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ABSTRACT

Experimentally elicited discount rates are frequently higher than what one would infer from market interest rates and seem unreasonable for economic decision-making. Such high rates have often been attributed to present bias and hyperbolic discounting. A commonly recognized bias of standard elicitation techniques is the use of linear preferences for identification. When attempts are made to correct this bias with additional experimental measures, researchers find exceptional degrees of utility function curvature. We present a new methodology for identifying time preferences, both discounting and utility function curvature, from simple allocation decisions. We estimate annual discount rates substantially lower than normally obtained, dynamically consistent discounting, and limited though significant utility function curvature.

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1 Introduction

Understanding and estimating time preferences is obviously of great importance to economists, marketers, and policy makers. Consumers decide how much to invest in savings, education, real estate, and life insurance, how much to diet, exercise, and smoke, whether to marry, when to have children, and what to leave in their wills.

While there has been substantial research estimating time preferences using aggregate consumption data,[1] the bulk of the effort has occurred in laboratory environments.[2] Among the many laboratory techniques employed, many recent studies have favored multiple price lists (MPL) with monetary payments.[3]

With MPLs, individuals are asked multiple times to choose between smaller payment amounts closer to the present and larger amounts further into the future. The interest rate increases monotonically in a price list, such that the point where an individual switches from preferring sooner payments to later payments carries information about their intertemporal preferences. Assuming time-separable stationary preferences and linear utility, individual discount rates can be bounded and potentially calculated from MPL switching points.[4]

A notable feature of MPLs (and other experimental methods) is that they yield high average discount rates. Estimates of annual discount rates over one hundred percent are common (Frederick et al., 2002). This is curiously at odds with aggregate models of discounting which imply much lower annual discount rates (Gourinchas and Parker, 2002; Cagetti, 2003; Laibson

[1]Examples include Hausman (1979); Gourinchas and Parker (2002); Cagetti (2003); Laibson, Repetto and Tobacman (2003, 2005).

[2]For a survey of the experimental literature, see Frederick, Loewenstein and O'Donoghue (2002). Recent contributions include Harrison, Lau and Williams (2002); Harrison, Lau, Rutstrom and Williams (2005); Andersen, Harrison, Lau and Rutstrom (2008); Benhabib, Bisin and Schotter (2007); Tanaka, Camerer and Nguyen (2009).

[3]The MPL with monetary payments in economics was motivated and popularized by Coller and Williams (1999) and Harrison et al. (2002). In psychology, a similar technique was employed by Kirby, Petry and Bickel (1999) and has been implemented in several economic laboratory experiments, including Chabris, Laibson, Morris, Schuldt and Taubinsky (2008a,b).

[4]Price list switching points indicate approximately where sooner and later payments are equally valued. Take a sooner payment, c_t a later payment c_{t+k}, and a utility function $U(c_t, c_{t+k})$. Under time-separable stationary utility, $U(c_t, c_{t+k}) = u(c_t) + \delta^k u(c_{t+k})$ and a switching point within a price list indicates where $u(c_t) \approx \delta^k u(c_{t+k})$. Under linear utility, $u(c) = c$ and δ is calculated as $\delta \approx (c_t/c_{t+k})^{1/k}$. Discount rates are then calculated as $IDR = 1/\delta - 1$.

et al., 2003). A possible explanation for this difference may lie in experimenters' frequent assumption of linear utility, which leads to upwards-biased discount rate estimates if utility is concave.[5] An important step in correcting this bias comes from Andersen et al. (2008) who separately administered MPLs and price list risk preference measures based on Holt and Laury (2002) (HL) to the same subjects. Using both time and risk price lists, they jointly estimated discounting and curvature parameters.[6] For brevity, we refer to this as the *Double Multiple Price List* (DMPL) approach.[7]

In this paper, we use a single, simple instrument to capture both discounting and concavity of utility in the same measure. Notice that the binary choice of an MPL task is akin to intertemporal optimization subject to a discontinuous budget. Though under linear preferences the discontinuity does not influence choice, individuals with concave utility will be constrained. The potentially problematic discontinuity suggests a simple solution: convexify the experimental budgets. Hence, we call our approach the *Convex Time Budget* (CTB) method.

Intertemporal allocations in CTBs are solutions to standard intertemporal constrained optimization problems. Analysis of the allocations is straightforward. Given a set of functional form assumptions about discounting and curvature of the utility function, preference parameters are estimable at either the group or individual level. Additionally, structural assumptions such as the dynamic consistency of time preferences can be tested in simple and familiar ways.

In a computerized experiment with 97 subjects, we show that the CTB method can be used to generate precise estimates of discounting and curvature parameters at both the aggregate

[5]Under linear utility, $u(c_t) = c_t$ and δ is calculated as $\delta_L \approx (c_t/c_{t+k})^{1/k}$. Rabin (2000a) shows that under expected utility theory, individuals should have approximately linear preferences for small stakes outcomes, such as those normally used in time preference experiments. However, a variety of studies show substantial curvature over small stakes outcomes (e.g., Holt and Laury, 2002). If there is curvature to the utility function, then $\delta_C \approx (u(c_t)/u(c_{t+k}))^{1/k}$. The direction of the bias $\delta_C - \delta_L$ depends on the shape of the utility function. Concavity generates downwards-biased discount factor (upwards-biased discount rate) estimates.

[6]Frederick et al. (2002) propose a similar strategy of separately identifying the utility function and discounting along with two other approaches for distinguishing time preferences from curvature: 1) eliciting utility judgements such as attractiveness ratings at two points in time; and 2) eliciting preferences over temporally separated probabilistic prospects to exploit the linearity-in-probability property of expected utility. The second approach is employed by Anderhub, Guth, Gneezy and Sonsino (2001).

[7]Tanaka et al. (2009) employ a similar approach with a risk price list task designed to elicit loss aversion. However, they do not use the risk price list to inform curvature of the utility function in estimation of time preference parameters.

and individual levels. These estimates require a minimal set of structural assumptions and are easily implemented econometrically. On average, estimates of individual discount rates are found to be considerably lower than in previous studies. Across specifications, we estimate average annual discount rates between 25 and 35 percent. We reject linearity of utility, although we find far less curvature than prior studies using price lists for risk preferences. Indeed, almost 35 percent of subjects exhibit behavior that is fully consistent with linear preferences. Finally, to our surprise, we find no evidence of present-bias or hyperbolic discounting.

We also compare within-subjects results of the computerized CTB and those obtained using a standard paper-and-pencil DMPL. Our design allows us to make individual level comparisons. Interestingly, though individual discounting correlates highly across elicitation mechanisms, estimated curvature from CTBs is found to be independent of DMPL risk experimental responses.

Our results raise several important questions for future research. First, why did we find no evidence of present bias or hyperbolic discounting? One hypothesis is that this may be the result of measures we took to equate transaction costs of sooner and later payments and to increase confidence of receiving future payments. This interpretation suggests that some of the behavior attributed to present bias in the literature may actually be an artifact of differential risk or transactions costs over sooner and later payments. A second, more fundamental, question is whether we should have expected to find present bias? Though present bias has been demonstrated many times in experiments using money, the underlying psychological models of temptation and self-control (Laibson, 1997; O'Donoghue and Rabin, 1999; Gul and Pesendorfer, 2001) make clear that present bias is about consumption utility rather than money. Indeed, if subjects have access to even modest amounts of liquidity, researchers should be surprised to measure any present bias in experiments with monetary rewards.[8] Third, we find substantial within-subject differences between our CTB and DMPL measures of utility function curvature. This may suggest a real difference in the utility parameters that apply in uncertain and certain environments. Utility differences across certainty and uncertainty arise in some form in many

[8]We thank Matthew Rabin for persistently and amicably reminding us of this point.

static and intertemporal models of decision making (Selden, 1978; Kreps and Porteus, 1978; Epstein and Zin, 1989; Schoemaker, 1982; Neilson, 1992; Schmidt, 1998; Diecidue, Schmidt and Wakker, 2004) and were originally suggested by Allais (1953).

The paper proceeds as follows: Section 2 explains the motivation of the CTB and design for the CTB experiment. Section 3 outlines our econometric specification while Section 4 presents group and individual analysis. Section 5 concludes.

2 Experimental Design: Convex Time Budgets

In each decision of an MPL, subjects choose either an amount c_t, available at time t, or an amount $c_{t+k} > c_t$, available after a delay of $k > 0$ periods. Let $(1+r)$ be the experimental gross interest rate and m be the experimental budget.[9] Assuming some utility function, $U(c_t, c_{t+k})$, the MPL task asks subjects to maximize utility subject to the discrete budget set:

$$((1 + r)c_t, c_{t+k}) \in \{(m, 0), (0, m)\}. \tag{1}$$

Assuming linear utility, the corner solution constraints implied by (1) are non-binding. However, if the utility function is concave, the constraints bind and one cannot infer a discounting measure from MPL switching points.

Imagine, instead of (1), we allow subjects to choose c_t and c_{t+k} continuously along a convex budget set:

$$(1 + r)c_t + c_{t+k} = m. \tag{2}$$

This is simply a standard future-value budget constraint. To operationalize (2) we provide

[9]Theoretically, extra-experimental interest rates and liquidity constraints should influence laboratory decisions (Coller and Williams, 1999). If subjects can borrow (save) at rates inferior (superior) to the rates offered in the lab, then they have an arbitrage opportunity. If subjects are credit constrained, they may choose sooner experimental payments to smooth consumption. In a controlled experiment with MPLs, Coller and Williams (1999) show that providing external interest rate information and elaborating possible arbitrage strategies makes treated subjects appear only slightly more patient. Meier and Sprenger (2010) show that objectively measured credit constraints taken from individual credit reports are generally uncorrelated with MPL responses. For further discussion on arbitrage opportunities and liquidity constraints see Appendix Section A.2.

subjects with a budget of experimental 'tokens.' Tokens can be allocated to either a sooner time t, or a later time $t+k$, at different 'token exchange rates.' The relative rate at which tokens translate into actual payments determines the gross interest rate, $(1+r)$. Subjects choose how many tokens to allocate to sooner and later periods. This is our Convex Time Budget (CTB) approach.

Substantial information can be obtained from allocations in this convex choice environment. Variations in delay lengths, k, and interest rates, $(1+r)$, allow for the identification of time discounting and utility function curvature. Variations to starting times, t, allow for the identification of present bias and hyperbolic discounting.

2.1 CTB Design Features

Our experiment was conducted at the University of California, San Diego in January of 2009. Subjects made decisions on 45 convex budgets. These 45 budgets involve 9 combinations of starting times, t, and delay lengths, k, and have annual interest rates that vary from zero to over 1000% per year.

A (3×3) design was implemented with three sooner payment dates, $t = (0, 7, 35)$ days from the experiment date, crossed with three delay lengths, $(k = 35, 70, 98)$ days.[10] Thus there are nine (t, k) cells and within each cell are five CTB questions, generating 45 choices for each subject. We refer to each (t, k) combination a 'choice set'. The t and k combinations used in our study were selected to avoid holidays (including Valentine's Day), school vacations, spring break, and final examination weeks. Payments were scheduled to arrive on the same day of the week (t and k are both multiples of 7), to avoid differential week-day effects.

In each CTB question, subjects were given a budget of 100 tokens. Tokens allocated to sooner payments had a value of a_t while tokens allocated to later payments had a value of a_{t+k}. In most cases, a_{t+k} was \$0.20 per token and a_t varied from \$0.20 to \$0.10 per token.[11] Note

[10] See below for the recruitment and payment efforts that allowed sooner payments, including those for $t = 0$, to be implemented in the same manner as later payments.

[11] In eight of 45 choices, a_{t+k} was \$0.25. If an individual allocated all her tokens in every choice to the later payment, she could expect to earn either \$20 or \$25. If she allocated all her tokens to the sooner payment in

that $a_{t+k}/a_t = 1 + r$, the gross interest rate over k days, so $(1 + r)^{1/k}$ gives the standardized daily interest rate. Daily net interest rates in the experiment varied considerably across the 45 budgets, from 0 to around 1 percent per day implying annual interest rates of between 0 and 1300 percent (compounded quarterly).

Each choice set featured $a_{t+k} = \$0.20$ and $a_t = \$0.16$ $(1 + r = 1.25)$. In eight of the nine choice sets, one convex budget represented a pure income shift relative to this choice. This was implemented with $a_{t+k} = \$0.25$ and $a_t = \$0.20$ $(1 + r = 1.25$ again). In the remaining choice set, $(t, k) = (7, 70)$, we instead implemented $a_t = \$.20$ and $a_{t+k} = \$.20$, a zero percent interest rate. Table 1 shows the token rates, interest rates, standardized daily interest rates and corresponding annual interest rates for all 45 budgets.

