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Intertemporal Choice under Timing Risk: An Experimental Approach

Abstract

This paper investigates how individuals evaluate and choose among delayed outcomes with more than one possible realization time. We first show that under a general expected discounted utility model, such decisions depend only on individuals' intertemporal preferences (i.e., the magnitude of the discount rates and the shape of the discount function). Next, we obtain several testable hypotheses using the EDU model as a benchmark and test these hypotheses in three experiments. In general, our results show that the EDU model is a poor predictor of intertemporal choice behavior in the presence of timing risk. In particular, we found evidence for timing risk aversion. Moreover, our findings show that individuals evaluate timing lotteries in a rank-dependent fashion, and the main driver of timing risk aversion is nothing but probabilistic risk aversion that stems from the nonlinear treatment of probabilities.

Keywords: Intertemporal choice; timing risk; non-expected utility

1. Introduction

In many managerial and consumer decision-making problems, individuals have to evaluate alternatives which yield payoffs in the future. An inherent feature of some of these intertemporal choice problems is that the exact realization time of the future payoff is unknown or uncertain at the outset. For instance, the completion time of large investment projects, such as R&D ventures, is usually uncertain at the beginning of the project. When choosing between different potential investments, a manager has to take this uncertainty into account (Perrakis and Henin, 1974; Perrakis and Sahin, 1976). Likewise, in many consumption contexts, such as mail order or online shopping platforms, consumers may need to deal with uncertain delivery times. The issue of timing uncertainty has received scant empirical attention in the intertemporal choice literature. In the present paper, we attempt to fill this gap by examining such intertemporal decisions concerning timing risk.[1]

Previous literature that looked at risky intertemporal choice has been quite limited. A few studies have investigated how individuals discount delayed gambles (e.g., Ahlbrecht and Weber, 1997; Sagristano, Trope and Liberman, 2002). However, the main focus of these studies is outcome risk rather than timing risk. In a recent theoretical paper, Maskin and Dasgupta (2005) proposed an evolutionary explanation for intertemporal preference reversals by allowing for uncertainty around the realization time. They argued that if an intertemporal choice situation involves some uncertainty about the realization time of the payoffs, the intertemporal preferences may entail hyperbolic discounting. In the present paper, we will take an experimental approach to have an explicit examination of *how* individuals make intertemporal choices under timing risk, rather than the consequences of such an uncertainty on preferences.

Some animal studies examined choices between payoffs with risky timing and sure timing (see Kacelnik and Bateson 1996 for a review of this literature). These studies found that animals generally prefer risky delays to fixed delays with the same average time to

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[1] Throughout this paper, we will refer to those situations where the decision maker has more than one possible delay as *risky timing* or *risky delays* since we investigate delays with known (objective) probabilities.

reinforcement. To our knowledge, there is only one empirical study on timing risk conducted with human participants (Chesson and Viscusi, 2003).[2] These authors used data from a survey conducted with 146 business managers, in which participants were asked to choose between a timing lottery (i.e., receiving a hypothetical reward either in t_1 or in t_2 years with equal probabilities) and a sure timing alternative with the same average delay to the payoff (i.e., receiving the reward in $(t_1 + t_2)/2$ years for sure). They found that 31% of the 146 subjects preferred the sure timing to the timing lottery with the same expected delay. This finding is intriguing since, as we will argue in the next section, these subjects behaved in a way opposite to the predictions of the expected discounted utility model. In addition to documenting aversion to timing risk, the authors also provided some evidence that there is a positive correlation between the subjects' attitude toward ambiguity for outcomes in the loss domain (i.e., when the payoffs are negative) and their attitude toward the timing risk in the gain domain (i.e., when the payoffs are positive). In particular, individuals who are averse to timing risk in the gain domain were found to be 1.5 times more likely to choose the less ambiguous option in the loss domain.

