Bridging Time Preferences and Social Preferences

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Abstract

While an immense volume of research has been conducted on time preferences and social preferences, limited studies have investigated whether there is any interaction and/or trade-off between these two important preferences in human decision-making. In this work, we fill this literature gap by investigating how time preferences (with a focus on procrastination) are affected by tasks' prosocial nature. To do so, we designed an experiment to test the hypothesis that people have varied preferences for timing flexibility in deadlines when working on prosocial tasks vs. self-interested tasks. We propose that people may procrastinate more on prosocial tasks, because they might procure positive diagnostic utilities of a superior self-image by merely committing to a prosocial task, instead of completing it. With the analyses of individuals' preferences for different working contracts based on conjoint analysis with three features – workload, earnings and deadlines – we found suggestive evidence that supports the hypothesis. Limitations on the current studies and plans for future research are also discussed.

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1 Introduction

Behavioral Economics integrates insight from psychology into economics. In this long tradition, time preferences and social preferences have been two of the most fundamental research themes (e.g., Rabin, 1998; Rabin, 2002; Camerer, 2006; DellaVigna, 2009; Pope & Syndor, 2015). Time preferences refer to decisions involving gains (or losses) that occur at different time points (see Frederick, Loewenstein, & O'Donoghue, 2002; Cohen, Ericson, Laibson, & White, 2020, for reviews). Social preferences refer to the tendency whereby people are not 100% self-interested; they also care about others' interests and well-being (e.g., Charness & Rabin, 2002; Loewenstein, Thompson, & Bazerman, 1989). While an immense volume of research has been conducted on both of these themes, limited studies have investigated whether there is any interaction between these two important preferences in human decision-making. For example, when both of these preferences are present in one's choice, what is the dynamic, and is there any trade-off between the associated decision weights? Is there any intertemporal discounting in prosocial preferences? How can prosocial incentives change the intertemporal cost-benefit analysis? In the present study, we attempt to fill this literature gap.

These two preferences have been linked to a wide range of real-world behaviors – for example, procrastination for time preferences, and charitable giving for social preferences. To study the potential interplay between time preferences and social preferences, we have developed an experimental paradigm within a context involving those associated behaviors. The research question we examine is: do people have variable time preferences (e.g., preferences for timing flexibility in deadlines) when working on prosocial tasks vs. self-interested tasks? (Our focus is on procrastination). If so, what are the underlying mechanisms?

Since the existing literature offers little theoretical or empirical documentation on this question, two opposing hypotheses of its processes and outcomes could be reasonable. People might procrastinate more in self-interested tasks. The reason for this could be that prosocial tasks may provide additional incentives (e.g., warm-glow giving, Andreoni, 1989, 1990), leading to overweighed benefits derived from prosocial tasks, relative to the self-interested ones. The opposite prediction would be that people procrastinate more on prosocial tasks. Built on self-signaling theory (e.g., Bodner and Prelec, 2003; Prelec and Bodner, 2003), we propose a novel explanation supporting this latter hypothesis: people may derive additional incentives and/or benefits (e.g., the diagnostic utility from self-signaling theory) when working on prosocial tasks (e.g., positive self-image and/or social reputation). However, to derive the positive diagnostic utility, it may be unnecessary for them to complete the tasks. Instead, people might attain those “benefits” as long as they commit to completing the tasks. Therefore, people might procrastinate more on prosocial tasks because they can procure the diagnostic utility of a superior self-image by merely committing to a task, instead of completing it.

To test this hypothesis, we developed an experimental paradigm which includes two conditions: *Self* (i.e., the earnings for completing the tasks are received by oneself) and *Charity* (i.e., the earnings are donated to charity). Based on conjoint analysis with three features – workload, earnings and deadlines – we designed a list of hypothetical working contracts, and presented it in pairs to participants. With the modeling analyses of participants’ preferences for those contracts, we were able to evaluate the utilities people place on various attribute levels, and compare how they would differ between the self and other contexts. In three studies, we found suggestive evidence that people prefer more flexibility on deadlines (which could lead to higher chance of procrastination) when working for charities than for themselves.

The remainder of the paper is organized as follows. Section 2 continues a review of the relevant literature. Section 3 presents experimental designs, analyses, and results from three studies based on various conjoint designs. Section 4 summarizes ongoing work and plans for the next steps. Section 5 discusses the theoretical and empirical contributions as well as limitations, and concludes.

2 Literature Review

2.1 Time Preferences and Procrastination

People often make decisions that involve trade-offs in costs (or rewards), either at the present moment or at some later time(s). These decisions are referred to as time preferences. They have also been called *intertemporal choice, time discounting,* and *delayed discounting* in domains such as psychology, economics, marketing, and recently, neuroscience. Several theoretical frameworks and models have been proposed to explain how people perceive and choose from options involving intertemporal trade-offs (see Doyle, 2013 for a review):

exponential discounting (Samuelson, 1937), hyperbolic discounting (Ainslie 1975; Loewenstein & Prelec, 1992), quasi-hyperbolic discounting (the β-δ model, Laibson, 1997), and a more recent development – heuristic models (e.g., the ITCH model from Ericson, White, Laibson, & Cohen, 2015; the DRIFT model from Read, Frederick, & Scholten, 2013).

Time preferences have been linked to a wide range of self-control problems, such as procrastination, which have been modeled as time-inconsistent, present-biased preferences. The economics theory of procrastination starts with Akerlof (1991), who discussed several behavioral pathologies, and proposed an early framework. O'Donoghue & Rabin (1999a, 1999b, 2001) developed theoretical models for demonstrating how people with inaccurate beliefs about their future self-control problems could have different time-inconsistent behaviors than those with accurate beliefs. By distinguishing *sophisticates* and *naïfs*, O'Donoghue & Rabin (1999a) illustrated how these two types of individuals' behaviors could be contingent on whether rewards or costs were immediate. They also explained the potential mechanisms of procrastination and preproperation, with the demonstration of two behavioral implications: the *present-bias effect* and the *sophistication effect*.

In terms of experimental work related to procrastination, the existing literature has reported how decision-makers battle self-control problems, e.g., the demand for commitment devices, especially in those intertemporal real effort decisions (e.g., Ariely & Wertenbroch, 2002; Kaur, Kremer, & Mullainathan, 2010; Augenblick, Niederle, & Sprenger, 2013; Bisin & Hyndman, 2020). For example, people are willing to self-impose costly deadlines to overcome procrastination, but the externally imposed deadlines are still more effective than self-imposed ones (Ariely & Wertenbroch, 2002). Furthermore, Augenblick & Rabin (2019) designed an experiment to identify each parameter in the present bias model with three choices: choice of immediate work, choice of future work, and predictions about future work. They also attempted to identify sophistication based on the differences between predictions about future work and the choice of immediate work. This has provided empirical evidence for the above-mentioned theoretical conceptualization.

Therefore, most of the existing empirical work on procrastination has been constrained to the experimental paradigms of field experiments and observation studies. Thus, the lack of studies in the settings of lab experiments and online environments calls for more attention.

2.2 Social Preferences and Signaling

While traditional economics assumes purely self-interested decision-makers, this assumption has been questioned by considerable empirical evidence (e.g., Fehr & Schmidt, 2001). A person exhibits social preferences if he/she cares not only about his/her own benefits and well-being, but also others' interests. Several economics games, including but not limited to the ultimatum game, the dictator game, and the trust game, have been used to examine social preferences (e.g., Charness & Rabin, 2002). One important form of social preference is altruism (Fehr & Fischbacher, 2002); it has been linked to a wide range of prosocial behaviors such as charity.

One pertinent economic theory to consider charity and altruism is the warm-glow giving theory (Andreoni, 1989, 1990). This argues that people derive joy and satisfaction from helping others. To study the incentives for prosocial behaviors, Bénabou and Tirole (2004, 2006) developed a theorical framework by considering image concerns – both social reputation and self-respect. Another line of research – the self-signaling model (Bodner & Prelec, 2003; Prelec & Bodner, 2003) distinguishes between *outcome utility* – the value of the causal consequences of choice, and *diagnostic utility* – the value of the estimate and learning of one's own dispositions or abilities, i.e., self-image, which would be the gain or loss of self-esteem. For example, keeping a healthy lifestyle, such as maintaining a long-term exercise plan, not only provides physical benefits (i.e., the outcome utility), but also improves self-image (e.g., self-discipline and perseverance, i.e., the diagnostic utility).

In terms of experimental evidence, Dhar & Wertenbroch (2012) have shown the self-signaling effect in the context of how consumers handle temptation – e.g., when people can interpret their choices as evidence of strong willpower, the utility of their choices is enhanced. However, when contrasting self-image and social-image concerns, based on a Bayesian signaling model, Grossman (2015) only found an effect of social-signaling, but not of self-signaling. These mixed results call for more work examining these two signaling effects, as well as more understanding of how different psychological driving forces may interact.

2.3 Bridging Time Preferences and Social Preferences

Among the limited research exploring both time preferences and social preferences, one of the most relevant works is a recent paper "Time Inconsistent Charitable Giving" by Andreoni & Garcia (2021). In their first experiment, the authors found that people were more likely to give when there was a delay between the decision to give and the transaction for that donation. The authors then proposed a theoretical model of social utility, and in another two experiments in which they tried to manipulate social image, they found that publicly announcing the giving decisions would increase this time inconsistent giving. Even though in their theoretical framework they considered and defined both social-signaling and self-signaling in this context, the authors only experimented with manipulates related to social-signaling, i.e., public announcements. Hence, it remains unclear how the dichotomy between self-signaling and social-signaling could play a role in the interaction between time preferences and social preferences.

Another relevant study is from a working paper by Chopra, Eisenhauer, Falk, & Graeber (2021). As indicated by its title, "Intertemporal Altruism", the paper examines the intertemporal choices involving payment to a decision-maker vs. payment to a charity. The authors propose two conceptually distinct utilities: consequence-dated and choice-dated. Choice-dated prosocial utility is defined as utility that is accrued when a donation decision is made, i.e., at an earlier time. Consequence-dated prosocial utility is defined as utility that is accrued when a donation payment is executed, i.e., at a later date. They predicted that while the consequence-dated utility would be discounted in a delayed payment to a charity, the choice-dated one would not. Their empirical results showed quantitative evidence for both motives – choice- and consequence-dated prosocial utility. However, as they stated in the end regarding their limitations: "…our analysis does not shed light on the sources of pure time preferences about the outcomes of others…". Additionally, their paper does not explore the psychological driving forces underlying the intertemporal dimension of prosocial behavior.

Finally, Kölle, & Wenner (2021) conducted an experiment examining time-inconsistent generosity with two types of allocation decisions. The first type was intrapersonal choices, in which participants only decided for themselves, or decided on behalf of another person. The second type was interpersonal choices, in which participants allocated tasks between themselves and someone else. They found a systematic difference in present bias in the first type of choices, but not in the second type of choices. In other words, they found that the discounting of one's own consumption was significantly different from others' consumption when these two decisions were considered separately. However, this difference disappeared when these two decisions were considered simultaneously. They concluded with no robust evidence for time inconsistency in the social domain, i.e., prosciality was unaffected by the timing of consequences.