2.2 Implementation and Protocol

One of the most challenging aspects of implementing any time discounting study is making all choices equivalent except for their timing. That is, transactions costs associated with receiving payments, including physical costs and confidence, must be equalized across all time periods. We took several unique steps in our subject recruitment process and our payment procedure in order to more closely equate transaction costs over time, which we discuss in the following subsections.

2.2.1 Recruitment

In order to participate in the experiment, subjects were required to live on campus. All campus residents are provided with an individual mailbox at their dormitory. Students frequently use these mailboxes as all postal service mail and intra-campus mail are received at this mailbox. Each mailbox is locked and individuals have keyed access 24 hours per day.

By special arrangement with the university mail services office, we were granted same-day access to a specific subset of campus mailboxes. These mailboxes were located at staffed

every choice, she would earn at least $10.

Table 1: Choice Sets

t (start date)	k (delay)	Token Budget	a_t	a_{t+k}	$(1+r)$	Daily Rate (%)	Annual Rate (%)
0	35	100	0.19	0.2	1.05	0.147	65.3
0	35	100	0.18	0.2	1.11	0.301	164.4
0	35	100	0.16	0.2	1.25	0.64	528.9
0	35	100	0.14	0.2	1.43	1.024	1300.9
0	35	100	0.2	0.25	1.25	0.64	528.9
0	70	100	0.19	0.2	1.05	0.073	29.6
0	70	100	0.18	0.2	1.11	0.151	67.4
0	70	100	0.16	0.2	1.25	0.319	178.1
0	70	100	0.14	0.2	1.43	0.511	362.1
0	70	100	0.2	0.25	1.25	0.319	178.1
0	98	100	0.19	0.2	1.05	0.052	20.5
0	98	100	0.16	0.2	1.25	0.228	113
0	98	100	0.13	0.2	1.54	0.441	286.4
0	98	100	0.1	0.2	2	0.71	637.1
0	98	100	0.2	0.25	1.25	0.228	113
7	35	100	0.19	0.2	1.05	0.147	65.3
7	35	100	0.18	0.2	1.11	0.301	164.4
7	35	100	0.16	0.2	1.25	0.64	528.9
7	35	100	0.14	0.2	1.43	1.024	1300.9
7	35	100	0.2	0.25	1.25	0.64	528.9
7	70	100	0.2	0.2	1	0	0
7	70	100	0.19	0.2	1.05	0.073	29.6
7	70	100	0.18	0.2	1.11	0.151	67.4
7	70	100	0.16	0.2	1.25	0.319	178.1
7	70	100	0.14	0.2	1.43	0.511	362.1
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7	98	100	0.16	0.2	1.25	0.228	113
7	98	100	0.13	0.2	1.54	0.441	286.4
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7	98	100	0.2	0.25	1.25	0.228	113
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35	35	100	0.18	0.2	1.11	0.301	164.4
35	35	100	0.16	0.2	1.25	0.64	528.9
35	35	100	0.14	0.2	1.43	1.024	1300.9
35	35	100	0.2	0.25	1.25	0.64	528.9
35	70	100	0.19	0.2	1.05	0.073	29.6
35	70	100	0.18	0.2	1.11	0.151	67.4
35	70	100	0.16	0.2	1.25	0.319	178.1
35	70	100	0.14	0.2	1.43	0.511	362.1
35	70	100	0.2	0.25	1.25	0.319	178.1
35	98	100	0.19	0.2	1.05	0.052	20.5
35	98	100	0.16	0.2	1.25	0.228	113
35	98	100	0.13	0.2	1.54	0.441	286.4
35	98	100	0.1	0.2	2	0.71	637.1
35	98	100	0.2	0.25	1.25	0.228	113

dormitory mail centers and so experimental payments could be immediately placed in a subject's locked mailbox. As such, subjects in our experiment were required to have one of the fixed number of campus mailboxes to which we had immediate access. We recruited 97 undergraduate freshman and sophomores meeting these criteria.

2.2.2 Experimental Payments

We employed six measures intended to equalize the costs of receiving payments. These measures not only attempt to equate transactions costs over sooner and later payments, but also to increase confidence that future payments will arrive. First, all sooner and later payments, including payments for $t = 0$, were placed in subjects' campus mailboxes. Subjects were fully informed of the method of payment and the special arrangement made with university mail services.[12] Eliminating payments in the lab ensures that subjects do not disproportionately prefer present in-lab payments because they are somehow more likely to be received than future extra-lab payments.

Second, upon beginning the experiment, subjects were told that they would receive a $10 thank-you payment for participating. This $10 was to be received in two payments: $5 sooner and $5 later, regardless of choices, and all experimental earnings were added to these two $5 thank-you payments. This eliminated any convenience gained by concentrating payments in one period – two check were sent regardless.

Third, two blank envelopes were provided to each subject. After receiving directions about the two thank-you payments, subjects were asked to address the envelopes to themselves at their campus mailbox, thus minimizing clerical errors on our part.

Fourth, at the end of the experiment, subjects were asked to write their payment amounts and dates on the inside flap of both envelopes, so they would see and verify the amounts written in their own handwriting when payments arrived, thus eliminating the cost of remembering the future amounts owed to them.

[12]See Appendix Section A.4 for the information provided to subjects.

Fifth, one choice for each subject was selected for payment by drawing a numbered card at random. All experimental payments were made by personal check from Professor James Andreoni drawn on an account at the campus credit union.[13] Individuals were informed that they could cash their checks (if they so desired) at this credit union, thus increasing the fidelity of the payment method.

Sixth, subjects were given the business card of Professor James Andreoni and told to call or email him if a payment did not arrive and that a payment would be hand-delivered immediately. This invitation to inconvenience a professor was intended to boost confidence that future payments would arrive as promised.

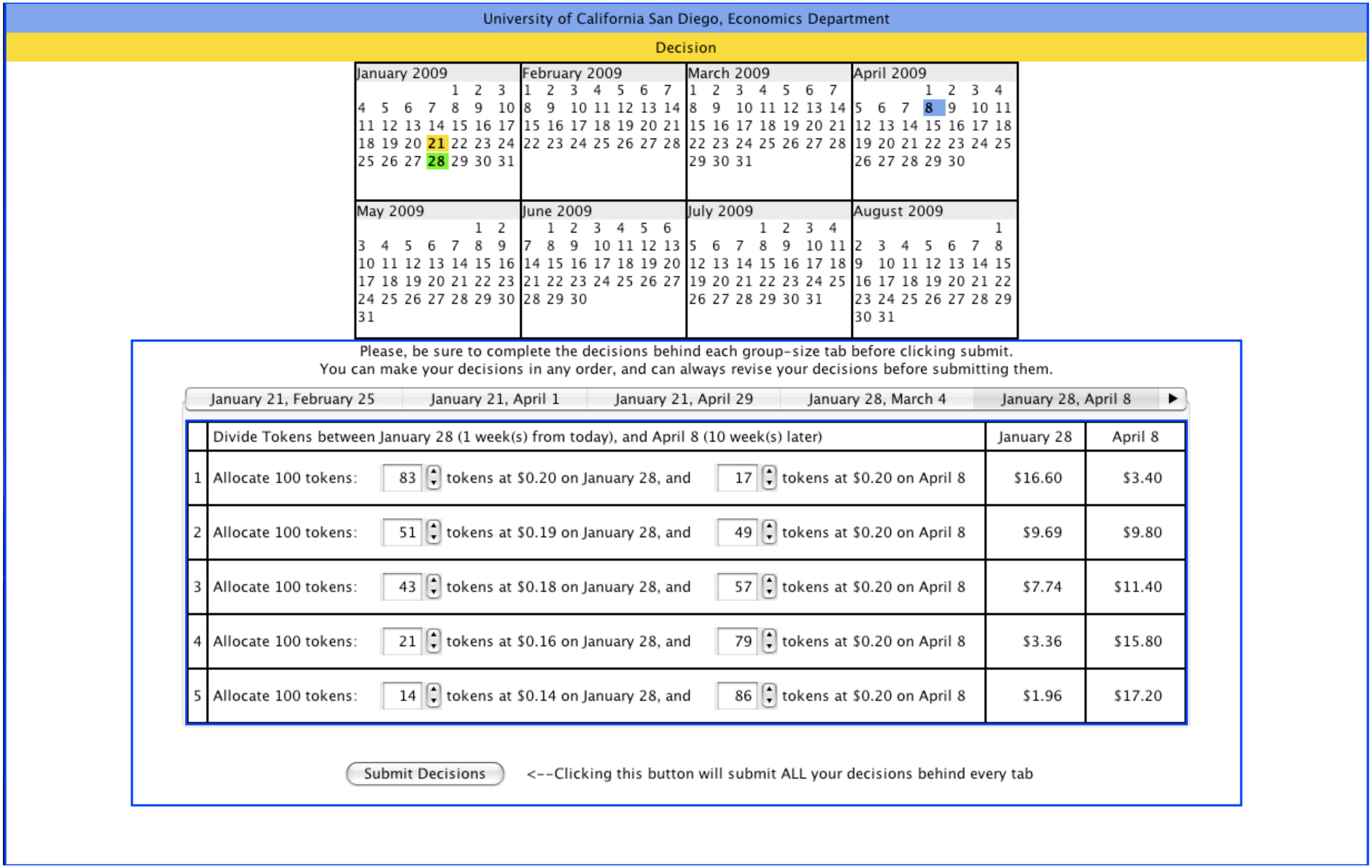
We believe that these efforts helped not only to equate transactions costs across payments, but also to engender trust between subject and experimenter. In an auxiliary survey, subjects were asked if they trusted that they would receive their experimental payments, and 97% of respondents replied yes.

2.2.3 Protocol

A Java™-based client/server system was written to implement the CTB experiment. The server program sent budget information, recorded subject choices, and reported experiment earnings. The client program provided instructions to subjects, elicited choices, and administered a post-experiment questionnaire.

[13] Payment choice was guided by a separate survey of 249 undergraduate economics students eliciting payment preferences. Personal checks from Professor Andreoni, Amazon.com gift cards, PayPal transfers and the university stored value system TritonCash were each compared to cash payments. Subjects were asked if they would prefer a twenty dollar payment made via each payment method or $\$X$ cash, where X was varied from 19 to 10. Personal check payments were found to have the highest cash-equivalent value.

Figure 1: Sample Decision Screen



Upon starting the experiment, subjects read through directions and CTB examples. The directions were read aloud and projected on a screen. Subjects' decision screens displayed a dynamic calendar and a series of nine "decision tabs." These decision tabs corresponded to the nine choice sets described above, one tab for each (t, k) combination. Subjects could respond to the decision tabs in any order they wished. Each decision tab had five budget decisions presented in order of increasing interest rate and then in order of increasing budget.[14] An image of the subjects' decision screen is presented in Figure 1.

For each decision, individuals were told how many tokens they were to allocate (always 100), the sooner token value a_t, and the later token value a_{t+k}.[15] As each budget decision was being made, the calendar in the subjects' screen highlighted the experiment date (in yellow), the sooner date t (in green), and the later date $t+k$ (in blue). This allowed subjects to visualize the delay length for a given decision.[16]

2.2.4 Background Consumption and DMPL

In addition to the CTB experiment, we implemented a series of three MPLs and two HL risk price list tasks (the components of the DMPL). The MPLs featured the (t, k) combinations: $(t = 0, k = 35)$, $(t = 0, k = 98)$, $(t = 35, k = 35)$. The MPLs can be used to create alternate measures of both discounting and present bias for comparison. The HL risk price lists were designed to elicit risk aversion or utility function curvature over \$20 and \$25, respectively.[17]

At the end of the computer-based CTB experiment, subjects were administered a questionnaire. Importantly, subjects were asked how much they spend in a typical week. The average

[14] For a disussion of order effects and a defense of presenting choices in order of increasing interest rate, see Harrison et al. (2005).

[15] Individuals were not told the gross interest rate, $(1+r)$. However, in a companion questionnaire individuals were asked several numeracy questions, including one on compound interest. Roughly 70% or respondents were able to correctly answer a standard compound interest question. The level of numeracy in the sample suggests that the majority would be able to calculate at least the interest rate over the delay, k.

[16] Because t and k were multiples of 7, all dates were described by the number of weeks (e.g., $t = 7, k = 35$ was described as "1 week from today" and "5 weeks later"). Note, also, that allocation amounts were initially blank on the decision screen and subjects used up and down arrows to make choices.

[17] The MPLs and HLs could also be chosen at random for payment. For directions and the price list tasks see Appendix Section A.5.

response was \$49.32 per week or \$7.05 per day of "background consumption." This figure is used later in our analysis (see Section 4.1.2).