In the current paper, we study the same type of decision problems in a more systematic way. We derive and test several hypotheses using the expected discounted utility (EDU hereafter) model as a benchmark model. Our findings on aversion to timing risk are consistent with the findings of Chesson and Viscusi (2003). That is, we found that, in the gain domain, a considerable number of individuals prefer the sure timing option (or the "less variable" option, as we will define later on) to the timing lottery with the same average delay to the payoff. In addition, our experimental manipulations imply that what seems like timing risk aversion is actually probabilistic risk aversion (Wakker, 1994). By manipulating the probabilities attached to possible realization times, we show that aversion to timing risk changes significantly from one timing lottery to another. Moreover, these changes are in the

[2] In another study, Leclerc, Schmitt and Dubé (1995) focused on risky decision making for waiting times, examining those situations where time itself is a resource. That is, they were interested in the value of time. In the current study, we are interested in the changes in an outcome's value as time changes. Thus, our problem is about time preferences rather than the utility for time.

direction predicted by overweighting small probabilities and underweighting large probabilities (Tversky and Kahneman, 1992; Prelec, 1998; Gonzalez and Wu, 1999; Wu and Gonzales, 1996). Hence, we conclude that individuals distort probabilities attached to risky delays in a similar manner they do for probabilities attached to risky payoffs.

Our second main experimental manipulation, namely the sign of the payoffs, reveals that individuals are not only using decision weights, but they also evaluate the timing lotteries in a rank-dependent fashion. The manipulation of outcome magnitude demonstrates that they tend to ignore the information about the outcomes when deciding between a timing lottery and a sure timing alternative. The present paper contributes to the timing risk literature by providing an explanation for the observed aversion to timing risk and to the non-expected utility theory literature by providing new evidence from another domain in which rank-dependent utility theories may have high descriptive power.

The paper proceeds as follows: In the next section, we will introduce some definitions and notations, in addition to deriving the predictions of a general discounted utility model for risky timing. In the following three sections, we will present the results of three experimental studies testing the predictions of this model. We will conclude with a general discussion of our findings and possible extensions for future research.

2. Discounted Utility Model and Timing Risk

This paper focuses on preferences over *timing lotteries* $(x; t_1, p_1; ...; t_n, p_n)$, where x denotes a sure outcome (e.g., a monetary payoff, a consumption good, etc.), t_is denote the possible delays and p_is denote the respective probabilities of these delays, where $\sum_i p_i = 1$.[3] A timing lottery gives a sure outcome in exactly one of the possible time periods.

A stream of outcomes distributed over time is generally evaluated by a discounted utility model in economics. Typically, this model combines a discount function that captures time preferences and a utility function that represents preferences over outcomes. We will

[3] We assume that x is a desirable outcome, that is, the decision maker's utility $u(.)$ is an increasing function of x.

employ a similar discounted utility framework to evaluate timing lotteries. We assume that individuals' preferences over consumption streams $(c_0, c_1, \ldots, c_T)$ can be represented by the following general discounted utility model, with the total utility of an outcome profile represented in an additively separable manner across time periods:

$$V(c_0, \ldots, c_T) = \sum_{t=0}^{T} D(t) u(c_t) \quad (1)$$

where $u(c_t)$ is a real-valued utility function, the direct utility derived from consuming c_t in period t, and $D(t)$ is the discount function, the weight given to the consumption in period t. Under the assumption of positive time preferences (i.e., preferring to consume earlier than later), $D(t)$ is a positive and declining function of delay with $D(0) = 1$.

In the classic discounted utility model (Koopmans, 1960; Samuelson, 1937), the discount function is modeled as an exponential function, $D(t) = [1/(1+r)]^t$, where the discount rate r is constant. The constant discounting assumption has been challenged by empirical studies which propose other discount functions with more descriptive power, among which is the hyperbolic discount function (Mazur, 1987; Loewenstein and Prelec, 1992). In hyperbolic discounting, the discount rate is decreasing over time. Two of the most widely-cited versions of hyperbolic discounting are the one-parameter function proposed by Mazur (1987), formulated as $D(t) = 1/(1+kt)$ where k is a constant and the two-parameter hyperbolic discounting function of Loewenstein and Prelec (1992), given by $D(t) = [1/(1+at)]^{b/a}$ where a and b are hyperbola coefficients. Note that all the discount functions proposed in the intertemporal literature so far, e.g., exponential, hyperbolic and quasi-hyperbolic functions, are strictly convex. In the following analysis, we will use a convex discount function, without any specific assumptions on its functional form[4].

