Did Money Change Them? Examining Hypothetical Bias When Eliciting Preferences for Personal and Social Benefits

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Abstract: The experimental economics literature has long incentivized subject decisions to mitigate hypothetical bias. This paper addresses whether the extent of hypothetical bias varies by payment type. Using experiments and assuming constant relative risk aversion, I estimate both risk and time preference parameters for two distinct types of payments: personal payments that accrue to the decision-maker and social payments that are donated to the charity of the decision-maker's choice. For each type of payment, I evaluate the effect of incentivizing subject responses to identify whether hypothetical questions bias or otherwise influence subject decisions using both reduced from and structural models. I find that personal payments are more susceptible to incentive effects than social payments, for which I find almost no evidence of incentive effects. While different models provide different results, the clearest conclusion is that incentivizing personal payment decisions increases risk aversion. No comparable increase in risk aversion is found by incentivizing social payment decisions.

The study of intertemporal choice has been a mainstay of the economics literature for the past fifty years. Studies frequently link impatience to observable characteristics and/or problematic behaviors (Odum et al. 2000; Tanaka, Camerer and Nguyen 2010). Economists additionally utilize discount rates when modeling intertemporal utility and examine anomalies and biases associated with intertemporal choice (Frederick et al. 2002). Similarly, risk tolerance has been linked to entrepreneurship, smoking, and participation in active sports (van Praag and Cramer 2001; Wang and Hanna 2007; Xiao *et al*. 2001; Dohmen *et al*. 2011) and is also crucial when modeling individual decision making and macroeconomic phenomena.

Standard economic models adhering to Expected Utility Theory (EUT) assume that the utility discount rate is constant. Subsequent models developed by economists in response to criticisms of the basic EUT model often relax this assumption. The most common adjustment involves hyperbolic discounting, or allowing instantaneous discount rates to change over time (Thaler 1981; Benhabib et al. 2010). Other work has allowed for dual-rate discounting, or different discount rates to be applied to different goods (Howard 2013; Chapman 1996; Ubfal 2012), while research on the magnitude effect suggests that discount rates may vary based on the size of value streams (Sun and Li 2010; Mitchell and Wilson 2010; Johnson and Bickel 2002), although the evidence of hyperbolic discounting, dual-rate discounting, and magnitude effects is mixed (see Andreoni and Sprenger 2012, Coller *et al*. 2012, Robberstan 2005, and Andersen et al. 2013). Additionally, several studies have explored the existence of hypothetical bias in the experimental elicitation of risk and time preferences (Coller and Williams 1999; Holt and Laury 2002; Harrison 2007; Johnson and Bickel 2002). This paper considers both time and risk preferences, and focuses on two particular areas within the broad field of preference parameter elicitation: the study of incentive effects (and hypothetical bias) in experimental elicitation and the study of preference parameter heterogeneity by payment type. This is the first study to compare hypothetical bias in risk and time preference elicitation for multiple payment types.

Time and risk preferences can be captured broadly using subjective ('patient-impatient' or 'willing-unwilling to take risks') measures (Dohmen et al. 2011; Vischer et al. 2013) or they can be parameterized using structural models with often restrictive parametric assumptions (Benhabib, Bisin, and Schotter 2010; Andreoni and Sprenger 20103). To this end, several papers have identified the critical interrelationship of time and risk preferences in expected utility theory (Andersen *et al*. 2008 and 2013; Howard 2013; Laury *et al*. 2012). The implication of this relationship is that attempts to satisfactorily identify discount rates without controlling for risk preferences may be stymied, especially if changing conditions lead to risk preference variations within a given study. This paper tests for hypothetical bias in an experimental setting for two separate payments: personal payments/benefits (direct payments to the subject) and social payments/benefits (payments made via anonymous contributions to a charity selected by the subject from a short list provided by the experimenter). I look for hypothetical bias in both risk preferences and time preferences for each type of payment. Furthermore, I estimate a reduced form model that treats risk and time preferences in isolation as well as a structural model that estimates the preference parameters jointly.

I find incentive effects in the experimental results, as well as evidence that incentive effects vary by both payment type and preference parameter. Specifically, personal payments exhibit greater incentive effects than social payments, and risk preference parameters suffer from greater incentive effects than do time preference parameters. The next section outlines the details of the experiment. This section is followed by a theoretical and empirical description of the structural model used to analyze the data, the results of both the reduced-form and structural model analyses, and concluding remarks.

Experimental Design

The data were obtained from lab experiments conducted at Ohio State University from May 2011 to September 2011[1]. The subject population is comprised of 285 undergraduate students. The general experimental design follows Andersen *et al.* (2008) and Howard (2013). Subjects are presented with four separate tasks. These tasks vary based on the benefit being considered (personal vs. social) and the preference parameter of interest (risk preference vs. time preference). These are used to jointly estimate risk and time preference parameters using the structural model outlined in the following section.

