Avoiding the Curves

Direct Elicitation of Time Preferences

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Abstract We propose and test a new method for eliciting curvature-controlled discount rates that are invariant to the form of the utility function. Our method uses a single elicitation task and has the advantage of obtaining individual discount rates without knowledge of risk attitude or parametric assumptions about the form of the utility function. We compare our method to a double elicitation technique in which the utility function and discount rate are jointly estimated. We use a laboratory experiment to perform a within-subjects comparison of discount rates from these two methods and find consistent results, which is reassuring given the wide range of estimates in the literature. In addition, the estimated discount rates in our study are "plausibly low" in contrast to the vast majority of discount rate studies. Our results are robust to relaxing the expected utility assumption of linearity in the probabilities, as we find little evidence of probability weighting in our data. In a second experiment, we find that discount rates are not sensitive to the length of the horizon, but are sensitive to the length of the front-end delay, suggesting present bias. We estimate average discount rates to be 12.2 percent in the first experiment and 11.3 percent in the second experiment when the front-end delay is at least two weeks.

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1 Introduction

A better understanding of how people weigh future consumption against current consumption is crucial to understanding many economic decisions. These decisions are important at both the individual level (e.g., how much one should invest in education, health care and savings) and the societal level (e.g., how much to invest in environmental preservation or damage amelioration). That said, there is no clear consensus regarding the amount by which future consumption is discounted. Reported discount rates have ranged from negative six percent to essentially infinity in various studies.[1] The disparity in observed discount rates is not entirely surprising given the methodological differences across studies. Differences include the source of data (field, survey, or laboratory), the type of good studied (including goods as diverse as appliances, money, pain in the form of electric shock, or heroin), and whether the observed choices have real consequences.

A recent focus of discount rate research addresses an important confound in most of the earlier literature. Previous estimates, such as those from the widely-cited Coller and Williams (1999) study, assume preferences are linear in wealth. Linear preferences are consistent with a risk-neutral decision maker; however, many studies provide direct evidence of widespread risk aversion, even over small monetary outcomes (e.g., Binswanger, 1980; Hey and Orme, 1994). If preferences are in fact concave rather than linear, the result of estimation incorrectly assuming linearity will be a positive bias in estimated discount rates (Andersen et al., 2008). Given that individual risk aversion increases with the size of the stakes (Holt and Laury, 2002), the bias becomes more severe in discount rate experiments that use higher stakes. Thus a more appropriate specification of discount-rate models should include a curvature-correction for such non-linearity in the utility function.

Recent work has suggested approaches to account for the influence of risk aversion on time preferences. Andersen et al. (2008) measure both risk and time preferences for each subject by using the procedure of Coller and Williams (1999)

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[1] See Frederick et al. (2002) for a review of the literature.

to elicit discount rates and the procedure of Holt and Laury (2002) to elicit risk attitudes. By jointly estimating both risk and time preferences, they obtain an estimated aggregate discount rate of 10.1 percent per year, which is significantly lower than under the assumption of linear utility. However, other recent studies that account for the curvature of the utility function in different ways (and also offer real, monetary rewards) have found vastly different results. Takeuchi (2011) uses an alternative procedure to estimate discount rates that is theoretically invariant to utility curvature, and estimates an average annual discount rate of 726 percent. Andreoni and Sprenger (2012) avoid the bias of linear preferences by eliciting time preferences with convex budget sets, and estimate an aggregate discount rate of 30 percent per year. Coble and Lusk (2010) use a joint estimation approach to estimate a Kreps-Porteus model (Kreps and Porteus, 1978) that nests the discounted expected utility model as a special case. Given their assumption of constant elasticity of substitution, they reject the discounted expected utility model and estimate a relatively high discount rate of 51.3 percent. Rohde (2010) presents a theoretical framework for eliciting preferences over outcomes with fixed payoffs but variable delays and using responses to develop the "hyperbolic factor," a measure of the time inconsistency of preferences that does not require specifying or estimating a utility function.

In this paper, we propose and test a new method for eliciting discount rates that yields curvature-controlled discount rates that are invariant to the form of the utility function. Following the suggestion of Frederick et al. (2002, p. 382), our method applies the binary lottery payment approach first used by Roth and Malouf (1979) in studying bilateral bargaining. We measure how much higher the probability of winning a fixed prize must be in order to delay consumption. The advantage of this method is that individual discount rates can be obtained without knowledge of risk attitude or parametric assumptions about the form of the utility function.

We compare our "curvature free" elicitation method to the Andersen et al. (2008) double elicitation technique in which the utility function and discount rates are jointly estimated. We conduct a laboratory experiment to perform a within-subjects comparison of discount rates from these two methods and find consistent results, which is reassuring given the wide range of estimates in the literature. In addition, the estimated discount rates in our study are "plausibly low," in contrast to the vast majority of other discount rate studies. Average discount rates are estimated to be 12.2 percent using our probability discounting elicitation compared to 14.1 percent using joint estimation, and confidence intervals substantially overlap. We find our participants to be risk averse on average, and failing to allow for these non-linear preferences substantially increases the estimated discount rate to 55.5 percent. We consider sensitivity to background consumption and find the jointly estimated discount rates increase modestly as background consumption is increased, while the results from our method are invariant by design. We also consider how our approach is a affected by relaxing the assumption of linearity in the probabilities, but empirically we find little evidence of probability weighting over the range of probabilities used in our experiment.

At the individual level, we find a substantial portion of participants are willing to defer consumption when offered a modest increase in probability of future payment, indicating a very low discount rate. We conduct a second experiment to explore the robustness of this finding and to obtain a within-subjects measure of the sensitivity of the discount rate to both the horizon and the front-end delay. In all treatments, we continue to find a substantial number of very patient participants. We also find evidence in favor of present bias rather than constant time preference.

In Section 2 below we describe an expected utility model with exponential discounting and illustrate our strategy of eliciting time preferences by varying probabilities rather than payoffs. To compare our method with the joint estimation method, we conduct a within-subjects experiment with real-valued payoffs using

both methods, as presented in Section 3. In Section 4, we describe our data, report results from maximum likelihood estimation, and present sensitivity tests. Next, in Section 5, we present a second experiment to measure sensitivity of time preferences to the length of the front-end delay and the time horizon. Section 6 concludes.

2 Theoretical Considerations

We begin by assuming exponential discounting and an additively-separable inter-temporal utility function. In the typical discount rate model, an individual decides between option A which yields extra income M_t at time t and option B which yields $M_{t+\tau}$ at time $t + \tau$ by choosing the option with the larger present value. We can express these present values as

$$PV_A = \left(\frac{1}{1+\delta}\right)^t U\left(\omega + M_t\right) + \left(\frac{1}{1+\delta}\right)^{t+\tau} U\left(\omega\right) \tag{1}$$

and

$$PV_B = \left(\frac{1}{1+\delta}\right)^t U\left(\omega\right) + \left(\frac{1}{1+\delta}\right)^{t+\tau} U\left(\omega + M_{t+\tau}\right), \tag{2}$$

where ω is the time invariant amount of background consumption, δ is the discount rate, and $U(\cdot)$ is the per-period expected utility function. By equating the present value expressions in Equations 1 and 2, we create the following indifference condition

$$U\left(\omega + M_t\right) + \left(\frac{1}{1+\delta}\right)^\tau U\left(\omega\right) = U\left(\omega\right) + \left(\frac{1}{1+\delta}\right)^\tau U\left(\omega + M_{t+\tau}\right), \tag{3}$$

and can now solve for the discount rate δ. If we further assume the utility function is linear in ω (as most discount rate studies do) this equation reduces to

$$M_t = \left(\frac{1}{1+\delta}\right)^\tau M_{t+\tau}. \tag{4}$$

Equation 4 has been the basis for many previous time preference studies. If, how-
ever, preferences are not linear, then Equations 3 and 4 clearly are not the same.
Any analysis incorrectly assuming linearity and applying Equation 4 will yield
upwardly-biased discount rate estimates. To better illustrate this bias, consider a
person who is indifferent between $1 now and $2 in one year. This indifference
condition implies an annual discount rate of 100 percent over *monetary* amounts.
However, concave preferences imply a diminishing marginal utility of money, and
so the utility of $2 in one year is actually less than twice the utility of $1 now.
This, in turn, results in an annual discount rate over *utility values* of less than 100
percent.

One solution to this upward bias of discount rate estimates is to obtain an
estimate of the curvature of the utility function and then apply it to Equation 3.
An alternative solution that is the focus of this paper is to apply the binary lottery
payoff procedure first introduced by Roth and Malouf (1979) to the elicitation of
discount rates.

Continuing with Equation 3, we now hold the amount of extra income constant
$(M_t = M_{t+\tau} = M)$ and instead vary the probability that the payment is made.
Let p_t be the probability of receiving extra income M at time t and $p_{t+\tau}$ be the
probability of receiving extra income at time $t + \tau$. An individual is indifferent
between these two options if

$$p_t U\left(\omega + M\right) + \left(1 - p_t\right) U\left(\omega\right) + \left(\frac{1}{1+\delta}\right)^\tau U\left(\omega\right) =$$
$$U\left(\omega\right) + \left(\frac{1}{1+\delta}\right)^\tau \left[p_{t+\tau} U\left(\omega + M\right) + \left(1 - p_{t+\tau}\right) U\left(\omega\right)\right]. \quad (5)$$

Without loss of generality, we let $U\left(\omega\right) = 0$ and $U\left(\omega + M\right) = 1$, and Equation 5
reduces to

$$p_t = \left(\frac{1}{1+\delta}\right)^\tau p_{t+\tau}. \quad (6)$$

This expression now provides us an approach to estimate discount rates with-
out having to parameterize and estimate the utility function. In Section 3.1 we

develop a simple elicitation procedure for individual discount rates in a manner similar to the widely-used risk aversion elicitation procedure of Holt and Laury (2002). Of course, this approach maintains the expected utility assumption that requires linearity in the objective probabilities.[2] Alternative assumptions about preferences, such as cumulative prospect theory, allow for probability weighting. We address this possibility in Section 2.4 and empirically in Section 4.3. We also consider consumption smoothing, background consumption, and non-exponential discounting.

