Estimating Time Preferences from Convex Budgets*

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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 dynamic inconsistency, as in present bias and hyperbolic discounting. A commonly recognized bias of standard elicitation techniques is the use of linear preferences for identification. We present a novel 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, and limited though significant utility function curvature. Additionally, our data show no evidence of dynamic inconsistency.

JEL classification: D81, D90

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1 Introduction

Intertemporal allocation of resources is a central theme in many aggregate and individual models of decision making. Consumers decide how much to save for the future, how much education to obtain, how much to exercise, diet, and smoke. Understanding and estimating time preferences is obviously of great importance to economists and policy makers. 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 real 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 on their intertemporal preferences. Under 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 remarkably 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;

[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 real 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 (see 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, $u(c_t) = c_t$ and δ is calculated as $\delta \approx (c_t/c_{t+k})^{1/k}$. Discount rates are then calculated as $IDR = 1/\delta - 1$.

Laibson et al., 2003). A possible reconciliation of experimental and aggregate estimates may lie in the assumption of linear utility. This frequently imposed restriction leads to upwards-biased discount rate estimates if utility is concave.[5] Andersen et al. (2008) suggest the solution of separately administering MPLs and price list risk preference measures based on Holt and Laury (2002) (HL) to the same subjects, and jointly estimating discounting and curvature parameters combining the two measures.[6] Tanaka et al. (2009) employ a similar approach with a risk price list task designed to elicit loss aversion. We term this the *Double Multiple Price List* (DMPL) approach.

We propose a single, simple instrument that can 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. The potentially problematic discontinuity suggests a simple solution: convexify the experimental budgets.

This paper explores the implications of performing this convexification to obtain the *Convex Time Budget* (CTB). 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 a computerized experiment with 97 subjects, we show that the CTB methodology can be used to generate precise estimates of discounting and curvature parameters at both the group and individual level. These estimates require a minimal set of structural assumptions

[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 (2000) 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 $\delta_C \approx (u(c_t)/u(c_{t+k}))^{1/k}$. 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).

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 20 and 35 percent. We reject linearity of utility, although we find much less curvature than prior studies. Finally, to our surprise, we find no evidence of present-bias or hyperbolic discounting in our sample.

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 leave open several avenues 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 some unique 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 transactions costs over sooner and later payments. Second, we find substantial differences between our CTB results and those obtained from prior DMPL experiments. It is important to know whether these differences are associated with presentation differences (computer interface vs. paper-and-pencil) or if the finding is robust to similar presentations of the stimuli. Third, we find little correlation between CTB estimated curvature and responses in HL risk experiments. This may suggest a real difference between the utility parameters that apply in intertemporal and probabilistic settings.

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 results at the group level and individual level. Section 5 provides a brief discussion of arbitrage opportunities in monetary experiments and Section 6 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.[7] 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 subjects with a budget of experiment '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. We will refer to this method of eliciting preferences as the Convex Time Budget (CTB) approach.

Substantial information on intertemporal preferences can be obtained from allocations in this convex choice environment. Variations to delay lengths, k, and interest rates, $(1+r)$, allow

[7]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 laboratory offered interest rates 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 Section 5.

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.

t and k: 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.[8] Thus there are nine (t, k) cells and within each cell are 5 CTB questions, generating 45 choices for each subject. We term each (t, k) combination a 'choice set'. The choice of t and k combinations was determined by the academic calendar. Payment dates were set 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.

Tokens and Interest Rates: 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 \$.20 per token and a_t varied from \$.20 to \$.10 per token.[9] Note that $a_{t+k}/a_t = 1 + r$, the gross interest rate over k days, and $(1 + r)^{1/k}$ 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

[8] 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.

[9] In eight of 45 choices, a_{t+k} was \$.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 every choice, she would earn at least \$10.

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.

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 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.

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
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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
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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

2.2.2 Experimental Payments

We employed six measures intended to equalize the costs of receiving payments. These measures not only serve to equate transactions costs over sooner and later payments, but also to increase confidence that future payments would 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.[10] Eliminating payments in the lab ensures that subjects do not disproportionately prefer present in-lab payments because they are somehow more likely to be paid 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. All experimental earnings were added to these $5 thank-you payments, such that subjects would receive at least $5 sooner and at least $5 later, regardless of their choices.

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 the amounts written in their own handwriting when payments arrived.

Fifth, one choice for each subject was chosen 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 university credit union.[11] Individuals were informed that they could cash their checks (if they so desired) at the university credit union.

Sixth, subjects were given the business card of Professor James Andreoni and told to call

[10]See Appendix Section A.1 for the information provided to subjects.

[11]Payment choice was guided by a separate survey of $N = 249$ 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.

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 in future payments.

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. 97% of respondents replied yes.