3 Parameter Estimation with the CTB

Given assumptions on the functional form of utility and the nature of discounting, the CTB provides a natural context in which to jointly estimate (and test hypotheses of) time preferences, present bias, and curvature of the utility function. We posit a time separable CRRA utility function discounted via the quasi-hyperbolic β-δ discounting function (Strotz, 1956; Phelps and Pollak, 1968; Laibson, 1997),

$$U(c_t, c_{t+k}) = (c_t - \omega_1)^\alpha + \beta\delta^k(c_{t+k} - \omega_2)^\alpha, \tag{3}$$

where δ is the one period discount factor and β is the present bias parameter. The quasi-hyperbolic form elegantly captures the notion of present-biased time preferences and nests the exponential discounting when $\beta = 1$. A value $\beta < 1$ indicates present bias and when $t > 0$ present bias does not influence choice. The values c_t and c_{t+k} are experimental earnings and α is the CRRA curvature parameter. The CRRA utility function is frequently estimated in experimental studies on both time and risk preferences and also used as the benchmark utility formulation across many fields of economics. The terms ω_1 and ω_2 are additional utility parameters which could be interpreted as classic Stone-Geary consumption minima, intertemporal reference points, or background consumption. For example, such utility parameters are used in Andersen et al. (2008), where experimental earnings are added to background consumption, B, such that $\omega_1 = \omega_2 = -B$. The parameter, B, is not estimated in their specification, but set to 118 Danish Kroner, the average value of daily consumption in Denmark in 2003, around \$25 US in 2009. Appendix Table A4 provides comparisons using various given values of ω_1 and ω_2.

Maximizing (3) subject to the future value budget (2) yields the tangency condition

$$\frac{c_t - \omega_1}{c_{t+k} - \omega_2} = \left\{ \begin{array}{ll} (\beta\delta^k(1+r))^{(\frac{1}{\alpha-1})} & if \quad t = 0 \\ \\ (\delta^k(1+r))^{(\frac{1}{\alpha-1})} & if \quad t > 0 \end{array} \right\}, \tag{4}$$

and the intertemporal formulation of a Stone-Geary linear demand for c_t,

$$c_t = \left\{ \begin{array}{ll} \frac{1}{1+(1+r)(\beta\delta^k(1+r))^{(\frac{1}{\alpha-1})}}]\omega_1 + [\frac{(\beta\delta^k(1+r))^{(\frac{1}{\alpha-1})}}{1+(1+r)(\beta\delta^k(1+r))^{(\frac{1}{\alpha-1})}}](m-\omega_2) & if \quad t = 0 \\ \\ \frac{1}{1+(1+r)(\delta^k(1+r))^{(\frac{1}{\alpha-1})}}]\omega_1 + [\frac{(\delta^k(1+r))^{(\frac{1}{\alpha-1})}}{1+(1+r)(\delta^k(1+r))^{(\frac{1}{\alpha-1})}}](m-\omega_2) & if \quad t > 0 \end{array} \right\}. \tag{5}$$

3.1 Estimation of Intertemporal Preferences

Notice the parameters (β, δ, α) and the data (r, k, t) enter into the tangency condition of (4) and the demand function of (5) in a non-linear fashion. Naturally, if $\alpha = 1$, only corner solutions are obtained. We discuss estimation of the parameters β, δ, α, ω_1 and ω_2 when $\alpha < 1$, and recognize that corner solutions may indeed arise in the data.[18] We motivate two regression techniques, each with their benefits and weaknesses.

The first technique estimates (5) and the parameters β, δ, α, ω_1 and ω_2 using non-linear least squares. Appendix Section A.1.1 provides the details of the estimator which can be implemented at either the aggregate or individual level. The strength of this methodology is that it estimates the Stone-Geary parameters ω_1 and ω_2. Its weakness is that it cannot account for the censored data issues inherent to potential corner solutions.

For the second technique, we consider the tangency condition of (4). If we assume ω_1 and

[18] With the employed utility formulation and $\alpha < 1$, corner solutions can be predicted provided ω_1 and $\omega_2 < 0$. As discussed in Section 4, corner solutions are frequent. Appendix Tables A5 and A6 provide individual estimates and demonstrate that for the motivated regression techniques, individuals with only corner solutions have estimated values of $\alpha = 0.999$, while individuals with more interior solutions are estimated to have more utility function curvature. This gives support to the employed regression techniques for identifying utility function curvature and near linear preferences. Indeed, estimated curvature is found to correlate strongly with the discussed bias in MPL-based discounting estimates. See Sub-section 4.2.1 for details.

ω_2 are (non-estimated) known values, we can take logs to obtain

$$ln(\frac{c_t - \omega_1}{c_{t+k} - \omega_2}) = \left\{ \begin{array}{ll} (\frac{ln\ \beta}{\alpha-1}) + (\frac{ln\ \delta}{\alpha-1}) \cdot k + (\frac{1}{\alpha-1}) \cdot ln(1+r) & if \quad t = 0 \\ (\frac{ln\ \delta}{\alpha-1}) \cdot k + (\frac{1}{\alpha-1}) \cdot ln(1+r) & if \quad t > 0 \end{array} \right\},$$

which is linear in the in the data, k and $ln(1+r)$, and reduces to,

$$ln(\frac{c_t - \omega_1}{c_{t+k} - \omega_2}) = (\frac{ln\ \beta}{\alpha - 1}) \cdot \mathbf{1}_{t=0} + (\frac{ln\ \delta}{\alpha - 1}) \cdot k + (\frac{1}{\alpha - 1}) \cdot ln(1+r),$$

where $\mathbf{1}_{t=0}$ is an indicator for the time period $t = 0$. Given an additive error structure, such a linear equation is easily estimated, with parameter estimates for δ, β, and α obtained via nonlinear combinations of coefficient estimates. The weakness of estimation based on the tangency condition of (4) is that it requires first that the background parameters ω_1 and ω_2 be known, and second that the consumption ratio $(c_t - \omega_1/c_{t+k} - \omega_2)$ be strictly positive, such that the log transform is well-defined. The strength, however, is that censoring issues are easily addressed. Two-limit tobit maximum likelihood regressions can be implemented to account for the positive probability of corner solutions (Wooldridge, 2002). Appendix A.1.2 provides the details. Given that each estimation strategy has its strengths and weaknesses, we provide both estimates and discuss any differences in our analysis.

4 Experimental Results

The results are presented in two sub-sections. First, we present aggregate CTB data and provide estimates of aggregate discounting, present bias and curvature. Second, we explore individual level results, estimating preference parameters and comparing the results within-subject to parameters obtained from DMPL methodology.

4.1 Aggregate Analysis

We identify experimental allocations as solutions to standard intertemporal optimization problems. These solutions are functions of our parameters of interest (discounting and curvature), and experimentally varied parameters (interest rates and delay lengths). Our experimental results should mirror this functional relationship. In Figure 2 we plot the mean number of tokens chosen earlier against the gross interest rate, $(1 + r)$, of each CTB decision. We plot separate points for the three experimental values of t ($t = 0$, 7, 35 days), and separate graphs for the three experimental values of k ($k = 35$, 70, 98 days). At each delay length, the number of tokens allocated to the earlier payment declines monotonically with the interest rate; and at comparable gross interest rates, the number of tokens allocated earlier increases with delay.

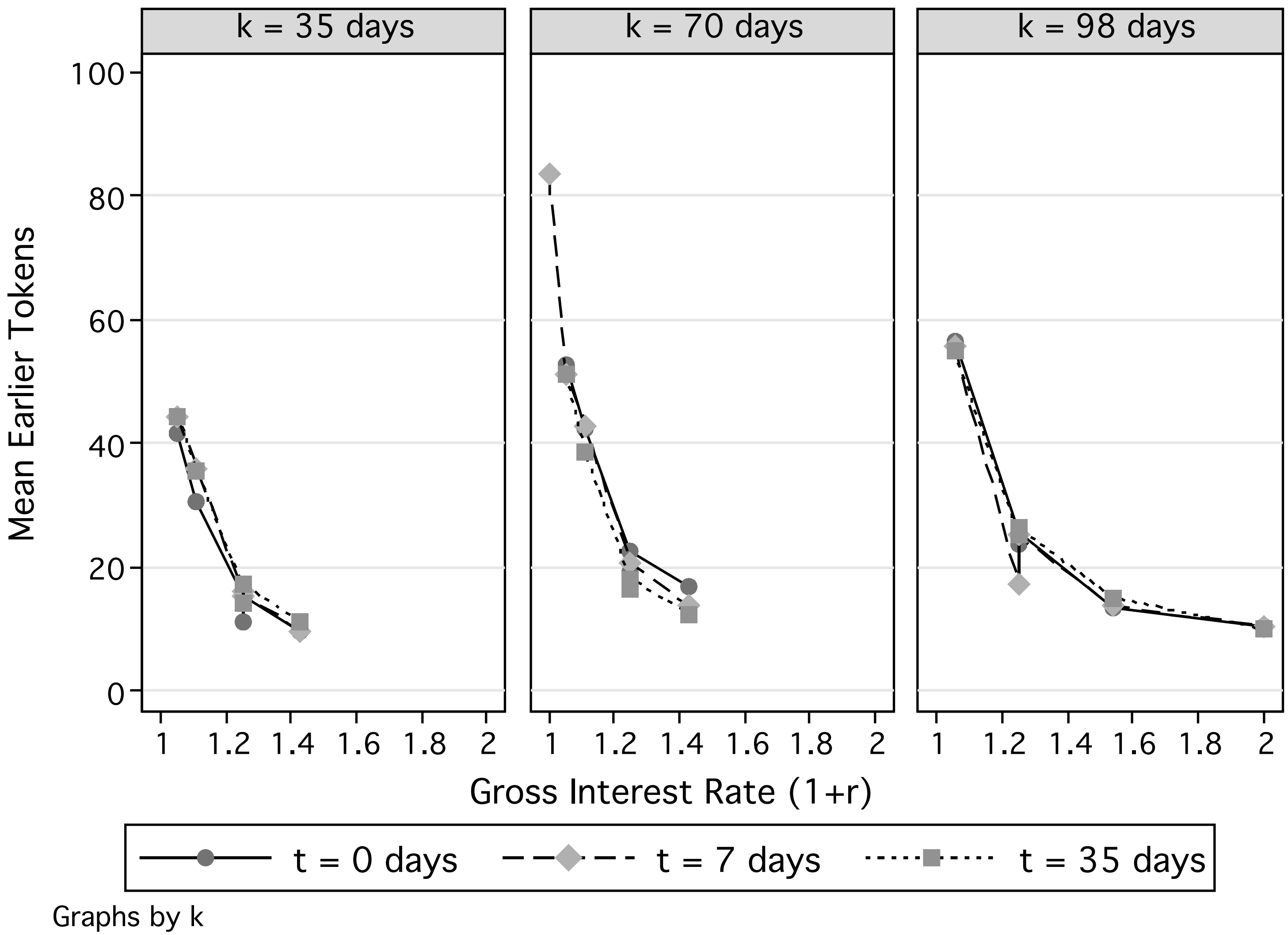
Evidence for present bias or hyperbolic discounting would be observed in Figure 2 as the mean level of tokens allocated earlier being substantially higher when $t = 0$ compared to $t = 7$ or 35. Instead, we observe that the mean number of earlier tokens at each interest rate is roughly constant across t.

Notice that Figure 2 also reveals that choices respond to both changing interest rates and delay lengths in predicted way.[19] Masked by these aggregate results, however, is important individual heterogeneity. Roughly 37 percent of subjects (36 of 97) have no interior choices in 45 convex budgets, consistent with linear preferences.[20] Additionally, for the remaining 61 subjects, in any given decision, an average of approximately 50% of responses are found at corners. In the following section we discuss estimation of aggregate preferences following the estimation procedures discussed in Section 3.1 that can and cannot account for such corner solutions. In Section 4.2, we discuss heterogeneity and provide individual estimates.

[19] Additionally, there is support for a homothetic utility function as the mean number of earlier tokens does not change appreciably with increased income. This aggregate result masks individual-level heterogeneity. Some subjects violate strict income monotonicity, by decreasing either c_t or c_{t+k} in response to an income increase. In eight experimental budget expansions, 72 of 97 subjects make two or fewer such monotonicity violations for c_t and 89 of 97 subjects make two or fewer violations for c_{t+k}. More than half of subjects (50 of 97) make zero violations of either sort. The volume of violations are focused on c_t likely because budgets were presented first by increasing interest rate and then by increasing income. Subjects allocating fewer tokens to the sooner payment as interest rates increase may continue to do so in error when the budget expands. Controlling for such subject error is critical to our analysis.

[20] See Appendix Tables A5 and A6 for individual censoring details and estimates.

Figure 2: Mean Experimental Responses Over Time



4.1.1 Estimating Aggregate Preferences

Table 2 presents estimates of aggregate preference parameters. In column (1), the annual discount rate, present bias parameter, utility function curvature and shift parameters $\hat{\omega}_1$ and $\hat{\omega}_2$ are estimated by non-linear least squares using the solution function stated in (5) with clustered standard errors.