2.1 Consumption Smoothing

When evaluating intertemporal consumption choices, it seems unduly restrictive to assume away consumption smoothing. Individuals may prefer to spread the consumption of M over several periods. We consider the dual-self model of impulse control proposed by Fudenberg and Levine (2006) and introduced into the context of discounting by Andersen et al. (2008). This model assumes individuals succumb to temptation for immediate gratification when offered short-term gains but are able to plan and smooth consumption when offered gains over a longer term. To apply the dual-self model, we assume that t is sufficiently far in the future that the short-run impulsive "self" is not involved in the decision.[3] Further, we assume that extra income is smoothed evenly over η time periods. Given these assumptions, we rewrite Equation 5 as

$$
p_t \sum_{k=0}^{\eta-1} \left(\frac{1}{1+\delta} \right)^k U\left(\omega + \frac{M}{\eta} \right) + (1-p_t) \sum_{k=0}^{\eta-1} \left(\frac{1}{1+\delta} \right)^k U(\omega) + \left(\frac{1}{1+\delta} \right)^\eta \sum_{k=0}^{\tau-1} \left(\frac{1}{1+\delta} \right)^k U(\omega) =
$$

$$
\sum_{k=0}^{\tau-1} \left(\frac{1}{1+\delta} \right)^k U(\omega) + \left(\frac{1}{1+\delta} \right)^\tau \left[p_{t+\tau} \sum_{k=0}^{\eta-1} \left(\frac{1}{1+\delta} \right)^k U\left(\omega + \frac{M}{\eta} \right) + (1-p_{t+\tau}) \sum_{k=0}^{\eta-1} \left(\frac{1}{1+\delta} \right)^k U(\omega) \right].
$$

$$(7)$$

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[2] Note that our approach does not require that Equation 6 holds for all combinations of p_t and $p_{t+\tau}$. We can cover a broad range of discount rates (0 to 347 percent) by varying p between 0.5 and .65, thus allowing us to avoid extreme probabilities where probability weighting has been shown to be most severe.

[3] We chose our experimental implementation to satisfy this assumption: all payments are made either three or twelve weeks in the future.

We assign $U(\omega) = 0$ and Equation 7 simplifies to

$$p_t \sum_{k=0}^{\eta-1} \left(\frac{1}{1+\delta} \right)^k U \left(\omega + \frac{M}{\eta} \right) = \left(\frac{1}{1+\delta} \right)^\tau p_{t+\tau} \sum_{k=0}^{\eta-1} \left(\frac{1}{1+\delta} \right)^k U \left(\omega + \frac{M}{\eta} \right). \quad (8)$$

We next divide both sides of this expression by $\sum_{k=0}^{\eta-1} \left(\frac{1}{1+\delta} \right)^k U \left(\omega + \frac{M}{\eta} \right)$, and see the expression simplifies to Equation 6. Thus, consumption smoothing – as long as consumption is even – does not alter our probability discounting approach for eliciting time preference.

2.2 Background Consumption

In our model, we assume background consumption ω to be constant over the time frame we analyze. This assumption seems reasonable given our experimental design: all payments were made at either three or twelve weeks with all payments made during a single semester.[4] Given constant background consumption, we see from Equation 6 that our procedure is invariant to the *level* of background consumption. In contrast, elicitation techniques that require estimating and controlling for the curvature of the utility function (e.g. Andersen et al. (2008) and Andreoni and Sprenger (2012)) are sensitive to the level of background consumption. We report a sensitivity analysis of such estimation to changing levels of background consumption in Section 4.2.

2.3 Non-exponential Discounting

We assume exponential discounting, but hyperbolic discounting models can also be considered. For example, Keller and Strazzera (2002) apply the hyperbolic model axiomatized by Harvey (1986) to obtain the hyperbolic equivalent of Equation 4 in which $\left(\frac{1}{1+\tau} \right)^{\delta'}$ replaces $\left(\frac{1}{1+\delta} \right)^\tau$. Unless utility is linear in wealth, this approach

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[4] Longer time horizons introduce the possibility of background consumption changing over time, which when not accounted for will bias discount rate estimates. See Noor (2009) for a discussion.

yields upwardly biased estimates of hyperbolic discount rates. Our approach combined with the assumption of hyperbolic discounting yields unbiased estimates of δ'.

2.4 Preferences with Non-linear Probabilities

We now consider how our approach is affected if we relax the assumption of linearity in the probabilities by allowing probability weighting. Suppose we assume that cumulative prospect theory (hereafter CPT) (Tversky and Kahneman, 1992) characterizes preferences rather than expected utility theory. Following CPT, we assume that $w(p)$ is the probability weighting function and $V_+(m)$ is the value function for gains, with $V_+(0) = 0$ and $V_+(M)$ increasing in M. CPT does not provide guidance about how to evaluate prospects that offer both immediate and future payouts, so we maintain our assumption of exponential discounting for future values and temporal separability. Given these assumptions, Equation 5 becomes

$$w\left(p_t\right) V_+\left(M\right) + \left(1 - w\left(p_t\right)\right) V_+\left(0\right) + \left(\frac{1}{1+\delta}\right)^\tau V_+\left(0\right) =$$
$$V_+\left(0\right) + \left(\frac{1}{1+\delta}\right)^\tau \left[w\left(p_{t+\tau}\right) V_+\left(M\right) + \left(1 - w\left(p_{t+\tau}\right)\right) V_+\left(0\right)\right]. \quad (5')$$

More intuitively, because $V_+\left(0\right) = 0$, this expression becomes

$$w\left(p_t\right) V_+\left(M\right) = \left(\frac{1}{1+\delta}\right)^\tau w\left(p_{t+\tau}\right) V_+\left(M\right), \qquad (9)$$

which shows that an individual is indifferent when the probability-weighted value of winning M at time t is equal to the discounted probability-weighted value of winning M at time τ. Finally, dividing both sides by $V_+\left(M\right) > 0$ gives

$$w\left(p_t\right) = \left(\frac{1}{1+\delta}\right)^\tau w\left(p_{t+\tau}\right). \qquad (6'')$$

This expression is our CPT analogue to Equation 6 where the probabilities have been replaced with the weighted probabilities. The advantage of using this expres-

sion to estimate discount rate is that we can avoid estimating the value function $V_+(m)$. We will, however, need to estimate $w(p)$, and that will require additional parametric assumptions. For example, we could assume Prelec's (1998) probability weighting function $w(p) = e^{-(-\ln p)^\gamma}$ and would then need to jointly estimate γ and δ. It is also worth noting that the importance of neglecting probability weighting will depend on the ratio $w(p_t)/w(p_{t+\tau})$, and this will vary over the range of probabilities used in the elicitation. In our case, we have set $p_t = 0.5$ and $0.5 < p_{t+\tau} < 0.67$. If $w(p)$ is well approximated by a ray through the origin over this range – that is, if there exists α such that $w(p) = \alpha p$ over the required range for p – then ignoring probability weighting will not appreciably bias our estimates.

3 Experimental Design

Our experiments are designed to elicit discount rates using the binary lottery payment approach in which we vary the probability (rather than the prize) over time. We call this the probability task. We also provide a within-subjects comparison of our "curvature-free" approach to the alternative of jointly estimating the utility function and discount rates using the joint elicitation procedure of Andersen et al. (2008). Given the huge variation of elicited discount rates in the literature, even among studies that adjust for curvature, it would be reassuring to find that two different methods yield similar results when applied in similar conditions. We begin by describing our probability discount rate elicitation task and then describe the two tasks we use as inputs for the joint elicitation comparison.

3.1 Probability Discount Rate Elicitation

In the Probability Discount Rate Task (Task P), subjects choose between a "Sooner" lottery to be played at time t and "Later" lottery with the same prize but greater chances of paying off.[5] The Sooner lottery offers a 50 percent chance of earning

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[5] In subject instructions and decision sheets, the Sooner option is referred to as Option A and the Later option as Option B.

$200 in 3 weeks. The later lottery offers the same cash prize of $200, but the prize is not paid until 12 weeks after the date of the experimental session. Each subject is presented with 20 of these paired choices in a multiple price list format. Table 1 (which is not shown to subjects) shows the choices presented to the subjects, along with associated annual effective interest rates (AEIR) and implied discount rate ranges.[6] In the first Decision row, the Later lottery has the same chances of paying as the Sooner option, corresponding to a 0 percent interest rate. Moving down the table, the probability of winning with the Later option increases indicating a higher expected rate of return for waiting the additional 9 weeks. In the last row, Decision 20, the choice is between a 50/50 chance of winning $200 in 3 weeks and a 64.7 percent chance of winning $200 in 12 weeks. In our experiment, interest is compounded daily between 3 and 12 weeks, resulting in an AEIR of between 0 and 346.79 percent across the 20 decisions.

Table 1 Probability discount rate elicitation (P Task) choices and implied ranges of discount rates

Row	Chance of $200 in 3 weeks (percent)	Chance of $200 in 12 weeks (percent)	Annual effective interest rate (percent)	Implied discount rate range if switching in this row (percent)
1	50.0	50.0	0.00	$\delta \leq 0.00$
2	50.0	50.1	1.01	$0.00 \leq \delta \leq 1.01$
3	50.0	50.2	2.02	$1.01 \leq \delta \leq 2.02$
4	50.0	50.4	4.08	$2.02 \leq \delta \leq 4.08$
5	50.0	50.5	6.18	$4.08 \leq \delta \leq 6.18$
6	50.0	50.7	8.33	$6.18 \leq \delta \leq 8.33$
7	50.0	50.9	10.52	$8.33 \leq \delta \leq 10.52$
8	50.0	51.1	12.75	$10.52 \leq \delta \leq 12.75$
9	50.0	51.2	15.02	$12.75 \leq \delta \leq 15.02$
10	50.0	51.4	17.35	$15.02 \leq \delta \leq 17.35$
11	50.0	51.6	19.72	$17.35 \leq \delta \leq 19.72$
12	50.0	51.8	22.13	$19.72 \leq \delta \leq 22.13$
13	50.0	52.0	25.22	$22.13 \leq \delta \leq 25.22$
14	50.0	52.2	28.39	$25.22 \leq \delta \leq 28.39$
15	50.0	52.7	34.97	$28.39 \leq \delta \leq 34.97$
16	50.0	53.6	49.15	$34.97 \leq \delta \leq 49.15$
17	50.0	54.5	64.82	$49.15 \leq \delta \leq 64.82$
18	50.0	56.9	111.54	$64.82 \leq \delta \leq 111.54$
19	50.0	59.4	171.46	$111.54 \leq \delta \leq 171.46$
20	50.0	64.7	346.79	$171.46 \leq \delta \leq 346.79$

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[6] The actual decision table presented to subjects is shown in Appendix A.

The point at which the subject switches from choosing the Sooner to the Later option reveals the interest rate the subject must receive in order to be willing to wait for the later lottery. For example, in Decision 15, the subject must choose between 50 percent chance of receiving $200 in 3 weeks and an 52.7 percent chance of winning $200 in 12 weeks. In this Decision, the increase in expected payoff from the Sooner to the Later option represents an annual effective interest rate of 34.97 percent with interest accruing starting 3 weeks from the experiment date (when the Sooner option pays out) until 12 weeks from the experiment date (when the Later option pays out). Participants who switch from the Sooner option to the Later option in Decision 15 reveal that their discount rates is between 28.39 and 34.97 percent.

In designing the decision choices in the P Task, we turned to the literature to form our priors about the key range of discount rates to explore. Estimates that ignore the curvature of the utility function are likely to be upwardly biased, and the curvature-corrected estimates of Andersen et al. (2008) are on the low end of the scale. To allow for very low discount rates to be revealed in our decision task, we begin with a zero AEIR and then increase the chances of winning with the Later option by small amounts. We include the zero interest rate choice in the first Decision Row as a check on whether participants understand the choices (or perhaps are choosing to wait as a form of enforced savings). While we hypothesize that some individual discount rates may be very low, we cannot rule out the possibility of shockingly high discount rates that have been reported in the literature. To allow for a sufficiently broad range of discount rates in our task without confronting subjects with an unwieldy number of decision rows, we gradually increase the increment between AEIRs for the higher decision rows.

