulting in unfulfilled demands and operational costs. For instance, when SVdP schedules "Pizza Friday" or "Dining Rooms," materials are prepared in advance, and in the presence of labor shortage, raw materials are wasted, and SVdP cannot feed the beneficiaries. SVdP managers emphasized that inviting too many volunteers to cover up for potential absences is not an option. This is because overstaffing of volunteers makes people feel they are not needed, and hence will decrease their future contributions (Smith 1998). Reviewing SVdP's volunteers' survey, we found many examples of volunteers complaining that they "did not have much work to do and went home because there were enough people already." This is aligned with Sampson (2006) survey analysis that shows both excess use

Table 2.1: Comparison of Formal and Episodic Volunteers. This Comparison is based on Observations from April 1, 2018 to March 1, 2020.

Volunteer	No. per month		Time between participation (days)	
Type	Mean	SD	Mean	SD
Episodic	3092	595	40	85
Formal	655	34	10	7

and non-utilization of volunteer labor discourage them from volunteering in the future.

Another prominent challenge is that some episodic volunteers waywardly invite their friends or family without notifying SVdP in advance, resulting in more volunteers than scheduled showing up to an event. Consequently, volunteer managers cannot accommodate everyone's task, and as a manager said: "[...] again, we encounter an overstaffing problem, and the event looks poorly organized." SVdP managers informed us that rejecting the *uninvited* volunteers is not a choice because, as a manager said: "Volunteering work is an experience [that] we offer to people and we want to give this experience to as many people as possible. But, at the same time, we do not want them to come here and only find there is not much to do." Because overstaffing has been a serious problem for SVdP for some years, SVdP management has made two changes hoping to improve the scheduling process. First, all volunteers are required to sign up individually. Second, SVdP does not disclose the location where individual volunteers were assigned until one day before the event. Still, these changes have not eliminated overstaffing challenge. Figure 2.2 illustrates this challenge by showing that the number of attendees often far exceeded the ideal team size of 9. In response to these challenges, SVdP prioritizes inviting formal volunteers for every task, and adds episodic volunteers to the team in order to fill the remaining spots.

2.2.3 Volunteering and Donation

A line of literature argues that individuals consider their time donation as a substitute for their monetary donation (Andreoni 2006; Bekkers 2010; Feldman 2010; Bauer *et al.* 2013), and so they conclude that volunteers are those who prefer to donate their time even

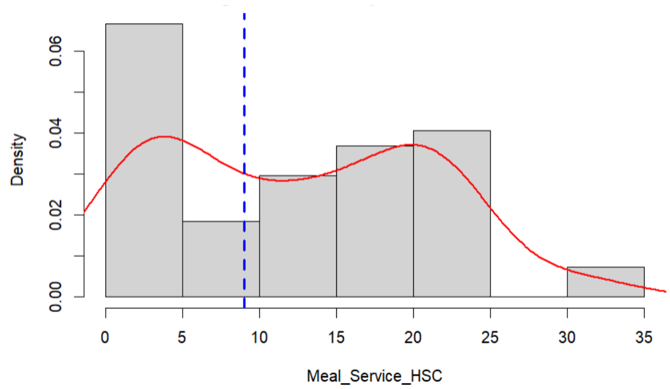


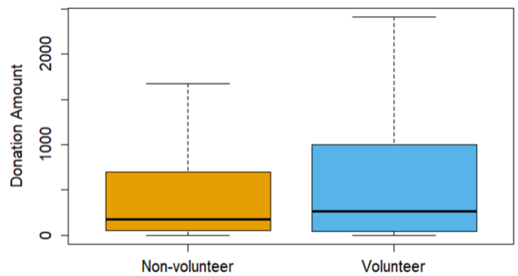
Figure 2.2: Episodic Volunteer Turnout Count Histogram and Density Graph on 54 Consecutive "Meal Service" Events. The Red Curve Line Represents the Density Curve, and the Blue Dotted Line Represents the Ideal Number of Volunteers that is nine.

when the opportunity cost is significant (Brown *et al.* 2019). On the other hand, others show that the relationship is complementary (Brown and Lankford 1992; Cappellari *et al.* 2011), and find that volunteering increases donations (Apinunmahakul *et al.* 2009). In fact, volunteering increases awareness of needs, improves charity's transparency and individuals' trust in the charity. Volunteering events are opportunities to solidify the connection between volunteers and the charity, significantly affecting individuals' future donation (Olsen and Eidem 2003; Feldman 2010; Bekkers and Wiepking 2011); Many volunteers prefer to "try out" the charity by volunteering before making donations (Fritz 2019), and volunteering is considered as the "gateway drug" for charitable giving (Dietz and Keller 2016). Liu and Aaker (2008) use multiple experiments to show that individuals who think of donating time first will be more likely to donate money as well.

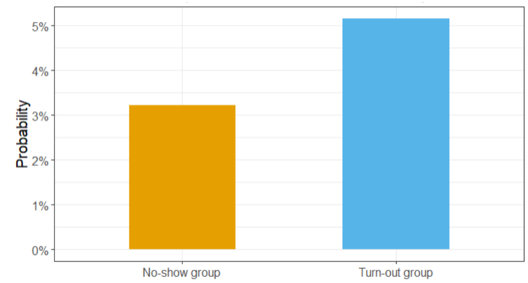
To show the causal effect of one's volunteering on her donation decision, in a separate study, we used SVdP's existing virtual volunteering task in a lab setting and found that participants who were assigned to the volunteering task were more likely to donate and in larger amounts, compared to those who did not serve as volunteers (Authors 2022). This finding is aligned with the survey conducted by Fidelity Charitable (2014) where more than half of volunteers indicate that volunteering leads them to donate financially.

We conducted additional analyses, based on SVdP's archival data, that confirm that a person's volunteering experience is associated with higher amount and likelihood of her future donations. First, conditioning on individuals who have made a monetary donation (i.e., all donors), we compared the average donation between those with and without volunteering experience. A t-test confirms a significant difference ($p \leq 0.001$) between the average donations of the two groups. On average, the 1,184 donors with volunteering experience donated \$856 while the 37,626 donors without such experience donated \$613 (Figure 2.3a), showing that volunteering experience is associated with individuals' amount of donation. Next, conditioning on the intent to volunteer and no donation history before their first volunteering sign-up event, we compared the donation probabilities of volunteers (who showed up in an event), and individuals who had registered for a volunteering event but never showed up. A one-way proportional comparison demonstrates a significant difference ($p \leq 0.010$). The likelihood of individuals with volunteering experience to donate is 5.16% (655 out of 12,705) while the likelihood that individuals without volunteering experience to donate is only 3.23% (26 out of 806) (Figure 2.3b). Accordingly, among all individuals who showed interest in volunteering and never donated before, those with actual volunteering experience were more likely to donate. This difference is substantial if one considers a typical fundraising campaign; The average response rate to a fundraising campaign is between 0.5% to 1% through direct mail (Charity Science 2017), and only 0.06% through email (NonProfit Source 2018).

Furthermore, to estimate the impact of one's volunteering on her subsequent donations, we use the same set of identified individuals who had registered to volunteer at SVdP but never donated before ($N = 13,511$). Comparing the donation amount between those who registered and showed up and those who registered but did not show up, we found that individuals who completed their volunteering service donated, on average, \$16.4 (SD = 286.8), while those who did not show up donated, on average, \$8.3 (SD = 105.4). This 49.4% loss is statistically significant at $p \leq 0.1$ level. Based on this result, we assume



(a) Donation comparison between volunteers and non-volunteers



(b) Donation probability between those who showed up in an event vs. those who did not.

Figure 2.3: Volunteering Experience Affects a Person's Donation Decision. Plot (a) Shows Monetary Donation of Volunteers is Higher (Sample Size for the t-test is $38,810$). Plot (b) Compares Donation Probability Between Who Registered for a Volunteering Event but did not Show Up and Those Who Served at a Volunteering Event (Sample Size for this test is 13,511).

that individuals who served as a volunteer, on average, make more monetary donations. Our data, however, does not enable us to describe the likelihood of donation based on an individual's quality of volunteering experience.

2.2.4 Team Composition

Our second assumption centers on the composition of volunteers at each event. This assumption relies on two facts. First, studies show that groups with homogeneous members contribute significantly more to public goods than groups with heterogeneous members (Burlando and Guala 2005; Gachter and Thoni 2005; Ai *et al.* 2016). A homogeneous group is defined as a group of members with similar identities, beliefs, and motivations (Charness and Chen 2020). For example, a group of formal volunteers who share similar beliefs about a social cause to support, and self-select into the highly committed group represents a group with a high degree of homogeneity. On the contrary, there is little consistency in episodic volunteers' motivations (Hyde *et al.* 2014); They are motivated by diverse reasons including altruism, benefits, involvement, leisure, and conformity (Dunn *et al.* 2016). Hence, inviting episodic volunteers increases the heterogeneity of the group. Homogeneous groups also create a higher level of group cohesion (Bugen 1977; Lieberman *et al.* 2005). Stronger group cohesion builds up members' collective psychological ownership (Pierce and Jussila 2010), which increases the likelihood of donations (Peck *et al.* 2021; Jami *et al.* 2021). On the other hand, heterogeneity in the group suppresses overall contribution, especially when members are aware of the heterogeneity (Ledyard 2020). SVdP managers also informed us that most formal volunteers are retired seniors who treat volunteering jobs seriously. Looking at SVdP's volunteers survey, we found that formal volunteers are more sensitive towards the group's identity and saw complaints such as "Some people are just here for fun, and it is difficult to work with them."

Second, frequent interactions create a group identity among the members. Therefore, it is not surprising that formal volunteers establish a different group identity from episodic volunteers due to their repetitive participation and frequent social interactions (Fraser *et al.* 2009; Gray and Stevenson 2020). Due to their commitment and repetitive interactions, formal volunteers establish group identity and form a cordial relationship among themselves (Lois 1999; Hustinx *et al.* 2008). This leads them to contribute more in public goods and to engage with higher level of pro-social behaviors (Burlando and Guala 2005; Ai *et al.* 2016). Studies show belonging to such a group will enhance in-group altruism (Silva and Mace 2014), and increase the probability of donations (Chen and Li 2009; Charness and Holder 2019). Aligned with these studies, SVdP managers told us that formal volunteers usually consider other formal volunteers a close group of friends. We found, in their survey, that some formal volunteers stated e.g., "I prefer to work with the usual group," "I love working with my regular fellow volunteers," and "It feels like the volunteers are a second family." This joyful experience affects donation decision of formal volunteers who typically are senior citizens (see, e.g., Mellor *et al.* 2008; Borgonovi 2008; Harris and Thoresen 2005). It is worth indicating that the relationship between productivity and team composition has been examined. Tan and Netessine (2019), for example, find that working with more skilled coworkers can boost the performance of the under-skilled workers. However, their study focuses on a commercial setting where all workers are motivated towards the same goal (i.e., meeting sales target). In our setting, episodic volunteers are motivated for various reasons and most of them are not as dedicated as the formal volunteers.

All in all, we understand that formal volunteers share similar identities as they are highly committed to the volunteering work (i.e., similar social identities), and form an inductive group identity (due to repetitive interactions). Consequently, a formal volunteer's joy of contributing to SVdP's mission, and so her future donations, is partially influenced by the endogenous decision of team composition. Hence, we assume that the formal volunteers will make more donations if they are paired with other formal volunteers. However, episodic volunteers are rather indifferent about their team composition.

2.2.5 Volunteer Turnout: Data Quality and Prediction Challenges

Data quality is a common challenge for most charities especially related to volunteer management, as a senior expert from American Philanthropic shared. While SVdP seems to be a learning organization, its data collection is far from ideal. The charity's data prior to 2018 has severe issues, e.g., there are only less than 100 total records in February 2018. The charity improved its data collection process in March 2018. Yet, even reviewing the data between 2018-03-31 and 2020-03-01, we observe many shortfalls. For instance, in the "volunteer" data set, we find that 19% of the records under "volunteer hour" are invalid (either empty, zero or a negative value), 18% of the records under "status" show "confirmed" (not indicating if the volunteer arrived or is a no-show), and 15% of the "no-show" records have comments indicating that either the volunteer had shown up, the shift should have been canceled, or others. Taken together, nearly 40% of all data records contain some degree of error.

Lack of quality data in charities is a common issue due to two reasons. First, given their constant efforts to reduce their overheads, they have little incentive to invest on their infrastructure (Parsa *et al.* 2022). Second, most charities hesitate to track the attendance and performance of volunteers. For example, an SVdP manager indicated: "We do not *grade* our volunteers because it is a sensitive subject. Our concern is that [our] judgment will turn them away." Lack of motivation to collect volunteer data leads to the absence of an automated and consistent data collection method.

This issue is further complicated at larger food banks like SVdP that offer a wide range of volunteering tasks because the process of recording attendance varies significantly among different volunteering programs. (SVdP offers about 44 different volunteering tasks, and creates new ones or stops some tasks based on need.) While in some programs, a dedicated staff member tracks volunteers' attendance, volunteers check in and check out by themselves in other programs. Nevertheless, volunteer survey shows that volunteers consider checking in and out for their volunteering events to be redundant and tedious. They do not like to record their volunteering hours because "it makes them feel they are working instead of volunteering." As a result, we also noticed many manual data entry errors in SVdP's attendance record (Figure 2.4). Thus, the attendance record of a volunteer who had participated in a recurring event for several months can either indicate "no-show" or empty. Sometimes, volunteer managers find the data error by the end of the program and fix it with a new record summarizing an "estimated total volunteering hours," or with comments indicating the missing entries. Thus, the actual volunteering record is lost in the process.

Data scarcity and data quality motivated our choice of a distributionally robust model in this study. In such a model, the optimal volunteer plan is derived without needing to specify a distribution for the random no-shows. This model choice is further motivated by the nature of volunteering where it is nearly impossible to predict whether or not a particular volunteer will show up. Stated differently, SVdP managers told us that, even with perfect data, it is almost impossible to predict a specific volunteer's attendance. On the one hand, the independent variables that can help predict volunteers' turnout are self-reported and non-mandatory. For example, among all records, only 9.5% of all data has information on volunteer's age, 27.3% are filled with gender, and a significant portion of the address information does not match zip code. On the other hand, a volunteer's attendance depends

Start Date	Status	Total Hours	Number of Volunteers	Court_Ordered	Probation	Workmans_Comp	Mandated	Intern	Comments
9/28/2019	Completed	1040	1	0	0	0	0	0	20 hours per week for 1 year unrecorded per Mesa Farm Report sd
9/28/2019	Completed	336	1	0	0	0	0	0	3 times a week at 28 missing weeks at 4 hours per time unclocked sd
9/26/2019	Completed	200	1	0	0	0	0	0	50 weeks unclocked at 4 hours a week sd
9/28/2019	Completed	182	1	0	0	0	0	0	correction of unclocked hours sd
12/31/2018	Completed	117	1	0	0	0	0	0	
10/5/2019	Completed	80	1	0	0	0	0	0	
12/31/2018	Completed	64	1	0	0	0	0	0	Total December hours
1/4/2019	Completed	57.24	1	0	0	0	0	0	
11/9/2019	Completed	40	1	0	0	0	0	0	12-Sep
12/31/2019	Completed	38.5	1	0	0	0	0	0	Total hours for 23, 24, 26, 27, 30
12/31/2018	Completed	38	1	0	0	0	0	0	Dec total
11/7/2019	Completed	36	1	0	0	0	0	0	
7/16/2019	Completed	36	1	0	0	0	0	0	One Step Beyond 9am-12pm
7/9/2019	Completed	36	1	0	0	0	0	0	One Step Beyond 9am-12pm
7/8/2019	Completed	36	1	0	0	0	0	0	One Step Beyond 9am-12pm
7/1/2019	Completed	36	1	0	0	0	0	0	One Step Beyond 9am-12pm
11/16/2018	Completed	36	1	0	0	0	0	0	9am-12pm
4/28/2019	Completed	36	1	0	0	0	0	0	month of April sd
8/9/2019	Completed	36	1	0	0	0	0	0	
10/3/2019	Completed	35.87	1	0	0	0	0	0	
3/10/2019	Completed	35.08	1	0	0	0	0	0	
7/13/2019	Completed	34	1	0	0	0	0	0	
5/21/2019	Completed	34	1	0	0	0	0	0	
6/20/2019	Completed	32.92	1	0	0	0	0	0	

Figure 2.4: Examples of Data Quality Issue: Blue Colored Cells Capture the Negative Volunteer Hours, and Yellow Colored Cells Represent Summarized Hours Missing Individual Records. The Orange Colored Cells Illustrate Examples of Contradictions Between Status and Comments.

on many factors completely unknown to the charity. The uncertainty is most challenging for episodic volunteers about whom SVdP has very limited or no data, and the charity cannot push for data from volunteers at the risk losing them. As Table 2.1 shows, on average 84% of SVdP's volunteers are episodic, meaning that for the majority of volunteers, it is almost impossible to predict turnout probability. Therefore, the policy of inviting volunteers is determined by the total availability of volunteers, characteristics of the task, and general historical information about the type of volunteers.

As opposed to our non-parametric robust approach, one may suggest that a parametric approach that assumes a specific distribution family (e.g., beta distributions) could be applied in this problem. However, the performance of a parametric approach heavily relies on the data quality and reliability of the measurement. As we discussed, this is a very strong assumption given that data quality is poor, and the measurement of the turnout is not consistent. Our non-parametric approach leverages imperfect historical data and conservatively assumes the first and second-moment information without specifying the distribution family. Moreover, the simple information required can be supplemented and corrected by volunteer managers who have a good sense of the popularity of the volunteer task and volunteers' reliability. In this way, charities' decisions are protected against unobserved shocks.

2.3 Model

This section presents our distributionally robust model for the charity's staffing problem. Motivated by the challenges of predicting volunteer turnout (see Section 2.2.5), the model assumes that there is limited information on the probability distribution of the random number of volunteers that show up at the scheduled time. The charity must determine how many volunteers of each type to schedule, to maximize the total expected utility from time donation and monetary donation. In Section 2.3.1, we first describe the probability of volunteer turnout. In Section 2.3.2, we model the effect of the volunteer composition, $\mathbf{x}$, on work completion. In Section 2.3.3, we model its effect on future monetary donations. Finally, in Section 2.3.4, we present the distributionally robust staffing decision problem.

2.3.1 Uncertainty in Volunteer Turnout

Suppose the charity invites $\mathbf{x} = (x_e, x_f)$ episodic and formal volunteers for the volunteering job. Due to their longstanding ties with the charity, all scheduled formal volunteers are committed to showing up to the job. While the formal volunteers are reliable in showing up, a random number of the episodic volunteers will be no-shows on the day of the job. We model this by introducing a non-negative random variable H. We refer to H as the *turnout proportion*. Although we refer to H as a proportion, it can generally attain a value greater than 1. Hence, the number of volunteers who show up to the event is (Hx_e, x_f). Let $p : [0, \infty] \mapsto \mathbb{R}^+$ be the probability density function of H. We use $\mathbb{E}_p[\cdot]$ to denote the expectation under distribution p. We let μ and σ denote the mean and standard deviation of H. Hence, p must belong to the distribution set:

$$\mathcal{P} := \left\{ p : \begin{array}{l} \mathbb{E}_p[1] = 1 \\ \mathbb{E}_p[H] = \mu \\ \mathbb{E}_p[H^2] = \mu^2 + \sigma^2 \end{array} \right\}. \tag{2.1}$$

2.3.2 Effect on Work Completion

Formal volunteers work more efficiently than episodic volunteers. Without loss of generality, we assume that an episodic volunteer contributes work equivalent to one "volunteer hour," while a formal volunteer contributes θ volunteer hours ($\theta \geq 1$). (If episodic and formal volunteers contribute a and θa volunteer hours, respectively, we can scale demand λ by a.) Hence, the total labor hours available for the job is $v = Hx_e + \theta x_f$. Since volunteer turnout is random, Hx_e and v are stochastic quantities.

Let λ denote the number of volunteer hours required to complete the work. Charity management prefers to have a sufficient workforce to ensure completing the volunteer work, and so it receives a per-unit operational benefit $w > 0$ for the total work completed, $\min(\lambda, v)$; Volunteer tasks that are completed yield a total operational benefit $w \min(\lambda, v)$. The charity incurs an understaffing cost if there is any unfinished volunteer work. A per-unit penalty cost $\tau > 0$ is applied for any unit of unfinished work $(\lambda - v)^+$. In addition to understaffing concerns, the charity incurs a cost of overstaffing. An overstaffed job implies that each volunteer does not feel she is contributing meaningfully, resulting in a loss of connection with the charity (Smith 1998). We model this as a per-unit overstaffing cost $\gamma > 0$ incurred for any idle volunteer hours, $(v - \lambda)^+$. Accordingly, the charity's total labor gain is

$$L^x(Hx_e, x_f) := w \min(\lambda, Hx_e + \theta x_f) - \tau(\lambda - Hx_e - \theta x_f)^+ - \gamma(Hx_e + \theta x_f - \lambda)^+. \tag{2.2}$$

We can define a new parameter $\beta := \tau + w$ to be the total labor shortage cost, and rewrite (2.2) as

$$L^x(Hx_e, x_f) = (w - \beta)\lambda + \beta(Hx_e + \theta x_f) - (\beta + \gamma)(Hx_e + \theta x_f - \lambda)^+. \tag{2.3}$$

2.3.3 *Effect on Monetary Donations*

Our analysis in Section 2.2.3 shows individuals donate more after they volunteer. From Section 2.2.4, this increase is exogenous for an episodic volunteer, whereas the group configuration influences it for a formal volunteer. We let $d_e > 0$ denote the average gain in monetary donation due to an episodic volunteer. The average donation gain from a formal volunteer consists of two parts: the gain driven by enhanced group identity and the gain driven by other unobserved factors (e.g., altruism, warm glow). Specifically, $d_f > 0$ is the gain due to unobserved factors, while $d'_f u(Hx_e, x_f)$ is the gain derived from the formal volunteer identifying with the volunteer group, where $u(Hx_e, x_f)$ is the utility of formal volunteers from a group with Hx_e episodic volunteers and x_f formal volunteers.

With abuse of notation, we can express u as a univariate function of the transformation variable $\rho := Hx_e/x_f$, i.e., the ratio of episodic-to-formal volunteers. Kesavan *et al.* (2014) similarly measure the labor mix by using part-time laborers divided by full-time laborers. While a formal volunteer has a stronger group identity if the volunteer group is composed of more formal volunteers, the marginal gain from additional formal volunteers is decreasing. For example, after the formal volunteer makes a few friends through the volunteering event, the additional formal volunteer adding to the group may have less impact on the group identity. Therefore, we assume that u is non-negative and convex decreasing in ρ. For example, u can take an exponential form, $u(\rho) = e^{\alpha-\rho}$, a quadratic form, $u(\rho) = (c - a\rho^2 + b\rho)^+$, an absolute value function form, $u(\rho) = (\alpha - |b - \rho|)^+$, or a linear form, $u(\rho) = (\alpha - \rho)^+$. If (Hx_e, x_f) is the number of volunteers on the day of the job, the charity gains a total benefit associated with monetary donations equal to

$$M^x(Hx_e, x_f) := d_e Hx_e + d_f x_f + d'_f x_f u\left(\frac{Hx_e}{x_f}\right). \tag{2.4}$$

2.3.4 *Distributionally Robust Staffing Decision Problem*

Let $\mathcal{X}$ represent the set of feasible staffing decisions. Suppose that the volunteer manager knows the true distribution of turnout p. Then if the manager is only concerned with the work completed, the staffing decision problem is $\max_{\mathbf{x}\in\mathcal{X}} \mathbb{E}_p\left[L^x(Hx_e, x_f)\right]$.

Alternatively, if the manager is concerned with how the staffing decision affects both the current work completion and the future monetary donations, then the staffing decision problem is $\max_{\mathbf{x}\in\mathcal{X}} \mathbb{E}_p\left[J^x(Hx_e, x_f)\right]$, where J^x is the joint objective $J^x(Hx_e, x_f) := L^x(Hx_e, x_f) + M^x(Hx_e, x_f)$. The novelty of the utility function $\mathbb{E}_p\left[J^x(Hx_e, x_f)\right]$ is that it compares the trade-off between (i) individuals' time and monetary donations, and (ii) labor shortage and surplus cost. To the best of our knowledge, no analytical studies have studied the trade-off between an individual's time and monetary donations in a workforce management setting. As highlighted in Section 2.2.5, due to the difficulty in predicting volunteers' turnout and data inaccuracy, the volunteer manager does not know the true distribution p. Instead, she only has limited information about it. Expressly, we assume that based on her experience, the manager can only reliably estimate μ and σ. If the volunteer manager misspecifies the distribution, then the resulting staffing solution may be suboptimal under the true (unknown) probability distribution. Hence, there is a need to develop a staffing decision model that is robust to distribution ambiguity.

A known approach for decision-making with limited distribution information is a distributionally robust optimization (DRO) approach. The DRO approach was popularized by Scarf (1958) for the classical newsvendor model, where the objective was to choose a solution that maximizes the worst-case expected profit under any distribution with mean μ and standard deviation σ. We will adopt a DRO approach for the charity's volunteer management problem, which we refer to as the *distributionally robust volunteer management* (DRVM) problem.

If the volunteer manager is only concerned with work completion, then she can solve the following DRVM variant:

$$L^* := \max_{\mathbf{x}\in\mathcal{X}} L(\mathbf{x}) := \max_{\mathbf{x}\in\mathcal{X}} \inf_{p\in\mathcal{P}} \mathbb{E}_p[L^x(Hx_e, x_f)]. \tag{DRVM-L}$$

We refer to this as the DRVM-L problem, where "L" refers to a labor objective. Suppose $\mathbf{x}^*$ is the solution to (DRVM-L). If the charity accepts $\mathbf{x}^*$ volunteers, then the charity can be assured that the expected labor benefit will be at least L^*. Note that solving the maximization problem in (DRVM-L) results in a staffing solution with the highest guarantee of the expected labor gain under the distribution set $\mathcal{P}$.