In the pertinent aforementioned work, several choice paradigms are employed, with various advantages and limitations. For example, Chopra et al., (2021) used the multiple price list format to elicit indifference points between payments. While this method has enabled researchers to identify parameters in the canonical discounted utility models, the disadvantages of this choice paradigm have been documented as well (e.g., Andersen, Harrison, Lau, & Rutström, 2006). In addition, in the second part of their experiment, Chopra et al., (2021) used another experimental paradigm (risk appointment) which may introduce confounders, such as risk preferences, into the existing dynamic. Furthermore, the second type of allocation decisions in Kölle & Wenner (2021) have enabled researchers to examine how people evaluate decisions involving consequences that simultaneously affect both oneself and others. However, combining the self-other attribute and the sooner-later attribute may introduce undesired complexities into this dynamic.

In sum, even though the intertemporal nature of prosocial behaviors has received attention of late, the results from the existing literature are mixed. Therefore, this literature gap calls for additional theoretical, conceptual, and empirical work to further our understanding of this self-other (and/or self-charity) tradeoff involving costs and benefits that occur at different time points.

3 Experiments

3.1 Experimental Design

Our experiment examines whether people have different preferences for flexibility in deadlines (i.e., length) – i.e., different levels of procrastination – when working on prosocial tasks vs. self-interested tasks – i.e., when they work for themselves vs. when they work for a charity.

The experiment started with the participants being explained a task in which they would need to label a large collection of photographs to help train an artificial intelligence program. Then they were asked to complete a sample task. In the next stage, participants were told that they would be asked to evaluate several hypothetical contracts involving different workloads, deadlines or earnings. For example, a contract could be "label 200 photos at any time in a week to get $4.00". At this stage, participants were randomly assigned to one of two conditions: in the "self" condition, they were informed that the earnings for completing the tasks indicated in their preferred contracts would be sent to themselves, while in the "charity" condition, they were told that the earnings for completing the tasks would be donated to a charity which they had picked. In both conditions, participants were notified that regardless of their preferences for the contracts, the earnings from the preferred contract would be sent on a date that was later than the latest deadline in the contracts.

After reading the aforementioned instructions, we presented participants with sixteen binary choices and asked them to indicate their preferences between the two options in each pair of contracts. The order of the two options was randomized in the following way: participants were randomized into one of two conditions, in the first condition, participants saw Option A first and then Option B during the first set of eight pairs; and they saw Option B first and then Option A during the second set of eight pairs; in the second condition, participants saw Option B first and then Option A during the first eight pairs, and they saw Option A first and then Option B during the second set of eight pairs. At the end, participants were asked to complete a set of demographic questions, including age, gender, income, and education.

While the experimental setups were the same in the following three studies, each study tested different lists of contracts which were based on varied conjoint designs (see details in the next section).

3.2 Methods

3.2.1 Conjoint Analyses

Conjoint analysis is popular in market research as a means of estimating consumers' preferences about a product (e.g., Green & Srinivasan, 1978, 1990). Conjoint analysis assumes that a product's total utility can be decomposed into several attributes, each of which can have several levels. These utility levels for conjoint attributes are called "part-worths". In our work, each contract was differentiated based on the following three attributes: workload (i.e., the number of photos to label), earnings (i.e., hourly wage), and timing (i.e., the flexibility in the deadline to complete the tasks). Note that it was the total earnings, instead of the hourly wage, that was shown in the contracts presented to participants.[1]

In Study 1, the contracts were specified on the following levels from the three attributes: timing (immediate, in 1 week, in 1 month), workload (30, 75, 150, 300, 600), and wage ($2.50, $4.00, $5.00, $6.00, $7.50). In Study 2, we kept the same three levels in the timing attribute, but had fewer levels in the other two attributes: workload (30, 100, 300, 600), wage ($3.00, $4.00, $5.00, $6.00). Hence, we could replicate the main structure in Study 1, but update the design with fewer parameters, leading to more statistical power in the later analyses. In Study 3, the timing attribute maintained a similar range, but including one more level (immediate, in 1 week, in 2 weeks, in 5 weeks), the workload attribute was revised to be within a narrower range (30, 50, 100, 180), and the wage attribute had a wider range ($8.00, $11.00, $14.00). The revision was based on Imas' (2014) suggestion that people work harder for charity than for themselves only when the incentives are low. While the wage ranges in the first two studies were low, we wanted to assess whether a wider wage range would make a difference in the parameters/effects in which we were interested.

We used JMP, a statistical software often used for conjoint analysis, to generate a set of 16 pairs of choices for each study. For details on all choice profiles in the studies, see Appendix 7.1.

3.2.2 Modeling Analyses

In this section, we present our modeling framework and statistical analyses for the binary choice-based conjoint analysis described above. Each participant was presented with the same sixteen pairs of contracts (each pair is donated as i), and each contract includes two options (denoted as A_i and B_i). The total utility for each contract (denoted as U_{A_i} and U_{B_i}) is defined as a linear combination of part-worths (denoted as β). The outcome variable is defined as the

[1] The earnings were calculated based on wage by the following formula:
$(\text{Workload} \times \text{Seconds to complete a task})/3{,}600 \times \text{Wage (hourly)}$.

probability of choosing A_i instead of B_i (denoted as $P(A_i)$), which is a function of the differences in the utilities of these two options. The following presents parameters in the model, as well as their coding:

- Choice pair: $i = 1, \ldots, 16$.
- A_i and B_i: the two options in each choice pair i.
- y_i: choice outcome; $y_i = 1$ if subjects chose A_i, and $y_i = 0$ if subjects chose B_i.[2]
- j and k: level j on attribute k; $j = 0$ is the default level with utility 0.
- $x_{A_i}^{jk}$: Option A_i has level j on attribute k; $x_{A_i}^{jk} = 1$ if $j \geq 1$, and $x_{A_i}^{jk} = 0$ otherwise.
- $x_{B_i}^{jk}$: Option B_i has level j on attribute k; $x_{B_i}^{jk} = 1$ if $j \geq 1$, and $x_{B_i}^{jk} = 0$ otherwise.

The utility models for the two options in each choice pair i:

$$U_{A_i} = \sum_{j \geq 1} \beta_{jk} \, x_{A_i}^{jk} + \varepsilon_{A_i} \tag{1}$$

$$U_{B_i} = \sum_{j \geq 1} \beta_{jk} \, x_{B_i}^{jk} + \varepsilon_{B_i} \tag{2}$$

Where β_{jk} is the utility of level $j = 1, 2, \ldots$ relative to the default level $j = 0$;

$\varepsilon_{A_i}/\varepsilon_{B_i}$ is the potential bias for Option A/Option B in choice pair i.

In terms of statistical analyses, two models – logistic regressions with maximum likelihood estimation (MLE), and linear regressions with ordinary least squares estimation (OLS) – were run to estimate the part-worths.

- The logistic regression model:

$$P(A_i) = \frac{\exp(U_{A_i} - U_{B_i})}{1 + \exp(U_{A_i} - U_{B_i})} \tag{3}$$

$$= \frac{\exp[\sum_{j \geq 1} \beta_{jk} \left(x_{A_i}^{jk} - x_{B_i}^{jk}\right)]}{1 + \exp[\sum_{j \geq 1} \beta_{jk} \left(x_{A_i}^{jk} - x_{B_i}^{jk}\right)]} \tag{4}$$

- The linear regression model:

$$P(A_i) = U_{A_i} - U_{B_i} = \sum_{j \geq 1} \beta_{jk} \left(x_{A_i}^{jk} - x_{B_i}^{jk}\right) \tag{5}$$

[2] The outcome variable in the logistic model was coded as 0/1, and the outcome variable in the linear model was coded as -1/+1.

Our main analysis of interest was to compare each estimated coefficient, i.e., part-worth, between the "self" and the "charity" conditions, and we employed two approaches. The first approach was to determine the estimates at the aggregate level. We began by running both of the models above twice: one with the data from the "self" condition, and the other with the data from the "charity" condition. This gave us two separate sets of estimates based on the two conditions. Then we ran the models with an expanded set of parameters -- adding variables indicating the differences in each of the original parameters between the conditions. This allowed us to conduct direct significance tests on the differences between the conditions. The second approach was to make estimates at the individual level. To do so, we ran the linear model using observations from each participant to obtain individual level estimates. With this set of individual coefficients, we conducted an unpaired t-test for inference about the differences in the estimated coefficients' mean values across all participants, between the two conditions.

3.2.3 Exclusion Criteria

In order to improve the quality of the data, we applied two exclusion criteria to detect any participants who might have responded randomly instead of being cautious enough in their responses. First, we excluded participants whose response times were outside the range of 10% - 90% of all participants, i.e., 20% of the participants. We did this because those who finished too slow might have been distracted, and not focused on our study; those who finished too quick might have rushed through the process.

Second, based on the estimates at the individual level, we excluded any participants who had too many "bad" estimated coefficients for wages. "Bad" was defined as negative estimates or a decreasing pattern along the estimated utilities for wages. A person with a decreasing utility in wage suggested that he/she places less value on higher wages, which contradicts the common laws of human decision-making. Therefore, we removed any participants with more than two "bad" estimates on wages from our analyses.

For robustness, we reported two sets of results: one was based on the data after applying both of the exclusion criteria, and this is reported in the next section; the other was based on the data only after applying the first exclusion criterion for response time, and this is reported in

Appendix 7.2. One caveat was that since each participant was presented with only 16 choice pairs, individual estimates were computed from models including about 10 parameters, but with only 16 observations. Hence, such a small sample size might have led to biased and/or unstable estimates and inference, due to the potential issues of underfitting and lack of statistical power.

3.3 Results and Discussion

3.3.1 Study 1

301 participants were recruited from U.S.-based Amazon Mechanical Turk and completed the study. After the two exclusion criteria: (1) excluding 59 participants based on the response time, and (2) excluding 66 participants based on the individual estimates for wages, 176 participants were included. Below are the results based on this sample size. Results from the same analyses but with a larger sample size (i.e., without the second exclusion criteria based on individual estimates) are reported in Appendix 7.2.1.

Table 1 shows regression results from both the logistic and linear models for the “self” condition, and Table 2 shows the ones for the “charity” condition. For both the “self” and “charity” conditions, across the logistic and linear models, all coefficients were estimated to be positive and significant in predicting the outcome, except for: (1) the ones on “Timing 1 Week” were not significant in the “self” condition, which suggests that people value more flexibility, even a shorter later deadline, when working for charities; (2) the ones on “Workload 600” had significantly negative coefficients, which suggests that the workload of labeling 600 photos was too heavy.