The payment date for both the Sooner and the Later options are set in the future. This front-end delay was introduced by Coller and Williams (1999), and it is used to control for transaction costs associated with returning for payment at a later date and any uncertainty about the reliability of receiving payment intro-

duced due to the time delay. In our discount rate tasks, subjects choose between receiving payment in either 3 or 12 weeks. Our subjects were university students and we believe it is important that subjects receive all payments during the course of one semester. If some subjects expect to graduate or leave the University between the Sooner and Later payment dates, this would introduce differences in transactions costs and possibly differences in background consumption between the two payment dates. Therefore the longest time horizon we could reasonably use was 12 weeks.

3.2 Joint Elicitation

For our joint elicitation procedure, we adapt the procedures described in Andersen et al. (2008). Utility curvature is measured using the Holt and Laury (2002) risk preference measure (Task R), and discount rates over dollar amounts are measured using the Coller and Williams (1999) time preference measure (Task D). Andersen et al. typically presented their subjects with 10 binary decisions per task; however, to be consistent with our Task P design, we present our subjects with 20 binary decisions in each task.

In the dollar discount rate task (Task D) subjects are shown 20 paired choices between receiving a sum of money in three weeks and receiving a typically larger sum of money in 12 weeks.[7] For each Decision row, the subject is asked to choose between a Sooner and Later option;[8] time delays of 3 and 12 weeks are used for consistency with the P-Task decisions. In all 20 decisions, the Sooner option entails receiving $200 in 3 weeks. For the Later option, the amount of money the subject would receive in 12 weeks starts at $200 in Decision 1 and increases to $258.96 in Decision 20. Subjects are also provided the annual interest rates and annual effective interest rates for each choice in Task D. Coller and Williams argued for

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[7] The instructions and decision sheets for all tasks in both experiments are available at http://www.excen.gsu.edu/swarthout/LMSV/ .

[8] As in Task P, in subject instructions and decision sheets these were labeled Option A and Option B.

including this information because it was available in many naturally-occurring situations in which individuals make decisions about whether to borrow or lend.[9] Table 2 summarizes the 20 choices and shows the AEIR associated with each choice. The AEIRs for each Decision row in Task P corresponds to that of the same row in Task D. The correspondence between the AEIR rows for the P Task and the D Task might be a problem if participants tend to switch at the same row across tasks. Note that under our hypothesis that most participants are risk averse, we predict that participants will switch to the Later option at an earlier row in the P Task than the D task. Thus, a simple switching heuristic between decision-making tasks (e.g., always switching in the fifth row) would bias decisions away from our expected finding.

The risk preference measurement task (Task R) follows procedures first introduced by Holt and Laury (2002), except that each subject is presented with 20 decisions instead of 10. Each subject is asked to make a choice between two paired lotteries, labeled Option A and Option B. Option A represents the "safe" lottery in that there is a relatively small difference between the high and low outcome. Option B represents the "risky" lottery because there is a relatively large difference between the high and low outcome. Table 3 summarizes the choices given to the subjects, although the range of implied risk aversion was not shown to subjects. Holt and Laury demonstrated that when the payoff scale is increased, the observed risk aversion coefficient increases as well. Therefore, we use monetary outcomes for these lotteries such that the expected value of the lotteries are (on average) at a scale consistent with the monetary outcomes in the discount rate task.

Option A involves a chance to receive either $180 or $144, and Option B involves a chance to receive either $346.50 or $9.[10] The chance of receiving the

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[9] Our pilot experiments had sessions with and without the AEIR information. Excluding this information did not appear to have substantial affect on the pilot results. Ultimately we decided to exclude the AEIR from the P-Task because there is no naturally-occurring counterpart for expressing probabilities as interest rates. Coller and Williams (1999) first introduced the AEIR information to the discount rate task and found that including the AEIR led to lower discount rate estimates and residual variance.

[10] These are the same payment levels used by Holt and Laury (2002) in their highest payment treatment.

Table 2 Dollar discount rate elicitation (D Task) choices and implied ranges of discount rates

Row	Amount paid in 3 weeks (dollars)	Amount paid in 12 weeks (dollars)	Annual effective interest rate (percent)	Implied discount rate range if switching in this row (percent)[1]
1	200.00	200.00	0.00	$\delta \leq 0.00$
2	200.00	200.35	1.01	$0.00 \leq \delta \leq 1.01$
3	200.00	200.69	2.02	$1.01 \leq \delta \leq 2.02$
4	200.00	201.39	4.08	$2.02 \leq \delta \leq 4.08$
5	200.00	202.08	6.18	$4.08 \leq \delta \leq 6.18$
6	200.00	202.78	8.33	$6.18 \leq \delta \leq 8.33$
7	200.00	203.48	10.52	$8.33 \leq \delta \leq 10.52$
8	200.00	204.18	12.75	$10.52 \leq \delta \leq 12.75$
9	200.00	204.89	15.02	$12.75 \leq \delta \leq 15.02$
10	200.00	205.60	17.35	$15.02 \leq \delta \leq 17.35$
11	200.00	206.31	19.72	$17.35 \leq \delta \leq 19.72$
12	200.00	207.02	22.13	$19.72 \leq \delta \leq 22.13$
13	200.00	207.92	25.22	$22.13 \leq \delta \leq 25.22$
14	200.00	208.82	28.39	$25.22 \leq \delta \leq 28.39$
15	200.00	210.62	34.97	$28.39 \leq \delta \leq 34.97$
16	200.00	214.29	49.15	$34.97 \leq \delta \leq 49.15$
17	200.00	218.01	64.82	$49.15 \leq \delta \leq 64.82$
18	200.00	227.61	111.54	$64.82 \leq \delta \leq 111.54$
19	200.00	237.62	171.46	$111.54 \leq \delta \leq 171.46$
20	200.00	258.96	346.79	$171.46 \leq \delta \leq 346.79$

[1] These discount rates apply to monetary amounts. If risk neutral, then these are the the true discount rates.

higher-payment outcome starts at 5 percent in Decision 1, and increases to 100 percent in Decision 20 (so in Decision 20 the choice is between \$180 and \$346.50 with certainty). The point at which the subject switches from Option A to Option B is used to infer an interval estimate of the subject's coefficient of risk aversion. A risk neutral subject will choose Option A as long as its expected value exceeds that of Option B, and then shift to Option B. In this task, the risk neutral prediction is to choose Option A for the first 8 Decision rows, and then to switch to Option B. A risk seeking person would choose Option A for fewer than the first 8 Decision rows, and a risk averse person would choose Option A for more than the first 8 Decision rows.

Table 3 Risk preference elicitation (R Task) choices and implied CRRA ranges

	Lottery A		Lottery B		
Row	chance of \$180 (percent)	chance of \$144 (percent)	chance of \$346.50 (percent)	chance of \$9 (percent)	Range of relative risk aversion for $u(x) = \frac{x^{1-r}}{1-r}$ if switching in this row
1	5	95	5	95	$r \leq -2.48$
2	10	90	10	90	$-2.48 \leq r \leq -1.71$
3	15	85	15	85	$-1.71 \leq r \leq -1.27$
4	20	80	20	80	$-1.27 \leq r \leq -0.95$
5	25	75	25	75	$-0.95 \leq r \leq -0.70$
6	30	70	30	70	$-0.70 \leq r \leq -0.49$
7	35	65	35	65	$-0.49 \leq r \leq -0.31$
8	40	60	40	60	$-0.31 \leq r \leq -0.14$
9	45	55	45	55	$-0.14 \leq r \leq 0.01$
10	50	50	50	50	$0.01 \leq r \leq 0.15$
11	55	45	55	45	$0.15 \leq r \leq 0.28$
12	60	40	60	40	$0.28 \leq r \leq 0.41$
13	65	35	65	35	$0.41 \leq r \leq 0.54$
14	70	30	70	30	$0.54 \leq r \leq 0.68$
15	75	25	75	25	$0.68 \leq r \leq 0.82$
16	80	20	80	20	$0.82 \leq r \leq 0.97$
17	85	15	85	15	$0.97 \leq r \leq 1.15$
18	90	10	90	10	$1.15 \leq r \leq 1.37$
19	95	5	95	5	$1.37 \leq r \leq 1.68$
20	100	0	100	0	$1.68 \leq r \leq 2.25$

3.3 Experiment Procedures

A total of 103 subjects participated in six experimental sessions at Georgia State University between September 14 and September 17, 2009. Each subject completed three decision tasks: a probability discount rate choice task (Task P), a dollar discount rate choice task (Task D), and a risk preference measurement task (Task R). The discount rate tasks were always given first and the order of those tasks was varied by session. In three sessions, 51 subjects faced Task P, then Task D, and then Task R. In the remaining three sessions, 52 subjects faced Task D, then Task P, and then Task R.

After subjects had completed all three decision tasks, they were taken individually to a private room to determine the outcomes (and earnings) from each of the three tasks. In each task, only one of the decision rows was used in the final payment phase of the experiment. In the instructions subjects were told: "Even

though you will make twenty Decisions, only one of these will end up possibly affecting your earnings, but you will not know in advance which Decision will be used. Each Decision has an equal chance of being used for payment."

After the binding decision was determined, earnings were determined for the task. In the standard discount rate task over changing dollar amounts, this was simply the dollar amount determined by their choice of the Sooner option or the Later option in the binding decision. Using Decision 15 as an example, if the subject chose the Sooner option, the outcome would be $200 in 3 weeks; if the subject chose the Later option, the outcome would be $210.62 in 12 weeks.

In the probability discounting task, after the binding decision was selected a die throw was used to determine whether the outcome was $200 or nothing. Using Decision 15 as an example once more, if the subject chose the Sooner option, there was a 50 percent chance that the monetary outcome would be $200; if the subject chose the Later option, there was a 52.7 percent chance that the monetary outcome would be $200. As described in the subject instructions, three 10-sided die were used to determine the outcome: a red die was used to determine the hundreds digit, a white die was used to determine the tens digit, and a blue die was used to determine the ones digit. For example, if the die-roll was a 3 on the red die, a 7 on the white die, and a 6 on the blue die the outcome was 376.

In the risk preference measurement task, after the binding decision was selected a 20-sided die was used to determine the monetary outcome. Using Decision 15 as an example, if the subject chose Option A and the die throw was between 1 and 15, the outcome would be $180, otherwise the outcome would be $144; if the subject chose Option B and the die throw was between 1 and 15, the outcome would be $346.40, otherwise the outcome would be $9.