If the volunteer manager is concerned with both the work completed and future monetary donations, then she can solve the following DRVM variant:

$$J^* := \max_{\mathbf{x}\in\mathcal{X}} J(\mathbf{x}) := \max_{\mathbf{x}\in\mathcal{X}} \inf_{p\in\mathcal{P}} \mathbb{E}_p[L^x(Hx_e, x_f) + M^x(Hx_e, x_f)]. \tag{DRVM-J}$$

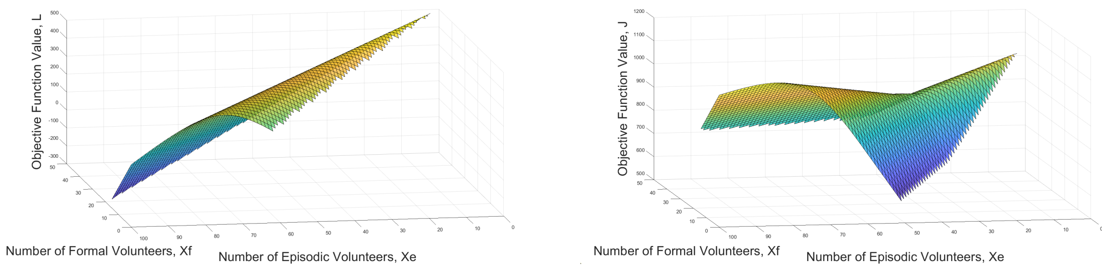
We refer to this problem as DRVM-J, where "J" refers to a joint objective of labor gain and monetary donations. Suppose $\mathbf{x}^*$ is the solution to (DRVM-J). If the charity accepts $\mathbf{x}^*$ volunteers, then the charity can be assured that the expected joint benefit will be at least J^*. As before, by solving the maximization problem in (DRVM-J), the resulting staffing solution would give the best guarantee of the expected joint benefit under $\mathcal{P}$.

Program managers prefer to have a minimum number of formal volunteers to join, given their experience and ability, to facilitate the volunteering job. Hence, we impose a lower bound constraint $x_f \geq x_{f,\ell}$. Also, there is a maximum number of formal volunteers that a charity can invite to a task. The charity only has a small pool of formal volunteers participating in volunteering events. We model this as the constraint $x_f \leq x_{f,u}$. We also consider an upper bound to the number of episodic volunteers, $x_{e,u}$. Hence, the feasible set is:

$$\mathcal{X} := \left\{ \mathbf{x} = (x_e, x_f) \in \mathbb{R}^+ \times \mathbb{R}^+ \ : \begin{array}{l} x_e \leq x_{e,u} \\ x_f \in [x_{f,\ell}, x_{f,u}] \end{array} \right\}. \tag{2.5}$$

2.4 Optimal Staffing Decisions under DRVM

In this section, we derive the optimal staffing decisions under the variants of the DRVM problem. By abuse of notation, we let $\mathbf{x}^* = (x_e^*, x_f^*)$ refer to the optimal solution where the model (L or J) is clear from the context.



(a) Function $L(\mathbf{x})$ **(b)** Function $J(\mathbf{x})$

Figure 2.5: The Functions $L(\mathbf{x})$ and $J(\mathbf{x})$ are Plotted Against Different Values of $\mathbf{x} = (x_e, x_f)$. Note the Non-concavity of J. For these Plots, We Set $\lambda = 50, w = \$10, \mu = 0.65, \sigma = 0.1, \theta = \alpha = 1, \gamma = \beta = 25, d_e = \$15.7, d_f = \$5.5, d'_f = \$5$.

2.4.1 Model DRVM-L

We analyze model DRVM-L whose objective function is $L(\mathbf{x}) := \inf_{p \in \mathcal{P}} \mathbb{E}_p[L^x(Hx_e, x_f)]$. From (2.3), $\mathbb{E}_p[L^x(Hx_e, x_f)]$ is a newsvendor objective with random yield, $Hx_e + \theta x_f$, and known demand, λ. So, for a given distribution p, $\mathbb{E}_p[L^x(Hx_e, x_f)]$ is jointly *concave* in $\mathbf{x}$. Hence, $L(\mathbf{x})$ is jointly concave in $\mathbf{x}$ since it is an infimum of concave functions. The concavity of L is illustrated in Figure 2.5a.

The closed-form expression of $L(\mathbf{x})$ (in Lemma 1) can be derived by solving the inner moment problem $\inf_{p \in \mathcal{P}} \mathbb{E}_p[L^x(Hx_e, x_f)]$ using the Scarf bound (Theorem 4). This closed-form expression allows us to derive the optimal solution to (DRVM-L), which is formalized next.

Theorem 1 *The solution to* (DRVM-L) *is* $x_f^* = \min\{x_{f,u}, \frac{\lambda}{\theta}\}$ *and* $x_e^* = \frac{(\lambda - \theta x_f^*)\mu}{\mu^2 + \sigma^2}\left(1 + \frac{\sigma(\beta - \gamma)}{\sqrt{\Delta_0}}\right)$, *where* $\Delta_0 := (\beta + \gamma)^2\sigma^2 + 4\mu^2\beta\gamma$. *The optimal value is* $L^* = w\lambda + \frac{1}{2}\left((\lambda - \theta x_f^*)\sigma \frac{\sigma(\gamma - \beta) - \sqrt{\Delta_0}}{\mu^2 + \sigma^2}\right)$.

Recall that each formal volunteer contributes θ volunteer hours. Hence $\bar{x}_f := \min\{x_{f,u}, \frac{\lambda}{\theta}\}$ is the maximum number of formal volunteers that can be used towards meeting the required volunteer hours λ. According to this theorem, when the charity optimizes only towards work completion, it is optimal to accept the maximum number of formal volunteers (i.e., $x_f^* = \bar{x}_f$). This result is intuitive because formal volunteers are preferred over episodic volunteers due to their experience at performing the task ($\theta \geq 1$) and their reliability at turning up.

2.4.2 Model DRVM-J

Unlike (DRVM-L) which is a convex optimization problem, the robust staffing problem with a joint objective (DRVM-J) is generally non-convex. Hence, we generally cannot use efficient convex optimization techniques in solving (DRVM-J).

For analytical tractability, we let $u(\rho) = (\alpha - \rho)^+$, where $\rho = Hx_e/x_f$ is the ratio of episodic-to-formal volunteers. If $\rho > \alpha$, a formal volunteer does not identify with the group since there are too few formal volunteers; hence, her monetary donation is not improved by the group identity. Even in the linear case, the objective function $J(\mathbf{x})$ is neither concave nor convex (see Figure 2.5b). In what follows, we will first study (DRVM-J) by deriving the closed-form solution in the case when the constraints (i.e., bounds on the volunteer types) are non-binding. Under binding constraints, we will present a tractable computational method for solving (DRVM-J).

Closed-form Expression:

A closed-form solution brings important practical value to charities because it can be easily incorporated into volunteer managers' scheduling process. For example, the solution can be coded in an Excel spreadsheet, providing simple guidance for volunteer managers on how many episodic and formal volunteers they need for their volunteering events. In addition, the solution under the relaxed bound constraints (i.e., assuming there will be sufficient volunteers in the long run) can guide program managers on what types of volunteers to recruit given their planned volunteering events.

If the group composition is (Hx_e, x_f), then under a linear utility, the combined labor and monetary donation gain, $J^x(Hx_e, x_f) := L^x(Hx_e, x_f) + M^x(Hx_e, x_f)$, is:

$$(w-\beta)\lambda + (d_e+\beta)Hx_e + (d_f+\beta\theta)x_f - (\beta+\gamma)(Hx_e+\theta x_f-\lambda)^+ + d'_f\,(\alpha x_f - Hx_e)^+ . \tag{2.6}$$

Note that $J^x(Hx_e, x_f)$ is neither concave nor convex in $\mathbf{x} = (x_e, x_f)$, a property that carries over to $J(\mathbf{x})$. Hence, we cannot solve (DRVM-J) using standard convex optimization techniques. However, $J^x(Hx_e, x_f)$ is a piecewise-linear function in H with two breakpoints, $h_0 := \frac{\lambda - \theta x_f}{x_e}$ and $h_f := \frac{\alpha x_f}{x_e}$. This latter property makes model (DRVM-J) suitable for closed-form analysis using duality.

Using duality analysis, we derive a closed-form expression for $J(\mathbf{x})$ (see Lemmas 4 and 5). Note that the duality-based analysis of $J(\mathbf{x})$ is more complicated than that of $L(\mathbf{x})$. A main reason is that $L^x(Hx_e, x_f)$ is piecewise-linear *concave* in H with *one* breakpoint, whereas the joint function $J^x(Hx_e, x_f)$ is a piecewise-linear *concave-convex* or *convex-concave* function with *two* breakpoints. As a result, there are many more forms for primal/dual optimal solutions to $\mathbb{E}_p[J^x(Hx_e, x_f)]$ and its dual. This results in the piecewise function $J(\mathbf{x})$ having up to six subdomains (see Lemmas 4 and 5).

Aided by the closed-form expression for $J(\mathbf{x})$, we can now derive the solution to (DRVM-J). A challenge is that $J(\mathbf{x})$ is neither concave nor convex (see Figure 2.5b). Hence, solving (DRVM-J) requires evaluating $J(\mathbf{x})$ over six subdomains of the feasible set $\mathcal{X}$. Note that the optimal solution depends on the values of the bounds $x_{f,\ell}$, $x_{f,u}$ and $x_{e,u}$ that define the feasible set $\mathcal{X}$. For a parsimonious model, we will derive the solution for the case when the bounds are non-constraining, i.e., $x_{f,\ell} = 0$ and both $x_{f,u}$ and $x_{e,u}$ are sufficiently large.

First, we discuss the case when volunteering has a notable effect on volunteers' donations. More specifically, we consider two cases: (1) the maximum donation gain of formal volunteers exceeds the cost of overstaffing that is $d_f + \alpha d'_f > \theta\gamma$, and (2) the episodic volunteers' average donation exceeds their amplified overstaffing cost caused by their turnout uncertainty that is $d_e > (1/2)\left((\gamma - \beta) + \frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)$. Recall that a formal volunteer's donation decreases as more episodic volunteers are added to her team. Hence, $d_f + \alpha d'_f$ is the maximum donation amount in a team of only formal volunteers. If an episodic volunteer shows up and there are already enough volunteers, she causes an overstaffing cost γ. However, due to turnout uncertainty, episodic volunteers may also be absent or even bringing more volunteers than invited. Hence, the overstaffing cost must be amplified by considering the understaffing cost β and turnout standard deviation σ. Note that $(1/2)\left((\gamma-\beta)+\frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)=\gamma$ when $\sigma=0$. Stated differently, episodic volunteer has overstaffing cost as γ if their turnout is certain.

Theorem 2 *Let $x_{f,\ell}=0$ and both $x_{f,u}$ and $x_{e,u}$ be sufficiently large. We have the following two cases:*

(a) *When $d_f+\alpha d'_f \geq \gamma\theta$, then $x^*_f = x_{f,u}$ and $x^*_e = 0$ if and only if d_e is sufficiently small. Moreover, there exists sufficiently large values of d_e and d_f such that $x^*_f > 0$ and $x^*_e > 0$.*

(b) *When $d_e > (1/2)\left((\gamma-\beta)+\frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)$, then $x^*_e = x_{e,u}$ if and only if d_f is sufficiently small. Moreover, there exists sufficiently large values of d_e and d_f such that $x^*_f > 0$ and $x^*_e > 0$.*

Theorem 2 indicates that when volunteering has a significant effect on at least one volunteer type's donation, the charity can still benefit from inviting excess number of volunteers. Case (a) in Theorem 2 holds when $d_f+\alpha d'_f \geq \gamma\theta$ that is when the maximum donation amount in a team of only formal volunteers $(d_f+\alpha d'_f)$ exceeds the cost of overstaffing $(\gamma\theta)$. In this case, the charity has an incentive to invite the maximum number of formal volunteers, $x^*_f = x_{f,u}$. Moreover, when episodic volunteers' donation is small, the charity will not benefit from inviting any episodic volunteer because their presence reduces the satisfaction of formal volunteers. Case (b) in Theorem 2 refers to when the episodic volunteers' average donation, d_e, cover their amplified overstaffing cost. In this case, the charity can choose a team with only episodic volunteers. Although formal volunteers are more reliable and may make additional donations if their presence is large enough to form a cohesive group relationship, episodic volunteers can be the sole source of labor supply if their average donation covers the labor cost caused by their random turnout. Lastly, Theorem 2 also states that if the average donation of volunteers is sufficiently large for both types, then it is reasonable to team formal and episodic volunteers even though this form leads to a less satisfactory environment for formal volunteers. Hence, despite the downside of episodic volunteers as pure labor suppliers, it is desirable for the charity to benefit from this group of volunteers.

While Cases (a) and (b) are realistic for some tasks (e.g., fundraising drives), they may not hold for all volunteering tasks in SVdP. Hence, we consider the cases where $d_f+\alpha d'_f < \gamma\theta$ and $d_e < (1/2)\left((\gamma-\beta)+\frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)$. In these conditions, the effect of volunteering on donations is moderate, and so SVdP should carefully balance the cost and benefit of adding a new volunteer to the group. We define the notation

$$\nu := \frac{(\gamma-\beta)}{2} + \frac{(2d_e+\beta-\gamma)\mu^2 - \sigma\sqrt{\Delta_e}}{2(\sigma^2+\mu^2)},$$

where $\Delta(d_e) := (\beta+\gamma)^2\sigma^2 + 4\mu^2(\beta+d_e)(\gamma-d_e)$. Note that ν is composed of terms relating to only the episodic volunteer donation parameter, d_e, turnout proportion statistics, μ and σ, and labor cost parameters, β, and γ. We can interpret ν as the marginal value of an episodic volunteer to the charity (that will be further elaborated in Section 2.5.1). Therefore, ν factors into the decision of whether SVdP prefers formal volunteers or episodic volunteers, as seen in the following theorem.

Theorem 3 *Suppose $x_{f,\ell}=0$ and both $x_{f,u}$ and $x_{e,u}$ are sufficiently large. If $d_f+\alpha d'_f < \gamma\theta$ and $d_e < (1/2)\left((\gamma-\beta)+\frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)$, then a solution to* (DRVM-J) *is:*

(a) *If $d_f+\alpha d'_f \le \theta\nu$, then $x_f^*=0$ and $x_e^* = \frac{(\lambda-\theta x_f^*)\mu}{\sigma^2+\mu^2}\left(1+\frac{\sigma(\beta-\gamma+2d_e)}{\sqrt{\Delta(d_e)}}\right)$. The optimal value is $J^* = w\lambda + \frac{\mu^2 d_e\lambda}{\mu^2+\sigma^2} + \frac{1}{2}\lambda\left(\frac{\sigma^2(\gamma-\beta)-\sigma\sqrt{\Delta(d_e)}}{\mu^2+\sigma^2}\right)$.*

(b) *Otherwise, $x_f^*=\lambda/\theta$ and $x_e^*=0$. The optimal value is $J^* = w\lambda + (d'_f\alpha+d_f)\frac{\lambda}{\theta}$.*

Observe in case (a) of Theorem 3, the optimal staffing decision is to invite only episodic volunteers. This case highlights that, even though episodic volunteers' labor efficiency and reliability are inferior to those of formal volunteers, it could be optimal to recruit them and keep them engaged in the charity's programs. Episodic volunteers become preferred when the expected donation from this group of volunteers is greater than the expected labor loss caused by the uncertainty of episodic volunteers and the maximum donation from formal volunteers (i.e., $d_f + \alpha d'_f \leq \theta\nu$). This is in contrast to Theorem 1 where formal volunteers are always preferred under the labor-only model (DRVM-L) due to their reliability and labor efficiency.

The closed-form expressions in Theorems 1 and 3 allow us to understand how x_e^* is affected by the parameters under models (DRVM-L) and (DRVM-J). If the charity invites x_f^* formal volunteers, then $\lambda - \theta x_f^*$ is the total work that episodic volunteers need to fill. If the number of episodic volunteers is $\bar{x}_e := \frac{(\lambda - \theta x_f^*)\mu}{\mu^2+\sigma^2}$, then the expected work they can produce is $\frac{\mu^2}{\mu^2+\sigma^2}(\lambda - \theta x_f^*)$. When the charity is only concerned with work completion, Theorem 1 suggests that $\bar{x}_e$ episodic volunteers is optimal if $\beta = \gamma$ (i.e., balanced costs of understaffing and overstaffing). Furthermore, the charity should invite more (resp., less) episodic volunteers than $\bar{x}_e$ when $\beta > \gamma$ (resp., $\beta < \gamma$). In contrast, Theorem 3 suggests that when the charity considers the donation of its volunteers, $\bar{x}_e$ is optimal when $\beta + d_e = \gamma - d_e$, and that the charity should invite more (resp., less) than $\bar{x}_e$ when $\beta + d_e > \gamma - d_e$ (resp., $\beta + d_e < \gamma - d_e$). Hence, when episodic volunteers are donors, then the understaffing (overstaffing) cost must be adjusted up (down) by the donation amount.

Computational Method:

Although we obtained a closed-form expression for $J(\mathbf{x})$, deriving a closed-form for the optimizer $\mathbf{x}^*$ is significantly more challenging if the distribution set $\mathcal{P}$ includes the support of the random turnout rate (i.e., $H \in [h_\ell, h_u]$). When considering this constraint, J becomes a piecewise-defined function with up to thirty-two subdomains of $\mathcal{X}$. Presenting an analytical solution for this problem is possible but cumbersome. However, we can utilize the piecewise structure of J to develop a computationally *tractable* method for solving (DRVM-J). Specifically, for each subdomain $\mathcal{X}_i \subseteq \mathcal{X}$, we can optimize $J(\mathbf{x})$ subject to $\mathbf{x} \in \mathcal{X}_i$. We can then choose the largest optimal value which is also the solution of (DRVM-J). With this method, we only need to solve up to thirty-two constrained convex optimization problems.

However, this computational method is difficult to incorporate into a charity's existing

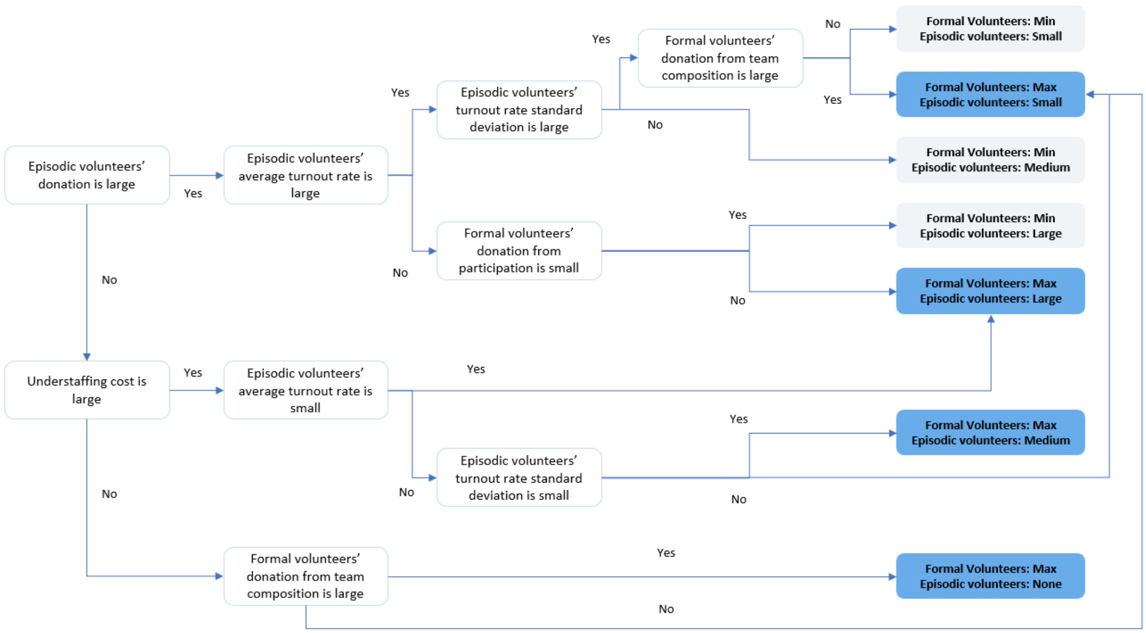


Figure 2.6: Decision Tree: A General Simplified Process to Determine Workforce Configuration

processes since it requires a convex optimization solver. Instead, we provided the charity with an interpretable decision model (decision tree) that has been trained from the solution of 100,000 randomly generated instances[3] of constrained (DRVM-J). The decision tree allows us to develop insights into how the parameters affect the optimal solution. It is worth noting that this approach can also be tuned for a specific volunteering task, and hence generated prescriptive insights for charities. We removed instances where the optimal policy is to invite overwhelming amount of volunteers (i.e., $x_e^* = x_{e,u}$) because this only represents less common cases (e.g., $d_e > \gamma$) and the insight is simple to conclude. Figure 2.6 presents the decision tree, where the dark (light) shaded leaf nodes correspond to optimal solutions where the formal volunteers are equal to the upper (lower) bound.

As shown in Figure 2.6, the factor that best splits the data is the magnitude of d_e, the

[3] To generate these instances, we uniformly draw β, γ from $[5, 35]$, d_e from $[0, 35]$, d_f, d_f' from $[0, 25]$, α, θ from $[1, 2]$, h_u (h_ℓ) is drawn from $[0.25, 0.45]$ ($[0.9, 1.1]$), μ from $[0.45, 0.9]$, and σ from $[0, \sigma_u]$ where $\sigma_u = \sqrt{(h_u - \mu)(\mu - h_\ell)}$ is the upper bound by Bhatia-Davis inequality. The lower and upper bound of formal volunteers ($x_{f,l}$ and $x_{f,u}$) are draw uniformly between $[0, \lambda h_\ell/(\alpha h_u + \theta h_\ell)]$ and $[\lambda h_u/(\alpha h_\ell + \theta h_u), \frac{\lambda}{\theta}]$. Last, we set $\lambda = 50$ and $x_{e,u} = \frac{\lambda}{h_\ell}$.

effect of volunteering on episodic volunteers' donation. When d_e is small, it is optimal to admit the maximum formal volunteers. The secondary factor is $d_f + \alpha d'_f$, the maximum donation from a formal volunteer. When the $d_f + \alpha d'_f$ is large, the optimal policy is to invite the maximum number of formal volunteers. Otherwise, the optimal policy is to invite a minimum number of formal volunteers. Finally, the factors that determine the optimal number of episodic volunteers are the average (μ) and standard deviation (σ) of episodic volunteer turnout. When μ is low, it is optimal to select the maximum number of episodic volunteers. On the other hand, when μ is large, it is optimal to invite the minimum or moderate number of episodic volunteers, depending on σ. Specifically, a more extensive σ means a lower number of episodic volunteers.

2.5 Implications for Process Improvements

Given the closed-form solutions in Theorem 1 and Theorem 3, we next discuss several process changes that improve the charity's utility.

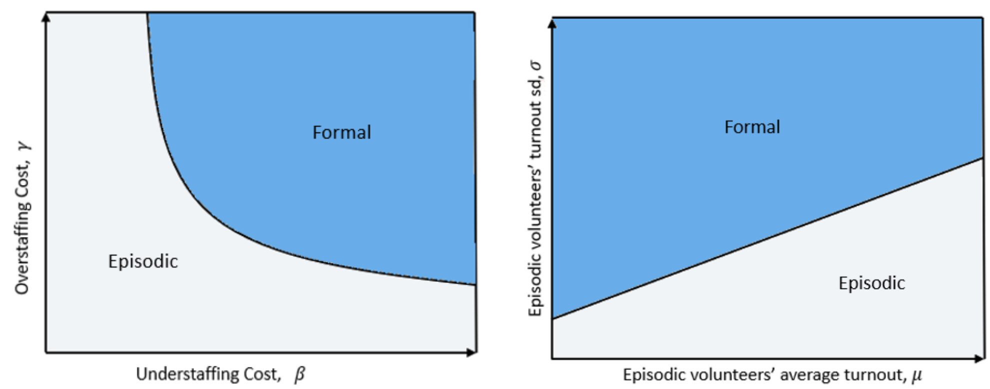
2.5.1 When and How can Charity Rely on Episodic Volunteers?

A key question for charities is to understand when they should prefer episodic volunteers as their main workforce. When only considering volunteers' labor value, formal volunteers are clearly the preferred group, due to their reliability and performance. Yet, if charities also consider monetary donations, episodic volunteers could be preferred as the main workforce. In particular, from Theorem 2, we can conclude that charities may prefer episodic volunteers when episodic volunteers' average donation is large enough to cover both the overstaffing cost and the understaffing cost caused by turnout uncertainty.

Further, from Theorem 3 where $d_e < (1/2)\left((\gamma - \beta) + \frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)$ and $d_f + \alpha d'_f < \gamma\theta$, charities should only invite episodic volunteers if the marginal value of episodic volunteers, ν, is larger than the maximum value provided by formal volunteers, $(d_f + \alpha d'_f)/\theta$. Note that the value of episodic volunteers decreases when labor cost (γ or β) increases ($\frac{\partial \nu}{\partial \beta} < 0$ and $\frac{\partial \nu}{\partial \gamma} < 0$). Simply put, although episodic volunteers do bring labor value to complete a task, their net contribution to the charity decreases as labor value becomes greater. When both labor costs (β and γ) are significant, it is optimal to invite only formal volunteers. This can be observed in the dark shaded region of Figure 2.7a; Although the increase in the monetary donation by episodic volunteers ($d_e = \$15$) is greater than the largest possible increase by formal volunteers ($d_f + \alpha d'_f = \$5$), the benefit does not overcome the high expected cost from the uncertain turnout of episodic volunteers.

This observation brings us to the second element that should be considered in this trade-off: the impact of episodic volunteers' turnout uncertainty. We can simply consider the coefficient of variation of the turnout, $c_v = \frac{\sigma}{\mu}$. Under model (DRVM-J), charities should only utilize episodic volunteers when the coefficient of variation of episodic volunteers is small enough. Figure 2.7b demonstrates how the optimal staffing plan is affected by μ and σ from Theorem 3. Note that the linear threshold that distinguishes the two policies is $\frac{\sigma}{\mu} = \frac{d_f + \alpha d'_f - \theta d_e}{\sqrt{(d_f + \alpha d'_f + \beta\theta)(\gamma\theta - d_f - \alpha d'_f)}}$ (equivalent to $d_f + d'_f \alpha = \theta\nu$), which is the largest coefficient of variation where the optimal policy is to invite episodic volunteers. Therefore, when coefficient of variation is larger than this threshold, the optimal policy is to only invite formal volunteers.