Figure 1 visualizes all estimated attribute utilities (i.e., part-worths) attained from the logit models between the “self” and “charity” condition. Figure 2 visualizes all estimated attribute utilities attained from the linear models between the “self” and “charity” condition. We also ran aggregate models with an expanded set of parameters -- adding variables indicating the differences in each of the original parameters between the conditions. Table 3 presents the estimated coefficients on the “diff-” parameters from the aggregate level models.

Table 1. Regression results for the "self" condition in Study 1.
(*p<0.05, **p<0.01, ***p<0.01)

	Model 1: Logistic + MLE			**Model 2: Linear + OLS**		
	Coef	SE	P-value	Coef	SE	P-value
Intercept	-0.7472	0.260	0.004**	-0.1529	0.046	0.001**
Timing in 1 Week	0.1120	0.168	0.505	0.0733	0.038	0.052
Timing in 1 Month	3.0368	0.641	0.000***	0.5482	0.087	0.000***
Workload 75	1.3435	0.245	0.000***	0.3591	0.043	0.000***
Workload 150	0.4577	0.355	0.197	0.3914	0.061	0.000***
Workload 300	1.9859	0.319	0.000***	0.7929	0.054	0.000***
Workload 600	-2.9334	1.375	0.033*	0.0860	0.188	0.674
Wage Rate 4	1.8664	0.236	0.000***	0.5161	0.040	0.000***
Wage Rate 5	3.0486	0.359	0.000***	0.7818	0.058	0.000***
Wage Rate 6	3.9566	0.510	0.000***	0.8898	0.071	0.000***
Wage Rate 7.5	7.6401	1.403	0.000***	1.4227	0.173	0.000***
Pseudo R^2/ R^2		0.478			0.547	
No. Observations		1376			1376	

Table 2. Regression results for the "charity" condition in Study 1.
(*p<0.05, **p<0.01, ***p<0.01)

	Model 1: Logistic + MLE			**Model 2: Linear + OLS**		
	Coef	SE	P-value	Coef	SE	P-value
Intercept	-0.8299	0.196	0.000***	-0.2184	0.052	0.000***
Timing in 1 Week	0.3580	0.139	0.010*	0.1606	0.043	0.000***
Timing in 1 Month	3.2577	0.428	0.000***	0.8693	0.099	0.000***
Workload 75	0.7084	0.189	0.000***	0.2237	0.049	0.000***
Workload 150	-0.0072	0.259	0.978	0.1830	0.070	0.009**
Workload 300	1.1537	0.216	0.000***	0.5424	0.062	0.000***
Workload 600	-3.3053	0.821	0.000***	-0.6228	0.214	0.004***
Wage Rate 4	1.5941	0.179	0.000***	0.5358	0.046	0.000***
Wage Rate 5	2.7330	0.267	0.000***	0.8581	0.066	0.000***
Wage Rate 6	3.5183	0.360	0.000***	1.0013	0.081	0.000***
Wage Rate 7.5	6.2708	0.839	0.000***	1.7746	0.198	0.000***
Pseudo R^2/ R^2		0.322			0.386	
No. Observations		1440			1440	

Figure 1. Comparing the estimated attribute utilities from logistic models between two conditions for Study 1.

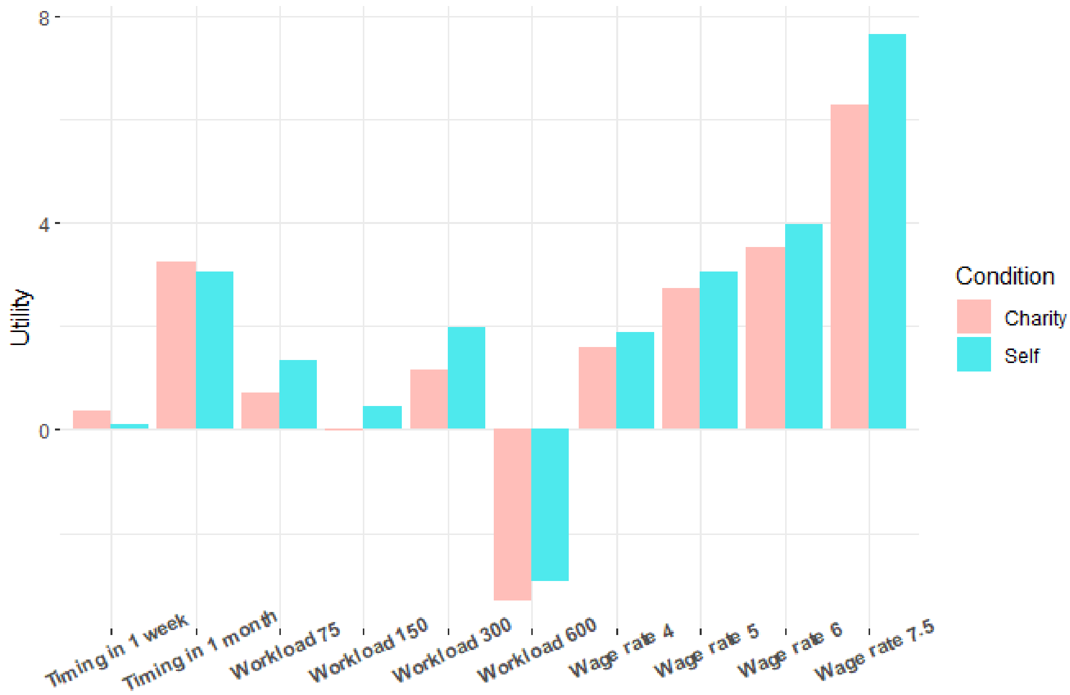

Figure 2. Comparing the estimated attribute utilities from linear models between two conditions for Study 1.

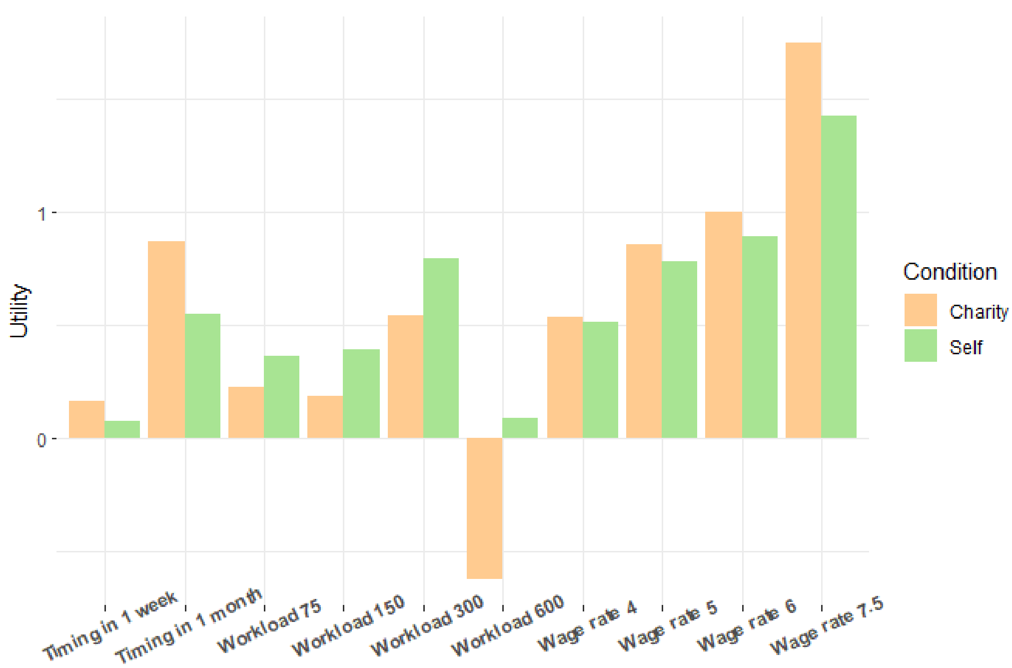

Table 3. The estimated coefficients on the “diff-” parameters for Study 1.
(*p<0.05, **p<0.01, ***p<0.01)

	Model 1: Logistic + MLE			**Model 2: Linear + OLS**		
	Coef	SE	P-value	Coef	SE	P-value
Diff Intercept	-0.0828	0.326	0.800	-0.0655	0.070	0.349
Diff Timing in 1 Week	0.2460	0.218	0.259	0.0873	0.057	0.128
Diff Timing in 1 Month	0.2209	0.771	0.774	0.3211	0.133	0.016*
Diff Workload 75	-0.6351	0.309	0.040*	-0.1354	0.065	0.037*
Diff Workload 150	-0.4649	0.439	0.290	-0.2084	0.093	0.025*
Diff Workload 300	-0.8322	0.385	0.031*	-0.2505	0.083	0.002**
Diff Workload 600	-0.3719	1.602	0.816	-0.7088	0.286	0.013*
Diff Wage Rate 4	-0.2723	0.296	0.358	0.0198	0.062	0.748
Diff Wage Rate 5	-0.3156	0.448	0.481	0.0763	0.088	0.387
Diff Wage Rate 6	-0.4383	0.625	0.483	0.1115	0.108	0.301
Diff Wage Rate 7.5	-1.3693	1.635	0.402	0.3219	0.264	0.223

In terms of the differences between the two conditions, the “diff-” parameters that we were interested in the most were those pertaining to timing. From both the logistic and linear models, the estimated utilities on “Timing in 1 week” and “Timing in 1 month” were greater for the “charity” condition than for the “self” condition. Specifically, we saw a significant difference in “Timing in 1 month” between the conditions from the linear model (β=0.321, p<0.05), but no significance from the logistic model. We also conducted unpaired two-sided t-tests based on individual estimates for the timing parameters: for “Timing in 1 week”, t=1.240, p=0.217; and for “Timing in 1 month”, t=2.798, p<0.01. These results suggest that people place more value on flexibility for completion time, and especially prefer later deadlines, when working for charities, as opposed to for themselves.

For the differences in another two sets of attributes: for workload, it seemed that people were willing to work more for themselves than for charity (but the significant differences across the four levels only appeared in the linear model, and only two of them were significant in the logistic model); for wages, there were no significances in either of the models.

3.3.2 Study 2

255 participants were recruited from U.S.-based Amazon Mechanical Turk and completed the study. After the two exclusion criteria: (1) excluding 51 participants based on response time, (2) excluding 43 participants based on individual estimates for wage rates, 161 participants were included. Below are the results based on this sample size. Results from the same analyses but with a larger sample size (i.e., without the second exclusion criteria based on individual estimates) are reported in Appendix 7.2.2.

Table 4 shows regression results from both the logistic and linear models for the "self" condition, and Table 5 shows the ones for the "charity" condition. For the "self" condition, estimated coefficients on workload and wage were positive and significant, except for the ones on timing. For the "charity" condition, the estimated coefficients on "Timing in 1 Month", "Wage Rate 6", and on all levels of workload were positive and significant. Consistent with Study 1, the ones on "Timing in 1 Month" were significant in the "charity" condition, but not in the "self" condition. This provides suggestive evidence again that people may value more timing flexibility when working for charities than for themselves.