The final payment phase determined whether the subject was paid the monetary outcome in one or more of the three tasks. There was a 10-percent chance that the subject would be paid in the standard dollar discount rate task and in the

risk preference measurement task. There was a 20-percent chance that the subject would be paid in the binary-lottery discount rate task.[11]

Subjects' earnings in the experiment were the sum of the earnings from the three decision-making tasks plus a \$20 participation payment (because only 10 percent of subjects on average receive payment in any task, the participation payment was set higher than usual: \$5 for arriving to the experiment on time plus another \$5 for each of the three decision-making tasks). Subjects received the participation payment and any earnings from the risk preference measurement task in cash before leaving the experimental session. Subjects who received payment from either discount rate tasks received a certificate for payment that could be redeemed in either 3 or 12 weeks. Subjects who were paid for an Option A choice received payment during the week of October 5, and subjects who were paid for an Option B choice received payment during the week of December 7.

Demographic characteristics of our subjects are presented in Table 4. The mean age of the participants was 21.77 years, ranging from 18 to 47 in the DPR treatment, and from 18 to 46 in the PDR treatment order. Subjects were about equally divided between male and female. The racial makeup of our subject pool is more diverse than most. About 43 percent reported being white, 35 percent black, and 13 percent Asian. The demographics appear to be well balanced between sessions. Sorting by treatment order, our analysis reveals no significant difference by task order, so we combine the the data for the analysis reported here.

4 Results

First, we turn to an overview of our data and then present results from maximum likelihood estimation. Figure 1 displays the proportion of subjects selecting the Sooner payment option (payment in 3 weeks) in each of the 20 decisions. Recall

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[11] This equates the expected value of the payment in the standard and binary-lottery discount rate tasks, as the baseline probability of payment was only 50 percent in Task P, but 100 percent in the two other tasks. Randomly determining whether a subject receives payment is used for consistency with earlier discount rate studies, including Coller and Williams (1999) and Andersen et al. (2008).

Table 4 Demographic characteristics.

Demographic Characteristic	All Participants	Order DPR	Order PDR
Average Age	21.77	21.78	21.76
Percent Male	51.4	49	54
Percent White	43	41	44
Percent Black	35	35	35
Percent Asian	13	12	13
Percent Raised in US	92	92	92
Percent Freshman	10	4	15
Percent Sophomore	31	33	29
Percent Junior	42	45	38
Percent Senior	17	16	17
Average GPA	3.23	3.19	3.27

that the AEIR increases as the subject moves down the decision sheet so that a greater number of Sooner choices implies a higher discount rate. Lines with square markers show the data for Task D (the standard dollar discount rate task), and lines with circle markers show the data for Task P (the binary lottery payment discount rate task). We see that participants appear much more impatient (a much higher proportion of subjects choose the Sooner option in each decision) when given the standard dollar discounting task than when given the probability discounting task. If subjects are risk neutral (that is, if utility is linear in wealth), then we expect to find the same discount rates in each task. Instead, we see that discount rates are higher in Task D than in Task P. For example, in Decision 6, 80 percent of subjects choose the Sooner option in Task D, compared to 50 percent of the same subjects who choose the Sooner option in Task P. This pattern is what we expect if participants have utility that is concave in wealth. In this case, we expect that the discount rate from the standard dollar task will overstate the true discount rate.

Based on the pattern of responses from the two discount rate tasks, we expect to find that the average participant is our study is risk averse. Table 5 shows the average responses for each task and confirms our hypothesis that the average participant has concave rather than linear preferences. In the risk aversion task, participants choose Option A, the "safe" choice that offers a lower variance in
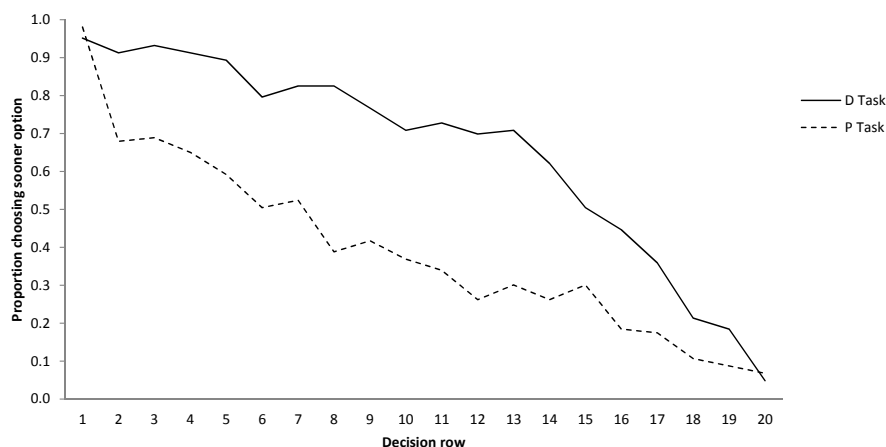
Fig. 1 Proportion of subjects selecting the Sooner option (option A) by decision row and treatment.

payoffs, for an average of 13 decisions. The risk neutral prediction is to choose Option A for the first 8 Decision rows, and then to switch to Option B. These results indicate a coefficient of relative risk aversion in the range of 0.41 to 0.54. These results are also consistent with the degree of risk aversion found by Holt and Laury (2002) for similar stakes.

Given risk averse participants, we expect to find a difference in average discount rates in Task D and Task P. Indeed, in Task D, subjects chose the Sooner option for an average of 13.0 decisions, compared to 7.9 Sooner choices for Task P. Because subjects made choices in both tasks, we can test for differences in the central tendency of choices using the nonparametric Wilcoxon Signed Ranks Test. This is a relatively powerful test of the differences between the two treatments that uses both the sign of the difference between a subject's choices in the two tasks and the size of the difference. The null hypothesis of no difference between the two tasks is rejected at any standard level of confidence.

Turning our attention to those subjects who do not exhibit multiple switch points between the Sooner and Later options, Table 6 shows the portion of par-

Table 5 Number of Safer (Task R) and Sooner (Task P and D) Choices in each Task

Task	Mean	Median	Standard Deviation
Risk aversion (Task R)	13.24	14	3.47
Standard dollar discounting (task D)	13.04	14	4.92
Binary lottery payment discounting (task P)	7.88	8	5.60

ticipants who switch in each decision row for each task.[12] In Task P we see a substantial portion of participants (33.7 percent) chose to switch in Decision 2, the first decision that yields a positive rate of interest.[13] This is consistent with a discount rate between 0 and 1.01 percent. Given contemporaneous market rates of interest,[14] low discount rates are entirely plausible, and yet, rarely seen in the literature on elicited discount rates. When we use the data from Task D, which does not account for the curvature in the utility function, we do not find such low discount rates. Instead we find only a handful of individuals willing to save until the interest rate is at least 6 percent.

Overall, our results indicate that using probabilities to elicit discount rates (Task P) reduces the upward bias caused by the assumption of linear utility in the more standard (dollar) discount rate elicitation method. The next section examines this issue more formally and allows a direct comparison of the discount rate elicited in Task P with the curvature-corrected discount rate obtained via joint-estimation of the parameters of the utility function.

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[12] It is common to exclude multi-switchers from analyses that focus on a single switch point. An advantage of the maximum likelihood estimation that follows is that we can add error terms to the model and include all decisions.

[13] In a pilot experiment with the P Task that did not include a zero percent interest rate choice (Morgan, 2009), 45.7 percent of participants choose Option B for all decisions implying a discount rate of less than 2.02 percent. The pilot experiments differed in other important dimensions (including lower stakes, shorter time horizon, AEIR provided in some sessions, and conducted at different university); yet, the pilot results are broadly consistent with the findings we report here.

[14] At the time the experiment was conducted, interest rates were quite low. For example, Bankrate.com's weekly survey of banks conducted October 21, 2009, found a yield for one-year CD of only 0.92 percent. `http://www.bankrate.com/finance/cd/national-cd-rate-averages8-134136.aspx`

Table 6 Distributions of switching behavior across tasks

	Risk task		Discounting Tasks		
	Range of relative	Proportion switching	Range of discount rate if switching	Proportion switching in this row	
Row	risk aversion if switching in this row[1]	in this row (percent)[2]	in this row (percent)[3]	Task D (percent)[4]	Task P (percent)[5]
1	$r \leq -2.48$	0.0	$\delta \leq 0.00$	2.5	1.30
2	$-2.48 \leq r \leq -1.71$	0.0	$0.00 \leq \delta \leq 1.01$	2.5	33.77
3	$-1.71 \leq r \leq -1.27$	0.0	$1.01 \leq \delta \leq 2.02$	0.0	2.60
4	$-1.27 \leq r \leq -0.95$	0.0	$2.02 \leq \delta \leq 4.08$	0.0	1.30
5	$-0.95 \leq r \leq -0.70$	0.0	$4.08 \leq \delta \leq 6.18$	1.2	3.90
6	$-0.70 \leq r \leq -0.49$	0.0	$6.18 \leq \delta \leq 8.33$	4.9	7.79
7	$-0.49 \leq r \leq -0.31$	1.3	$8.33 \leq \delta \leq 10.52$	1.2	1.30
8	$-0.31 \leq r \leq -0.14$	0.0	$10.52 \leq \delta \leq 12.75$	1.2	7.79
9	$-0.14 \leq r \leq 0.01$	1.3	$12.75 \leq \delta \leq 15.02$	3.7	1.30
10	$0.01 \leq r \leq 0.15$	12.5	$15.02 \leq \delta \leq 17.35$	3.7	3.90
11	$0.15 \leq r \leq 0.28$	7.5	$17.35 \leq \delta \leq 19.72$	1.2	3.90
12	$0.28 \leq r \leq 0.41$	3.8	$19.72 \leq \delta \leq 22.13$	3.7	5.19
13	$0.41 \leq r \leq 0.54$	3.8	$22.13 \leq \delta \leq 25.22$	3.7	2.60
14	$0.54 \leq r \leq 0.68$	6.3	$25.22 \leq \delta \leq 28.39$	2.5	2.60
15	$0.68 \leq r \leq 0.82$	16.3	$28.39 \leq \delta \leq 34.97$	12.4	1.30
16	$0.82 \leq r \leq 0.97$	10.0	$34.97 \leq \delta \leq 49.15$	9.9	5.19
17	$0.97 \leq r \leq 1.15$	13.8	$49.15 \leq \delta \leq 64.82$	8.6	2.60
18	$1.15 \leq r \leq 1.37$	5.0	$64.82 \leq \delta \leq 111.54$	17.3	6.49
19	$1.37 \leq r \leq 1.68$	10.0	$111.54 \leq \delta \leq 171.46$	4.9	2.60
20	$1.68 \leq r \leq 2.25$	7.5	$171.46 \leq \delta \leq 346.79$	8.6	0.00

[1] Assuming $u(x) = \frac{x^{1-r}}{1-r}$.

[2] Including only the 80 of 103 subjects who did not multiswitch in R Task. One subject always chose Lottery B implying a risk aversion parameter of at least 2.25.

[3] These discount rates apply to monetary amounts for the D task and to the true discount rates over utility for the P Task. If risk neutral, then these are the same across tasks.

[4] Including only the 81 of 103 subjects who did not multiswitch in the D task. Five subjects always chose the Sooner option implying a discount rate over money of at least 346.79 percent.

[5] Including only the 77 of 103 subjects who did not multiswitch in the P task. Two subjects always chose the Sooner option implying a discount rate of at least 346.79 percent.