We next discuss how c_v impacts the charity's utility. For (DRVM-L), the charity is worse off when c_v increases because $\frac{\partial L^*}{\partial c_v} < 0$ in Theorem 1. For model (DRVM-J), under the conditions of Theorem 3, we can also check that $\frac{\partial J^*}{\partial c_v} \leq 0$, where the inequality is strict if $d_f + \alpha d'_f < \theta\nu$. It can also be established that, under model (DRVM-J), when the condition of Theorem 2 holds, J^* is nondecreasing in μ and nonincreasing in σ (which can be shown using envelope theorem and Lemma 4 and Lemma 5). Hence, for both models (DRVM-L) and (DRVM-J), the charity is better off reducing the variability of episodic volunteers' turnout by either reducing the standard deviation σ or improving average turnout μ. To reduce overstaffing caused by turnout uncertainty, charities may require volunteers to sign up each individual who is planning to participate. Furthermore, research shows that understanding the value of the volunteering task can strengthen volunteers' psychological



(a) Cost Regions of Problem (DRVM-J) in Theorem 3

(b) Uncertainty Set Regions of Problem (DRVM-J) in Theorem 3

Figure 2.7: Region of Costs (β and γ) and Uncertainty Set (μ and σ) that Determine the Optimal Staffing Strategy. In Both Panels, We Set $\mu = 0.65, \sigma = 0.2$, $\theta = 1$, $\alpha = 1$, $\beta = 16$, $\gamma = 18$, $d_e = 15$ and $d_f = d'_f = 2.5$.

contract (Vantilborgh *et al.* 2012) that is likely to reduce the chances of their no-shows. Therefore, charities may consider communicating the importance of the task to volunteers, for example, through emails or text messages, to minimize the likelihood of absenteeism.

2.5.2 Training Programs for Formal Volunteers

A common practice adopted by charities is to provide additional training programs to their formal volunteers. We analyze whether or not this practice is always beneficial. Consider a charity that is only concerned with work completion when making staffing decisions. For example, volunteers at health clinic charities or mental health charities are usually valued for their expertise and experience with the job, not monetary donations. From Theorem 1, we can check that $\frac{\partial L^*}{\partial \theta} \geq 0$, where the inequality is strict if $\theta < \lambda/x_{f,u}$. So, the charity's utility always increases with the efficiency level θ. The intuition behind this is that if formal volunteers are more efficient, fewer episodic volunteers need to be invited, which benefits the charity since the latter group introduces turnout uncertainty. Therefore, the charity should invest in training and developing formal volunteers' skills at completing the tasks. However, once the efficiency level of formal volunteers is sufficiently high (i.e., $\theta \geq \lambda/x_{f,u}$), the charity does not need episodic volunteers to complete the job. Further training will not yield additional benefits to the charity and $\frac{\partial L^*}{\partial \theta} = 0$.

Interestingly, if the charity is concerned with both work completion and monetary donations when staffing jobs, additional training to formal volunteers could *decrease* the charity's utility. When the optimal solution is to only invite formal volunteers, then additional training always decreases the charity's utility since $\frac{\partial J^*}{\partial \theta} > 0$. The intuition is that, as θ increases, the charity will need fewer formal volunteers to complete the job, resulting in lower total donations for the invited volunteers. However, when the optimal solution is a mixture of formal and episodic volunteers, then the effect of θ on the charity's utility is more nuanced. In particular, J^* increases with θ if and only if $\beta + \gamma > d'_f$ and $\beta > C\gamma$ for some scaling factor C that depends on μ and σ. Otherwise, the charity can actually be worse off by training its formal volunteers. The intuition for the latter observation is that, when formal volunteers become more efficient, the charity will require fewer of both types of volunteers. Although this benefits work completion due to having fewer (unreliable) episodic volunteers, this ultimately hurts the charity due to a larger reduction in the charity's future donations.

An interesting case is when the constraints are binding and $x_{f,u} < \lambda/\theta$. Under some conditions (see Figure 2.6), the optimal number of formal volunteers is $x^*_f = x_{f,u}$, so training these volunteers does not impact the number of formal volunteers but decreases the episodic volunteers needed. If d_e far exceeds d'_f, the fewer episodic volunteers will have a negative net effect on the charity's utility; Although the formal volunteers will increase their donation due to the decrease in ρ (episodic-to-formal volunteers ratio), it is not enough to compensate for the loss of monetary donation from the fewer episodic volunteers. Accordingly, more experienced formal volunteers could crowd out other volunteers' participation, thus possibly decreasing the total monetary donation. This conclusion is also confirmed by SVdP's volunteers survey. For example, a volunteer commented "There is a couple who had volunteered a couple of years before and they are clearly dedicated and generous volunteers. Here's the however: they arrive 90 minutes before the scheduled time and get the dining room set up and many tasks accomplished. While on one hand that is great, on the other, it means there is nothing for others to do who arrive at the published start of the shift. I totally appreciate the kind-hearts of the couple who arrive early, but also think it discourages other volunteers." Since formal volunteers have a longstanding relationship with the charity, they can also gain experience and skills over time if they are assigned to repetitive tasks. Likewise, the charity could spend resources creating challenging and rewarding volunteering tasks (so that formal volunteers' efficiency does not crowd out other volunteers) rather than training volunteers on existing work. Alternatively, charities can position the experienced volunteers to take the leading role to guide other volunteers instead of finishing the jobs by themselves. In addition, they can design tasks such that the total demand is flexible (and so overstaffing cost will likely be small) such that formal volunteers will not crowd out other volunteers' experience.

2.6 Application to the Case of SVdP

First, with the proposed closed-form solutions, SVdP is able to schedule volunteers based on the characteristics of volunteer tasks. For example, the charity's special fundraising events have low overstaffing cost (i.e., γ is small) because volunteers are asked to solicit donations across different locations and are able to work independently without overlapping. Therefore, the optimal policy is to invite an excess number of volunteers, $(x_{e,u}, x_{f,u})$ or $(0, x_{f,u})$. Nevertheless, SVdP's housing projects (e.g., building temporary shelters) have high understaffing cost and low overstaffing cost (i.e., β is large and γ is small). This is because providing shelters is time-sensitive and any delay can hurt beneficiaries' welfare. Moreover, this task requires multiple events to be completed, and there are plenty of work for volunteers. Therefore, the optimal policy is to only invite maximum number of formal volunteers, $(0, x_{f,u})$.

The majority of SVdP's volunteering tasks (e.g., "Dining Rooms," "Family Evening Meal," and "Thrift Stores.") have large understaffing and overstaffing costs. On the one hand, these tasks require enough labor to meet demand. On the other hand, they are confined by space, and can only offer limited volunteering spots while leaving the extra volunteers idle. Therefore, the optimal policy for these tasks is to invite either $(x_e^*, 0)$ or $(0, \frac{\lambda}{\theta})$.

As indicated earlier, to obtain our closed-form solution, we relaxed some operational constraints, such as the limited availability of formal volunteers. Therefore, we evaluate the performance of our proposed DRO approach based on a set of numerical experiments. To do so, we first establish a baseline for SVdP's traditional scheduling process. As discussed in Section 2.2.2, volunteer managers prioritize formal volunteers for all tasks, and use episodic volunteers (considering their turnout rate) only to fill out the shortage. We refer to this heuristic as "Base". We also consider an additional heuristic ("TNL") based on a truncated normal distribution. The truncated normal distribution provides a good heuristic for charities because if historical data of volunteer turnout is accurate, managers would be able to approximate the turnout distribution using a (truncated) normal distribution. Note that volunteer managers may assume the turnout follows a binomial distribution. While this approach is easy to implement, it ignores the variability of turnout (σ) and becomes infeasible if the average turnout exceeds one. However, when the number of Bernoulli trials (x_e) becomes large enough, we can approximate the binomial distribution as a normal distribution (Ross 2017). Based on SVdP data, since $x_e \geq 15$ in most events, a truncated normal distribution is a suitable approximation to make optimal scheduling decisions based on expected utility.

Next, we compare the optimality gaps of these two heuristic policies and our proposed DRO policy under four distributions (i.e., truncated normal (TN), uniform (UN), u-quadratic (UQ), shifted beta (B)). Not all distributions use first and second moment information (e.g., uniform distribution), but all share the same support. To provide a benchmark for all policies, we consider a clairvoyant solution assuming that full information about the specific distribution F is known. The utility value of the clairvoyant policy is the upper-bound, denoted as J_F^*. Next, we calculate the expected value using our three established policies J_{DRO}, J_{Base} and J_{TNL} and the optimality gap represents the performance

Table 2.2: Summary Statistics for Sampled Volunteer Tasks

Volunteer task	Instances	μ	σ^2	h_ℓ	h_u
"Pizza Friday" (PF)	83	0.75	0.08	0.3	1.2
"Family Evening Meal" (FEM)	93	0.85	0.06	0.3	1.2

of each policy. We use two representative volunteer tasks for these experiments; "Pizza Friday" (PF) and "Family Evening Meal" (FEM). The summary statistics for the volunteering tasks are included in Table 2.2. Due to the limited data, we use SVdP's volunteer managers' expertise to estimate the volunteer turnout uncertainty (i.e., μ and σ).

Furthermore, both volunteering tasks require $\lambda = 25$ volunteers with benefit $w = \$20$. We consider $d_e = \$9.2$, $d_f = \$4.7$ and $d'_f = \$3$.[4] We assume formal volunteers' efficiency level is $\theta = 1.2$ and $\alpha = 1$. We further set lower and upper bounds on the number of formal volunteers, $x_{f,\ell} = 5$ and $x_{f,u} = 15$, which are close to the range of formal volunteers in SVdP data. We estimate the understaffing cost according to the hourly pay for kitchen staff, $\beta = 30$ per event (i.e., 3 hours times \$10 per hour). The overstaffing cost, γ, can be estimated based on the impact of overstaffing on one's future contribution. For example, if a volunteer feels she is not needed for the volunteering event due to overstaffing, there is a lower chance that she would return as a volunteer or would make monetary contribution. Instead of using a fixed number for understaffing and overstaffing costs, we outline a range of values $\gamma \in [10, 20]$ (equivalently, a range of critical ratio from 60% to 75%) and then randomly draw 100 instances. Each pair of (β, γ) is a unique observation for the computational experiment. All numerical examples are implemented in Matlab. The inner problems (SOCP problem) are solved with `cvx` package in Matlab. On average, each problem takes 230 seconds to

[4] We estimate the donations as follows. From the data, we find that episodic volunteers on average donate \$18.6 per volunteer event, and formal volunteers on average donate \$15.6 per attendance. Then, we estimate the donation increase due to volunteering by applying 49.4% from Section 2.2.3 to both values. Therefore, episodic volunteers on average donate \$9.2 per volunteering event while formal volunteers on average donate \$7.7 per attendance.

solve on a 1.8 GHz 4-Core Intel Core i7 processor.

We derive the average optimality gap between J_F^* and J_{DRO}, J_{Base}, and J_{TNL} for each task. For each observation, we generate solutions according to four different policies and then test the solutions under four distributions. We also evaluate their overall performance, which is the weighted average of the optimality gap of all four distributions. Table 2.3 summarizes the average and standard deviation of the optimality gap for each task. As shown in Table 2.3, the DRO solution has the lowest overall optimality gap for both tasks. This emphasizes the value of robustness approach. Moreover, the optimality gap of DRO also has a small range, indicating that DRO policy is a distribution-free that guarantees performance under various distributions. A more direct way to observe the value of robustness is illustrated in Figure 2.8a, which is the violin chart of the optimality gap for the volunteering task "Pizza Friday." The fat bell shape of DRO policy indicates a clear advantage in avoiding severe operational losses. Moreover, examining the overall performance over all 100 instances, we find that the SVdP can save as much as 35% of total volunteering and donation values by adopting our proposed DRO policy against their conventional Base policy.

Second, we discuss the policy differences between Base, TNL, and DRO. The average number of formal and episodic volunteers adopted by each policy is shown in Table 2.3. There is a significant increase in the number of episodic volunteers when considering both labor and donations (DRO) than only considering labor (Base and TNL). This also confirms our conclusion that charities should rely on more episodic volunteers when considering volunteers' donations.

Third, we can separate the objective function between labor and monetary value. In particular, we consider the cases where the charity may have different weights on volunteers' donation value. Therefore, we solve the model with a discount factor that allows the charity to discount its donation value. Figure 2.8b demonstrates the efficient frontier of the objective function for volunteering task PF. The horizontal axis represents the expected

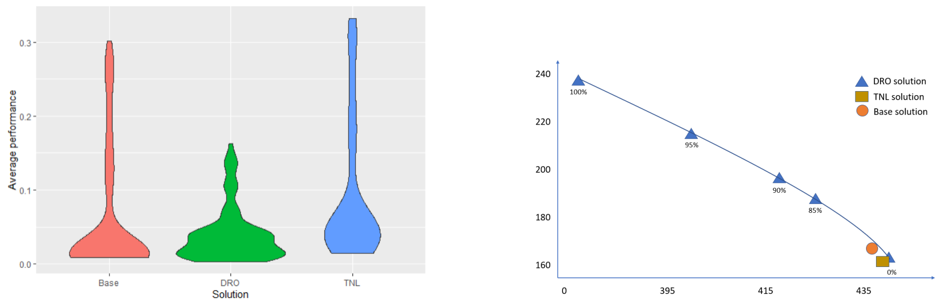
Table 2.3: Optimality Gap on 100 Instances under Four Different Distributions. The Value in Parenthesis is the Standard Deviation. The "Overall" Value is the Weighted Average Optimality Gap from Four Distributions. All Values are in Percentage except for Average x_e and x_f, which are in Absolute Numbers.

Volunteering Task	Distribution and Policy	Base	TNL	DRO
Pizza Friday	TN	5.59 (6.70)	7.60 (7.61)	4.86 (7.15)
	UN	4.98 (7.48)	7.73 (8.35)	3.72 (5.12)
	UQ	8.96 (10.87)	13.22 (12.04)	5.76 (4.26)
	BETA	4.92 (7.89)	7.69 (8.80)	2.91 (3.78)
	Overall	6.07 (8.10)	8.96 (9.06)	4.26 (4.58)
	Average x_f	15.0	15.0	12.5
	Average x_e	12.0	10.0	23.4
Family Evening Meal	TN	14.26 (9.38)	9.56 (8.87)	6.92 (6.00)
	UN	16.89 (9.55)	10.73 (9.38)	6.69 (4.54)
	UQ	17.47 (14.12)	15.13 (13.29)	9.84 (8.59)
	BETA	8.14 (8.65)	5.16 (7.93)	3.39 (5.20)
	Overall	14.08 (10.26)	9.96 (9.69)	6.56 (5.50)
	Average x_f	15.0	15.0	13.8
	Average x_e	8.0	9.0	15.6

labor value of the task, and the vertical axis represents the monetary value of the task. Each triangular sign represents the DRO solution with different discount factor on monetary donation (100%, 95%, 90%, 85%, 0%). Note that the charity still benefits from our DRO solution even when only considering the labor value (i.e., 0%). At this point, the DRVM-J model will converge to the DRVM-L model and still utilizes the DRO framework. Therefore, the charity's utility is protected against various distributions.

2.7 Conclusion

This paper studies the volunteer staffing problem from a strategic perspective. To develop a nuanced picture of an actual situation, we collaborated with a large food bank and a nonprofit consulting firm. We consider two unique features in volunteer management. First, contrary to the literature that assumes volunteers are homogeneous, we characterize



(a) Performance comparison **(b)** Efficient frontier and policy comparison

Figure 2.8: Performance Evaluation of Different Approaches for Pizza Friday

volunteers based on their turnout reliability and work performance. Second, we consider volunteers' value in both labor contribution and monetary donations, where the endogenous decision of team composition partially influences monetary donation.

We study two variants of DRVM models; First, we present a labor-only objective model (DRVM-L) that provides a baseline, which resembles charity's current practice. Next, we present DRVM-J model that considers volunteers' labor and donations, but the model is more complex as it is neither concave nor concave. We obtain closed-form expressions for both models by assuming information on the first and second moment of episodic volunteers' turnout probability. Results show that although formal volunteers are always preferred and prioritized in the DRVM-L model, episodic volunteers can serve as the primary workforce when charity considers their monetary donations, too. Moreover, we obtain additional insights regarding how understaffing and overstaffing costs and the reliability of episodic volunteers influence the optimal policy and generalize implications for process improvements. Considering the operational constraints, we use an interpretable machine learning model to generate managerial insights in simple terms. Last, our numerical experiments show that charity can avoid up to 35% of their profit loss with our proposed DRO policy comparing with their existing scheduling process.

Chapter 3

IMPROVING THE QUALITY OF IN-KIND DONATIONS: A FIELD EXPERIMENT

3.1 Introduction

Individuals' in-kind donations constitute a substantial portion of supply to charities and humanitarian organizations. Estimations show that, for example in 2017, 52% of Americans gave clothing, food, or other personal items to humanitarian organizations (Non Profit Source 2018). In-kind donations contribute to charities' triple bottom line by generating additional revenue for them, contributing to social welfare, and reducing environmental waste through rechanneling of used items (Montgomery and Mitchell 2014). Food, clothing, and hygiene products donated to charities can be directly sent to beneficiaries, donated furniture and electronic equipment can support the general operations of a charity or be sold through their thrift stores to generate additional revenue. In 2020, despite the COVID-19 pandemic, the Salvation Army reported $598 million in revenue from 1,116 thrift stores in the United States, capturing 18% of the organization's total revenue (Salvation Army 2021). Further, these donations extend product usage and promote environmental sustainability. For instance, Goodwill diverted 3.3 billion pounds of usable goods from landfills, in 2020 (Goodwill 2021). However, some donated goods are not useful. Low-quality items such as stained clothes, torn blankets, or broken furniture can neither be resold in a thrift store nor used for the beneficiaries. Instead, these junk donations cost charities significant resources to discard. For example, Goodwill Northern New England spends over one million dollars annually to dispose of 13 million pounds of unsuitable items only for 30 thrift stores (Bookman 2021). To estimate the social cost of inappropriate material donations, one may consider that there are more than $3,000$ Goodwill thrift stores, and $25,000$ nonprofit resale shops in the United States (U.S. Census Bureau 2021). In addition to substantial trash bills, most charities incur additional logistic and operational costs (e.g., labor, fuel, and other overhead expenses) due to the free pickup service they offer to encourage the in-kind donations. As a result, donors' good deeds turn out to be detrimental, as the unwanted donations instead place considerable financial pressure on the charities they intend to support.

In practice, charities hesitate to decline inappropriate material (hereafter, *junk*) donations for fear that declining a goodwill offer might hurt the relationship with the donors, and put their future support at risk (Islam 2013). Daniels and Valdés (2021) demonstrate that donors learn from their donation experience, and use rejection as a self-serving excuse not to give in the future. This concern is important given that, for example, in the United States, recurring donors are estimated to donate 440% more to the charity over their lifetime than one-time donors (Classy 2018). Therefore, rejecting donations may serve a charity's short-term goal of minimizing junk donations but hurt their long-term sustainability.

The goal of this paper is to find a practical solution to reduce the number of junk donations a charity receives without losing donors. We employed behavioral interventions in a field experiment. A key advantage of behavioral interventions, as opposed to the harder forms of policies (e.g., taxes and regulatory bans), is their flexibility and respect towards individual freedom of choice (Thaler and Sunstein 2009). Specifically, behavioral interventions steer the actions of individuals in a desired direction by relying on their voluntary participation (Croson and Treich 2014). This strategy has clear benefits in the setting of in-kind donations because it causes less tension between the charity and their donors than directly rejecting the donations. Moreover, because most behavioral interventions are cost-free and easy to implement, establishing an effective behavioral solution is a practical option for resource-limited charities. We employed two interventions – *information disclosure* and *social norm* – to nudge donors to voluntarily increase the quality of their in-kind donations. The effectiveness of both interventions is supported by a growing body of literature.

Information disclosure refers to disclosing content-related information that is assumed to significantly affect individuals' behaviors (Loewenstein *et al.* 2014). For example, providing calorie information encourages consumers to adopt a healthy diet, or providing supplementing fuel efficiency data motivates people to choose environmentally friendly vehicles (Thaler and Sunstein 2009). Jones *et al.* (2015) show that informing consumers about the payment due date and penalties for late payment on credit card bills boosts consumers' debt payoff rate. Other examples include Nelson *et al.* (2021) that demonstrate displaying information about how plastic bags damage the ocean environment significantly reduces consumers' plastic bag usage, and emphasizing the public benefits significantly enhanced the adoption of pro-social behaviors, such as self-isolation, during the Covid-19 pandemic (Griggs 2021).

In the setting of charitable giving, the goal of information disclosure is to equip individuals with the knowledge of how their actions might benefit or hurt others (Fisher *et al.* 2008). Individuals are more likely to choose actions that benefit others, when the benefits become more salient (Nelson *et al.* 2006; Pittman 2020). Thus, this intervention is conventionally applied by charities when communicating with their donors. For example, charities' solicitation messages often include a clear reason to give, detailing the need to support and how individuals' donations will be used for that particular cause (e.g., building temporary shelters due to extreme weather, food provision to reduce food insecurity). Another example is Gneezy *et al.* (2014), which demonstrated that informing donors that the overhead costs (e.g., administrative and fundraising costs) will be covered, thereby allowing donors' contribution to go entirely to beneficiaries, can significantly increase the overall donation probability and average donation amount. Although this intervention is one of the most popular methods adopted among charities (Leonhardt and Peterson 2019), there is no consensus regarding its effectiveness.

The second intervention in our experiment is sharing social norm, which informs the subjects about what is commonly done by others. According to the social psychology literature, social reference exerts a normative influence on behaviors, either by conveying what ought to be done (i.e., injunctive norm refers to what is approved by others) or what has been done (i.e., descriptive norm refers to what is actually done by others) (Cialdini *et al.*

1990). Our study utilized the descriptive social norm, which has proven effective in different fields, such as voting (Gerber and Rogers 2009), environmental conservation (Goldstein *et al.* 2008), and charity fundraising (Martin and Randal 2008; Shang and Croson 2009; Croson *et al.* 2009). For example, Martin and Randal (2008) conducted a field experiment in an art museum where visitors were exposed to different amounts of money in a transparent box (so individuals could see dollar bills and coins), as a signal of social norm, and found that people demonstrate strong desire to conform to social norms when making donation decisions. Similarly, Shang and Croson (2009) conducted a field experiment through a public radio station, and found that new donors give more when informed about others' high contributions.

We conducted our field experiment in collaboration with a local charity, the Society of St. Vincent de Paul of Arizona (SVdP), between October 31st and November 11th, 2020. We collected a panel data set of 763 households who made in-kind donations. The charity already had an existing system to send emails to confirm donation pickup, and so we embedded the behavioral mechanisms into an additional email as informal interventions. We designed a between-subject field experiment with three groups. One group received an email with social norm content, the second group received an email with information disclosure messages, and the third group did not receive any further message.

Our results show that social norm intervention effectively influenced individuals to improve the quality of their donations. Contrary to conventional wisdom, the information disclosure intervention did not alter donors' behavior. Moreover, we collected additional data on 1,301 in-kind donations whose donors had received social norm intervention during February 2021. Our results show that the effect size of social norm intervention on quality of in-kind donations is stable over different time periods, providing further evidence on the generalizability and reliability of this intervention. Next, we tracked the number of returned in-kind donors in all three groups in the following 12 months. We observed an initial decline of the number of returned donors in both the social norm and information disclosure groups. Yet, the disparity in donor retention converged at the 12-month mark, indicating that the detrimental effect is only temporary and would ultimately dissipate. Consequently, the social norm intervention did not harm charity's long-term performance. This is important because, despite the general advantages of behavioral interventions, the success of a particular intervention is not guaranteed in all contexts (Goswami and Urminsky 2016; Kristal and Whillans 2020; DellaVigna and Linos 2022; Morvinski *et al.* 2022); Some interventions may even backfire and create a negative effect (Sunstein 2017; Damgaard and Gravert 2018; Bicchieri and Dimant 2019; Bolton *et al.* 2019). For an accurate assessment of the overall effects of behavioral interventions, not only should policy makers consider the direct impact on targeted choices, but also potential spillover effects of the initial behavior prompted by the intervention on subsequent, related behaviors. In principle, such behavioral spillovers could amplify, eliminate or even reverse the initially positive effects of choice defaults, when judging their impact on the aggregate of relevant behaviors (Dolan and Galizzi 2015). Determining SVdP's precise savings on logistics is rather impossible. Yet, based on the charity's operations record, a conservative estimate illustrates that SVdP received 50% fewer junk donations, while implementing this intervention did not impose any direct operating cost, as SVdP already had the required infrastructure of sending emails.

3.2 Contribution to the Existing Literature

This paper contributes to two strands of literature. First, it focuses on in-kind donations, which is a much-less considered topic compared to individuals' cash and time donations. This nascent literature discusses in-kind donation distribution channels and the challenges that charities encounter in managing in-kind donations (Islam 2013), individuals' motivation to make in-kind donations (Mainardes *et al.* 2017), and using in-kind donations to serve beneficiaries (Ahire and Pekgun 2018). For example, Ahire and Pekgun (2018) estimate the expected food and cash donations based on the historical data of a charity's fundraising campaigns, and develop an integer programming model to maximize the total donations. The closest paper to current study is Daniels and Valdés (2021). In a lab experiment, they demonstrate that individuals whose donations are rejected will be negatively biased that their subsequent donation will be accepted, and so are less likely willing to donate in the future, particularly when the donation effort is significant. The present paper, therefore, offers a feasible solution to the critical issue raised by Daniels and Valdés (2021).

This study also contributes to a line of research concentrating on the application of behavioral interventions in nonprofit operations. There is evidence that behavioral interventions that function in one context may not work in others. For example, material rewards are effective in motivating people to donate blood (Lacetera *et al.* 2014; Goette and Stutzer 2020), but also discourage individuals to volunteer their time and effort (Conrads *et al.* 2016; Gneezy and Rustichini 2000). While some show that social norms increase individuals' cash donations (Martin and Randal 2008; Shang and Croson 2009; Agerström *et al.* 2016), others show that providing social references does not encourage people's participation in volunteering (Moseley *et al.* 2018). Likewise, providing positive feedback on charitable giving has opposite impacts: While learning that one's blood donation made a positive impact reduces the intention to donate again (Goette and Tripodi 2020), receiving positive feedback about one's volunteering efforts can effectively increase one's productivity (Mertins and Walter 2021b).

The first intervention, information disclosure, relies on sharing content-related information to motivate individuals to take the desired actions. This intervention has been broadly advocated as an appropriate response to a wide range of social and economic problems (Loewenstein *et al.* 2014; Jones *et al.* 2015; Nelson *et al.* 2021). Nevertheless, recent studies unveil mixed effects of this intervention (Willis 2011; Loewenstein *et al.* 2014). For example, Riggs *et al.* (2017) show that emphasizing how forfeiting unnecessary public health service can benefit others did not reduce the overuse of the health services. Similarly, Downs *et al.* (2013) find the providing calorie recommendations to consumers did not reduce their calorie consumption, but increased it.

