Excusing Selfishness in Charitable Giving:  
The Role of Risk

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Abstract

It is no surprise that people give less to a charity if they are unsure about the impact of their donation. It is less clear as to whether this reduction can be fully explained by risk preferences, or whether some other mechanism is relevant. I show the latter is the case by conducting a controlled laboratory experiment. When participants do not tradeoff their own money with the charity’s money, they respond very similarly to risk with money for themselves or the charity. However, when participants must tradeoff their own money with the charity’s money, their response to risk alters in a self-serving manner. In particular, they opt-out of giving by now treating charity risk as substantially less desirable, or treating risk as an excuse to not give.

Keywords: charitable giving; prosocial behavior; risk preferences; uncertainty

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1 Introduction

In the United States, 1 in 4 adults volunteer and 1 in 2 adults give to charities for an estimated combined value of $500 billion dollars per year.\(^1\) Since this high prevalence of giving exceeds the level suggested by a pure public goods model in a large economy, economists often turn to other models to explain this giving (Andreoni, 1988). For instance, leading models now incorporate behavioral motivations, such as the desire to improve one’s social image or to experience a “warm glow.”\(^2\) In this paper, I also seek to explain giving behavior but approach this topic from a slightly different angel by considering why do people not give?

One potential and perhaps unsurprising answer to this question is people give less when the impact or use of their donation involves risk.\(^3\) For instance, people may give less to charities with lower effectiveness or efficiency measures, as there is more risk that donations will be used ineffectively or inefficiently. People may similarly give less when they are unsure if the charity will receive their donations, or if they are unsure which programs or services will be funded by their donations. While limiting exposure to all of these kinds of risk may seem beneficial for charities, this paper suggests a more nuanced approach. In particular, the extent to and manner in which charities should limit their exposure to risk depends on the channel through which risk impacts giving.

I consider three channels through which risk impacts giving. Standard risk preferences imply reduced giving in the presence of risk because of the corresponding lower expected value, which may be compounded by risk aversion.\(^4\) Charity-specific risk preferences allow for the possibility that people feel more or less favorably about risk involving money for a charity, as opposed to money for themselves. For instance, people may receive a warm glow from giving irrespective of the impact of their giving, which then corresponds with less aversion to risk charitable in giving (Niehaus, 2013). While these channels impact how much a charity would benefit from reducing risk, the third channel - excuse driven risk preferences - suggests more nuanced policy implications. While this third channel intuitively captures the idea that people “use risk as an excuse to not give,” it also implies behavior that is inconsistent with existing models and is more precisely defined later.

To consider the relevance of these channels, I first turn to a laboratory setting that allows me to control the types of risk participants face in their charitable giving decisions. That is, I examine participants’ response to objective risk in “charity lotteries” and “self lotteries.” These lotteries involve the experimenter giving the American Red Cross or a participant, respectively, a non-zero payment with probability \(p\) and $0 with probability \(1-p\) (i.e., risk decreases in \(p\)). In this setting, I can tease apart the three channels by

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\(^2\)Among many others, papers on image motivation include Harbaugh (1998); Bénabou and Tirole (2006); Andreoni and Bernheim (2009); Ariely, Bracha and Meier (2009); Linardi and McConnell (2011); Exley (2014). Also among many other, papers on warm glow include Andreoni (1990); Null (2011).

\(^3\)For instance, people give less in a dictator game when the recipient’s outcome involves risk Brock, Lange and Ozbay (2013), or when relatively unknown charities have lower third-party ratings Yörük (2013). Or, more generally, people give less to unidentified instead of identified victims (Small and Loewenstein, 2003), to general instead of specific causes (Li et al., 2013), or via cash instead of in-kind donations (Batista, Silverman and Yang, 2013).

\(^4\)In this paper, I will use “risk aversion” loosely to encompass risk preferences, such as probability weighting.
eliciting participants' lottery valuations in two contexts.

In the no self-charity tradeoff context, participants do not make tradeoffs between money for themselves or the charity, so there is no scope for using risk as an excuse to not give. Instead, participants evaluate each charity lottery by making binary decisions between the charity lottery and various certain payments for the charity. Or, participants evaluate each self lottery by making binary decisions between the self lottery and various certain payments for themselves. Panel A of Figure 1 plots how these valuations change as the probability $p$ of the non-zero payment increases, i.e., as risk decreases. For the ease of comparison, note that the valuations for the self and charity lotteries are shown as percentages of how much participants value the self and charity lotteries with no risk, respectively. It then easily follows that participants’ response to risk in charity and self lotteries are nearly indistinguishable, so I can rule out the possibility of charity-specific risk preferences.

In the self-charity tradeoff context, by contrast, participants must make tradeoffs between money for themselves and the charity. While standard risk preferences imply that participants' lottery valuations should mirror those from the no self-charity tradeoff context, excuse driven risk preferences imply a particular divergence in how participants respond to risk. First, when participants choose between charities lotteries and self certain amounts, excuse driven risk preferences imply that they should choose self certain amounts, over charity lotteries, more often than their non-excuse driven risk preferences from the no self-charity tradeoff context would imply. Panel B of Figure 1 confirms this behavior, as participants’ charity lottery valuations now fall further below the risk neutral line. This reduction is substantial; for instance, there is a 32% reduction in response to only 5% risk in the charity lottery, which is four-times larger than the apparent risk aversion in the no self-charity tradeoff context would imply. Second, when participants choose between self lotteries and charity certain amounts, excuse driven risk preferences imply that they should choose self lotteries, over charity certain amounts, more often than their non-excuse driven risk preferences would imply. Panel B of Figure 1 also confirms this behavior, as participants elf lottery valuations now appear further above the risk neutral line. In other words, participants appear to use risk - regardless of whether it is charity risk or self risk - as an excuse to not give when choosing between money for themselves and the charity.

An alternative framing of these results is useful when considering possible policy implications. In particular, the no self-charity tradeoff context shows that conditional on giving (i.e., when deciding between charity lotteries and charity certain amounts), people are relatively tolerant of charity risk. By contrast, the self-charity tradeoff context shows that unconditional on giving (i.e., when deciding between charity lotteries and self certain amounts), people are act very averse to risk - more so than their non-excuse driven risk preferences would imply. While charities may leverage this information in several ways, such as encouraging donors to commit to giving before asking them to fund risky projects, the relevance of such policy implications depends on the generalizability of excuse driven risk preferences. I thus consider two additional applications of my results.

First, I replicate these results in a non-charity prosocial context where participants decide between
money for themselves and a fellow participant in the study, as opposed to the American Red Cross. Second, I sacrifice the benefits of having precisely defined risk in order to show that participants also use more common types of risk, involving the likelihood of a charity using its donations effectively or efficiently, as an excuse to not give. The existence of excuse driven risk preferences in this domain are particularly relevant given the increasing pressure for charities to provide information on their effectiveness and efficiency (Ebrahim and Rangan, 2010). In fact, these results suggest that people may give less to charities with lower third party quality ratings (Yörük, 2013) or in the presence of aid effectiveness information (Karlan and Wood, 2014) because they use this information as an excuse to not give.

Perhaps the most closely related strand of literature to this paper involves a well known phenomenon believed to be excuse driven - i.e., “moral wiggle room.”\(^5\) In line with Dana, Weber and Kuang (2007), moral wiggle room involves people behaving more selfishly when it is unclear as to whether or not their action is selfish, or when they can maintain some illusion of less selfish behavior. While participants in my study always know whether or not their action is selfish (as they choose between options that either benefit the charity or themselves exclusively), I find it plausible that my results are driven by a similar underlying excuse motivation. In fact, by having participants complete a separate moral wiggle room task at the end of the study, I can show a strong correlation between excuse driven risk preferences and moral wiggle room.

This paper proceeds as follows. For the objective risk study, Section 2 details the experimental design and Section 3 details the results. For the applications, Section 4 explains the design and results. Section 5 returns to the objective risk study to consider other types of excuse behavior more closely, and Section

\(^5\)Other related excuse behavior involves self serving biases and the avoiding of responsibility in papers such as Konow (2000); Haisley and Weber (2010); Hamman, Loewenstein and Weber (2010); Coffman (2011); Eil and Rao (2011); Mobius et al. (2011); Stutzer, Goette and Zehnder (2011); Bartling and Fischbacher (2012); Falk and Szech (2013).
6 concludes by discussing possible policy implications and further avenues for research.

2 Data and Design

From November 2013 - January 2014, 100 undergraduate students participated in one of five study sessions via the Stanford Economics Research Laboratory. After participants listen to instructions and correctly answer several understanding questions, they proceed to complete 30 prices lists. Each price list involves a series of binary decisions, from which one randomly selected decision is implemented for payments and added to their minimum participation fee of $20. After participants complete these price lists, they answer several follow-up questions, which include demographic questions and moral wiggle room questions described later (see Section **). Participants are then paid in cash and exit the study. All decisions in this study remain anonymous.

The main results arise from participants’ binary decisions in the price lists, which will imply valuations of charity lotteries and self lotteries for various risk levels. A “charity lottery” with probability p involves the experimenter giving the American Red Cross (ARC) a non-zero payment of $X with probability p and $0 with probability 1-p. A “self lottery” with probability p involves the experimenter giving a participant $10 with probability p and $0 with probability 1 - p. To ensure that charity lotteries are comparable to self lotteries, each participant faces an X such that they are indifferent between themselves receiving $10 and the ARC receiving $X. In other words, this study will yield valuations for:

\[P_s: \text{self lottery with probability } p\]
\[p(10, 0) + (1 - p)(0, 0)\]

\[P_c: \text{charity lottery for probability } p\]
\[p(0, X) + (1 - p)(0, 0)\]

where
\[(10, 0) \sim (0, X), \text{ and } p \in \{0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95\}.

In order to estimate X for each participant, the participants first complete a “normalization” price list. Participants are unaware that their choices in the normalization price list will determine the X they face in charity lotteries. Instead, the normalization price list just presents them with 16 binary decisions involving two options (A and B). Option A always involves the participants receiving $10 with certainty. However, as they proceed down the rows of the price list, Option B increases from the charity receiving $0, $1.50, ..., to $30 with certainty. See Appendix A.1 for a screenshot displaying the normalization price list.

From these decisions, I then estimate participant-specific Xs such that participants are indifferent between themselves receiving $10 and the charity receiving $X. For example, assume a participant switches...
from choosing Option A to Option B on the $i^{th}$ row, and that this corresponds to the charity receiving $B_i$. It then follows that $B_{i-1} \leq X \leq B_i$, and I estimate $X$ as its upper bound of $B_i$. I choose the upper bound as overestimations of $X$ will lead to an underestimation of my main results.\footnote{In particular, my main results show that participants respond more negatively to risk in charity lotteries, or their valuations of charity lotteries significantly decrease as the probability $p$ decreases. This decrease will be estimated relative to assuming participants value the charity lottery with $p=1$ at $\$10$ for themselves. If they instead value the charity lottery with $p = 1$ higher than $\$10$ for themselves, then the drop in their valuations of charity lotteries as $p$ decreases will be underestimated.}

There are two cases where $X$ cannot be accurately estimated. In the first case, a participant may have “multiple switch points.” Since Option A is fixed and Option B is increasing as you proceed down the rows, a multiple switch point occurs if a participant chooses Option B on row $i$ but does not choose a higher valued Option B on some later row $i + j$ - implying a violation of monotonicity in preferences. This only occurs with 1 participant (out of 100), so this participant is excluded from the remaining analysis. In the second case, a participant may never choose Option B, which implies $X > \$30$ but the upper bound of $X$ is unknown. This choice pattern occurs for 42 (out of 100) “censored” participants. In other words, 42% of the participants are unwilling to give up $\$10$ for themselves in order for the charity to receive $\$30$. This compares favorably to Engel (2011)’s meta study finding that 36% of dictators never give any positive amount - which normally could be as little as $\$1$ - to their recipients in dictator games. While I exclude the censored participants from the main results, I find similar results when I include the censored participants by assuming $X$ is equal to its lower bound of $\$30$.

One way to consider this exclusion is that my results are most relevant among a population interested in donating to the ARC. This explanation is bolstered by participants’ decisions in the second price list. In particular, the second price list only differs from the normalization price list by replacing the $\$10$ payment for participants in Option A with a $\$5$ payment for participants. In return, I find 69% of censored participants are also unwilling to given up $\$5$ for themselves in order for the ARC to receive $\$30$.

While excluding the censored participants likely excludes the least prosocial participants, the remaining participants are still clearly self-interested. For instance, 87% of the participants prefer $\$10$ for themselves over $\$10$ for the charity, as their estimated values of $X$, shown in Figure 2, exceed $\$10$. In fact, on average, participants are only willing to give up $\$10$ in exchange for the charity receiving a donation if said donation is greater than $\$17.30$.\footnote{3% of the participants seem oddly “too prosocial,” as they have an $X = \$5$. In this case, a seemingly dominant option would have been for them to choose $\$10$ for themselves, as this would then allow them (after the study, at least) to donate $\$5$ to the charity and still have $\$5$ remaining for themselves. It seems likely that their choices result from a desire to appear prosocial to the experiment or confusion, although it could also be that they have very high transaction costs of donating to the charity.}

After completing the first and second price lists, participants complete the remaining 28 price lists which will yield their valuations of the lotteries. In each of the “valuation” price lists, participants make 21 binary decisions between two options (A and B). In a given price list, Option A is constant across all
Each bar shows the percent of the participants with a given X value, where X is estimated for each participants such that they are indifferent between themselves receiving $10 and the charity receiving $X, or $(10, 0) \sim (0, X)$. The results include data for the 57 uncensored participants without multiple switch points in the normalization task.

rows, and always involves a charity lottery or a self lottery, which recall are as follows.

charity lottery ≡ the ARC receives $X$ with probability p, and $0$ with probability $(1-p)$

self lottery ≡ the participant receives $10$ with probability p, and $0$ with probability $(1-p)$

On the other hand, Option B always involves a charity certain amount or a self certain amount that increases as they proceed down the rows of the price list, where

charity certain amount ≡ the ARC receives $0, \frac{X}{20}, ..., to X$ with certainty

self certain amount ≡ the participant receives $0, 0.50, ..., to 10$ with certainty

Since price lists differ according to who receives money in Option A and who receives money in Option B, the price lists are presented in four blocks. Each block involves 7 price lists with the same recipients in Option A and Option B, and the price lists are presented in order of decreasing probability p, where $p \in$
{0.95, 0.90, 0.75, 0.50, 0.25, 0.10, 0.05}. The order of the four blocks is randomly determined for each participant. See Appendices A.3 - A.6 for example price lists from each block.

From participants decisions’ in the valuation price lists, I then estimate their lottery valuations in two different contexts. As explained later in Section 3, these two different contexts will allow me to determine the channels through which risk impacts giving.

First, in the no self-charity tradeoff context, the lottery valuations result from decisions involving no tradeoffs between money for participants and money for the charity. That is, participants’ binary decisions between self lotteries and self certain amounts, or charity lotteries and charity certain amounts yield the following valuations:

$$Y^s(P^s), 0) \sim p(10, 0) + (1 - p)(0, 0),$$

and

$$0, Y^c(P^c) \sim p(0, X) + (1 - p)(0, 0).$$

Second, in the self-charity tradeoff context, the lottery valuations result from decision involving tradeoffs between money for participants and money for the charity. That is, participants’ binary decisions between self lotteries and charity certain amounts, or charity lotteries and self certain amounts yield the following valuations:

$$Y^s(P^c), 0) \sim p(0, X) + (1 - p)(0, 0),$$

and

$$0, Y^c(P^s) \sim p(10, 0) + (1 - p)(0, 0).$$

Since the valuations in both contexts result from binary decisions, I can easily estimate the valuations. For example, imagine that a participant switches from choosing a lottery in Option A to some certain amount in Option B on the $i^{th}$ row. Since the certain amount in Option B always increases as participants proceed down the rows, their valuation falls between $B_{i-1}$ and $B_i$. I then follow previous literature by estimating their valuations as the midpoint - i.e., $\frac{B_{i-1} + B_i}{2}$.

While censoring is empirically not a problem in these lottery valuations, 1% of the valuation price lists involve multiple switch points. This occurrence is significantly less than the typical 15% observed in the
literature.\textsuperscript{10} Also, since a poor estimation of a lottery valuation is less severe than a poor estimation of X (which then impacts all charity lotteries), I treat multiple switch points in lottery valuations differently; instead of excluding any participant with a multiple switch point in the lottery valuation, I follow Meier and Sprenger (2010), among others, by assuming the first switch point is the true switch point in my main results. However, robustness checks show that the results hold if I instead exclude any participant who ever has a multiple switch point or exclude any valuation that involves a multiple switch point.

\textsuperscript{10}This lower occurrence of multiple switch points likely results from my design following Andreoni and Sprenger (2012) by providing clarifying instructions before price lists and preselecting Option A in the first row of each price lists where Option B is a certain amount of $0 (see Appendix A).
3 Results

As detailed in the previous section, this study yields valuations for the following self lotteries and charity lotteries:

\[ p(10, 0) + (1 - p)(0, 0) \quad \text{and} \quad p(0, X) + (1 - p)(0, 0) \]

where

\( P_s: \) self lottery with probability \( p \)

\( P_c: \) charity lottery for probability \( p \)

\( (10, 0) \sim (0, X), \text{ and } p \in \{0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95\}. \)

Since \( (10, 0) \sim (0, X) \), most models imply that participants should be indifferent between corresponding charity lotteries and self lotteries, or

\[ p(10, 0) + (1 - p)(0, 0) \sim p(0, X) + (1 - p)(0, 0), \quad \forall p. \]

For instance, this indifference is directly implied by the independence axiom, as in the case of von Neumann-Morgenstern expected utility. Even if one allows for probability weighting in models such as cumulative prospect theory, this indifference should still hold. That is, if participants have standard risk preferences, participants should equivalently value self lotteries and charity lotteries with the same risk levels. By contrast, if participants have charity-specific risk preferences, then different probability weighting functions or risk preferences for money given to themselves versus money given to the charity may cause this indifference to not hold.