Given this brief background, we return to our question, that is, how an individual whose preferences over consumption streams can be represented by (1) would choose between the

[4] We will refer, to a generalized discounted utility model, where the discount function can take any form, as an expected discounted utility (EDU) model hereafter.

timing lottery L: $(x; t_1, p; t_2, (1-p))$ and the sure timing alternative S: $(x; s)$ which offers the same payoff x at the sure delay s where $t_1 < s < t_2$. Let us assume that the baseline consumption is c in all time periods t_1, s and t_2. The timing lottery offers the consumption stream $(c+x, c, c)$ with probability p and $(c, c, c+x)$ with probability $(1-p)$; and the sure consumption profile is $(c, c+x, c)$ with certainty. The expected discounted utility of the timing lottery would be:

$$\begin{aligned} V(L) &= p\left[D(t_1)u(c+x) + D(s)u(c) + D(t_2)u(c)\right] \\ &\quad + (1-p)\left[D(t_1)u(c) + D(s)u(c) + D(t_2)u(c+x)\right] \end{aligned} \tag{2}$$

Likewise, the discounted utility of the sure consumption stream, denoted by $V(S)$, would be:

$$V(S) = D(t_1)u(c) + D(s)u(c+x) + D(t_2)u(c) \tag{3}$$

Subtracting (3) from (2) would give us the additional utility that the individual would derive from having chosen the risky consumption plan over the sure one:

$$V(L) - V(S) = \left(pD(t_1) + (1-p)D(t_2) - D(s)\right)\left(u(c+x) - u(c)\right) \tag{4}$$

Which alternative would the individual prefer? Assuming $u(.)$ is an increasing function of x, the individual would be *indifferent* between the risky consumption plan and the certain one if and only if:

$$pD(t_1) + (1-p)D(t_2) = D(s) \tag{5}$$

Equation 4 also implies that in the gain domain, i.e., when $x > 0$, the timing lottery is preferred to the sure alternative if and only if:

$$pD(t_1) + (1-p)D(t_2) > D(s) \tag{6}$$

since $u(c+x) - u(c) > 0$, for all $x > 0$. Likewise, in the loss domain, when $x < 0$, the timing lottery is preferred to the sure alternative if and only if:

$$pD(t_1) + (1-p)D(t_2) < D(s) \tag{7}$$

In this formulation, what determines the preference between a timing lottery and a sure timing alternative is the value that the discount function takes at given delays and the probabilities attached to those delays. Since both options yield the same outcome *x*, the shape of the utility function does not play any role in such decisions.

In order to see which alternative would be preferred, all that is needed is to check under which conditions the inequality $pD(t_1)+(1-p)D(t_2)>D(s)$ is satisfied. Since the sure delay is assumed to be between the two possible delays of the timing lottery, we can always write *s* as a linear combination of t_1 and t_2. In other words, we can always find an a, $0<a<1$, such that $s=at_1+(1-a)t_2$. Then, we can rewrite Inequality (7) as:

$$pD(t_1)+(1-p)D(t_2)-D(at_1+(1-a)t_2)>0 \tag{8}$$

Inequality (8) would be satisfied when $D(.)$ is convex and if $p\geq a$.[5] We summarize the predictions of the EDU model and formulate our first experimental hypothesis as follows:

> ***Hypothesis 1:*** *A decision maker, whose intertemporal utility function can be written as in Equation (1), with a convex-shaped discounting function, would always prefer the timing lottery L:* $(x;t_1,p;t_2,(1-p))$ *to the sure timing option S:* (x,s)*, where* $s=a\,t_1+(1-a)t_2$ *in the gain domain (i.e., when x>0) and would always prefer the sure timing option to the timing lottery in the loss domain (i.e., when x < 0), for all* $p\geq a$.