Both risk and time preference tasks take the form of choice tasks, in which subjects are presented with two payment options and must select which option they prefer. Constructed in this manner, choice tasks allow the experimenter to derive an interval estimate, rather than a point estimate, for the preference parameter in question. This is because an indifference point is necessary to obtain a point estimate for the parameter in question. Since a point estimate is generally preferred to an interval estimate,[2] subjects were also given the option of expressing indifference between payment options.

The risk preference task is adapted from Holt and Laury (2002) and uses a multiple price list (MPL) format. MPLs provide subjects with a series of binary choices, typically in the format

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[1] Instructions and forms used in the experiment are available upon request.
[2] This is true so long as we can have some degree of confidence in our point estimate. As Keynes said, "It is better to be roughly right than precisely wrong."

of rows of a table. Table 1 presents an example of this risk preference task. Subjects choose between two binary lotteries, a safe lottery (denoted Lottery A to subjects) and a risky lottery (Lottery B to subjects). The choice rows are identical in the payouts of each lottery but differ in the probability assigned to the high and low payouts. The final choice row acts as a rationality test, as it offers the choice between a certain payment of $180 and $300.

Table 2 presents an example of the time preference task. Time preference tasks also use MPLs and are adapted from Coller and Williams (1999). In each choice row, subjects are given two payment options. The early payment (Payment Option A to subjects) offers a payment of $100 dollars. This payment always occurs one week from the date of the experiment. The distant payment (Payment Option B to subjects) pays some value greater than or equal to $100 and occurs 14 weeks from the date of the experiment. In addition, subjects were provided the annual and effective annual interest rate[3] associated with accepting the distant payment in favor of the early payment[4]. In all permutations of this task, both payment options are delayed in order to avoid immediacy bias and the potential impact of quasi-hyperbolic discounting (Harrison, Lau and Williams 2002; Harrison *et al.* 2005).

One set of risk and time preference tasks, intended to capture preferences for personal benefits, focused on monetary payments made to the subject. The second set of tasks was intended to capture preferences toward social benefits. Before completing the social benefit

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[3] The annual interest rate assumes quarterly compounding. The annual effective interest rate is the interest rate that would yield the same annual return compounding annually instead of quarterly.

[4] In the early sessions, the distant payment was presented as occurring 13 weeks, or approximately 3 months and 1 week, in the future. 3 months and 1 week is actually 14 weeks. In addition, the interest rates reported to correspond to the distant payment were accurate for 14 weeks rather than 13 weeks. It seems likely that subjects simply accepted that the difference between payments was 3 months, in which case the data should be treated as if the payment occurred in 14 weeks rather than 13. The data was tested assuming 13 and 14 weeks and there is no qualitative difference in the results.

tasks, subjects chose a charity that they would be most interested in making a donation from a list of 7 local charities.[5] When completing the social risk and time preference tasks, subjects were told that their decisions related to anonymous charitable donations to their selected charity. The donations were anonymous to ensure that the value subjects place on social payments was separated from potential reputation effects they may enjoy from visible charitable contributions. For each task, subjects were given time to read the instructions and had the instructions read to them by the experimenter. Task order was varied by session to control for order effects. In addition, subjects were randomly given one of two different MPLs for each task to control for formatting bias (Andersen *et al*. 2006).

All subjects were recruited in an identical manner, specifically with the promise of $10 compensation for participation that would take no longer than one hour. At the beginning of each session, subjects were randomly split into two groups: A hypothetical group and an incentivized group. These groups completed the experiment in separate rooms. In the hypothetical group, subjects completed the various tasks of the experiment and were paid $10 as they left the session. In the incentivized group, subjects were given a 1 in 12 chance of having additional payments based on their responses in addition to the $10 show-up fee received by everyone. This was explained at the beginning of the experiment, so subjects were aware that there is an incentive for them to answer truthfully. In both hypothetical and incentivized groups, each time preference task consisted of 16 choice rows and each risk preference task consisted of 14 choice rows. In all, each subject made 60 decisions, split 30-30 relating to social-personal benefits and 32-28 relating to time-risk preference. As the last task of each experiment, subjects also completed a questionnaire containing demographic and background questions.

[5] Specifically, they were then asked, "If given money to donate to one of the above charities, which charity would you choose?"

For subjects in the incentivized group randomly selected to receive it, the additional payment was based on one choice row randomly selected from all 60 rows completed in the experiment. In this way, the additional payment could entail a monetary payment to the subject or an anonymous donation to the charity of the subject's choosing. Additional monetary payments accruing to the subject were paid via check. If the payment resulted from the discounting task, the check was post-dated either 1 or 14 weeks in the future depending on whether the subject chose Option A or B. In all cases the check was given to the subject at the end of the session to eliminate any asymmetries due to either transaction costs or beliefs about the experimenter's willingness/ability to pay the promised amount. If the payment was determined to go to charity, the experimenter filled out a check made to the charity in front of the subject. The dating for this check was identical to the dating for checks made out to the subject. If the subject indicated indifference for the choice row selected for payment, the experimenter would determine which lottery/option to use as payment by flipping a coin. Every subject received at least $10 for participating, and in the hypothetical group every subject received exactly $10. In the incentivized group, the majority of subjects received exactly $10, and a minority of subjects received substantially more (on average $208)[6]. The average payment in the incentivized group was $26.50, with a standard deviation of $58.