Figure 3 visualizes all estimated attribute utilities attained from the logit models between the "self" and "charity" condition. Figure 4 visualizes all estimated attribute utilities attained from the linear models between the "self" and "charity" condition. Table 6 presents the estimated coefficients on the "diff-" parameters which indicate the differences in each of the original parameters between the conditions.

Table 4. Regression results for the "self" condition in Study 2.
(*p<0.05, **p<0.01, ***p<0.01)

	Model 1: Logistic + MLE			Model 2: Linear + OLS		
	Coef	SE	P-value	Coef	SE	P-value
Intercept	0.1848	0.089	0.038*	0.0910	0.027	0.000***
Timing in 1 Week	-0.0152	0.207	0.941	0.0168	0.056	0.763
Timing in 1 Month	1.3191	0.780	0.091	0.2222	0.158	0.159
Workload 100	0.8917	0.137	0.000***	0.2916	0.038	0.000***
Workload 300	2.0819	0.168	0.000***	0.7578	0.042	0.000***
Workload 600	2.0424	0.169	0.000***	0.7462	0.045	0.000***
Wage Rate 4	0.6232	0.152	0.000***	0.2177	0.043	0.000***
Wage Rate 5	0.4190	0.242	0.083	0.1273	0.061	0.038
Wage Rate 6	3.1533	0.706	0.000***	0.8315	0.132	0.000***
Pseudo R^2/ R^2		0.385			0.457	
No. Observations		1328			1328	

Table 5. Regression results for the "charity" condition in Study 2.
(*p<0.05, **p<0.01, ***p<0.01)

	Model 1: Logistic + MLE			Model 2: Linear + OLS		
	Coef	SE	P-value	Coef	SE	P-value
Intercept	0.2044	0.076	0.007***	0.0918	0.031	0.003**
Timing in 1 Week	0.0255	0.172	0.882	0.0160	0.070	0.819
Timing in 1 Month	2.8524	0.656	0.000***	0.8534	0.198	0.000***
Workload 100	0.3977	0.116	0.001**	0.1839	0.047	0.000***
Workload 300	1.2414	0.129	0.000***	0.5677	0.052	0.000***
Workload 600	0.8885	0.138	0.000***	0.4109	0.056	0.000***
Wage Rate 4	0.0003	0.132	0.998	0.0019	0.053	0.971
Wage Rate 5	-0.2615	0.194	0.179	-0.1042	0.077	0.176
Wage Rate 6	3.0408	0.604	0.000***	0.9466	0.166	0.000***
Pseudo R^2/ R^2		0.152			0.194	
No. Observations		1248			1248	

Figure 3. Comparing the estimated attribute utilities from logistic models between two conditions for Study 2.

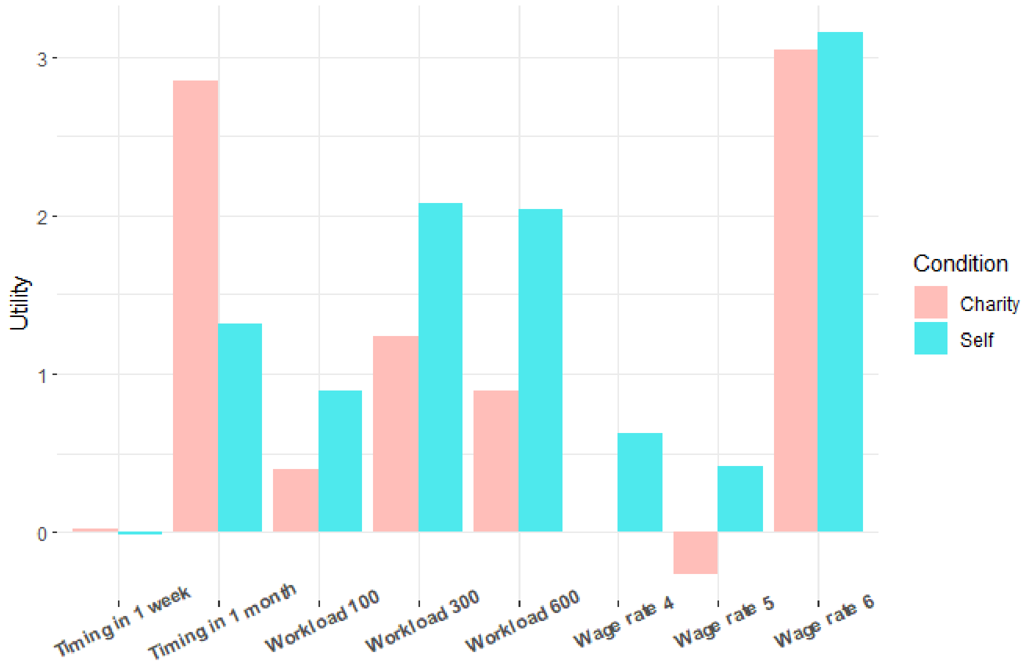

Figure 4. Comparing the estimated attribute utilities from linear models between two conditions for Study 2.

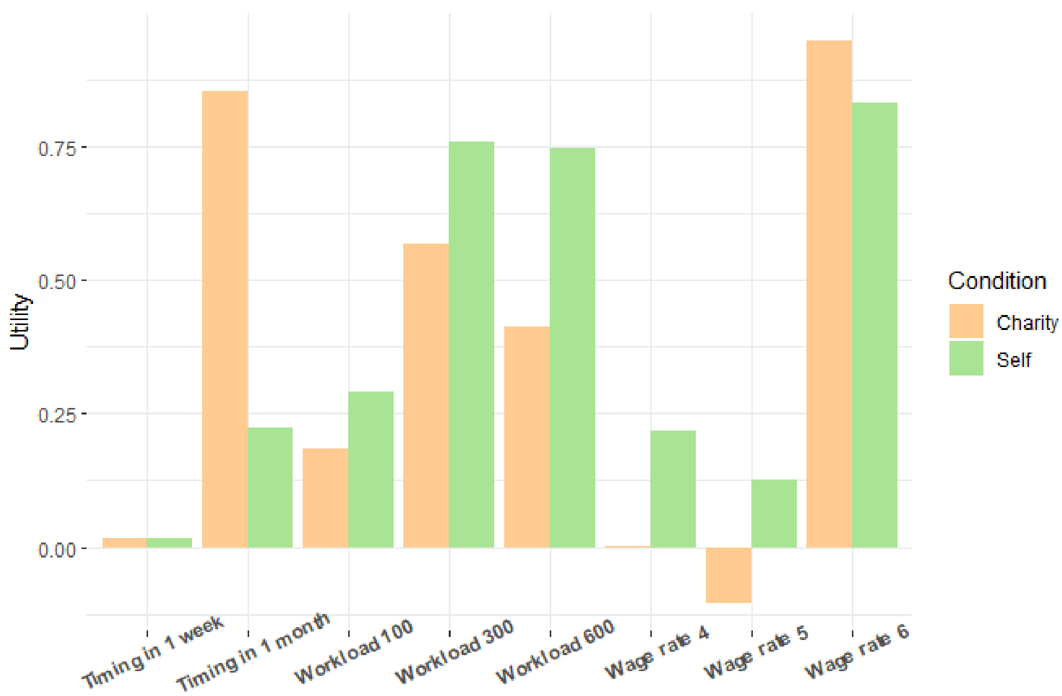

Table 6. The estimated coefficients on the “diff-” parameters for Study 2.
(*p<0.05, **p<0.01, ***p<0.01)

	Model 1: Logistic + MLE			**Model 2: Linear + OLS**		
	Coef	SE	P-value	Coef	SE	P-value
Diff Intercept	0.0195	0.117	0.868	0.0008	0.039	0.984
Diff Timing in 1 Week	0.0407	0.269	0.880	-0.0008	0.089	0.993
Diff Timing in 1 Month	1.5333	1.019	0.132	0.6312	0.251	0.012*
Diff Workload 100	-0.4940	0.179	0.006**	-0.1076	0.060	0.074
Diff Workload 300	-0.8405	0.212	0.000***	-0.1900	0.067	0.004**
Diff Workload 600	-1.1539	0.219	0.000***	-0.3354	0.072	0.000***
Diff Wage Rate 4	-0.6228	0.201	0.002**	-0.2158	0.068	0.001**
Diff Wage Rate 5	-0.6805	0.310	0.028*	-0.2315	0.098	0.018*
Diff Wage Rate 6	-0.1125	0.929	0.904	0.1151	0.211	0.586

In terms of the differences in the timing attributes between the two conditions, the differences in “Timing in 1 Month” was significant from the linear model (β=0.6312, p<0.05). The t-tests results based on individual estimates also showed significance on “Timing in 1 Month” between the two conditions: t=3.502, p<0.001. These results were consistent with those in Study 1, which provide suggestive evidence again that people value more on the flexibility for completion time, especially prefer a later deadline, when working for charities than for themselves.

For the differences in another two sets of attributes: most estimated coefficients on workload and wages were negative and significant, suggest that people prefer less workload and lower wage when working for charities than for themselves. However, we also observed significant differences only on the two lower wage rates but not on the largest one (i.e., “Diff Wage Rate 6”). This might suggest that, only when wage rates are low, people demand less on wages when working for charities than for themselves, but this might no longer be true when the wage rates are high.

3.3.3 Study 3

299 participants were recruited from U.S.-based Amazon Mechanical Turk and completed the study. After the two exclusion criteria: (1) excluding 60 participants based on response time,

(2) excluding 35 participants based on individual estimates for wage rates, 204 participants were included. Below are the results based on this sample size. Results from the same analyses but with a larger sample size (i.e., without the second exclusion criteria based on individual estimates) are reported in Appendix 7.2.3.

Table 7 shows regression results from both the logistic and linear models for the "self" condition, and Table 8 shows the ones for the "charity" condition. For both the "self" and "charity" conditions, across the logistic and linear models, most estimated coefficients were estimated to be positive and significant in predicting the outcome, except for: (1) the ones on "Timing in 2 Weeks" were negative and significant; (2) the ones on "Timing 1 Week" were not significant; (3) the ones on "Timing in 5 Weeks" were positive and significant only in the "charity" condition from the linear model; (4) the ones on "Workload 50" were positive and significant only in the condition of "self", but not in the condition of "charity".

Figure 5 visualizes all estimated attribute utilities attained from the logit models between the "self" and "charity" condition. Figure 6 visualizes all estimated attribute utilities attained from the linear models between the "self" and "charity" condition. Table 9 presents the estimated coefficients on the "diff-" parameters which indicate the differences in each of the original parameters between the conditions.