In the context of charitable giving, an information disclosure message contains two parts of information: (i) the needs of others, and (ii) how charitable giving will benefit them. First, awareness of the need is the pre-requisite for charitable giving (Bekkers and Wiepking 2011), and learning about the needs of others will lead to an altruistic motivation, a motivational state with the ultimate goal of reducing that need (Batson *et al.* 2015). Hence, donors are more likely to respond to the charity's ask when they learn of the needs. Second, this intervention also conveys information on how charitable giving will benefit others. Altruism is an essential motivation for charitable giving (Bekkers and Wiepking 2011), and people donate because they want to advance the welfare of others (Bendapudi *et al.* 1996). In our study, people donate their goods, at least partially, due to altruism, and their goal is to contribute to social welfare through supporting a charity. The key to an effective information disclosure intervention is to increase the salience of certain information, which in turn can steer people's behavior in a desired direction (Loewenstein *et al.* 2014). In our context, providing the relevant information regarding the need for donation quality and how improving donation quality could benefit the charity would align with the donors' altruistic motivation, draw their attention to the charity's quality requirement, and nudge donors to improve their donation qualities.

Our second implemented behavioral intervention uses the descriptive social norm. Studies show that individuals demonstrate a strong preference to conform to social norms due to their social-image and self-image (Bénabou and Tirole 2006; Ariely *et al.* 2009; Gross and Vostroknutov 2022). A positive social-image is beneficial for the individual as it increases the chance of being seen as trustworthy, being chosen as an interaction partner, and receiving help from others (Gross and Vostroknutov 2022). When one's actions are observed by others, they are more likely to behave pro-socially as their actions can boost their social-images (Ariely *et al.* 2009). On the other hand, self-image theories propose that people also like to see themselves as moral beings (Bodner and Prelec 2003), and act pro-socially to signal themselves about their moral identities (Bénabou and Tirole 2006). Hence, conforming to the pro-social norm also primes one's moral identity and boosts self-image. However, an effort to invoke social norms might not work if people do not care about social norms, or if they want to defy them.

Social norm intervention is more likely to be effective when two conditions are met: (i) ambiguity and (ii) appropriateness of the social norm (Croson *et al.* 2009). Research shows that people are more likely to be influenced by social norms when there is a perception of ambiguity about what is "correct" in the given context (Nook *et al.* 2016). If no such ambiguity exists (i.e., there is an obvious or correct thing to do), then what others do does not influence an individual's behavior (Reno *et al.* 1993). Second, a social norm intervention may actually increase undesirable behavior, if the targeted subjects do not consider such norm to be "appropriate" and want to defy the norm (Werch *et al.* 2000; Perkins *et al.* 2005). Consequently, for this experiment, we considered a sample of donors who had not had previous experience of making in-kind donations to SVdP, hence were less likely to have a concrete reference on which donations are acceptable and which are not. Additionally, improving in-kind donation quality is an appropriate norm as it benefits the charity's missions. In this way, social norm interventions are expected to effectively impact people's behavior, as they can merely imitate what others are doing (Cialdini *et al.* 1990).

Last, a behavioral intervention can be ineffective or even create negative impacts if it provokes reactance feelings or induces compensating behaviors from the individuals (Sunstein 2017). A reactance feeling can be triggered by psychological costs such as guilt or perceived social pressure (Andreoni *et al.* 2017; DellaVigna *et al.* 2012). It also includes practical costs such as time and attention (Knutsson *et al.* 2013). Therefore, some behavioral interventions might have *some* influence on the desired conduct, but also produce compensating behavior through spillover effects on other dimensions, nullifying the overall effect. For example, mandating customers to acknowledge their donation decisions increases the average donation amount and probability, but also creates a long-term detrimental effect, since fewer customers return to the same purchase channel (Adena and Huck 2020). In our study, donors are asked to comply with the charity's policy, which requires them to spend effort on selecting proper in-kind donations. Taking action requires donors' attention, time, and physical effort. It may also hurt their emotions as they may need to remove some items they planned to donate. In summary, it is both necessary and essential for charities to monitor the potential spillover effect on individuals' long-term behaviors.

To the best of our knowledge, this is the first field experiment that shows the impact of these behavioral interventions in the context of individuals' in-kind donations. This paper proposes a simple, yet effective, solution to minimize the amount of junk donations sent to a charity.

3.3 Experimental Setting

This experiment was conducted in collaboration with SVdP which is a large nonprofit organization located in the Phoenix metropolitan area of Arizona. It provides homeless and low-income individuals and families with services such as free medical and dental clinics, meals, clothes, and housing. In 2021, SVdP received \$93.6 million in funds, with \$32.2 million in monetary donations and \$24.2 million in in-kind goods from individuals, corporations, government, and other nonprofit organizations. Individuals contributed the most, accounting for 45% of all donations.

Since the "stay-at-home" orders were issued due to the COVID-19 pandemic, individuals' in-kind donations have become more prevalent as people had more time to organize their homes and donate household items to help local charities. For example, during the summer of 2020, SVdP received, on average, 400 in-kind donations every week. While a negligible percentage of donors bring donations to SVdP's donation center, most rely on SVdP's free pickup service. Collected goods are then sorted, sanitized, and distributed among SVdP's thrift stores. Thrift stores attract about 14,000 customers who generate over 70,000 sales transactions every month, improving environmental and economic sustainability for the community. Moreover, SVdP also provides direct support for the beneficiaries with their "Bringing Help Home" program through which, every month, 70 families receive shopping vouchers that can be redeemed in any of SVdP's thrift stores. In 2021, SVdP's six thrift stores located in the Phoenix metropolitan area together contributed more than \$6.2 million in revenue. However, unusable, broken, or unsellable donated items consume significant resources. By July 2020, SVdP received so many junk donations such that their docks were always stacked with items waiting for the disposal service to pick up. The volume of junk donations received raised to a level that the original junk removal service was not able to handle, thereby the charity was forced to pay for and rely on additional trash removal services.

Figure 3.1: SVdP's Thrift Store and Donation Pickup Service

3.3.1 Experiment Procedure

The donation process in SVdP is standard among charities. To initiate donation pickups, donors can submit their requests online or by phone. During the sign-up process, SVdP reviews the donation policy and procedure with the donor and ensures the products are suitable for thrift stores. For example, it is indicated that oversized furniture and appliances, as well as damaged, broken, or stained household items are unacceptable. Once donors acknowledge that they have read the list and understood what donations are acceptable, they are prompted to the scheduling stage to select a pickup date and submit the information for the donation (e.g., name, address, amount, and type of donated goods). Shortly after receiving the pickup request, SVdP sends an automatic email through their Sendgrid system to the donors confirming the pickup address and date for the donation. The email reinforces the criteria on what items are acceptable, and details the instructions for handling and preparing the donated goods. For example, donors are asked to leave their donations at the curbside or in a parking lot accessible to the pickup truck. Prior to this experiment, SVdP did not send any additional emails besides this confirmation email. This was because the donors confirmed their understanding of the donation policy once while registering, and then again were reminded by the confirmation email. As a result, SVdP opted not to send more identical emails emphasizing the donation policy lest that additional nudging be perceived as excessive communication and disliked by donors.

Requests for pickup are received on a rolling basis, and prospective donors may select a pickup date up to 7-28 days in advance. SVdP closes the pickup requests and finalizes its pickup list within a week. On the day of the pickup request, SVdP informs the donors of the driver's arrival 30 minutes before the scheduled pickup. Upon picking up the donated goods, SVdP's truck driver leaves a donation receipt that the donors can use on their tax returns. All donated goods are delivered to a centralized location and sorted for resale in thrift stores. Products in acceptable conditions are cleaned and sanitized, and products categorized as "junk donations" are thrown away.

In order to measure the quality of each donation, we developed a rating system for the drivers to inspect and evaluate each donation during pickup. We also designed a mobile application that is customized within the routing software Geopointe, as shown in Figure 3.2. (The routing optimization software Geopointe determines the pickup routes by optimizing transit time, considering location, traffic, and pickup loads in each request. The routing software predicts the number of pickups per truckload, and the truck utilization rate is stable between 95–100% per trip before the experiment.) SVdP provided the phone with this application installed to all eight drivers. The application provides directions with Google Maps, requires the drivers to check in for each location when they arrive, and automatically asks the drivers to rate the donation once the pickup is finished. Utilizing a mobile application, as opposed to the conventional method of collecting ratings through

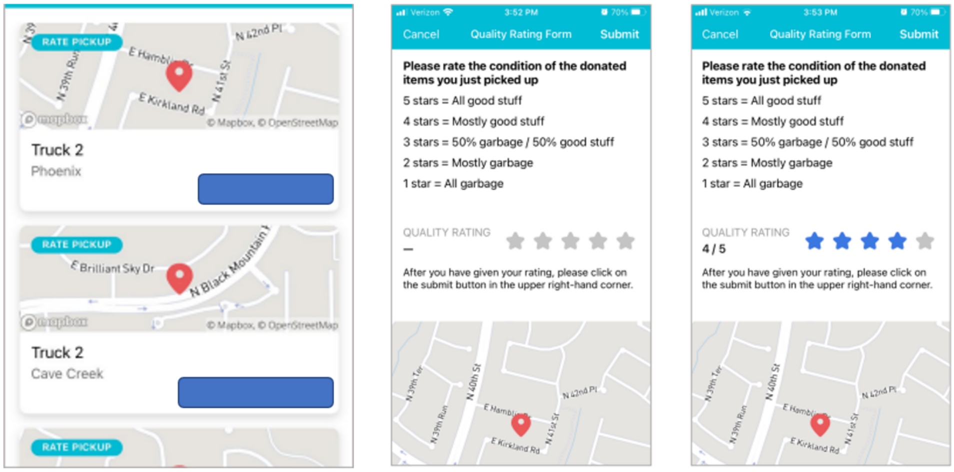


Figure 3.2: Example of Routing and Rating in the Application (Address is Blocked).

paper survey, offers several important advantages. First, using the application ensures drivers' full compliance with rating each donation they pickup. Drivers had to rate each donation before they could proceed to the next address. Second, because drivers were required to complete the rating after each pickup, the data would provide the most accurate assessment on the donation quality. Third, because the application is linked to SVdP's Salesforce system, the ratings are automatically uploaded into the system, reducing the possibility of manual data entry errors and ensuring data quality.

The quality rating system uses a Likert-type scale from 1 to 5 (with 5 showing the highest quality): "all garbage," "mostly garbage," "50% garbage and 50% good stuff," "mostly good stuff," and "all good stuff," respectively. One month before the experiment, the drivers received several training sessions to use this application and the rating system. In each training session, drivers rated 20 items based on the product images (see Figure 3.3, as an example). To ensure the independence of the observation, we asked the drivers to complete the ratings independently without communication. We measured the degree of consensus among drivers with Fleiss' kappa score, a generalized measurement of inter-rater agreement used to determine the level of agreement among several raters (more than two) (Fleiss 1971). Since our focus is to understand if SVdP needs to dispose of the item or not,

Figure 3.3: Examples of Items in the Training Session. Quality Ratings are Indicated on each Picture. For instance, the Chairs (rated 3) are Good Though not Clean and the Donor Attached Some Dirty Lamp Shades to the Gifted Chairs. The Armoire (rated 4) is Mostly Good but Drawers do not Slide Well.

our goal is to reach a "moderate" strength of agreement with $\kappa \in [0.41, 0.6]$ (Altman 1990). Nevertheless, in the last training session, Fleiss' kappa showed that the drivers reached a "good" agreement among them, $\kappa = .73$ (Altman 1990). Therefore, we concluded the training and launched the experiment.

Furthermore, to ensure the internal validity of the study, we performed additional procedures. First, the intervention condition was blind to the drivers. They were unaware of the treatment conditions for the donations they picked up. This ensures no observer-expectancy effect. Second, we included each driver as a fixed-effect control variable in our regression analysis and did not find significant effects on any of the drivers. Figure 3.5 summarizes the process of the pickup service and our intervention.

SVdP executed this experiment for 12 days between October 31st and November 11th, 2020, as part of their regular pickup practices. Our intervention was scheduled to be sent by SVdP email two days before the donation pickup date. All registered donors were randomized into one of the three groups. We used complete randomization in batches (Imbens and Rubin 2015) since our experiment was scheduled in 10 waves. In other words, each group received one-third of the total subjects every day. Note that we did not randomize by block (e.g., estimated household income based on zip code) because we received subjects in small batches, and we were unable to predict the future subjects' social-economic status. There are an average of 75 donation pickups every day, with 25 observations per group. The first treatment group received an email with the standard information disclosure content, the second treatment group received an email that contained the social norm content, and the third group did not receive any email. (Figure 3.4 demonstrates the template for the two treatment texts.)

1. *Information disclosure*: "Please know that we only accept items that are gently used. Items that we would have high difficulty selling at our stores such-as items that are damaged, stained, have pet hair, have missing pieces, or are otherwise unsellable-end up costing us tens of thousands of dollars every month to dispose of them, which diverts money away from our mission."

2. *Social norm*: "The majority of donors give us items that are in very good condition, and have a high likelihood of being sold at our thrift stores around the Valley. Items donated that are damaged, stained, have pet hair, have missing pieces, or are otherwise unsellable, end up costing us money to dispose of them."

We designed the social norm message similar to Goldstein *et al.* (2008), emphasizing that the norm of in-kind donations is that the majority of the donors donate items in good shape. A text reflecting information disclosure intervention should fit in specific settings, and so there is no standard form of message, in the literature, for this intervention (Loewenstein *et al.* 2014). Therefore, we constructed the information disclosure message based on the need of SVdP and the benefits of taking the right action.[1] In particular, the message highlights that SVdP accepts only gently used items and includes more detailed information (e.g., the

[1]Note that there is a subtle difference between the literature on charity giving and our study about the framing of information disclosure. While previous studies provided "direct" information such as how people's donations can affect the beneficiaries (Erlandsson *et al.* 2018), ours shared "indirect" information about how improving donation quality would benefit the charity, hence providing more resources towards public goods. Although the framing is different in our context, we anticipated this intervention still be effective for two reasons. First, as we discussed in section 3.2, information disclosure primes individuals' altruism to drive their actions in desired directions. Second, while the literature concentrated on stimulating the act of

Figure 3.4: Template of the Email Interventions

cost and consequences of junk donations). Furthermore, while the social norm intervention establishes a psychological anchor based on social-proof behavior (i.e., the majority of the donors donate goods in good condition), the information disclosure intervention relies on sharing the logical reasoning for improving donation quality (i.e., junk donations cost SVdP additional resources which can be used for other pro-social activities).

The third group who did not receive any email represented the status quo of SVdP's operations, and offered a baseline for measuring the effectiveness as well as potential spillover effects of the interventions. It is worth indicating that the treatment email, in our setting, is different than the role of the typical reminder emails. A reminder email is commonly used to curb the forgetfulness by bringing a particular decision or task to recipients' attention,

giving (e.g., soliciting donations), we sought to transform the act of giving (e.g., inducing compliance). In particular, subjects in this study had already decided what goods to donate and, by extension, the quality of their donations. Our treatment aimed to improve the quality of their donations by changing their previous behaviors. Although not directly applied in our context, information disclosure has found success in inducing behavior compliance in areas such as lowering electricity usage (Jessoe and Rapson 2014) and encouraging pro-environmental (Nelson *et al.* 2021) and pro-social (Griggs 2021) behaviors.

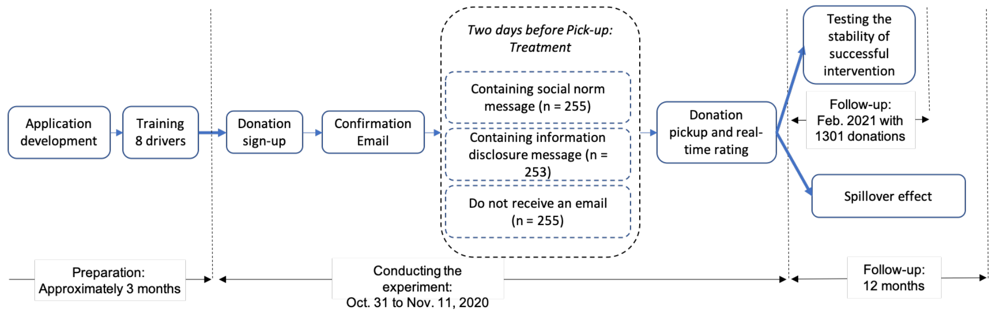


Figure 3.5: Phases of Research Study

such as making a donation (Damgaard and Gravert 2018). However, in our study, subjects had already decided to make a donation, and self-selected into the group whose donations met the quality policy. Hence, the goal of treatment emails is not to remind subjects for an action that has not been taken.

3.3.2 Dependent and Control Variables

Our dependent variable is the quality of each donation that is observable through the rating system. For data analysis, we included two sets of control variables. The first set of control variables was related to experiment implementation. Specifically, we employed nine dummy variables $Wave_i$ to represent the pickup date fixed-effect, and seven dummy variables $Driver_j$ to capture the driver's fixed-effect. These control variables allow us to identify the treatment's true effect without potential bias on the selected pickup date or a particular rater (driver). We also included another set of control variables associated with the donors' characteristics. According to SVdP's historical data, none of the subjects in the experiment had previously given an in-kind donation. However, a few donors had made cash donations before the experiment started. Therefore, for each donor k, a binary variable $ExistingDonor_k$ was included to indicate whether this donor had made cash donations before. Because donors are not required to provide social-demographic information (e.g., age, gender, race), we are unable to control for these variables, though these variables are not crucial because our analysis is conducted at the household level, not the individual level.

Yet, we approximated the donors' annual income level by combining the pickup address zip code with the household median income from the American Community Survey (ACS) 2020. Last, one may also suggest using the monetary value of an in-kind donation as either a control or another dependent variable. However, SVdP does not collect information on the resale value of the in-kind donations because the pickup policy is designed to ensure fairness in all donations. Putting a price tag on people's donations may alienate some donors. Therefore, our objective is to improve donation quality regardless of the donation value.

3.4 Results

First, we examine the exogeneity of covariates by randomization. Table 3.1 includes the summary statistics among the three groups. During the experiment, about 2.88% of donors canceled their donation pickup that included 12 donors of the social norm group, 5 donors from the information disclosure and 5 from the control groups. One concern is that donors canceled because they felt their donation was inadequate, which could have reduced the total donations SVdP received. However, note that the number of cancellations is small, and there was no significant difference in the attrition rate across the three groups. Also, even if the donors canceled their donations because of the intervention, these donations would likely be categorized as "junk donations" and would not provide value to SVdP. Therefore, we do not further interpret the cancellation cases and removed these observations from our analysis. Next, we also examined the donation history among the three groups. While none of the subjects had made an in-kind donation before, 4.19% of them had made cash donations at least once. We also did not observe a statistically significant difference between the social norm and information disclosure groups in terms of the proportion of donors that opened the emails. Finally, using the pickup address zip code, we measured each donor's household median income and found no significant difference among them.

Table 3.1: Summary Statistics by Treatment

	Social Norm [N = 255]	Information Disclosure [N = 253]	Baseline [N = 255]
Cancellation	12	5	5
Cash donor in the past	14	9	9
Email opened	196	189	–
Household Median Income in $1000	86.63 (28.38)	84.98 (29.83)	83.69 (28.71)

Note: The values in parentheses represent standard deviation. None of the pairwise comparisons – proportion test and t-test – above is statistically significant at $p = 0.1$ level.

3.4.1 Treatment Effect on Donation Quality Ratings

We compared the intent-to-treat effect of donation quality ratings under each treatment condition. Figure 3.6 revealed that the donation of donors who had received the social norm message rated higher (i.e., better quality) than the other two groups. The social norm group had an average rating of 3.22 (SE = 0.08), while the information disclosure and baseline groups had an average rating of 2.68 (SE = 0.08) and 2.83 (SE = 0.08), respectively. The difference in ratings between social norm and information disclosure (baseline) group is statistically significant at $p < 0.001$ ($p < 0.001$) level.[2] It is worth indicating that all p-values are obtained from a two-sample Wilcoxon rank-sum (Mann-Whitney) test against the null hypothesis of equal means. Also, there is no significant difference between the information disclosure and baseline groups, $p = 0.246$.

Moreover, we ran regression analyses controlling for the time and driver fixed-effects, donors' household median income, and whether or not they had previously donated to SVdP. In Table 3.2, column 1 replicates the non-parametric test, and column 2 includes the additional fixed-effect variables, in which $Wave_i$ represents the date of donation pick up, and

[2] The unit of analysis is the completed donations (i.e., without cancellation). The Wilcoxon test between social norm and information disclosure (baseline) groups has a total of 491 (498) observations.

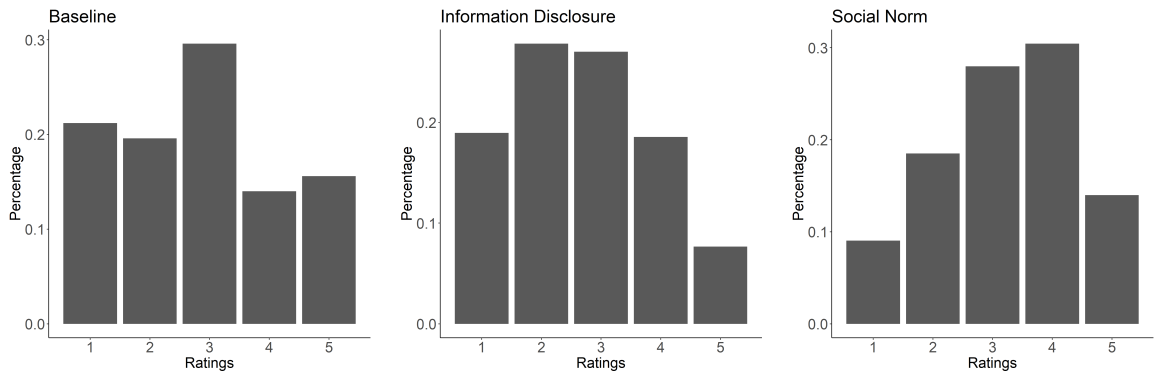


Figure 3.6: Frequency Plot Comparison

$Driver_i$ refers to each specific driver. Column 3 in Table 3.2 includes additional demographic data such as donors' household median income and if they had donated – *Existing Donor*. Note that column 3 had fewer observations because some records did not find a match in the households' median income. Although an ordinal (or multinomial) logit model is preferred over OLS for ranked discreet dependent variables, empirical results showed that the difference between OLS and the logistic regressions is neglectable (Angrist and Pischke 2009, Section 3.4.2). Moreover, OLS is more robust against violation of assumptions (e.g., multicollinearity) and offers easy interpretations. Therefore, we used OLS regression for the analysis. Additional analyses can be found in appendix. Across three models, our finding is consistent: Donations received by those who had received the social norm message had significantly better quality ratings than the other two groups.

To further confirm the internal validity of the intervention, we investigated the treatment effects on donors who opened the intervention email, and those who did not. If the lift in the quality rating was indeed due to the intervention, we expect to observe a significant effect among the donors who have opened the email (i.e., compliers) and insignificant effect among the donors who did not open the email (i.e., non-compliers). Conditioning upon opening the email, we found that the social norm group had an average rating of 3.33 (SE = 0.08) and the information disclosure group had an average rating of 2.69 (SE = 0.09). Therefore, the compliers in the social norm group had a better rating when we only focused

Table 3.2: Intent-to-treat Effect of All Groups (OLS regression)

	Dependent Variable: Ratings		
	(1)	(2)	(3)
Social Norm	0.386***	0.430***	0.404***
	(0.111)	(0.112)	(0.112)
Information Disclosure	−0.151	−0.119	−0.151
	(0.111)	(0.112)	(0.112)
Households Median Income			0.006***
			(0.002)
Existing Donor			−0.078
			(0.222)
Constant	2.832***	2.628***	2.172***
	(0.078)	(0.378)	(0.396)
Observations	741	741	731
R^2	0.032	0.068	0.091
Adjusted R^2	0.030	0.045	0.065
Residual Std. Error	1.238 (df = 738)	1.228 (df = 722)	1.214 (df = 710)
Time and Rater Fixed Effect	No	Yes	Yes
F Statistic	12.257*** (df = 2; 738)	2.944*** (df = 18; 722)	3.547*** (df = 20; 710)

Note: *p<0.1; **p<0.05; ***p<0.01

on those who opened the email. In contrast, the ratings of the information disclosure had no significant difference. Similarly, we also compared the ratings for the non-compliers. The social norm group had an average rating of 2.86 (SE = 0.16) and the information disclosure group had an average rating of 2.67 (SE = 0.14). Comparing the compliers and non-compliers in the social norm group shows a statistically significant difference with $p = 0.005$, while there is no difference between the compliers and non-compliers in the information disclosure group ($p = 0.998$). There is no statistically significant difference in the quality of donations between the non-compliers and the control group ($p = 0.643$). Additional regression analyses, including all the control variables, also confirm consistent results (see Table 3.3). Moreover, as results in Table 3.3 show, there is no difference in quality ratings between the social norm and information disclosure groups for non-compliers, indicating the impact of the intervention and reducing the possibility of a false-positive conclusion.

3.4.2 Implementation and Long-term Effect

Given the statistically and economically significant results, SVdP decided to implement the social norm intervention for all in-kind donors. A concern was that we conducted the experiment around the holiday season, and so results could have been biased due to time-dependent confounding factors. Stated differently, the treatment effect size may differ in other periods because people may respond differently to the intervention at different times of the year. Therefore, SVdP collected additional ratings on $1,301$ in-kind donations during February 2021. The aggregated observations by week are displayed in Table 3.4, and the corresponding bar chart with 95% confidence interval is presented in Figure 3.7. Overall, the average rating was slightly lower than during the experiment. Nevertheless, the difference was statistically insignificant ($p = 0.308$) providing additional evidence of the generalizability of the social norm intervention.