Structural Model

[6] One could argue that the entire experiment was hypothetical rather than incentivized, since even the majority of subjects in the incentivized treatment did not receive payment based on their responses. However, subjects knew that they had a chance to be paid based on their responses, and that the payments were large. As Howard (2013, p. 587) notes: "Those subscribing to expected utility theory would argue that subjects would generally view this as being a modest incentive in expectation, while proponents of prospect theory would argue that the expected incentive is even larger given that people tend to overweight small probability events. While this is admittedly somewhat tongue in cheek, the point remains that subjects knew they had a chance to be paid a large amount based on their responses, which should be more likely to yield incentivized responses than hypothetical ones."

The basic structural model was developed by Andersen *et al.* (2008) and utilized by Laury *et al.* (2012). This theoretical model assumes additively separable utility that is a function of a single consumption good and exhibits CRRA of the form

$$W = \sum_{t=0}^{\infty} \frac{C_t^{1-\sigma}}{(1-\sigma)(1+\rho)^t}. \tag{3}$$

In this formulation, ρ is the utility discount rate and σ is the coefficient of relative risk aversion. Deviating from these previous models and following Howard (2013), the model treats utility in each period as a function of two distinct goods, the consumption good (C) and the environmental/social good (S). I also assume additive separability of the utility function in period *t*. The welfare function faced by the infinitely-lived agent now

$$W = \sum_{t=0}^{\infty} \frac{C_t^{1-\sigma_C}}{(1-\sigma_C)(1+\rho_C)^t} + \frac{S_t^{1-\sigma_S}}{(1-\sigma_S)(1+\rho_S)^t} \tag{4}$$

where ρ and σ are allowed to vary by good type, with consumption goods denoted with subscript *C* and social good denoted with subscript *S*. This is similar to models developed by Banerjee and Mullainathan (2010) and Futagami and Hori (2010). In this formulation, the quantity of each good that enters the welfare function in period *t* is the sum of background consumption for the good ($\omega_{t,C}$ and $\omega_{t,S}$ for the consumption and social good, respectively) and any payments made at that time.[7] The indifference equation between personal payment *X* made at time *t* and personal payment *Y* made at time $t + \tau$ becomes

[7] Andersen and his coauthors define background consumption as "the optimized consumption stream based on wealth and income that is perfectly anticipated before allowing for the effects of the money offered in the experimental tasks. (Andersen *et al*. 2008, p. 583)" For a broader discussion of the role of background consumption in discount rate elicitation, see Andersen *et al*. (2008) and Howard (2012). In our model we assume zero background consumption. We also examine whether our results are sensitive to this assumption. Using reported subject income,

$$\frac{(\omega_{t,C} + X)^{1-\sigma_C}}{1-\sigma_C} + \frac{\omega_{t,S}^{\ 1-\sigma_S}}{1-\sigma_S} + \frac{\omega_{t+\tau,C}^{\ 1-\sigma_C}}{(1-\sigma_C)(1+\rho_C)^\tau} + \frac{\omega_{t+\tau,S}^{\ 1-\sigma_S}}{(1-\sigma_S)(1+\rho_S)^\tau} = \tag{5}$$

$$\frac{\omega_{t,C}^{\ 1-\sigma_C}}{1-\sigma_C} + \frac{\omega_{t,S}^{\ 1-\sigma_S}}{1-\sigma_S} + \frac{(\omega_{t+\tau,C} + Y)^{1-\sigma_C}}{(1-\sigma_C)(1+\rho_C)^\tau} + \frac{\omega_{t+\tau,S}^{\ 1-\sigma_S}}{(1-\sigma_S)(1+\rho_S)^\tau}.$$

If the payment options are entirely personal, the indifference equation allows for all social inputs into the welfare function to cancel. The converse is also true; if all payments are social in nature, personal consumption inputs to the welfare function cancel.

This paper proceeds with two empirical structural models, one which focuses on preference parameters (i.e. utility discount rate and CRRA coefficient) related to personal consumption and another which focuses on preference parameters related to charitable donations. For each model, I use maximum likelihood to jointly estimate these parameters. The log-likelihood function for the risk preference task is constructed as follows. As the equations are identical for personal and social good models, I suppress the good type subscript in the following equations for simplicity. The expected utility of playing lottery i, with $i = S, R$ representing the safe and risky lotteries, respectively, for choice set j of the risk preference task is given by

$$EU_{ij} = p_j(X_i)\frac{(\omega_t + X_i)^{1-\sigma}}{(1-\sigma)} + (1 - p_j(X_i))\frac{(\omega_t + Y_i)^{1-\sigma}}{(1-\sigma)}. \tag{6}$$

Here, $p_j(X_i)$ is the probability of payout X in Lottery i for choice set j and X_i and Y_i are the two possible payouts of Lottery i. Probability is indexed by j but not i because the probabilities are the same for safe and risky lotteries but vary by choice row. Conversely, the payments X and Y