Table 7. Regression results for the "self" condition in Study 3.
(*p<0.05, **p<0.01, ***p<0.01)

	Model 1: Logistic + MLE			**Model 2: Linear + OLS**		
	Coef	SE	P-value	Coef	SE	P-value
Intercept	0.0353	0.072	0.625	0.0134	0.032	0.679
Timing in 1 Week	0.0723	0.106	0.497	0.0015	0.046	0.973
Timing in 2 Weeks	-0.6462	0.178	0.000***	-0.3410	0.075	0.000***
Timing in 5 Weeks	-0.0156	0.389	0.968	0.1439	0.161	0.373
Workload 50	0.3431	0.115	0.003**	0.1170	0.046	0.012*
Workload 100	0.8173	0.130	0.000***	0.3041	0.049	0.000***
Workload 180	1.5104	0.342	0.000***	0.7061	0.148	0.000***
Wage Rate 11	0.7015	0.106	0.000***	0.2641	0.041	0.000***
Wage Rate 14	2.0432	0.611	0.001**	1.0391	0.261	0.000***
Pseudo R^2/ R^2		0.084			0.104	
No. Observations		1664			1664	

Table 8. Regression results for the "charity" condition in Study 3.
(*p<0.05, **p<0.01, ***p<0.01)

	Model 1: Logistic + MLE			**Model 2: Linear + OLS**		
	Coef	SE	P-value	Coef	SE	P-value
Intercept	0.0722	0.073	0.321	0.0305	0.034	0.367
Timing in 1 Week	0.1359	0.106	0.198	0.0504	0.049	0.300
Timing in 2 Weeks	-0.6314	0.175	0.000***	-0.3100	0.079	0.000***
Timing in 5 Weeks	0.5997	0.375	0.109	0.3334	0.169	0.048*
Workload 50	0.1860	0.110	0.092	0.0754	0.049	0.121
Workload 100	0.5299	0.119	0.000***	0.2255	0.052	0.000***
Workload 180	1.6764	0.341	0.000***	0.7879	0.155	0.000***
Wage Rate 11	0.4073	0.099	0.000***	0.1700	0.043	0.000***
Wage Rate 14	2.3771	0.602	0.000***	1.1412	0.273	0.000***
Pseudo R^2/ R^2		0.053			0.070	
No. Observations		1600			1600	

Figure 5. Comparing the estimated attribute utilities from logistic models between two conditions for Study 3.

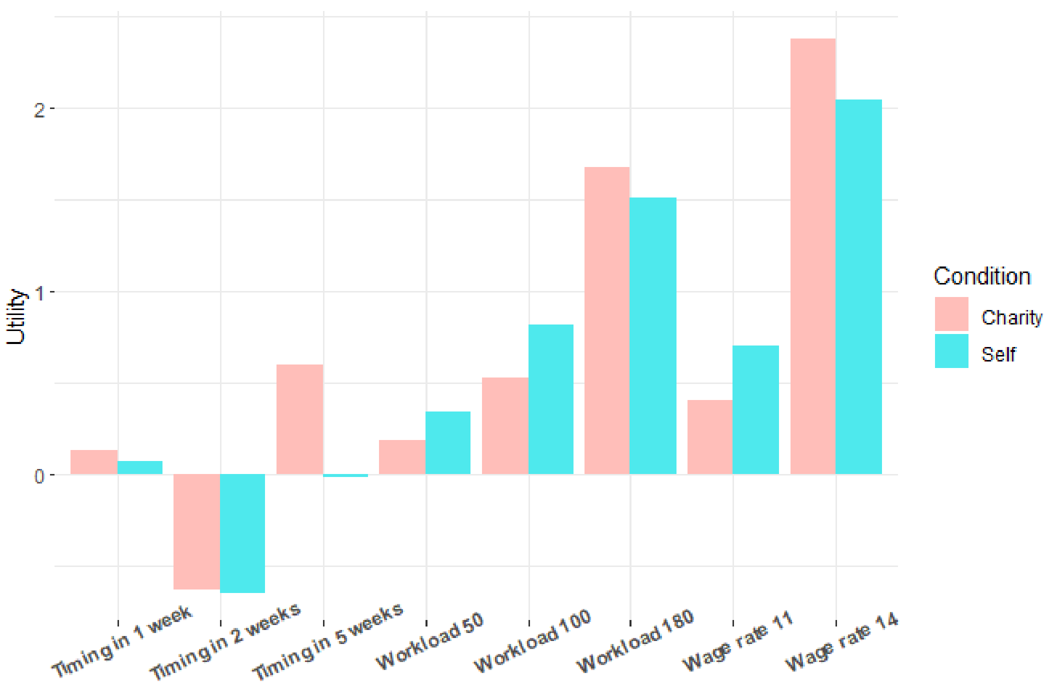

Figure 6. Comparing the estimated attribute utilities from linear models between two conditions for Study 3.

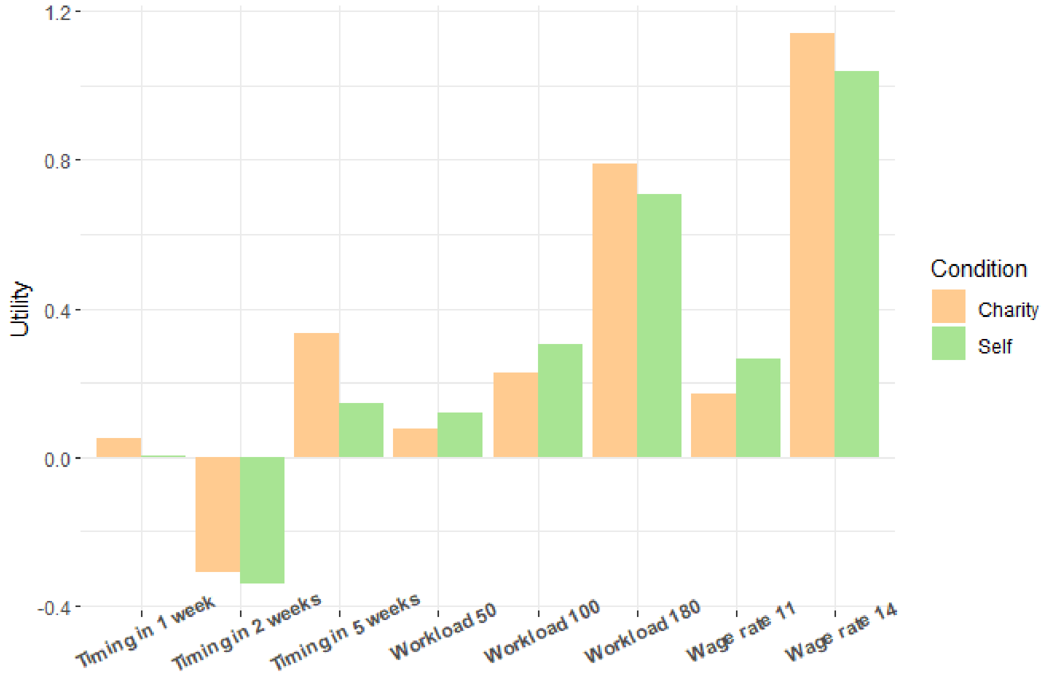

Table 9. The estimated coefficients on the "diff-" parameters for Study 3. (*p<0.05, **p<0.01, ***p<0.01)

	Model 1: Logistic + MLE			**Model 2: Linear + OLS**		
	Coef	SE	P-value	Coef	SE	P-value
Diff Intercept	0.0369	0.102	0.718	0.0171	0.047	0.715
Diff Timing in 1 Week	0.0636	0.150	0.672	0.0488	0.067	0.467
Diff Timing in 2 Weeks	0.0149	0.249	0.952	0.0309	0.109	0.777
Diff Timing in 5 Weeks	0.6153	0.540	0.254	0.1896	0.233	0.417
Diff Workload 50	-0.1571	0.159	0.324	-0.0416	0.067	0.535
Diff Workload 100	-0.2874	0.176	0.102	-0.0786	0.072	0.272
Diff Workload 180	0.1660	0.483	0.731	0.0818	0.215	0.703
Diff Wage Rate 11	-0.2942	0.146	0.043*	-0.0941	0.060	0.115
Diff Wage Rate 14	0.3339	0.858	0.697	0.1021	0.378	0.787

In terms of the differences between the conditions, even though we still saw the estimated coefficients on the timing attributes were larger in the "charity" condition than in the "self" condition, very few differences were significant, except the one on "Diff Wage Rate 11" from the logistic model which was negative and significant. There are a couple of reasons that could potentially lead to these results – for example, the conjoint and the choice profiles constructed from the conjoint analysis were not designed optimally. Future research should look into how results could be affected by different conjoint designs.

4 Work in Progress and Future Research

In this section, we discuss our work in progress and plans for next steps. Detailed reasoning behind some of the following new thoughts can be found in the next section.

First, in order to explore whether we can draw additional insight from the current experimental paradigm and analyses, we are working on the following. In terms of statistical analysis, we plan to: (1) add interaction terms for the attributes into the current models to see if the addition could improve model performance and bring new insight; (2) try parametric bootstrapping to compare the resulting distributions of the individual estimates in these two conditions for additional hypothesis testing; (3) use prediction accuracy to compare the performance of the linear and logistic models. In terms of experimental design, we plan to try two revised pilots: (1) updating the "charity" condition by adding a manipulation of "recognition/appreciation public vs. private", e.g., add the description "Your donation will be acknowledged publicly on the website." or "You will receive a mailed 'Thank You' card." (2) adding a condition to examine whether the tasks' meaningfulness/prosociality makes a difference: for example, a prosocial task could be to prepare materials for an online program that helps detect colorblindness in children, and a non-prosocial task could be to detect objects from a photo which helps with training machine learning algorithms.

Second, in terms of designing new experimental paradigms, we plan to try a couple of new pilots: (1) instead of testing multiple attributes (e.g., timing, wage, workload in the current studies) at the same time, having a single-attribute (i.e., timing) choice might help us to disentangle undesired confounders in the current tests; (2) adopting an allocation paradigm in which participants will be asked to allocate their effort (i.e., task amount or expected working time) into a couple of time slots (e.g., present vs. future), so that we can see if the allocation patterns will be different when people work for themselves vs for others.

Third, we have some new research ideas on a related but different direction – instead of bridging time preference and social preference, bridging social preference and risk preference. Specifically, one research question could be to test how social preference could be affected by the riskiness/probability of a certain task, such as volunteering. One hypothesis will be that the smaller the probability of the realization of the task in the future, the larger the willingness to volunteer at the present (but not the actual willingness or the actual completion rate). This idea could be related to probabilistic giving (Bodner, 1995).

Fourth, all studies and ideas discussed so far focus on individual behavior and decision-making. What about group level decision-making? The existing theoretical frameworks and models on procrastination are mostly for a one-time activity. What will the dynamic look like in a multiple-time context? What about interpersonal decision-making? For example, "collective procrastination" in which one's decision making would be influenced by others or even social norm? Future studies are needed to answer these questions.

5 General Discussion and Conclusion

Building on the vast literature which has proposed theoretical and empirical work on time preferences and social preferences, in the current work, we bridge these two important themes in Behavioral Economics. Additionally, we explore whether there is any interaction and/or trade-off between these two dimensions in human decision-making. The research question we examine is: do people have varied preferences for timing flexibility in deadlines (i.e., level of procrastination) when working on prosocial tasks vs. self-interested tasks (i.e., work for a charity vs. oneself)? Our hypothesis is that people may procrastinate more on prosocial tasks than on self-interested ones. One potential mechanism, based on self-signaling theory, is that people might procure positive diagnostic utilities of a superior self-image by merely committing to a prosocial task instead of completing it, while positive outcome utility may only be attainable after completion, not merely commitment.