Column (1) indicates, first, the aggregate annual discount rate is estimated at 0.300 (s.e. 0.064). This discount rate is lower than those estimated by most other researchers.[21]

Second, aggregate curvature is precisely estimated at $\hat{\alpha} = 0.920$ (s.e. $= 0.006$), significantly different from 1 ($F_{1,96} = 155.18,\ p < .01$), but far closer to linear utility than estimated from the DMPL approach employing HL risk measures or other experimental estimates of risk aversion. For comparison, using DMPL methodology with a representative sample of Danish consumers, Andersen et al. (2008) find a curvature parameter of 0.259. When allowing for this level of curvature and setting both ω_1 and ω_2 equal to minus average daily spending in Denmark, Andersen et al. (2008) find a discount rate of 0.101. When assuming linear utility, they obtain a discount rate of 0.251.

The third, and most prominent finding is that, echoing Figure 2, we find no evidence of present bias. That is, $\hat{\beta}$ is estimated to be 1.004 (s.e. $= .002$). The hypothesis of no present bias, $\beta = 1$, is marginally rejected ($F_{1,96} = 2.82,\ p < .10$), with the favored alternative being future bias, $\beta > 1$. Obtaining a precisely estimated $\hat{\beta}$ so close to 1 is of specific interest. The general finding in both monetary and non-monetary experiments and aggregate analyses is of substantial present bias (Frederick et al., 2002), with a suggested value for β of around 0.7 (Laibson et al., 2003).

The finding of no aggregate present bias is at striking odds with a body of experimental results in both economics and psychology. Reconciling our findings with others is an important issue. A potential explanation is associated with our experimental methodology. First, experimental evidence suggests that present bias may be conflated with subjects' assessment

[21]Notable exceptions of similarly low discount rates include Coller and Williams (1999); Harrison et al. (2002, 2005) which all assume linear preferences and Andersen et al. (2008), employing the DMPL technique.

Table 2: Discounting and Curvature Parameter Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Method:	NLS	NLS	NLS	Tobit	NLS	Tobit
Annual Discount Rate	0.300	0.377	0.371	0.324	0.246	0.275
	(0.064)	(0.087)	(0.091)	(0.173)	(0.128)	(0.162)
Present Bias Parameter: $\hat{\beta}$	1.004	1.006	1.007	1.023	1.026	1.026
	(0.002)	(0.006)	(0.006)	(0.010)	(0.008)	(0.010)
Curvature Parameter: $\hat{\alpha}$	0.920	0.921	0.897	0.977	0.706	0.873
	(0.006)	(0.006)	(0.009)	(0.004)	(0.017)	(0.018)
$\hat{\omega}_1$	1.368					
	(0.275)					
$\hat{\omega}_2$	-0.085					
	(1.581)					
$\hat{\omega}_1 = \hat{\omega}_2$		1.350	0	-0.01	-7.046	-7.046
		(0.278)	-	-	-	-
R^2 / LL	0.4911	0.4908	0.4871	-7642.74	0.4499	-5277.56
# Observations	4365	4365	4365	4365	4365	4365
# Uncensored, $c_t \in (0, m/1+r)$	-	-	-	1329	-	1329
# Clusters	97	97	97	97	97	97

Notes: NLS and two-limit tobit ML estimators. Column (1): Unrestricted regression. Column (2): Regression with restriction $\omega_1 = \omega_2$. Columns (3) and (4): Regression with restriction $\omega_1 = \omega_2 = 0$. Columns (5) and (6): Regression with restriction $\omega_1 = \omega_2 = -7.046$ (the negative of average reported daily spending). Clustered standard errors in parentheses. Annual discount rate calculated as $(1/\hat{\delta})^{365} - 1$. Standard errors calculated via the delta method.

of the risk of receiving experimental payments (Halevy, 2008).[22] Keren and Roelofsma (1995) and Weber and Chapman (2005) find in two of three experiments that when applying increasing levels of risk to both present and future payments, present bias decreases to some degree. Our experimental methodology is designed to eliminate differential risk between sooner and later payments. Indeed, in Andreoni and Sprenger (2010) we show that when differential payment risk is exogenously added back into the decision environment, a hyperbolic pattern of discounting appears.

Though eliminating differential payment reliability represents one possible explanation for

[22] Indeed, this is the motivating argument for experimental front-end delays. See, for example, Harrison et al. (2002, 2005).

our findings, many others exist. Principal among these explanations is that present bias is a visceral response only activated when sooner rewards are actually immediate. For example, dynamic inconsistency is shown to manifest itself in immediate choices over healthy and unhealthy snacks (Read and van Leeuwen, 1998), juice drinks (McClure, Laibson, Loewenstein and Cohen, 2007) and more immediate monetary rewards (McClure, Laibson, Loewenstein and Cohen, 2004).[23] In order to equate transaction costs over sooner and later payments we were unable to provide truly immediate rewards. Viewed in this light, our findings represent a potential bound on present bias. With delays of a few hours in between decision and reward receipt, present bias may be effectively eliminated. A second explanation is that monetary payments should perhaps not elicit present bias to the same extent as more tempting primary goods. Though the body of experimental evidence on present bias has used monetary payments, and high correlations are obtained across primary and monetary intertemporal rewards (Reuben, Sapienza and Zingales, 2008), the underlying psychological models are very clearly focused on the temptation of consumption utility and not on monetary rewards (Laibson, 1997; O'Donoghue and Rabin, 1999; Gul and Pesendorfer, 2001). It must also be recognized that our findings are only one data point on present bias among many, and further research is necessary before firm conclusions can be drawn.

4.1.2 The Effect of Setting ω_1 and ω_2 from Consumption Data

Extra-experimental consumption poses an important challenge for studies of time preferences. While experimenters are able to vary experimental payments, subjects make choices over consumption streams including both experimental payments and non-experimental consumption. It is generally assumed that individuals do not adjust their non-experimental consumption. That is, ω_1 and ω_2 are taken as non-estimated, fixed parameters. Prior research has either set these parameters to zero or fixed $-\omega_1$ and $-\omega_2$ to match the average value of daily consumption (Andersen et al., 2008).

[23] In McClure et al. (2004), immediate monetary rewards were received via e-mail in the form of Amazon gift certificates directly after the experiment.

In column (1) of Table 2, we report estimates of both Stone-Geary parameters $\hat{\omega}_1$ and $\hat{\omega}_2$. The hypothesis that $\omega_1 = \omega_2$ is not rejected ($F_{1,96} = 0.87,\ p = 0.35$). In column (2) we report estimates of an identical NLS procedure with the restriction that $\omega_1 = \omega_2$ and obtain very similar results. This suggests the restriction that $\omega_1 = \omega_2$ is not costly.

Columns (3) through (6) of Table 2 examine whether the results are influenced by procedures that fix rather than estimate ω_1 and ω_2. Additionally, fixed values of ω_1 and ω_2 allow us to easily compare results across the estimators motivated in Section 3.1. We estimate non-linear least squares regressions identical to columns (1) and (2) and impose varying restrictions on the values of ω_1 and ω_2. We also provide two-limit tobit maximum likelihood regressions accounting for corner solution censoring, corresponding to the same restrictions.

In columns (3) and (4), the imposed restriction is $\omega_1 = \omega_2 = 0$.[24] In columns (5) and (6), we restrict $\omega_1 = \omega_2 = -7.05$, based on a post-experiment questionnaire which elicited average daily consumption of our subjects to be \$7.05.

Some differences in estimated parameters are obtained across econometric techniques. In particular, curvature is less pronounced when accounting for the censored nature of the data, as should be expected. Across econometric techniques, estimated preference parameters are found to be sensitive to the choice of background parameters. Both the estimated discount rate and $\hat{\alpha}$ decrease appreciably as the restricted value of the ω parameters moves from 0 to -7.05. The present bias parameter $\hat{\beta}$ varies in a tight range. These results suggest that the method of determining the ω parameters is potentially of great relevance. In Appendix Table A4, we demonstrate the effect of changing the values of ω_1 and ω_2 on estimated preference parameters for both NLS and tobit estimaors. The results indicate substantial sensitivity of estimated parameters (particularly curvature) to increasingly negative values of ω_1 and ω_2. Corresponding R^2 and likelihood values diminish accordingly.

[24] In column (4), the restriction is $\omega_1 = \omega_2 = -0.01$, such that the log consumption ratio $log(c_t - \omega_1 / c_{t+k} - \omega_2)$ is well-defined.

4.2 Individual Analysis

Table 3 presents estimates of discounting, present bias and curvature parameters at the individual level. For each subject, we estimate the parameters of equation (5). To limit the number of estimated parameters and facilitate comparison with DMPL methodology, we restrict $\omega_1 = \omega_2 = 0$ as in Table 2, columns (3) and (4). The parameters $\hat{\beta}$, $\hat{\delta}$, and $\hat{\alpha}$ are estimated by non-linear least squares.[25] As robustness tests we first conduct estimation restricting $\omega_1 = \omega_2$ at various levels and, second, we allow ω_1 and ω_2 to equal minus self-reported daily consumption. Additionally, we provide tobit and OLS estimates. Obtained values are similar to Table 3 and reported in Appendix Tables A1 through A3.

Time preferences and curvature parameters are estimable for 86 of 97 subjects.[26] The results are broadly consistent with those estimated at the aggregate level. The median estimated annual discount rate is 0.41, close to the aggregate values obtained in Table 2. Echoing the aggregate results, individual present bias is limited as the median estimated $\hat{\beta}$ is 1.001. The median estimated $\hat{\alpha}$ is 0.967, suggesting that individual curvature, like aggregate curvature, is limited. In addition to median values, Table 3 reports the 5th-95th percentile range for individual estimates of the annual discount rate, $\hat{\delta}$, $\hat{\beta}$, and $\hat{\alpha}$ along with the minimum and maximum values estimated. For the majority of subjects the employed estimation strategy generates reasonable parameter estimates. However, extreme observations do exist. Figure 3, Panel A presents histograms of individual curvature and discounting estimates from the CTB methodology. The histograms demonstrate that a large proportion of subjects have low discount rates, limited present bias and limited utility function curvature. Estimation results for all subjects are in Appendix Tables A5 and A6.

[25] We opt for the NLS estimator to accommodate the restriction $\omega_1 = \omega_2 = 0$. Additionally, the tobit estimator requires a sufficient number of non-censored interior solutions for estimation. Given that 36 of 97 subjects have no interior solutions, consistent with linear preferences, this condition would not be met for a number of experimental subjects. See Appendix A.1.2 for details.

[26] We do not study the 11 remaining subjects. Eight of these subjects had zero variance in their experimental responses, allocating the same number of sooner tokens in each choice set. Estimation convergence is not achieved for two subjects and the last remaining subject gave an identical pattern of sooner token choices in every choice set: 4 tokens in the first decision, 3 in the second, 2 in the third, 1 in the fourth and 0 in the fifth.