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we construct an average daily consumption level for our subject population. Using this value ($30) as the background consumption figure in the model has only one qualitative impact. Specifically, the negative effect of incentives on the noise term in the risk task is significant at the 90% confidence level.

are indexed by i but not by j because they are constant across choice rows but by lottery. As in the time preference notation, Y represents the high payout and X represents the low payout. The probability of choosing the safe lottery in choice row j of the risk preference task ($_S^{Risk}$), given the expected utilities from both lotteries, is defined as

$$Pr_S^{Risk}(j) = \frac{EU_{Sj}^{1/\mu R}}{EU_{Sj}^{1/\mu R} + EU_{Rj}^{1/\mu R}}, \tag{7}$$

where μR is a behavioral noise parameter or cognitive error term associated with the risk preference task and "*Risk*" identifies the probability value as related to the risk preference task.

The behavioral noise parameter captures the possibility that agents will make an error by choosing the lottery with lower expected utility. A value of μR approaching zero collapses to the deterministic case where subjects always choose the lottery with higher expected utility. As μR approaches infinity, the probability approaches 0.5, regardless of the expected utilities of the lotteries. Additionally, we can think of the noise parameter as an indicator of the level of unobserved heterogeneity in the subject population. Our model allows for some heterogeneity based on observed characteristics (e.g. whether the subject's responses were incentivized and the format of the subject's choice table), but subject preference heterogeneity is not explicitly modeled here beyond the inclusion of a noise parameter. Using this interpretation, a small value of the noise parameter implies a relatively homogeneous subject pool, while larger values imply greater heterogeneity. The conditional log-likelihood function for the risk preference task can be written

$$\ln L^{Risk}(\sigma, \mu_R \mid \omega_t, x) = \sum_j \begin{matrix} [\ln(Pr_S^{Risk}(j) \mid x_j = S) + \ln(1 - Pr_S^{Risk}(j) \mid x_j = R) + \\ \ln(0.5(Pr_S^{Risk}(j)) + 0.5(1 - Pr_S^{Risk}(j)) \mid x_j = I)] \end{matrix}, \tag{8}$$

where $x_j = S, R,$ are indicators for whether the subject chose the safe lottery, risky lottery, and indifference for choice j of the risk preference task, respectively, and x is the set of all choices made in the risk preference task.

The log-likelihood function for the time preference task is similarly structured. The present value (PV) of each payment for choice j of the time preference task is given by the following equations:

$$PV_{Aj} = \frac{(\omega_t + X_j)^{1-\sigma}}{(1-\sigma)(1+\rho)^t} + \frac{(\omega_{t+\tau})^{1-\sigma}}{(1-\sigma)(1+\rho)^{t+\tau}}, \tag{9}$$

$$PV_{Bj} = \frac{(\omega_t)^{1-\sigma}}{(1-\sigma)(1+\rho)^t} + \frac{(\omega_{t+\tau} + Y_j)^{1-\sigma}}{(1-\sigma)(1+\rho)^{t+\tau}}. \tag{10}$$

Here the subscript A refers to Payment Option A (the early payment) and the subscript B refers to Payment Option B (the later payment). The probability that a subject will choose Option A for choice j of the time preference task ($_A^{Disc}$) is given by

$$Pr_A^{Disc}(j) = \frac{PV_{Aj}^{1/\mu D}}{PV_{Aj}^{1/\mu D} + PV_{Bj}^{1/\mu D}}, \tag{11}$$

where μD is a behavioral noise parameter or cognitive error term associated with the time preference task and "*Disc*" identifies that the probability value pertains to the time preference task. The behavioral noise parameter for the time preference task can be interpreted similarly to the behavioral noise parameter for the risk preference task. The conditional log-likelihood function for the time preference task can be written

$$\ln L^{Disc}(\sigma, \rho, \mu_D, \mu_R \mid \omega_t, \omega_{t+\tau}, x) =$$

$$\sum_j \begin{array}{c} [\ln(Pr_A^{Disc}(j) \mid x_j = A) + \ln(1 - Pr_A^{Disc}(j) \mid x_j = B) + \\ \ln(0.5(Pr_A^{Disc}(j)) + 0.5(1 - Pr_A^{Disc}(j)) \mid x_j = I)] \end{array}, \tag{12}$$

where $x_j = A, B,$ and I are indicators for whether the subject chose Option A, Option B, or indifference, respectively, for choice j of the time preference task and x is the set of all choices in the time preference task. By combining equations (8) and (12), the joint log-likelihood function can be written

$$ln\ L(\sigma, \rho, \mu_D, \mu_R \mid \omega_t, \omega_{t+\tau}, x) = ln\ L^{Disc} + ln\ L^{Risk}. \quad (12)$$

Maximum likelihood is used to jointly estimate four parameters: a CRRA parameter, a utility discount rate, and two noise parameters. In some models, these parameters will be estimated assuming preference homogeneity. In other models, this assumption is relaxed and parameters are allowed to vary based on experimental conditions. Specifically, these models will test whether incentivized responses, task ordering, and table formatting have a significant impact on preference and noise parameter estimates.