Our goal was to encourage donors to reduce their unacceptable donations without deterring them from making future donations. Therefore, in addition to measuring the immediate effect on donation quality, we were also interested in the post-experiment spillover effects on

Table 3.3: Comparison between the Social Norm and Information Disclosure Groups (OLS Regression)

	Dependent Variable: Ratings		
	(Full Sample)	(Opened Email)	(Did Not Open Email)
Social Norm	0.574***	0.667***	0.356
	(0.107)	(0.124)	(0.233)
Household Median Income	0.005**	0.005**	0.004
	(0.002)	(0.002)	(0.004)
Existing Donor	−0.306	−0.105	−0.785
	(0.253)	(0.296)	(0.517)
Constant	2.610***	3.551***	1.769**
	(0.459)	(0.634)	(0.705)
Observations	482	364	118
R^2	0.114	0.154	0.189
Adjusted R^2	0.078	0.107	0.032
Residual Std. Error	1.165 (df = 462)	1.155 (df = 344)	1.153 (df = 98)
Time and Rater Fixed Effect	Yes	Yes	Yes
F Statistic	3.139*** (df = 19; 462)	3.289*** (df = 19; 344)	1.204 (df = 19; 98)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.4: Ratings for Each Week in February, 2021

Week	Observations	Average Rating	SE of Ratings
Feb 01	307	3.07	0.06
Feb 08	356	3.17	0.07
Feb 15	308	3.17	0.08
Feb 22	330	3.12	0.07

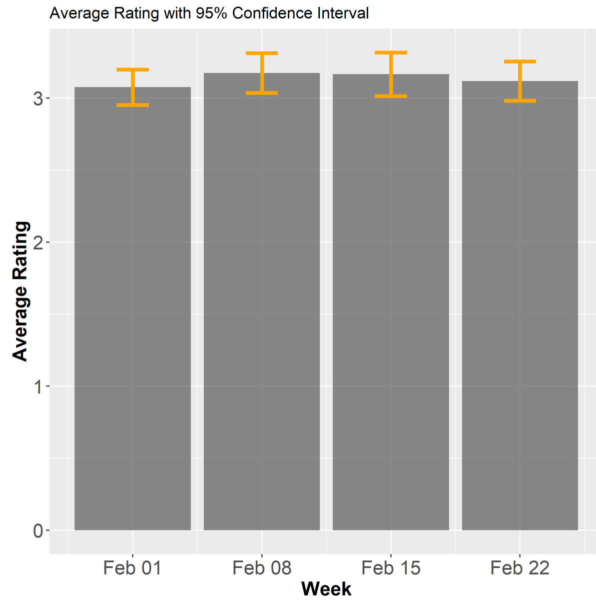


Figure 3.7: Average Ratings with 95% Confidence Interval During February, 2021

future donations. We tracked the cumulative number of in-kind donors who made another donation three months, six months, nine months, and one year after the experiment. Figure 3.8 presents the cumulative number of returned in-kind donors from each group. In the first three months, 42 donors from the baseline group made at least one in-kind donation, while only 25 and 22 donors in the social norm and information disclosure groups made a donation. The difference in donation probability is statistically significant between the control group (16.73%) and the social norm group (9.05%), with $p = 0.016$. The donation probability does not differ significantly between the social norm and information disclosure groups (10.08%), with $p = 0.815$. In the short term, it is likely that the additional email with behavioral interventions may temporarily reduce the additional in-kind donations. However, the number of cumulative returned in-kind donors among the three groups converges over time, and there is no significant difference among the three groups at the 12-month mark. Therefore, the intervention emails did not have a negative long-term impact on in-kind donor retention. It is worth mentioning that we checked whether the in-kind donors volunteered. However, among all subjects, we only found six individuals also had volunteer

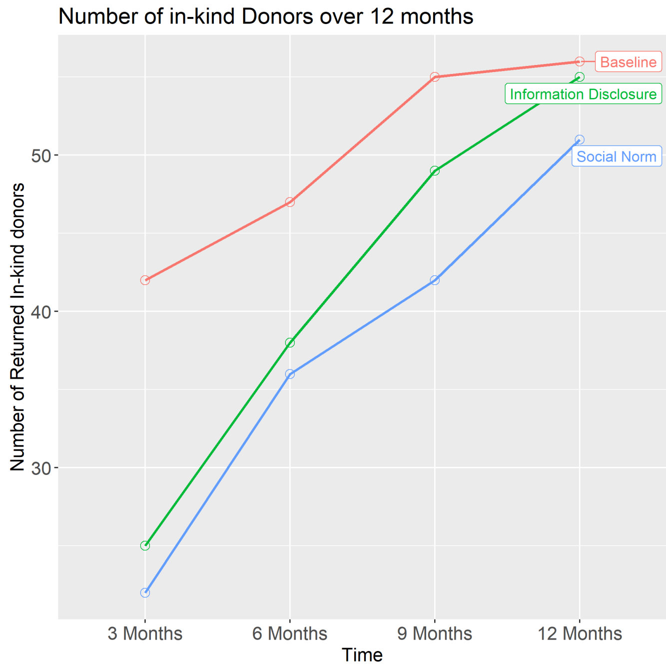


Figure 3.8: In-kind Donor Retention over 12 Months

experience. Therefore, we do not further explore the spillover effect on volunteering.

3.5 Discussion and Conclusion

As shown in Table 3.1, both social norm and information disclosure groups have a similar open rate. Yet, the information disclosure group did not take action to improve the quality of their in-kind donation, meaning that only social norm intervention seems to be effective. Although informing donors about the need of the charity and highlighting the logic reasoning to support may be effective at encouraging charitable giving behaviors (e.g., soliciting donations), the information disclosure intervention did not motivate donors to comply with charity's donation policy. Indeed, some interventions may be effective at inducing behavior, but not at inducing compliance, which requires effort from individuals to deviate from their status quo (Miesler *et al.* 2017). In our setting, several reasons might contribute to this difference. First, these two interventions leverage different information processing systems. In particular, people have two types of thinking processes: (1) an automatic system, which is intuitive, unconscious, and effortless; and (2) a reflective system, which is self-aware, effortful, and requires deductive thinking (Thaler and Sunstein 2009). In particular, information disclosure intervention relies on people's reflective systems because one must first understand the altruistic needs in this particular setting, and then make deductive connections between the ask (improving in-kind donation quality) and the other-benefit outcome. In contrast, social norm intervention only depends on people's automatic systems because one can simply follow what others are doing, without analyzing the situation. Another difference between these two interventions is that they induce different utilities. More specifically, social norm intervention directs people's attention to the social identity utility, and conforming to the social norm will enhance one's social image. On the other hand, information disclosure intervention primes one's altruism, which has a lower chance of success because making the in-kind donation already fulfills this purpose, and effort in this category will only generate a diminishing return of utility. Last, the third possible explanation that information disclosure does not work is that people were avoiding the information: When information is unpleasant to deal with, people often fail to pay attention to it because attention imposes a welfare loss (Loewenstein *et al.* 2014). Hence, donors may ignore the messages if they consider that the information disclosure message imposes a potential welfare loss on their intended donations.

Charitable organizations are often hesitant to send too many emails to donors. In our context, additional email may irritate donors, hence increasing the likelihood of donor attrition. Therefore, we also considered the spillover effect on donor retention. At the 3-month mark, we observed a temporary drop in the number of returned in-kind donors. At the outset, this short-term decline is aligned with the findings in the previous literature, suggesting that additional emails may discourage donors' from making subsequent donation behaviors (Damgaard and Gravert 2018). Nevertheless, the intervention did not dissuade repeat donors over time, since the level of donors converged to a similar level at the 12-month point. Several reasons could explain the phenomena. For example, the intervention emails may have altered donors' belief of the acceptability and utility of the donation quality criterion for SVdP. As a result, donors were more cautious with their donations, reconsidering whether or not their donations could benefit SVdP. Donors in the baseline group, on the other hand, did not raise the bar for the quality of their donation, continued to donate in the following months. Ultimately, donors in the social norm and information disclosure group would likely have accumulated enough eligible items to make a second contribution as time passes. Therefore, there is no long-term difference of the repeat donors among the three groups.

It is also plausible that the treatments caused some annoyance costs, causing donors to avoid SVdP. For example, the social norm intervention is naturally related to a perceived social pressure to engage or not engage in specific behaviors (Ajzen 1991). In our context, donors may feel pressured to follow the group norm and comply with the group behaviors even if it requires extra effort. Hence, donors may churn from making additional donations in order to avoid potential social pressure. The information disclosure group may also experience some degree of discouragement. Despite the fact that information disclosure intervention did not improve the quality of donations, around 76% of donors in this group opened the email and received the treatment. Hence, it is likely that the information disclosure message caused donors to question whether or not they should donate to SVdP. In particular, the donors may consider their donations to SVdP would not be properly used, knowing SVdP "only accepts items that are gently used" and unqualified donations instead cost SVdP "tens of thousands of dollars every month" and divert money away from their mission. Hence, the sense of failing to make a proper charitable giving provides them an excuse not to give in the future (Daniels and Valdés 2021). In contrast, donors in the baseline group did not have any of these concerns and made a second gift in the subsequent months. Nevertheless, the negative spillover effects of the intervention may diminish over time and donors may return to SVdP in the long term.

Results of this study have contributions to both practice and theory. First, with the full implementation of social norm intervention, SVdP observed a significant reduction in junk donations, and found that trucks carry less loads per trip. This reduction in junk donations has been beneficial for SVdP. Before implementing the intervention, SVdP received roughly 90 truckloads of junk donations per month. With the social norm intervention, SVdP handles about 45 truckloads of junk donations per month. This 50% reduction in junk donation translates to substantial savings in transportation, operations and labor. It is important to note, however, that our study only experimentally demonstrated that social norm intervention can be successful among new donors, but the effect size may be smaller or perhaps nonexistent among the existing donors (i.e., donors who have previously donated goods). Social norm intervention is most effective in an ambiguous context, where the norm would be deemed as an important input for decision-making. For instance, new donors to a radio campaign were influenced by social norm, but renewing donors were not (Shang and Croson 2009). As renewing donors are familiar with the context, the donation amount is not ambiguous to them; as a result, social norm has a limited or no influence in this case (Bekkers 2012). New donors, on the other hand, are unaware of such a reference amount, and hence seek a social signal regarding the appropriate donation amount. Therefore, we expect the social norm intervention may produce less impact among the existing donors in our context and recommend caution for charities to implement the intervention among these donors.

Second, our field data challenges the common notion of the effectiveness of information disclosure. Furthermore, the social norm intervention is found to have promising outcomes. Not only does our analysis confirm the effectiveness of this intervention by analyzing the treatment effect within compliers and non-compliers, it also offers additional evidence of generalizability of this effect, such that it is stable and valid across multiple time periods. In conjunction with the substantial logistical savings, the confirmatory evidence strongly supports our statistically and economically significant interventions.

Third, the post-experiment analysis of the donor retention rate serves as an alarm for future research. While the intervention may have successfully reduced the number of junk donations, it may have also discouraged some donors from giving. Therefore, charities should be cognizant of the potential negative spillover effects of interventions, and researchers need to include a baseline group to capture any potential negative effects due to behavioral interventions.

Finally, the problem of junk donations is even more severe in the aftermath of a sudden-onset disaster. Unwanted in-kind donations consume precious storage and transportation capacity and engage scarce human resources to sort and discard in disaster zones. This delays the delivery of essential supplies and drains the time and energy of rescue workers (Thomas and Fritz 2006). Holguín-Veras *et al.* (2016) found that 60% of the in-kind donations are "completely useless" in the aftermath of a disaster, and Holguín-Veras *et al.* (2012) identify the issue of junk donations as one of the most crucial, yet understudied, challenges in the context of disaster relief operations. Despite the fact that our experiment is undertaken in the context of development program, the findings may also provide a viable path for nonprofit organizations operating in emergency contexts. In fact, evaluating behavioral interventions in an emergency context could be extremely challenging and costly due to the difficulty of identifying those who would respond to disaster relief or humanitarian crises with in-kind donations. For example, nonprofit organizations could implement the social norm intervention using mass media engagement to improve the quality of in-kind donations.

This study also identifies potential future research. For instance, additional measures, such as the rate of junk contribution decrease and the overall number of gifts, would give more insight into how different treatments impact donor behavior. Another interesting question is how the resale value of donated goods can influence a donor's decision. While charitable giving triggers the emotional mindset of a donor, priming monetary value in the nudges may backfire on a donor's altruistic motives (Liu and Aaker 2008; Costello and Malkoc 2022) or impose a targeting effect on the donors (Martin and Randal 2008).

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APPENDIX A

CHAPTER 1

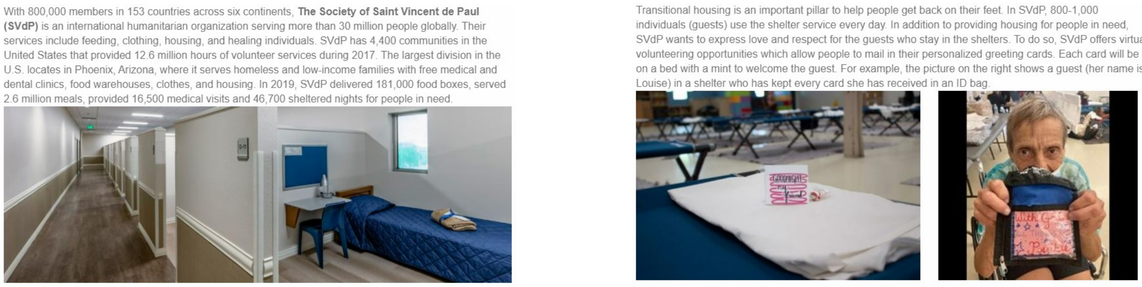
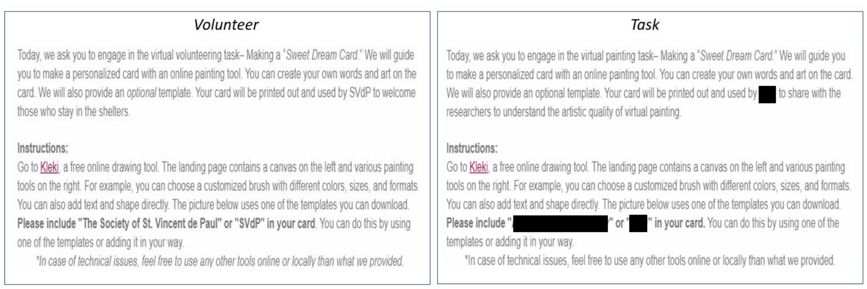


Figure A.1: Stage 1 in Experiments 1 and 2

Procedure in experiments 1 and 2

The first stage was the same for both experiments. Participants read a short description regarding SVdP, and related information for the virtual volunteering task (Figure A.1). The context for the *Volunteer* and *Task* groups are presented in Figure A.2. There are three differences between the two treatments. First, in experiment 1, the *Volunteer* group was told to engage in the virtual volunteering task, while the *Task* group was told to engage in the virtual painting task. Second, the *Volunteer* group was told that their card will be used to welcome those who will be staying in SVdP's shelters, and the *Task* group's cards will be used by researchers to understand the artistic quality of "virtual painting." The language was purposely chosen to avoid giving an impression to the *Task* group that their work will be judged. The last difference was to add the name of SVdP or the authors' research institute on the card. Experiment 2 had the same procedures and task descriptions as the *Volunteer* group in experiment 1. In addition, we provided the same detailed instructions on how to use the coloring pattern for both groups.



Volunteer

Today, we ask you to engage in the virtual volunteering task– Making a "*Sweet Dream Card.*" We will guide you to make a personalized card with an online painting tool. You can create your own words and art on the card. We will also provide an *optional* template. Your card will be printed out and used by SVdP to welcome those who stay in the shelters.

Instructions:
Go to Kleki, a free online drawing tool. The landing page contains a canvas on the left and various painting tools on the right. For example, you can choose a customized brush with different colors, sizes, and formats. You can also add text and shape directly. The picture below uses one of the templates you can download. **Please include "The Society of St. Vincent de Paul" or "SVdP" in your card.** You can do this by using one of the templates or adding it in your way.
**In case of technical issues, feel free to use any other tools online or locally than what we provided.*

Task

Today, we ask you to engage in the virtual painting task– Making a "*Sweet Dream Card.*" We will guide you to make a personalized card with an online painting tool. You can create your own words and art on the card. We will also provide an optional template. Your card will be printed out and used by [redacted] to share with the researchers to understand the artistic quality of virtual painting.

Instructions:
Go to Kleki, a free online drawing tool. The landing page contains a canvas on the left and various painting tools on the right. For example, you can choose a customized brush with different colors, sizes, and formats. You can also add text and shape directly. The picture below uses one of the templates you can download. **Please include "[redacted]" or "[redacted]" in your card.** You can do this by using one of the templates or adding it in your way.
*In case of technical issues, feel free to use any other tools online or locally than what we provided.

Figure A.2: Task Description

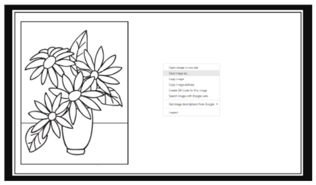
In experiment 2, we provided detailed instructions to streamline the drawing process.

Alternative models in Experiment 1

For robustness checks, we ran three probit regressions to control for different variables, including demographic and familiarity information. As for control variables, we have four levels for all demographic variables (*Gender*, *Age*, *Income*, and *Education*). *Income* is categorized into: L1 (those with household income below $50,000), L2 (those with household income between $50,000 to $100,000), and L3 (those with income above $100,000); *Age* is categorized into: L1 (those under 30) , L2 (between 30 to 40), and L3 (41 and older); *Education* L1 (those with up to an associate degree), L2 (bachelor's degree), and L3 (a

Today, we ask you to engage in the virtual volunteering task– Making a "*Sweet Dream Card*." We will guide you to make a personalized card with an online painting tool **in three steps**. You will download the provided template, color it with an online painting platform, and create your own words and art on the card. In the end, you can upload your finished product, and we will print out the card and use it to welcome those who stay in SVdP's shelters.

Instructions - 1/3:
In the first step, you will **download** and **save** the template we provide. First, click the following link in "templates download", and it will open up a new window in your browser. Second, **right-click** your mouse, and it will allow you to save the template to a local folder on your computer. Make sure to save it in a location where you can find it.



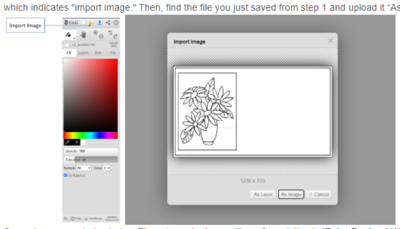
By default, it should be saved either in your *downloads* folder or a *recently downloaded* folder.
Once saved, please check the question below, and we will move to the next step.

Templates Download:
card_template.PNG

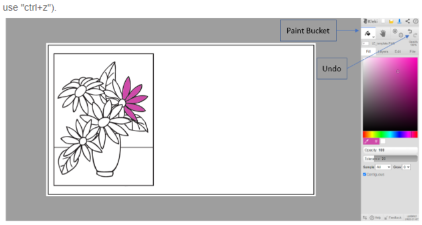
*The coloring pattern is supported by ColorWithFuzzy.com.

Instructions - 2/3:
In this step, you will color the template and add any customized words and art.

Go to Kleki, a free online drawing tool. The landing page contains a blank canvas on the left and various painting tools on the right. First, go to the top right corner and click the folder icon, which indicates "import image." Then, find the file you just saved from step 1 and upload it "As image."

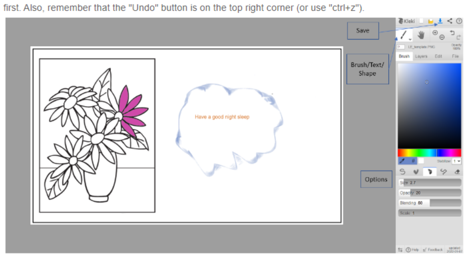


Second, you can start coloring. The primary tool you will use for painting is "**Paint Bucket**." With this tool and your choice of color, you can easily fill the shape with one click. Use any colors you like and make your own painting. Also, you can zoom in an area by clicking the plus button ("+") on top right. If you want to "**Undo**" any painting, the button is on the top right corner (or use "ctrl+z").



Once you finish coloring, please proceed to the last step. Please do not close Kleki.

Instructions - 3/3:
Now that you have finished coloring, feel free to add any words or other art on the blank part. For example, you can choose a customized **brush** with different colors, sizes, and formats. You can also add **Text** and **Shape** directly. However, once you add text or shape, it is not convenient to move it around. So it is *highly recommended* to determine the location of the text first. Also, remember that the "Undo" button is on the top right corner (or use "ctrl+z").



Do not close the page before you save your work! You can save your card by clicking the "Save Image" button on the top right corner. Same as before, save it in a local folder where you can find it.

Figure A.3: Instruction for Experiment 2 master's degree or above). Last, *Prior* is a binary variable and equals to 1 if the participants already knew SVdP before the experiment.

Table A.1 shows the significance of covariates include *Gender*, *Age*, and *Income*. Column 1 replicates the results from the non-parametric tests. Column 2 shows the results after adding demographic variables (i.e., age, gender, income, and education), and Column 3 shows the results after controlling for additional variables related to a participant's previous knowledge about SVdP. Across three models, we observe a highly significant treatment difference at $p \leq 0.01$ level. Our findings are robust after including the control variables, and the effects are economically relevant. Specifically, consistent with the literature (Simmons and Emanuele 2007), female participants donated more. In addition, the population with household incomes more than $\$100,000$ donated more. Finally, *Prior* control is the post-treatment question on whether the participants were familiar with SVdP before this experiment. Due to salient effect, it is likely that those who were familiar with the charity would donate more. Table A.1 includes the three probit regressions with the same set of control variables. In general, the same result holds for the *Volunteer* treatment, as the treatment effect is also significant at $p \leq 0.01$ level.

Table A.1: Regression Results for Donation Amount and Probability

	Dependent Variables:					
	Donation Amount			Donation Amount		
	OLS			*probit*		
	(1)	(2)	(3)	(4)	(5)	(6)
Volunteer	0.101^{***}	0.102^{***}	0.101^{***}	0.238^{***}	0.237^{***}	0.238^{***}
	(0.038)	(0.038)	(0.037)	(0.087)	(0.089)	(0.089)
Age L2		−0.040	−0.044		−0.150	−0.159
		(0.046)	(0.046)		(0.108)	(0.108)
Age L3		0.074	0.050		0.064	0.018
		(0.046)	(0.047)		(0.110)	(0.112)
Age NA		−0.473	−0.488		−9.899	−9.528
		(0.432)	(0.429)		(288.645)	(182.434)
Gender Male		-0.089^{**}	-0.076^{**}		−0.142	−0.120
		(0.038)	(0.038)		(0.090)	(0.091)
Gender third gender		−0.008	−0.023		0.296	0.272
		(0.157)	(0.156)		(0.396)	(0.398)
Gender NA		0.130	0.131		4.700	4.591
		(0.433)	(0.430)		(229.383)	(144.579)
Income L2		0.030	0.035		−0.017	−0.006
		(0.045)	(0.045)		(0.106)	(0.106)
Income L3		0.106^{**}	0.112^{**}		0.114	0.130
		(0.053)	(0.052)		(0.125)	(0.125)
Income NA		0.027	0.074		−0.012	0.080
		(0.169)	(0.169)		(0.397)	(0.399)
Education L2		0.026	0.013		0.005	−0.019
		(0.044)	(0.044)		(0.104)	(0.104)
Education L3		0.050	0.035		0.058	0.029
		(0.055)	(0.055)		(0.129)	(0.130)
Education NA		−0.425	−0.477		−5.388	−5.206
		(0.381)	(0.379)		(194.996)	(123.950)
Prior			0.142^{***}			0.274^{***}
			(0.042)			(0.102)
Constant	0.485^{***}	0.463^{***}	0.430^{***}	0.234^{***}	0.303^{***}	0.240^{**}
	(0.027)	(0.050)	(0.050)	(0.062)	(0.117)	(0.119)
Observations	866	866	866	866	866	866
R^2	0.008	0.034	0.047			
Adjusted R^2	0.007	0.020	0.031			
Log Likelihood				−562.842	−552.482	−548.865
Akaike Inf. Crit.				1,129.684	1,132.963	1,127.730
Residual SE	0.552	0.549	0.545			
F Statistic	7.281^{***}	2.331^{***}	3.001^{***}			

Note: *p<0.1; **p<0.05; ***p<0.01

In both regression models, prior awareness of SVdP significantly increases both the probability and amount of donation. Table A.2 shows the results. The first three columns show the number (percentage) of participants donated, and the other three columns show the average (standard error) of donation amount in each group.

Table A.2: Conditional Treatment Effect Comparison on Familiarity with SVdP in Experiment 1

Measurement	Donation Probability		Donation Amount	
Familiarity/Group	Task	Volunteer	Task	Volunteer
Familiar with SVdP	78 (66.7%)	98 (76.0%)	0.626 (0.054)	0.676 (0.051)
New to SVdP	169 (56.3%)	208 (65.0%)	0.430 (0.029)	0.551 (0.031)

Alternative models in Experiment 2

We repeated the same set of regression models in experiment 2. Results are robust across all specifications. We also compared the measurements with conditional treatment effect. Consistent with previous result in experiment 1, prior familiarity with SVdP significantly increased donations in both likelihood and amount.