A special case is when $p=a$, that is, when the sure timing is the expected time of the timing lottery. In this case, we would expect the decision maker to prefer the timing lottery in the gain domain and the sure timing in the loss domain. For instance, a timing lottery that gives 1000€, either in one month with 50% probability or in eleven months with 50% probability, should be preferred to the sure timing option that gives 1000€ for sure in six months simply because of the time preferences implied by convex discounting. Intuitively, this is due to the fact that delaying the reception of the payoff from one month to six months causes a bigger decrease in the discounted utility of the prize than delaying it from six months

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[5] To see this, consider the following inequalities: $pD(t_1)+(1-p)D(t_2)\geq aD(t_1)+(1-a)D(t_2)$, since $p\geq a$ and $aD(t_1)+(1-a)D(t_2)>D(at_1+(1-a)t_2)$, due to convexity of $D(.)$. These two inequalities together would imply $pD(t_1)+(1-p)D(t_2)-D(at_1+(1-a)t_2)>0$ for all $p\geq a$.

to eleven months. As the discount rate of the decision maker increases, her preference for the timing lottery would become stronger, since the discount function would become even more convex.

If we relax the assumption that the individual's discount function is convex, the expected discounted utility model would still predict that the decision maker would switch her preference between the certain timing option and the timing lottery when the sign of the payoff is changed (see (6) and (7) above). Hypothesis 2 below summarizes this prediction:

Hypothesis 2: *An expected discounted utility maximizing decision maker would always reverse her preference between a timing lottery L:* $(x; t_1, p; t_2, (1-p))$ *and a sure timing alternative S:* (x, s) *whenever the sign of the payoff x is changed.*

INSERT TABLE 1 HERE

Table 1 shows a summary of the predicted preferences between the two alternatives under different conditions. Another prediction of the EDU model is that if an individual prefers the timing lottery to its expected timing alternative for a given probability distribution, then she should have the same preference ordering for any probability distribution. This prediction will constitute our third hypothesis:

Hypothesis 3: *An expected discounted utility maximizer's preference ordering between a timing lottery L:* $(x; t_1, p; t_2, (1-p))$ *and its expected timing alternative S:* $(x; pt_1 + (1-p)t_2)$ *should remain the same for all* $0 \le p \le 1$.

Note that none of these predictions depends on the shape of the individual utility function, i.e., the results would hold for any increasing utility function. We will test the descriptive validity of these predictions in the following sections.

3. Study 1: Pairwise comparisons with Sure Timing Alternative

In the first study, we test the predictions of the general discounted utility model introduced in the previous section by using three different response modes: pairwise comparisons, certain timing equivalents and attractiveness ratings. Based on our previous analysis, we predict that under the EDU model, individuals would be timing risk prone (i.e., prefer the timing lottery to the sure timing option with the same average delay to the outcome) in the gain domain and timing risk averse in the loss domain.

3.1. Method

Fifty-five first-year undergraduate economics students at Bogaziçi University, Istanbul, were recruited to participate in a paper-and-pencil questionnaire. All subjects were paid a flat rate of 5 NTL for their participation.[6]

In a within-subject design, participants answered a series of hypothetical intertemporal choice questions on simple timing lotteries, i.e., a sure payoff with two possible realization times with known probabilities. In total, there were six different timing lotteries resulting from crossing two payoff levels (x = winning 160 NTL or x = losing 140 NTL) with three levels of probabilities of early realization times (p= .20, .50, .90). The early and late realization times were fixed at t_1 at 1 month and t_2 at 11 months for all lotteries. In each scenario, the sure timing option corresponded to the expected time of the given timing lottery. Hence, the sure timing options were 2 months for the .90-lottery, 6 months for the .50-lottery and 9 months for the .20-lottery.