To test this hypothesis, we developed an experimental paradigm in which participants were either informed they would be working for themselves or working for a charity they picked. In three studies, we presented participants with several hypothetical working contracts which were constructed based on varied conjoint analysis with three features – workload, earnings and deadlines. By comparing the utility for each attribute level, i.e., part-worth, between the two conditions, the results from the first two studies show that people place higher utilities on the timing attributes, especially on “Timing in 1 Month”. This suggests that people prefer more flexibility on deadlines (which could lead to a higher likelihood of procrastination) when working for charities than for themselves. In other words, people might procrastinate more when working on prosocial tasks, which we called “prosocial procrastination”. However, more studies are needed to further our understanding of the size of this effect and its contextual generatability.

Our work contributes to the following streams of literature.

First, among the limited research related to both time preferences and social preferences, most of the existing studies (Andreoni & Garcia, 2021; Chopra, et al., 2021; Kölle, & Wenner, 2021), as indicated by their titles “Intertemporal Altruism” and “Time Inconsistent Charitable Giving”, have examined the intertemporal nature of prosocial behaviors, i.e., how prosociality would be affected by the timing of consequences. However, in our study, what we have called “prosocial procrastination” is a first step towards investigating how time preferences (with a focus on procrastination) could be affected by the prosocial nature of the tasks. Hence, our study furthers our understanding of how these two preferences might interact. We also hope our work will provide new insight, both conceptually and empirically, for future research in bridging multiple preferences – e.g., not only time preferences and social preferences, but also social preferences and risk preferences.

Second, our work also explores the psychological driving forces underlying the interplay between incentives and preferences. This not only furthers our understanding of human motivation and prosocial behaviors (e.g., Kamenica, 2012; Bénabou and Tirole, 2003), but also offers new insight into developing more comprehensive theoretical frameworks and models of decision-making – for example, adding additional factors into the existing theoretical models which explain procrastination (e.g., Rabin, 1999).

Third, while there have been limited experimental studies on self-signaling theory (Bodner & Prelec, 2003; Prelec & Bodner, 2003), our work adds early-stage empirical evidence, and also proposes an explanation for the potential mechanism of "prosocial procrastination". Furthermore, most studies on procrastination have employed field experiments or observational studies; our work offers early stage experience in employing online lab experiments to study procrastination.

Our work also has the following limitations.

Firstly, the experiments in this paper employed hypothetical questions, instead of tasks requiring real effort. While hypothetical questions provide a good starting point for studying this, future work should employ tasks which require real effort, as a means to improve external validity.

Secondly, we included a set of statistical analyses to get individual level estimates. However, one caveat was that since each participant was presented with only 16 choice pairs, individual estimates were computed from models including about 10 parameters, but with only 16 observations. Hence, such a small sample size might have led to biased and/or unstable estimates and inferences. Future work could employ better designs on conjoint analyses to address these potential statistical issues.

Thirdly, we used conjoint analysis to design the working contracts. While conjoint analysis enabled us to examine the independent effects of each attribute/level, there are instances in which interaction effects could add important explanatory power. For example, in our case, if one contract has a large workload but a short time period to complete it, the interaction between these two attributes should be addressed. Hence, as mentioned in the "Work in Progress" section, we will try to add interaction terms into the modeling analyses, and assess whether this could offer new insight. However, adding interaction effects might be costly, since it would require a significant increase in the number of tasks for each participant.

In conclusion, our work is a one of the first steps towards bridging time preferences and social preferences. We hope our work will inspire more work to further our understanding of this self-other (and/or self-charity) tradeoff involving costs and benefits that occur at different time points – which could include two directions: how prosociality would be affected by the timing of consequences, and how time preferences could be affected by the prosocial nature of the tasks.

6 References

Ainslie, G. (1975). Specious reward: a behavioral theory of impulsiveness and impulse control. Psychological bulletin, 82(4), 463.

Akerlof, G. A. (1991). Procrastination and obedience. *The american economic review*, *81*(2), 1-19.

Andreoni, J. (1989). Giving with impure altruism: Applications to charity and Ricardian equivalence. *Journal of political Economy*, *97*(6), 1447-1458.

Andreoni, J. (1990). Impure altruism and donations to public goods: A theory of warm-glow giving. *The economic journal*, *100*(401), 464-477.

Andreoni, J., & Serra-Garcia, M. (2021). Time inconsistent charitable giving. *Journal of Public Economics*, *198*, 104391.

Ariely, D., & Wertenbroch, K. (2002). Procrastination, deadlines, and performance: Self-control by precommitment. *Psychological science*, *13*(3), 219-224.

Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2006). Elicitation using multiple price list formats. *Experimental Economics*, *9*(4), 383-405.

Augenblick, N., & Rabin, M. (2019). An experiment on time preference and misprediction in unpleasant tasks. *Review of Economic Studies*, *86*(3), 941-975.

Augenblick, N., Niederle, M., & Sprenger, C. (2015). Working over time: Dynamic inconsistency in real effort tasks. *The Quarterly Journal of Economics*, *130*(3), 1067-1115.

Bénabou, R., & Tirole, J. (2003). Intrinsic and extrinsic motivation. *The review of economic studies*, *70*(3), 489-520.

Bénabou, R., & Tirole, J. (2004). Willpower and personal rules. *Journal of Political Economy*, *112*(4), 848-886.

Bénabou, R., & Tirole, J. (2006). Incentives and prosocial behavior. *American economic review*, *96*(5), 1652-1678.

Bisin, A., & Hyndman, K. (2020). Present-bias, procrastination and deadlines in a field experiment. *Games and Economic Behavior*, *119*, 339-357.

Bodner, R., & Prelec, D. (2003). Self-signaling and diagnostic utility in everyday decision making. *The psychology of economic decisions*, *1*(105), 26.

Bodner, R. (1995) unpublished PhD dissertation: Self-knowledge and the diagnostic value of one’s actions

Camerer, C. F. (2006). Behavioral economics.

Charness, G., & Rabin, M. (2002). Understanding social preferences with simple tests. *The quarterly journal of economics*, *117*(3), 817-869.

Chopra, F., Eisenhauer, P., Falk, A., & Graeber, T. (2021). Intertemporal Altruism. *Available at SSRN 3771742*.

Cohen, J., Ericson, K. M., Laibson, D., & White, J. M. (2020). Measuring time preferences. *Journal of Economic Literature*, *58*(2), 299-347.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic literature*, *47*(2), 315-72.

Dhar, R., & Wertenbroch, K. (2012). Self-signaling and the costs and benefits of temptation in consumer choice. *Journal of Marketing Research*, *49*(1), 15-25.

Doyle, J. R. (2013). Survey of time preference, delay discounting models.

Fehr, E., & Fischbacher, U. (2002). Why social preferences matter–the impact of non-selfish motives on competition, cooperation and incentives. *The economic journal*, *112*(478), C1-C33.

Fehr, E., & Schmidt, K. M. (2001). Theories of fairness and reciprocity-evidence and economic applications. *Available at SSRN 264344*.

Frederick, S., Loewenstein, G., & O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of economic literature*, *40*(2), 351-401.

Green, P. E., & Srinivasan, V. (1978). Conjoint analysis in consumer research: issues and outlook. *Journal of consumer research*, *5*(2), 103-123.

Green, P. E., & Srinivasan, V. (1990). Conjoint analysis in marketing: new developments with implications for research and practice. *Journal of marketing*, *54*(4), 3-19.

Grossman, Z. (2015). Self-signaling and social-signaling in giving. *Journal of Economic Behavior & Organization*, *117*, 26-39.

Imas, A. (2014). Working for the "warm glow": On the benefits and limits of prosocial incentives. *Journal of Public Economics*, *114*, 14-18.

Kamenica, E. (2012). Behavioral economics and psychology of incentives. *Annu. Rev. Econ.*, *4*(1), 427-452.

Kölle, F., & Wenner, L. (2021). Is Generosity Time-Inconsistent? Present Bias across Individual and Social Contexts. *The Review of Economics and Statistics*, 1-45.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics*, *112*(2), 443-478.

Loewenstein, G. F., Thompson, L., & Bazerman, M. H. (1989). Social utility and decision making in interpersonal contexts. *Journal of Personality and Social psychology*, *57*(3), 426.

Loewenstein, G., & Prelec, D. (1992). Anomalies in intertemporal choice: Evidence and an interpretation. *The Quarterly Journal of Economics*, *107*(2), 573-597.

Marzilli Ericson, K. M., White, J. M., Laibson, D., & Cohen, J. D. (2015). Money earlier or later? Simple heuristics explain intertemporal choices better than delay discounting does. *Psychological science*, *26*(6), 826-833.

O'Donoghue, T., & Rabin, M. (1999a). Doing it now or later. *American economic review*, *89*(1), 103-124.

O'Donoghue, T., & Rabin, M. (1999b). Incentives for procrastinators. *The Quarterly Journal of Economics*, *114*(3), 769-816.

O'Donoghue, T., & Rabin, M. (2001). Choice and procrastination. *The Quarterly Journal of Economics*, *116*(1), 121-160.

Pope, D. G., & Sydnor, J. R. (2015). Behavioral economics: Economics as a psychological discipline. *The Wiley Blackwell Handbook of Judgment and Decision Making*, *2*, 800-827.

Prelec, D., & Bodner, R. (2003). Self-signaling and self-control. In G. Loewenstein, D. Read, & R. Baumeister (Eds.), *Time and decision: Economic and psychological perspectives on intertemporal choice* (pp. 277–298). Russell Sage Foundation.

Rabin, M. (1998). Psychology and economics. *Journal of economic literature*, *36*(1), 11-46.

Rabin, M. (2002). A perspective on psychology and economics. *European economic review*, *46*(4-5), 657-685.

Read, D., Frederick, S., & Scholten, M. (2013). DRIFT: An analysis of outcome framing in intertemporal choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *39*(2), 573.

Samuelson, P. A. (1937). A note on measurement of utility. *The review of economic studies*, *4*(2), 155-161.