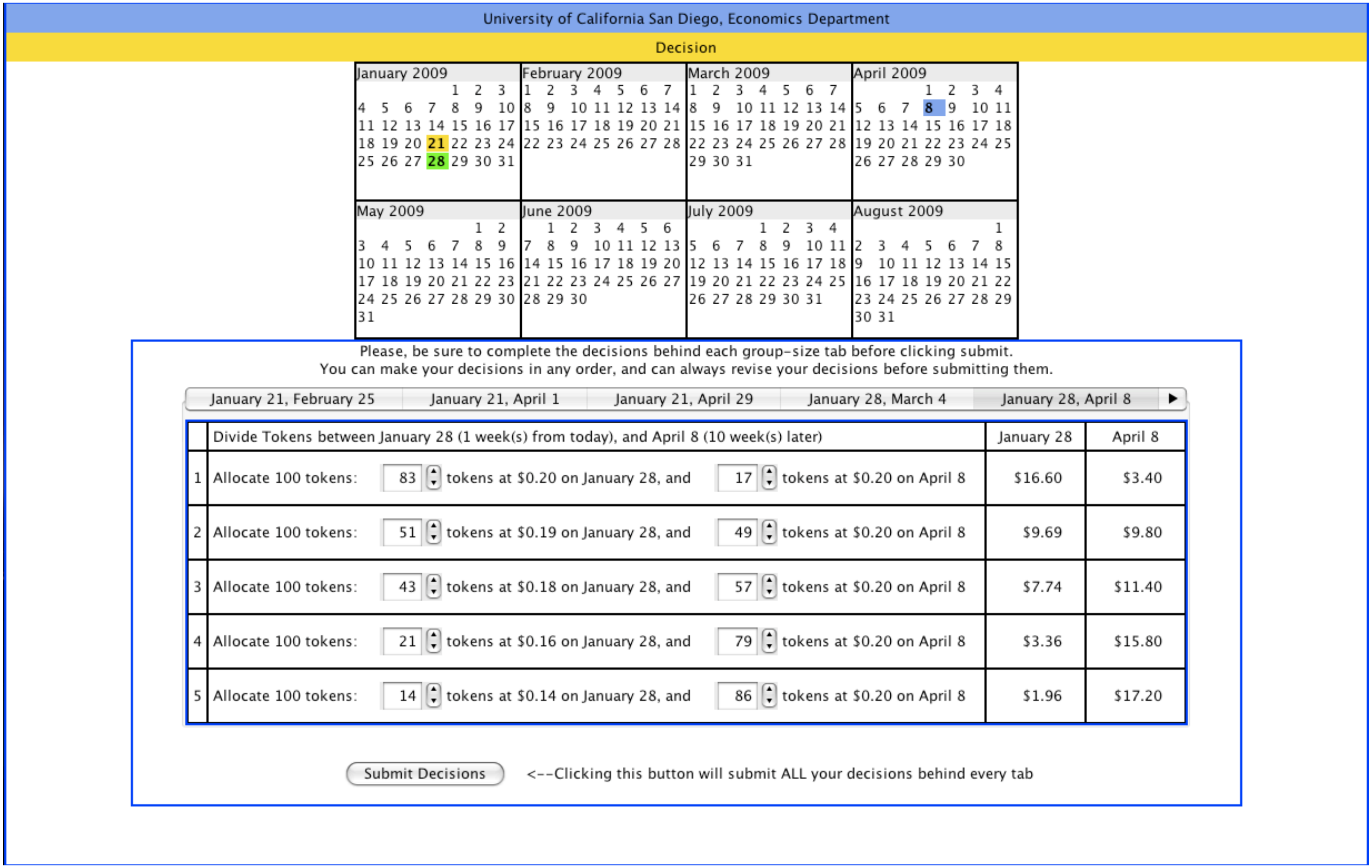
2.2.3 Protocol

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 subject choices, and administered a post-experiment questionnaire.

Upon starting the experiment, subjects read through directions and CTB examples. The directions were read aloud and projected on a screen. In the CTB experiment, subjects' decision screens displayed a dynamic calendar and a series of nine "decision tabs." These decision tabs corresponded to the nine CTBs described above, one decision 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.[12] An image of the subjects' decision screen is presented in Figure 1.

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

Figure 1: Sample Decision Screen



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}.[13] As each budget decision was being made, the calendar in the subjects' screen would highlight 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.[14]

2.2.4 Background Consumption and DMPL

At the end of the computer-based CTB experiment, subjects were administered an auxiliary questionnaire. Importantly, subjects were asked how much they usually spend in a normal week. The average response was \$49.32 per week or \$7.05 per day. This figure is used later in our analysis (see Section 4.1.2).

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 HL risk price lists were designed to elicit curvature over \$20 and \$25, respectively.[15] The results of these additional measures are analyzed in Section 4.2.1.

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 and curvature of the utility function. Following convention, we posit a time separable,

[13] 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.

[14] 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").

[15] The MPLs and HLs could also be chosen at random for payment. For directions and the price list tasks see Appendix Section A.2.

exponentially discounted CRRA utility function,

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

where c_t and c_{t+k} are experimental earnings, α is a curvature parameter and δ is a one period discount factor. ω_1 and ω_2 are additional utility parameters which could be interpreted as classic Stone-Geary minima.[16]

Maximizing (3) subject to the future value budget (2) yields the intertemporal formulation of a Stone-Geary linear demand for c_t:

$$c_t = [\frac{1}{1 + (1+r)(\delta^k(1+r))^{(\frac{1}{\alpha-1})}}]\omega_1 + [\frac{(\delta^k(1+r))^{(\frac{1}{\alpha-1})}}{1 + (1+r)(\delta^k(1+r))^{(\frac{1}{\alpha-1})}}](m - \omega_2).$$

Notice the parameters (δ, α) and the data (r, k) enter into the demand function in a non-linear fashion.[17] For simplicity, rewrite this demand function as

$$c_t = g(m, r, k; \delta, \alpha, \omega_1, \omega_2). \tag{4}$$

In the following section we discuss estimation of the parameters δ, α, ω_1 and ω_2.

3.1 Estimation of Intertemporal Preferences

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 (4) but that these decisions are made with some mean-zero, potentially correlated error. That is,

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

[16]Similar utility parameters are used in Andersen et al. (2008). In their construction experimental earnings are added to background consumption, B, and utility does not have a Stone-Geary interpretation. For comparison to these results, one should set $\omega_1 = \omega_2 = -B$. 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.

[17]In a Stone-Geary expenditure system, demands are linear in m, ω_1, and ω_2.