Table A.3: Regression Results for Donation Amount and Probability in Experiment 2

	Dependent variable:					
	Donation Amount			Donation Amount		
	OLS			*probit*		
	(1)	(2)	(3)	(4)	(5)	(6)
HE	−0.077**	−0.069*	−0.065*	−0.214**	−0.211**	−0.203**
	(0.037)	(0.036)	(0.036)	(0.083)	(0.084)	(0.085)
Education L2		0.094**	0.092**		0.169*	0.165*
		(0.041)	(0.041)		(0.095)	(0.095)
Education L3		0.136**	0.123**		0.264**	0.238*
		(0.054)	(0.054)		(0.126)	(0.127)
Education NA		1.103**	1.035**		4.460	4.170
		(0.459)	(0.456)		(142.673)	(145.368)
Income L2		0.035	0.035		0.087	0.086
		(0.043)	(0.042)		(0.100)	(0.100)
Income L3		0.040	0.044		−0.101	−0.094
		(0.051)	(0.051)		(0.117)	(0.118)
Income NA		0.011	0.007		−0.060	−0.076
		(0.125)	(0.124)		(0.288)	(0.289)
Age L2		−0.030	−0.047		−0.205**	−0.242**
		(0.044)	(0.044)		(0.101)	(0.102)
Age L3		0.110**	0.064		−0.010	−0.113
		(0.046)	(0.048)		(0.108)	(0.112)
Age NA		0.833	0.859		4.266	4.326
		(0.559)	(0.556)		(235.034)	(235.034)
Gender Male		−0.153***	−0.141***		−0.228***	−0.197**
		(0.038)	(0.038)		(0.087)	(0.088)
Gender third gender		0.190**	0.191**		0.100	0.105
		(0.090)	(0.089)		(0.214)	(0.215)
Gender NA		−0.349	−0.263		4.556	4.654
		(0.457)	(0.455)		(142.673)	(145.368)
Prior			0.174***			0.427***
			(0.047)			(0.115)
Constant	0.579***	0.537***	0.514***	0.446***	0.497***	0.442***
	(0.026)	(0.045)	(0.045)	(0.058)	(0.106)	(0.107)
Observations	947	947	947	947	947	947
R^2	0.005	0.061	0.074			
Adjusted R^2	0.004	0.048	0.061			
Log Likelihood				−618.906	−606.548	−599.410
Akaike Inf. Crit.				1,241.812	1,241.096	1,228.819
Residual Std. Error	0.570	0.557	0.553			
F Statistic	4.334**	4.641***	5.352***			
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A.4: Conditional Treatment Effect Comparison on Familiarity with SVdP in Experiment 2

Measurement	Donation Probability		Donation Amount	
Familiarity/Group	LE	HE	LE	HE
Familiar with SVdP	108 (80.1%)	83 (69.9%)	0.754 (0.055)	0.676 (0.068)
New to SVdP	386 (63.5%)	370 (56.8%)	0.530 (0.029)	0.463 (0.028)

APPENDIX B

CHAPTER 2

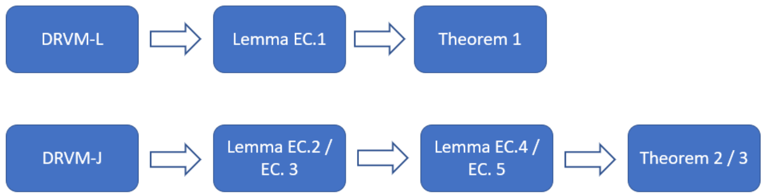


Figure B.1: Roadmap of Lemma and Theorem

Data Description and Categorization Definition

Through our collaboration with the Society of SVdP, we have received two main data sets; *donations* and *hours*. The *donations* data set includes each transaction's account type, amount, time of donation, and a brief description regarding the donation (e.g., Trust, Foundation, Individual). Meanwhile, the *volunteers*' data set contains information about dates and hours of volunteering, volunteering tasks and some demographic data (e.g., city, state, zip code). The dataset includes information on individuals' records between 2017-01-01 to 2020-03-01. Prior to 2017, the volunteer data is not recorded. Meanwhile, data after March 2020 is influenced by the Covid-19 pandemic (very limited volunteering capacity during pandemic). With these criteria, we have 195,751 records for donations dataset, 148,488 records for hours dataset. Moreover, the data recording process is not always consistent. Between 2017-01-01 and 2018-03-31, volunteer data is only partially available. First, SVdP change their database management tool from legacy system to Salesforce during first quarter in 2018, and partial data is lost during the transition. Second, individual volunteer can sign up for multiple person for a volunteering event prior to the system change. After the system update, all volunteers have to sign up individually. The data analysis results hold even when we limit the data set between 2018-03-31 to 2020-03-01.

Overall, we identify 97,701 unique donors and 14,285 distinct volunteers, and 1,528 individuals who are both donors and volunteers. Moreover, We categorized individual volunteers into two types: *Formal* and *Episodic* volunteers. In practice, the boundaries between formal and episodic volunteers are difficult to establish (Cnaan and Handy 2005). Therefore, we define the criteria based on past literature and volunteer manager's expertise. Hustinx *et al.* (2008) specify episodic volunteers as those who has showed up less than once a month. Meanwhile, volunteer managers in SVdP use participation frequency and volunteering lifetime (duration between first and last volunteering event) as the distinguishing criteria. They consider those who have participated frequently and have volunteered more than six months as formal volunteers. According to volunteering data and given the fact that some formal volunteers "leave" the charity, we adopt both definitions and strictly define those who have participated at least 24 times and volunteering lifetime at least 6 months as formal volunteers[1]. Moreover, table 2.1 shows that formal and episodic volunteers have significant difference in their volunteering behavior. Therefore, our definition is able to categorizes the volunteers according to their behaviors.

Proof of Lemma 1

We will start with a statement of the Scarf (1958) bound:

[1] General results hold with two alternative threshold: (1) participated 36 times (2) participated 24 times. We use this threshold to capture more formal volunteers as some may have joined in 2018-2019.

Theorem 4 (Scarf 1958) *For any q,*

$$\sup_{p\in\mathcal{P}'} \mathbb{E}_p\left[(H-q)^+\right] = \frac{1}{2}(\mu-q) + \frac{1}{2}\sqrt{(\mu-q)^2+\sigma^2}. \tag{B.1}$$

As we will establish next, $L(\mathbf{x})$ has a closed-form expression. Lemma 1 presents the closed-form expression.

Lemma 1 *Let $h_0 := (\lambda-\theta x_f)/x_e$. Then,*

$$L(\mathbf{x}) = w\lambda + \frac{(\gamma-\beta)(\lambda-\theta x_f)}{2} + \mu x_e\left(\frac{\beta-\gamma}{2}\right) - \frac{(\beta+\gamma)\sqrt{(\mu x_e+\theta x_f-\lambda)^2+\sigma^2 x_e^2}}{2}$$

Proof 1 *Proof.*

Here, $h_0 := (\lambda-\theta x_f)/x_e$ is the ideal turnout proportion where the available labor equals the supply λ. Note that $L(\mathbf{x})$ is equivalent to

$$\inf_{p\in\mathcal{P}} \mathbb{E}_p[L(Hx_e,x_f)] = (w-\beta)\lambda + \beta(\mu x_e+\theta x_f) - (\beta+\gamma)\sup_{p\in\mathcal{P}} \mathbb{E}_p\left[(Hx_e+\theta x_f-\lambda)^+\right]. \tag{B.2}$$

Define $h_0 := \frac{\lambda-\theta x_f}{x_e}$. Hence, in order to prove the lemma, we will need to analyze the term

$$\sup_{p\in\mathcal{P}} \mathbb{E}_p\left[(Hx_e+\theta x_f-\lambda)^+\right] = x_e\cdot\sup_{p\in\mathcal{P}} \mathbb{E}_p\left[\left(H+\theta\frac{x_f}{x_e}-\frac{\lambda}{x_e}\right)^+\right] = x_e\cdot\sup_{p\in\mathcal{P}} \mathbb{E}_p\left[(H-h_0)^+\right].$$

The expression for $L(\mathbf{x})$ in Lemma 1 is a consequence of plugging in the closed-form expression of $\sup_{p\in\mathcal{P}}\mathbb{E}_p\left[(Hx_e+\theta x_f-\lambda)^+\right]$ (equation (B.1)*) into* (B.2). ■

Proof of Theorem 1

Proof 2 *Proof.*

The closed-form expression of $L(\mathbf{x})$ is given in Lemma 1. We can check that the Hessian of L is negative semi-definite, and hence $L(\mathbf{x})$ is jointly concave in $\mathbf{x}$. Analyzing the gradient

$$\nabla L(\mathbf{x}) = \left(\frac{\mu(\beta-\gamma)}{2} - \frac{(\beta+\gamma)\left[x_e(\mu^2+\sigma^2)+(\theta x_f-\lambda)\mu\right]}{2\sqrt{(\mu x_e+\theta x_f-\lambda)^2+\sigma^2 x_e^2}},\ \frac{\theta(\beta-\gamma)}{2} - \frac{(\beta+\gamma)(\mu x_e+\theta x_f-\lambda)\theta}{2\sqrt{(\mu x_e+\theta x_f-\lambda)^2+\sigma^2 x_e^2}}\right),$$

we observe that $\nabla L(\mathbf{x}) = 0$ does not have a solution. Hence, the solution to $\max_{\mathbf{x}} L(\mathbf{x})$, which we denote as $\mathbf{x}^* = (x_e^*, x_f^*)$, must lie on the boundary of region X. We will next derive the value of x_e on $x_f = 0$ and $x_f = \bar{x}_f$.

$$L(x_e,0) = w\lambda + \frac{(\gamma-\beta)(\lambda)}{2} + \mu x_e\left(\frac{\beta-\gamma}{2}\right) - \frac{(\beta+\gamma)\sqrt{(\mu x_e-\lambda)^2+\sigma^2 x_e^2}}{2},$$
$$L(x_e,\bar{x}_f) = w\lambda + \frac{(\gamma-\beta)(\lambda-\theta\bar{x}_f)}{2} + \mu x_e\left(\frac{\beta-\gamma}{2}\right) - \frac{(\beta+\gamma)\sqrt{(\mu x_e+\theta\bar{x}_f-\lambda)^2+\sigma^2 x_e^2}}{2}$$

which have their global optimum are achieved at $x_{e,0}^* = \frac{(\lambda)\mu\sqrt{\Delta_0}(\sqrt{\Delta_0}+\sigma(\beta-\gamma))}{(\mu^2+\sigma^2)\Delta_0}$ and $x_{e,f}^* = \frac{(\lambda-\theta\bar{x}_f)\mu\sqrt{\Delta_0}(\sqrt{\Delta_0}+\sigma(\beta-\gamma))}{(\mu^2+\sigma^2)\Delta_0}$, where $\Delta_0 := (\beta+\gamma)^2\sigma^2 + 4\mu^2\beta\gamma$. The corresponding local optimal objective values are $L^*(x_{e,0}^*,0) = w\lambda + \frac{1}{2}\left((\lambda\sigma\frac{\sigma(\gamma-\beta)-\sqrt{\Delta_0}}{\mu^2+\sigma^2}\right)$ and $L^*(x_{e,f}^*,\bar{x}_f) = w\lambda + \frac{1}{2}\left((\lambda-\theta\bar{x}_f)\sigma\frac{\sigma(\gamma-\beta)-\sqrt{\Delta_0}}{\mu^2+\sigma^2}\right)$. Last, $L^*(x_{e,f}^* > L^*(x_{e,0}^*,0)$ because $\sigma(\gamma-\beta)-\sqrt{\Delta_0}\leq 0$. Therefore, the global optimal solution is unique, $\mathbf{x}^* = \left((\lambda-\theta\bar{x}_f)\frac{\mu\sqrt{\Delta_0}(\sqrt{\Delta_0}+\sigma(\beta-\gamma))}{(\mu^2+\sigma^2)\Delta_0}, \bar{x}_f\right)$.

■

Lemma 2, Lemma 3, and proofs

In this section, we will derive the closed-form expression for

$$\sup_{p\in\mathcal{P}} \mathbb{E}_p\left[(H-q)^+ - a(z-H)^+\right]$$

for some $a, q \geq 0$. As it will become apparent, the proof covers many cases since $(H-q)^+ - a(z-H)^+$ is neither concave nor convex.

In the following result (Lemma 2), we present and derive the closed-form expression when $a \in [0,1]$. The expression when $a > 1$ (Lemma 3) is similar with slight modification.

Lemma 2 *If $a \in [0,1]$ and $\zeta := \frac{az-q}{a-1}$, then*

$$\sup_{p\in\mathcal{P}} \mathbb{E}_p\left[(H-q)^+ - a(z-H)^+\right] =$$

$$\begin{cases} \frac{1}{2}(\mu-q) + \frac{1}{2}\sqrt{(\mu-q)^2+\sigma^2} - a(z-\mu), & \text{Case f(a): } \textit{if } q < z \textit{ and } \sigma^2 \leq (z-\mu)(z+\mu-2q), \\ \frac{(z-\mu)^2(q-z)}{\sigma^2+(\mu-z)^2} + z - q - a(z-\mu), & \text{Case f(b): } \textit{if } q < z \textit{ and } (z-\mu)(z+\mu-2q) \leq \sigma^2 \leq (z-\mu)(z+\mu-2\zeta), \\ \frac{1}{2}(1-a)(\zeta + \sqrt{\sigma^2+(\mu-\zeta)^2}) + \frac{1}{2}(a+1)\mu - q, & \text{Case f(c): } \textit{if } q < z \textit{ and } \sigma^2 \geq (z-\mu)(z+\mu-2\zeta), \\ \frac{1}{2}(\mu-q) + \frac{1}{2}\sqrt{(\mu-q)^2+\sigma^2}, & \text{Case e(a): } \textit{if } q \geq z \textit{ and } \sigma^2 \leq (\mu-z)(2q-z-\mu), \\ \frac{(z-q)(\mu-z)^2}{\sigma^2+(\mu-z)^2} + \mu - z, & \text{Case e(b): } \textit{if } q \geq z \textit{ and } (\mu-z)(2q-z-\mu) \leq \sigma^2 \leq (z-\mu)(z+\mu-2\zeta), \\ \frac{1}{2}(1-a)(\zeta + \sqrt{\sigma^2+(\mu-\zeta)^2}) + \frac{1}{2}(a+1)\mu - q, & \text{Case e(c): } \textit{if } q \geq z \textit{ and } \sigma^2 \geq (z-\mu)(z+\mu-2\zeta) \end{cases}$$

Proof 3 *Proof.*

Note that due to weak duality theorem for moment problems, we have:

$$\begin{aligned} \sup_{p\in\mathcal{P}} \mathbb{E}_p\left[(H-q)^+ - a(z-H)^+\right] \quad \leq \quad & \inf_{t_0,t_1,t_2} t_0 + t_1\mu + t_2(\mu^2+\sigma^2) \\ & s.t. \quad t_0 + t_1 h + t_2 h^2 \geq (h-q)^+ - a(z-h)^+, \quad \forall h. \end{aligned}$$

In order to prove the lemma, we only need to show a feasible dual solution (t_0, t_1, t_2) and a feasible primal distribution $p \in \mathcal{P}$ where the dual objective and the primal objective are equal. Since their objectives match, these are dual and primal optimal by weak duality.

Let us focus on the dual problem. Let $g_1(h; t_0, t_1, t_2) := t_0 + t_1 h + t_2 h^2$ be a quadratic function, where the dual variables (t_0, t_1, t_2) are the parameters of this function. Let $g_2(h) := (h-q)^+ - a(z-h)^+$ be a piecewise linear function of h. Then, (t_0, t_1, t_2) is a feasible dual solution if $g_1(h; t_0, t_1, t_2) \geq g_2(h)$ for all h.

We first derive the expression for cases f(a)-f(c). Since $q \leq z$, the moment problem is:

$$\begin{aligned} \inf_{t_0,t_1,t_2} \quad & t_0 + t_1\mu + t_2(\mu^2+\sigma^2) \\ s.t. \quad & t_0 + t_1 h + t_2 h^2 \geq -a(z-h), && \forall h \leq q \\ & t_0 + t_1 h + t_2 h^2 \geq (h-q) - a(z-h), && \forall h \in [q, z] \\ & t_0 + t_1 h + t_2 h^2 \geq (h-q), && \forall h \geq z \end{aligned} \tag{B.3}$$

Note that $g_2(h)$ is neither concave nor convex in h. It is convex for $h \leq z$, and concave for $h \geq q$.

Under case f(a), consider the dual solution: $t_0^{f(a)} = \frac{\left(q-\sqrt{(\mu-q)^2+\sigma^2}\right)^2}{4\sqrt{(\mu-q)^2+\sigma^2}} - az$, $t_1^{f(a)} = \frac{1}{2} - \frac{q}{2\sqrt{(\mu-q)^2+\sigma^2}} + a$, *and* $t_2^{f(a)} = \frac{1}{4\sqrt{(\mu-q)^2+\sigma^2}}$. *We can check that* $g_1(\cdot; t^{f(a)})$ *is a convex function that intersects* $g_2(\cdot)$ *at exactly two points:*

$$H = \begin{cases} q - \sqrt{(\mu-q)^2+\sigma^2}, & \text{with probability } \frac{1}{2} + \frac{1}{2}\frac{q-\mu}{\sqrt{(\mu-q)^2+\sigma^2}} \\ q + \sqrt{(q-\mu)^2+\sigma^2}, & \text{with probability } \frac{1}{2} - \frac{1}{2}\frac{q-\mu}{\sqrt{(q-\mu)^2+\sigma^2}} \end{cases} \tag{B.4}$$

This distribution has mean μ *and standard deviation* σ*. We can also verify that the primal objective value of* (B.4) *and the dual objective value of* $t^{f(a)}$ *are both equal to* $\frac{1}{2}(\mu-q) + \frac{1}{2}\sqrt{(\mu-q)^2+\sigma^2} + a(z-\mu)$*. Hence, they are primal and dual optimal, respectively. This completes the proof for f(a).*

For case f(b), consider the dual solution $t^{f(b)}$ *where* $t_0^{f(b)} = \frac{(z-q)(\sigma^2+\mu^2-z\mu)^2}{(\sigma^2+(\mu-z)^2)^2} - az$, $t_1^{f(b)} = -\frac{2(z-q)(z-\mu)((z-\mu)\mu-\sigma^2}{(\sigma^2+(\mu-z)^2)^2} + a$, *and* $t_2^{f(b)} = \left(\frac{(z-\mu)\sqrt{z-q}}{\sigma^2+(\mu-z)^2}\right)^2$. *We can check that* $g_1(\cdot; t^{f(b)})$ *is a convex function that intersects* $g_2(\cdot)$ *at exactly two points:*

$$H = \begin{cases} \mu - \frac{\sigma^2}{z-\mu} & \text{with probability } \frac{(\mu-z)^2}{\sigma^2+(\mu-z)^2} \\ z & \text{with probability } \frac{\sigma^2}{\sigma^2+(\mu-z)^2}. \end{cases} \tag{B.5}$$

This distribution has mean μ *and standard deviation* σ*. We can also verify that the primal objective value of* (B.5) *and the dual objective value of* $t^{f(b)}$ *are both equal to* $\frac{(z-\mu)^2(q-z)}{\sigma^2+(\mu-z)^2} + z - q - a(z-\mu)$*. This completes the proof for f(b).*

Under case f(c), consider the dual solution $t_0^{f(c)} = \frac{1-a}{4}\left(\frac{\zeta^2}{\sqrt{\sigma^2+(\mu-\zeta)^2}} + \sqrt{\sigma^2+(\mu-\zeta)^2}\right) + \frac{1}{2}(\zeta(1-a)) - q$, $t_1^{f(c)} = \frac{1}{2}(a+1+\frac{(a-1)\zeta}{\sqrt{\sigma^2+(\mu-\zeta)^2}})$, *and* $t_2^{f(c)} = \frac{1-a}{4\sqrt{\sigma^2+(\mu-\zeta)^2}}$, *where* $\zeta = \frac{az-q}{a-1}$*. We can check that* $g_1(\cdot; t^{f(c)})$ *is a convex function that intersects* $g_2(\cdot)$ *at exactly two points. Assuming* $\mu < \zeta$ *(in the case* $\mu > \zeta$*, probability is switched), the two-point distribution* $p^{f(c)}$ *is:*

$$H = \begin{cases} \zeta - \sqrt{\sigma^2+(\mu-\zeta)^2} & \text{with probability } \frac{1}{2}(1+\sqrt{\frac{(\zeta-\mu)^2}{\sigma^2+(\mu-\zeta)^2}}) \\ \zeta + \sqrt{\sigma^2+(\mu-\zeta)^2} & \text{with probability } \frac{1}{2}(1-\sqrt{\frac{(\zeta-\mu)^2}{\sigma^2+(\mu-\zeta)^2}}). \end{cases} \tag{B.6}$$

This distribution has mean μ *and standard deviation* σ*. We can also verify that the primal objective value of* (B.6) *and the dual objective value of* $t^{f(c)}$ *are both equal to* $\frac{1}{2}(1-a)(\zeta + \sqrt{\sigma^2+(\mu-\zeta)^2}) + \frac{1}{2}(a+1)\mu - q$*. Hence, they are primal and dual optimal. This completes the proof for f(c).*

We next derive the expression for cases e(a)-e(c). Since $z \le q$*, the moment problem is:*

$$\begin{aligned} \inf_{t_0,t_1,t_2} \; & t_0 + t_1\mu + t_2(\mu^2+\sigma^2) \\ s.t. \; & t_0 + t_1 h + t_2 h^2 \ge -a(z-h), \quad \forall h \le z \\ & t_0 + t_1 h + t_2 h^2 \ge 0, \quad \forall h \in [z,q] \\ & t_0 + t_1 h + t_2 h^2 \ge (h-q), \quad \forall h \ge q \end{aligned} \tag{B.7}$$

For case e(a), the solution is the same as f(a). The objective value of $t^{e(a)}$ is $\frac{1}{2}(\mu-q)+\frac{1}{2}\sqrt{(\mu-q)^2+\sigma^2}$. This completes the proof for e(a).

For part e(b), consider the solution $t^{e(b)}$ where $t_0^{e(b)}=(q-z)\frac{z(\mu-z)}{\sigma^2+(\mu-z)^2}\left(\frac{z(\mu-z)}{\sigma^2+(\mu-z)^2}+2\right)-z$, $t_1^{e(b)}=1-2(q-z)\frac{(\mu-z)}{\sigma^2+(\mu-z)^2}\left(\frac{z(\mu-z)}{\sigma^2+(\mu-z)^2}+1\right)$, and $t_2^{e(b)}=\left(\frac{(\mu-z)\sqrt{q-z}}{\sigma^2+(\mu-z)^2}\right)^2$. We can check that $g_1(\cdot;t^{e(b)})$ is a convex function that intersects $g_2(\cdot)$ at exactly two points:

$$H=\begin{cases} z & \textit{with probability } \frac{\sigma^2}{(\mu-z)^2+\sigma^2} \\ \mu+\frac{\sigma^2}{\mu-z} & \textit{with probability } \frac{(\mu-z)^2}{(\mu-z)^2+\sigma^2}. \end{cases} \tag{B.8}$$

This distribution has mean μ and standard deviation σ. We can also verify that the primal objective value of (B.8) *and the dual objective value of $t^{e(b)}$ are both equal to $\frac{(z-q)(\mu-z)^2}{\sigma^2+(\mu-z)^2}+\mu-z$. This completes the proof for e(b).*

Under case e(c), consider the dual solution $t^{f(c)}$ and the corresponding two-point distribution (B.6) *which we earlier showed to be primal and dual feasible. This is because in both cases the first and third constraints are the same. The primal and dual feasible solutions also share same objective, equal to $\frac{1}{2}(1-a)(\zeta+\sqrt{\sigma^2+(\mu-\zeta)^2})+\frac{1}{2}(a+1)\mu-q$. This proves e(c).* ■

Lemma 3 *If $a>1$ and $\zeta:=\frac{az-q}{a-1}$, then*

$$\sup_{p\in\mathcal{P}}\mathbb{E}_p\left[(H-q)^+-a(z-H)^+\right]=$$
$$\begin{cases} \frac{1}{2}(\mu-q)+\frac{1}{2}\sqrt{(\mu-q)^2+\sigma^2}-a(z-\mu), & \text{Case f(a): } \textit{if } q<z,\ \sigma^2\le(z-\mu)(z+\mu-2q) \textit{ and } \mu<z, \\ \frac{(z-\mu)^2(q-z)}{\sigma^2+(\mu-z)^2}+z-q-a(z-\mu), & \text{Case f(b): } \textit{if } q<z,\ (z-\mu)(z+\mu-2q)\le\sigma^2 \textit{ and } \mu<z, \\ \mu-q, & \text{Case f(c): } \textit{if } q<z \textit{ and } \mu\ge z, \\ \frac{1}{2}(\mu-q)+\frac{1}{2}\sqrt{(\mu-q)^2+\sigma^2}, & \text{Case e(a): } \textit{if } q\ge z,\ \sigma^2\le(\mu-z)(2q-z-\mu) \textit{ and } \mu\ge z, \\ \frac{(z-q)(\mu-z)^2}{\sigma^2+(\mu-z)^2}+\mu-z, & \text{Case e(b): } \textit{if } q\ge z,\ (\mu-z)(2q-z-\mu)\le\sigma^2 \textit{ and } \mu\ge z, \\ a(\mu-z), & \text{Case e(c): } \textit{if } q\ge z \textit{ and } \mu<z \end{cases}$$

Proof 4 *Proof.* *The proof of this result is the same as Lemma 2, with slight modification. Specifically, when $a>1$, the dual solution constructed for f(c) and e(c) are not feasible anymore.*

Hence, when $a>1$, under case f(c), consider the dual solution: $t_0^{f(c)}=-q$, $t_1^{f(c)}=1$, and $t_2^{f(c)}=0$. This solution is dual feasible since $g_1(\cdot;t^{f(c)})$ is a linear function that touches $g_2(\cdot)$ for all $h>z$. The objective value is $\mu-q$. This proves f(c)

When $a>1$, under case e(c), consider the dual solution: $t_0^{e(c)}=-az$, $t_1^{e(c)}=a$, and $t_2^{e(c)}=0$. This solution is dual feasible since $g_1(\cdot;t^{e(c)})$ is a linear function that touches $g_2(\cdot)$ for all $h\le z$. The objective value is $a(\mu-z)$. This proves e(c). ■

Proof of Lemma 4, Lemma 5

We next present two lemmas that state the closed-form expression of $J(\mathbf{x}):=\inf_{p\in\mathcal{P}}\mathbb{E}_p\left[L^y(Hx_e,x_f)+M^y(Hx_e,x_f)\right]$. These lemmas are straightforward applications of Lemmas 2 and 3. The proofs follow the statement of the lemmas.