Importantly though, these implications of standard and charity-specific risk preferences are not dependent on whether or not valuations are elicited in the no self-charity tradeoff context or in the self-charity tradeoff context. However, a third potential channel for risk preferences, excuse driven risk preferences, is dependent on these two contexts. When valuations are in the no self-charity tradeoff context, participants do not make tradeoffs between money for themselves and money for the charity, so there is no scope for using risk as an excuse to not give. By contrast, when valuations are in the self-charity tradeoff context, participants make tradeoffs between money for themselves and money for charity, so there is scope for using risk as an excuse to not give. Hence, if participants have excuse driven risk preferences, their charity and self lottery valuations should diverge across these two contexts in a particular manner.

In Section 3.1, I consider standard and charity-specific risk preferences by examining participants’ valuations in the no self-charity tradeoff context. As I find similar valuations for charity lotteries and self lotteries, I provide evidence against charity specific risk preferences. In Section 3.2, I examine participants’ valuations in the self-charity tradeoff context. As participants’ valuations of charity lotteries and self lotteries now differ, I provide evidence against standard risk preferences alone being able to explain the results. In Section 3.3, I then detail how participants’ responses to risk change across these two contexts.
in a manner that supports excuse driven risk preferences. In Section 3.4, I discuss potential extensions of existing models to account for excuse driven risk preferences.

### 3.1 Evidence against Charity-Specific Risk Preferences

To examine whether standard or charity-specific risk preferences are relevant, I consider participants’ self lottery and charity lottery valuations in the no self-charity tradeoff context. Self lottery valuations result from binary decisions between self lotteries and self certain amounts, and hence yield the valuation, $Y^s(P^s)$, such that participants are indifferent between themselves receiving $Y^s(P^s)$ with certainty and themselves receiving the outcome of the self lottery with probability $p$, $P^s$. That is, $Y^s(P^s)$ is the self dollar valuation of the self lottery $P^s$, defined as:

$$Y^s(P^s), 0) \sim_p p(10, 0) + (1 - p)(0, 0).$$

Charity lottery valuations result from binary decisions between charity lotteries and charity certain amounts, and hence yield the valuation, $Y^c(P^c)$, such that participants are indifferent between the charity receiving $Y^c(P^c)$ with certainty and the charity receiving the outcome of the charity lottery with probability $p$, $P^c$. That is, $Y^c(P^c)$ is the charity dollar valuation of the charity lottery $P^c$, defined as:

$$(0, Y^c(P^c)) \sim p(0, X) + (1 - p)(0, 0).$$

Since these valuations are elicited in different units (i.e., in dollars given to participants or dollars given to the charity), I present scaled results. Self dollar valuations of the self lottery, $Y^s(P^s)$, are scaled as percentages of $\$10$, the maximum outcome in the self lottery. Charity dollar valuations of the charity lottery, $Y^c(P^c)$, are scaled as percentages of $\$X$, the maximum outcome in the charity lottery. While this rescaling is merely a 1-1 transformation if I assume linear utility, my results are robust to specifications not involving any rescaling.\(^{11}\)

Figure 3 plots the corresponding self lottery and charity lottery valuations in the no self-charity context. Most of the error bars for these valuations are overlapping, or in other words, participants respond very similarly to risk in charity lotteries and self lotteries. Regression results show that these lottery valuations are robust when standard errors are clustered on the individual level (see Appendix Table B.1), or when estimated via an interval regression (see Appendix Table B.2). Regression results in Appendix Table B.3 show that these differences between the self and charity lottery valuations at each probability, although sometimes statistically significant, are small in magnitude - never exceeding more than 3.6%. These results are robust to dropping observations involving multiple switch points (see Appendix Table B.4), dropping

\(^{11}\)There are some reasons to believe that assuming a linear utility is reasonable though. For instance, my study and similar past studies estimate $\alpha$ to be near 1 when assuming a utility function of $U(x) = \pi(p)x^\alpha$
participants who ever have multiple switch points (see Appendix Table B.5), or including the censored participants and looking at corresponding Tobit regressions results (see Appendix B.6). These results are even robust on the individual level. When considering an individuals’ self and charity lottery valuations for a given risk level, 42% are exactly the same, and 83% differ by no more than 10%.

**Figure 3: Valuations in No Self-Charity Tradeoff Context**

The self lottery data indicate the self dollar valuations of self lotteries, \( Y^s(P^s) \). The charity lottery data indicate the charity dollar valuations of charity lotteries, \( Y^c(P^c) \). Recall that self dollar valuations are scaled as percentages of $10, and charity dollar valuations are scaled as percentages of $X. Recall that \( P^s \) involves the participants receiving $10 with probability \( p \) and $0 otherwise, and \( P^c \) involves the charity receiving $X with probability \( p \) and $0 otherwise. The Expected Value line indicates the expected value for a lottery given the probability \( p \). The error bars show the confidence interval for two standard errors. The results include data for the 57 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.

In other words, these results present evidence against charity-specific risk preferences, as participants respond similarly to risk in charity lotteries and self lotteries. This is the first study, to my knowledge, to show this equivalence in how participants respond to risk with their own money and money for a charity. This equivalence somewhat contrasts with existing literature that suggests individuals may be less responsive to charity risk. For instance, given the common finding that donors do not care to learn or under respond to the benefit of their donations (Hope Consulting, 2010; Fong and Oberholzer-Gee, 2011; Null, 2011). Niehaus (2013) develops a theory of good intentions where donors receive a warm glow from thinking they did good and hence are optimistic in their beliefs about their donations. In the case of my
study, if participants do not learn the outcome of charity lotteries, this theory suggests that participants will optimistically believe the non-zero payment of $X occurs regardless of the actual risk level in charity lotteries, and hence participants will act more risk tolerant in charity lotteries than self lotteries. However, participants in my study do learn the outcome of their randomly selected decision after they make all of their decisions, so while optimistic beliefs still seem plausible, it would not be a prediction from this theory.

Putting aside participants’ relative responses to risk in charity lotteries and self lotteries, the charity risk results and self risk results are separately consistent with past findings. First, existing literature, such as Brock, Lange and Ozbay (2013) in the case of dictator games, shows that people reduce their giving in response to increased risk. More generally, people give less when uncertainty in aid effectiveness is highlighted Karlan and Wood (2014), or when it is less clear that an organization will use donations well because of lower third-party quality ratings (Yörük, 2013). People also give less for general instead of specific causes (Li et al., 2013), for unidentified instead of identified victims (Small and Loewenstein, 2003), or for cash instead of in-kind donations (Batista, Silverman and Yang, 2013) - all of which may result from increased risk or uncertainty in how donations will be used.

Second, the self lottery results correspond nicely with the large literature seeking to identify how individuals respond to risk with their own money. In studies that also involve objective risk with relatively small stakes, the standard empirical finding is that individuals act risk seeking with low probabilities (high risk) and risk averse with high probabilities (low risk). Such behavior yields the inverse-S pattern taken on by self lottery valuations in Figure 3.

This inverse-S shape pattern contrasts with expected utility models where individuals’ utilities are typically strictly concave, linear, or strictly convex, and hence would imply participants are risk averse, risk neutral, or risk seeking for all probabilities. However, there are two general classes of models that allow for this inverse-S pattern between self dollar valuations, or certainty equivalents, and the probabilities involved in the self lottery. The first class allows for curvature in the utility function, such as in Holt and Laury (2002), where the utility is concave or convex over different ranges. The second class allows for curvature via a probability weighting function. Instead of assuming $U(X) = \sum p_i u(x_i)$, these models assume $U(x) = \sum \pi(p_i) u(x_i)$ where $\pi(p)$ is the probability weighting function.

To determine if my data corresponds nicely with previous studies, I estimate results for the second class of models that use probability weighting functions. While there are several potential functional forms for the weighting function (see Prelec (1998) for an overview), this paper follows the cumulative prospect theory formulation (Tversky and Kahneman, 1992) by using $\pi(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^\gamma}$. As shown in Figure 4, this probability weighting function leads to a down-weighting of high probabilities and an up-weighting of low probabilities, and the intensity of this weighting increases as $\gamma$ decreases. This paper also follows the literature by assuming a power bernoulli utility of $u(x) = x^\alpha$ and ensuring the probability weights add up
to one. That is, I assume:

\[ U(P^s) = \pi(p)u(10) - (1 - \pi(p))u(0) \]
\[ = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{\frac{1}{\gamma}}}10^\alpha \]

Then, solving for the certainty equivalent or self dollar valuation of the self lottery, \( Y^s(P^s) \), as a function of \( p \) yields the following.

\[ Y^s(P^s) = \left[ \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{\frac{1}{\gamma}}}10^\alpha \right]^{\frac{1}{\alpha}} \quad (1) \]

Figure 4: Probability Weighting Function

This graph plots the probability weighting function \( \pi(p) \) for several values of \( \gamma \). As in Tversky and Kahneman (1992), I consider a probability weighting function of \( \pi(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{\frac{1}{\gamma}}} \).

Estimating Equation 1 via non-linear least squares with clustered standard errors yields \( \alpha = 1.14 \) and \( \gamma = 0.77 \), parameters which nicely reproduce the inverse-S shape relationship between probabilities and certainty equivalents, as shown in Figure 5.\(^{12}\) Figure 5 also shows that these estimates are encouragingly similar to Andreoni and Sprenger (2012), whose design and stakes were closest to this study, and are relatively comparable to Tversky and Kahneman (1992) even though they used stakes up to twenty times larger than this study.

\(^{12}\) \( H_0 : \alpha = 1 \) is rejected since \( F(1, 56) = 9.29 \) and \( p = 0.004 \). \( H_0 : \gamma = 1 \) is rejected since \( F(1, 56) = 82.70 \) and \( p = 0.00002 \).
My data indicates the self dollar valuations of self lotteries, $Y^s(P^s)$. Recall that self dollar valuations are scaled as percentages of $10, and $P^s$ involves the participants receiving $10 with probability p and $0 otherwise. The error bars show the confidence interval for two standard errors. The results include data for the 57 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed. My estimates are from the non-linear least square estimates of Equation 1, and yield $\alpha = 1.14$ and $\gamma = 0.77$. The Andreoni & Sprenger graph estimates of Equation 1 assuming their parameters of $\alpha = 1.07$ and $\gamma = 0.73$ from Andreoni and Sprenger (2012). The Tversky & Kahnemann graph estimates of Equation 1 assuming their parameters of $\alpha = 0.88$ and $\gamma = 0.61$ from Tversky and Kahneman (1992).

### 3.2 Evidence against standard risk preferences

The previous subsection finds similar responses to risk in charity and self lotteries in the no charity-self tradeoff context, which rules out charity-specific risk preferences. However, these findings are consistent with both standard risk preferences and excuse driven risk preferences. While I will examine excuse driven risk preferences in the next subsection, I now consider whether the results in self-charity tradeoff context also support standard risk preferences, which again imply equivalent responses to risk in charity and self lotteries.

In the self-charity tradeoff context, self lottery valuations result from binary decisions between self lotteries and charity certain amounts, and hence yield the valuation, $Y^c(P^s)$, such that participants are indifferent between the charity receiving $\$Y^c(P^s)$ with certainty and themselves receiving the outcome of the self lottery with probability p, $P^s$. That is, $Y^c(P^s)$ is the charity dollar valuation of the self lottery $P^s$. 
defined as:

\[ (0, Y^c(P^c)) \sim p(10, 0) + (1 - p)(0, 0). \]

Charity lottery valuations result from binary decisions between charity lotteries and self certain amounts, and hence yield the valuation, \( Y^s(P^c) \), such that participants are indifferent between themselves receiving \$Y^s(P^c)\) with certainty and the charity receiving the outcome of the charity lottery with probability \( p, \ P^c \). That is, \( Y^s(P^c) \) is the self dollar valuation of the charity lottery \( P^c \), defined as:

\[ (Y^s(P^c), 0) \sim p(0, X) + (1 - p)(0, 0). \]

Figure 6 plots the corresponding self lottery and charity lottery valuations in the self-charity tradeoff context. In contrast to the no self-charity tradeoff context, most error bars are not overlapping, or in other words, participants respond differently to risk in charity lotteries and self lotteries. Regression results show that these lottery valuations are robust when standard errors are clustered on the individual level (see Appendix Table B.1), or when estimated via an interval regression (see Appendix Table B.2). Regression results in Appendix Table B.3 confirm that these differences are substantial - ranging from 10\% - 20\% depending on the probability. As before, these results are robust to dropping observations involving multiple switch points (see Appendix Table B.4) or dropping participants who ever have multiple switch points (see Appendix Table B.5). If I include the censored participants and examine corresponding Tobit regressions results, then the results are even larger with the differences ranging from 29\%-43\% (see Appendix B.6). The results are also robust on the individual level. When considering an individuals’ self and charity lottery valuations for a given risk level, 78\% are not the same, and 54\% differ by more than 10\%.

Since this divergence in how participants respond to risk in self and charity lotteries demonstrates that standard risk preferences alone cannot explain these results, I more closely examine excuse driven risk preferences, which can be consistent with this divergence, in the next subsection.
Figure 6: Valuations when there are Tradeoffs between Money for Self and Charity

The self lottery data indicate the charity dollar valuations of self lotteries, $Y^c(P^s)$. The charity lottery data indicate the self dollar valuations of charity lotteries, $Y^s(P^c)$. Recall that self dollar valuations are scaled as percentages of $10, and charity dollar valuations are scaled as percentages of $X$. Recall that $P^s$ involves the participants receiving $10 with probability p and $0 otherwise, and $P^c$ involves the charity receiving $X with probability p and $0 otherwise. The Expected Value line indicates the expected value for a lottery given the probability p. The error bars show the confidence interval for two standard errors. The results include data for the 57 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.

3.3 Evidence for excuse driven risk preferences

To more closely consider evidence for excuse driven risk preferences, I begin by re-examining how participants respond to the charity risk. In the no self-charity tradeoff context, participants choose between charity lotteries and charity certain amounts, so they only decide how to give, as opposed to whether or not to give. This context clearly leaves no scope for using risk as an excuse to not give, so the extent to which participants choose charity certain amounts over charity lotteries merely results from their non-excuse driven risk preferences.

However, in the self-charity tradeoff context, participants choose between charity lotteries and self certain amounts. In this context, if participants use risk as an excuse to not give, they should choose self certain amounts, over charity lotteries, more often than their non-excuse driven risk preferences would imply. Such behavior would, in return, make participants appear more risk averse in the self-charity tradeoff.
context. As shown in Figure 7, this is precisely what occurs as participants’ charity lottery valuations fall further below the risk neutral line in the self-charity tradeoff context. Introducing 5% risk in the charity lottery leads to a 32% reduction in the self-charity tradeoff context, which is four-times larger than the 8% reduction in the no self-charity tradeoff context. More generally, self-charity tradeoffs lead to an additional 7 - 24% drop in charity lottery valuations for low risk levels (i.e., $p \geq 0.50$). Appendix Table B.7 confirms that these self-charity tradeoff valuations are significantly lower than the no self-charity tradeoff valuations. These results are robust to dropping observations involving multiple switch points (see Appendix Table B.8) or dropping participants who ever have multiple switch points (see Appendix Table B.9). If I include the censored participants and examine corresponding Tobit regressions results, then the results are even larger with the self-charity tradeoffs leading to a 8%-43% drop in charity lottery valuations for $p \geq 0.25$ (see Appendix B.10).

Figure 7: Charity Lottery Valuations

The no self-charity tradeoff data indicate the charity dollar valuations of charity lotteries, $Y^c(P^c)$. The self-charity tradeoff data indicate the self dollar valuations of charity lotteries, $Y^s(P^c)$. Recall that self dollar valuations are scaled as percentages of $10$, and charity dollar valuations are scaled as percentages of $X$. Recall $P^c$ involves the charity receiving $X$ with probability $p$ and $0$ otherwise. The Expected Value line indicates the expected value for a lottery given the probability $p$. The error bars show the confidence interval for two standard errors. The results include data for the 57 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.

The charity risk results may parallel nicely with results on charitable giving outside of the lab. In particular, imagine that an individual must decide whether or not to give money to a charity in the presence of some risk, such as risk about the impact of their donation. My results suggest that individuals
may choose to not give because they will use the risk as an excuse to not give, or act more aversely to
the risk then their non-excuse driven risk preferences would imply. While I will examine more real word
contexts like these in a separate study detailed in Section 4, one key advantage of a laboratory study is that
I can bolster my evidence for excuse driven risk preferences by examining another context, even though
this context is not commonly observed outside of the lab.

In particular, I will further examine if participants’ valuations for self lotteries are consistent with excuse
driven risk preferences. In the no self-charity tradeoff context, participants choose between self lotteries
and self certain amounts, so they cannot give money to the charity and hence these results merely indicate
their non-excuse driven risk preferences. However, in the self-charity tradeoff context, participants choose
between self lotteries and charity certain amounts. If participants then use risk as an excuse to not give,
they should choose self lotteries, over charity certain amounts, more often than their non-excuse driven
risk preferences would imply. Such behavior would, in return, make participants appear less risk averse in
the self-charity tradeoff context.

Figure 8 thus provides further evidence for excuse driven risk preferences as participants’ self lottery
valuations rise further above the risk neutral line in the self-charity tradeoff context. In particular, Ap-
pendix Table B.7 confirms that these self-charity valuations are significantly higher than the no self-charity
valuations for high risk levels (i.e., \( p \leq 0.50 \)). These results are robust to dropping observations involving
multiple switch points (see Appendix Table B.8) or dropping participants who ever have multiple switch
points (see Appendix Table B.9). If I include the censored participants and examine corresponding Tobit
regressions results, then the self-charity tradeoffs lead to a significant increase, by up to 30%, in self lottery
valuations for all probabilities. (see Appendix B.10).