Stacking the P observations for individual j, we have

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

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

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

We assume that the terms e_{ij} may be correlated within individuals but that the errors are uncorrelated across individuals, $E(\mathbf{e_j'e_k}) = 0$ for $j \neq k$. 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 $S(m, r, k; \delta, \alpha, \omega_1, \omega_2)$ as the sum of squared residuals,

$$S(m, r, k; \delta, \alpha, \omega_1, \omega_2) = \sum_{j=1}^{N} \sum_{i=1}^{P} (c_{t_{ij}} - g(m, r, k; \delta, \alpha, \omega_1, \omega_2))^2, \tag{5}$$

and minimize $S(\cdot)$ using non-linear least squares with standard errors clustered on the individual level to obtain $\hat{\delta}$, $\hat{\alpha}$, $\hat{\omega}_1$ and $\hat{\omega}_2$.[18] 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. Provided additional assumptions on the individual covariance matrix $\mathbf{V_j}$, individual parameter estimates can also be obtained (see Section 4.2).

[18]NLS procedures permitting the estimation of preference parameters at the aggregate or individual level are implemented in many standard econometrics packages (e.g., *Stata*) and the single line of NLS code is available from the authors.

4 Experimental Results

The results are presented in two sections. To begin, we present aggregate CTB data and provide estimates of aggregate discounting and curvature along with tests of hyperbolic discounting. In a second step, we explore individual level results, estimating preference parameters and comparing the results within-subject to parameters obtained from DMPL methodology.

4.1 Aggregate Results

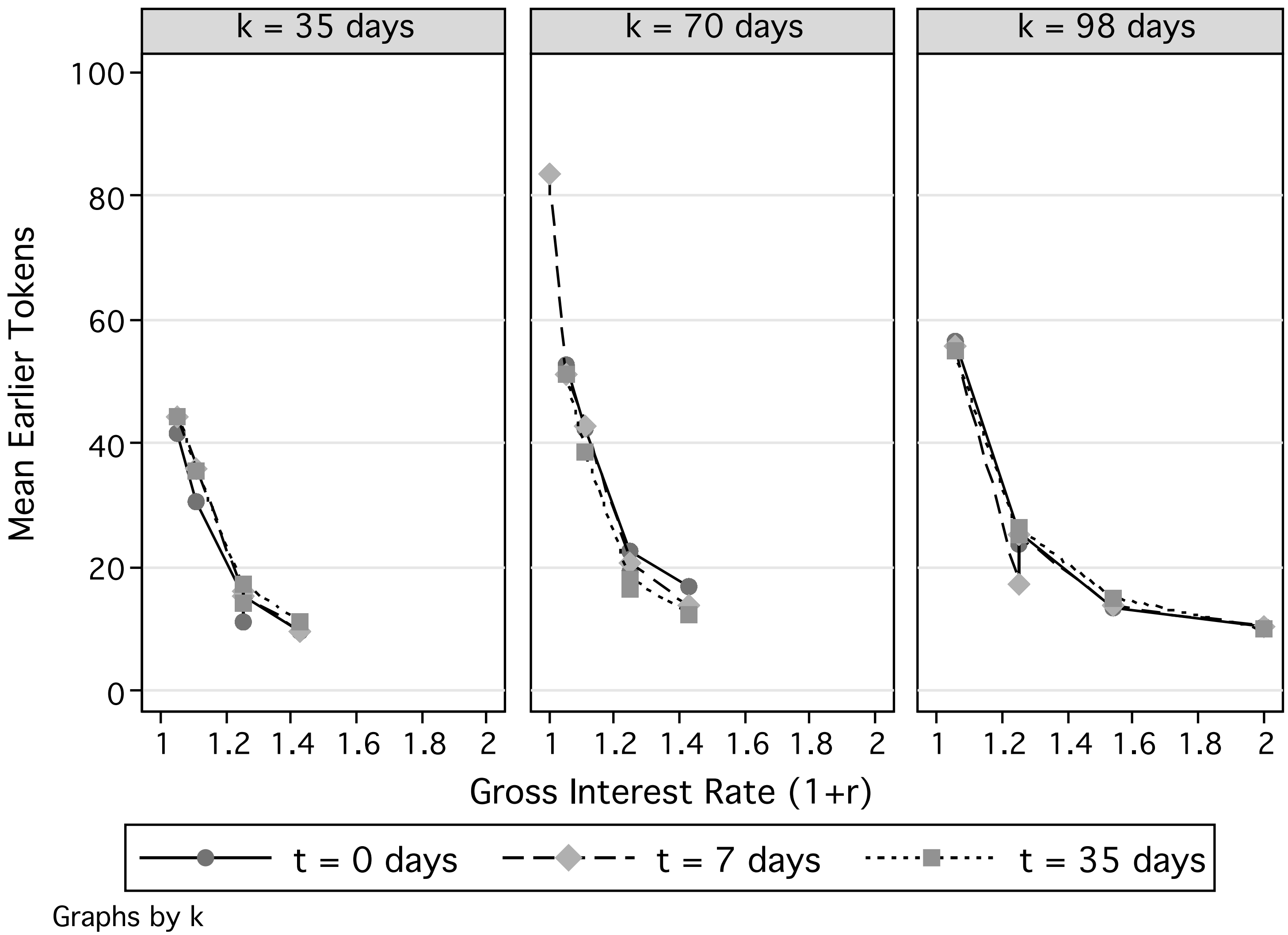
We identify experimental allocations as solutions to standard intertemporal optimization problems. These solutions are functions of our parameters of interest (discounting and curvature), and experimentally varied parameters (interest rates and delay lengths). Our experimental results should mirror this functional relationship. In Figure 2 we plot the mean number of chosen earlier tokens 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 length. Surprisingly, Figure 2 reveals no evidence of present bias or hyperbolic discounting. Evidence for these phenomena would be observed 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.