4.1 Model Estimation

We now turn to our estimation procedures. First, we describe the likelihood functions for the probability discount rate estimation and the joint estimation. Next, we report the estimation results and consider the sensitivity to changing values of background consumption. And finally, we introduce probability weighting into the estimation to gauge robustness to allowing for preferences that are non-linear in both probabilities and wealth.

4.1.1 Probability Discount Rate Model Specification

We now construct a likelihood function for our Task P time preference choices. Returning to our normalization used to derive Equation 6, we define the normalized present value for each lottery presented in a Task P choice. Recall that lottery A provided payoff at future time t, and lottery B provided payoff at future time $t+\tau$. The present value of lottery A is

$$NPV_A = \left(\frac{1}{1+\delta}\right)^t \times p_A \tag{10}$$

and the present value of lottery B is

$$NPV_B = \left(\frac{1}{1+\delta}\right)^{t+\tau} \times p_B \tag{11}$$

where p_i is the probability of earning the larger payoff in lottery i. We use these normalized present value expressions to construct a probabilistic choice rule for the P Task decisions.[15] We let $Pr_i^P(A)$ be the probability of choosing outcome A over outcome B in choice i of Task P, and express this as

$$Pr_i^P(A) = \frac{NPV_A^{1/\xi}}{NPV_A^{1/\xi} + NPV_B^{1/\xi}} \tag{12}$$

where ξ is a noise parameter that relates the sensitivity of choice probabilities to payoffs. Note that $\xi \to 0$ implies the lottery with larger expected value is given full weight, while $\xi \to \infty$ implies purely random choice with each lottery receiving equal weight. The conditional log likelihood function for time preference decisions is

$$\ln L^P(\delta, \xi; y) = \sum_i \left(\left(\ln(Pr_i^P(A)|y_i = A\right) + \left(\ln(1 - Pr_i^P(A)|y_i = B)\right) \right) \tag{13}$$

where $y_i = j$ denotes selection of lottery j in observation i.

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[15] This is the same stochastic choice specification used by Holt and Laury (2002). See Harrison and Rutström (2008, Sections 2.2 and 2.3) for further discussion of stochastic error terms, and see Wilcox (2008) for a thorough discission of stochastic models under risk.

4.1.2 Joint Estimation Model Specification

Our specification for joint estimation of risk and time preferences generally follows from Andersen et al. (2008). First, we specify the likelihood function for choices made in the risk task to estimate the risk parameter, r. Each pairwise choice made in the risk task was between two lotteries, and each lottery had two possible outcomes. For each lottery i, we write outcome j as M_{ij} and we let the probability of this outcome be $p(M_{ij})$. We express the expected utility of a given lottery as

$$EU_i = \sum_{j=1,2} p(M_{ij}) \times U(\omega + M_{ij}). \tag{14}$$

In order to specify a likelihood function for joint estimation, we must first assume a parametric form for utility. Note that this assumption is not required for the probability discounting likelihood function defined above in Equation 13. We assume the CRRA form for utility and that the risk coefficient r does not vary over the time period under consideration. We now rewrite EU_i as

$$EU_i = \sum_{j=1,2} p(M_{ij}) \times \frac{(\omega + M_{ij})^{1-r}}{1-r}. \tag{14$'$}$$

We introduce probabilistic choice function $Pr_i^R(A)$ as the probability of a subject choosing lottery A instead of lottery B in choice i of task R, and define the probability as

$$Pr_i^R(A) = \frac{EU_A^{1/\mu}}{EU_A^{1/\mu} + EU_B^{1/\mu}}, \tag{15}$$

where μ is the associated behavioral noise parameter. We now write the conditional log-likelihood function as

$$\ln L^{\mathrm{R}}(r, \mu; y, \omega) = \sum_i \left(\left(\ln(Pr_i^R(A) | y_i = A \right) + \left(\ln(1 - Pr_i^R(A) | y_i = B \right) \right), \tag{16}$$

where $y_i = j$ denotes selection of lottery j in observation i.

Next, we construct a similar likelihood function for time preferences by using the D Task choices. Recall that each of these choices consisted of two options: option A provided monetary amount M_A at time t, and option B paid M_B at time $t + \tau$. By assuming CRRA as the form of the utility function as before, we can rewrite Equations 1 and 2 as

$$PV_A = \left(\frac{1}{1+\delta}\right)^t \times \frac{(\omega + M_A)^{1-r}}{1-r} + \left(\frac{1}{1+\delta}\right)^{t+\tau} \times \frac{\omega^{1-r}}{1-r} \qquad (1')$$

and

$$PV_B = \left(\frac{1}{1+\delta}\right)^t \times \frac{\omega^{1-r}}{1-r} + \left(\frac{1}{1+\delta}\right)^{t+\tau} \times \frac{(\omega + M_B)^{1-r}}{1-r}. \qquad (2')$$

We now use these present values to construct another probabilistic choice rule – this time for the D task choices. We let $Pr_i^D(A)$ be the probability of a subject choosing outcome A instead of outcome B in choice i of task D, and define this probability as

$$Pr_i^D(A) = \frac{PV_A^{1/\nu}}{PV_A^{1/\nu} + PV_B^{1/\nu}}, \qquad (17)$$

where ν is a noise parameter as before. We now write the conditional log-likelihood function for choices from the time discounting task D as

$$\ln L^{\mathrm{D}}(\delta, r, \mu, \nu; y, \omega) = \sum_i \left(\left(\ln(Pr_i^D(A)|y_i = A \right) + \left(\ln(1 - Pr_i^D(A)|y_i = B) \right) \right), \qquad (18)$$

where $y_i = j$ denotes selection of outcome j in choice i.

By combining Equations 16 and 18, we can write the joint log likelihood as

$$\ln L(\delta, r, \mu, \nu; y, \omega) = \ln L^{\mathrm{R}} + \ln L^{\mathrm{D}}. \qquad (19)$$

The joint likelihood above allows for nonlinear preferences over wealth. We can impose the assumption of risk neutrality on our data by re-estimating the equation above with the constraint that the CRRA coefficient is equal to one. The results from the constrained estimation serve as our benchmark for gauging the sensitivity of our discount rates estimates to nonlinearity in the utility function.

4.1.3 Maximum Likelihood Estimation Results

We maximize the likelihood functions defined above with version 10 of the Stata statistical software application.[16] Because each subject provided 20 responses for each of the three tasks, we allow for within-subject clustered standard errors. Table 7 presents our maximum-likelihood estimates. We estimate an aggregate annual discount rate of 12.2 percent with the probability discounting (Task P) specification. The 95 percent confidence interval bounds put the estimate between 4.6 percent and 19.7 percent. This is on the lower end of previous estimates, and we wish to know how much higher our estimate would be had we followed the earlier literature in assuming risk neutrality. To do this, we use the joint estimation likelihood function described above but constrain the CRRA coefficient to be equal to one. These estimates are shown in the middle of Table 7. The maximum likelihood point estimate under the assumption of risk linear preferences is 55.5 percent with a lower 95 percent confidence interval bound of 41.8 percent. Thus, we find that there is no overlap between the confidence intervals between the two estimation techniques. Failing to control for risk aversion drastically overstates the degree of impatience in our sample. Our lower estimates from the probability task are more plausible in theory and in comparison to naturally-occurring rates. Our estimate is also in line with the 10.1 percent found by Andersen et al. (2008) in their nationally representative sample of adult Danes using the joint estimation technique to account for curvature. Nonetheless, it is quite a surprise to find this degree of patience among US undergraduates. To see whether this unexpected result is an anomaly of the elicitation procedure, we turn to the within-subjects comparison of results from unconstrained joint estimation.

We begin by looking at the estimates of risk aversion in the jointly-estimated model. The risk coefficient is estimated to be 0.702 and the confidence interval does not include zero. This confirms the hypothesis that our subjects are risk

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[16] Both the data and estimation routines are available at `http://www.excen.gsu.edu/swarthout/LMSV/` .

Table 7 Estimates of risk and time preferences, assuming zero background consumption

Parameter	Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Probability Discounting Estimation (Task P)					
δ	0.122	0.039	0.000	0.046	0.197
ξ	0.045	0.008	0.000	0.030	0.060
Joint Estimation Constrained to Risk Neutrality (Task D)					
δ	0.555	0.066	0.000	0.418	0.674
ν	0.041	0.004	0.000	0.033	0.050
Joint estimation (Tasks R and D)					
r	0.702	0.069	0.000	0.567	0.838
δ	0.141	0.038	0.000	0.066	0.215
μ	0.132	0.026	0.000	0.081	0.183
ν	0.012	0.003	0.000	0.006	0.019

averse. Given this evidence of curvature of the utility function, we expect that the unconstrained jointly-estimated discount rate will be significantly lower than the joint estimation constrained to risk neutrality. Indeed, the discount rate is found to be 14.1 percent when utility curvature in taken into account compared to 55.5 percent when utility is assumed to be linear. The discount rate we found in our P task is slightly lower; however, the confidence intervals for the two estimates have substantial overlap. The two estimates are also very similar in terms of precision.

The estimates of the behavioral error terms ξ, ν, and μ in Table 7 exhibit an interesting pattern. Recall that estimates of zero indicate that no noise is present in the decision process. In all tasks and specifications, we find evidence of some noise: none of the confidence intervals include zero. We find the estimated amount of noise is highest in the risk aversion task and lowest in the dollar discounting task. Andersen et al. (2008) also find a larger estimate of noise for the risk aversion task than the discount rate task and hypothesize that the risk aversion tasks were cognitively harder. The estimated noise in our probability discounting task is intermediate suggesting a more difficult task than dollar discounting but still cognitively easier than the risk aversion task of Holt and Laury (2002).

4.2 Sensitivity to Background Consumption

The probability discounting estimates developed in this paper are independent of the level of background consumption. Alternative estimation techniques, including those of Andersen et al. (2008) and Andreoni and Sprenger (2012), require an estimate of background consumption in order to estimate and control for the curvature of the utility function. For the above estimates, we assumed that $\omega = 0$, but we can easily vary this assumption to gauge the sensitivity of our estimates. Andersen et al. (2008) find that their estimated discount rates are not very sensitive to the assumed level of ω, while Andreoni and Sprenger (2012) find estimated discount rates double when estimated daily consumption is varied between \$3.52 to \$14.09. We show in Figure 2 the range of estimated average discount rates as the level of background consumption is varied.[17] We see that discount rates from joint estimation increase from a low of 14.2 percent that we report in Table 7 to a high of about 20 percent as the background consumption parameter is increased. The estimated discount rate from our P Task do not vary with the assumed level of back ground consumption and are closest to the joint estimation results when background consumption is assumed to be zero.

4.3 Probability Weighting

We now relax our prior assumption that the utility function is linear in probabilities. We assume the probability weighting function to have the form proposed by Tversky and Kahneman (1992), with

$$w\left(p\right) = \frac{p^{\gamma}}{\left(p^{\gamma} + \left(1 - p\right)^{\gamma}\right)^{1/\gamma}} \tag{20}$$

for $0 < p < 1$, $w\left(0\right) = 0$, and $w\left(1\right) = 1$.