In summary, I provide evidence for excuse driven risk preferences by showing that participants act more
averse to charity risk and less averse to self risk in the self-charity tradeoff contexts. While the results so
far are on the aggregate level, Figure 9 shows that these results also hold on the individual level. In the
no self-charity tradeoff context, the fraction of lottery valuations that are less than or greater than their
expected value is not statistically different for charity lotteries or for self lotteries. By contrast, in the
self-charity tradeoff context, charity lotteries are significantly more likely to be greater than their expected
value, and self lotteries are significantly more likely to be less than their expected value.

While the above aggregate level and individual level results rely on scaled lottery valuations, I can
also provide evidence for excuse driven risk preferences in a different manner that does not rely on the
scaled valuations. In particular, Figure 10 presents results such that only lottery valuations elicited in the
same units are compared. In the left panel where valuations are elicited in self dollars, excuse driven risk
preferences are only relevant for the charity lottery valuations and would imply that participants choose
self certain amounts, over charity lotteries, more often. While the left panel shows the corresponding
implication - that participants appear more risk averse in charity lotteries than self lotteries, Appendix
Table B.11 confirms that the charity lottery valuations are significantly lower, by up to 22%, for \( p \geq 0.25 \).

By contrast, in the right panel where valuations are elicited in charity dollars, excuse driven risk pref-
The no self-charity tradeoff data indicate the self dollar valuations of self lotteries, $Y_s(P_s)$. The self-charity tradeoff data indicate the charity dollar valuations of self lotteries, $Y_c(P_s)$. Recall that self dollar valuations are scaled as percentages of $10$, and charity dollar valuations are scaled as percentages of $X$. Recall $P_s$ involves the participant receiving $10$ with probability $p$ and $0$ otherwise. The Expected Value line indicates the expected value for a lottery given the probability $p$. The error bars show the confidence interval for two standard errors. The results include data for the 57 uncensored participants without multiple switch points in the normalization task. For the $1\%$ of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.

Differences are only relevant for self lottery valuations and would imply that participants choose self lotteries, over charity certain amounts, more often. While the right panels shows the corresponding implication - that participants appear less risk averse in self lotteries than charity lotteries, Appendix Table B.11 confirms that the self lottery valuations are significantly higher, by up to $12\%$, for $p \geq 0.50$.

More generally, both the self dollar and charity dollar valuations results are robust to dropping observations involving multiple switch points (see Appendix Table B.12) or dropping participants who ever have multiple switch points (see Appendix Table B.13). If I include the censored participants and examine corresponding Tobit regressions results, then magnitude of the results increases by about two-fold (see Appendix B.14).
The calculations for the self-charity tradeoff context result from the charity dollar valuations of charity lotteries, $Y^c(P^c)$, and the self dollar valuations of self lotteries, $Y^s(P^s)$. The calculations for the self-charity tradeoff context result from the self dollar valuations of charity lotteries, $Y^s(P^c)$, and the charity dollar valuations of self lotteries, $Y^c(P^s)$. Recall that self dollar valuations are scaled as percentages of $\$10$, and charity dollar valuations are scaled as percentages of $\$X$. Recall $P^s$ involves the participant receiving $\$10$ with probability $p$ and $\$0$ otherwise. The error bars show the confidence interval for two standard errors. The results include data for the 57 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.
In the left panel, the estimates are self dollar valuations: the self lottery data indicate the self dollar valuations of self lotteries, $Y^s(P^s)$; the charity lottery data indicate the self dollar valuations of charity lotteries, $Y^s(P^c)$. In the right panel, the estimates are charity dollar valuations: the self lottery data indicate the charity dollar valuations of self lotteries, $Y^c(P^s)$; the charity lottery data indicate the charity dollar valuations of charity lotteries, $Y^c(P^c)$. Recall that: $P^s$ involves a participant receiving $10$ with probability $p$ and $0$ otherwise, and $P^c$ involves the charity receiving $X$ with probability $p$ and $0$ otherwise. The Expected Value line indicates the expected value for a lottery given the probability $p$. The results include data for the 57 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.
3.4 Considering relevant theory for excuse driven risk preferences

Since the results provide strong evidence for excuse driven risk preferences, and rule out standard or charity specific risk preferences, a natural question is how to consider these results in the context of existing theory. In particular, there are a couple features of these results that are difficult to theoretically reconcile, absent just allowing for excuse driven risk preferences. First, excuse driven risk preferences allow for the possibility, and these particular results require, that participants can be indifferent between $10 for themselves and $X for the charity but still differently value lotteries that involve these stakes at the same risk level. That is,

\[(10, 0) \sim (0, X)\]

\[\not\Rightarrow\]

\[P^s: \text{self lottery with probability } p\]

\[\sim\]

\[P^c: \text{charity lottery for probability } p\]

Second, participants’ decisions in this study imply some violations of transitivity. For instance, 42% of participants have the following choice pattern:

- \(Y^c(0.95c) \geq Y^c(0.90c) \rightarrow 0.95c \succ 0.90c\),
- \(Y^c(0.90c) \geq Y^c(0.90s) \rightarrow 0.95c \succ 0.90s\), but
- \(Y^s(0.95c) < Y^c(0.90s) \rightarrow 0.95c \prec 0.90s\).

Even if I consider lottery valuations to indicate indifference if they do not differ by more than 5, 10, 15, or 20%, then the fraction of participants with this violation of transitivity slightly increases. Similarly, 33% of participants have the following choice pattern:

- \(Y^c(0.95c) \geq Y^c(0.75c) \rightarrow 0.95c \succ 0.75c\),
- \(Y^c(0.75c) \geq Y^c(0.75s) \rightarrow 0.95c \succ 0.75s\), but
- \(Y^s(0.95c) < Y^c(0.75s) \rightarrow 0.95c \prec 0.75s\).

The fraction of participants with this violation of transitivity also increases if I consider lottery valuations to indicate indifferent if they do not differ by more than 5, 10, 15, or 20%.

While existing models cannot easily reconcile these above features, generous interpretations of some models may be conceptually helpful. First, temptation models, such as Gul and Pesendorfer (2001), could allow us to consider “not giving” as a tempting goods. This allowance could then explain why participants sometimes choose self certain amounts, over charity lotteries, or self lotteries, over charity certain amounts, more often than their non-excuse driven risk preferences would imply. While this is plausible, it also runs counter to the growing consensus that people often get “tempted” to give and hence may explain why
people avoid being asked to give (Andreoni, Rao and Trachtman, 2011; DellaVigna, List and Malmendier, 2012).

Second, although there exist probability weighting functions that could explain these results, we would need to allow probability weighting functions to be very malleable. Just allowing for separate probability weighting functions for charity and self lotteries could not explain the results. Instead, we would need to allow participants probability weighting functions to change in a self serving manner when self-charity tradeoffs are involved. Important to this possibility is that even the direction of the self-serving change would be context dependent; in this study, participants’ self serving decisions correspond with both an over-weighing of risk in charity lotteries and an under-weighing of risk in self lotteries.

Third, these results can also be thought of via the lens of models that incorporate image motivation, such as Bénabou and Tirole (2006). In particular, it may be reasonable to assume that participants do not update on their prosocial image when they make decisions in the no self-charity tradeoff context, which then corresponds with similar reposes to risk in self and charity lotteries. By contrast, participant may update on their prosocial image when they make decisions in the self-charity tradeoff context. The existence of risk in some of these decisions may then cause less updating on their prosocial image. For instance, participants may attribute their decision to choose a self certain amount, over a charity lottery, to reflect less about their prosocial preferences as it also conveys information on their risk preferences. To the extent this is the case, participants would update less negatively on their prosocial image when choosing a selfish option in the presence of risk than when choosing a selfish option in the absence of risk. Such updating would then encourage more selfish behavior in decisions that also involve risk.

While this discussion clearly does not provide a new theoretical framework that accounts for the excuse driven risk preferences found in this paper, I view future such work as promising.
4 Applications

An alternative framing of my results is useful when considering possible policy implications. In the no
self-charity tradeoff context, participants act relatively tolerant of charity risk. Or, conditional on giving
(i.e., choosing between charity lotteries and charity certain amounts), people are willing to give via a risky
option. By contrast, in the self-charity tradeoff context, participants act very averse to charity risk. Or
unconditional on giving (i.e., choosing between charity lotteries and self certain amounts), people are not
willing to give.

Charities may be able to leverage this information in several ways, such as targeting more committed
donors who are more likely to be in the conditional on giving state differently than uncommitted donors.
However, since the relevance of such policy implications depends on the generalizability of excuse driven
risk preferences, I now consider two additional applications of my results.

First, in Section 4.1, I replicate my study in a non-charity prosocial context where participants decide
between money for themselves and a fellow participant in the study, as opposed to the American Red Cross.
Second, in Section 4.2 I sacrifice the benefits of having precisely defined risk in order to explore whether or
nor participants use subjective risk, conveyed through information on a charity’s effectiveness or efficiency,
as an excuse to not give.

4.1 Non-Charity Prosocial Context

In March 2014, 44 undergraduate students participated in one of two study sessions via the Stanford
Economics Research Laboratory. The design features of this new version only differ from Section 2 in two
ways.

First, half of the participants are assigned to be in the Left Group and the remaining half of the
participants are assigned to be in the Right Group, according to the side of the lab in which they were seated.
Instead of one randomly selected decision being implemented for each participant, only one randomly
selected decision is implemented for each participant in the randomly selected group (i.e., the Left Group
or the Right Group).

Second, any choices involving the American Red Cross are changed to now involve a participant’s
partner. Participants’ partners are randomly and anonymously selected to be another participant not in
their group (i.e., participants in the Left Group have partners in the Right Group, and vice versa). When
participants make decisions involving their partner, note that these decisions should not be impacted by
realized reciprocity since only a decision made by a participant or a decision made by a participant’s partner
will be implemented. One additional implication of this change is participants are paid in the same manner
as their partners - a feature that could not be achieved in the earlier study that involves payments to the
American Red Cross.

As shown in Figure 11, I find nearly identical results for other regarding behavior towards partners, as
previously observed towards the American Red Cross. If anything, the results are slightly larger. In the no
self-partner tradeoff context, participants respond to risk very similarly. In the self-partner tradeoff context, participants respond to risk differently. In particular, they act more averse to partner risk and less averse to self risk. Regression results in Appendix Table B.15 confirm that these differences are substantial - ranging from 15% - 25% depending on the probability. As before, these results are robust to dropping observations involving multiple switch points (see Appendix Table B.16) or dropping participants who ever have multiple switch points (see Appendix Table B.17). If I include the censored participants and examine corresponding Tobit regressions results, then the results are even larger with the differences in the self-partner tradeoff context ranging from 22%-39% (see Appendix B.18).

Figure 11: Valuations in No Tradeoff and Tradeoff Context

In the left panel, the estimates are valuations in the no tradeoff context: the self lottery data indicate the self dollar valuations of self lotteries, $Y^s(p^s)$; the partner lottery data indicate the partner dollar valuations of partner lotteries, $Y^p(p^p)$. In the right panel, the estimates are valuations in the tradeoff context: the self lottery data indicate the partner dollar valuations of self lotteries, $Y^p(p^s)$; the charity lottery data indicate the self dollar valuations of partner lotteries, $Y^s(p^p)$. Recall that: $P^s$ involves a participant receiving $10 with probability p and $0 otherwise, and $P^p$ involves the partner receiving $X with probability p and $0 otherwise. The Expected Value line indicates the expected value for a lottery given the probability p. The results include data for the 29 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.

4.2 Subjective Risk related to Effectiveness and Efficiency Measures

In April 2014, 50 undergraduate students participated in one of three study sessions via the Stanford Economics Research Laboratory. The design features of this new version differ from Section 2 in two ways. First, this study involves three types of charities, so participants answer each price lists three times - once for each charity type. In particular, participants first loop through the normalization price list and second price list (that replicates the normalization one but involves a $5 self certain amount instead of a $10 self certain amount). Participants then loop through the 28 valuation price lists. The order of each
loop, in terms of which charity type is involved, is randomly determined.

Second, this study will not involve any risk in terms of whether or not the charities will receive money - i.e., all charity options will involve the relevant charities receiving a certain amount. Instead, I introduce subjective “risk” into the charity options by directing money towards charities that have “high, medium, or low” measures of efficiency and effectiveness. Determining if participants use this kind of subjective risk is particularly relevant given the increasing pressure for charities to provide information on their effectiveness and efficiency (Ebrahim and Rangan, 2010).

Broadly speaking, I consider higher risk to correspond with a lower chance that donations are used efficiently or effectively. Since none of the charities are 100% efficient or effective, the normalization price list determines \( X_i \) for each charity type \( i \) such that participants are indifferent between themselves receiving $10 and the “high-rated” charity (i.e., the charity with a high measure of effectiveness of efficiency) receiving \( X_i \). Then, for each charity type \( i \), the valuation price lists elicit valuations for the “medium-rated” charity \( i \) receiving \( X_i \), and for a “low-rated” charity \( i \) receiving \( X_i \).

In the no self-charity context, valuations for a P-rated charity \( i \) result from participants’ binary decisions between the P-rated charity \( i \) receiving \( X_i \) and high charity certain amounts. High charity certain amounts involve in the high charity \( i \) receiving $0, \( \frac{X_i}{20} \), ... , or \( X_i \). This yields the valuation \( Y^c(Pc) \), such that participants are indifferent between the high-rated charity receiving \( Y^c(Pc) \) with certainty and the P-rated charity receiving \( X_i \). That is, \( Y^c(Pc) \) is the charity dollar valuation of the P-rated charity.

In the self-charity context, valuations for a P-rated charity \( i \) result from participants’ binary decisions between the P-rated charity \( i \) receiving \( X_i \) and self certain amounts. Self certain amounts involve the participants receiving $0, $0.50, ... , or $10. This yields the valuation \( Y^s(Pc) \), such that participants are indifferent between themselves receiving \( Y^s(Pc) \) with certainty and the P-rated charity receiving \( X_i \). That is, \( Y^s(Pc) \) is the self dollar valuation of the P-rated charity.

While I do not share my high, medium, or low classifications of the charities, I present participants with the other information below.

1. **Make-A-Wish Foundation**: Make-A-Wish foundation “grants the wishes of children with life-threatening medical conditions to enrich the human experience with hope, strength, and joy.” They have various state chapters that vary according to their program expense rates. Their program expense rates are shown on Charity Navigator (www.charitynavigator.org), which “has become the nation’s largest and most-utilized evaluator of charities.” Importantly, Charity Navigator says the higher the program expense rate, the better - as non-program expenses typically involve overhead costs that do not directly fulfill a charity’s mission. The three Make-A-Wish foundation state chapters used in this study are as follows.

   - **High Level of Efficiency**: Make-A-Wish Foundation state chapter in New Hampshire with a program expense rate of 90%
   - **Medium Level of Efficiency**: Make-A-Wish Foundation state chapter in Rhode Island with
a program expense rate is 80%

- Low Level of Efficiency: Make-A-Wish Foundation state chapter in Maine with a program expense rate is 71%

2. KIPP Charter Schools: According to their website (http://www.kipp.org), "The mission of KIPP is to create a respected, influential, and national network of public schools that are successful in helping students from educationally underserved communities develop the knowledge, skills, character and habits needed to succeed in college and the competitive world beyond [...] There are currently 141 KIPP schools in 20 states and the District of Columbia serving 50,000 students. More than 86 percent of our students are from low-income families and eligible for the federal free or reduced-price meals program, and 95 percent are African American or Latino.” On average, out of the students who have completed the 8th grade at a KIPP charter school, the college matriculation rate for KIPP alumni is 80%. The three KIPP Charter school used in this study are as follows.

- High Level of Effectiveness: the KIPP charter schools in Chicago IL which, out of the students who have completed the 8th grade at their schools, had a college matriculation rate of 92%
- Medium Level of Effectiveness: the KIPP charter schools in Philadelphia PA which, out of the students who have completed the 8th grade at their schools, had a college matriculation rate of 74%
- Low Level of Effectiveness: the KIPP charter schools in Denver CO which, out of the students who have completed the 8th grade at their schools, had a college matriculation rate of 61%

3. Bay Area Animal Shelters: According to their website (http://www.maddiesfund.org), Maddie’s Fund is a foundation dedicated to animal welfare and provides information on live release rate for various animal shelters. An animal shelter’s live release rate is the percentage of their dogs that have live outcomes - i.e., are adopted, transferred to another rescue organization, or are returned to their owner/guardian. Maddie’s Fund aims to help shelters become "no-kill", which means that they do not kill any healthy or treatable animals. An animal shelter with a live release rate above 90% is considered no-kill. The three Bay Area animal shelters used in this study are as follows.

- High Level of Effectiveness: the San Francisco Society for the Prevention of Cruelty to Animals which has a live release rate is 97%
- Medium Level of Effectiveness: the Humane Society of Silicon Valley which has a live release rate is 82%
- Low Level of Effectiveness: the San Jose Animal Care and Services which has live release rate is 66%
In the no self-charity tradeoff context, participants choose between P-rated charities and high charity certain amounts. Since they are only deciding how to give, the corresponding valuations indicate their non-excuse driven risk preferences. In the self-charity tradeoff context, participants choose between P-rated charities and self certain amounts. Since they are now deciding whether or not to give, the corresponding valuations indicate their excuse-driven risk preferences. In particular, if participants use this subjective risk as an excuse to not give, they should choose the self certain amounts, over the P-rated charities, more often than their non-excuse driven risk preferences would imply. Such behavior would, in return, make participants have lower valuations of the P-rated charities in the self-charity tradeoff context. As shown in Figure 12, this is precisely what occurs as participants’ valuations in the self-charity tradeoff context fall 10-12% below their valuations in the no self-charity tradeoff context. Appendix Table B.19 confirms that this reduction is statistically significant.

Figure 12: All Charity Types Pooled: Valuations in No Tradeoff and Tradeoff Context

The no self-charity tradeoff data indicate charity dollar valuations of the P-rated charities. The self-charity tradeoff data indicate the self dollar valuations of the P-rated charities. For each charity type $i$, the P-rated charity $i$ receives $X_i$. For each charity type, the results include data from uncensored participants without multiple switch points in the normalization task. This yields 35 participants for Make-A-Wish Foundation, 31 participants for KIPP charter schools, and 31 participants for Bay Area animal shelters. For the 6% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.