Figure 2 provides critical support for our solution function estimation strategy as aggregate choices respond to both changing interest rates and delay lengths. Figure 2 also provides support for estimating dynamically consistent preferences as no initial indications of aggregate present bias or hyperbolic discounting are observed.[19]

[19] Additionally, there is support for estimating the homothetic (CRRA) utility function motivated in Section 3 as the mean number of earlier tokens does not change appreciably with increased income.

Figure 2: Mean Experimental Responses Over Time



4.1.1 Estimating Aggregate Preferences

Table 2 presents estimates of aggregate preference parameters. To begin, we assume a standard exponential discount factor, δ, a single curvature parameter, α, and background parameters, ω_1 and ω_2. In column (1) of Table 2, the annual discount rate, utility function curvature and background parameters, $\hat{\omega}_1$ and $\hat{\omega}_2$, are estimated by non-linear least squares using the criterion function stated in (5) with clustered standard errors.

Table 2: Discounting and Curvature Parameter Estimates

	(1)	(2)	(3)	(4)
Annual Discount Rate	0.298	0.367	0.359	0.207
	(0.063)	(0.088)	(0.093)	(0.127)
Curvature Parameter: $\hat{\alpha}$	0.921	0.922	0.897	0.710
	(0.006)	(0.005)	(0.008)	(0.017)
$\hat{\omega}_1$	1.372			
	(0.276)			
$\hat{\omega}_2$	0.184			
	(1.614)			
$\hat{\omega}_1 = \hat{\omega}_2$		1.356	0	-7.046
		(0.279)	-	-
R-Squared	0.4909	0.4907	0.4870	0.4487
Root MSE	6.11	6.11	6.13	6.35
N	4365	4365	4365	4365
Clusters	97	97	97	97

Notes: NLS Solution Function Estimators. Column (1): Unrestricted regression. Column (2): Regression with restriction $\omega_1 = \omega_2$. Column (3): Regression with restriction $\omega_1 = \omega_2 = 0$. Column (4) 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.

We identify two main results. First, the aggregate annual discount rate is estimated at 0.298 (s.e. 0.063). This discount rate is substantially lower than those estimated by most other researchers, excepting most prominently Anderson, et al

We identify two main results. First, the aggregate annual discount rate is estimated at

0.298 (s.e. 0.063). This discount rate is substantially lower than those estimated by most other researchers, excepting most prominently Andersen et al. (2008). Second, aggregate curvature is precisely estimated at $\hat{\alpha} = 0.921$ (s.e. $= 0.006$). The curvature parameter is found to be significantly different from 1 ($F_{1,96} = 155.17,\ p < .01$), but far closer to linear utility than estimated from the DMPL approach employing HL risk measures. For comparison, using DMPL methodology with a representative sample of Danish consumers, Andersen et al. (2008) find a coefficient of relative risk aversion of 0.741, implying a curvature parameter of 0.259. When allowing for this level of curvature and setting $\omega_1 = \omega_2$ 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.

In column (1) of Table 2, we report estimates of both background parameters $\hat{\omega}_1$ and $\hat{\omega}_2$. The values are positive, but low; and the hypothesis that $\omega_1 = \omega_2$ is not rejected ($F_{1,96} = 0.56,\ p = 0.46$). In column (2) we report estimates of an identical NLS procedure with the restriction that $\omega_1 = \omega_2$ and obtain very similar results. The estimated discount rate is lower than most previous experimental studies and estimated curvature is closer to linear than that estimated from the DMPL approach.

4.1.2 The Effect of Background Consumption

Background consumption parameters pose an important challenge for experimental 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 equal to *negative* the average value of daily consumption (Andersen et al., 2008).

Columns (3) and (4) of Table 2 examine whether our results are influenced by such simplifications. We estimate non-linear least squares regressions identical to column (2) and impose varying restrictions on the value of background consumption. In column (3) of Table 2, the imposed restriction is $\omega_1 = \omega_2 = 0$. In column (4) of Table 2 we restrict $\omega_1 = \omega_2 = -7.05$, which is minus the average daily value of self-reported spending obtained from an auxiliary survey of our subjects.

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 background parameter moves from 0 to minus the average daily consumption.

To better understand the degree to which estimated parameters are influenced by the choice of background parameter values, we additionally estimate with ω_1 and ω_2 equal to minus half the average daily spending and minus twice the average daily spending. When $\omega_1 = \omega_2 = -3.52$ the estimated annual discount rate is 0.287 and curvature is 0.812. When $\omega_1 = \omega_2 = -14.09$ the estimated annual discount rate is 0.127 and curvature is 0.517. Estimated patience and curvature are notably sensitive to changes in chosen background parameters.[20]

These results suggest that the choice of background parameters is potentially of great importance.[21] Our methodology and estimation strategy allow not only for imposing different restrictions on background parameters, but also for estimating them. Thus, different levels of background parameters can be compared to an estimated baseline both in terms of resulting preference estimates and goodness of fit.

4.1.3 Hyperbolic Discounting and Present Bias

Time discount functions are frequently argued to follow a hyperbolic or present-biased pattern (Thaler, 1981; Laibson, 1997; O'Donoghue and Rabin, 1999). Individuals are suggested to be impatient in the present, but relatively patient in the future. Such dynamic inconsistency is argued to at least partially account for the high average discount rates obtained in experimental

[20] In Appendix Table A1, we demonstrate the effect of changing the values of ω_1 and ω_2 on estimated preference parameters and goodness of fit. The results indicate substantial sensitivity of estimated parameters (particularly curvature) to increasingly negative values of ω_1 and ω_2. Corresponding R^2 values diminish accordingly.

[21] Andersen et al. (2008) do some sensitivity analysis and show that estimated risk preferences do vary with background consumption, though discount rates in their estimation strategy are less sensitive.

studies (Frederick et al., 2002). Our experimental design and estimation methodology provide a simple framework in which to test hypotheses of present bias and hyperbolic discounting.