Figure 3: Histograms of CTB Estimates and DMPL Calculations

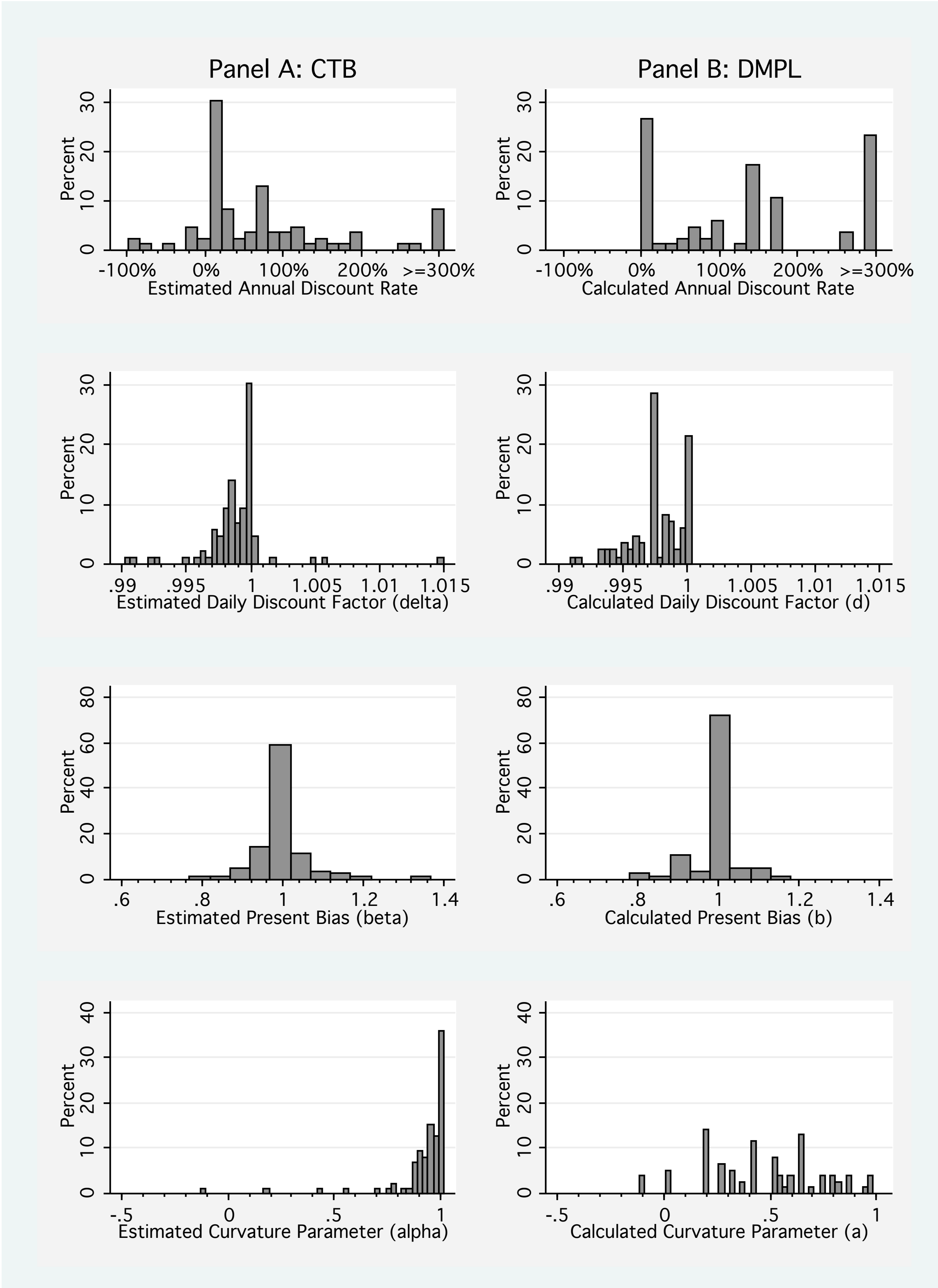


Table 3: Individual Discounting, Present Bias and Curvature Parameter Estimates

	N	Median	5th Percentile	95th Percentile	Min	Max
Annual Discount Rate	86	0.4076	-0.1784	5.618	-0.9949	35.3555
Daily Discount Factor: $\hat{\delta}$	86	0.9991	0.9948	1.0005	0.9902	1.0146
Present Bias Parameter: $\hat{\beta}$	86	1.0011	0.9121	1.1075	0.7681	1.3241
Curvature Parameter: $\hat{\alpha}$	86	0.9665	0.7076	0.9997	-0.1331	0.9998

Notes: NLS estimators with restriction $\omega_1 = \omega_2 = 0$.

4.2.1 Correlation Between CTB Parameter Estimates and DMPL Calculations

For completeness, we compare individual discounting and curvature parameter estimates from the CTB to those calculated from DMPL methodology. Three standard time multiple price lists and two HL risk price lists were administered to all subjects. From the three price lists, we calculate daily discount factors following standard practice.[27] Given a switching point, X, a later payment, Y, and a delay length, k, in a price list, l, we calculate the daily discount factor as $d_l = (X/Y)^{1/k}$. This is equivalent to positing a linear utility function and background $\omega_1 = \omega_2 = 0$. We examine the average of the three measures, $d = 1/3 \cdot (d_1 + d_2 + d_3)$. From the two HL risk price lists, we calculate curvature parameters also following standard practice.[28] Given a switching probability pair, $(p, 1-p)$, and two HL lotteries, A and B, in a specific price list l we take the value a_l that equates the CRRA expected utility of lottery A and lottery B. We take the midpoint of the interval in which this value lies as the calculated curvature parameter, a_l. We examine the average value, $a = 1/2 \cdot (a_1 + a_2)$. In both MPLs and HLs, individuals must exhibit a unique switching point to have a calculable discount factor or curvature parameter.

Of the subjects for whom we estimate $\hat{\delta}$, 84 of 86 have a calculable discount factor, d.

[27] MPL switch points yield an interval of the individual discount factor (Coller and Williams, 1999), which is easily accounted for with interval regression techniques (Coller and Williams, 1999; Harrison et al., 2002). However, common practice for calculation takes one point in the interval (see, for example Ashraf, Karlan and Yin, 2006; Burks, Carpenter, Goette and Rustichini, 2009; Meier and Sprenger, 2010). We choose the point of the interval that makes subjects appear the *most* patient.

[28] HL switch points yield an interval of the individual curvature parameter (Holt and Laury, 2002), which can be accounted for with either interval regression techniques or alternative estimators (Harrison et al., 2005). However, common practice for calculation takes one point in the interval or alternatively the number of lottery A choices (see, for example Dohmen, Falk, Huffman, Sunde, Schupp and Wagner, 2005; Holt and Laury, 2002).

The median value implies an annual discount rate of 137 percent, which replicates the very high observed discount rates in MPL experiments assuming linear utility. We can also identify present bias in the MPLs by the standard methodology of comparing the $(t, k) = (0, 35)$ MPL to the $(t, k) = (35, 35)$ MPL. Fourteen of 84 subjects (16.7%) are classified as present-biased, $(d_{(t=0,k=35)} < d_{(t=35,k=35)})$, while the median present bias parameter, b, is 1.[29] For comparison, using similar MPL methods, Ashraf et al. (2006), Dohmen, Falk, Huffman and Sunde (2006), and Meier and Sprenger (2010) find around 30-35% of subjects to be present-biased. This further supports the notion that our unique payment methods resulted in fewer instances of apparent present bias. Of the subjects for whom we estimate $\hat{\alpha}$, 77 of 86 have a calculable curvature parameter, a. The median value is 0.513 indicating substantial utility curvature.

Figure 3, Panel B provides histograms of these calculations for comparison with CTB estimates. Figure 3 shows that present bias is found to be similar across elicitation techniques. Discount rates and curvature, however, differ substantially. Time and risk price lists yield systematically higher discount rates and utility function curvature than CTB estimates. As in Andersen et al. (2008), correcting for curvature from the HL risk measures yields lower discounting estimates. Performing such an exercise, we obtain a median discount rate estimate of 33 percent per year. However, such a correction may be misguided given the wide difference between HL risk measures and the CTB estimates. This motivates careful examination of the correlation of obtained preference parameters across elicitation methods.

Figure 4 plots calculated DMPL and estimated CTB parameters against each other. In Panel A the calculated discount factor, d, is plotted against the estimated parameter, $\hat{\delta}$, along with an estimated regression line and 45 degree line. Panel B is similar for a and $\hat{\alpha}$. No panel is presented for b and β, because of the sheer volume of responses near to $(b, \hat{\beta}) = (1, 1)$. However, estimated present bias from CTB methodology, $\hat{\beta}$, and calculated present bias from MPL methodology b are significantly correlated $(\rho = 0.255,\ p < 0.05)$ as are $\hat{\beta}$ and the frequently-used categorical variable classifying present-biased (1) , dynamically consistent (0) and future

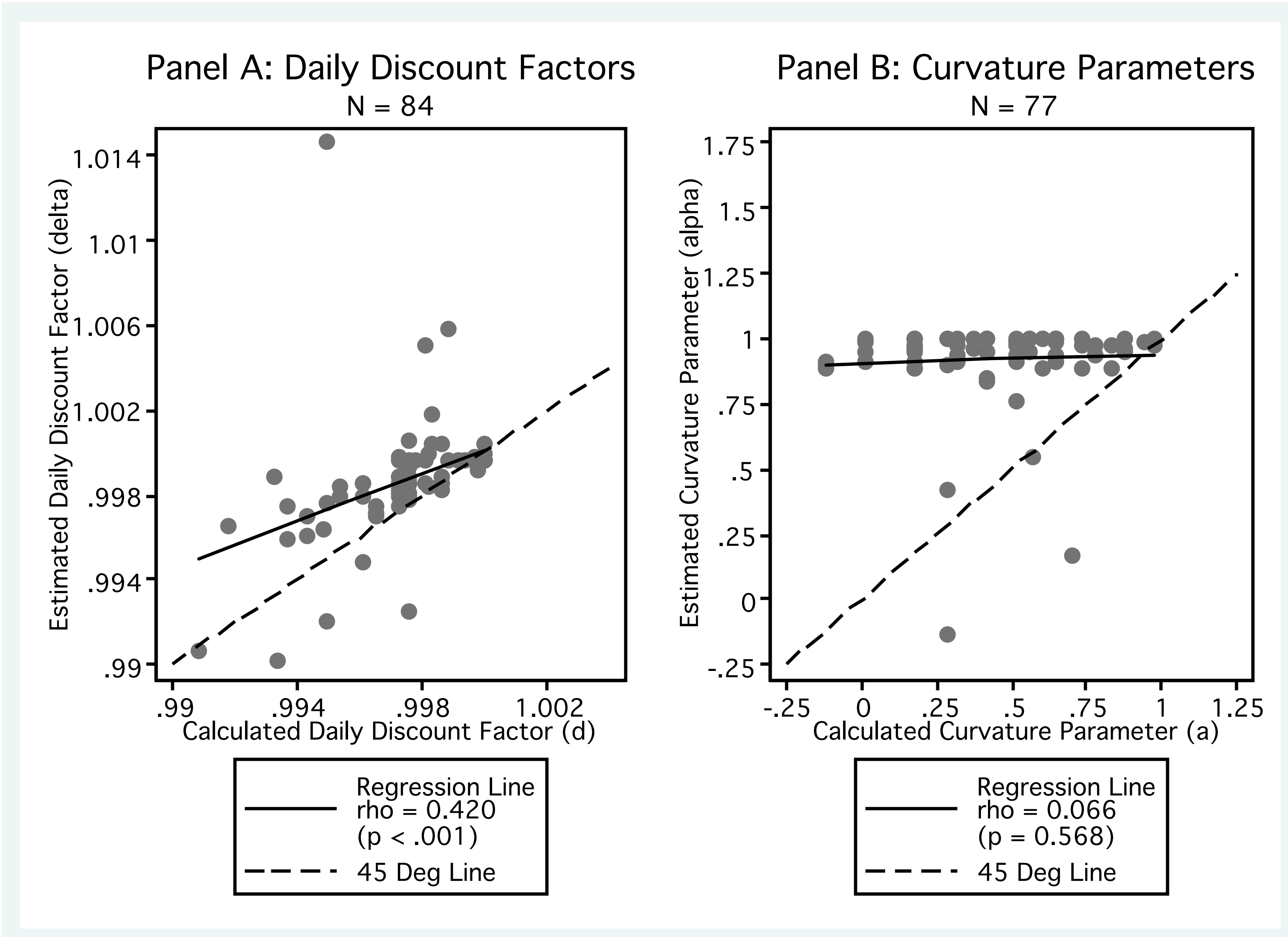
[29] Present bias b, is calculated as $(d_{(t=0,k=35)}/d_{(t=35,k=35)})^{35}$. Nine subjects are classified as future-biased $(d_{(t=0,k=35)} > d_{(t=35,k=35)})$ and 61 are classified as dynamically consistent $(d_{(t=0,k=35)} = d_{(t=35,k=35)})$

biased (-1) subjects, ($\rho = -0.274,\ p < 0.05$).

Panel A of Figure 4 shows a high degree of correlation between MPL calculated and CTB estimated discount factors ($\rho = 0.420,\ p < 0.001$). However, most of the data lies above the 45 degree line, consistent with standard arguments that, under concave utility, discount factors calculated from price lists alone will be downwards-biased. Additionally, we can examine the difference, $\hat{\delta} - d$, as a measure of price list-induced bias. Interestingly, this discounting bias measure is negatively correlated with CTB estimated curvature, $\hat{\alpha}$, ($\rho = -0.743,\ p < 0.001$). Subjects who are closer to linear utility will have less biased MPL-calculated discount factors. This indicates that, though biased, standard MPLs do yield useful measures of time preference and that the bias attenuates with utility function curvature as theoretically predicted. Importantly, HL measured curvature does not correlate with the bias in any appreciable way ($\rho = -0.092,\ p = 0.431$).

The lack of correlation between HL curvature and price list-induced discounting bias is not surprising. It is generated by the apparent zero correlation in Panel B of Figure 4 between HL calculated curvature, a, and CTB estimated curvature $\hat{\alpha}$ ($\rho = 0.066,\ p = 0.568$). This is interesting because, under CRRA utility, the two elicitation methodologies ostensibly measure the same utility construct. Not only is the level of curvature inconsistent between the two, but also the correlation is remarkably low. Additionally, HL curvature cannot account for the bias induced in MPL discounting experiments. These findings suggest that the practice of using HL *risk* experiments to identify and correct for curvature in *discounting* may be problematic.