When the charity types are considered separately, the same excuse-driven behavior appears as shown in Figure 13. In the case of Make-A-Wish Foundation, participants respond more negatively to low program expense rates, or the percentage of expenditures not spent on overhead, in the self-charity tradeoff context.
In particular, as confirmed in Appendix Table B.19, self-charity tradeoffs lead to a statistically significant 14-15% reduction in responses to lower program expense rates. This highlights a potential downside of charities and third-party evaluators placing such importance on a charity’s overhead cost. For instance, Charity Navigator, a popular online site that provides information on the performance of over 7,000 charities says: “Savvy donors know that the financial health of a charity is a strong indicator of the charity’s programmatic performance. They know that in most cause areas, the most efficient charities spend 75% or more of their budget on their programs and services and less than 25% on fundraising and administrative fees.”

While Charity Navigator also provides caveats to this statement and encourages donors to consider multiple factors, if potential donors are excuse-seeking, they may then be very willing to use overhead costs as an excuse to not give.

**Figure 13: By Charity Types: Valuations in No Tradeoff and Tradeoff Context**

The no self-charity tradeoff data indicate charity dollar valuations of the P-rated charities. The self-charity tradeoff data indicate the self dollar valuations of the P-rated charities. For each charity type i, the P-rated charity i receives $X_i$. For each charity type, the results include data from uncensored participants without multiple switch points in the normalization task. This yields 35 participants for Make-A-Wish Foundation, 31 participants for KIPP charter schools, and 31 participants for Bay Area animal shelters. For the 6% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.

While overhead costs are often a common measure across various types of charities, measures of success or effectiveness are more dependent on the situation. In the case of KIPP charter school, college matriculation rates are a key indicator of success since they strive to prepare students for college. In the case of Bay Area animal shelters, live release rates are a key indicator of success.
case of animal shelters, live releases rates are a key indicator of success since they strive to save homeless dogs and cats. In both of these situations, participants respond more negatively to lower measures of success in the self-charity tradeoff context. However, as shown in Appendix Table B.19, while self-charity tradeoffs lead to a statistically significant 9-14% reductions in response to lower college matriculation rates, the corresponding reductions in response to lower live releases are not statistically significant. Participants’ answers in the follow-up survey suggest that this latter finding may result from some participants not wanting to give to animal shelters with very high live release rates because “they do no need any help.” In this sense, people may be able to use both good and poor performance measures as excuses to not give.
5 Other Excuse Behavior Results

In this section, I will examine if there are excuse-driven “types” of participants. In other words, are participants with excuse-driven risk preferences at one probability, the same participants with excuse-driven risk preferences at another probability? If so, does the robustness of the excuse-driven type extend to other contexts? I will examine the first question by returning to the main results discussed in Section 3, but with a focus on individual-level results. I will examine the second question by presenting additional results from a task in the follow-up survey that involves another context where individuals are believed to behave in an excuse-driven manner.

To begin, I consider how to measure the extent to which a participant has excuse driven risk preferences. Recall that in the no self-charity context, participants’ response to charity risk and self risk merely reflects their non-excuse driven risk preferences. However, if participants have excuse driven risk preferences, then their response to risk may change via two channels in the self-charity tradeoff context. First, participants may choose self lotteries, over charity certain amounts, more often than their non-excuse driven risk preferences would imply - i.e.,

\[ D_{self} = Y^c(P^s) - Y^s(P^s) \]

increases. Second, participants may choose self certain amounts, over the charity lotteries, more often than their non-excuse driven risk preferences would imply - i.e.,

\[ D_{charity} = Y^s(P^c) - Y^c(P^c) \]

declines. Considering these two channels together then implies that participants with more excuse driven risk preferences will have larger difference-in-differences, \( \text{DID}(p) \) where

\[
\text{DID}(p) = \frac{D_{self}(p)}{D_{charity}(p)} \left( Y^c(P^s) - Y^s(P^s) \right) - \frac{D_{charity}(p)}{D_{self}(p)} \left( Y^s(P^c) - Y^c(P^c) \right).
\]

As an example, consider that valuations for a participant without excuse driven risk preferences, as shown in Figure 14. This participant always responds to self risk and charity risk in the same manner across the no self-charity and self-charity tradeoff context, so \( \text{DID}(p) = 0, \forall p \). By contrast, Figure 15 displays valuations for a participant with excuse driven risk preferences. This participant always responds to self risk and charity risk in a more self-serving manner in the self-charity tradeoff context, so \( \text{DID}(p) > 0, \forall p \).

For the two example participants, their types in this study are clear: the first never responds to risk in an excuse driven manner, while the second always responds to risk in an excuse driven manner. To test if this individual level of consistency is more generally true, Table 1 displays the rank correlations of \( \text{DID}(p) \). The corresponding positive and statistically significant rank correlations confirm that participants tend to respond to risk in a consistently excuse driven (or not) manner across all probabilities. Since this suggests that there are excuse driven types of participants, I next consider whether these types persist in a different environment.

In particular, I turn to an environment that involves a well known phenomenon believed to be excuse driven - i.e., “moral wiggle room.” As described in Dana, Weber and Kuang (2007), moral wiggle room involves people behaving more selfishly when it is unclear as to whether or not their action is selfish,
In the left panel, the estimates are charity lottery valuations: the no self-charity tradeoff data indicate the charity dollar valuations of charity lotteries, $Y^c(P^c)$; the self-charity tradeoff data indicate the self dollar valuations of charity lotteries, $Y^s(P^c)$. In the right panel, the estimates are self lottery valuations: the no self-charity tradeoff data indicate the self dollar valuations of self lotteries, $Y^s(P^s)$; the self-charity tradeoff data indicate the charity dollar valuations of self lotteries, $Y^c(P^s)$. Recall that: $P^s$ involves a participant receiving $10 with probability $p$ and $0 otherwise, and $P^c$ involves the charity receiving $X with probability $p$ and $0 otherwise. The Expected Value line indicates the expected value for a lottery given the probability $p$. These results are from a participant whose valuations are not consistent with excuse driven risk preferences.

or when they can maintain some illusion of less selfish behavior. Since participants in my study always know whether or not their action is selfish (as they choose between options that either benefit the charity or themselves exclusively), moral wiggle room provides a useful environment with which to test the robustness of excuse-driven types to other contexts.

The particular context I will examine closely follows two treatments from Dana, Weber and Kuang (2007). Both treatments involve modified dictator games, where the dictator chooses between two options - A and B. The treatments are run in an across-subject design. In their first treatment, dictators can choose between a "selfish" option $A: ($6, $1) and a "fair" option $B: ($5, $5), where the bundle $(U, V)$ corresponds with the dictator receiving $U and the recipient receiving $V. I will refer to these payments occurring in an unaligned state, since $A$ is best for the dictator and $B$ is best for the recipient. In their second treatment, dictators face payments in an unaligned state or an aligned state. While the unaligned stated again involves $A: ($6, $1) and $B: ($5, $5), the aligned state involves $A: ($6, $5) and $B: ($5, $1). Dictators are not told which state they are in, but they are told that either state occurs with equal probability. Dictators can reveal their state for free before choosing between A and B, or they can choose between A and B without revealing their state.

From these two treatments, Dana, Weber and Kuang (2007) find evidence for moral wiggle room
In the left panel, the estimates are charity lottery valuations: the no self-charity tradeoff data indicate the charity dollar valuations of charity lotteries, $Y^c(P^c)$; the self-charity tradeoff data indicate the self dollar valuations of charity lotteries, $Y^s(P^c)$. In the right panel, the estimates are self lottery valuations: the no self-charity tradeoff data indicate the self dollar valuations of self lotteries, $Y^s(P^s)$; the self-charity tradeoff data indicate the charity dollar valuations of self lotteries, $Y^c(P^s)$. Recall that: $P^s$ involves a participant receiving $10 with probability $p$ and $0 otherwise, and $P^c$ involves the charity receiving $X with probability $p$ and $0 otherwise. The Expected Value line indicates the expected value for a lottery given the probability $p$. These results are from a participant whose valuations are consistent with excuse driven risk preferences.

behavior. In the first treatment, when dictators always know they are in the unaligned, only 26% of dictators choose the selfish option A. However, in the second treatment, when dictators can choose whether or not to reveal their state, 63% of dictators in the unaligned state choose the selfish option A. This increase in selfish behavior seems to be driven by the fact that half of these dictators chose to not reveal their state, and among that half, 100% choose the selfish option A. Dana, Weber and Kuang (2007) explain this behavior by pointing to moral wiggle room, or that "many dictators appear to exploit the payoff uncertainty as an excuse for behaving self-interestedly."

In my study, participants face a similar moral wiggle room task via a follow-up survey that they complete after completing all of their lottery valuations. In particular, so that I can classify participants as being susceptible (or not) to this particular type of moral wiggle room, participants answer three questions, although only one is randomly selected to count for payments. In each question, the participants choose between two options - A and B, which corresponds with payments for themselves and the charity (the American Red Cross). These payments, as shown in Table 2, involve a bundle $(U, V)$ that corresponds with the participant receiving $U and the charity receiving $V. In the aligned state, the options are $A : (6, 5)$ and $B : (5, 1)$, so both the participants and the charity receive the most money from A. In the unaligned state, the options are $A : (6, 1)$ and $B : (5, 5)$, so the participant receives the most money from A but the charity receives the most money from B.
Table 1: Rank Correlations of \(DID(p)\)

<table>
<thead>
<tr>
<th>(DID(.95))</th>
<th>(DID(.90))</th>
<th>(DID(.75))</th>
<th>(DID(.50))</th>
<th>(DID(.25))</th>
<th>(DID(.10))</th>
<th>(DID(.05))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.921***</td>
<td>0.825***</td>
<td>0.790***</td>
<td>0.650***</td>
<td>0.649***</td>
<td>0.250*</td>
</tr>
<tr>
<td>(DID(.90))</td>
<td>1</td>
<td>0.867***</td>
<td>0.849***</td>
<td>0.682***</td>
<td>0.666***</td>
<td>0.309**</td>
</tr>
<tr>
<td>(DID(.75))</td>
<td>0.825***</td>
<td>1</td>
<td>0.847***</td>
<td>0.720***</td>
<td>0.616***</td>
<td>0.302**</td>
</tr>
<tr>
<td>(DID(.50))</td>
<td>0.790***</td>
<td>0.849***</td>
<td>1</td>
<td>0.791***</td>
<td>0.692***</td>
<td>0.486***</td>
</tr>
<tr>
<td>(DID(.25))</td>
<td>0.650***</td>
<td>0.682***</td>
<td>0.720***</td>
<td>1</td>
<td>0.768***</td>
<td>0.494***</td>
</tr>
<tr>
<td>(DID(.10))</td>
<td>0.649***</td>
<td>0.666***</td>
<td>0.616***</td>
<td>0.791***</td>
<td>1</td>
<td>0.540***</td>
</tr>
<tr>
<td>(DID(.05))</td>
<td>0.250*</td>
<td>0.309**</td>
<td>0.302**</td>
<td>0.486***</td>
<td>0.494***</td>
<td>1</td>
</tr>
</tbody>
</table>

\(N = 57\)

* \(p < 0.10\), ** \(p < 0.05\), *** \(p < 0.01\). This table shows the ranked correlations of \(DID(p)\), where \(DID(p) = D_{self}(p) - D_{charity}(p)\), and \(D_{self} = Y^c(P^s) - Y^s(P^s)\) and \(D_{charity} = Y^s(P^c) - Y^c(P^c)\). In case of ties, the lowest rank is given. \(Y^c(P^s)\) is the charity dollar valuations of self lotteries, \(Y^s(P^s)\) is the self dollar valuations of self lotteries, \(Y^s(P^c)\) is the self dollar valuations of charity lotteries, and \(Y^c(P^c)\) is the charity dollar valuations of charity lotteries. Recall that: \(P^s\) involves a participant receiving $10 with probability \(p\) and $0 otherwise, and \(P^c\) involves the charity receiving $X with probability \(p\) and $0 otherwise. The Expected Value line indicates the expected value for a lottery given the probability \(p\). These results include data for the 57 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.

In the first question, or choice-to-reveal question, participants face payments in an unaligned state or an aligned state. Participants are not told which state they are in, but they are told that either state occurs with equal probability. Participants can reveal their state for free before choosing between A and B, or they can choose between A and B without revealing their state. In the second question, or revealed unaligned state question, participants know they are in the unaligned state and then must choose between A and B. In the third question, or revealed aligned state question, participants know they are in the aligned state, and then must choose between A and B.

Table 2: Moral Wiggle Room Payoffs

<table>
<thead>
<tr>
<th>Option</th>
<th>Unaligned State</th>
<th>Aligned State</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>(6,1)</td>
<td>(6,5)</td>
</tr>
<tr>
<td>B</td>
<td>(5,5)</td>
<td>(5,1)</td>
</tr>
</tbody>
</table>

The bundle \((U,V)\) corresponds with the participant receiving $U and the charity receiving $V.

Table 3 shows the percentages of participants choosing A across the three questions. First, consider that cases where the state is always revealed - i.e., in the revealed aligned state question or revealed unaligned state question. When the payments are aligned, 100% of participants choose the their highest payment of $6 which is the dominant option - \(A : ($6, $5) \succ B : ($5, $1)\). However, when the payment are not aligned, only 44% choose their highest payment of $6 which is now "selfish" - \(A : ($6, $1) \succ B : ($5, $5)\).

Second, consider the case where participants can choose whether or not to reveal the state - i.e., in...
the choice-to-reveal question. When abstracting away from participants’ choice to reveal, note that it again follows that nearly all - 97.96% - of the participants choose their highest payment and the dominant option of $6 for themselves in the aligned state - $A: (6, 5) > B: (5, 1)$. However, when they are in the unaligned state, it now follows that 68.63% of participants choose the selfish option and their highest payment of $6 - A: (6, 1) > B: (5, 5)$. As shown in the third row of Table 3, 68.63% of the participants choosing the selfish option is significantly larger than the 39.22% of the same participants who chose the selfish option when the state is always revealed (a t-test rejects the equality of these percentages with $p < 0.0001$).

Table 3: Percentage of Participants Choosing Option A

<table>
<thead>
<tr>
<th></th>
<th>Revealed</th>
<th>Choice-to-Reveal</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Aligned State</strong></td>
<td>100.00%</td>
<td>97.96%</td>
</tr>
<tr>
<td>$A: (6, 5), B: (5, 1)$</td>
<td>(n=100)</td>
<td>(n=49)</td>
</tr>
<tr>
<td><strong>Unaligned State</strong></td>
<td>44.00%</td>
<td>68.63%</td>
</tr>
<tr>
<td>$A: (6, 1), B: (5, 5)$</td>
<td>(n=100)</td>
<td>(n=51)</td>
</tr>
<tr>
<td><strong>Unaligned State</strong>*</td>
<td>39.22%</td>
<td>68.63%</td>
</tr>
<tr>
<td>$A: (6, 1), B: (5, 5)$</td>
<td>(n=51)</td>
<td>(n=51)</td>
</tr>
</tbody>
</table>

The bundle $(U, V)$ corresponds with the participant receiving $U$ and the charity receiving $V$. $n$ denotes the relevant sample size for each cell. In the third row, * indicates that the sample is restricted to participants who had the $A: (6, 1)$ and $B: (5, 5)$ payments in question 1.

To determine what is driving participants to behave more selfishly, Table 4 provides more details on participants’ decisions when they can choose whether or not to reveal their state. When participants are in the unaligned state, 54.90% choose to not reveal their state, and among these participants, 100% choose Option A. That is, participants are choosing the selfish option more often by choosing to not reveal their state and hence not know with certainty that they chose the selfish option. Or, in line with moral wiggle room, they are choosing the selfish action by maintaining some illusion of less selfish behavior.

Since each participant answers each question, I can classify whether or not participants avoid information to choose the selfish option. In particular, I classify participants as being a “Wiggler”, or susceptible to the moral wiggle room if and only if:

- they do not choose the selfish option when they always know their payments (i.e., $B: (5, 5) > A: (6, 1)$ in question 2), but

---

15For participants who choose to reveal their state, the survey software, Qualtrics, randomly assigns them to one of the two states. For participants who do not choose to reveal their state, I replicate what Qualtrics would have done by randomly assigning them to one of the two states.
Table 4: Choice to Reveal State Results

<table>
<thead>
<tr>
<th></th>
<th>% Chose No Reveal</th>
<th>% Chose A among those who Chose No Reveal</th>
<th>% Chose A among those who Chose Reveal</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Aligned State</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$A : (6, 5), B : (5, 1)$</td>
<td>55.10%</td>
<td>100.00%</td>
<td></td>
</tr>
<tr>
<td>(n=49)</td>
<td>(n=27)</td>
<td>(n=22)</td>
<td></td>
</tr>
<tr>
<td><strong>Unaligned State</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$A : (6, 1), B : (5, 5)$</td>
<td>54.90%</td>
<td>30.43%</td>
<td></td>
</tr>
<tr>
<td>(n=51)</td>
<td>(n=28)</td>
<td>(n=23)</td>
<td></td>
</tr>
</tbody>
</table>

The bundle $(U, V)$ corresponds with the participant receiving $U$ and the charity receiving $V$. $n$ denotes the relevant sample size for each cell. This data is only from question 1, where participants could choose to reveal their state or not before choosing Option A or Option B.

- they do choose the selfish option when they avoid knowing their payments (i.e., $A : (6, X) \succ B : (5, Y)$ and choose to not reveal X and Y in question 1)

In other words, “Wigglers”, which account for 20% of the participants, only act selfishly when they can and do avoid (free) information on how their action impacts the charity. Consistent with the existence of excuse driven types, I find a correlation between being classified as a Wiggler and more excuse driven risk preferences- i.e., larger $DID(p)$.