Under hyperbolic discounting, estimated discount rates should be highest when $t = 0$, lower when $t = 7$ and even lower when $t = 35$. Columns (1) and (2) of Table 3 follow the estimation strategies of Table 2 columns (1) and (2), but estimate separate discount rates for each value of t. The hyperbolic pattern of discounting is not observed and the three estimated values of the discount rate do not differ significantly ($F_{2,96} = 1.85,\ 2.25;\ p = .16,\ .11$, respectively).

Likewise, if individual discounting is quasi-hyperbolic, then estimated discount rates should be higher when $t = 0$ and lower when $t = 7$ and $t = 35$. Columns (3) and (4) of Table 3 estimate two separate discount rates: one for $t = 0$ and one for $t \neq 0$. The two estimated discount rates are virtually identical ($F_{1,96} = 0.34,\ 0.37;\ p = 0.56,\ 0.55$, respectively). The calculated present bias parameter, $\hat{\beta} = \hat{\delta}_{t=0}/\hat{\delta}_{t\neq 0}$, and its standard error (obtained via the delta method), indicate an aggregate point estimate of $\beta = 1$ with a standard error of 0.000. Our data thus provide evidence that is fully supportive of time consistency with no present bias.

This 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 of the risk of receiving experimental payments (Halevy, 2008).[22] Keren and Roelofsma (1995) and Weber and Chapman (2005) find that when applying increasing levels of risk to both present and future payments, present bias decreases substantially. Our experimental methodology is designed to eliminate differential risk between sooner and later payments. Indeed, in Andreoni and Sprenger (2009b) 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 our findings, many others exist. Principal among these explanations is that present bias is a

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

Table 3: Hyperbolic Discounting and Present Bias

	(1)	(2)	(3)	(4)
Annual Rate$_{t=0}$	0.283	0.352	0.285	0.353
	(0.060)	(0.091)	(0.060)	(0.091)
Annual Rate$_{t=7}$	0.329	0.401		
	(0.068)	(0.088)		
Annual Rate$_{t=35}$	0.267	0.335		
	(0.069)	(0.094)		
Annual Rate$_{t\neq 0}$			0.303	0.372
			(0.067)	(0.089)
Present Bias Parameter: $\hat{\beta}$			1.000	1.000
			(0.000)	(0.000)
$\hat{\alpha}$	0.920	0.921	0.921	0.922
	(0.006)	(0.006)	(0.006)	(0.005)
$\hat{\omega}_1$	1.373		1.371	
	(0.276)		(0.276)	
$\hat{\omega}_2$	0.167		0.185	
	(1.624)		(1.622)	
$\hat{\omega}_1 = \hat{\omega}_2$		1.356		1.355
		(0.279)		(0.278)
F- Statistic (H_0 : Equality)	1.85	2.25	0.34	0.37
p-value	0.16	0.11	0.56	0.55
R^2	0.4911	0.4910	0.4909	0.4908
N	4365	4365	4365	4365
Clusters	97	97	97	97

Notes: NLS Solution Function Estimators. Columns (1-2): Estimation of discounting by t (F-test for Annual Rate$_{t=0}$ = Annual Rate$_{t=7}$ = Annual Rate$_{t=35}$). Columns (3-4): Present Bias in Discounting (F-test for Annual Rate$_{t=0}$ = Annual Rate$_{t\neq 0}$). Clustered standard errors in parentheses. Annual discount rate calculated as $(1/\hat{\delta})^{365} - 1$, $\hat{\beta}$ calculated as $\hat{\delta}_{t=0}/\hat{\delta}_{t\neq 0}$; standard errors calculated via the delta method.

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

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

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 making and reward receipt, present bias may be effectively eliminated. This suggests that the visceral present-biased reaction to immediacy may pass quickly. 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.

4.2 Individual Results

Here we present estimates of discounting and curvature parameters at the individual level. Each subject makes 45 CTB decisions in 9 (t, k) choice sets. In order to estimate time preferences at the individual level, we take $\mathbf{V_j}$ to be a block diagonal matrix of choice set level clusters.[24]

For each subject, we estimate the parameters of $g(\cdot)$, defined by (4). To limit the number of estimated parameters, we restrict $\omega_1 = \omega_2 = 1.356$ as obtained in Table 2, column (2). The parameters $\hat{\delta}$, $\hat{\alpha}$ are estimated by non-linear least squares with standard errors clustered on the choice set level. For each individual, the annual discount rate is calculated based on $\hat{\delta}$ with standard errors obtained via the delta method.

Time preference and curvature parameters are estimable for 89 of 97 subjects.[25] The results are broadly consistent with those estimated at the aggregate level. The median estimated annual discount rate is 32.3%, close to the aggregate values obtained in Table 2. The median estimated $\hat{\alpha}$ is 0.975, suggesting that individual curvature, like aggregate curvature, is limited.[26]

Table 4 reports the median value and the 5th-95th percentile range for individual estimates

certificates directly after the experiment.

[24]Though one could assume a diagonal matrix and estimate preference parameters accordingly, we prefer this specification. In each choice set there are 5 decisions with responses and therefore errors that are potentially correlated.

[25]We do not study the 8 remaining subjects. Seven of these subjects had zero variance in their experimental responses, taking the same number of sooner tokens in all 45 questions. The last remaining subject gave an identical pattern of sooner token choices in every CTB: 4 tokens in the first decision, 3 in the second, 2 in the third, 1 in the fourth and 0 in the fifth. Re-estimating aggregate parameter measures without these individuals does not qualitatively change the results (available on request).