The timing lotteries were put in two different scenarios to induce gain and loss framings. In the gain domain, the scenario was as follows:[7]

> Imagine that you are working in a large company and all the employees, including you, will receive **160 NTL** each as an end-of-year bonus this year. Imagine that your employer gives you two options for the *reception time* of your **160 NTL** end-of-year bonus.
>
> **Option A** You will receive your bonus **in 6 months**.
>
> **Option B** There will be a random draw and you will receive your bonus
> either in **1 month** with **50%** probability
> or in **11 months** with **50%** probability

[6] At the time of the experiment, 1 Euro was approximately 1.6 New Turkish Liras.
[7] The scenario that we used in the loss domain was similar. In that scenario, participants were asked to imagine that they were going to pay a tax and they could choose between the two timing options.

Subjects were told that the uncertainty about the timing of outcomes was going to be resolved immediately after they made their choices. They proceeded with the experimental tasks after reading the scenarios. The questionnaire included several tasks in the order of matching task, choice task, attractiveness ratings and elicitation of discount rates. In the matching task, we asked participants to provide *certain timing equivalents* (CTEs), i.e., the certain time horizon for which they are indifferent between receiving the reward at that time and playing the timing lottery. More formally, the CTE for the timing lottery $(x; t_1, p; t_2, (1-p))$ is defined as $(x; CTE) \sim (x; t_1, p; t_2, (1-p))$.

The matching task was followed by a choice task in which participants made a choice between a timing lottery $(x; t_1, p; t_2, (1-p))$ and the corresponding sure timing option $(x; \bar{t})$ where $\bar{t} = pt_1 + (1-p)t_2$. After they made their choices, subjects rated the strength of their preferences on a 7-point Likert scale which also allowed them to express indifference between the options. Finally, we asked for subjects' present values (PVs) for winning 160 NTL and losing 140 NTL at var ious delay intervals in order to elicit their discount rates. The given delay intervals were 1, 2, 6, 9 and 11 months. We counterbalanced the order of the six timing lotteries but not the order of the tasks, so for each timing lottery, subjects had to answer questions in the following order: matching task, choice task, attractiveness ratings and elicitation of discount rates. [8]

3.2. Results

Preliminary analyses found no difference between different presentation orders, so we combine results across orders. We first report our findings on discounting behavior under sure timing. The mean values for the average monthly discount rates under different delay lengths are plotted in Figure 1.[9] The results show that all participants have positive time preference

[8] Experimental instructions are available from the authors upon request.
[9] We imposed a concave utility function $u(x) = x^{.88}$ to calculate the average monthly discount rates. We used the formula $(e^{-r_i T})X^{.88} = PV_i^{.88}$ where T is the number of months, X is the delayed amount, PV_i is the present value by participant i and r_i is the average monthly discount rate of participant i.

(i.e., their discount rates were positive). As seen in the graph, the average monthly discount rate is decreasing with the delay length. An individual level analysis shows that the individual discount rates are also decreasing consistent with hyperbolic discounting. This indicates that subjects' discount functions are convex-shaped. Thus, our predictions about subjects' choices remain valid.

INSERT FIGURE 1 HERE

Choice Task. In this part of the experiment, participants chose between timing lotteries and sure timing options with the same expected delay to the payoffs. As we proposed in Hypothesis 1, the EDU model predicts a preference for the timing lottery in the gain domain and for the sure timing option in the loss domain. Table 2 summarizes the percentage of subjects that behaved in the predicted direction. As seen from the table, the percentages are all quite different from 100% (the predicted ratio by the model).

INSERT TABLE 2 HERE

Hypothesis 2 predicts a switch in preference between the risky and sure options when the sign of the payoff changes. The last row of Table 2 shows the proportion of subjects that made the switch: 65% for the .90-lottery, 60% for the .50-lottery and 84% for the .20-lottery, which are all lower than 100%.