Lemma 4 *If $d'_f < \beta+\gamma$, and let $h_0(\mathbf{x}) := (\lambda - \theta x_f)/x_e$, $h_f(\mathbf{x}) := \alpha x_f/x_e$ and $\zeta := \frac{(\beta+\gamma)h_0 - d'_f h_f}{\beta+\gamma-d'_f}$, then*

1. *Case $f(a)$: If $h_0 \le h_f$ and $\sigma^2 \le (h_f-\mu)(h_f+\mu-2h_0)$, $J(\mathbf{x}) = w\lambda + \frac{(\gamma-\beta)h_0 x_e}{2} + \mu x_e\left(d_e - d'_f + \frac{\beta-\gamma}{2}\right) + (d_f+\alpha d'_f)x_f - \frac{(\beta+\gamma)x_e\sqrt{(\mu-h_0)^2+\sigma^2}}{2}$*
2. *Case $f(b)$: If $h_0 \le h_f$ and $(h_f-\mu)(h_f+\mu-2h_0) \le \sigma^2 \le (h_f-\mu)(h_f+\mu-2\zeta)$, $J(\mathbf{x}) = w\lambda + \frac{(h_f-\mu)^2(x_e(\beta+\gamma)(h_f-h_0))}{(\sigma^2+(h_f-\mu)^2)} + \mu x_e(d_e - d'_f + \beta) + \gamma h_0 x_e - (\beta+\gamma)h_f x_e + (d_f+\alpha d'_f)x_f$.*
3. *Case $f(c)$: If $h_0 \le h_f$ and $\sigma^2 > (h_f-\mu)(h_f+\mu-2\zeta)$, $J(\mathbf{x}) = w\lambda + \frac{1}{2}(d'_f h_f - (\beta-\gamma)h_0))x_e + \frac{\mu(\beta+2d_e-d'_f-\gamma)x_e}{2} - \frac{(\beta+\gamma-d'_f)x_e\sqrt{(\zeta-\mu)^2+\sigma^2}}{2} + d_f x_f$*
4. *Case $e(a)$: If $h_0 > h_f$ and $\sigma^2 < (\mu-h_f)(2h_0-h_f-\mu)$, $J(\mathbf{x}) = w\lambda + \frac{(\gamma-\beta)x_e h_0}{2} + \mu x_e(d_e + \frac{\beta-\gamma}{2}) - \frac{(\beta+\gamma)x_e\sqrt{(\mu-h_0)^2+\sigma^2}}{2} + d_f x_f$*
5. *Case $e(b)$: If $h_0 > h_f$ and $(h_f-\mu)(h_f+\mu-2h_0) \le \sigma^2 \le (h_f-\mu)(h_f+\mu-2\zeta)$, $J(\mathbf{x}) = w\lambda + \frac{(\mu-h_f)^2(x_e(\beta+\gamma)(h_0-h_f))}{\sigma^2+(\mu-h_f)^2} + \mu x_e(d_e-\gamma) - \beta h_0 x_e + (\beta+\gamma)h_f x_e + d_f x_f$*
6. *Case $e(c)$: If $h_0 > h_f$ and $\sigma^2 > (h_f-\mu)(h_f+\mu-2\zeta)$, $J(\mathbf{x}) = w\lambda + \frac{1}{2}(d'_f h_f - (\beta-\gamma)h_0)x_e + \frac{\mu(\beta+2d_e-d'_f-\gamma)x_e}{2} - \frac{x_e(\beta+\gamma-d'_f)\sqrt{(\zeta-\mu)^2+\sigma^2}}{2} + d_f x_f$*

Lemma 5 *If $d'_f \ge \beta+\gamma$, and let $h_0(\mathbf{x}) := (\lambda - \theta x_f)/x_e$, $h_f(\mathbf{x}) := \alpha x_f/x_e$ and $\zeta := \frac{(\beta+\gamma)h_0 - d'_f h_f}{\beta+\gamma-d'_f}$, then*

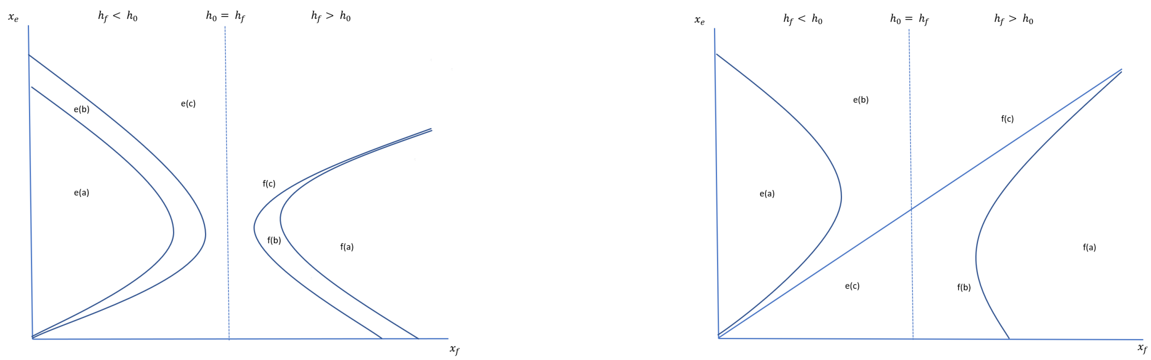
1. *Case $f(a)$: If $h_0 \le h_f$, $\sigma^2 \le (h_f-\mu)(h_f+\mu-2h_0)$, and $\mu < h_f$, $J(\mathbf{x}) = w\lambda + \frac{(\gamma-\beta)h_0 x_e}{2} + \mu x_e\left(d_e - d'_f + \frac{\beta-\gamma}{2}\right) + (d_f+\alpha d'_f)x_f - \frac{(\beta+\gamma)x_e\sqrt{(\mu-h_0)^2+\sigma^2}}{2}$*
2. *Case $f(b)$: If $h_0 \le h_f$, $\sigma^2 \ge (h_f-\mu)(h_f+\mu-2h_0)$, and $\mu < h_f$,*
   $J(\mathbf{x}) = w\lambda + \frac{(h_f-\mu)^2(x_e(\beta+\gamma)(h_f-h_0))}{(\sigma^2+(h_f-\mu)^2)} + \mu x_e(d_e - d'_f + \beta) + \gamma h_0 x_e - (\beta+\gamma)h_f x_e + (d_f+\alpha d'_f)x_f$.
3. *Case $f(c)$: If $h_0 \le h_f$ and $\mu > h_f$, $J(\mathbf{x}) = w\lambda + h_0 x_e\gamma + \mu(d_e-\gamma)x_e + d_f x_f$*
4. *Case $e(a)$: If $h_0 > h_f$, $\sigma^2 < (\mu-h_f)(2h_0-h_f-\mu)$ and $\mu < h_f$, $J(\mathbf{x}) = w\lambda + \frac{(\gamma-\beta)x_e h_0}{2} + \mu x_e(d_e + \frac{\beta-\gamma}{2}) - \frac{(\beta+\gamma)x_e\sqrt{(\mu-h_0)^2+\sigma^2}}{2} + d_f x_f$*
5. *Case $e(b)$: If $h_0 > h_f$, $\sigma^2 \ge (h_f-\mu)(h_f+\mu-2h_0)$, and $\mu < h_f$,*
   $J(\mathbf{x}) = w\lambda + \frac{(\mu-h_f)^2(x_e(\beta+\gamma)(h_0-h_f))}{\sigma^2+(\mu-h_f)^2} + \mu x_e(d_e-\gamma) - \beta h_0 x_e + (\beta+\gamma)h_f x_e + d_f x_f$
6. *Case $e(c)$: If $h_0 > h_f$ and $\mu > h_f$, $J(\mathbf{x}) = w\lambda + h_0 x_e\gamma + \mu(d_e-\gamma)x_e + d_f x_f$*

We next prove the lemmas.

Proof 5 *Proof of Lemma 4 and Lemma 5.*

Let $a = \frac{d'_f}{\beta+\gamma}$. Hence, we have

$$\begin{aligned}
J(\mathbf{x}) &= \inf_{p\in\mathcal{P}} \mathbb{E}_p\left[L^y(Hx_e, x_f) + M^y(Hx_e, x_f)\right] \\
&= (w-\beta)\lambda + (d_e+\beta)\mu x_e + (d_f+\beta\theta)x_f \\
&\qquad - (\beta+\gamma)x_e \cdot \sup_{p\in\mathcal{P}} \mathbb{E}_p\left[\left(H - \frac{\lambda-\theta x_f}{x_e}\right)^+ - \frac{d'_f}{\beta+\gamma}\left(\frac{\alpha x_f}{x_e} - H\right)^+\right] \\
&= (w-\beta)\lambda + (d_e+\beta)\mu x_e + (d_f+\beta\theta)x_f - (\beta+\gamma)x_e \cdot \sup_{p\in\mathcal{P}} \mathbb{E}_p\left[(H-h_0)^+ - a(h_f-H)^+\right].
\end{aligned} \tag{B.9}$$



(a) Subregions of $\mathcal{X}$ when $d'_f < \beta + \gamma$

(b) Subregions of $\mathcal{X}$ when $d'_f \geq \beta + \gamma$

Figure B.2: Subregions of $\mathcal{X}$

Lemmas 2 and 3 provide closed-form expressions of $\sup_{p\in\mathcal{P}} \mathbb{E}_p\left[(H-q)^+ - a(z-H)^+\right]$ *for when* $a \in [0,1]$ *and* $a > 1$*, respectively, where we set* $q = h_0$ *and* $z = h_f$*. This completes the proof of Lemma 4 and Lemma 5.* ■

Proof of Theorem 2 and Theorem 3

Proof 6 *Proof.*

Given the closed-form expression for $J(\mathbf{x})$*, we will solve* (DRVM-J) *which minimizes* $J(\mathbf{x})$ *over the feasible region* $\mathcal{X}$*. Since* $x_{f,\ell} = 0$ *and* $x_{f,u} \geq \lambda/\theta$*, the constraint* $x_f \in [x_{f,\ell}, x_{f,u}]$ *in* $\mathcal{X}$ *is redundant. From Lemma 4 and Lemma 5, we have six cases in total for the closed-form of* $J(\mathbf{x})$*. We define the following regions of* $\mathcal{X}$*:*

$$X_f := \left\{\mathbf{x} = (x_e, x_f) \in \mathbb{R}\times\mathbb{R} \ : \ x_f, x_e \geq 0, \ \ h_0 := \frac{\lambda - \theta x_f}{x_e} \leq h_f := \frac{\alpha x_f}{x_e}\right\}$$

$$X_e := \left\{\mathbf{x} = (x_e, x_f) \in \mathbb{R}\times\mathbb{R} \ : \ x_f, x_e \geq 0, \ \ h_0 := \frac{\lambda - \theta x_f}{x_e} > h_f := \frac{\alpha x_f}{x_e}\right\}$$

These regions are illustrated in Figure B.2 and labeled as 'e' and 'f'. Note that the regions X_e *and* X_f *each are polyhedra, since they are defined by linear constraints. If* $\mathbf{x} \in X_f$ *(*$\mathbf{x} \in X_e$*), then the closed-form expression of* $J(\mathbf{x})$ *corresponds to cases f(a)-f(c) (cases e(a)-e(c)). Figure B.2a shows the subregions for the cases f(a)-f(c) and e(a)-e(c) when* $d'_f < \beta + \gamma$ *(see Lemma 4). Figure B.2b shows those subregions for when* $d'_f \geq \beta + \gamma$ *(see Lemma 5).*

Given a subregion label ℓ*, we will use* J_ℓ *to refer to its closed form expression. For example, if* $\mathbf{x} \in X_{e(a)}$*, then* $J(\mathbf{x}) = J_{e(a)}(\mathbf{x})$ *where* $J_{e(a)}(\mathbf{x}) := w\lambda + \frac{(\gamma-\beta)x_e h_0}{2} + \mu x_e\left(d_e + \frac{\beta-\gamma}{2}\right) - \frac{(\beta+\gamma)x_e\sqrt{(\mu-h_0)^2+\sigma^2}}{2} + d_f x_f$*. We similarly define functions* $J_{e(i)}$ *and* $J_{f(i)}$ *for* $i \in \{a,b,c\}$*. Our goal is to find global maximizer of* $J(\mathbf{x})$ *among all the subregions of* $\mathcal{X}$*. Hence, to solve the maximization problem* (DRVM-J)*, we should analyze the maximum of* $J_e(\cdot)$ *and* $J_f(\cdot)$*, in all subregions of* X_e *and* X_f*, respectively. We solve the problem in two steps. In the first step, we will show that maximizing* $J(\mathbf{x})$ *over each subregion attains a solution that is at the boundary of the subregion. In the second step, we will compare the values of* J *on the boundary of each subregion, in order to derive the global optimal solution.*

Step 1: *We will prove that the local maximizer of J within each subregion of X_e and X_f is at the boundary of the subregion. These boundaries are illustrated in Figure B.2. We use the notation $bd(X)$ to refer to the boundary of a region X.*

Subregion $X_{e(a)}$. From Lemma 5 case (a), we can check that $J_{e(a)}(\mathbf{x}) = L_a(\mathbf{x}) + \mu x_e d_e + d_f x_f$ is jointly concave in $\mathbf{x}$ since the Hessian of L_a is negative semi-definite. Further, we can check that $\nabla J_{e(a)}(\mathbf{x}) = 0$ does not have a solution. This implies that the optimal solution to $\max_{\mathbf{x}\in X_{e(a)}} J(\mathbf{x})$ must lie on the boundary $bd\left(X_{e(a)}\right)$.

Subregion $X_{f(a)}$. From Lemma 4 case (a), we can check that $J_{f(a)}(\mathbf{x}) = L_a(\mathbf{x}) + \mu x_e(d_e - d'_f) + (\alpha d'_f + d_f)x_f$ is jointly concave in $\mathbf{x}$ since the Hessian of L_a is negative semi-definite. Further, we can check that $\nabla J_{f(a)}(\mathbf{x}) = 0$ does not have a solution. This implies that the optimal solution to problem $\max_{\mathbf{x}\in X_{f(a)}} J(\mathbf{x})$ must lie on the boundary $bd(X_{f(a)})$.

Subregion $X_{e(b)}$. Next, we show that $J_{e(b)}$ is neither concave nor convex and the solution to $\nabla J_{e(b)}(\mathbf{x}) = 0$ is a saddle point. We only need to show that the determinant of the Hessian matrix is negative. Taking the second-order partial derivatives, we have:

$$
\begin{aligned}
\frac{\partial^2 J_{e(b)}}{\partial x_e^2} &= \frac{2x_f\alpha(\beta+\gamma)(x_f(\alpha+\theta)-\lambda)\sigma^2(x_f^3\alpha^3 - 3x_e^2x_f\alpha(\mu^2+\sigma^2) + 2x_e^3\mu(\mu^2+\sigma^2))}{(x_e^2\sigma^2 + (x_f\alpha - x_e\mu)^2)^3}\\
\frac{\partial^2 J_{e(b)}}{\partial x_f^2} &= \frac{2x_e^2\alpha(\beta+\gamma)\sigma^2}{(x_e^2\sigma^2 + (x_f\alpha - x_e\mu)^2)^3}\cdot\big[(x_f\alpha - x_e\mu)^2(x_f\alpha(\alpha+\theta) - 3\alpha\lambda + 2x_e(\alpha+\theta)\mu)\\
&\qquad + x_e^2(-3x_f\alpha(\alpha+\theta) + \alpha\lambda + 2x_e(\alpha+\theta)\mu)\sigma^2\big]\\
\frac{\partial^2 J_{e(b)}}{\partial x_f\partial x_e} &= \frac{2x_e\alpha(\beta+\gamma)\sigma^2}{((x_f\alpha - x_e\mu)^2 + x_e^2\sigma^2)^3}\cdot\big[-(x_f\alpha - x_e\mu)^2(x_f\alpha(x_f(\alpha+\theta) - 2\lambda) + x_e(2x_f(\alpha+\theta) - \lambda)\mu)\\
&\qquad + x_e^2(x_f\alpha(3x_f(\alpha+\theta) - 2\lambda) + x_e(-2x_f(\alpha+\theta) + \lambda)\mu)\sigma^2\big]
\end{aligned}
$$

Therefore, we can compute the Hessian of $J_{e(b)}$. Its determinant is negative since

$$\det\left(H_{J_{e(b)}}\right) = -\frac{4x_e^2\alpha^2(\beta+\gamma)^2\lambda^2(x_f\alpha - x_e\mu)^2\sigma^4}{(x_e^2\sigma^2 + (x_f\alpha - x_e\mu)^2)^4} < 0$$

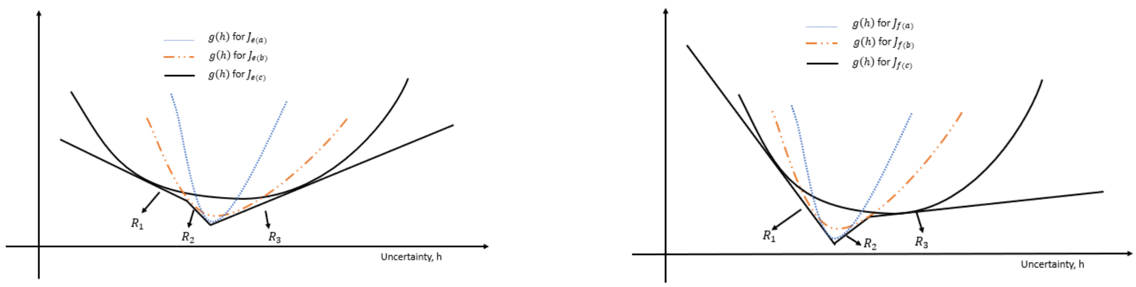
. Therefore, the solution of $\max_{\mathbf{x}\in X_{e(b)}} J(\mathbf{x})$ is at the boundary $bd\left(X_{e(b)}\right)$.

Subregion $X_{f(b)}$. Next, we show that $J_{f(b)}$ is neither concave nor convex and the solution to $\nabla J_{f(b)}(\mathbf{x}) = 0$ is a saddle point. We only need to show that the determinant of the Hessian matrix is negative. Taking the second-order partial derivatives, we have:

$$
\begin{aligned}
\frac{\partial^2 J_{f(b)}}{\partial x_e^2} &= -\frac{2x_f\alpha(\beta+\gamma)(x_f(\alpha+\theta)-\lambda)\sigma^2(x_f^3\alpha^3 - 3x_e^2x_f\alpha(\mu^2+\sigma^2) + 2x_e^3\mu(\mu^2+\sigma^2))}{(x_e^2\sigma^2 + (x_f\alpha - x_e\mu)^2}\\
\frac{\partial^2 J_{f(b)}}{\partial x_f^2} &= -\frac{2x_e^2\alpha(\beta+\gamma)\sigma^2}{(x_e^2\sigma^2 + (x_f\alpha - x_e\mu)^2 + x_e^2\sigma^2)^3}\cdot\big[(x_f\alpha - x_e\mu)^2(x_f\alpha(\alpha+\theta) - 3\alpha\lambda + 2x_e(\alpha+\theta)\mu)\\
&\qquad + x_e^2(-3x_f\alpha(\alpha+\theta) + \alpha\lambda + 2x_e(\alpha+\theta)\mu)\sigma^2\big]\\
\frac{\partial^2 J_{f(b)}}{\partial x_f\partial x_e} &= \frac{2x_e\alpha(\beta+\gamma)\sigma^2}{((x_f\alpha - x_e\mu)^2)^3}\cdot\big[(x_f\alpha - x_e\mu)^2(x_f\alpha(x_f(\alpha+\theta) - 2\lambda) + x_e(2x_f(\alpha+\theta) - \lambda)\mu)\\
&\qquad + x_e^2(x_f\alpha(-3x_f(\alpha+\theta) + 2\lambda) + x_e(2x_f(\alpha+\theta) - \lambda)\mu)\sigma^2\big]
\end{aligned}
$$

Therefore, we can compute the Hessian of $J_{f(b)}$. Its determinant is negative since

$$\det\left(H_{J_{f(b)}}\right) = -\frac{4x_e^2\alpha^2(\beta+\gamma)^2\lambda^2(x_f\alpha - x_e\mu)^2\sigma^4}{(x_e^2\sigma^2 + (x_f\alpha - x_e\mu)^2)^4} < 0.$$



(a) Cases for $J_{e(a)}$, $J_{e(b)}$, $J_{e(c)}$

(b) Cases for $J_{f(a)}$, $J_{f(b)}$, $J_{f(c)}$

Figure B.3: Cases for Inner Solutions

Therefore, the solution of $\max_{\mathbf{x}\in X_{f(b)}} J(\mathbf{x})$ *is at the boundary* $bd(X_{f(b)})$*.*

Subregions $X_{e(c)} \cup X_{f(c)}$ *From cases (c) of Lemmas 4 and 5, we can check that* $J_{e(c)} = J_{f(c)}$ *when* $d'_f < \beta + \gamma$*. Also,* $J_{e(c)}$ *is jointly concave in* $\mathbf{x}$*, which can be checked from the second-order partial derivatives:*

$$\frac{\partial^2 J_{e(c)}}{\partial x_e^2} = -\frac{(\beta+\gamma-d'_f)(d'_f x_f \alpha + (\beta+\gamma)(\theta x_f - \lambda))^2\sigma^2}{2\sqrt{\sigma^2+(\zeta-\mu)^2}(x_e(d'_f(x_f\alpha - x_e\mu) + (\beta+\gamma)(x_f\theta - \lambda + x_e\mu))^2 + x_e^3(\beta+\gamma-d'_f)^2\sigma^2)} < 0$$

$$\frac{\partial^2 J_{e(c)}}{\partial x_f^2} = -\frac{x_e(\beta+\gamma-d'_f)(d'_f\alpha + (\beta+\gamma)\theta)^2\sigma^2}{2\sqrt{\sigma^2+(\zeta-\mu)^2}((d'_f(x_f\alpha - x_e\mu) + (\beta+\gamma)(\theta x_f - \lambda + x_e\mu))^2 + x_e^2(\beta+\gamma-d'_f)^2\sigma^2)} < 0$$

$$\frac{\partial^2 J_{e(c)}}{\partial x_e \partial x_f} = \frac{(\beta+\gamma-d'_f)(d_f\alpha + (\beta+\gamma)\theta)(d'_f x_f\alpha + (\beta+\gamma)(x_f\theta - \lambda))\sigma^2}{2\sqrt{\sigma^2+(\zeta-\mu)^2}((d'_f(x_f\alpha - x_e\mu) + (\beta+\gamma)(\theta x_f - \lambda + x_e\mu))^2 + x_e^2(\beta+\gamma-d'_f)^2\sigma^2)}.$$

Since a solution to $\nabla J_{e(c))}(\mathbf{x}) = 0$ *does not exist, then this means that the optimal solution to* $\max_{\mathbf{x}\in X_{e(c))}\cup X_{f(c)}} J(\mathbf{x})$ *lies in the boundary* $bd(X_{e(c)} \cup X_{f(c)})$*. Alternatively, when* $d'_f > \beta + \gamma$*, both* $J_{e(c)}$ *and* $J_{f(c)}$ *are linear in* x_e *and* x_f *and therefore the optimal solution must be at the boundary of* $bd(X_{e(c)} \cup X_{f(c)})$*. In conclusion, in all the 6 subregions in* X_e *and* X_f*, the local optimizer of* $J(\mathbf{x})$ *is at a boundary of the subregion.*

Step 2: *Next, we analyze the value of* $J(\mathbf{x})$ *on the candidate optimal solutions identified in Step 1. Note that these candidate solutions are the boundaries of the subregions in* X_e *and* X_f *in Figure B.2. In this step, we further eliminate boundaries as candidate solutions.*

Boundary lines $bd(X_{f(a)}) \cap bd(X_{f(b)})$ *and* $bd(X_{e(a)}) \cap bd(X_{e(b)})$*. We can use contradiction to show that global optimal solution cannot exist on the boundary lines between regions* $X_{f(a)}$ *and* $X_{f(b)}$ *and between regions* $X_{e(a)}$ *and* $X_{e(b)}$*.*

Suppose that the global optimal solution is on the boundary lines between regions $X_{e(a)}$ *and* $X_{e(b)}$ *and let us denote the point as* $\mathbf{X}^*$*. Since* $\mathbf{X}^*$ *is the global optimal solution,* $J(\mathbf{X}^*) > J(\mathbf{x})$ *for* $x \in bd(X_{e(a)}) \cap bd(X_{e(b)})$*. Moreover, since* $\nabla J_{e(a)}(\mathbf{x}) = 0$ *does not have a solution,* $J_{e(a)}$ *must be continuously increasing and there must exist a point in* $bd(X_{e(b)})$ *(denoted as* $\mathbf{X}^+$*) such that* $J_{e(a)}(\mathbf{X}^+) > J(\mathbf{X}^*)$*. Moreover, since* $\mathbf{X}^*$ *is the global optimal solution, we must have* $J(\mathbf{X}^*) > J_{e(b)}(\mathbf{X}^+)$*. By transitive property of inequality, we must have* $J_{e(a)}(\mathbf{X}^+) > J_{e(b)}(\mathbf{X}^+)$*. However, we can use the dual problem to show that* $J_{e(b)}(\mathbf{X}^+) > J_{e(a)}(\mathbf{X}^+)$ *and thus contradict the conclusion.*

Note that both $J_{e(a)}$ *and* $J_{e(b)}$ *have the same moment problem* (B.7)*. The difference is the touch points of the quadratic function* g_1 *on the piece-wise linear constraint* g_2 *(which* *is also the primal distribution point). These two cases are illustrated in figure B.3 as case $J_{e(a)}$ and $J_{e(b)}$. Moreover, we denote the three piece-wise linear constraints as R_1, R_2, and R_3. In $J_{e(a)}$, the two touch points are within interior range of R_2 and R_3, while in $J_{e(b)}$, one touch point is equal to z and the other one is in the interior range of R_3. This means that in $J_{e(a)}$, the constraints include (1) $g_1 > R_2$ for all $h \in H$, (2) $g_1 > R_3$ for all $h \in H$, and (3) $g_1 > R_1$ for $h < h_f$. Meanwhile, in $J_{e(b)}$, the constraints include (1) $g_1 > R_2$ for $h \in (h_f, h_0)$, (2) $g_1 > R_3$ for all $h \in H$, and (3) $g_1 > R_1$ for $h < h_f$. Since the only difference between $J_{e(a)}$ and $J_{e(b)}$ is that $J_{e(b)}$ has less constraints than $J_{e(a)}$, we have $J_{e(b)}(x) > J_{e(a)}(x)$ for all $x \in bd(X_{e(b)})$. Therefore, we must have $J_{e(b)}(\mathbf{X}^+) > J_{e(a)}(\mathbf{X}^+)$ and this contradicts the previous conclusion. Therefore, the global optimal solution cannot exist on the boundary lines regions $X_{e(a)}$ and $X_{e(b)}$.*

Similarly, we can eliminate any points on the boundary curve between regions $X_{f(a)}$ and $X_{f(b)}$.

Boundary curves $bd(X_{e(b)}) \cap bd(X_{e(c)})$ and $bd(X_{f(b)}) \cap bd(X_{f(c)})$. We can use contradiction to show that global optimal solution cannot exist on the boundary lines between regions $X_{f(b)}$ and $X_{f(c)}$ and between regions $X_{e(b)}$ and $X_{e(c)}$.