Figure 4: Comparison of CTB Estimates and DMPL Calculations



5 Conclusion

MPLs and other experimental methods frequently produce high estimates of annual discount rates at odds with non-laboratory measures. A possible bias of MPLs is the imposition of linear preferences, generating upwards-biased discount rate estimates if utility is actually concave. Solutions to this bias to date have relied on Double Multiple Price List methodology: identifying time preferences with MPLs and utility function curvature with HL risk measures.

We propose a single simple instrument that can identify discounting and utility function curvature at the aggregate and individual level, that we call Convex Time Budgets. Allocations in Convex Time Budgets are viewed as solutions to standard intertemporal optimization problems with convex choice sets. Given assumptions on functional form, discounting and curvature parameters are estimable. Additionally, tests of present-biased time preferences are easily implemented.

In a computer-based experiment with 97 subjects, we show that CTBs precisely identify discounting and curvature parameters at both the aggregate and individual levels. Assuming an exponentially-discounted CRRA utility function we find an aggregate discount rate of around 30% per year, substantially lower than most experimental estimates. Linear utility is rejected econometrically, though we find less utility function curvature than obtained with DMPL methodology or most studies using HL risk measures. Additionally, we find no evidence of present bias. In fact, parameter estimates are surprisingly supportive of time-consistent preferences.

When examining individual estimates, we find that MPL-elicited discount rates, though upwards-biased, do correlate with CTB estimates. HL risk measures, however, are found to be virtually uncorrelated with either CTB estimated utility function curvature or the bias of MPL-elicited discount rates.

These findings raise several natural and important questions. First, why did we find no evidence of present bias, while so many other studies using cash rewards do find present bias? The most likely answer, it appears to us, lies in the unique steps we took to equate the costs and risks associated with sooner and later payments. This is surely the most consequential aspect of our findings, and as such invites rigorous replication and testing.

Second, why do we find substantial differences between CTB estimates and those obtained with DMPL methodology? In particular, why is the curvature over time obtained from CTBs so different from and uncorrelated with the curvature over risk obtained from HL measures. Why can't HL risk measures account for MPL-induced bias in discounting? At a minimum, these results indicate that using risk experiments to identify curvature in discounting may be problematic. They also suggest that future research is necessary on the interactions between risk and time. Particular attention should be given to investigating the link between payment risk and present bias. We begin this investigation in Andreoni and Sprenger (2010).

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A Appendix

A.1 Estimating Preference Parameters

A.1.1 Nonlinear Least Squares

Let there be N experimental subjects and P CTB budgets. Assume that each subject j makes her $c_{t_{ij}}$, $i = 1, 2, ..., P$, decisions according to (5) but that these decisions are made with some mean-zero, potentially correlated error. That is let

$$g(m,r,k,t;\beta,\delta,\alpha,\omega_1,\omega_2) = \left\{ \begin{array}{ll} \frac{1}{1+(1+r)(\beta\delta^k(1+r))^{(\frac{1}{\alpha-1})}}]\omega_1 + [\frac{(\beta\delta^k(1+r))^{(\frac{1}{\alpha-1})}}{1+(1+r)(\beta\delta^k(1+r))^{(\frac{1}{\alpha-1})}}](m-\omega_2) & if \quad t=0 \\ \frac{1}{1+(1+r)(\delta^k(1+r))^{(\frac{1}{\alpha-1})}}]\omega_1 + [\frac{(\delta^k(1+r))^{(\frac{1}{\alpha-1})}}{1+(1+r)(\delta^k(1+r))^{(\frac{1}{\alpha-1})}}](m-\omega_2) & if \quad t>0 \end{array} \right\},$$

then

$$c_{t_{ij}} = g(m,r,k,t;\beta,\delta,\alpha,\omega_1,\omega_2) + e_{ij}.$$

Stacking the P observations for individual j, we have

$$\mathbf{c_{t_j}} = \mathbf{g}(m,r,k,t;\beta,\delta,\alpha,\omega_1,\omega_2) + \mathbf{e_j}.$$

The vector $\mathbf{e_j}$ is zero in expectation with variance covariance matrix $\mathbf{V_j}$, a $(P \times P)$ matrix, allowing for arbitrary correlation in the errors e_{ij}. We stack over the N experimental subjects to obtain

$$\mathbf{c_t} = \mathbf{g}(m,r,k,t;\beta,\delta,\alpha,\omega_1,\omega_2) + \mathbf{e}.$$

We assume that the terms e_{ij} may be correlated within individuals but that the errors are uncorrelated across individuals, $E(\mathbf{e_j'e_g}) = 0$ for $j \neq g$. And so $\mathbf{e}$ is zero in expectation with covariance matrix $\mathbf{\Omega}$, a block diagonal $(NP \times NP)$ matrix of clusters, with individual covariance matrices, $\mathbf{V_j}$.

We define the usual criterion function $S(m, r, k; \beta, \delta, \alpha, \omega_1, \omega_2)$ as the sum of squared residuals,

$$S(m, r, k, t; \beta, \delta, \alpha, \omega_1, \omega_2) = \sum_{j=1}^{N} \sum_{i=1}^{P} (c_{t_{ij}} - g(m, r, k, t; \beta, \delta, \alpha, \omega_1, \omega_2))^2,$$

and minimize $S(\cdot)$ using non-linear least squares with standard errors clustered on the individual level to obtain $\hat{\beta}$, $\hat{\delta}$, $\hat{\alpha}$, $\hat{\omega}_1$ and $\hat{\omega}_2$. NLS procedures permitting the estimation of preference parameters at the aggregate or individual level are implemented in many standard econometrics packages (in our case, *Stata*). Additionally, an estimate of the annual discount rate can be calculated as $(1/\hat{\delta})^{365} - 1$ with standard error obtained via the delta method. $\hat{\mathbf{\Omega}}$ is estimated as the individual-level clustered error covariance matrix. Given additional assumptions on the individual covariance matrix $\mathbf{V_j}$, such as diagonal or block-diagonal, individual parameter estimates can also be obtained via the same estimation procedure.

It is important to recognize the strengths and weaknesses of such an NLS preference estimator. Background parameters ω_1 and ω_2 can be estimated as opposed to assumed, which is an advantage. A potential disadvantage is that the NLS estimator is not well-suited to the censored data issues inherent to potential corner solutions.

A.1.2 Censored Regression Techniques

Next we consider censored regression techniques that can address corner solution issues. We consider the tangency condition of (4). If we assume ω_1 and ω_2 are non-estimated, known values, we can take logs to obtain

$$ln(\frac{c_t - \omega_1}{c_{t+k} - \omega_2}) = \left\{ \begin{array}{lll} (\frac{ln\ \beta}{\alpha-1}) + (\frac{ln\ \delta}{\alpha-1}) \cdot k + (\frac{1}{\alpha-1}) \cdot ln(1+r) & if & t = 0 \\ (\frac{ln\ \delta}{\alpha-1}) \cdot k + (\frac{1}{\alpha-1}) \cdot ln(1+r) & if & t > 0 \end{array} \right\},$$

which is linear in the in the data, k and $ln(1+r)$, and reduces to,

$$ln(\frac{c_t - \omega_1}{c_{t+k} - \omega_2}) = (\frac{ln\ \beta}{\alpha - 1}) \cdot \mathbf{1}_{t=0} + (\frac{ln\ \delta}{\alpha - 1}) \cdot k + (\frac{1}{\alpha - 1}) \cdot ln(1+r),$$

where $\mathbf{1}_{t=0}$ is an indicator for the time period $t = 0$.

Let there be N experimental subjects and P CTB budgets. Assume that each subject j makes her $c_{t_{ij}}$, $i = 1, 2, ..., P$, decisions according to the above log-linearized relationship but that these decisions are made with some additive mean-zero, potentially correlated error. That is,

$$ln(\frac{c_t - \omega_1}{c_{t+k} - \omega_2})_{ij} = (\frac{ln\ \beta}{\alpha - 1}) \cdot \mathbf{1}_{t=0} + (\frac{ln\ \delta}{\alpha - 1}) \cdot k + (\frac{1}{\alpha - 1}) \cdot ln(1 + r) + e_{ij},$$

Stacking the P observations for individual j, we have

$$\mathbf{ln}(\frac{\mathbf{c_t} - \omega_\mathbf{1}}{\mathbf{c_{t+k}} - \omega_\mathbf{2}})_\mathbf{j} = (\frac{ln\ \beta}{\alpha - 1}) \cdot \mathbf{1}_{t=0} + (\frac{ln\ \delta}{\alpha - 1}) \cdot \mathbf{k} + (\frac{1}{\alpha - 1}) \cdot \mathbf{ln(1 + r)} + \mathbf{e_j}$$

The vector $\mathbf{e_j}$ is zero in expectation with variance covariance matrix $\mathbf{V_j}$, a $(P \times P)$ matrix, allowing for arbitrary correlation in the errors e_{ij}. We stack over the N experimental subjects to obtain

$$\mathbf{ln}(\frac{\mathbf{c_t} - \omega_\mathbf{1}}{\mathbf{c_{t+k}} - \omega_\mathbf{2}}) = (\frac{ln\ \beta}{\alpha - 1}) \cdot \mathbf{1}_{t=0} + (\frac{ln\ \delta}{\alpha - 1}) \cdot \mathbf{k} + (\frac{1}{\alpha - 1}) \cdot \mathbf{ln(1 + r)} + \mathbf{e}$$

We assume that the terms e_{ij} may be correlated within individuals but that the errors are uncorrelated across individuals, $E(\mathbf{e_j'e_g}) = 0$ for $j \neq g$. And so $\mathbf{e}$ is zero in expectation with covariance matrix $\mathbf{\Omega}$, a block diagonal $(NP \times NP)$ matrix of clusters, with individual covariance matrices, $\mathbf{V_j}$.

The above linear model is easily estimated with ordinary least squares. However the log consumption ratio is censored by corner solution responses,

$$ln(\frac{c_t - \omega_1}{c_{t+k} - \omega_2}) \in [ln(\frac{0 - \omega_1}{c_{t+k} - \omega_2}), ln(\frac{c_t - \omega_1}{0 - \omega_2})],$$

motivating censored regression techniques such as the two-limit tobit model more appropriate. Wooldridge (2002) presents corner solutions as the primary motivation for two-limit tobit regression techniques and Chapter 16, Problem 16.3 corresponds closely to the above. Parameters can be estimated via the two-limit tobit regression.

$$\mathbf{ln}(\frac{\mathbf{c_t} - \omega_\mathbf{1}}{\mathbf{c_{t+k}} - \omega_\mathbf{2}}) = \gamma_1 \cdot \mathbf{1}_{t=0} + \gamma_2 \cdot \mathbf{k} + \gamma_3 \cdot \mathbf{ln(1+r)} + \mathbf{e}$$

With parameters of interest recovered via the non-linear combinations

$$\hat{\alpha} = \frac{1}{\hat{\gamma}_3} + 1 \ ; \ \hat{\delta} = exp(\frac{\hat{\gamma}_2}{\hat{\gamma}_3}) \ ; \ \hat{\beta} = exp(\frac{\hat{\gamma}_1}{\hat{\gamma}_3}),$$

and standard errors obtained via the delta method. Additionally, an estimate of the annual discount rate can be calculated as $(1/\hat{\delta})^{365} - 1$ with standard error obtained via the delta method. $\hat{\mathbf{\Omega}}$ is estimated as the individual-level clustered error covariance matrix.

Given additional assumptions on the individual covariance matrix $\mathbf{V_j}$, such as diagonal or block-diagonal as well as a sufficient number of non-censored observations (one less than the number of parameters), individual parameter estimates can also be obtained via the same estimation procedure.

Censored regression techniques are helpful in addressing the critical issues of corner solutions. However, there are disadvantages to the technique. First, the values ω_1 and ω_2 must be assumed rather than estimated from the data. Second, the consumption ratio $(\frac{c_t - \omega_1}{c_{t+k} - \omega_2})$ must be strictly positive such that the log consumption ratio is well defined. This restricts the values of ω_1 and ω_2 to be strictly negative.

A.2 About Arbitrage

A relevant issue with monetary incentives in time preference experiments, as opposed to experiments using primary consumption as rewards, is that, in theory, monetary payments should be subject to extra-lab arbitrage opportunities. Subjects who can borrow (save) at external interest rates inferior (superior) to the rates offered in the lab should arbitrage the lab by taking the later (sooner) experimental payment. As such, discount rates measured using monetary incentives should collapse to the interval of external borrowing and savings interest rates. In the

CTB context, this arbitrage argument also implies that subjects should *never* choose intermediate allocations unless they are liquidity constrained.[30] Furthermore, for 'secondary' rewards, such as money, it is possible that there could be less of a visceral temptation for immediate gratification than for 'primary' rewards that can be immediately consumed. As a result, one might expect limited present bias when monetary incentives are used.