While the average $DID(p)$ for Non-Wigglers is 11.10%, the average $DID(p)$ for Wigglers is nearly twice as large - 19.69%.\(^{16}\) While this implies that Wigglers have a 8.59% higher $DID(p)$ on average, Appendix Table B.20 shows that this increase is even larger - 13.29% - when controlling for demographic variables. Additionally, as shown in Appendix Table B.20, $DID(p)$ is a statistically significant predictor of whether or not participants are classified as Wigglers.

In addition to Wigglers, there may exist other groups that are more likely to have excuse driven risk preferences. For instance, avoiding of information may indicate that participants want to find an excuse to not give. I correspondingly find that $DID(p)$ is 7.31% significantly higher, on average, for participants who avoid knowing their payments in the moral wiggle room task.\(^{17}\) Similarly, participants who are more selfish may be more likely to use excuses to not give. Based off of their moral wiggle room choices, more selfish participants choose $A : (6, 1) \succ B : (5, 5)$ when payments are always revealed. These participants correspondingly have 6.84% significantly higher $DID(p)$, on average.\(^{18}\) Or, when considering participants’ decisions in the normalization price list, more selfish participants have higher values of X such that they are indifferent between themselves receiving $10 and the charity receiving $X. It similarly follows that participants whose values of X are in the top 50th percentile have 9.11% significantly higher $DID(p)$, on average.\(^{19}\)

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\(^{16}\)T-test of $H_0 : DID_{Wigglers}(p) = DID_{Non-Wigglers}(p)$ is rejected, $p = 0.007$

\(^{17}\)T-test of $H_0 : DID_{avoiders}(p) = DID_{non-avoiders}(p)$ is rejected, $p = 0.009$

\(^{18}\)T-test of $H_0 : \text{DID}_{A(6,1) \succ B(5,5)}(p) = \text{DID}_{A(6,1) \preceq B(5,5)}(p)$ is rejected, $p = 0.036$

\(^{19}\)T-test of $H_0 : \text{DID}_{highX}(p) = \text{DID}_{lowX}(p)$ is rejected, $p = 0.001$
6 Conclusion

This paper first examines how participants respond to objective risk in self lotteries and charity lotteries. When participants make decisions that do not involve tradeoffs between money for themselves or the charity (i.e., in the no self-charity tradeoff context), participants respond very similarly to self risk and charity risk. This rules out the possibility that participants have charity-specific risk preferences that may cause them to be more or less averse to charity risk than self risk. When participants make decisions that involve tradeoffs between money for themselves and the charity though (i.e., in the self-charity tradeoff context), they no longer respond similarly to self risk and charity risk. This finding is particularly difficult to rationalize given existing theories, as it implies violations of the independence axiom and the transitivity of preferences.

However, the manner in which participants change their responses to risk in the self-charity tradeoff context coincides well with excuse driven risk preferences. First, they act more averse to charity risk, which involves them choosing self certain amounts, over charity lotteries, more often than their non-excuse driven risk preferences would imply. Second, they act less averse to self risk, which involves them choosing self lotteries, over charity certain amounts, more often than their non-excuse driven risk preferences would imply. That is, participants seem to overweigh or underweigh risk in a self serving manner, or use risk as an excuse to not give. Contributing to the robustness of these results, excuse-driven risk preferences are correlated with other excuse behavior in a moral wiggle room task.

While this controlled setting allows me to tease apart excuse driven risk preferences from other possibilities, individuals outside of the lab are unlikely to face objective risk when making charitable donation decisions. In a separate study, I thus turn to a more applications based environment that involves more common types of risk commonly observed in the nonprofit sector. I correspondingly find similar excuse driven behavior in response to charity performance information that conveys different levels of risk in terms of whether or not donations will be used effectively or efficiently. In particular, lower performance information reduces giving more when there are self-charity tradeoffs, or when participants are deciding whether or not to give on the “extensive” margin. Alternatively, lower performance information is less harmful when there are no self-charity tradeoffs, or when participants are just deciding how to give on the “intensive” margin.

In light of the application results, there are potentially several policy implications worth pursuing. For instance, charities may benefit from a two-stage donation processes. In the first stage, charities may ask people to commit to donating or supporting them. In the second stage, charities may then want to ask committed donors to fund risky projects, as already committed donors cannot use risk as an excuse to not give.

Alternatively, charities may target donors based on their level of commitment. Since new donors are likely deciding whether or not give, and hence may desire excuses to not give, charities may want to ask new donors to fund non-risky projects. By contrast, past donors or committed donors are likely deciding how to give, and hence charities may target them for funding of risky projects. This corresponds well with Karlan and Wood (2014), as they find that small previous donors respond negatively to aid effectiveness.
information (that highlights potential uncertainty), while large previous donors respond positively.

More generally, people using excuses to opt-out of giving gives rise to many questions in light of previous research. Do people avoid solicitors for charities (Andreoni, Rao and Trachtman, 2011; DellaVigna, List and Malmendier, 2012) in part as an excuse to not give? Can charities eliminate uncertainty related excuses - such as by allowing donors to direct their donations - to then solicit more donations (Eckel, Herberich and Meer, 2014)? Are people unwilling to invest in learning the most beneficial ways to donate their money (Fong and Oberholzer-Gee, 2011; Null, 2011; Hope Consulting, 2010) because they only care about effectiveness to the extent that it serves as an excuse to not give? If so, do people then seek or avoid certain information to find excuses to not give?
References


A Instructions
A.1 Normalization Price List

In this list:

- **Option A** will always be you receive $10 dollars (and the ARC receives nothing).

- **Option B** will be the ARC receives some dollar amount (and you receive nothing). As you proceed down the rows of a list, the amount the ARC receives will increase from $0 to $30.

For each row, all you have to do is decide whether you prefer Option A or Option B. Indicate your preference by selecting the corresponding button. **Most people begin by preferring Option A and then switch to Option B, so one way to complete this list is to determine the best row to switch from Option A to Option B.**

Now, please make your decisions below.

<table>
<thead>
<tr>
<th>Option A (you receive)</th>
<th>Option B (the ARC receives)</th>
</tr>
</thead>
<tbody>
<tr>
<td>You: $10</td>
<td>ARC: $0</td>
</tr>
<tr>
<td>You: $10</td>
<td>ARC: $2</td>
</tr>
<tr>
<td>You: $10</td>
<td>ARC: $4</td>
</tr>
<tr>
<td>You: $10</td>
<td>ARC: $6</td>
</tr>
<tr>
<td>You: $10</td>
<td>ARC: $8</td>
</tr>
<tr>
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<tr>
<td>You: $10</td>
<td>ARC: $28</td>
</tr>
<tr>
<td>You: $10</td>
<td>ARC: $30</td>
</tr>
</tbody>
</table>
A.2 Second Price List

In this list:

- **Option A** will always be you receive $5 dollars (and the ARC receives nothing).

- **Option B** will be the ARC receives some dollar amount (and you receive nothing). As you proceed down the rows of a list, the amount the ARC receives will increase from $0 to $30.

For each row, all you have to do is decide whether you prefer Option A or Option B. Indicate your preference by selecting the corresponding button. Most people begin by preferring Option A and then switch to Option B, so one way to complete this list is to determine the best row to switch from Option A to Option B.

Now, please make your decisions below.

<table>
<thead>
<tr>
<th>Option A (you receive)</th>
<th>Option B (the ARC receives)</th>
</tr>
</thead>
<tbody>
<tr>
<td>You: $5</td>
<td>ARC: $0</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $2</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $4</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $6</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $8</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $10</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $12</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $14</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $16</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $18</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $20</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $22</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $24</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $26</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $28</td>
</tr>
<tr>
<td>You: $5</td>
<td>ARC: $30</td>
</tr>
</tbody>
</table>
A.3 Valuation Price List: Example from Self Dollar Valuation of Self Lottery, $Y^s(P^s)$, Block

Lists 1 - 7 have $p \in \{0.95, 0.9, 0.75, 0.5, 0.25, 0.10, 0.05\}$. Order of Blocks 2-5 is random.

In this list:

- **Option A** will always be you receive $10 dollars with probability 95%, and $0 otherwise (and the ARC receives nothing).

- **Option B** will be you receive some dollar amount (and the ARC receives nothing). As you proceed down the rows of a list, the amount you receive will increase from $0 to $10.

For each row, all you have to do is decide whether you prefer Option A or Option B. Indicate your preference by selecting the corresponding button. **Most people begin by preferring Option A and then switch to Option B, so one way to complete this list is to determine the best row to switch from Option A to Option B.**

Now, please make your decisions below.

<table>
<thead>
<tr>
<th>Option A (you receive)</th>
<th>Option B (you)</th>
</tr>
</thead>
<tbody>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $0</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $0.50</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $1</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $1.50</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $2</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $2.50</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $3</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $3.50</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $4</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $4.50</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $5</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $5.50</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $6</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $6.50</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $7</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $7.50</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $8</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $8.50</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $9</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $9.50</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>You: $10</td>
</tr>
</tbody>
</table>
A.4 Valuation Price List: Example from Charity Dollar Valuation of Charity Lottery, $Y^c(P^c)$, Block

Lists 1 - 7 have $p \in \{0.95, 0.9, 0.75, 0.5, 0.25, 0.10, 0.05\}$. Order of Blocks 2-5 is random.

In this list:

- **Option A** will always be the ARC receives $20$ dollars with probability 95%, and $0$ otherwise (and you receive nothing).

- **Option B** will be the ARC receives some dollar amount (and you receive nothing). As you proceed down the rows of a list, the amount the ARC receives will increase from $0$ to $20$.

For each row, all you have to do is decide whether you prefer Option A or Option B. Indicate your preference by selecting the corresponding button. **Most people begin by preferring Option A and then switch to Option B**, so one way to complete this list is to determine the best row to switch from Option A to Option B.

Now, please make your decisions below.

<table>
<thead>
<tr>
<th>Option A (the ARC receives)</th>
<th>Option B (the ARC receives)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $0$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $1$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $2$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $3$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $4$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $5$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $6$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $7$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $8$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $9$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $10$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $11$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $12$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $13$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $14$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $15$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $16$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $17$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $18$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $19$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>ARC: $20$</td>
</tr>
</tbody>
</table>
A.5 Valuation Price List: Example from Self Dollar Valuation of Charity Lottery, $Y^s(P^c)$, Block

Lists 1 - 7 have $p \in \{0.95, 0.9, 0.75, 0.5, 0.25, 0.10, 0.05\}$. Order of Blocks 2-5 is random.

In this list:

- **Option A** will always be the ARC receives $20$ dollars with probability 95%, and $0$ otherwise (and you receive nothing).

- **Option B** will be you receive some dollar amount (and the ARC receives nothing). As you proceed down the rows of a list, the amount you receive will increase from $0$ to $10$.

For each row, all you have to do is decide whether you prefer Option A or Option B. Indicate your preference by selecting the corresponding button. Most people begin by preferring Option A and then switch to Option B, so one way to complete this list is to determine the best row to switch from Option A to Option B.

Now, please make your decisions below.

<table>
<thead>
<tr>
<th>Option A (the ARC receives)</th>
<th>Option B (you)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $0$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $0.50$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $1$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $1.50$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $2$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $2.50$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $3$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $3.50$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $4$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $4.50$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $5$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $5.50$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $6$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $6.50$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $7$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $7.50$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $7.50$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $8$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $8.50$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $9$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $9.50$</td>
</tr>
<tr>
<td>ARC: $20$ with probability 95%, and $0$ otherwise</td>
<td>You: $10$</td>
</tr>
</tbody>
</table>
A.6 Valuation Price List: Example from Charity Dollar Valuation of Self Lottery, $Y^c(P^s)$, Block

Lists 1 - 7 have $p \in \{0.95, 0.9, 0.75, 0.5, 0.25, 0.10, 0.05\}$. Order of Blocks 2-5 is random.

In this list:

- **Option A** will always be you receive $10 dollars with probability 95%, and $0 otherwise (and the ARC receives nothing).

- **Option B** will be the ARC receives some dollar amount (and you receive nothing). As you proceed down the rows of a list, the amount the ARC receives will increase from $0 to $20.

For each row, all you have to do is decide whether you prefer Option A or Option B. Indicate your preference by selecting the corresponding button. **Most people begin by preferring Option A and then switch to Option B, so one way to complete this list is to determine the best row to switch from Option A to Option B.**

Now, please make your decisions below.

<table>
<thead>
<tr>
<th>Option A</th>
<th>Option B</th>
</tr>
</thead>
<tbody>
<tr>
<td>(you receive)</td>
<td>(the ARC receives)</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $0</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $1</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $2</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $3</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $4</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $5</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $6</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $7</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $8</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $9</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $10</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $11</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $12</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $13</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $14</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $15</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $16</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $17</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $18</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $19</td>
</tr>
<tr>
<td>You: $10 with probability 95%, and $0 otherwise</td>
<td>ARC: $20</td>
</tr>
</tbody>
</table>
B Additional Results
Table B.1: OLS of Lottery Valuations

<table>
<thead>
<tr>
<th></th>
<th>No Self-Charity Tradeoff Context:</th>
<th>Self-Charity Tradeoff Context:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$Y_s(P_s)$</td>
<td>$Y_c(P_c)$</td>
</tr>
<tr>
<td>$Y_c(P_s)$</td>
<td>100.000</td>
<td>100.000</td>
</tr>
<tr>
<td></td>
<td>(.)</td>
<td>(.)</td>
</tr>
<tr>
<td>$p = 1$</td>
<td>100.000</td>
<td>100.000</td>
</tr>
<tr>
<td>($p = 0.95$)</td>
<td>90.526***</td>
<td>92.368***</td>
</tr>
<tr>
<td></td>
<td>(0.941)</td>
<td>(0.947)</td>
</tr>
<tr>
<td>($p = 0.90$)</td>
<td>84.518***</td>
<td>86.360***</td>
</tr>
<tr>
<td></td>
<td>(1.415)</td>
<td>(1.588)</td>
</tr>
<tr>
<td>($p = 0.75$)</td>
<td>71.096***</td>
<td>75.351***</td>
</tr>
<tr>
<td></td>
<td>(1.579)</td>
<td>(2.021)</td>
</tr>
<tr>
<td>($p = 0.50$)</td>
<td>51.096***</td>
<td>59.956***</td>
</tr>
<tr>
<td></td>
<td>(1.677)</td>
<td>(2.693)</td>
</tr>
<tr>
<td>($p = 0.25$)</td>
<td>19.781***</td>
<td>27.632***</td>
</tr>
<tr>
<td></td>
<td>(1.793)</td>
<td>(3.253)</td>
</tr>
<tr>
<td>($p = 0.10$)</td>
<td>13.553***</td>
<td>18.772***</td>
</tr>
<tr>
<td></td>
<td>(1.431)</td>
<td>(2.915)</td>
</tr>
<tr>
<td>($p = 0.05$)</td>
<td>10.050***</td>
<td>15.482***</td>
</tr>
<tr>
<td></td>
<td>(1.341)</td>
<td>(2.220)</td>
</tr>
</tbody>
</table>

|                  | 456                               | 456                             | 456                             | 456                             |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the subject level and shown in parentheses. Regression results are from $Y_i = \beta_0I(p = 1)_i + \beta_1I(p = 0.95)_i + \beta_2I(p = 0.9)_i + \beta_3I(p = 0.75)_i + \beta_4I(p = 0.5)_i + \beta_5I(p = 0.25)_i + \beta_6I(p = 0.1)_i + \beta_7I(p = 0.05)_i + \epsilon_i$. The dependent variable, $Y_i$, is the individual $i$’s self dollar valuation or the self lottery ($Y_s(P_s)$), charity dollar valuation of the charity lottery ($Y_c(P_c)$), self dollar valuation of the charity lottery ($Y_s(P_c)$), or charity dollar valuation of the self lottery ($Y_c(P_s)$), respectively. Self dollar valuations are scaled as percentages of $10$, and charity dollar valuations are scaled as percentages of $X$. Each column shows data for the 57 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.
Table B.2: Interval Regression of Lottery Valuations

<table>
<thead>
<tr>
<th></th>
<th>No Self-Charity Tradeoff Context:</th>
<th>Self-Charity Tradeoff Context:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$Y^s(P^s)$</td>
<td>$Y^c(P^c)$</td>
</tr>
<tr>
<td></td>
<td>$Y^c(P^s)$</td>
<td>$Y^s(P^c)$</td>
</tr>
<tr>
<td>$p = 1$</td>
<td>100.000</td>
<td>100.000</td>
</tr>
<tr>
<td></td>
<td>(.)</td>
<td>(.)</td>
</tr>
<tr>
<td>$p = 0.95$</td>
<td>90.629***</td>
<td>92.646***</td>
</tr>
<tr>
<td></td>
<td>(0.958)</td>
<td>(0.999)</td>
</tr>
<tr>
<td>$p = 0.90$</td>
<td>84.516***</td>
<td>88.274***</td>
</tr>
<tr>
<td></td>
<td>(1.404)</td>
<td>(0.991)</td>
</tr>
<tr>
<td>$p = 0.75$</td>
<td>71.096***</td>
<td>74.181***</td>
</tr>
<tr>
<td></td>
<td>(1.448)</td>
<td>(1.179)</td>
</tr>
<tr>
<td>$p = 0.50$</td>
<td>51.098***</td>
<td>50.396***</td>
</tr>
<tr>
<td></td>
<td>(1.664)</td>
<td>(1.416)</td>
</tr>
<tr>
<td>$p = 0.25$</td>
<td>31.974***</td>
<td>29.871***</td>
</tr>
<tr>
<td></td>
<td>(1.566)</td>
<td>(1.383)</td>
</tr>
<tr>
<td>$p = 0.10$</td>
<td>19.783***</td>
<td>17.066***</td>
</tr>
<tr>
<td></td>
<td>(1.779)</td>
<td>(1.588)</td>
</tr>
<tr>
<td>$p = 0.05$</td>
<td>13.554***</td>
<td>11.012***</td>
</tr>
<tr>
<td></td>
<td>(1.420)</td>
<td>(1.330)</td>
</tr>
<tr>
<td>N</td>
<td>456</td>
<td>456</td>
</tr>
</tbody>
</table>