Results

Table 3 provides variable definitions, while Tables 4 and 5 provide reduced form analyses of the data. Each column of the tables represents one set of tasks: personal time preference (PT), personal risk preference (PR), social time preference (ST) and social risk preference (SR). Table 4 presents the results of Poisson regressions, as the dependent variable for each column is a count of the number of times a subject selected Option A in the relevant choice task. I test for over- and under-dispersion in each Poisson model and find over-dispersion for both personal and social time preference models. To account for this over-dispersion, the last two columns of the table report negative binomial estimations of the time preference data. The results of Poisson and negative binomial regressions are qualitatively similar. Furthermore, the reported negative binomial regression results impose constant dispersion for all observation. Allowing for dispersion to be a function of mean values has no discernable impact on the model.[8] Table 5 uses the log of this count for each column, and accordingly the regressions are OLS. Option A refers to the early payment in the time preference tasks and the safe lottery in the risk preference tasks; as such high counts in the time and risk tasks correspond with higher discount rates and greater levels of risk aversion, respectively. Explanatory variables include an indicator for whether the task was incentivized (Real) and variables capturing format (Skew High) and order effects (Social First and TP First).

Poisson/negative binomial and OLS analyses find no significant effect of incentives, and so no evidence of hypothetical bias, regarding the social tasks. A link exists between incentives and behavior in personal risk and time preference tasks, with subjects exhibiting more risk averse behavior when incentivized in both regressions. Evidence regarding the impact of incentives on personal discount rates is mixed. The log-linear estimation points to larger discount rates when incentives are present, while the Poisson regression finds no significant relationship. Order effects appear scattered but consistent between both Poisson and OLS models.

The reduced form models cannot directly test the presence of format effects, but they can give an indication of where format effects are more likely. In the presence of format effects, subjects would tend to choose Option A the same number of times regardless of choice table format, which would manifest itself as coefficients for the format variable that are not

[8] Coefficients and statistical significance stay qualitatively similar. Log pseudolikelihood values are nearly identical (for example, -781.887 vs. -780.895), implying that both models fit the data roughly equally.

statistically different from zero. Thus, any tasks with large and significant coefficients for the format variable are less likely to suffer from substantial format effects. Format variables are significant, at least at the 90% confidence level, in all four Poisson models. Similarly, both risk tasks have significant coefficients in the OLS models, although this is not true for time preference tasks. It is important to note that a significant coefficient for the format variable does not preclude format effects. It is possible that subjects can partially adjust for format effects but still be influenced by them. This is true of incentive and order effects as well. While reduced form models can account for qualitative changes in response counts, a more detailed structural model is needed to disentangle the quantitative effects these experimental adjustments have on the manifestation of time and risk preference parameters.

Tables 6 and 7 present maximum likelihood estimates of the structural models for personal and social payments, respectively. In Column I of each table, the parameters of interest are estimated alone, with no explanatory variables that allow for heterogeneity based on experimental conditions. In Column II, the preference parameters (CRRA coefficient and utility discount rate) are allowed to vary by incentive scheme. This is done by introducing in indicator variable (denoted Real) equal to one if the response was incentivized and equal to zero otherwise. Column III allows all four estimated parameters to vary by incentive scheme. Column IV is identical to Column III, but the preference parameters are additionally tested for order (Social First and TP First) and format (Skew High) effects.

As with the reduced form estimations, I find very little evidence of incentive effects in the social benefits model. Specifically, all columns suggest that incentives increase risk aversion for charitable contribution decisions, but the effect is not statistically significant. Incentives also tend to decrease discount rates applied to social payments, but while Column III finds marginal significance in this result the finding disappears once the model controls for format and order effects. There is more evidence of an incentive effect when subjects consider personal payments. Subjects display significantly more risk aversion when decisions are incentivized. Indeed, in Columns III and IV the CRRA parameter for subjects completing hypothetical tasks is not significantly different from zero, which implies risk neutrality. While the model does not find evidence that incentives impact discount rates, it is clear that incentives still impact subject behavior in the time preference task for personal payments. Specifically, the noise parameter value is lower when subjects are incentivized that when decisions are hypothetical. This decrease in noise can be interpreted in two different ways, each with its own implications.

First, one may interpret this as evidence that subjects are making fewer cognitive errors when they are incentivized. This interpretation would argue that, while incentives don't change the estimated discount rate, they improve focus and eliminate noise due to cognitive error. The second possible explanation relates to heterogeneity of preferences in the subject population. The model does not account for unobserved sources of heterogeneity, so any unobserved heterogeneity is captured in the noise term. Using this interpretation, a decrease in the noise term is associated with a decrease in unobserved heterogeneity. If we assume the population has a distribution of individual discount rates, we can think of the point estimate as analogous to the average and the noise term as representing the dispersion of individual rates. A decreased noise term when subjects are incentivized implies that the dispersion of individual discount rates decreases when subjects are incentivized, even as the average discount rate in the population remains unchanged.