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[17] In comparing Andreoni and Sprenger (2012) to our results, note that in their model ω has the opposite sign to ours.
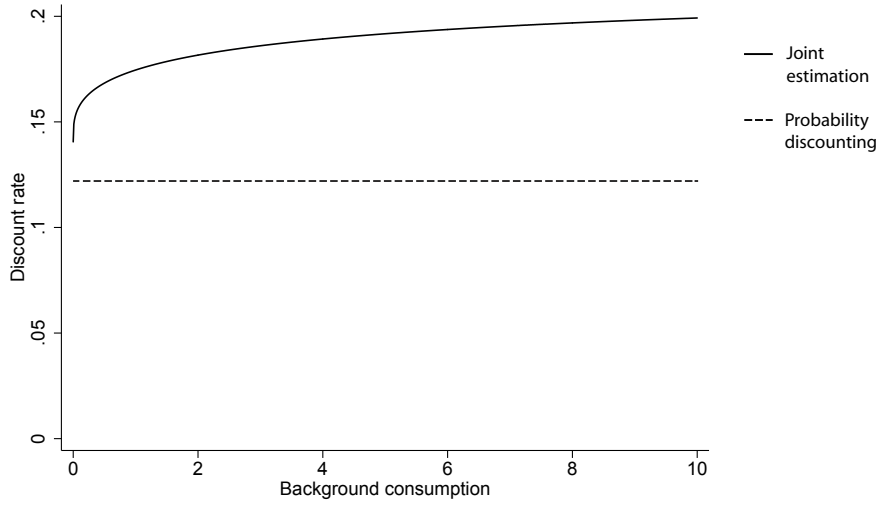
Fig. 2 Estimated discount rates as daily background consumption varies between zero and ten dollars.

We use a joint estimation technique by combining subject responses from all three tasks to estimate the three unknown parameters: (i) the γ of probability weighting function, (ii) the curvature parameter of the utility function r, and the discounting parameter δ. Essentially this estimation approach boils down to using three equations to solve for three unknowns. The responses in each decision task depend on different combinations of two of the three unknown parameters, and it is only by combining all three tasks that we can identify all three parameters.

We proceed by modifying the log likelihood expressions associated with the two tasks involving uncertainty: the risk task and the binary payoff lottery discounting task. We first modify Equation $14'$ by introducing the probability weighting function and denoting the higher paying outcome as M_{i1}, to give us

$$_{w}EU_i = w\left(p\left(M_{i1}\right)\right) \times \frac{\left(\omega + M_{i1}\right)^{1-r}}{1-r} + \left(1 - w\left(p\left(M_{i1}\right)\right)\right) \times \frac{\left(\omega + M_{i2}\right)^{1-r}}{1-r}. \quad (14'')$$

Thus, Equation 15 becomes

$$_{w}Pr_i^R(A) = \frac{_{w}EU_A^{1/\mu}}{_{w}EU_A^{1/\mu} + _{w}EU_B^{1/\mu}}. \quad (15')$$

And finally we have a modified log-likelihood function with probability weighting
for the choices from the risk task, given as

$$\ln{}_w L^{\mathrm{R}}(r,\mu,\gamma;y,\omega) = \sum_i \left(\left(\ln({}_w Pr_i^R(A)|y_i = A\right) + \left(\ln(1 - {}_w Pr_i^R(A)|y_i = B \right) \right).$$

$$(16')$$

Similarly, we allow for probability weighting by constructing a modified log likeli-
hood function for the P task choices. Following the derivation given in Equation $6''$,
Equations 10 and 11 become

$$_w NPV_A = \left(\frac{1}{1+\delta} \right)^t \times w\left(p_A \right) \qquad (10')$$

and

$$_w NPV_B = \left(\frac{1}{1+\delta} \right)^{t+\tau} \times w\left(p_B \right). \qquad (11')$$

This allows us to reexpress Equation 12 as

$$_w Pr_i^P(A) = \frac{_w NPV_A^{1/\xi}}{_w NPV_A^{1/\xi} + {}_w NPV_B^{1/\xi}}. \qquad (12')$$

And now we have a log likelihood function for the P Task choices which allows for
probability weighting, and is expressed as

$$\ln{}_w L^{\mathrm{P}}(\delta,\xi,\gamma;y) = \sum_i \left(\left(\ln({}_w Pr_i^P(A)|y_i = A\right) + \left(\ln(1 - {}_w Pr_i^P(A)|y_i = B \right) \right)$$

$$(13')$$

Because there is no uncertainty in the dollar discounting task, the likelihood con-
tribution from the D Task data is unchanged by allowing for probability weighting.
That is, $\ln{}_w L^{\mathrm{D}} = \ln L^{\mathrm{D}}$. Thus, we can express a joint log likelihood function for
all three tasks as

$$\ln{}_w L(\delta,r,\gamma,\mu,\nu,\xi;y,\omega) = \ln{}_w L^{\mathrm{R}} + \ln{}_w L^{\mathrm{D}} + \ln{}_w L^{\mathrm{P}}. \qquad (21)$$

The results of estimation allowing for probability weighting are shown in Table
8. The estimated discount rate of 13.0 percent is almost identical to that found

Table 8 Estimates of Risk and Time Preferences with Probability Weighting

Parameter	Estimate	Standard Error	p-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
r	0.722	0.062	0.000	0.601	0.843
δ	0.130	0.031	0.000	0.068	0.191
γ	0.996	0.098	0.000	0.804	1.187
μ	0.126	0.023	0.000	0.080	0.171
ν	0.011	0.003	0.000	0.006	0.017
ξ	0.045	0.008	0.000	0.028	0.061

when we assume probability weighting is absent. The CRRA coefficient is also similar to what we find when we use only the D Task and R Task data and assume no probability weighting. These results suggest that probability weighting has little impact in our experiment, and this is borne out by the fact that the confidence interval for γ includes 1. That is, we cannot reject the hypothesis that preferences are linear in probabilities. These results may be sensitive to our choice of probability weighting function, but we defer a more thorough exploration of parameterizations in the manner of Stott (2006) for a later date. Future work should also consider the link between an individual's probability weighting and hyperbolicity of time preferences as suggested by the findings of Epper et al. (2011).

5 Sensitivity Test of Payment Delay

A striking feature of these data is the large proportion of subjects who are willing to delay receiving payment at the lowest possible positive interest rate in the Probability Discount Rate Task. We do not observe this behavioral pattern in the Dollar Discount Rate Task in which discount rates are higher. The mean discount rate from the P-Task is 10.52-12.75 percent, but over one-third of all subjects reveal an individual discount rate below 1.01 percent. These subjects choose a 50.1 percent chance to earn $200 in 12 weeks over a 50.0 percent chance to earn $200 in 3 weeks.

We find it surprising that so many subjects respond so strongly to such a small increase in probability that they are willing to wait an additional nine weeks to receive payment. Because the joint-estimation technique yields only an aggregate curvature-free estimate of the discount rate, we cannot compare the distribution of individual discount rates obtained in the P Task to data from our jointly-estimated tasks. It is possible that this behavioral pattern may be the result of the specific parameters used for our probability discounting elicitation method in the first experiment. We conduct a second experiment to gauge sensitivity to parameter choices.

5.1 Experimental Design and Procedures

We implement four treatments in our second experiment (hereafter Experiment 2) to explore whether elicited discount rates are sensitive to the length of time participants must wait for payment. We manipulate both the horizon (i.e., the delay between the Sooner and Later payment dates) and the front-end delay (FED) (i.e., the waiting period before the payment date of the Sooner option). Table 9 defines the treatments. While our first experiment had a 3 week FED to hold constant the transaction costs and risks of receiving payment, our new experiment has FEDs of 2 weeks, 1 day, or 0 (i.e., payment is made at the end of the session before the subject leaves the laboratory). If preferences are hyperbolic (Ainslie, 1992) or quasi-hyperbolic (Laibson, 1997), then we expect to find that elicited discount rates will increase as the FED is reduced. Prior experimental research on the effects of the FED are mixed: Coller and Williams (1999) find that eliminating the FED significantly increases discount rates, while Anderson and Stafford (2009) find that reducing the FED to 1 day has no significant effects. We also vary the time horizon from 7 weeks to 1 week to investigate whether horizon influences the discount rate.

Note that the baseline treatment uses a 2 week FED and a 7 week horizon, which is slightly shorter in both dimensions than our previous experiment. Com-

Table 9 Experiment 2 Treatments

Treatment	Front-End Delay (days)	Horizon (days)
Experiment 1 (P Task)	21	63
Baseline	14	49
No front-end delay (No FED)	0	49
Short front-end delay (Short FED)	1	49
Short Horizon	14	7

paring discount rates from Experiment 1 and the baseline for Experiment 2 will give us a gauge on whether the discount rate distribution is excessively sensitive to the specific parameters chosen in Experiment 1.

Table 10 shows the probabilities of payment for the Later option given on the decision sheet for each treatment and the implied discount rate ranges. We use the results from Experiment 1 to inform our choice of discount rate intervals in the current experiment. In Experiment 1, 60 percent of subjects switch to the later payment date by Row 8, with switch points after this roughly evenly distributed across decision rows. Therefore, in Experiment 2 we keep the discount rate intervals the same as in Experiment 1 for the first 8 rows, but use wider intervals for the remaining decisions (and eliminate the very highest discount rate intervals where we see very little switching in Experiment 1).

We modify the procedures and instructions slightly for the new experiment.[18] First, subjects make only P-Task elicitation decisions. Second, prior to subjects making any decisions, we go through two examples of how payoffs are determined with a sample P-Task decision sheet in the instructions. The parameters in the sample decision sheet differed from those used in the actual experiment. Third, we add a cover sheet to each task to draw attention to the time dimension for the choices in that task. One possible explanation for our Experiment 1 data is that some subjects may not have fully considered the time horizon difference and instead focused only on the probability of receiving payment. If this is so, then subjects would be more likely to switch to the Later option whenever it had the

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[18] The instructions and decision sheets for all tasks in both experiments are available at http://www.excen.gsu.edu/swarthout/LMSV/ .

Table 10 Experiment 2 choices and implied ranges of discount rates.

Row	Chance of receiving $100 from Later option(percent)		Range of discount rate if switching in this row (percent)
	Baseline, No front-end delay, Short front-end delay	Short horizon	
1	50.00	50.00	$\delta \leq 0.00$
2	50.07	50.01	$0.00 \leq \delta \leq 1.01$
3	50.13	50.02	$1.01 \leq \delta \leq 2.02$
4	50.27	50.04	$2.02 \leq \delta \leq 4.08$
5	50.40	50.06	$4.08 \leq \delta \leq 6.18$
6	50.54	50.08	$6.18 \leq \delta \leq 8.33$
7	50.68	50.10	$8.33 \leq \delta \leq 10.52$
8	50.81	50.12	$10.52 \leq \delta \leq 12.75$
9	51.09	50.15	$12.75 \leq \delta \leq 17.35$
0	51.36	50.19	$17.35 \leq \delta \leq 22.13$
11	51.71	50.24	$22.13 \leq \delta \leq 28.39$
12	52.05	50.29	$28.39 \leq \delta \leq 34.97$
13	52.76	50.38	$34.97 \leq \delta \leq 49.15$
14	55.29	50.72	$49.15 \leq \delta \leq 111.54$

Note: the chance of receiving $100 from the Sooner option is always 50%.

higher probability of payment. The cover sheet included the payment amount (which was fixed across all tasks) and the payment dates but did not include the probabilities. For example, the cover sheet for the baseline treatment stated:

Before Making Any Decisions in This Task, Please Note:

Your choice in this Task is between two options that offer a chance of being paid $100 at different times this semester.