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the subject level and shown in parentheses. Results are from interval regressions of $Y_l, Y_u = \beta_0 I(p = 1)_i + \beta_1 I(p = 0.95)_i + \beta_2 I(p = 0.9)_i + \beta_3 I(p = 0.75)_i + \beta_4 I(p = 0.5)_i + \beta_5 I(p = 0.25)_i + \beta_6 I(p = 0.1)_i + \beta_7 I(p = 0.05)_i + \epsilon_i$. The dependent variables, $Y_l$ and $Y_u$, represent the lower and upper bound valuations of the individual $i$'s self dollar valuation or the self lottery ($Y^s(P^s)$), charity dollar valuation of the charity lottery ($Y^c(P^c)$), self dollar valuation of the charity lottery ($Y^c(P^s)$), or charity dollar valuation of the self lottery ($Y^s(P^c)$), respectively. Self dollar valuations are scaled as percentages of $\$10$, and charity dollar valuations are scaled as percentages of $\$X. Each column shows data for the 57 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.
Table B.3: OLS of (Self Lottery - Charity Lottery) Valuations

<table>
<thead>
<tr>
<th></th>
<th>No Self-Charity Tradeoff Context:</th>
<th>Self-Charity Tradeoff Context:</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$D_{NSC} = Y^s(P^s) - Y^c(P^c)$</td>
<td>$D_{SC} = Y^c(P^s) - Y^s(P^c)$</td>
<td>$DID = D_{SC} - D_{NSC}$</td>
</tr>
<tr>
<td>$p = 0.95$</td>
<td>-1.842*</td>
<td>21.316***</td>
<td>23.158***</td>
</tr>
<tr>
<td></td>
<td>(0.953)</td>
<td>(4.011)</td>
<td>(4.322)</td>
</tr>
<tr>
<td>$p = 0.90$</td>
<td>-3.596***</td>
<td>21.272***</td>
<td>24.868***</td>
</tr>
<tr>
<td></td>
<td>(1.264)</td>
<td>(3.905)</td>
<td>(4.472)</td>
</tr>
<tr>
<td>$p = 0.75$</td>
<td>-3.026**</td>
<td>18.421***</td>
<td>21.447***</td>
</tr>
<tr>
<td></td>
<td>(1.318)</td>
<td>(3.972)</td>
<td>(4.310)</td>
</tr>
<tr>
<td>$p = 0.50$</td>
<td>0.702</td>
<td>16.842***</td>
<td>16.140***</td>
</tr>
<tr>
<td></td>
<td>(1.731)</td>
<td>(3.769)</td>
<td>(3.887)</td>
</tr>
<tr>
<td>$p = 0.25$</td>
<td>2.105*</td>
<td>14.868***</td>
<td>12.763***</td>
</tr>
<tr>
<td></td>
<td>(1.183)</td>
<td>(3.992)</td>
<td>(4.078)</td>
</tr>
<tr>
<td>$p = 0.10$</td>
<td>2.719</td>
<td>9.254***</td>
<td>6.535*</td>
</tr>
<tr>
<td></td>
<td>(1.863)</td>
<td>(3.310)</td>
<td>(3.770)</td>
</tr>
<tr>
<td>$p = 0.05$</td>
<td>2.544**</td>
<td>3.289</td>
<td>0.746</td>
</tr>
<tr>
<td></td>
<td>(1.122)</td>
<td>(2.996)</td>
<td>(2.832)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(.)</td>
<td>(.)</td>
<td>(.)</td>
</tr>
<tr>
<td>$N$</td>
<td>456</td>
<td>456</td>
<td>456</td>
</tr>
</tbody>
</table>

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the subject level and shown in parentheses. Results are from OLS regressions of $Z_i = \beta_0 I(p = 1)_i + \beta_1 I(p = 0.95)_i + \beta_2 I(p = 0.9)_i + \beta_3 I(p = 0.75)_i + \beta_4 I(p = 0.5)_i + \beta_5 I(p = 0.25)_i + \beta_6 I(p = 0.1)_i + \beta_7 I(p = 0.05)_i + \epsilon_i$. In the first column, the dependent variable, $D_{NSC} = Y^s(P^s) - Y^c(P^c)$, is individual $i$’s difference in their self lottery and charity lottery valuations in the no self-charity tradeoff context. In the second column, the dependent variable, $D_{SC} = Y^c(P^s) - Y^s(P^c)$, is individual $i$’s difference in their self lottery and charity lottery valuations in the self-charity tradeoff context. In the third column, the dependent variable, $DID = D_{SC} - D_{NSC}$, is individual $i$’s difference of their differences in self lottery and charity lottery valuations across the two contexts. Self dollar valuations are scaled as percentages of $10, and charity dollar valuations are scaled as percentages of $X. Each column shows data for the 57 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.
Table B.4: Excluding Observations that involve Multiple Switch Point: OLS of (Self Lottery - Charity Lottery) Valuations

<table>
<thead>
<tr>
<th>No Self-Charity Tradeoff Context: $D_{NSC} = Y^s(P^s) - Y^c(P^c)$</th>
<th>Self-Charity Tradeoff Context: $D_{SC} = Y^c(P^s) - Y^s(P^c)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p = 0.95$</td>
<td>$p = 0.95$</td>
</tr>
<tr>
<td>$-1.842^*$</td>
<td>$20.972^{***}$</td>
</tr>
<tr>
<td>$(0.953)$</td>
<td>$(4.181)$</td>
</tr>
<tr>
<td>$p = 0.90$</td>
<td>$p = 0.90$</td>
</tr>
<tr>
<td>$-3.596^{***}$</td>
<td>$20.759^{***}$</td>
</tr>
<tr>
<td>$(1.265)$</td>
<td>$(3.941)$</td>
</tr>
<tr>
<td>$p = 0.75$</td>
<td>$p = 0.75$</td>
</tr>
<tr>
<td>$-3.026^{**}$</td>
<td>$18.750^{***}$</td>
</tr>
<tr>
<td>$(1.318)$</td>
<td>$(4.030)$</td>
</tr>
<tr>
<td>$p = 0.50$</td>
<td>$p = 0.50$</td>
</tr>
<tr>
<td>$0.818$</td>
<td>$17.273^{***}$</td>
</tr>
<tr>
<td>$(1.693)$</td>
<td>$(3.892)$</td>
</tr>
<tr>
<td>$p = 0.25$</td>
<td>$p = 0.25$</td>
</tr>
<tr>
<td>$2.232^*$</td>
<td>$15.500^{***}$</td>
</tr>
<tr>
<td>$(1.197)$</td>
<td>$(4.070)$</td>
</tr>
<tr>
<td>$p = 0.10$</td>
<td>$p = 0.10$</td>
</tr>
<tr>
<td>$2.000$</td>
<td>$10.509^{***}$</td>
</tr>
<tr>
<td>$(1.713)$</td>
<td>$(3.406)$</td>
</tr>
<tr>
<td>$p = 0.05$</td>
<td>$p = 0.05$</td>
</tr>
<tr>
<td>$2.232^{**}$</td>
<td>$3.437$</td>
</tr>
<tr>
<td>$(1.096)$</td>
<td>$(3.047)$</td>
</tr>
<tr>
<td>Constant</td>
<td>Constant</td>
</tr>
<tr>
<td>$-0.000$</td>
<td>$0.000$</td>
</tr>
<tr>
<td>$(.)$</td>
<td>$(.)$</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td><strong>N</strong></td>
</tr>
<tr>
<td>450</td>
<td>443</td>
</tr>
</tbody>
</table>

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the subject level and shown in parentheses. Results are from OLS regressions of $Z_i = \beta_0 I(p = 1)_i + \beta_1 I(p = 0.95)_i + \beta_2 I(p = 0.9)_i + \beta_3 I(p = 0.75)_i + \beta_4 I(p = 0.5)_i + \beta_5 I(p = 0.25)_i + \beta_6 I(p = 0.1)_i + \beta_7 I(p = 0.05)_i + \epsilon_i$. In the first column, the dependent variable, $D_{NSC} = Y^s(P^s) - Y^c(P^c)$, is individual $i$’s difference in their self lottery and charity lottery valuations in the no self-charity tradeoff context. In the second column, the dependent variable, $D_{SC} = Y^c(P^s) - Y^s(P^c)$, is individual $i$’s difference in their self lottery and charity lottery valuations in the self-charity tradeoff context. Self dollar valuations are scaled as percentages of $10, and charity dollar valuations are scaled as percentages of $X. Each column shows data for the 57 uncensored participants without multiple switch points in the normalization task, excluding any observations in the valuation task that involve multiple switch points.
Table B.5: Excluding Participants that ever have Multiple Switch Points: OLS of (Self Lottery - Charity Lottery) Valuations

<table>
<thead>
<tr>
<th></th>
<th>No Self-Charity Tradeoff Context:</th>
<th>Self-Charity Tradeoff Context:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( D_{NSC} = Y_s(P_s) - Y_c(P_c) )</td>
<td>( D_{SC} = Y_c(P_s) - Y_s(P_c) )</td>
</tr>
<tr>
<td>( p = 0.95 )</td>
<td>-1.650(^*)</td>
<td>18.900(^{**})</td>
</tr>
<tr>
<td></td>
<td>(0.968)</td>
<td>(4.308)</td>
</tr>
<tr>
<td>( p = 0.90 )</td>
<td>-3.250(^{**})</td>
<td>19.350(^{**})</td>
</tr>
<tr>
<td></td>
<td>(1.325)</td>
<td>(4.248)</td>
</tr>
<tr>
<td>( p = 0.75 )</td>
<td>-2.400(^*)</td>
<td>18.500(^{**})</td>
</tr>
<tr>
<td></td>
<td>(1.377)</td>
<td>(4.417)</td>
</tr>
<tr>
<td>( p = 0.50 )</td>
<td>1.900</td>
<td>17.600(^{***})</td>
</tr>
<tr>
<td></td>
<td>(1.572)</td>
<td>(4.191)</td>
</tr>
<tr>
<td>( p = 0.25 )</td>
<td>2.500(^*)</td>
<td>15.350(^{**})</td>
</tr>
<tr>
<td></td>
<td>(1.299)</td>
<td>(4.242)</td>
</tr>
<tr>
<td>( p = 0.10 )</td>
<td>3.500(^{**})</td>
<td>9.500(^{**})</td>
</tr>
<tr>
<td></td>
<td>(1.567)</td>
<td>(3.471)</td>
</tr>
<tr>
<td>( p = 0.05 )</td>
<td>2.500(^{**})</td>
<td>5.450(^*)</td>
</tr>
<tr>
<td></td>
<td>(1.191)</td>
<td>(3.195)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(.)</td>
<td>(.)</td>
</tr>
<tr>
<td>N</td>
<td>400</td>
<td>400</td>
</tr>
</tbody>
</table>

\(^*\) \ p < 0.10, \(^{**}\) \ p < 0.05, \(^{***}\) \ p < 0.01. Standard errors are clustered at the subject level and shown in parentheses. Results are from OLS regressions of \( Z_i = \beta_0 I(p = 1) + \beta_1 I(p = 0.95) + \beta_2 I(p = 0.9) + \beta_3 I(p = 0.75) + \beta_4 I(p = 0.5) + \beta_5 I(p = 0.25) + \beta_6 I(p = 0.1) + \beta_7 I(p = 0.05) + \epsilon_i \). In the first column, the dependent variable, \( D_{NSC} = Y_s(P_s) - Y_c(P_c) \), is individual \( i \)'s difference in their self lottery and charity lottery valuations in the no self-charity tradeoff context. In the second column, the dependent variable, \( D_{SC} = Y_s(P_s) - Y_c(P_c) \), is individual \( i \)'s difference in their self lottery and charity lottery valuations in the self-charity tradeoff context. Self dollar valuations are scaled as percentages of $10, and charity dollar valuations are scaled as percentages of \$X. Each column shows data for the 50 uncensored participants without multiple switch points in the normalization task and without multiple switch points in the valuation task.
Table B.6: Including Censored Participants: OLS of (Self Lottery - Charity Lottery) Valuations

<table>
<thead>
<tr>
<th></th>
<th>No Self-Charity Tradeoff Context: $D_{NSC} = Y_s(P_s) - Y_c(P_c)$</th>
<th>Self-Charity Tradeoff Context: $D_{SC} = Y_c(P_s) - Y_s(P_c)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p = 0.95$</td>
<td>-2.576***</td>
<td>43.677***</td>
</tr>
<tr>
<td></td>
<td>(0.857)</td>
<td>(3.920)</td>
</tr>
<tr>
<td>$p = 0.90$</td>
<td>-3.207***</td>
<td>44.061***</td>
</tr>
<tr>
<td></td>
<td>(1.025)</td>
<td>(3.892)</td>
</tr>
<tr>
<td>$p = 0.75$</td>
<td>-4.747***</td>
<td>42.879***</td>
</tr>
<tr>
<td></td>
<td>(1.226)</td>
<td>(4.011)</td>
</tr>
<tr>
<td>$p = 0.50$</td>
<td>-0.606</td>
<td>40.051***</td>
</tr>
<tr>
<td></td>
<td>(1.532)</td>
<td>(4.138)</td>
</tr>
<tr>
<td>$p = 0.25$</td>
<td>0.354</td>
<td>38.182***</td>
</tr>
<tr>
<td></td>
<td>(1.219)</td>
<td>(4.332)</td>
</tr>
<tr>
<td>$p = 0.10$</td>
<td>1.970</td>
<td>33.788***</td>
</tr>
<tr>
<td></td>
<td>(1.292)</td>
<td>(4.328)</td>
</tr>
<tr>
<td>$p = 0.05$</td>
<td>2.045**</td>
<td>28.586***</td>
</tr>
<tr>
<td></td>
<td>(0.931)</td>
<td>(4.345)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(.)</td>
<td>(.)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>792</td>
<td>792</td>
</tr>
</tbody>
</table>

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the subject level and shown in parentheses. Results are from Tobit regressions of $Z_{li}, Z_{ui} = \beta_0 I(p = 1) + \beta_1 I(p = 0.95) + \beta_2 I(p = 0.95) + \beta_3 I(p = 0.75) + \beta_4 I(p = 0.5) + \beta_5 I(p = 0.25) + \beta_6 I(p = 0.1) + \beta_7 I(p = 0.05) + \epsilon_i$. In the first column, the dependent variable, $D_{NSC} = Y_s(P_s) - Y_c(P_c)$, is individual $i$’s difference in their self lottery and charity lottery valuations in the no self-charity tradeoff context. In the second column, the dependent variable, $D_{SC} = Y_c(P_s) - Y_s(P_c)$, is individual $i$’s difference in their self lottery and charity lottery valuations in the self-charity tradeoff context. Self dollar valuations are scaled as percentages of $\$10$, and charity dollar valuations are scaled as percentages of $\$X$. Each column shows data for all 99 uncensored and censored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.
Table B.7: OLS of (Self-Charity Tradeoff - No Self-Charity Tradeoff) Valuations

<table>
<thead>
<tr>
<th>p</th>
<th>Charity Lottery Valuations: $Y^s(P^c) - Y^c(P^c)$</th>
<th>Self Lottery Valuations: $Y^c(P^s) - Y^s(P^s)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.95</td>
<td>-24.298***</td>
<td>-1.140</td>
</tr>
<tr>
<td></td>
<td>(3.360)</td>
<td>(1.785)</td>
</tr>
<tr>
<td>0.90</td>
<td>-23.026***</td>
<td>1.842</td>
</tr>
<tr>
<td></td>
<td>(3.241)</td>
<td>(2.105)</td>
</tr>
<tr>
<td>0.75</td>
<td>-17.193***</td>
<td>4.254*</td>
</tr>
<tr>
<td></td>
<td>(2.860)</td>
<td>(2.247)</td>
</tr>
<tr>
<td>0.50</td>
<td>-7.281***</td>
<td>8.860***</td>
</tr>
<tr>
<td></td>
<td>(2.217)</td>
<td>(2.598)</td>
</tr>
<tr>
<td>0.25</td>
<td>-2.544</td>
<td>10.219***</td>
</tr>
<tr>
<td></td>
<td>(1.721)</td>
<td>(3.202)</td>
</tr>
<tr>
<td>0.10</td>
<td>1.316</td>
<td>7.851**</td>
</tr>
<tr>
<td></td>
<td>(1.699)</td>
<td>(3.336)</td>
</tr>
<tr>
<td>0.05</td>
<td>4.474*</td>
<td>5.219*</td>
</tr>
<tr>
<td></td>
<td>(2.280)</td>
<td>(2.994)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(.)</td>
<td>(.)</td>
</tr>
<tr>
<td>N</td>
<td>456</td>
<td>456</td>
</tr>
</tbody>
</table>

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the subject level and shown in parentheses. Results are from OLS regressions of $Z_i = \beta_0 I(p = 1)_i + \beta_1 I(p = 0.95)_i + \beta_2 I(p = 0.9)_i + \beta_3 I(p = 0.75)_i + \beta_4 I(p = 0.5)_i + \beta_5 I(p = 0.25)_i + \beta_6 I(p = 0.1)_i + \beta_7 I(p = 0.05)_i + \epsilon_i$. In the first column, the dependent variable, $Y^s(P^c) - Y^c(P^c)$, is individual $i$’s difference in their charity lottery valuations across the self-charity tradeoff and no self-charity tradeoff contexts. In the second column, the dependent variable, $Y^c(P^s) - Y^s(P^s)$, is individual $i$’s difference in their self lottery valuations across the self-charity tradeoff and no self-charity tradeoff contexts. Self dollar valuations are scaled as percentages of $10, and charity dollar valuations are scaled as percentages of $X. Each column shows data for the 57 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.
Table B.8: Excluding Observations that involve Multiple Switch Point: OLS of (Self-Charity Tradeoff - No Self-Charity Tradeoff) Valuations