7 Appendix

7.1 Choice Profiles from Conjoint Analysis

7.1.1 Study 1

Choice Set	Timing	Workload	Wage Rate	Earnings
1	in 1 month	300	4	4
1	in 1 month	150	2.5	1.25
2	Immediate	300	2.5	2.5
2	in 1 month	600	6	12
3	Immediate	600	5	10
3	in 1 week	600	4	8
4	Immediate	300	5	5
4	Immediate	30	4	0.4
5	in 1 month	300	2.5	2.5
5	in 1 week	75	5	1.25
6	Immediate	150	6	3
6	in 1 week	600	7.5	15
7	Immediate	75	2.5	0.625
7	Immediate	150	4	2
8	in 1 month	75	6	1.5
8	in 1 month	30	2.5	0.25
9	Immediate	600	7.5	15
9	in 1 week	75	2.5	0.625
10	Immediate	600	6	12
10	in 1 week	600	5	10
11	in 1 month	600	7.5	15
11	in 1 week	75	4	1
12	in 1 month	30	6	0.6
12	Immediate	300	7.5	7.5
13	in 1 month	150	5	2.5
13	in 1 week	30	6	0.6
14	in 1 week	30	5	0.5
14	Immediate	600	7.5	15
15	Immediate	30	5	0.5
15	in 1 week	150	6	3
16	in 1 week	300	6	6
16	Immediate	75	4	1

7.1.2 Study 2

Choice Set	Timing	Workload	Wage Rate	Earnings
1	Immediate	600	5	10
1	in 1 week	100	3	1
2	in 1 week	30	3	0.3
2	Immediate	300	5	5
3	in 1 week	300	4	4
3	Immediate	100	5	1.67
4	in 1 week	300	6	6
4	in 1 month	600	3	6
5	in 1 month	300	5	5
5	Immediate	600	6	12
6	in 1 month	600	4	8
6	Immediate	30	6	0.6
7	in 1 week	600	6	12
7	Immediate	300	3	3
8	in 1 month	30	5	0.5
8	Immediate	600	6	12
9	Immediate	300	5	5
9	Immediate	30	3	0.3
10	in 1 month	100	4	1.33
10	Immediate	300	6	6
11	Immediate	100	5	1.67
11	in 1 week	300	4	4
12	Immediate	30	4	0.4
12	in 1 week	300	3	3
13	Immediate	100	4	1.33
13	in 1 week	30	3	0.3
14	in 1 week	600	3	6
14	in 1 week	30	5	0.5
15	in 1 week	100	3	1
15	Immediate	30	4	0.4
16	in 1 week	600	3	6
16	in 1 week	100	4	1.33

7.1.3 Study 3

Choice Set	Timing	Workload	Wage Rate	Earnings
1	Immediate	100	8	13.3
1	in 1 week	30	11	5.5
2	in 5 weeks	100	11	18.3
2	in 1 week	180	8	24

3	in 5 weeks	180	11	33
3	Immediate	30	14	7
4	in 1 week	50	8	6.67
4	Immediate	30	11	5.5
5	Immediate	180	8	24
5	in 2 weeks	50	14	11.7
6	Immediate	30	14	7
6	in 5 weeks	180	11	33
7	in 2 weeks	30	14	7
7	Immediate	50	14	11.7
8	in 5 weeks	100	11	18.3
8	Immediate	180	8	24
9	in 2 weeks	100	14	23.3
9	Immediate	180	8	24
10	Immediate	50	11	9.17
10	in 1 week	100	8	13.3
11	in 2 weeks	50	8	6.67
11	in 1 week	30	11	5.5
12	in 5 weeks	30	8	4
12	in 2 weeks	100	14	23.3
13	Immediate	30	14	7
13	in 5 weeks	180	11	33
14	in 2 weeks	30	8	4
14	in 1 week	50	11	9.17
15	in 1 week	30	8	4
15	Immediate	100	11	18.3
16	in 2 weeks	30	11	5.5
16	in 1 week	100	8	13.3

7.2 Results based on samples without the exclusion on individual estimates

Note: The following tables in Appendix (Table A3, A6, A9) present the aggregate level of estimates: the first set of results is the estimated coefficients for the "self" condition; the second set of "diff" coefficients is the estimated differences between the "charity" and "self" conditions; the set of estimated coefficients for the "charity" condition could be computed directly by combing the first and second sets of estimates.

7.2.1 Study 1

Figure A1. Comparing the estimated attribute utilities from logistic models between two conditions for Study 1 (without the second exclusion)

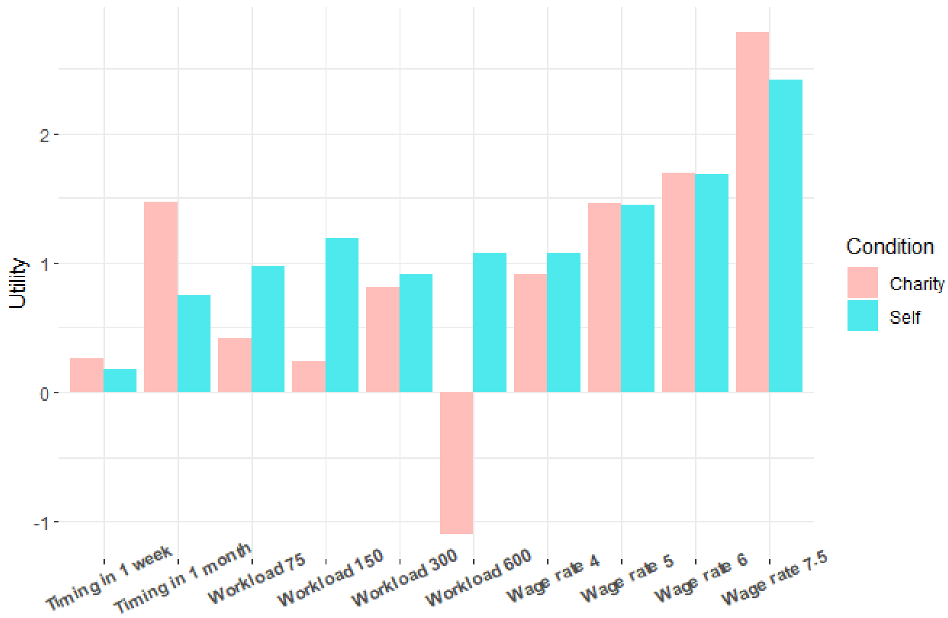

Figure A2. Comparing the estimated attribute utilities from linear models between two conditions for Study 1 (without the second exclusion)

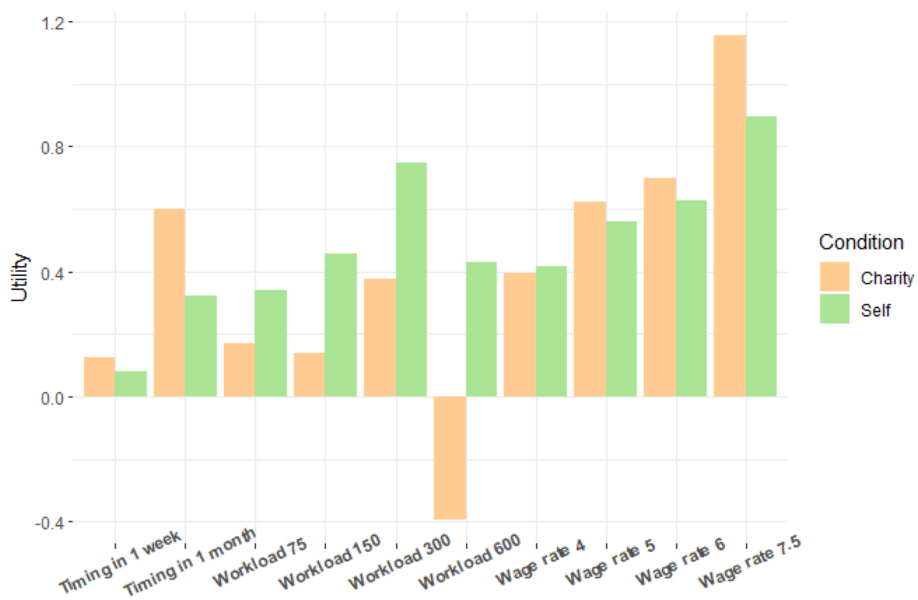

Table A3. Regression results for Study 1 (without individual exclusion)

	Model 1: Logistic + MLE			**Model 2: Linear + OLS**		
	Coef	SE	P-value	Coef	SE	P-value
Intercept	-0.0706	0.168	0.675	-0.0554	0.050	0.267
Diff Intercept	-0.3002	0.211	0.155	-0.0924	0.069	0.180
Timing in 1 Week	0.1816	0.122	0.137	0.0819	0.041	0.046*
Timing in 1 Month	0.7538	0.234	0.030*	0.3225	0.095	0.001**
Workload 75	0.9761	0.163	0.000***	0.3383	0.046	0.000***
Workload 150	1.1902	0.226	0.000***	0.4564	0.066	0.000***
Workload 300	1.9120	0.209	0.000***	0.7498	0.059	0.000***
Workload 600	1.0772	0.754	0.153	0.4290	0.204	0.036*
Wage Rate 4	1.0805	0.147	0.000***	0.4184	0.044	0.000***
Wage Rate 5	1.4465	0.203	0.000***	0.5609	0.063	0.000***
Wage Rate 6	1.6821	0.269	0.000***	0.6255	0.077	0.000***
Wage Rate 7.5	2.4137	0.707	0.001***	0.8951	0.188	0.000***
Diff Timing in 1 Week	0.0725	0.158	0.645	0.0414	0.057	0.464
Diff Timing in 1 Month	0.7201	0.425	0.090	0.2787	0.131	0.033*
Diff Workload 75	-0.5591	0.203	0.006**	-0.1661	0.064	0.009**
Diff Workload 150	-0.9587	0.282	0.001**	-0.3191	0.092	0.001**
Diff Workload 300	-1.1040	0.256	0.000***	-0.3732	0.081	0.000***
Diff Workload 600	-2.1742	0.912	0.017*	-0.8226	0.282	0.004**
Diff Wage Rate 4	-0.1660	0.186	0.373	-0.0232	0.061	0.702
Diff Wage Rate 5	0.0090	0.259	0.972	0.0612	0.087	0.481
Diff Wage Rate 6	0.0155	0.337	0.963	0.0739	0.106	0.486
Diff Wage Rate 7.5	0.3677	0.859	0.669	0.2603	0.260	0.317
Pseudo R^2/ R^2		0.228			0.283	
No. Observations		3872			3872	

7.2.2 Study 2

Figure A4. Comparing the estimated attribute utilities from logistic models between two conditions for Study 2 (without the second exclusion)