Contrary to the arbitrage argument, others have shown that experimentally elicited discount rates are generally not measured in a tight interval near market rates (Coller and Williams, 1999; Harrison et al., 2002); they are not remarkably sensitive to the provision of external rate information or to the elaboration of arbitrage opportunities (Coller and Williams, 1999); and they are uncorrelated with credit constraints (Meier and Sprenger, 2010). In our CTB environment, a sizeable proportion of chosen allocations are intermediate (30.4% of all responses, average of 13.7 per subject) and the number of intermediate allocations is uncorrelated with individual liquidity proxies such as credit-card holdership ($\rho = -0.049,\ p = 0.641$) and bank account holdership ($\rho = -0.096,\ p = 0.362$).

Despite the fact that money is not a primary reward, monetary experiments do generate evidence of present-biased preferences (Dohmen et al., 2006; Meier and Sprenger, 2010). Of further interest is the finding by McClure et al. (2004, 2007) that discounting and present bias over primary and monetary rewards have very similar neural images. As well, discount factors elicited over primary and monetary rewards correlate highly at the individual level (Reuben et al., 2008). The fact that we find significant but limited utility function curvature is therefore consistent with the evidence of strict convexity of preferences in the presence of arbitrage.

[30] If an arbitrage opportunity exists, the lab offered budget set is inferior to the extra-lab budget set everywhere except one corner solution. This corner should be the chosen allocation. Liquidity constraints could yield intermediate allocations if individuals are unable to move resources through time outside of the lab and desire smooth consumption streams. Additionally intermediate allocations could be obtained if the lab-offered rate lay in between borrowing and savings rates. Cubitt and Read (2007) provide substantial discussion on the limits of the preference information that can be obtained from intertemporal choice experiments.

A.3 Additional Individual Estimates

In this appendix we provide three summary tables of additional individual level estimates with alternative specifications and estimators. All three tables are in the form of Table 3. In A1 we impose the restriction $\omega_1 = \omega_2 = -7.05$, minus average daily background consumption, and provide NLS estimates. In A2, we impose the same restriction and provide tobit estimators. For individuals with one or fewer interior solutions, we estimate via OLS as the tobit requires at least two uncensored observations for estimation. See Appendix Section A.1.2 for details. In A3 we impose the restriction $\omega_1 = \omega_2 = -B$, where B corresponds to the subject's own self-reported daily background consumption, and provide NLS estimates for responders. The number of subjects for whom estimation is achieved is also reported and varies across tables.

Table A1: Individual Discounting, Present Bias and Curvature Parameter Estimates

	N	Median	5th Percentile	95th Percentile	Min	Max
Annual Discount Rate	88	.4277	-.8715	5.6481	-1	55.4768
Daily Discount Factor: $\hat{\delta}$	88	.999	.9948	1.0056	.989	1.031
Present Bias Parameter: $\hat{\beta}$	88	1.0285	.8963	1.1566	.8016	1.1961
Curvature Parameter: $\hat{\alpha}$	88	.7536	.1293	.8977	-3.273	.9052

Notes: NLS estimators with restriction $\omega_1 = \omega_2 = -7.05$.

Table A2: Individual Discounting, Present Bias and Curvature Parameter Estimates

	N	Median	5th Percentile	95th Percentile	Min	Max
Annual Discount Rate	84	.3923	-.9868	7.9005	-1	42.9775
Daily Discount Factor: $\hat{\delta}$	84	.9991	.994	1.0119	.9897	1.4535
Present Bias Parameter: $\hat{\beta}$	84	1.0238	.9102	1.3384	.8426	5.7041
Curvature Parameter: $\hat{\alpha}$	84	.7836	-.0838	.9846	-50.4261	.9916

Notes: Tobit and OLS (for subjects with one or fewer uncensored observations) estimators with restriction $\omega_1 = \omega_2 = -7.05$.

Table A3: Individual Discounting, Present Bias and Curvature Parameter Estimates

	N	Median	5th Percentile	95th Percentile	Min	Max
Annual Discount Rate	82	.3734	-.9169	3.7477	-.9989	80.6357
Daily Discount Factor: $\hat{\delta}$	82	.9991	.9957	1.0068	.988	1.0187
Present Bias Parameter: $\hat{\beta}$	82	1.0087	.905	1.2156	.8208	1.2223
Curvature Parameter: $\hat{\alpha}$	82	.7987	-.0155	.9859	-.6922	.9955

Notes: NLS estimators with restriction $\omega_1 = \omega_2 = -B$, the subject's own self-reported daily background consumption. Reporters only.

A.4 Welcome Text and Payment Explanation

Welcome and thank you for participating

Eligibility for this study: To be in this study, you need to meet these criteria. You must have a campus mailing address of the form:

YOUR NAME

9450 GILMAN DR 92(MAILBOX NUMBER)

LA JOLLA CA 92092-(MAILBOX NUMBER)

You must live in:

- XXX College.
- XXX College AND have a student mail box number between 92XXXX and 92XXXX
- XXX College AND have a student mail box number between 92XXXX through 92XXXX.

Your mailbox must be a valid way for you to receive mail from now through the end of the Spring Quarter. You must be willing to provide your name, campus mail box, email address, and student PID. This information will only be seen by Professor Andreoni and his assistants. After payment has been sent, this information will be destroyed. Your identity will not be a part of any subsequent data analysis.

You must be willing to receive your payment for this study by check, written to you by Professor James Andreoni, Director of the UCSD Economics Laboratory. The checks will be drawn on the USE Credit Union on campus. This means that, if you wish, you can cash your checks for free at the USE Credit Union any weekday from 9:00 am to 5:00 pm with valid identification (drivers license, passport, etc.). The checks will be delivered to you at your campus mailbox at a date to be determined by your decisions in this study, and by chance. The latest you could receive payment is the last week of classes in the Spring Quarter.

If you do not meet all of these criteria, please inform us of this now.

A.4.1 Payment Explanation

Earning Money

To begin, you will be given a $10 thank-you payment, just for participating in this study! You will receive this thank-you payment in two equally sized payments of $5 each. The two $5 payments will come to you at two different times. These times will be determined in the way described below.

In this study, you will make 47 choices over how to allocate money between two points in time, one time is "earlier" and one is "later." Both the earlier and later times will vary across decisions. This means you could be receiving payments as early as today, and as late as the last week of classes in the Spring Quarter, or possibly two other dates in between. Once all 47 decisions have been made, we will randomly select one of the 47 decisions as the decision-that-counts. We will use the decision-that-counts to determine your actual earnings. Note, since all decisions are equally likely to be chosen, you should make each decision as if it will be the decision-that-counts. When calculating your earnings from the decision-that-counts, we will add to your earnings the two $5 thank you payments. Thus, you will always get paid at least $5 at the chosen earlier time, and at least $5 at the chosen later time.

IMPORTANT: All payments you receive will arrive to your campus mailbox. That includes payments that you receive today as well as payments you may receive at later dates. On the scheduled day of payment, a check will be placed for delivery in campus mail services by Professor Andreoni and his assistants. *By special arrangement, campus mail services has* *guaranteed delivery of 100% of your payments on the same day.*

As a reminder to you, the day before you are scheduled to receive one of your payments, we will send you an e-mail notifying you that the payment is coming.

On your table is a business card for Professor Andreoni with his contact information. Please keep this in a safe place. If one of your payments is not received you should immediately contact Professor Andreoni, and we will hand-deliver payment to you.

Your Identity

In order to receive payment, we will need to collect the following pieces of information from you: name, campus mail box, email address, and student PID. This information will only be seen by Professor Andreoni and his assistants. After all payments have been sent, this information will be destroyed. Your identity will not be a part of subsequent data analysis.

You have been assigned a participant number. This will be linked to your personal information in order to complete payment. After all payments have been made, only the participant number will remain in the data set.

On your desk are two envelopes: one for the sooner payment and one for the later payment. Please take the time now to address them to yourself at your campus mail box.

A.5 Multiple Price Lists and Holt Laury Risk Price Lists

NAME: ______________________________________ PID:______________________

How It Works:

In the following sheets you are asked to choose between smaller payments closer to today and larger payments further in the future. For each row, choose one payment: either the smaller, sooner payment or the larger, later payment. There are 22 decisions in total. Each decision has a number from 1 to 22.

NUMBERS 1 THROUGH 7: Decide between payment <u>today</u> and payment in <u>five weeks</u>
NUMBERS 8 THROUGH 15: Decide between payment <u>today</u> and payment <u>in fourteen weeks</u>
NUMBERS 16 THROUGH 22: Decide between payment <u>in five weeks</u> and payment <u>in ten weeks</u>

This sheet represents one of the 47 choices you make in the experiment. If the number 47 is drawn, this sheet will determine your payoffs. If the number 47 is drawn, a second number will also be drawn from 1 to 22. This will determine which decision (from 1 to 22) on the sheet is the decision-that-counts. The payment you choose (either sooner or later) in the decision that counts will be added to either your earlier $5 thank-you payment or your later $5 thank-you payment.

Remember that each decision could be the decision-that-counts! Treat each decision as if it could be the one that determines your payment.

TODAY VS. FIVE WEEKS FROM TODAY

WHAT WILL YOU DO IF YOU GET A NUMBER BETWEEN 1 AND 7?

Decide for **each** possible number if you would like the smaller payment for sure **today** or the larger payment for sure in **five weeks**? Please answer for each possible number (1) through (7) by filling in one box for each possible number.

Example: If you prefer $19 today in Question 1 mark as follows: ☑ *$19* ***today*** *or* ☐ *$20 in* ***five weeks***
If you prefer $20 in five weeks in Question 1, mark as follows: ☐ *$19* ***today*** *or* ☑ *$20 in* ***five weeks***

If you get number (1):	Would you like to receive ☐ $19 **today**	or ☐ $20 in **five weeks**
If you get number (2):	Would you like to receive ☐ $18 **today**	or ☐ $20 in **five weeks**
If you get number (3):	Would you like to receive ☐ $16 **today**	or ☐ $20 in **five weeks**
If you get number (4):	Would you like to receive ☐ $14 **today**	or ☐ $20 in **five weeks**
If you get number (5):	Would you like to receive ☐ $11 **today**	or ☐ $20 in **five weeks**
If you get number (6):	Would you like to receive ☐ $8 **today**	or ☐ $20 in **five weeks**
If you get number (7):	Would you like to receive ☐ $5 **today**	or ☐ $20 in **five weeks**

TODAY VS. FOURTEEN WEEKS FROM TODAY

WHAT WILL YOU DO IF YOU GET A NUMBER BETWEEN 8 AND 15?

Decide for **each** possible number if you would like the smaller payment for sure **<u>today</u>** or the larger payment for sure in **<u>fourteen weeks</u>**? Please answer for each possible number (8) through (15) by filling in one box for each possible number.

Example: If you prefer $19 today in Question 8 mark as follows: ☑ *$19* ***today*** *or* ☐ *$20 in* ***14 weeks***
If you prefer $20 in fourteen weeks in Question 8, mark as follows: ☐ *$19* ***today*** *or* ☑ *$20 in* ***14 weeks***

If you get number (8):	Would you like to receive	☐ $20 **<u>today</u>**	or	☐ $20 in **<u>fourteen weeks</u>**
If you get number (9):	Would you like to receive	☐ $19 **today**	or	☐ $20 in **fourteen weeks**
If you get number (10):	Would you like to receive	☐ $18 **today**	or	☐ $20 in **fourteen weeks**
If you get number (11):	Would you like to receive	☐ $16 **today**	or	☐ $20 in **fourteen weeks**
If you get number (12):	Would you like to receive	☐ $13 **today**	or	☐ $20 in **fourteen weeks**
If you get number (13):	Would you like to receive	☐ $10 **today**	or	☐ $20 in **fourteen weeks**
If you get number (14):	Would you like to receive	☐ $7 **today**	or	☐ $20 in **fourteen weeks**
If you get number (15):	Would you like to receive	☐ $4 **today**	or	☐ $20 in **fourteen weeks**

FIVE WEEKS FROM TODAY VS. TEN WEEKS FROM TODAY

WHAT WILL YOU DO IF YOU GET A NUMBER BETWEEN 16 AND 22?

Decide for **each** possible number if you would like the smaller payment for sure in **five weeks** or the larger payment for sure in **ten weeks**? Please answer for each possible number (16) through (22) by filling in one box for each possible number.

Example: If you prefer $19 in four weeks in Question 16 mark as follows: ☑ *$19* ***in 5 weeks or*** ☐ *$20 in* ***10 weeks***
If you prefer $20 in ten weeks in Question 16, mark as follows: ☐ *$19* ***in 5 weeks*** *or* ☑ *$20 in* ***10 weeks***

If you get number (16):	Would you like to receive	☐ $19 **in five weeks**	or	☐ $20 in **ten weeks**
If you get number (17):	Would you like to receive	☐ $18 **in five weeks**	or	☐ $20 in **ten weeks**
If you get number (18):	Would you like to receive	☐ $16 **in five weeks**	or	☐ $20 in **ten weeks**
If you get number (19):	Would you like to receive	☐ $14 **in five weeks**	or	☐ $20 in **ten weeks**
If you get number (20):	Would you like to receive	☐ $11 **in five weeks**	or	☐ $20 in **ten weeks**
If you get number (21):	Would you like to receive	☐ $8 **in five weeks**	or	☐ $20 in **ten weeks**
If you get number (22):	Would you like to receive	☐ $5 **in five weeks**	or	☐ $20 in **ten weeks**

2.