<table>
<thead>
<tr>
<th>p</th>
<th>Charity Lottery Valuations: $Y^s(P^c) - Y^c(P^c)$</th>
<th>Self Lottery Valuations: $Y^c(P^s) - Y^s(P^s)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.95</td>
<td>-24.018*** (3.409)</td>
<td>-1.000 (1.805)</td>
</tr>
<tr>
<td>0.90</td>
<td>-22.545*** (3.262)</td>
<td>1.842 (2.106)</td>
</tr>
<tr>
<td>0.75</td>
<td>-17.054*** (2.908)</td>
<td>4.254* (2.248)</td>
</tr>
<tr>
<td>0.50</td>
<td>-7.545*** (2.275)</td>
<td>9.107*** (2.633)</td>
</tr>
<tr>
<td>0.25</td>
<td>-2.818 (1.767)</td>
<td>9.955*** (3.248)</td>
</tr>
<tr>
<td>0.10</td>
<td>1.273 (1.731)</td>
<td>7.500** (3.175)</td>
</tr>
<tr>
<td>0.05</td>
<td>4.474* (2.280)</td>
<td>5.864* (3.011)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.000 (.)</td>
<td>0.000 (.)</td>
</tr>
<tr>
<td>N</td>
<td>447</td>
<td>447</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors are clustered at the subject level and shown in parentheses. Results are from OLS regressions of $Z_i = \beta_0 I(p = 1) + \beta_1 I(p = 0.95) + \beta_2 I(p = 0.9) + \beta_3 I(p = 0.75) + \beta_4 I(p = 0.5) + \beta_5 I(p = 0.25) + \beta_6 I(p = 0.1) + \beta_7 I(p = 0.05) + \epsilon_i$. In the first column, the dependent variable, $Y^s(P^c) - Y^c(P^c)$, is individual i’s difference in their charity lottery valuations across the self-charity tradeoff and no self-charity tradeoff contexts. In the second column, the dependent variable, $Y^c(P^s) - Y^s(P^s)$, is individual i’s difference in their self lottery valuations across the self-charity tradeoff and no self-charity tradeoff contexts. Self dollar valuations are scaled as percentages of $10, and charity dollar valuations are scaled as percentages of $X. Each column shows data for the 57 uncensored participants without multiple switch points in the normalization task, excluding any observations in the valuation task that involve multiple switch points.
Table B.9: Excluding Participants that ever have Multiple Switch Points: OLS of (Self-Charity Tradeoff - No Self-Charity Tradeoff) Valuations

<table>
<thead>
<tr>
<th>Charity Lottery Valuations:</th>
<th>Self Lottery Valuations:</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Y^s(P_c) - Y^c(P_c)$</td>
<td>$Y^c(P_s) - Y^s(P_s)$</td>
</tr>
<tr>
<td>$p = 0.95$</td>
<td>-22.550***</td>
</tr>
<tr>
<td></td>
<td>(3.615)</td>
</tr>
<tr>
<td>$p = 0.90$</td>
<td>-21.600***</td>
</tr>
<tr>
<td></td>
<td>(3.536)</td>
</tr>
<tr>
<td>$p = 0.75$</td>
<td>-16.950***</td>
</tr>
<tr>
<td></td>
<td>(3.206)</td>
</tr>
<tr>
<td>$p = 0.50$</td>
<td>-6.800***</td>
</tr>
<tr>
<td></td>
<td>(2.385)</td>
</tr>
<tr>
<td>$p = 0.25$</td>
<td>-2.600</td>
</tr>
<tr>
<td></td>
<td>(1.902)</td>
</tr>
<tr>
<td>$p = 0.10$</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>(1.863)</td>
</tr>
<tr>
<td>$p = 0.05$</td>
<td>2.500</td>
</tr>
<tr>
<td></td>
<td>(1.587)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(.</td>
</tr>
<tr>
<td>N</td>
<td>400</td>
</tr>
</tbody>
</table>

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the subject level and shown in parentheses. Results are from OLS regressions of $Z_i = \beta_0I(p = 1)_i + \beta_1I(p = 0.95)_i + \beta_2I(p = 0.9)_i + \beta_3I(p = 0.75)_i + \beta_4I(p = 0.5)_i + \beta_5I(p = 0.25)_i + \beta_6I(p = 0.1)_i + \beta_7I(p = 0.05)_i + \epsilon_i$. In the first column, the dependent variable, $Y^s(P_c) - Y^c(P_c)$, is individual $i$'s difference in their charity lottery valuations across the self-charity tradeoff and no self-charity tradeoff contexts. In the second column, the dependent variable, $Y^c(P_s) - Y^s(P_s)$, is individual $i$'s difference in their self lottery valuations across the self-charity tradeoff and no self-charity tradeoff contexts. Self dollar valuations are scaled as percentages of $10$, and charity dollar valuations are scaled as percentages of $X$. Each column shows data for the 50 uncensored participants without multiple switch points in the normalization task and without multiple switch points in the valuation task.
Table B.10: Including Censored Participants: OLS of (Self-Charity Tradeoff - No Self-Charity Tradeoff ) Valuations

<table>
<thead>
<tr>
<th></th>
<th>Charity Lottery Valuations: ( Y^s(P^c) - Y^c(P^c) )</th>
<th>Self Lottery Valuations: ( Y^c(P^s) - Y^s(P^s) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( p = 0.95 )</td>
<td>-43.131***</td>
<td>2.778**</td>
</tr>
<tr>
<td></td>
<td>(3.367)</td>
<td>(1.376)</td>
</tr>
<tr>
<td>( p = 0.90 )</td>
<td>-40.101***</td>
<td>6.995***</td>
</tr>
<tr>
<td></td>
<td>(3.182)</td>
<td>(1.665)</td>
</tr>
<tr>
<td>( p = 0.75 )</td>
<td>-32.399***</td>
<td>15.227***</td>
</tr>
<tr>
<td></td>
<td>(2.863)</td>
<td>(2.175)</td>
</tr>
<tr>
<td>( p = 0.50 )</td>
<td>-15.556***</td>
<td>25.101***</td>
</tr>
<tr>
<td></td>
<td>(2.334)</td>
<td>(2.976)</td>
</tr>
<tr>
<td>( p = 0.25 )</td>
<td>-8.030***</td>
<td>29.798***</td>
</tr>
<tr>
<td></td>
<td>(1.865)</td>
<td>(3.591)</td>
</tr>
<tr>
<td>( p = 0.10 )</td>
<td>-1.364</td>
<td>30.455***</td>
</tr>
<tr>
<td></td>
<td>(1.448)</td>
<td>(3.979)</td>
</tr>
<tr>
<td>( p = 0.05 )</td>
<td>2.475</td>
<td>29.015***</td>
</tr>
<tr>
<td></td>
<td>(1.559)</td>
<td>(4.083)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(.)</td>
<td>(.)</td>
</tr>
<tr>
<td>N</td>
<td>792</td>
<td>792</td>
</tr>
</tbody>
</table>

* \( p < 0.10 \), ** \( p < 0.05 \), *** \( p < 0.01 \). Standard errors are clustered at the subject level and shown in parentheses. Results are from Tobit regressions of \( Z_i = \beta_0 I(p = 1)_i + \beta_1 I(p = 0.95)_i + \beta_2 I(p = 0.9)_i + \beta_3 I(p = 0.75)_i + \beta_4 I(p = 0.5)_i + \beta_5 I(p = 0.25)_i + \beta_6 I(p = 0.1)_i + \beta_7 I(p = 0.05)_i + \epsilon_i \). In the first column, the dependent variable, \( Y^s(P^c) - Y^c(P^c) \), is individual \( i \)'s difference in their charity lottery valuations across the self-charity tradeoff and no self-charity tradeoff contexts. In the second column, the dependent variable, \( Y^c(P^s) - Y^s(P^s) \), is individual \( i \)'s difference in their self lottery valuations across the self-charity tradeoff and no self-charity tradeoff contexts. Self dollar valuations are scaled as percentages of $10, and charity dollar valuations are scaled as percentages of $X. Each column shows data for all 99 uncensored and censored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.
Table B.11: OLS of (Self Lottery - Charity Lottery) Valuations

<table>
<thead>
<tr>
<th></th>
<th>Self Dollar Valuations: $Y^s(P^s) - Y^s(P^c)$</th>
<th>Charity Dollar Valuations: $Y^c(P^s) - Y^c(P^c)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p = 0.95$</td>
<td>22.456***</td>
<td>-2.982*</td>
</tr>
<tr>
<td></td>
<td>(3.186)</td>
<td>(1.626)</td>
</tr>
<tr>
<td>$p = 0.90$</td>
<td>19.430***</td>
<td>-1.754</td>
</tr>
<tr>
<td></td>
<td>(3.027)</td>
<td>(1.619)</td>
</tr>
<tr>
<td>$p = 0.75$</td>
<td>14.167***</td>
<td>1.228</td>
</tr>
<tr>
<td></td>
<td>(2.800)</td>
<td>(2.081)</td>
</tr>
<tr>
<td>$p = 0.50$</td>
<td>7.982***</td>
<td>9.561***</td>
</tr>
<tr>
<td></td>
<td>(2.325)</td>
<td>(2.890)</td>
</tr>
<tr>
<td>$p = 0.25$</td>
<td>4.649***</td>
<td>12.325***</td>
</tr>
<tr>
<td></td>
<td>(1.724)</td>
<td>(3.309)</td>
</tr>
<tr>
<td>$p = 0.10$</td>
<td>1.404</td>
<td>10.570***</td>
</tr>
<tr>
<td></td>
<td>(2.009)</td>
<td>(3.193)</td>
</tr>
<tr>
<td>$p = 0.05$</td>
<td>-1.930</td>
<td>7.763**</td>
</tr>
<tr>
<td></td>
<td>(2.366)</td>
<td>(3.284)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(.)</td>
<td>(.)</td>
</tr>
<tr>
<td>$N$</td>
<td>456</td>
<td>456</td>
</tr>
</tbody>
</table>

*p < 0.10, **p < 0.05, ***p < 0.01. Standard errors are clustered at the subject level and shown in parentheses. Results are from OLS regressions of $Z_i = \beta_0 I(p = 1)_i + \beta_1 I(p = 0.95)_i + \beta_2 I(p = 0.9)_i + \beta_3 I(p = 0.75)_i + \beta_4 I(p = 0.5)_i + \beta_5 I(p = 0.25)_i + \beta_6 I(p = 0.1)_i + \beta_7 I(p = 0.05)_i + \epsilon_i$. In the first column, the dependent variable, $Y^s(P^s) - Y^s(P^c)$, is individual $i$’s difference in their self lottery and charity lottery valuations when valuations are elicited in self dollar valuations. In the second column, the dependent variable, $Y^c(P^s) - Y^c(P^c)$, is individual $i$’s difference in their self lottery and charity lottery valuations when valuations are elicited in charity dollar valuations. Self dollar valuations are scaled as percentages of $10$, and charity dollar valuations are scaled as percentages of $\$X$. Each column shows data for the 57 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.
<table>
<thead>
<tr>
<th></th>
<th>Self Dollar Valuations: $Y^S(P^s) - Y^S(P^c)$</th>
<th>Charity Dollar Valuations: $Y^C(P^s) - Y^C(P^c)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p = 0.95$</td>
<td>22.500***</td>
<td>-3.000*</td>
</tr>
<tr>
<td></td>
<td>(3.243)</td>
<td>(1.579)</td>
</tr>
<tr>
<td>$p = 0.90$</td>
<td>19.241***</td>
<td>-1.754</td>
</tr>
<tr>
<td></td>
<td>(3.076)</td>
<td>(1.619)</td>
</tr>
<tr>
<td>$p = 0.75$</td>
<td>14.063***</td>
<td>1.228</td>
</tr>
<tr>
<td></td>
<td>(2.849)</td>
<td>(2.082)</td>
</tr>
<tr>
<td>$p = 0.50$</td>
<td>8.545***</td>
<td>10.000***</td>
</tr>
<tr>
<td></td>
<td>(2.352)</td>
<td>(2.890)</td>
</tr>
<tr>
<td>$p = 0.25$</td>
<td>5.091***</td>
<td>12.188***</td>
</tr>
<tr>
<td></td>
<td>(1.756)</td>
<td>(3.366)</td>
</tr>
<tr>
<td>$p = 0.10$</td>
<td>1.364</td>
<td>11.136***</td>
</tr>
<tr>
<td></td>
<td>(2.081)</td>
<td>(3.281)</td>
</tr>
<tr>
<td>$p = 0.05$</td>
<td>-1.964</td>
<td>8.438**</td>
</tr>
<tr>
<td></td>
<td>(2.408)</td>
<td>(3.271)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(.</td>
<td>(.</td>
</tr>
<tr>
<td>N</td>
<td>446</td>
<td>448</td>
</tr>
</tbody>
</table>

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the subject level and shown in parentheses. Results are from OLS regressions of $Z_i = \beta_0 I(p = 1)_i + \beta_1 I(p = 0.95)_i + \beta_2 I(p = 0.9)_i + \beta_3 I(p = 0.75)_i + \beta_4 I(p = 0.5)_i + \beta_5 I(p = 0.25)_i + \beta_6 I(p = 0.1)_i + \beta_7 I(p = 0.05)_i + \epsilon_i$. In the first column, the dependent variable, $Y^S(P^s) - Y^S(P^c)$, is individual $i$’s difference in their self lottery and charity lottery valuations when valuations are elicited in self dollar valuations. In the second column, the dependent variable, $Y^C(P^s) - Y^C(P^c)$, is individual $i$’s difference in their self lottery and charity lottery valuations when valuations are elicited in charity dollar valuations. Self dollar valuations are scaled as percentages of $\$10$, and charity dollar valuations are scaled as percentages of $\$X$. Each column shows data for the 57 uncensored participants without multiple switch points in the normalization task, excluding any observations in the valuation task that involve multiple switch points.
Table B.13: Excluding Participants that ever have Multiple Switch Points: OLS of (Self Lottery - Charity Lottery) Valuations

<table>
<thead>
<tr>
<th></th>
<th>Self Dollar Valuations: $Y^s(P^s) - Y^s(P^c)$</th>
<th>Charity Dollar Valuations: $Y^c(P^s) - Y^c(P^c)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p = 0.95$</td>
<td>20.900*** (3.445)</td>
<td>-3.650*** (1.704)</td>
</tr>
<tr>
<td>$p = 0.90$</td>
<td>18.350*** (3.326)</td>
<td>-2.250 (1.786)</td>
</tr>
<tr>
<td>$p = 0.75$</td>
<td>14.550*** (3.174)</td>
<td>1.550 (2.212)</td>
</tr>
<tr>
<td>$p = 0.50$</td>
<td>8.700*** (2.573)</td>
<td>10.800*** (2.814)</td>
</tr>
<tr>
<td>$p = 0.25$</td>
<td>5.100*** (1.814)</td>
<td>12.750*** (3.695)</td>
</tr>
<tr>
<td>$p = 0.10$</td>
<td>2.500 (1.813)</td>
<td>10.500*** (3.369)</td>
</tr>
<tr>
<td>$p = 0.05$</td>
<td>-0.000 (1.650)</td>
<td>7.950** (3.248)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.000 (0.000)</td>
<td>0.000 (0.000)</td>
</tr>
<tr>
<td>N</td>
<td>400</td>
<td>400</td>
</tr>
</tbody>
</table>

* *p < 0.10, ** *p < 0.05, *** *p < 0.01. Standard errors are clustered at the subject level and shown in parentheses. Results are from OLS regressions of $Z_i = \beta_0 I(p = 1)_i + \beta_1 I(p = 0.95)_i + \beta_2 I(p = 0.9)_i + \beta_3 I(p = 0.75)_i + \beta_4 I(p = 0.5)_i + \beta_5 I(p = 0.25)_i + \beta_6 I(p = 0.1)_i + \beta_7 I(p = 0.05)_i + \epsilon_i$. In the first column, the dependent variable, $Y^s(P^s) - Y^s(P^c)$, is individual $i$’s difference in their self lottery and charity lottery valuations when valuations are elicited in self dollar valuations. In the second column, the dependent variable, $Y^c(P^s) - Y^c(P^c)$, is individual $i$’s difference in their self lottery and charity lottery valuations when valuations are elicited in charity dollar valuations. Self dollar valuations are scaled as percentages of $\$10$, and charity dollar valuations are scaled as percentages of $\$X$. Each column shows data for the 50 uncensored participants without multiple switch points in the normalization task and without multiple switch points in the valuation task.
Table B.14: Including Censored Participants: OLS of (Self Lottery - Charity Lottery) Valuations

<table>
<thead>
<tr>
<th></th>
<th>Self Dollar Valuations: $Y^s(P^s) - Y^s(P^c)$</th>
<th>Charity Dollar Valuations: $Y^c(P^s) - Y^c(P^c)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p = 0.95$</td>
<td>40.556***</td>
<td>0.202</td>
</tr>
<tr>
<td></td>
<td>(3.205)</td>
<td>(1.228)</td>
</tr>
<tr>
<td>$p = 0.90$</td>
<td>36.894***</td>
<td>3.788**</td>
</tr>
<tr>
<td></td>
<td>(3.115)</td>
<td>(1.527)</td>
</tr>
<tr>
<td>$p = 0.75$</td>
<td>27.652***</td>
<td>10.480***</td>
</tr>
<tr>
<td></td>
<td>(2.704)</td>
<td>(1.929)</td>
</tr>
<tr>
<td>$p = 0.50$</td>
<td>14.949***</td>
<td>24.495***</td>
</tr>
<tr>
<td></td>
<td>(2.016)</td>
<td>(2.918)</td>
</tr>
<tr>
<td>$p = 0.25$</td>
<td>8.384***</td>
<td>30.152***</td>
</tr>
<tr>
<td></td>
<td>(1.590)</td>
<td>(3.445)</td>
</tr>
<tr>
<td>$p = 0.10$</td>
<td>3.333**</td>
<td>32.424***</td>
</tr>
<tr>
<td></td>
<td>(1.468)</td>
<td>(3.847)</td>
</tr>
<tr>
<td>$p = 0.05$</td>
<td>-0.429</td>
<td>31.061***</td>
</tr>
<tr>
<td></td>
<td>(1.515)</td>
<td>(4.111)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>792</td>
<td>792</td>
</tr>
</tbody>
</table>