What do these results suggest? There is ample evidence that risk and time preference may vary based on the nature of the benefits in question (Howard 2013, CITE). This study further suggests that the effects of experimental design on preference elicitation also vary by benefit type. This result likely extends to experimental decisions beyond the use of incentives. Indeed, both the reduced form and structural models find that order effects influence time preference estimates when the benefits being considered are personal, but not when they relate to charitable donations.

An incredulous observer may reasonably object that failure to find hypothetical bias in the social benefit tasks may simply mean that subjects treat all social payments as roughly hypothetical, or at least that they expend the same amount of cognitive effort in hypothetical and incentivized tasks when benefits flow to society rather than to the individual. To fully explore this objection, it is important to formalize why an individual may suffer from hypothetical bias. First, and to my mind least likely, subjects may want to believe something about their preferences to be true when if actuality it is not. If this were the case, it would be perfectly costless to represent themselves in this (to the mind of the subject) favorable light when response are hypothetical. As the responses become incentivized, however, the cost of portraying oneself in this favorable light increase and subjects are more likely to abandon pretense and show their "true colors." This is similar to the arguments put forth for the existence of hypothetical bias when using contingent valuation to value environmental amenities. People like to believe they would pay $100 to save a whale, and are willing to say as much if the question is hypothetical, but affirmative responses decline when money must actually leave his or her pocket. While theoretically tractable, upon closer scrutiny this argument seems flimsy. This argument would require individuals to consider being risk neutral as more desirable or favorable to being risk averse. This is plausible, but certainly not self-evident. Additionally, since previous research has suggested that incentivizing responses tends to lower discount rates, this theory would require subjects to prefer to be seen as impatient, which seems unlikely.

The other explanation of hypothetical bias relies argues that subjects use less cognitive effort when responses are hypothetical. Incentives encourage subjects to think more about their responses, which makes them more reflective of subjects' true preferences. This is a more plausible explanation for hypothetical bias. Fortunately, an explanation of hypothetical bias based on cognitive effort allows for an indirect test of the hypothesis that subjects are treating all social payment tasks as hypothetical. The test relies on the assumption that format effects should influence responses more if subjects are putting forth relatively less cognitive effort when making decisions. Thus, if even incentivized subjects are acting like hypothetical subjects and putting forth less cognitive effort, format effects should be more pronounced for social benefits than for personal benefits. This is not the case, and indeed the structural model presents mild evidence to the contrary; there are no significant format effects for social preference parameters, while the format effect for personal risk preferences is significant, albeit only at the 90% confidence level.

Conclusion

This research uses experimental data to examine the impact of incentives on time and risk preferences. I use both a reduced form method and a structural model that allows for risk and time preference parameters to be estimated jointly. Additionally, I elicit these preferences for two distinct benefit streams: personal payments and charitable contributions. Previous research has indicated that individuals discount different benefits at different rates; this research investigates whether hypothetical bias relating to risk and time preferences may vary based on benefit type as well.

Indeed, both the reduced form and structural models suggest that incentivizing subject responses will have different effects based on the nature of the benefits being considered. There is evidence of hypothetical bias in subject responses related to risk preferences for personal payments, with subjects displaying greater levels of risk aversion when tasks are incentivized. The reduced form model presents mixed results for the existence of hypothetical bias in time preferences for personal payments, with the Poisson model finding no significant effect and the log-linear model finding subjects are more impatient when rewards are real. While there is no significant hypothetical bias for discount rates in the personal payment structural model, there is evidence that incentives influence the behavior of the subject pool. Specifically, the noise parameter in the incentivized group was significantly less than in the hypothetical group. This could point to a decrease in cognitive errors made by subjects, to decreased heterogeneity of individual discount rates, or to some combination of both explanations. In contrast, this research finds very little evidence of hypothetical bias when benefits are social in nature. Both reduced form and structural models fail to find any statistically significant incentive effects at the 95% confidence level. While absence of evidence is not the same as evidence of absence, this research suggests that incentive effects are more substantial and observable when payments are personal in nature.

An interesting extension of this line of work would be to explore the relationship between incentive effects and magnitude effects. There is substantial research on the magnitude effect in risk and time preference elicitation, but despite this the relationship between incentive effects and magnitude effects is somewhat murky. Interestingly, the relationship between incentive and magnitude effects is most likely analogous to either exponential or beta-delta discounting. I would hypothesize that the two most likely scenarios for this relationship are either that the magnitude and incentive effects are simply one continuous effect, in which case the incentive effect shown when changing payments from hypothetical to $X is the same as the magnitude effect expected when increasing payments from $0 to $X. This continuous effect is similar in design and explication to exponential discounting. The other likely scenario, akin to beta-delta discounting, would be for two separate and in principle isolatable effects that need share no specific relationship or continuity: An incentive effect that occurs when payments change from zero to nonzero (analogous to the beta in beta-delta discounting, which captures the constant rate of discount applied to all payments that are not immediate) and a magnitude effect that increases as the magnitude of the payment increases (analogous to the delta, whose impact on the discount factor is a function of the temporal distance of the payment).[9]

The resolution of this question may, as is common practice, lead to additional research questions of interest, especially if future research supports the beta-delta analogy. For instance, if the incentive and magnitude effects are indeed separate, how do subjects approach experiments where one in *N* subjects are randomly chosen to receive compensation (as in this study, Andersen *et al.* (2013), Laury *et al.* (2012), Halevy (2013), and numerous others)? For instance, how would changing the probability influence responses? Would increasing the probability of payment increase risk aversion due to increasing the magnitude of the subjects expected payment, or would it increase risk aversion due to a decrease in the degree of hypothetical bias I suffer?