[26]As a robustness test we also estimate with $\omega_1 = \omega_2$ unrestricted. We are able to estimate for only 87 individuals and outlier estimates become more extreme. However, the median estimated discount rate is 32.1% and the median estimated curvature is 0.975, similar to the values obtained in Table 4.

of the annual discount rate, $\hat{\delta}$ and $\hat{\alpha}$ along with the minimum and maximum values estimated. For the majority of subjects, the employed estimation strategy works well, generating reasonable parameter estimates. However, extreme observations do exist. Ranges for estimated standard errors are also presented. Though median standard errors are low, there are some individuals for whom parameters are imprecisely estimated. Estimation results for all subjects are in Appendix Tables A2 - A5.

Table 4: Individual Discounting and Curvature Parameter Estimates

	Median	5th Percentile	95th Percentile	Min	Max
Annual Discount Rate	.3234	-.1340	8.8873	-.9909	28.3541
Annual Discount Rate$_{SE}$	.0841	0	4.7875	0	16.299
$\hat{\delta}$	.9992	.9937	1.0004	.9908	1.013
$\hat{\delta}_{SE}$	.0002	0	.0022	0	.0172
$\hat{\alpha}$	.9749	.7359	.9996	.2786	.9998
$\hat{\alpha}_{SE}$	.0085	0	.0627	0	.3387

Notes: NLS solution function estimators with restriction $\omega_1 = \omega_2 = 1.356$. Standard errors clustered on the choice set level. Percentiles calculated from 89 individual-level estimates.

4.2.1 Correlation Between CTB Parameter Estimates and DMPL Calculations

As an auxiliary test of the CTB design and estimation strategy, we compare individual discounting and curvature parameter estimates to those calculated from standard binary MPL and HL experiments, the components of the DMPL.

Three standard multiple price lists and two Holt-Laury risk price lists were administered to all subjects. From the three price lists, we calculate daily discount factors following standard practice[27] and examine the average, d. From the two Holt-Laury risk price lists, we calculate curvature parameters following standard practice[28] and examine the average, a. In both MPLs

[27] Given a switching point, X, a later payment, Y, and a delay length, k, we calculate the daily discount factor as $d = (X/Y)^{1/k}$. This is equivalent to positing a linear utility function and zero background consumption.

[28] Given a switching probability pair, $(p, 1-p)$, and two Holt-Laury lotteries, A and B, we take the value a

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 $\hat{\delta}$, 87 of 89 have a calculable discount factor, d. The median value implies an annual discount rate of 137 percent; in line with the very high observed discount rates in MPL experiments. We can also test for present bias in the MPLs by comparing the $(t = 0, k = 35)$ MPL to the $(t = 35, k = 35)$ MPL. Fifteen of 87 subjects (17%) are classified as present-biased, $(d_{(t=0,k=35)} < d_{(t=35,k=35)})$, and the average present bias parameter is 0.9997, (s.e. 0.0002). For comparison, using similar MPL methodology Ashraf, Karlan and Yin (2006); Dohmen, Falk, Huffman and Sunde (2006) and Meier and Sprenger (2010), find around 30-35% of subjects to be present-biased and average present bias parameters substantially lower than one. This further supports the notion that something associated with our experimental methodology is limiting present bias in this setting. Of the subjects for whom we estimate $\hat{\alpha}$, 80 of 89 have a calculable curvature parameter, a. The median value is 0.5125 indicating substantial concavity of the utility function, in line with prior findings using HL risk measures.

that equates the expected utility of lottery A and lottery B. Following standard practice, we take the midpoint of the interval in which this value lies as the calculated curvature parameter, a.