NAME: ______________________________________ PID:______________________

<u>How It Works:</u>

In the following two sheets you are asked to choose between options: Option A or Option B. On each sheet you will make ten choices, one on each row. For each decision row you will have to choose either Option A or Option B. You make your decision by checking the box next to the option you prefer more. You may choose A for some decision rows and B for other rows, and you may change your decisions and make them in any order.

There are a total of 20 decisions on the following sheets. The sheets represent one of the 47 choices you make in the experiment. If the number 46 is drawn, these sheets will determine your payoffs. If the number 46 is drawn, a second number will also be drawn from 1 to 20. This will determine which decision (from 1 to 20) on the sheets is the decision-that-counts. The option you choose (either Option A or Option B) in the decision-that-counts will then be played. You will receive your payment from the decision–that-counts immediately. Your $5 sooner and later thank-you payments, however, will still be mailed as before. The sooner payment will be mailed today and the later payment will be mailed in 5 weeks.

Playing the Decision-That-Counts:

Your payment in the decision-that-counts will be determined by throwing a 10 sided die. Now, please look at Decision 1 on the following sheet. Option A pays $10.39 if the throw of the ten sided die is 1, and it pays $8.31 if the throw is 2-10. Option B yields $20 if the throw of the die is 1, and it pays $0.52 if the throw is 2-10. The other Decisions are similar, except that as you move down the table, the chances of the higher payoff for each option increase. In fact, for Decision 10 in the bottom row, the die will not be needed since each option pays the highest payoff for sure, so your choice here is between $10.39 or $20.

Remember that each decision could be the decision-that-counts! It is in your interest to treat each decision as if it could be the one that determines your payoff.

Decision	Option A							Option B					
		If the die reads	you receive	and	If the die reads	you receive			If the die reads	you receive	and	If the die reads	you receive
1	☐	1	10.39		2-10	8.31		☐	1	20		2-10	0.52
2	☐	1-2	10.39		3-10	8.31		☐	1-2	20		3-10	0.52
3	☐	1-3	10.39		4-10	8.31		☐	1-3	20		4-10	0.52
4	☐	1-4	10.39		5-10	8.31		☐	1-4	20		5-10	0.52
5	☐	1-5	10.39		6-10	8.31		☐	1-5	20		6-10	0.52
6	☐	1-6	10.39		7-10	8.31		☐	1-6	20		7-10	0.52
7	☐	1-7	10.39		8-10	8.31		☐	1-7	20		8-10	0.52
8	☐	1-8	10.39		9-10	8.31		☐	1-8	20		9-10	0.52
9	☐	1-9	10.39		10	8.31		☐	1-9	20		10	0.52
10	☐	1-10	10.39		-	8.31		☐	1-10	20		-	0.52

Decision	Option A							Option B					
		If the die reads	you receive	and	If the die reads	you receive			If the die reads	you receive	and	If the die reads	you receive
11	☐	1	13.89		2-10	5.56		☐	1	25		2-10	0.28
12	☐	1-2	13.89		3-10	5.56		☐	1-2	25		3-10	0.28
13	☐	1-3	13.89		4-10	5.56		☐	1-3	25		4-10	0.28
14	☐	1-4	13.89		5-10	5.56		☐	1-4	25		5-10	0.28
15	☐	1-5	13.89		6-10	5.56		☐	1-5	25		6-10	0.28
16	☐	1-6	13.89		7-10	5.56		☐	1-6	25		7-10	0.28
17	☐	1-7	13.89		8-10	5.56		☐	1-7	25		8-10	0.28
18	☐	1-8	13.89		9-10	5.56		☐	1-8	25		9-10	0.28
19	☐	1-9	13.89		10	5.56		☐	1-9	25		10	0.28
20	☐	1-10	13.89		-	5.56		☐	1-10	25		-	0.28

A.6 Appendix Tables

Table A4: Background Consumption, Parameter Estimates and Goodness of Fit

	NLS Estimates				*Two-Limit Tobit Estimates*			
$\omega_1 = \omega_2$	Discount Rate (s.e.)	$\hat{\beta}$ (s.e)	$\hat{\alpha}$ (s.e.)	R^2	Discount Rate (s.e.)	$\hat{\beta}$ (s.e)	$\hat{\alpha}$ (s.e.)	Log-Likelihood
-25	.151	1.04	.24	.433	.264	1.027	.711	-4173.8
	(.151)	(.01)	(.045)		(.16)	(.01)	(.041)	
-20	.159	1.039	.361	.434	.266	1.027	.754	-4393.04
	(.149)	(.009)	(.037)		(.16)	(.01)	(.035)	
-15	.175	1.037	.487	.437	.268	1.027	.799	-4660.35
	(.145)	(.009)	(.03)		(.161)	(.01)	(.029)	
-14	.18	1.036	.513	.438	.269	1.027	.808	-4721.82
	(.144)	(.009)	(.028)		(.161)	(.01)	(.028)	
-13	.186	1.035	.539	.439	.27	1.027	.817	-4786.7
	(.142)	(.009)	(.027)		(.161)	(.01)	(.026)	
-12	.192	1.034	.566	.44	.27	1.027	.826	-4855.43
	(.141)	(.009)	(.025)		(.161)	(.01)	(.025)	
-11	.2	1.033	.593	.441	.271	1.027	.835	-4928.58
	(.139)	(.009)	(.024)		(.161)	(.01)	(.024)	
-10	.209	1.032	.621	.443	.272	1.027	.845	-5006.81
	(.137)	(.008)	(.022)		(.161)	(.01)	(.022)	
-9	.22	1.03	.649	.445	.273	1.027	.854	-5091.02
	(.134)	(.008)	(.02)		(.161)	(.01)	(.021)	
-8	.232	1.028	.678	.447	.274	1.026	.864	-5182.36
	(.131)	(.008)	(.019)		(.162)	(.01)	(.02)	
-7	.246	1.026	.707	.45	.275	1.026	.874	-5282.39
	(.127)	(.008)	(.017)		(.162)	(.01)	(.018)	
-6	.263	1.023	.737	.453	.277	1.026	.884	-5393.3
	(.123)	(.008)	(.016)		(.162)	(.01)	(.017)	
-5	.282	1.02	.767	.458	.279	1.026	.894	-5518.36
	(.118)	(.007)	(.014)		(.162)	(.01)	(.015)	
-4	.302	1.017	.796	.463	.281	1.026	.904	-5662.8
	(.113)	(.007)	(.013)		(.163)	(.01)	(.014)	
-3	.323	1.014	.824	.468	.284	1.026	.916	-5835.85
	(.107)	(.007)	(.012)		(.163)	(.01)	(.012)	
-2	.342	1.011	.851	.475	.288	1.026	.928	-6056.91
	(.101)	(.006)	(.01)		(.164)	(.01)	(.01)	
-1	.359	1.009	.875	.481	.295	1.025	.943	-6382.19
	(.095)	(.006)	(.009)		(.166)	(.01)	(.008)	

Notes: NLS and two-limit tobit estimators with restriction $\omega_1 = \omega_2$ equal to first column. 4365 observations (1329 uncensored) for each row. Clustered standard errors in parentheses. Annual discount rate calculated as $(1/\hat{\delta})^{365} - 1$, standard errors calculated via the delta method.

Table A5: Individual Estimates 1

				Proportion of Responses		
Subject #	Annual Rate	$\hat{\beta}$	$\hat{\alpha}$	Interior	Zero Tokens Sooner	All Tokens Sooner
1	.123	.958	.984	.4	.56	.04
2	.73	1.054	1	.16	.64	.2
3	.931	.988	.986	0	.71	.29
4	.55	1.017	.935	.6	.27	.13
5	.117	1.001	.999	0	.98	.02
6	.117	1.001	.999	0	.98	.02
7	.339	1.02	.979	.18	.78	.04
8	1.906	1	.911	.13	.44	.42
9	.117	1.001	.999	0	.98	.02
10	.	.	.	0	1	0
11	.735	.931	1	.07	.62	.31
12	1.966	.979	.955	.13	.38	.49
13	.496	1.027	.993	.51	.4	.09
14	.	.	.	0	.22	.78
15	.965	.993	.98	0	.69	.31
16	.305	.994	.916	.51	.49	0
17	.723	.938	.996	0	.71	.29
18	14.452	1.107	.951	.31	.09	.6
19	1.318	1.105	.885	.84	.11	.04
20	-.16	.904	.956	.16	.84	0
21	1.592	.984	.952	.13	.49	.38
22	5.618	.971	.772	.13	.2	.67
23	.707	.999	1	0	.8	.2
24	.117	1.001	.999	0	.98	.02
25	.117	1.001	.999	0	.98	.02
26	.117	1.001	.999	0	.98	.02
27	1.145	.993	.975	.07	.56	.38
28	2.742	.994	.933	.42	.22	.36
29	.	.	.	1	0	0
30	.676	1.043	.906	.64	.29	.07
31	.144	1.015	.966	.33	.64	.02
32	.73	.973	.963	.49	.42	.09
33	.788	1.002	.954	0	.73	.27
34	17.243	.912	.927	.18	.04	.78
35	.	.	.	0	0	1
36	.117	1.001	.999	0	.98	.02
37	.736	1.006	.997	.07	.71	.22
38	-.837	.852	.167	1	0	0
39	1.134	1.131	.887	.98	0	.02
40	.117	1.001	.999	0	.98	.02
41	1.81	.911	.885	.6	.04	.36
42	1.186	.967	.933	.58	.2	.22
43	.899	.975	.935	.18	.6	.22
44	.257	.979	1	0	.89	.11
45	.1	1.033	.89	.96	.04	0
46	-.995	.999	-.133	1	0	0
47	.476	1.078	.975	.22	.73	.04
48	.	.	.	0	1	0
49	1.545	1.062	.953	.36	.33	.31
50	.116	.94	.997	0	.89	.11

Table A6: Individual Estimates 2

Subject #	Annual Rate	$\hat{\beta}$	$\hat{\alpha}$	Proportion of Responses Interior	 Zero Tokens Sooner	 All Tokens Sooner
51	29.583	1.138	.918	.13	0	.87
52	.	.	.	.04	.76	.2
53	2.536	1.191	.847	.71	.09	.2
54	.219	1.003	.976	.16	.82	.02
55	.169	.975	.968	.09	.87	.04
56	.744	.916	.95	.16	.56	.29
57	-.144	1.042	.944	.38	.62	0
58	.306	1.01	.999	0	.91	.09
59	-.88	.974	.771	.98	.02	0
60	3.462	.768	.915	.11	.2	.69
61	1.511	.957	.904	.89	0	.11
62	-.123	1.037	.419	1	0	0
63	.513	.992	.761	1	0	0
64	.732	.949	1	.16	.62	.22
65	.126	1	.993	.69	.29	.02
66	1.073	.957	.834	.91	.04	.04
67	.291	1.003	.951	.36	.6	.04
68	.117	1.001	.999	0	.98	.02
69	.117	1.001	.999	0	.98	.02
70	3.225	.959	.89	.71	0	.29
71	.117	1.001	.999	0	.98	.02
72	35.356	1.324	.991	0	.22	.78
73	.117	1.001	.999	0	.98	.02
74	.117	1.001	.999	0	.98	.02
75	.109	1.059	.884	.42	.58	0
76	-.474	1.003	.708	1	0	0
77	.117	1.001	.999	0	.98	.02
78	0	1.003	.999	.02	.98	0
79	.	.	.	0	1	0
80	-.178	.982	.913	.47	.53	0
81	.834	1.009	.907	.56	.38	.07
82	.219	.986	.543	1	0	0
83	.117	1.001	.999	0	.98	.02
84	.	.	.	.8	.2	0
85	-.001	1.007	.973	.87	.13	0
86	.117	1.001	.999	0	.98	.02
87	.	.	.	0	0	1
88	1.206	.959	.972	.49	.22	.29
89	.117	1.001	.999	0	.98	.02
90	1.954	.935	.905	.38	.16	.47
91	.732	1.027	.943	.62	.33	.04
92	.999	.986	.967	.36	.49	.16
93	.	.	.	0	1	0
94	.117	1.001	.999	0	.98	.02
95	.117	1.001	.999	0	.98	.02
96	.555	1.051	.938	.76	.22	.02
97	.	.	.	0	.64	.36