[9] In putting forth these potential relationships between the incentive and magnitude effects, I make no assumptions about the constant or nonconstant nature of the magnitude effect, although a nonconstant magnitude effect would not mirror beta-delta discounting as closely as a constant magnitude effect.

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Table 1: Risk Preference Task Example

Lottery A				Lottery B				(5)
(1A) Prob. Of High Payout	(2A) High Payout	(3A) Prob. Of Low Payout	(4A) Low Payout	(1B) Prob. Of High Payout	(2B) High Payout	(3B) Prob. Of Low Payout	(4B) Low Payout	Preferred Lottery
10%	$180	90%	$160	10%	$300	90%	$20	A I B
20%	$180	80%	$160	20%	$300	80%	$20	A I B
30%	$180	70%	$160	30%	$300	70%	$20	A I B
40%	$180	60%	$160	40%	$300	60%	$20	A I B
50%	$180	50%	$160	50%	$300	50%	$20	A I B
60%	$180	40%	$160	60%	$300	40%	$20	A I B
65%	$180	35%	$160	65%	$300	35%	$20	A I B
70%	$180	30%	$160	70%	$300	30%	$20	A I B
75%	$180	25%	$160	75%	$300	25%	$20	A I B
80%	$180	20%	$160	80%	$300	20%	$20	A I B
85%	$180	15%	$160	85%	$300	15%	$20	A I B
90%	$180	10%	$160	90%	$300	10%	$20	A I B
95%	$180	5%	$160	95%	$300	5%	$20	A I B
100%	$180	0%	$160	100%	$300	0%	$20	A I B

Table 2: Time Preference Task Example

(1) Payment Alternative	(2) Payment Option A (Pays amount below in 1 week)	(3) Payment Option B (Pays amount below in 14 weeks)	(4) Annual Interest Rate (In percent)	(5) Annual Effective Interest Rate (In percent)	(6) Preferred Payment Option
1	$100	$100	0	0	A I B
2	$100	$100.75	3	3.03	A I B
3	$100	$102	8	8.24	A I B
4	$100	$103.75	15	15.87	A I B
5	$100	$105	20	21.55	A I B
6	$100	$110	40	46.41	A I B
7	$100	$112.50	50	60.18	A I B
8	$100	$117.50	70	90.61	A I B
9	$100	$122.50	90	125.19	A I B
10	$100	$125	100	144.14	A I B
11	$100	$127.50	110	164.27	A I B
12	$100	$128.75	115	174.78	A I B
13	$100	$130.50	122	190.03	A I B
14	$100	$131.25	125	196.75	A I B
15	$100	$131.75	127	201.30	A I B
16	$100	$132.50	130	208.22	A I B

Table 3: Variable Definitions

Variable	Description
Constant	Estimate of parameter when all dummy variables are 0
Real	Dummy equal to 1 if response was incentivized
Skew High	Dummy equal to 1 if the task table was skewed to offer higher late payments for time preference tasks and higher probabilities of receiving high payouts for risk preference tasks
Social First	Dummy equal to 1 if subject answered social tasks before personal tasks
TP First	Dummy equal to 1 if time preference task was given before risk preference task

Table 4: Reduced-form Poisson and Negative Binomial Regressions on Option/Lottery A Counts

	Poisson				Negative Binomial	
	PT	ST	PR	SR	PT	ST
Real	0.094 (0.261)	-0.065 (0.453)	0.129*** (<0.005)	0.063 (0.112)	0.135 (0.144)	-0.071 (0.447)
Skew High	-0.160* (0.057)	-0.243*** (0.006)	-0.309*** (<0.005)	-0.237*** (<0.005)	-0.195** (0.032)	-0.208** (0.029)
Social First	0.070 (0.405)	0.044 (0.659)	-0.057 (0.168)	-0.120** (0.012)	0.045 (0.622)	0.012 (0.912)
TP First	-0.300*** (<0.005)	0.074 (0.447)	0.020 (0.614)	-0.005 (0.916)	-0.278*** (<0.005)	0.065 (0.532)
Constant	1.955*** (<0.005)	1.831*** (<0.005)	2.111*** (<0.005)	2.164*** (<0.005)	1.951*** (<0.005)	1.837*** (<0.005)
Observations	285	285	285	285	285	285
Deviance Statistic	953.43*** (<0.005)	931.76*** (<0.005)	273.90 (0.592)	298.51 (0.213)		

Notes: PT, ST, PR and SR denote personal time preference, social time preference, personal risk preference, and social risk preference tasks, respectively. Higher values for risk preference tasks translate to more safe decisions, implying greater risk aversion. Higher values for time preference tasks translate to the selection of more early payments, implying greater impatience. P values are presented in parentheses. *, **, and *** indicate significance at the 90%, 95%, and 99% levels, respectively.