Figure 3: Comparison of CTB Estimates and DMPL Calculations

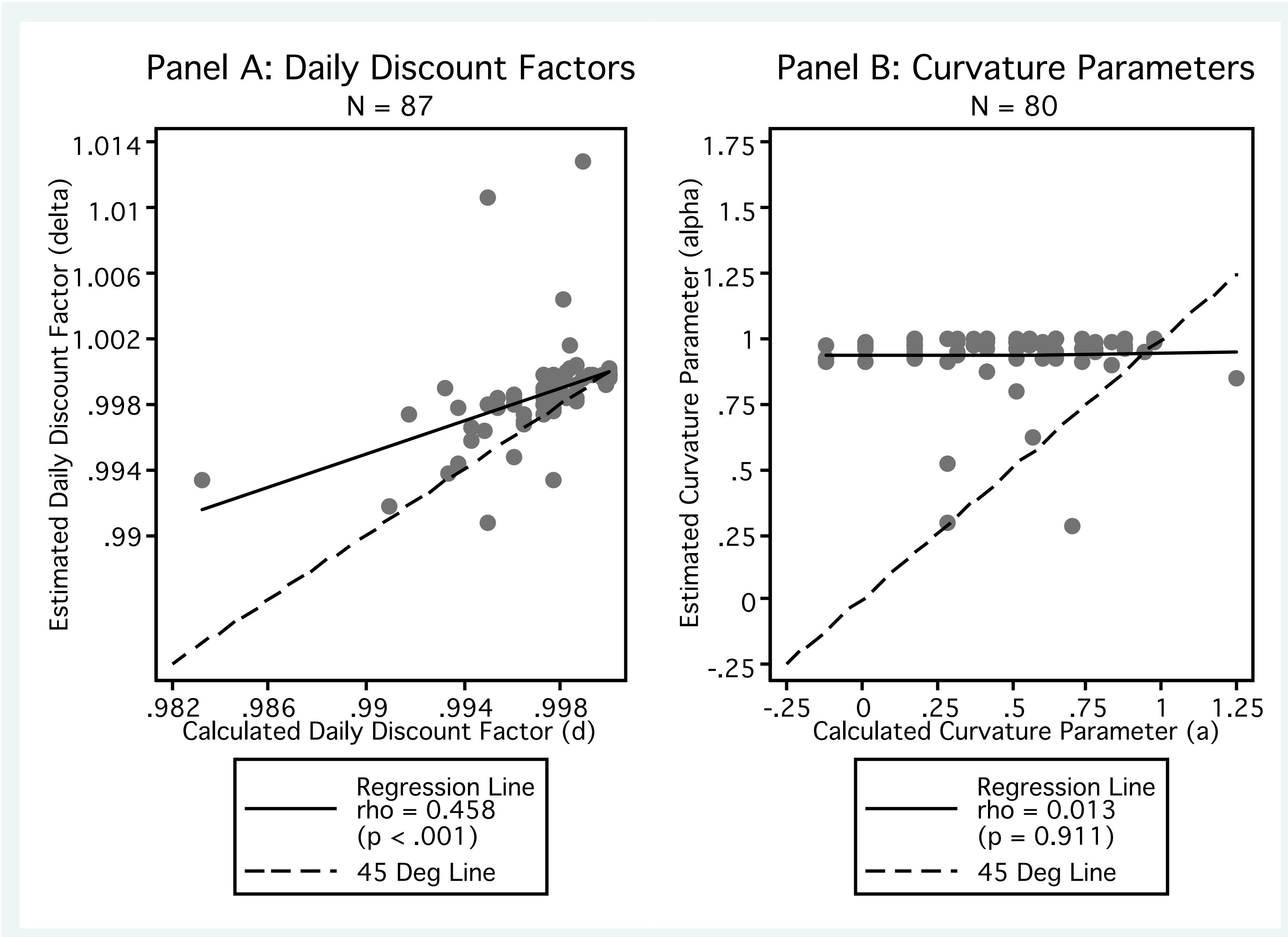


Figure 3 plots calculated and estimated parameters against each other. In Panel A the calculated discount factor, d, is plotted against the estimated parameter, $\hat{\delta}$, along with an estimated regression line. Panel B is similar for a and $\hat{\alpha}$. The 45 degree line is also presented to see how far the data lie from $d = \hat{\delta}$ and $a = \hat{\alpha}$.

Panel A of Figure 3 shows substantial observable correlation between MPL calculated and CTB estimated discount factors ($\rho = 0.458,\ p < 0.001$). However, most of the data lies above the 45 degree line indicating the the discount factor accounting for curvature is greater than the discount factor assuming linear utility. This is consistent with standard bias 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 the bias. This bias measure is negatively correlated with $\hat{\alpha}$, ($\rho = -0.618,\ p < 0.001$), such that subjects who are closer to linear utility will have less biased MPL-calculated discount factors. This indicates that, though biased, standard MPLs do yield measures of time preferences that correlate with true patience and that the bias attenuates in a predictable way with utility function curvature.

Interestingly, in Panel B of Figure 3, Holt-Laury calculated curvature and CTB estimated curvature show little observable correlation ($\rho = 0.013,\ p = 0.911$). This is surprising because under CRRA expected 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 individual correlation is remarkably small.[29] This second finding suggests that the practice of using Holt-Laury *risk* experiments to identify curvature in *discounting* may be problematic.

5 About Arbitrage

A relevant issue with monetary time preference experiments, as opposed to experiments with primary consumption, is that, in theory, monetary payments should be subject to extra-lab arbitrage opportunities. Subjects who can borrow (save) at an external interest rate inferior

[29] Additionally, Holt-Laury measured curvature does not correlate with the bias in discount factors discussed above ($\rho = 0.097,\ p = 0.401$).

(superior) to the lab-offered rate should arbitrage the lab by taking the later (sooner) experimental payment. As such, measured discount rates in monetary experiments 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 such, one might expect limited present bias in monetary discounting experiments.

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, Sapienza and Zingales, 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.

6 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 Holt-Laury risk measures.

We propose a single simple instrument that can identify discounting and utility function curvature at the aggregate and individual level, what 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 dynamic inconsistency such as present bias and hyperbolic discounting 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 level. 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. Additionally, we find no evidence of present bias or hyperbolic discounting. In fact, parameter estimates are remarkably 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 our estimated utility function curvature.

Our results raise a number of interesting questions. First, why did we find no evidence of present bias? We argue that this may be related to the steps we took to equate transaction costs of sooner and later payments. Future work with CTBs and other aspects of our methodology are necessary to understand how dynamic inconsistency appears in the lab. Second, why do we find substantial differences between our estimates and those obtained with DMPL methodology? It is important to know whether these results are due to differential stimuli (computer interface vs. paper-and-pencil) or if they are robust to a common elicitation environment. Third, why is the curvature estimated from CTBs virtually uncorrelated with HL risk measures? Exploring the relationship between curvature in intertemporal settings and risk aversion in probabilistic settings is an important next step, which we take up in Andreoni and Sprenger (2009b).

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A Appendix

A.1 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.1.1 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.2 Multiple Price Lists and Holt Laury Risk Price Lists

NAME: ______________________________________ PID:______________________

<u>How It Works:</u>

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 **today** or the larger payment for sure in **fourteen weeks**? 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 **today**	or	☐ $20 in **fourteen weeks**
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.3 Appendix Tables