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the subject level and shown in parentheses. Results are from Tobit regressions of $Z_i$, $Z_{ui} = \beta_0 I(p = 1) + \beta_1 I(p = 0.95) + \beta_2 I(p = 0.75) + \beta_3 I(p = 0.5) + \beta_4 I(p = 0.25) + \beta_5 I(p = 0.1) + \beta_6 I(p = 0.05) + \epsilon_i$. In the first column, the dependent variable, $Y^s(P^s) - Y^s(P^c)$, is individual $i$’s difference in their self lottery and charity lottery valuations when valuations are elicited in self dollar valuations. In the second column, the dependent variable, $Y^c(P^s) - Y^c(P^c)$, is individual $i$’s difference in their self lottery and charity lottery valuations when valuations are elicited in charity dollar valuations. Self dollar valuations are scaled as percentages of $\$10$, and charity dollar valuations are scaled as percentages of $\$X$. Each column shows data for all 99 uncensored and censored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.
Table B.15: OLS of (Self Lottery - Partner Lottery) Valuations

<table>
<thead>
<tr>
<th>No Self-Partner Tradeoff Context:</th>
<th>Self-Partner Tradeoff Context:</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_{NSP} = Y_s(P^s) - Y_p(P^p)$</td>
<td>$D_{SP} = Y_p(P^s) - Y_s(P^p)$</td>
</tr>
<tr>
<td>$p = 0.95$</td>
<td></td>
</tr>
<tr>
<td>-6.207***</td>
<td>22.414***</td>
</tr>
<tr>
<td>(2.133)</td>
<td>(5.567)</td>
</tr>
<tr>
<td>$p = 0.90$</td>
<td></td>
</tr>
<tr>
<td>-4.655**</td>
<td>24.741***</td>
</tr>
<tr>
<td>(2.137)</td>
<td>(5.594)</td>
</tr>
<tr>
<td>$p = 0.75$</td>
<td></td>
</tr>
<tr>
<td>-3.103*</td>
<td>22.586**</td>
</tr>
<tr>
<td>(1.679)</td>
<td>(5.843)</td>
</tr>
<tr>
<td>$p = 0.50$</td>
<td></td>
</tr>
<tr>
<td>-1.552</td>
<td>18.793***</td>
</tr>
<tr>
<td>(1.970)</td>
<td>(5.416)</td>
</tr>
<tr>
<td>$p = 0.25$</td>
<td></td>
</tr>
<tr>
<td>0.345</td>
<td>20.086***</td>
</tr>
<tr>
<td>(2.253)</td>
<td>(6.116)</td>
</tr>
<tr>
<td>$p = 0.10$</td>
<td></td>
</tr>
<tr>
<td>2.069</td>
<td>20.431***</td>
</tr>
<tr>
<td>(1.543)</td>
<td>(5.796)</td>
</tr>
<tr>
<td>$p = 0.05$</td>
<td></td>
</tr>
<tr>
<td>-0.172</td>
<td>15.431***</td>
</tr>
<tr>
<td>(1.458)</td>
<td>(5.575)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td></td>
</tr>
<tr>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>(. )</td>
<td>( . )</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td><strong>232</strong></td>
</tr>
</tbody>
</table>

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the subject level and shown in parentheses. Results are from OLS regressions of $Z_i = \beta_0 I(p = 1)_i + \beta_1 I(p = 0.95)_i + \beta_2 I(p = 0.9)_i + \beta_3 I(p = 0.75)_i + \beta_4 I(p = 0.5)_i + \beta_5 I(p = 0.25)_i + \beta_6 I(p = 0.1)_i + \beta_7 I(p = 0.05)_i + \epsilon_i$. In the first column, the dependent variable, $D_{NSP} = Y_s(P^s) - Y_p(P^p)$, is individual $i$’s difference in their self lottery and partner lottery valuations in the no self-partner tradeoff context. In the second column, the dependent variable, $D_{SP} = Y_p(P^s) - Y_s(P^p)$, is individual $i$’s difference in their self lottery and partner lottery valuations in the self-partner tradeoff context. Self dollar valuations are scaled as percentages of $\$10$, and partner dollar valuations are scaled as percentages of $\$X^p$. Each column shows data for the 29 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.
Table B.16: Excluding Observations that involve Multiple Switch Point: OLS of (Self Lottery - Partner Lottery) Valuations

<table>
<thead>
<tr>
<th>No Self-Partner Tradeoff Context:</th>
<th>Self-Partner Tradeoff Context:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$D_{NSP} = Y^s(P^s) - Y^p(P^p)$</td>
</tr>
<tr>
<td>$p = 0.95$</td>
<td>-6.207***</td>
</tr>
<tr>
<td></td>
<td>(2.133)</td>
</tr>
<tr>
<td>$p = 0.90$</td>
<td>-4.655**</td>
</tr>
<tr>
<td></td>
<td>(2.137)</td>
</tr>
<tr>
<td>$p = 0.75$</td>
<td>-3.103*</td>
</tr>
<tr>
<td></td>
<td>(1.679)</td>
</tr>
<tr>
<td>$p = 0.50$</td>
<td>-1.552</td>
</tr>
<tr>
<td></td>
<td>(1.970)</td>
</tr>
<tr>
<td>$p = 0.25$</td>
<td>0.345</td>
</tr>
<tr>
<td></td>
<td>(2.253)</td>
</tr>
<tr>
<td>$p = 0.10$</td>
<td>2.069</td>
</tr>
<tr>
<td></td>
<td>(1.543)</td>
</tr>
<tr>
<td>$p = 0.05$</td>
<td>-0.172</td>
</tr>
<tr>
<td></td>
<td>(1.458)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(.</td>
</tr>
<tr>
<td>N</td>
<td>232</td>
</tr>
</tbody>
</table>

*p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors are clustered at the subject level and shown in parentheses. Results are from OLS regressions of $Z_i = \beta_0I(p = 1) + \beta_1I(p = 0.95)i + \beta_2I(p = 0.9)i + \beta_3I(p = 0.75)i + \beta_4I(p = 0.5)i + \beta_5I(p = 0.25)i + \beta_6I(p = 0.1)i + \beta_7I(p = 0.05)i + \epsilon_i$. In the first column, the dependent variable, $D_{NSP} = Y^s(P^s) - Y^p(P^p)$, is individual $i$’s difference in their self lottery and partner lottery valuations in the no self-partner tradeoff context. In the second column, the dependent variable, $D_{SP} = Y^p(P^s) - Y^s(P^p)$, is individual $i$’s difference in their self lottery and partner lottery valuations in the self-partner tradeoff context. Self dollar valuations are scaled as percentages of $\$10$, and partner dollar valuations are scaled as percentages of $\$X^p$. Each column shows data for the 29 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task without multiple switch points in the normalization task, excluding any observations in the valuation task that involve multiple switch points.
Table B.17: Excluding Participants that ever have Multiple Switch Points: OLS of (Self Lottery - Partner Lottery) Valuations

<table>
<thead>
<tr>
<th>No Self-Partner Tradeoff Context: $D_{NSP} = Y^s(P^s) - Y^p(P^p)$</th>
<th>Self-Partner Tradeoff Context: $D_{SP} = Y^p(P^s) - Y^s(P^p)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p = 0.95$</td>
<td></td>
</tr>
<tr>
<td>-6.111***</td>
<td>24.259***</td>
</tr>
<tr>
<td>(2.193)</td>
<td>(5.751)</td>
</tr>
<tr>
<td>$p = 0.90$</td>
<td></td>
</tr>
<tr>
<td>-4.444*</td>
<td>25.278***</td>
</tr>
<tr>
<td>(2.193)</td>
<td>(5.934)</td>
</tr>
<tr>
<td>$p = 0.75$</td>
<td></td>
</tr>
<tr>
<td>-2.037</td>
<td>24.630***</td>
</tr>
<tr>
<td>(1.611)</td>
<td>(6.073)</td>
</tr>
<tr>
<td>$p = 0.50$</td>
<td></td>
</tr>
<tr>
<td>-0.185</td>
<td>19.815***</td>
</tr>
<tr>
<td>(1.850)</td>
<td>(5.780)</td>
</tr>
<tr>
<td>$p = 0.25$</td>
<td></td>
</tr>
<tr>
<td>-0.370</td>
<td>21.204***</td>
</tr>
<tr>
<td>(2.301)</td>
<td>(6.525)</td>
</tr>
<tr>
<td>$p = 0.10$</td>
<td></td>
</tr>
<tr>
<td>1.481</td>
<td>22.315***</td>
</tr>
<tr>
<td>(1.578)</td>
<td>(6.020)</td>
</tr>
<tr>
<td>$p = 0.05$</td>
<td></td>
</tr>
<tr>
<td>-0.000</td>
<td>16.389**</td>
</tr>
<tr>
<td>(1.559)</td>
<td>(5.958)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.000</td>
</tr>
<tr>
<td>(,)</td>
<td>(,)</td>
</tr>
<tr>
<td>N</td>
<td>216</td>
</tr>
</tbody>
</table>

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the subject level and shown in parentheses. Results are from OLS regressions of $Z_i = \beta_0 I(p = 1) + \beta_1 I(p = 0.95) + \beta_2 I(p = 0.9) + \beta_3 I(p = 0.75) + \beta_4 I(p = 0.5) + \beta_5 I(p = 0.25) + \beta_6 I(p = 0.1) + \beta_7 I(p = 0.05) + \epsilon_i$. In the first column, the dependent variable, $D_{NSP} = Y^s(P^s) - Y^p(P^p)$, is individual $i$'s difference in their self lottery and partner lottery valuations in the no self-partner tradeoff context. In the second column, the dependent variable, $D_{SP} = Y^p(P^s) - Y^s(P^p)$, is individual $i$'s difference in their self lottery and partner lottery valuations in the self-partner tradeoff context. Self dollar valuations are scaled as percentages of $\$10$, and partner dollar valuations are scaled as percentages of $\$X^p$. Each column shows data for the INSERT uncensored participants without multiple switch points in the normalization task and without multiple switch points in the valuation task.
Table B.18: Including Censored Participants: OLS of (Self Lottery - Partner Lottery) Valuations

<table>
<thead>
<tr>
<th>No Self-Partner Tradeoff Context:</th>
<th>Self-Partner Tradeoff Context:</th>
</tr>
</thead>
<tbody>
<tr>
<td>( D_{NSP} = Y^S(P^s) - Y^P(P^p) )</td>
<td>( D_{SP} = Y^P(P^s) - Y^S(P^p) )</td>
</tr>
<tr>
<td>( p = 0.95 )</td>
<td>( p = 0.90 )</td>
</tr>
<tr>
<td>(-3.214 )</td>
<td>( 35.771^{***} )</td>
</tr>
<tr>
<td>(2.976)</td>
<td>(5.268)</td>
</tr>
<tr>
<td>( p = 0.90 )</td>
<td>( p = 0.75 )</td>
</tr>
<tr>
<td>(-2.560 )</td>
<td>( 38.994^{***} )</td>
</tr>
<tr>
<td>(2.226)</td>
<td>(5.400)</td>
</tr>
<tr>
<td>( p = 0.75 )</td>
<td>( p = 0.50 )</td>
</tr>
<tr>
<td>(-3.274 )</td>
<td>( 34.995^{***} )</td>
</tr>
<tr>
<td>(2.146)</td>
<td>(5.629)</td>
</tr>
<tr>
<td>( p = 0.50 )</td>
<td>( p = 0.25 )</td>
</tr>
<tr>
<td>( 1.964 )</td>
<td>( 32.070^{***} )</td>
</tr>
<tr>
<td>(2.218)</td>
<td>(5.517)</td>
</tr>
<tr>
<td>( p = 0.25 )</td>
<td>( p = 0.10 )</td>
</tr>
<tr>
<td>( 2.321 )</td>
<td>( 28.609^{***} )</td>
</tr>
<tr>
<td>(2.002)</td>
<td>(5.698)</td>
</tr>
<tr>
<td>( p = 0.10 )</td>
<td>( p = 0.05 )</td>
</tr>
<tr>
<td>( 3.393^{**} )</td>
<td>( 28.729^{***} )</td>
</tr>
<tr>
<td>(1.475)</td>
<td>(5.728)</td>
</tr>
<tr>
<td>( p = 0.05 )</td>
<td>( )</td>
</tr>
<tr>
<td>( 1.845 )</td>
<td>( 22.083^{***} )</td>
</tr>
<tr>
<td>(1.382)</td>
<td>(5.135)</td>
</tr>
<tr>
<td>Constant</td>
<td>Constant</td>
</tr>
<tr>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>(.)</td>
<td>(.)</td>
</tr>
<tr>
<td>N</td>
<td>336</td>
</tr>
</tbody>
</table>

* \( p < 0.10 \), ** \( p < 0.05 \), *** \( p < 0.01 \). Standard errors are clustered at the subject level and shown in parentheses. Results are from Tobit regressions of \( Z_{li}, Z_{ui} = \beta_0 I(p = 1) + \beta_1 I(p = 0.95) + \beta_2 I(p = 0.9) + \beta_3 I(p = 0.75) + \beta_4 I(p = 0.5) + \beta_5 I(p = 0.25) + \beta_6 I(p = 0.1) + \beta_7 I(p = 0.05) + \epsilon. \) In the first column, the dependent variable, \( D_{NSP} = Y^S(P^s) - Y^P(P^p), \) is individual \( i \)'s difference in their self lottery and partner lottery valuations in the no self-partner tradeoff context. In the second column, the dependent variable, \( D_{SP} = Y^P(P^s) - Y^S(P^p), \) is individual \( i \)'s difference in their self lottery and partner lottery valuations in the self-partner tradeoff context. Self dollar valuations are scaled as percentages of $10, and partner dollar valuations are scaled as percentages of $X^p. \) Each column shows data for all 44 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.
Table B.19: OLS of (Self-Charity Tradeoff Context - No Self Charity Tradeoff Context) Valuations

<table>
<thead>
<tr>
<th>Charity Types</th>
<th>Make-A-Wish Foundation State Chapters</th>
<th>KIPP Charter Schools</th>
<th>Bay Area Animal Shelters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(4.149)</td>
<td>(5.722)</td>
<td>(4.318)</td>
</tr>
<tr>
<td></td>
<td>(4.026)</td>
<td>(5.622)</td>
<td>(3.923)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(.)</td>
<td>(.)</td>
<td>(.)</td>
</tr>
<tr>
<td>N</td>
<td>291</td>
<td>105</td>
<td>93</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors are clustered at the subject level and shown in parentheses. Results are from OLS regressions of $Z_i = \beta_0 + \beta_1 I(\text{Medium Rated Charity})_i + \beta_2 I(\text{Low Rated Charity})_i + \epsilon_i$. The dependent variable, $Y^*(P^c) - Y^c(P^c)$, is individual $i$’s difference in their charity valuations across the self-charity tradeoff and no self-charity tradeoff contexts. While the first column pulls all of the data, the second through fourth column only show data for the shown charity type $k$. Self dollar valuations are scaled as percentages of $\$10$, and charity dollar valuations are scaled as percentages of $\$X^k$ for each charity type $k$. Each column shows data for the relevant 31-35 uncensored participants without multiple switch points in the normalization task. For the 6% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.
Table B.20: Regressions examining relationships between $DID(p)$ and Being Classified as a Wiggler

<table>
<thead>
<tr>
<th>OLS Regression: $DID(p)$</th>
<th>Probit Regression: 1${Wiggler}$</th>
<th>Probit Regression (Marginal Effects): 1${Wiggler}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1{Wiggler}$</td>
<td>13.294**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.297)</td>
<td></td>
</tr>
<tr>
<td>$DID(p)$</td>
<td>0.010**</td>
<td>0.003**</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Feels neutral about ARC</td>
<td>15.265**</td>
<td>-0.305</td>
</tr>
<tr>
<td></td>
<td>(7.452)</td>
<td>(0.492)</td>
</tr>
<tr>
<td>U.S. Citizen</td>
<td>23.524***</td>
<td>-1.127**</td>
</tr>
<tr>
<td></td>
<td>(6.124)</td>
<td>(0.554)</td>
</tr>
<tr>
<td>Female</td>
<td>7.292</td>
<td>-0.432</td>
</tr>
<tr>
<td></td>
<td>(5.646)</td>
<td>(0.393)</td>
</tr>
<tr>
<td>Constant</td>
<td>-16.285***</td>
<td>0.340</td>
</tr>
<tr>
<td></td>
<td>(7.333)</td>
<td>(0.582)</td>
</tr>
<tr>
<td>Observations</td>
<td>456</td>
<td>456</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors are clustered at the subject level and shown in parentheses.

The first column shows results from an OLS regression of $DID(p)$ on $1\{Wiggler\}$. The second and third columns show results from Probit regressions of $1\{Wiggler\}$ on $DID(p)$. $1\{Wiggler\}$ is an indicator for if a participant is classified as a Wiggler. $DID = (Y^c(P^s) - Y^s(P^s)) - (Y^s(P^c) - Y^c(P^c))$, which is individual $i$’s difference of their differences in self lottery valuations across the two contexts and charity lottery valuations across the two contexts. Self dollar valuations are scaled as percentages of $10, and charity dollar valuations are scaled as percentages of $X$. The controls are indicators for if a participants feels neutral about the ARC (this includes one participant who felt unfavorably about the ARC), is a U.S. citizen, and is female. Each column shows data for the 57 uncensored participants without multiple switch points in the normalization task. For the 1% of observations in the valuation task that involve a multiple switch point, the first switch point is assumed.