Table 5: Reduced-form OLS Regressions on Log of Option/Lottery A Counts

	PT	ST	PR	SR
Real	0.459** (0.048)	-0.126 (0.593)	0.229* (0.054)	0.182 (0.132)
Skew High	-0.254 (0.256)	-0.193 (0.393)	-0.349*** (<0.005)	-0.338*** (<0.005)
Social First	-0.046 (0.839)	-0.121 (0.605)	-0.100 (0.447)	-0.340** (0.036)
TP First	-0.411* (0.072)	0.027 (0.907)	0.088 (0.465)	-0.070 (0.652)
Constant	1.240*** (<0.005)	1.223*** (<0.005)	1.905*** (<0.005)	2.056*** (<0.005)
Observations	285	285	285	285
R^2	0.0335	0.0042	0.0452	0.0595

Notes: PT, ST, PR and SR denote personal time preference, social time preference, personal risk preference, and social risk preference tasks, respectively. Higher values for risk preference tasks translate to more safe decisions, implying greater risk aversion. Higher values for time preference tasks translate to the selection of more early payments, implying greater impatience. P values are presented in parentheses. *, **, and *** indicate significance at the 90%, 95%, and 99% levels, respectively.

Table 6: Structural Model Maximum Likelihood Results: Personal Tasks

Variable		I	II	III	IV
CRRA Coefficient (σ)	Constant	0.1838*** (<0.005)	0.1400** (0.024)	0.0581 (0.356)	0.0372 (0.653)
	Real	-	0.0737 (0.308)	0.2521*** (0.005)	0.2174** (0.025)
	Skew High	-	-	-	0.1136* (0.078)
	Social First	-	-	-	0.0380 (0.607)
	TP First	-	-	-	-0.0771 (0.279)
Time Preference Parameter (ρ)	Constant	0.3889*** (<0.005)	0.3832*** (<0.005)	0.4191*** (<0.005)	0.4433*** (<0.005)
	Real	-	0.0166 (0.808)	-0.0730 (0.362)	-0.0773 (0.315)
	Skew High	-	-	-	0.0637 (0.339)
	Social First	-	-	-	0.0443 (0.487)
	TP First	-	-	-	-0.1512** (0.019)
Risk Task Noise Term (μ_R)	Constant	0.1854*** (<0.005)	0.1850*** (<0.005)	0.1984*** (<0.005)	0.1953*** (<0.005)
	Real	-	-	-0.0326 (0.323)	-0.0325 (0.327)
Discounting Task Noise Term (μ_D)	Constant	0.0650*** (<0.005)	0.0656*** (<0.005)	0.0788*** (<0.005)	0.0734*** (<0.005)
	Real	-	-	-0.0266** (0.020)	-0.0223* (0.053)
Number of Observations		8547	8547	8547	8547
Log Pseudolikelihood		-3965.08	-3959.72	-3947.93	-3893.77

Table 7: Structural Model Maximum Likelihood Results: Social Tasks

Variable		I	II	III	IV
CRRA Coefficient (σ)	Constant	0.2346*** (<0.005)	0.2010*** (0.010)	0.1776** (0.029)	0.1265 (0.421)
	Real	-	0.0607 (0.518)	0.1109 (0.303)	0.0889 (0.711)
	Skew High	-	-	-	0.0373 (0.664)
	Social First	-	-	-	0.1124 (0.355)
	TP First	-	-	-	0.0987 (0.516)
Time Preference Parameter (ρ)	Constant	0.2842*** (<0.005)	0.3407*** (<0.005)	0.3530*** (<0.005)	0.3036*** (<0.005)
	Real	-	-0.1058 (0.102)	-0.1289* (0.078)	-0.1101 (0.368)
	Skew High	-	-	-	0.0149 (0.793)
	Social First	-	-	-	0.0149 (0.852)
	TP First	-	-	-	0.0023 (0.975)
Risk Task Noise Term (μ_R)	Constant	0.2300*** (<0.005)	0.2303*** (<0.005)	0.2485*** (<0.005)	0.2335*** (<0.005)
	Real	-	-	-0.0370 (0.415)	-0.0282 (0.621)
Discounting Task Noise Term (μ_D)	Constant	0.0668*** (<0.005)	0.0669*** (<0.005)	0.0681*** (<0.005)	0.0617*** (<0.005)
	Real	-	-	-0.0029 (0.829)	-0.0025 (0.919)
Number of Observations		8548	8548	8548	8548
Log Pseudolikelihood		-4278.07	-4272.11	-4269.85	-4245.27