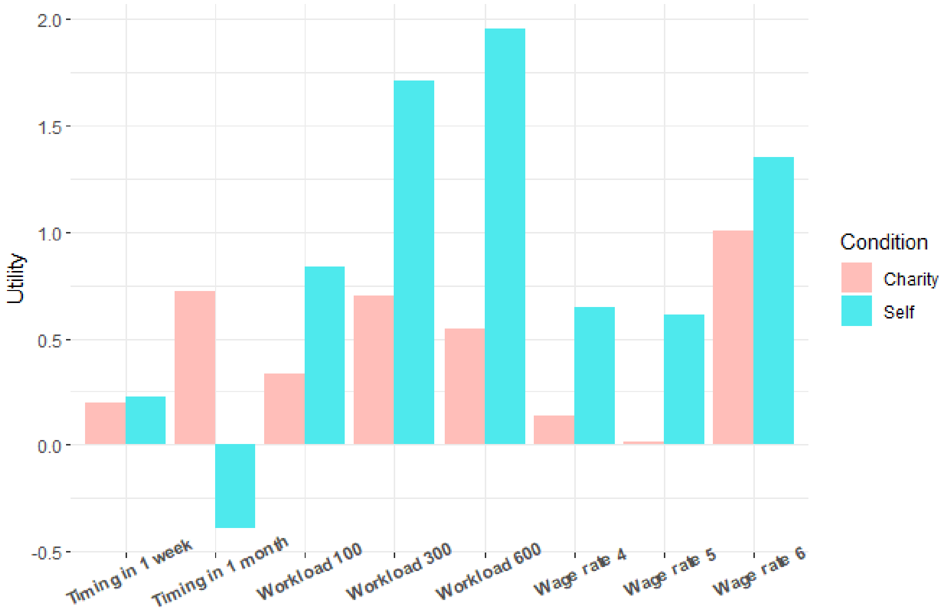

Figure A5. Comparing the estimated attribute utilities from linear models between two conditions for Study 2 (without the second exclusion)

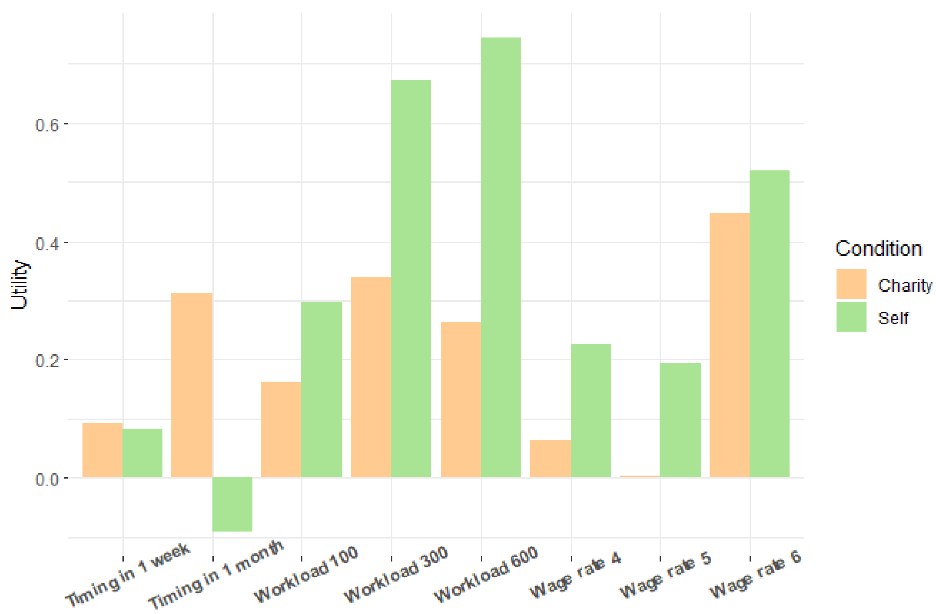

Table A6. Regression results for Study 2 (without individual exclusion)

	Model 1: Logistic + MLE			**Model 2: Linear + OLS**		
	Coef	SE	P-value	Coef	SE	P-value
Intercept	0.1679	0.077	0.029*	0.0834	0.027	0.002**
Diff Intercept	-0.0055	0.098	0.956	-0.0067	0.037	0.856
Timing in 1 Week	0.2241	0.178	0.207	0.0832	0.061	0.172
Timing in 1 Month	-0.3903	0.544	0.474	-0.0904	0.172	0.600
Workload 100	0.8389	0.119	0.000***	0.2985	0.041	0.000***
Workload 300	1.7133	0.140	0.000***	0.6715	0.046	0.000***
Workload 600	1.9538	0.150	0.000***	0.7439	0.049	0.000***
Wage Rate 4	0.6445	0.133	0.000***	0.2254	0.047	0.000***
Wage Rate 5	0.6142	0.208	0.003**	0.1931	0.067	0.004**
Wage Rate 6	1.3486	0.458	0.003**	0.5187	0.145	0.000***
Diff Timing in 1 Week	-0.0242	0.226	0.915	0.0095	0.085	0.911
Diff Timing in 1 Month	1.1108	0.682	0.104	0.4034	0.240	0.093
Diff Workload 100	-0.5055	0.152	0.001**	-0.1371	0.058	0.017*
Diff Workload 300	-1.0137	0.174	0.000***	-0.3327	0.064	0.000***
Diff Workload 600	-1.4078	0.188	0.000***	-0.4795	0.069	0.000***
Diff Wage Rate 4	-0.5080	0.171	0.003**	-0.1626	0.065	0.012*
Diff Wage Rate 5	-0.6005	0.260	0.021*	-0.1891	0.093	0.043*
Diff Wage Rate 6	-0.3409	0.576	0.554	-0.0707	0.202	0.726
Pseudo R^2/ R^2		0.182			0.227	
No. Observations		3264			3264	

7.2.3 Study 3

Figure A7. Comparing the estimated attribute utilities from logistic models between two conditions for Study 3 (without the second exclusion)

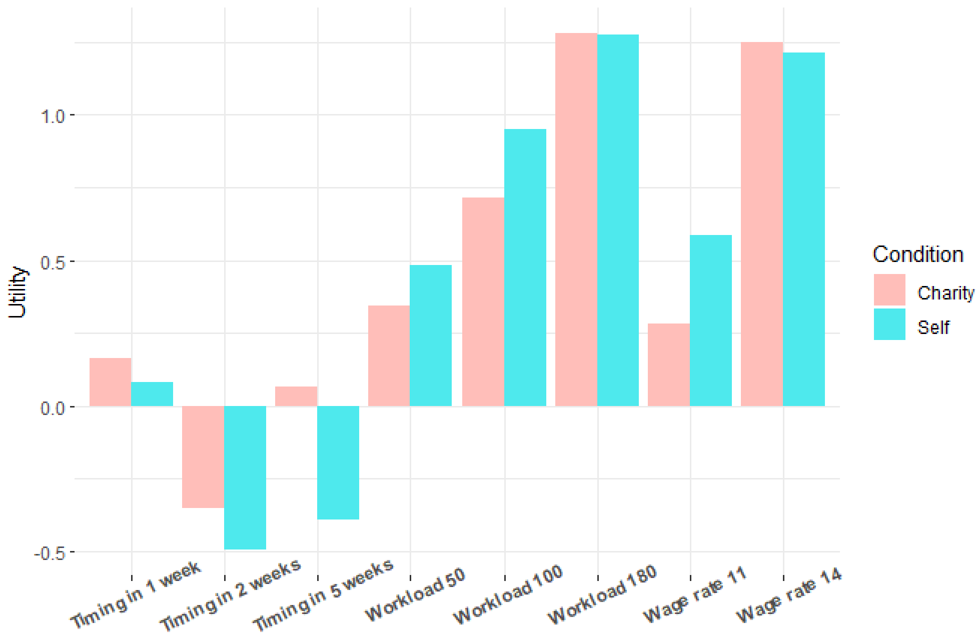

Figure A8. Comparing the estimated attribute utilities from linear models between two conditions for Study 3 (without the second exclusion)

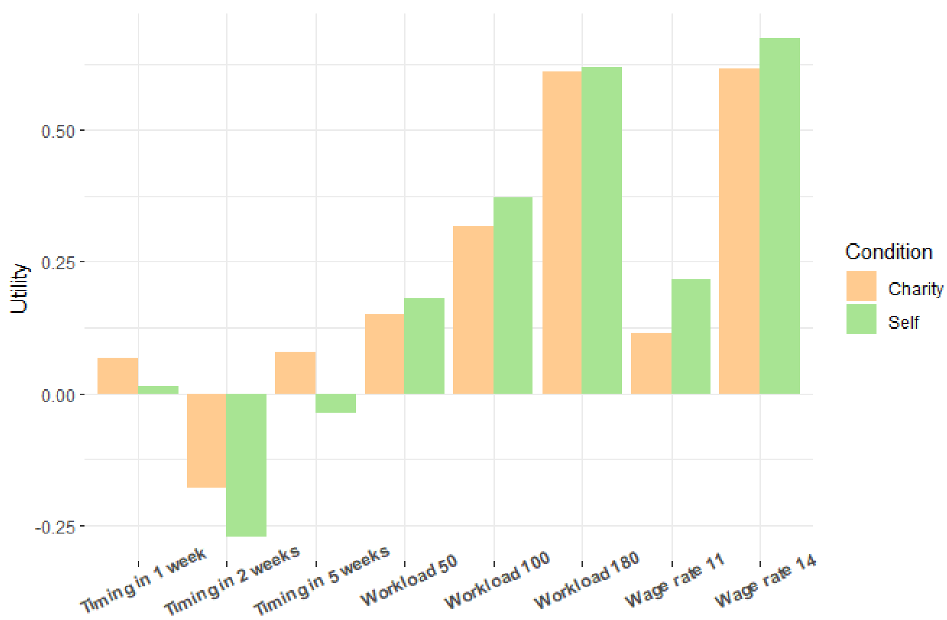

Table A9. Regression results for Study 3 (without individual exclusion)

	Model 1: Logistic + MLE			**Model 2: Linear + OLS**		
	Coef	SE	P-value	Coef	SE	P-value
Intercept	-0.0158	0.067	0.813	-0.0060	0.031	0.844
Diff Intercept	0.0120	0.094	0.899	0.0032	0.043	0.942
Timing in 1 Week	0.0799	0.099	0.418	0.0120	0.044	0.785
Timing in 2 Weeks	-0.4954	0.163	0.002**	-0.2719	0.071	0.000***
Timing in 5 Weeks	-0.3930	0.358	0.273	-0.0354	0.153	0.817
Workload 50	0.4813	0.104	0.000***	0.1804	0.044	0.000***
Workload 100	0.9486	0.119	0.000***	0.3716	0.047	0.000***
Workload 180	1.2741	0.315	0.000***	0.6173	0.140	0.000***
Wage Rate 11	0.5838	0.098	0.000***	0.2168	0.039	0.000***
Wage Rate 14	1.2132	0.560	0.030*	0.6729	0.247	0.007**
Diff Timing in 1 Week	0.0820	0.138	0.553	0.0559	0.062	0.370
Diff Timing in 2 Weeks	0.1467	0.228	0.519	0.0928	0.101	0.359
Diff Timing in 5 Weeks	0.4601	0.494	0.352	0.1134	0.217	0.600
Diff Workload 50	-0.1401	0.143	0.329	-0.0309	0.062	0.620
Diff Workload 100	-0.2343	0.161	0.146	-0.0557	0.066	0.402
Diff Workload 180	0.0061	0.441	0.989	-0.0084	0.199	0.966
Diff Wage Rate 11	-0.3021	0.134	0.024*	-0.1012	0.055	0.067
Diff Wage Rate 14	0.0372	0.780	0.962	-0.0572	0.351	0.871
Pseudo R^2/ R^2		0.060			0.077	
No. Observations		3824			3824	