Suppose that the global optimal solution is on the boundary lines between regions $X_{e(b)}$ and $X_{e(c)}$ and let us denote the point as $\mathbf{X}^*$. Since $\mathbf{X}^*$ is the global optimal solution, $J(\mathbf{X}^*) > J(\mathbf{x})$ for $x \in bd(X_{e(b)}) \cap bd(X_{e(c)})$. Moreover, since $\nabla J_{e(c)}(\mathbf{x}) = 0$ does not have a solution, $J_{e(c)}$ must be continuously increasing and there must exist a point in $bd(X_{e(b)})$ (denoted as $\mathbf{X}^+$) such that $J_{e(c)}(\mathbf{X}^+) > J(\mathbf{X}^*)$. Moreover, since $\mathbf{X}^*$ is the global optimal solution, we must have $J(\mathbf{X}^*) > J_{e(b)}(\mathbf{X}^+)$ and hence $J_{e(c)}(\mathbf{X}^+) > J_{e(b)}(\mathbf{X}^+)$. Next, we use the dual problem to show that $J_{e(b)}(\mathbf{X}^+) > J_{e(c)}(\mathbf{X}^+)$ and this contradicts the conclusion.

Note that both $J_{e(c)}$ and $J_{e(b)}$ have the same moment problem (B.7). *The difference is the touch points of the quadratic function g_1 on the piece-wise linear constraint g_2 (which is also the primal distribution point). These two cases are illustrated in figure B.3 as case $J_{e(a)}$ and $J_{e(b)}$. Moreover, we denote the three piece-wise linear constraints as R_1, R_2, and R_3. In $J_{e(c)}$, two touch points are within interior range of R_1 and R_3, while in $J_{e(b)}$, one touch point is equal to z and the other one is within interior range of R_3. This means that in $J_{e(c)}$, the constraints include (1) $g_1 > R_1$ for all $h \in H$, (2) $g_1 > R_2$ for $h \in (h_f, h_0)$, and (3) $g_1 > R_3$ for all $h \in H$. Meanwhile, in $J_{e(b)}$, the constraints include (1)$g_1 > R_1$ for $h < h_f$, (2) $g_1 > R_2$ for $h \in (h_f, h_0)$, and (3) $g_1 > R_3$ for all $h \in H$. Since the only difference between $J_{e(c)}$ and $J_{e(b)}$ is that $J_{e(b)}$ has less constraints than $J_{e(c)}$, we have $J_{e(b)}(x) > J_{e(c)}(x)$ for all $x \in bd(X_{e(b)})$. Therefore, we must have $J_{e(b)}(\mathbf{X}^+) > J_{e(c)}(\mathbf{X}^+)$ and this contradicts the previous conclusion. Therefore, the global optimal solution cannot exist on the boundary lines regions $X_{e(c)}$ and $X_{e(b)}$.*

Similarly, we can eliminate any points on the boundary curve between regions $X_{f(c)}$ and $X_{f(b)}$. It is worth mentioning that these two curves do not have a closed-form solution and cannot be ruled out with standard analysis.

***Step 3:** After the previous steps, we know that the global maximum solution can only exists on the linear constraints $x_f = 0$, $x_f = x_{f,u}$, $x_e = 0$, and $x_e = x_{e,u}$. We next analyze the objective function on those lines. Table B.1 and Table B.2 include all the possible solutions given different conditions.*

- *Line $x_f = 0$: On this line, the objective function is equivalent to*

  $J_1(x_e) := w\lambda + \frac{(\gamma-\beta)\lambda}{2} + \mu x_e(d_e + \frac{\beta-\gamma}{2}) - \frac{(\beta+\gamma)\sqrt{(x_e\mu-\lambda)^2+x_e^2\sigma^2}}{2}$. *We analyze the maximizer of this function:*

Table B.1: When $d'_f < \beta + \gamma$

	$d_f < \theta\gamma - \alpha d'_f$	$\theta\gamma - \alpha d'_f \le d_f \le \theta\gamma$	$d_f > \theta\gamma$
$d_e < \frac{\left((\gamma-\beta)+\frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)}{2}$	$(x^*_{e,1}, 0)$ or $(0, \frac{\lambda}{\theta})$	$(0, x_{f,u})$	
$d_e > \frac{\left((\gamma-\beta)+\frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)}{2}$	$(x_{e,u}, x_{f,4a})$ or $(0, \frac{\lambda}{\theta})$	$(x_{e,u}, x_{f,4a})$ or $(0, x_{f,u})$	$(x_{e,u}, x_{f,u})$ or $(0, x_{f,u})$

Table B.2: When $d'_f > \beta + \gamma$

	$d_f < \theta\gamma - \alpha d'_f$	$\theta\gamma - \alpha d'_f \le d_f \le \theta\gamma$	$d_f > \theta\gamma$
$d_e < \gamma$	$(x^*_{e,1}, 0)$ or $(0, \frac{\lambda}{\theta})$	$(0, x_{f,u})$	
$\gamma < d_e < \frac{\left((\gamma-\beta)+\frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)}{2}$		$(0, x_{f,u})$	$(x_{e,u}, x_{f,u})$ or $(0, x_{f,u})$
$d_e > \frac{\left((\gamma-\beta)+\frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)}{2}$	$(x_{e,u}, 0)$ or $(x_{e,u}, \frac{\lambda}{\alpha+\theta})$ or $(0, \frac{\lambda}{\theta})$	$(x_{e,u}, 0)$ or $(x_{e,u}, \frac{\lambda}{\alpha+\theta})$ or $(0, x_{f,u})$	

1. *If $d_e > \frac{1}{2}\left(\gamma - \beta + (\beta+\gamma)\sqrt{\mu^2+\sigma^2}/\mu\right)$, then J_1 is increasing in x_e. So the objective is maximized at $x_e = x_{e,u}$. The function value is $J_1(x_{e,u})$.*
2. *Otherwise, J_1 is maximized at the point $x^*_{e,1} := \frac{\mu\lambda(\sigma(\beta-\gamma+2d_e)+\sqrt{\Delta_e})}{\sqrt{\Delta_e}(\sigma^2+\mu^2)}$ where $\Delta_e = (\beta+\gamma)^2\sigma^2 + 4\mu^2(\beta+d_e)(\gamma-d_e)$. The function value is $J_1(x^*_{e,1})$*

- *Line $x_e = 0$: On this line, the objective function is equal to $J_2(x_f) := w\lambda - \gamma(\theta x_f - \lambda)^+ - \beta(\lambda - \theta x_f)^+ + (d'_f\alpha + d_f)x_f$. We analyze the maximizer of this function:*

  1. *If $d_f + \alpha d'_f > \theta\gamma$, then J_2 is increasing, so it is maximized at $x_f = x_{f,u}$. The function value is $J_2(x_{f,u})$.*
  2. *Otherwise, the maximum value is attained at $x_f = \lambda/\theta$. The function value is $J_2(\lambda/\theta)$.*

- *Line $x_f = x_{f,u}$: On this line, if $d'_f < \beta + \gamma$, then the objective function is equivalent to*

$$J_{3a}(x_e) := \begin{cases} w\lambda + \frac{1}{2}(\alpha d'_f x_{f,u} - (\beta-\gamma)(\lambda - \theta x_{f,u})) + \frac{\mu(\beta + 2d_e - d'_f - \gamma)x_e}{2} + d_f x_{f,u} \\ -\frac{1}{2}(\beta+\gamma-d'_f)\sqrt{\left(\frac{(\beta+\gamma)(\lambda-\theta x_{f,u}) - d'_f\alpha x_{f,u}}{\beta+\gamma-d'_f} - x_e\mu\right)^2 + x_e^2\sigma^2}, & \textit{if } x_e \in X_{f(c)} \\ w\lambda + \frac{(\gamma-\beta)(\lambda-\theta x_f)}{2} + \mu x_e\left(d_e - d'_f + \frac{\beta-\gamma}{2}\right) + (d_f + \alpha d'_f)x_{f,u} \\ -\frac{(\beta+\gamma)\sqrt{(x_e\mu - \lambda + \theta x_{f,u})^2 + x_e^2\sigma^2}}{2}, & \textit{if } x_e \in X_{f(a)} \\ w\lambda + \frac{(\alpha x_{f,u} - \mu x_e)^2((\beta+\gamma)((\alpha+\theta)x_{f,u} - \lambda))}{(x_e^2\sigma^2 + (\alpha x_{f,u} - \mu x_e)^2)} + \mu x_e(d_e - d'_f + \beta) + \gamma(\lambda - \theta x_{f,u}) \\ -(\beta+\gamma)\alpha x_{f,u} + (d_f + \alpha d'_f)x_{f,u}, & \textit{if } x_e \in X_{f(b)} \end{cases}$$

And if $d'_f \geq \beta + \gamma$,

$$J_{3b}(x_e) := \begin{cases} w\lambda + (\lambda - \theta x_{f,u})\gamma + \mu(d_e - \gamma)x_e + d_f x_{f,u}, & \text{if } x_e \in X_{f(c)} \\ w\lambda + \dfrac{(\gamma-\beta)(\lambda - \theta x_f)}{2} + \mu x_e \left(d_e - d'_f + \dfrac{\beta-\gamma}{2}\right) + (d_f + \alpha d'_f)x_{f,u} & \\ -\dfrac{(\beta+\gamma)\sqrt{(x_e\mu - \lambda + \theta x_{f,u})^2 + x_e^2\sigma^2}}{2}, & \text{if } x_e \in X_{f(a)} \\ w\lambda + \dfrac{(\alpha x_{f,u} - \mu x_e)^2((\beta+\gamma)((\alpha+\theta)x_{f,u} - \lambda))}{(x_e^2\sigma^2 + (\alpha x_{f,u} - \mu x_e)^2)} + \mu x_e(d_e - d'_f + \beta) + \gamma(\lambda - \theta x_{f,u}) & \\ -(\beta+\gamma)\alpha x_{f,u} + (d_f + \alpha d'_f)x_{f,u}, & \text{if } x_e \in X_{f(b)} \end{cases}$$

Recall that we have concluded that the optimal solution cannot exist in the region of $X \in X_{f(b)}$ *in Step 1 an 2. Hence, we only need to focus on* $X \in X_{f(a)} \cup X_{f(c)}$. *Moreover,* $J_{3a}(x_e)$ *is also concave in* x_e *since it is jointly concave in* (x_e, x_f). *Therefore, the optimal solution can only exist in* $x_e = 0$, $x_e = x_{e,u}$, *or the first order condition solutions* $x_{e(a),3a}, x_{e(c),3a}$.

First, let us consider the case when $d'_f < \beta + \gamma$ *so the objective is equivalent to* J_{3a}. *The solution to the first-order condition of* J_{3a} *when* $x_e \in X_{f(a)}$ *is* $x_{e(a),3a} := \frac{\mu(\lambda - \theta x_{f,u})(\sigma(\beta-\gamma+2d_e-2d'_f)+\sqrt{\Delta_{f(a)}})}{\sqrt{\Delta_{f(a)}}(\sigma^2+\mu^2)}$ *where* $\Delta_{f(a)} = (\beta+\gamma)^2\sigma^2 + 4\mu^2(\beta + d_e - d'_f)(\gamma - d_e + d'_f)$. *Since* $x_{f,u} \geq \lambda/\theta$ *(by the condition of Theorem 2 and Theorem 3), we can also check* $x_{e(a),3a} \leq 0$ *and is infeasible.*

Similarly, the solution to the first-order condition of J_{3a} *when* $x_e \in X_{f(c)}$ *is* $x_{e(c),3a} := \frac{\mu}{\mu^2+\sigma^2}\frac{(\alpha x_{f,u}d'_f+(\beta+\gamma)(x_{f,u}\theta-\lambda))}{d'_f-\beta-\gamma}\left(1 + \frac{\sigma(\beta+2d_e-d'_f-\gamma)}{\sqrt{\Delta_{f(c)}}}\right)$, *where* $\Delta_{f(c)} := (\beta+\gamma-d'_f)^2\sigma^2 + 4\mu^2(\beta + d_e - d'_f)(\gamma - d_e)$. *Since* $d'_f < \beta + \gamma$ *and* $x_{f,u} \geq \lambda/\theta$, *we can check that* $x_{e(c),3a} \leq 0$ *and is infeasible.*

Second, when $d'_f \geq \beta + \gamma$, $J_{3b}(x_e)$ *is a linear function of* x_e *when* $x_e \in X_{f(c)}$, *and increases in* x_e *if* $d_e > \gamma$. *Moreover,* $J_{3b}(x_e) = J_{3a}(x_e)$ *when* $x_e \in X_{f(a)}$. *Therefore, the optimal solution is* $x_e = 0$ *with a value* $J_{3b}(0)$, *or* $x_e = x_{e,u}$ *with a value* $J_{3b}(x_{e,u})$. *In summary, both first order condition solutions are infeasible and the function is optimized at either* $x_e = 0$, *or at* $x_e = x_{e,u}$.

- *Line* $x_e = x_{e,u}$: *On this line, if* $d'_f < \beta + \gamma$, *then the objective function is equivalent to*

$$J_{4a}(x_f) := w\lambda + \frac{1}{2}(d'_f\alpha x_f - (\beta-\gamma)(\lambda - \theta x_f)) + \frac{\mu(\beta + 2d_e - d'_f - \gamma)x_{e,u}}{2} - \frac{x_{e,u}(\beta+\gamma-d'_f)\sqrt{((\frac{(\beta+\gamma)(\lambda-\theta x_f)-d'_f\alpha x_f}{(\beta+\gamma-d'_f)x_{e,u}} - \mu)^2 + \sigma^2)}}{2} + d_f x_f$$

And if $d'_f \geq \beta + \gamma$, *the objective is equal to*

$$J_{4b}(x_f) := \begin{cases} w\lambda + \dfrac{(\mu x_{e,u} - \alpha x_f)^2((\beta+\gamma)(\lambda - (\theta+\alpha)x_f))}{\sigma^2 x_{e,u}^2 + (\mu x_{e,u} - \alpha x_f)^2} + \mu x_{e,u}(d_e - \gamma) & \\ \quad -\beta(\lambda - \theta x_f) + (\beta+\gamma)\alpha x_f + d_f x_f, & \text{if } x_f < \lambda/(\alpha+\theta) \\ w\lambda + (\lambda - \theta x_f)\gamma + \mu(d_e - \gamma)x_{e,u} + d_f x_f, & \text{otherwise} \end{cases}$$

First, consider the case when $d_f' < \beta+\gamma$. If $d_f > \theta\gamma$, the function J_{4a} is increasing in x_f. Hence, it is maximized at $x_f = x_{f,u}$. If $d_f < \theta\gamma$, the first order condition of J_{4a} is solved by $x_{f,4a} := \frac{\mu x_{e,u} d_f' + (\beta+\gamma)(\lambda - \mu x_{e,u}) + \frac{\sigma x_{e,u}(2d_f + \alpha d_f' + (\beta-\gamma)\theta)(\beta+\gamma-d_f')}{2\sqrt{(\theta\gamma - d_f)(d_f+\alpha d_f' + \beta\theta)}}}{\alpha d_f' + (\beta+\gamma)\theta}$ and the maximum objective value is $J_{4a}(x_{f,4a})$.

Second, consider the case when $d_f' \geq \beta+\gamma$. Since $x_{e,u} \geq \lambda/\mu$ (by the condition of Theorems 2 and 3), we can check that J_{4b} is a convex function in the range $[0, \lambda/(\alpha+\theta)]$, and is a linear function in the range $[\lambda/(\alpha+\theta), x_{f,u}]$. Therefore, the optimal value can only be at $x_f = 0$, $x_f = \lambda/(\alpha+\theta)$, or $x_f = x_{f,u}$. We can further evaluate the functions values: $J_{4b}(0) = w\lambda + \frac{\mu^2}{\mu^2+\sigma^2}(\beta+\gamma)\lambda + \mu x_{e,u}(d_e-\gamma) - \beta\lambda$ and $J_{4b}(\lambda/(\alpha+\theta)) = w\lambda + \mu x_{e,u}(d_e-\gamma) + \lambda\gamma + (d_f - \theta\gamma)\frac{\lambda}{\alpha+\theta}$. In summary, we have the following cases:

- *When $d_f > \theta\gamma$, $J_{4b}(x_{f,u}) > J_{4b}(\lambda/(\alpha+\theta)) > J_{4b}(0)$, and the optimal solution is $(x_{e,u}, x_{f,u})$.*
- *When $d_f < \frac{\theta\mu^2 - \alpha\sigma^2}{\mu^2+\sigma^2}\gamma - \frac{\sigma^2(\alpha+\theta)}{\mu^2+\sigma^2}\beta$, $J_{4b}(x_{f,u}) < J_{4b}(\lambda/(\alpha+\theta)) < J_{4b}(0)$ and the optimal solution is $(x_{e,u}, 0)$.*
- *when $d_f \in (\frac{\theta\mu^2 - \alpha\sigma^2}{\mu^2+\sigma^2}\gamma - \frac{\sigma^2(\alpha+\theta)}{\mu^2+\sigma^2}\beta, \theta\gamma)$, $J_{4b}(\lambda/(\alpha+\theta)) > \max(J_{4b}(x_{f,u}), J_{4b}(0))$ and the optimal solution is $(x_{e,u}, \frac{\lambda}{\theta+\alpha})$.*

Last, we compare the optimal conditions and objective values at each point to summarize the final results in Table B.1 and Table B.2.

First, when $d_f' < \beta+\gamma$, we have the following cases which are summarized in Table B.1.

- *When $d_f < \theta\gamma - \alpha d_f'$ and $d_e < (1/2)\left((\gamma-\beta) + \frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)$, there are only two possible optimal solutions: $(x_{e,1}^*, 0)$, $(0, \lambda/\theta)$. The optimal solution is $(x_{e,1}^*, 0)$ if $\nu = \frac{(\gamma-\beta)}{2} + \frac{(2d_e+\beta-\gamma)\mu^2 - \sigma\sqrt{\Delta(d_e)}}{2(\sigma^2+\mu^2)} > (d_f + \alpha d_f')/\theta$, and the optimal solution is $(0, \lambda/\theta)$ otherwise. This completes the proof for Theorem 3.*
- *when $d_f < \theta\gamma - \alpha d_f'$ and $d_e > (1/2)\left((\gamma-\beta) + \frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)$, the optimal solution is $(x_{e,u}, x_{f,4a})$ if $J_{4a}(x_{f,4a}) > (d_f + \alpha d_f')\lambda$, and the optimal solution is $(0, \lambda/\theta)$ otherwise.*
- *when $d_f > \theta\gamma - \alpha d_f'$ and $d_e < (1/2)\left((\gamma-\beta) + \frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)$, the only optimal solution is $(0, x_{f,u})$ because $J_2(x_{f,u})^* \geq \max(J_1(x_{e,1}^*), J_2(\lambda/\theta))$ always holds under this condition. First, $J_2(x_{f,u})^* \geq J_2(\lambda/\theta)$ because $d_f > \theta\gamma - \alpha d_f'$. Second, note that $J_1(x_{e,1}^*)$ is monotone increasing in d_e and reaches the maximum value when $d_e = (1/2)\left((\gamma-\beta) + \frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)$. Substituting the value into $J_1(x_{e,1}^*)$ and we have $J_1(x_{e,1}^*) = w\lambda + \frac{\lambda}{2}(\gamma - \beta + (\beta+\gamma)\frac{\mu}{\sqrt{\mu^2+\sigma^2}}) \leq w\lambda + \gamma\lambda$. Next, note that $J_2(x_{f,u}) = w\lambda + (d_f'\alpha + d_f - \gamma)x_{f,u} + \lambda\gamma \geq w\lambda + \gamma\lambda \geq J_1(x_{e,1}^*)$ when $d_f'\alpha + d_f \geq \gamma$. Therefore, when $d_f'\alpha + d_f \geq \gamma$ and $d_e < (1/2)\left((\gamma-\beta) + \frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)$, $J_2(x_{f,u})^* \geq J_1(x_{e,1}^*)$ always holds.*

- *When* $d_e > (1/2)\left((\gamma-\beta)+\frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)$ *and* $d_f > \theta\gamma - \alpha d'_f$*, the policy* $(x^*_{e,1}, 0)$ *is not feasible and the policy* $(0, \lambda/\theta)$ *always results in a lower value than* $(0, x_{f,u})$*. When* $d_f > \theta\gamma$*, there are two possible optimal policies:* $(x_{e,u}, x_{f,u})$ *or* $(0, x_{f,u})$*. The optimal solution is* $(x_{e,u}, x_{f,u})$ *if* $J_{4a}(x_{f,u}) > J_2(x_{f,u})$ *and the optimal solution is* $(0, x_{f,u})$ *otherwise. Last, when* $d_f \in (\theta\gamma - \alpha d'_f, \theta\gamma)$*, there are also two possible optimal policies:* $(x_{e,u}, x_{f,4a})$ *and* $(0, x_{f,u})$*. The optimal solution is* $(x_{e,u}, x_{f,4a})$ *if* $J_{4a}(x_{f,4a}) > J_2(x_{f,u})$ *and the optimal solution is* $(0, x_{f,u})$ *otherwise.*

Next, when $d'_f > \beta + \gamma$*, most of the cases are the same and we will only discuss the different cases below. The results are summarized in Table B.2.*

- *The first difference is that the optimal policy* $(x_{e,u}, x_{f,4a})$ *(when* $d'_f > \beta+\gamma$*) becomes* $(x_{e,u}, 0)$ *or* $(x_{e,u}, \frac{\lambda}{\alpha+\theta})$*. This is because* J_{4a} *is concave and* J_{4b} *is convex in* $x_f < \lambda/(\alpha+\theta)$*. Therefore, there are three possible optimal solutions when* $d_e > (1/2)\left((\gamma-\beta)+\frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)$ *and* $d_f < \theta\gamma - \alpha d'_f$*. Comparing the function values* $J_{4b}(0), J_{4b}(\lambda/(\alpha+\theta))$*, and* $J_2(\lambda/\theta)$ *will give the conditions for optimal results. Similarly, there are three possible optimal solutions when* $d_e > (1/2)\left((\gamma-\beta)+\frac{(\beta+\gamma)\sqrt{\mu^2+\sigma^2}}{\mu}\right)$ *and* $\theta\gamma - \alpha d'_f < d_f < \theta\gamma$*. Comparing the function values* $J_{4b}(0), J_{4b}(\lambda/(\alpha+\theta))$*, and* $J_2(x_{f,u})$ *will give the conditions for optimal results.*
- *The second difference is that optimal solution* $(x_{e,u}, x_{f,u})$ *has a larger feasible region. This is because the worst-case distribution results in a concave function* $J_{3a}(x_e)$ *when* $d'_f < \beta+\gamma$*, but* $J_{3b}(x_e)$ *is linear when* $d'_f > \beta+\gamma$*. Therefore, when* $d_f > \gamma$ *and* $d_e > \gamma$*,* $(x_{e,u}, x_{f,u})$ *is one of the optimal solutions.*

APPENDIX C

CHAPTER 3

Alternative Models for Treatment Effects

We include the alternative models for treatment effects to estimate the treatment effects. Note that our dependent variables are based on Likert Scale ratings, and hence are discreet and ranked variables. Following the instruction of Liang *et al.* (2020), we test the parallel regression assumption for the ordinal logit models (p-value for omnibus < 0.05) and find that the assumption does not hold. Therefore, we have to use multinomial logit regression as an alternative model. Nevertheless, the results should be interpreted with caution as the multinomial logit model ignored the rank relationship between different levels. In this study, a choice of 5 implies a selection of 2, 3, and 4 since we choose 1 as the default level. However, using a multinomial model cannot represent this implicit relationship. In table C.1, we show three models similar to table 3.2. Since our dependent variable has 5 levels, we chose 1 as the default level and 2-5 as alternative choices. Overall, we observe the same result as table 3.2 where social norm is an effective treatment to improve donation quality and information disclosure is not.

Table C.1: Intent-to-treat Effect of Reminder Email (Multinomial Logit Regression)

	Dependent variable (ratings, 1 as the default level):											
	2	3	4	5	2	3	4	5	2	3	4	5
Social Norm	0.794**	0.795***	1.628***	0.742**	0.573*	0.819**	1.728***	0.763**	0.590*	0.818**	1.744***	0.762**
	(0.327)	(0.304)	(0.326)	(0.346)	(0.347)	(0.320)	(0.344)	(0.355)	(0.351)	(0.326)	(0.352)	(0.361)
Information Disclosure	0.462*	0.021	0.393	−0.599*	0.283	−0.004	0.437	−0.653*	0.215	−0.043	0.367	−0.770**
	(0.274)	(0.262)	(0.301)	(0.344)	(0.295)	(0.280)	(0.319)	(0.354)	(0.298)	(0.283)	(0.325)	(0.362)
					(1.039)	(1.021)	(0.962)	(0.449)	(1.041)	(1.029)	(0.992)	(0.460)
Households Median Income									0.001	0.006	0.013***	0.015***
									(0.005)	(0.005)	(0.005)	(0.005)
Existing Donor									0.467	0.341	−0.339	0.002
									(0.654)	(0.617)	(0.750)	(0.747)
Constant	−0.078	0.334*	−0.415*	−0.307	−0.082	−0.493	0.163	−13.058***	−0.161	−0.894	−0.822	−13.715***
	(0.198)	(0.180)	(0.218)	(0.211)	(0.994)	(1.001)	(0.878)	(0.416)	(1.064)	(1.070)	(0.976)	(0.558)
Time and Rater Fixed Effect	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Akaike Inf. Crit.	2,312.110	2,312.110	2,312.110	2,312.110	2,163.909	2,163.909	2,163.909	2,163.909	2,126.321	2,126.321	2,126.321	2,126.321
Note:												*p<0.1; **p<0.05; ***p<0.01

Table C.2: Comparison between the Social Norm and Information Disclosure Groups (Multinomial Logit Regression)

	Dependent variable (ratings, 1 as the default level):											
	2	3	4	5	2	3	4	5	2	3	4	5
Social Norm	0.332	0.774**	1.235***	1.341***	0.098	0.908**	1.504***	1.296***	0.712	0.355	0.121	1.587*
	(0.322)	(0.310)	(0.319)	(0.386)	(0.387)	(0.359)	(0.368)	(0.437)	(0.603)	(0.620)	(0.678)	(0.846)
Constant	0.384**	0.355*	−0.022	−0.906***	0.348	0.308	−0.087	−0.811***	0.492	0.492	0.167	−1.299**
	(0.189)	(0.190)	(0.207)	(0.272)	(0.218)	(0.220)	(0.241)	(0.300)	(0.383)	(0.383)	(0.410)	(0.651)
Akaike Inf. Crit.	1,517.263	1,517.263	1,517.263	1,517.263	1,141.084	1,141.084	1,141.084	1,141.084	372.967	372.967	372.967	372.967
Note:												*p<0.1; **p<0.05; ***p<0.01