Payment for Option A will be in <u>14 days (2 weeks)</u> – on Tuesday, October 11

Payment for Option B will be in <u>63 days (7 weeks)</u> – on Tuesday, November 29

If you have any questions, raise your hand and one of us will come to you.

This experiment was conducted in two sessions on Tuesday, September 27, 2011. The sessions were held on the same day so that all future dates were held constant across sessions. We purposefully chose to conduct the experiment on a Tuesday so that all future payment dates were either on a Tuesday or Wednesday, when most students are already on campus. We also ensured that none of the future

payment dates conflicted with a holiday or final exams. A total of 75 undergraduate students participated.

In the new experiment, subjects participated in four decision-making tasks. Because they completed one additional task (relative to Experiment 1), we reduced the number of decisions subjects made from 20 to 14 in each of the four tasks. All subjects made decisions in all four tasks, but we randomly varied the order of tasks for each subject. After all four tasks were completed, subjects filled out a demographic questionnaire and then were paid privately their experiment earnings.

To determine experiment earnings, one of the four decision-making tasks was randomly chosen to count for payment. For this chosen decision-making task, a die-throw determined which one of the 14 decisions would count for payment. For this selected decision, the subject's choice of the Sooner or Later payment determined the probability of earning \$100 (and on what date). A final die throw determined whether the subject earned \$100 or nothing.

In addition to these experiment earnings (\$100 or nothing), each subject also received a \$25 participation payment (\$5 for each of the four tasks plus \$5 for completing the demographic questionnaire). Thus, each subject earned either \$25 or \$125.

5.2 Results

Figure 3 displays the proportion of subjects selecting the Sooner payment in each of the 14 decisions for each treatment. Recall that the AEIR increases as the subject moves down the decision sheet so that a greater number of Sooner choices implies a higher discount rate. In all treatments, there is a sizeable drop in the fraction of subjects choosing the Sooner option between the first and second decisions, which corresponds to an increase in the AEIR from 0 percent to 1 percent. This is similar to the pattern we saw in Figure 1 for the P-Task data in the corresponding interest rate range. As the AEIR is raised further, we see that the portion selecting the Sooner option continues to drop but at a more gradual pace. In comparing across
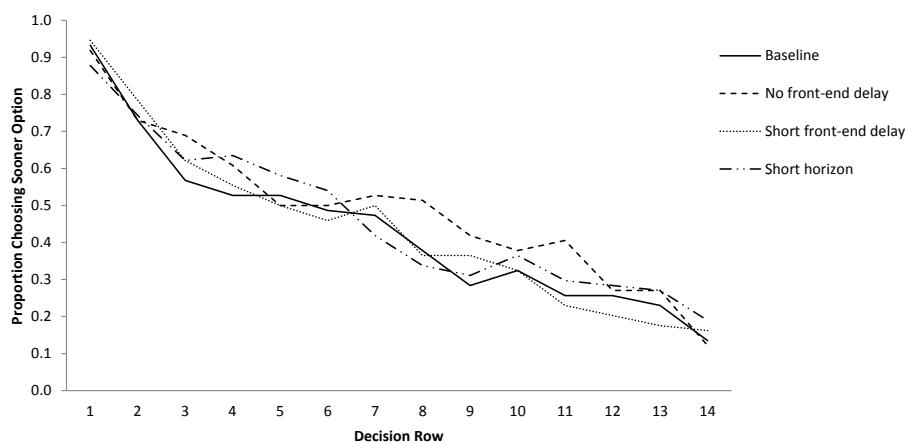
Fig. 3 Proportion of subjects choosing the Sooner option (option A) in Experiment 2 by decision row and treatment.

Table 11 Wilcoxon Signed Rank tests of equal distributions. All tests are two-tailed.

	All subjects			Excluding multiswitchers		
Test	n	z	prob > $|z|$	n	z	prob > $|z|$
Baseline = No front-end delay	75	-2.019	0.0435	53	-1.749	0.0803
Baseline = Short front-end delay	75	-0.586	0.5579	52	-0.838	0.4019
Baseline = Short horizon[1]	74	-1.079	0.2805	53	-1.250	0.2112

[1] We exclude one subject who circled both options on row 5 of the Short horizon treatment.

the treatments, the No FED treatment typically has a higher proportion of Sooner choices at any decision row relative to the Baseline while the other treatments are less obviously distinct. Wilcoxon Signed Rank tests comparing the distribution of the number of Sooner responses confirm this pattern. Table 11 reports these tests. We observe statistically significant present bias only for the No FED treatment. For the Short FED and Short Horizon treatments, we cannot reject the null that the distribution of the number of Sooner choices is the same relative to the Baseline treatment.

This pattern of behavior can also be seen in Table 12, which shows switching behavior and implied discount ranges in each of our four new treatments.[19] The overall pattern of behavior is quite similar to that observed with the parameters

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[19] As with Table 6, subjects who switch more than once are excluded from this tabulation.

Table 12 Experiment 2 choices, implied discount rate ranges, and switching behavior by treatment.

		Proportion switching in this row (percent)			
Row	Range of discount rate if switching in this row (percent)	Baseline[1]	No front-end delay[2]	Short front-end delay[3]	Short horizon[4]
1	$\delta \leq 0.00$	3.57	1.69	3.51	5.17
2	$0.00 \leq \delta \leq 1.01$	26.79	20.34	21.05	22.41
3	$1.01 \leq \delta \leq 2.02$	10.71	10.17	12.28	3.45
4	$2.02 \leq \delta \leq 4.08$	3.57	10.17	7.02	6.90
5	$4.08 \leq \delta \leq 6.18$	1.79	3.39	1.75	3.45
6	$6.18 \leq \delta \leq 8.33$	5.36	3.39	5.26	5.17
7	$8.33 \leq \delta \leq 10.52$	3.57	1.69	3.51	13.79
8	$10.52 \leq \delta \leq 12.75$	5.36	0.00	7.02	6.90
9	$12.75 \leq \delta \leq 17.35$	10.71	8.47	8.77	1.72
0	$17.35 \leq \delta \leq 22.13$	1.79	3.39	0.00	0.00
11	$22.13 \leq \delta \leq 28.39$	3.57	0.00	5.26	5.17
12	$28.39 \leq \delta \leq 34.97$	1.79	10.17	7.02	0.00
13	$34.97 \leq \delta \leq 49.15$	5.36	3.39	1.75	3.45
14	$49.15 \leq \delta \leq 111.54$	7.14	10.17	5.26	8.62

[1] Including only the 56 subjects who did not multiswitch. Five subjects always chose the Sooner option, implying a discount rate of at least 111.54 percent.
[2] Including only the 59 subjects who did not multiswitch. Eight subjects always chose the Sooner option, implying a discount rate of at least 111.54 percent.
[3] Including only the 57 subjects who did not multiswitch. Six subjects always chose the Sooner option, implying a discount rate of at least 111.54 percent.
[4] Including only the 58 subjects who did not multiswitch. Eight subjects always chose the Sooner option, implying a discount rate of at least 111.54 percent.

used in Experiment 1: the modal discount rate is between 0.00 and 1.01 percent, and the vast majority of subjects make choices consistent with a discount rate below 12.75 percent. We do see differences, however. In the Baseline treatment, just over 30 percent of all subjects exhibit a discount rate below 1.01 percent, which is lower than the 33.8 percent shown in Table 6. When there is no front-end delay, this falls substantially: just 22.03 percent of subjects exhibit a discount rate below 1.01. Elicited discount rates fall between these extremes for our other two treatments, short FED (24.56 percent of subjects show a discount rate below 1.01 percent) and short horizon (27.58 percent of subjects with a discount rate below 1.01 percent). Overall, it appears that discount rates are more sensitive to the front-end-delay than the time-horizon between payment periods. We continue to investigate the effect of FED and horizon with a structural model in the next section.

Table 13 Estimation of time preferences in Experiment 2 allowing for treatment effects

Parameter	Estimate	Standard Error	p-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
δ^B	0.113	0.035	0.001	0.044	0.183
δ^{NF}	1.574	0.322	0.000	0.943	2.205
δ^{SF}	1.049	0.197	0.000	0.663	1.435
δ^{SH}	0.000	0.001	0.852	-0.002	0.002
ξ	0.027	0.004	0.000	0.019	0.035

5.2.1 Structural Estimation

We design the estimation procedure specifically to test for treatment effects. We construct binary indicator variables for each of the non-Baseline treatments[20] and otherwise follow the model specification of Section 4.1.1. Estimating this model will provide us with a parameter estimate of δ^B, the discount rate associated with baseline observations, as well as the additive change in the discount rate associated with each of the non-baseline treatments, as given by δ^{NF}, δ^{SF}, and δ^{SH}.

Table 13 reports the maximum likelihood estimation of this model specification. We see that the discount rate associated with the Baseline treatment is 11.3 percent, which is very close to the 12.2 percent discount rate obtained from the prior experiment P-Task estimation. Further, the confidence intervals associated with both of these estimates are nearly identical. We view this similarity as a successful replication of the P-task results from the first experiment.

We now examine treatment effects. The most extreme effect is the increased discount rate in the No FED treatment; having no delay for the sooner payment increases the estimated discount rate to 168.7 percent. Similarly, a one day FED results in an estimated discount rate of 116.2 percent. Both of these treatment effects are significant at any standard level of confidence. Because future payments have higher transaction costs and risks, we expect the discount rate to increase

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[20] **d_NF** is equal to 1 if an observation is from the No FED treatment, 0 otherwise; **d_SF** is equal to 1 if an observation is from the Short FED treatment, 0 otherwise; **d_SH** is equal to 1 if an observation is from the Short Horizon treatment, 0 otherwise. We now express the discount rate as $\delta = \delta^B + \delta^{NF} \times \mathbf{d\_NF} + \delta^{SF} \times \mathbf{d\_SF} + \delta^{SH} \times \mathbf{d\_SH}$.

when the FED is eliminated (Coller and Williams, 1999). Considering only the no FED treatment, we cannot disentangle the effects of transaction costs from a "passion for the present." However, by comparing the no FED and one-day FED results, we infer that a "passion for the present" accounts for at least two-thirds of the observed discount rate increase in the No FED treatment. Finally, we estimate no change from the baseline discount rate in the Short Horizon treatment; the estimated effect associated with this treatment is less than 0.1 percent.