Table A1: Background Consumption, Parameter Estimates and Goodness of Fit

(1)	(2)	(3)	(4)	(5)
$\omega_1 = \omega_2$	Discount Rate (s.e.)	$\hat{\alpha}$ (s.e)	Root MSE	R^2
-26	.091	.226	6.46	.43
	(.149)	(.045)		
-24	.094	.273	6.46	.431
	(.149)	(.042)		
-22	.098	.321	6.45	.431
	(.148)	(.039)		
-20	.103	.369	6.45	.432
	(.147)	(.036)		
-18	.109	.418	6.44	.433
	(.146)	(.033)		
-16	.117	.468	6.44	.434
	(.144)	(.03)		
-14	.128	.519	6.43	.436
	(.142)	(.027)		
-12	.142	.572	6.41	.438
	(.14)	(.024)		
-10	.162	.626	6.4	.441
	(.136)	(.021)		
-8	.19	.682	6.37	.446
	(.131)	(.018)		
-6	.228	.741	6.33	.452
	(.123)	(.015)		
-4	.275	.799	6.28	.462
	(.113)	(.012)		
-2	.324	.852	6.2	.474
	(.102)	(.01)		
0	.359	.897	6.13	.487
	(.093)	(.008)		
2	.364	.932	6.11	.49
	(.086)	(.008)		
4	.337	.96	6.26	.464
	(.082)	(.008)		
6	.313	.976	6.72	.384
	(.083)	(.007)		

Notes: NLS solution function estimators with restriction $\omega_1 = \omega_2$ equal to column (1). Clustered standard errors in parentheses. Annual discount rate calculated as $(1/\hat{\delta})^{365} - 1$, standard errors calculated via the delta method.

Table A2: Individual Estimates 1

Subject #	Annual Rate (S.E)	$\hat{\alpha}$ (S.E)
1	.184	.982
	(.077)	(.014)
2	.75	.978
	(.152)	(.01)
3	.96	.99
	(.273)	(.008)
4	.481	.954
	(.205)	(.012)
5	.114	1
	(0)	(0)
6	.1	1
	(0)	(0)
7	.295	.986
	(.027)	(.006)
8	1.949	.927
	(.374)	(.031)
9	.114	1
	(0)	(0)
10		
11	1.052	.986
	(.108)	(.004)
12	2.196	1
	(.)	(.)
13	.323	.999
	(.013)	(0)
14	10.636	.85
	(12.818)	(.051)
15	.99	.985
	(.144)	(.011)
16	.316	.931
	(.06)	(.006)
17	.872	.977
	(.233)	(.012)
18	10.262	.943
	(3.327)	(.019)
19	1.035	.914
	(.296)	(.029)
20	-.083	.956
	(.169)	(.032)
21	1.709	.961
	(.321)	(.016)
22	6.05	.806
	(4.419)	(.074)
23	.711	1
	(.005)	(0)
24	.114	1
	(0)	(0)
25	.114	.999
	(0)	(0)

Table A3: Individual Estimates 2

Subject #	Annual Rate (S.E)	$\hat{\alpha}$ (S.E)
26	.128	1
	(0)	(0)
27	1.161	.984
	(.083)	(.007)
28	2.85	.949
	(.501)	(.007)
29		
30	.594	.928
	(.174)	(.016)
31	.145	.981
	(.051)	(.008)
32	.851	.972
	(.108)	(.005)
33	.78	.963
	(.344)	(.02)
34	28.354	.941
	(8.873)	(.014)
35		
36	.114	1
	(0)	(0)
37	.703	.991
	(.174)	(.054)
38	-.801	.279
	(.261)	(.339)
39	.776	.922
	(.181)	(.013)
40	.114	1
	(0)	(0)
41	2.229	.903
	(.574)	(.016)
42	1.249	.951
	(.202)	(.008)
43	1.087	.952
	(.225)	(.018)
44	.303	.999
	(.007)	(0)
45	.079	.921
	(.037)	(.009)
46	-.979	.3
	(.039)	(.326)
47	.305	.984
	(.076)	(.009)
48		
49	1.26	.962
	(.309)	(.007)
50	.165	.969
	(.146)	(.027)

Table A4: Individual Estimates 3

Subject #	Annual Rate (S.E)	$\hat{\alpha}$ (S.E)
51	19.593 (16.299)	.918 (.016)
52	.714 (.004)	1 (0)
53	1.629 (.783)	.869 (.039)
54	.214 (.012)	.981 (.011)
55	.209 (.166)	.968 (.019)
56	1.151 (.104)	.986 (.007)
57	-.042 (.084)	.973 (.015)
58	.301 (.011)	.999 (0)
59	-.991 (.056)	.736 (.271)
60	6.853 (4.787)	.909 (.06)
61	1.633 (.291)	.922 (.013)
62	-.134 (.158)	.527 (.052)
63	.544 (.135)	.803 (.004)
64	.893 (.15)	.983 (.005)
65	.092 (0)	1 (0)
66	1.185 (.321)	.87 (.01)
67	.28 (.1)	.964 (.011)
68	.114 (0)	.999 (0)
69	.114 (0)	1 (0)
70	3.655 (.415)	.926 (.02)
71	.114 (0)	1 (0)
72	8.887 (4.813)	.944 (.028)

Table A5: Individual Estimates 4

Subject #	Annual Rate (S.E)	$\hat{\alpha}$ (S.E)
73	.114	.999
	(0)	(0)
74	.114	1
	(0)	(0)
75	.147	.974
	(.039)	(.012)
76	-.428	.778
	(.218)	(.063)
77	.114	1
	(0)	(0)
78	0	.998
	(0)	(0)
79		
80	.078	.975
	(.043)	(.01)
81	.813	.931
	(.216)	(.019)
82	.261	.619
	(.098)	(.026)
83	.114	1
	(0)	(0)
84		
85	.005	.984
	(.008)	(.004)
86	.114	1
	(0)	(0)
87		
88	1.372	.972
	(.192)	(.008)
89	.114	1
	(0)	(0)
90	2.563	.917
	(.936)	(.029)
91	.666	.957
	(.066)	(.007)
92	1.077	.979
	(.079)	(.005)
93		
94	.114	1
	(0)	(0)
95	.114	1
	(0)	(0)
96	.426	.957
	(.074)	(.01)
97	.903	.998
	(.018)	(0)