Much of the literature finding evidence in favor of hyperbolic over exponential discounting has relied on parametric assumptions about the utility function (Rohde, 2010). Our estimation results do not require such assumptions, and so provide new evidence against constant discounting, particularly when there is the chance at an immediate or one-day payment. However, if the soonest payment date is at least two weeks in the future, then we do not reject constant discounting in Experiment 2. Moreover, we also see that discount rates are in the same range across Experiment 1 and the Baseline treatment of Experiment 2. These results suggest that over this time range, the exponential model may be a reasonable local approximation of time preferences.

6 Conclusion

We develop a simple probability-based elicitation of time preferences and find a surprisingly low discount rate relative to the literature. The advantage of varying probabilities rather than prizes is that if expected utility is linear in probabilities, we can avoid the issues associated with estimating and correcting for the curvature of the utility function. Using the probability discounting elicitation method, we find average discounts rates of 12.2 percent in the first experiment and 11.3 percent in the second experiment when the front-end delay is at least two weeks. Because of the huge variation of discount rate estimates in the literature – even for those that address the curvature confound and, like ours, use real-valued rewards – we conduct a within-subjects comparison between our elicitation procedure and that of

Andersen et al. (2008). We find very similar results with both methods, though this similarity depends on the parametric assumptions of the utility function required for joint estimation. Given that the two different methods elicit preferences in two different dimensions (probabilities versus monetary amounts), we are encouraged by these results. We observe low discount rates among a population hither-to-now thought to be (at least by the authors) excessively impatient. Given prevailing interest rates at the time the study was conducted, perhaps we should not be so surprised to find one-third of our participants were willing to save with us for the duration of the semester when offered as little as 1.02 percent.

We conduct a second experiment to explore the robustness of our findings to a reduction in front-end delay and time horizon of payment. We find that when the sooner payment takes place at the conclusion of the experimental session during which decisions are made (zero FED), estimated discount rates are significantly higher than in our baseline treatment with a two-week FED. However, even with no FED, 22 percent of subjects are willing to wait to receive payment at an AEIR of just 1.01 percent. Increasing the FED to one day also leads to a significant increase in the estimated discount rate relative to the baseline FED of two weeks. Both of these results indicate significant present-bias in our data. In contrast, changing the time horizon between payment dates from one week to seven weeks has no significant effect on the estimated discount rate.

A potential advantage of a single elicitation procedure, as compared with a dual elicitation procedure, is ease of implementation, which is a non-trivial consideration in field settings. In addition, the discount rate estimate from the P Task is independent of any errors in estimating the curvature of the utility function (as long as preferences are linear in probabilities).The same logic that shows the importance of correcting for the curvature of the utility function also shows that an error in estimating curvature will be propagated to the discount rate estimate. Overestimate the curvature and the discount rate will be biased downward. Underestimate, and the discount rate will be biased upward. Another vexing issue

with estimating the curvature of the utility function is the need to estimate other parameters such as the level of background consumption. As long as background consumption is invariant over the time frame of the elicitation, we can safely avoid the need to estimate this parameter by use of the probability discounting procedure.

Moving forward with this research, more work needs to be done to consider non-expected utility frameworks. Our method does assume that preferences are linear in probabilities. Because of this, we test for evidence of probability weighting in our data. We do not find support for such weighting, given our subject pool and parameter values. In other populations and for other parameter values this may not be the case. We show in Section 2 that judicious choice of the parameter values may enable an experimenter with a good *a priori* sense of the form of probability weighting in her population to minimize it's impact. The alternative would be to administer multiple probability discounting tasks and then estimate both the probability weighting function as well as the discount rate. Note that there is still an advantage to using probability discounting tasks rather than monetary discounting tasks, in that at least we can avoid specifying and estimating the value function.

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A Experiment 1 Task P Instructions and Decision Sheet

(The instructions and decision sheets for all tasks in both experiments are available at `http://www.excen.gsu.edu/swarthout/LMSV/` .)

Each person in this room has the chance to earn a large sum of money from this part of the experiment. The amount of money you earn in this part of the experiment will depend both on your choices and also on chance. We will first explain to you the choices that you will be making, and then how your earnings are determined.

YOUR CHOICES

In this part of the experiment, you will be asked to make a series of choices between Option A and Option B. On the lab monitors, you can see three 10-sided die: a red die, a white die, and a blue die.

Your earnings in this part of the experiment depend, in part, on the outcome from rolling these three die. We will throw the dice, and then record the outcomes as a three digit number:

$$\underline{RedDie\#} \qquad \underline{WhiteDie\#} \qquad \underline{BlueDie\#}$$

For example, if we threw a "6" on the Red Die, a "4" on the White Die, and a "0" on the Blue Die, the number recorded would be 640. On the other hand, if we threw a "0" on the Red Die, "6" on the White Die and a "4" on the Blue Die, the number recorded would be 064. Notice that there are one thousand possible outcomes of the drawing. They can be listed as:

$$\{001, 002, 003, 004, \dots, 996, 997, 998, 999, 000\}$$

Each of these numbers has a 1-in-1000 chance of being thrown (if three zeros are thrown, this will represent an outcome of 1000).

Please look at the Decision Table. Each Decision row gives you a choice between Option A and Option B. As an example, look at the row for Decision 2. Option A pays $200 in three weeks if the number thrown on the die is between 001 to 500. Thus, there are 500-in-1000 chances of receiving $200 if you choose Option A. This represents a 50% chance of winning. Now look at Option B for Decision 2. Option B pays $200 in 12 weeks if the number thrown on the die is between 001 to 501. There are 501-in-1000 chances (50.1%) that the number drawn will be in this range. As you move down the table, Option A is always the same, but with Option B the chances of winning increase.

Looking down the rows of the Decision Table you can see that you have 20 Decisions to make. In each of these Decisions, Option A represents a chance to earn $200 in three weeks if

the number thrown on the die is between 001 and 500. In each of these Decisions, Option B represents a chance to earn $200 in 12 weeks, with the chance of earning this money increasing as you move down the rows of the table. For example, in Decision 16, there is a 500-in-1000 chance of earning $200 in 3 weeks if you choose Option A and a 536-in-1000 chance of earning $200 in 12 weeks if you choose Option B.

You will make twenty choices. For each Decision row, you will have to choose between Option A and Option B. You may choose A for some Decision rows and B for other rows, and you may change your choice and make them in any order. So now please look at the boxes on the right side of the record sheet. You will have to circle your choice of A or B for each of the twenty Decisions.

Even though you will make twenty Decisions, only one of these will end up possibly affecting your earnings, but you will not know in advance which Decision will be used. Each Decision has an equal chance of being used for payment.

HOW YOU WILL YOU BE PAID

For each Decision row, choose whether you prefer A or B for that row. After you have made all 20 Decisions, we will throw a black 20-sided die. You can see this die on the lab monitors. The number that is thrown on the 20-sided die will determine which one of your 20 Decisions will count for payment. For example, if we throw a 12, we will look at Decision Row 12 to see if you chose Option A or Option B. We will not look at any of your other Decisions when we determine your earnings for this part of the experiment.

Next, we will throw the three colored 10-sided dice to determine whether the monetary outcome is $200, as we described above. Continuing with the example for Decision 12, the table below illustrates the outcomes that would occur depending on the 3-digit die throw and whether you chose Option A or Option B.

Die Throw	Outcome If You Choose Option A	Outcome If You Choose Option B
001 - 500	$200 in 3 weeks	$200 in 12 weeks
501 - 518	$0	$200 in 12 weeks
519 - 000	$0	$0

Suppose instead that when we threw the 20-sided die we had determined that Decision 3 was the one that counts for payment. In this case, the table below illustrates the outcomes that would occur depending on the 3-digit die throw and whether you chose Option A or Option B.

Die Throw	Outcome If You Choose Option A	Outcome If You Choose Option B
001 - 500	$200 in 3 weeks	$200 in 12 weeks
501 - 502	$0	$200 in 12 weeks
503 - 000	$0	$0

After this, we will throw a Black 10-sided die for the final payment phase. If the outcome is between 2 and 9, then none of your choices in this part of the experiment will count for payment. If the outcome is a 0 or 1, then your choices and the earlier rolls will determine your earnings as described above.

Note that we will roll the dice individually for each person, and so each person is equally likely to receive payment in the final payment phase of the experiment. More than one person may be selected for payment, and each person selected will be paid the amount determined by their choices and die rolls as described above.

If you earn $200 in this task, we will give you a certificate for $200 redeemable in cash here in the Andrew Young School Building in three weeks or 12 weeks, depending on the option you choose. If you do earn this money, then at the end of the experiment we will give you more detailed instructions for redeeming your certificate and the location in this building where you will go to redeem your certificate.

SUMMARY

1. You will choose Option A or Option B for each of the 20 rows of the Decision Table.

2. We will throw a Black 20-sided die to determine which ONE of these Decisions will count.

3. We will look at the choice you made in this Decision, and then throw the three 10-sided dice (one red, one blue, and one white).

4. We will look at the three-digit-number that comes from the dice roll and also at your choice for this one Decision to determine the monetary outcome: receive $0, receive $200 in three weeks, or receive $200 in 12 weeks.

5. Finally, we will throw a 10-sided die to determine whether or not this outcome will be paid. If we throw a 2-9 then you will not be paid for your Decision. If we throw a 0 or 1, then you will receive payment according to the outcome in step #4. If the outcome is for you to receive $200, then you will receive a certificate for $200 that may be redeemed in three- or 12-weeks (depending on whether you chose Option A or Option B).

We will next go through a simple demonstration of this task before you make your choices. This demonstration is to help you better understand the task and will not count for money. Please listen and watch the demonstration before making your own choices.

If you have any questions, please raise your hand and one of us will come to your desk to answer it.

(Originally printed on legal paper.)

Task P Decision Table

Decision	Option A (Pays $200 in three weeks)		Option B (Pays $200 in twelve weeks)		Preferred Option (Circle A or B)	
	Winning Numbers for Option A	Chances of winning	Winning Numbers for Option B	Chances of winning		
1	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	A	B
2	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 0 1.	50.1%	A	B
3	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 0 2.	50.2%	A	B
4	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 0 4.	50.4%	A	B
5	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 0 5.	50.5%	A	B
6	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 0 7.	50.7%	A	B
7	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 0 9.	50.9%	A	B
8	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 1 1.	51.1%	A	B
9	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 1 2.	51.2%	A	B
10	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 1 4.	51.4%	A	B
11	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 1 6.	51.6%	A	B
12	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 1 8.	51.8%	A	B
13	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 2 0.	52.0%	A	B
14	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 2 2.	52.2%	A	B
15	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 2 7.	52.7%	A	B
16	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 3 6.	53.6%	A	B
17	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 4 5.	54.5%	A	B
18	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 6 9.	56.9%	A	B
19	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 5 9 4.	59.4%	A	B
20	You receive $200 in three weeks if the # rolled is between 0 0 1 and 5 0 0.	50.0%	You receive $200 in twelve weeks if the # rolled is between 0 0 1 and 6 4 7.	64.7%	A	B

ID Num	Decision Row Roll		Outcome Roll		Selection for Payment Roll
	Black-20	Red-10	White-10	Blue-10	Black-10 (0 or 1 = pay)