The EDU model also predicts that individuals' preferences between the timing lottery and the sure timing option do not depend on the probabilities attached to the realization times (Hypothesis 3). In other words, the proportion of subjects that prefer the timing gamble should remain the same in all three choice questions. Our results show that this is not the case: In the gain domain, the percentage of subjects who prefer the lottery went up from 25% to 78% as the probability of the early realization time went down from .90 to .20. The difference among the three proportions, namely 25%, 38% and 78%, is statistically significant (Cochran test, $c^2(2, N = 55) = 25$, $p < .001$). Likewise, in the loss domain, the difference among the three proportions, namely 7%, 60% and 91%, is also statistically significant, $c^2(2, N = 55) = 57.9$, $p < .001$. A pairwise comparison within each domain gave the same results, except for the difference between the .90-lottery (25%) and the .50-lottery (38%), $p = .097$.

Attractiveness Ratings. The responses from the attractiveness task clarify the picture revealed by the choice task. Controlling for indifference between the two options, the Likert-scale responses were in the same direction with the responses from the choice task. In other words, a participant who preferred the timing lottery in the choice task, also gave a response above 4 on the Likert scale, indicating a preference for the timing lottery. Table 3 shows the proportion of implied choices in this task for the gain domain. As seen from the last row of the table, the percentage of subjects who prefer the timing lottery is even lower than the ones in the choice task. In conclusion, what we observe is mostly risk aversion for the .90 and .50 lotteries and risk prone behavior for the .20-lottery.

Table 4 shows the distribution of implied choices for the gambles in the loss domain. Again, allowing subjects to express indifference between the two options decreased the responses that are consistent with the predictions of the EDU model: Individuals are generally risk-prone for the .90- and .50-lotteries and risk-averse for the .20-lottery.

INSERT TABLE 3 AND TABLE 4 HERE

Matching Task. In the matching task, we elicited participants' CTEs using direct judgments. The EDU model predicts that for both gains and losses, the CTEs would be smaller than the expected time. Previous research shows that direct judgments of certainty equivalents (certain timing equivalents in our case) can be biased (e.g., Birnbaum 1992). However, since we use the CTEs only comparatively, the bias due to direct judgments should not be a concern. We summarize the findings in Table 5.

INSERT TABLE 5 HERE

As shown in the table, the mean CTE for the .90-lottery is significantly higher than the expected time of 2 months in both gain and loss domains, $t(54) = 9.54$, $p<0.001$ and $t(54) = 15.27$, $p<0.001$. Moreover, none of the participants' CTE is smaller than 2. Likewise, for the .50-lottery in the gain domain, the mean CTE is higher than 6 months, $t(54) = 4.42$, $p<0.001$. However, in the loss domain, we cannot reject the null hypothesis of 6 months, $p=0.29$. On the other hand, for the .20-lottery, the mean CTE is smaller than the expected time of 9 months in both domains, $t(54) = -8.71$, $p<0.001$ and $t(54) = -9.48$, $p<0.001$, respectively. In short, the results are very similar to those of the choice task: Subjects are timing risk-averse (risk-prone) for the .90- and.50-lotteries and timing risk-prone (risk-averse) for the .20-lottery in the gain (loss) domain.

3.3 Discussion

In all three tasks, the observed deviations from the EDU predictions have a systematic pattern with respect to the probabilities of realization times. In particular, the number of subjects who choose the timing lottery in the gain domain and the sure timing option in the loss domain increase as the probability attached to early realization times gets lower. This robust pattern cannot be explained by the EDU model, which assumes that individuals treat probabilities linearly. If one assumes a linear probability weighting function, these results would violate the assumption of convexity of the discount function. However, the convexity of the discount function is a robust phenomenon, confirmed both in our experiment and also by previous research (see Frederick, Loewenstein and O'Donoghue, 2002 for a review). Our results might be better captured by a model in which probabilities are distorted, such as an inverse S-shaped probability weighting model proposed in the literature (e.g., Kahneman and Tversky 1979; Prelec 1998; Tversky and Kahneman 1992; Wu and Gonzalez 1996). For instance, an inverse S-shaped probability weighting function would imply that individuals would underweight a probability of .90 and use a smaller decision weight. This would make the .90-lottery less attractive compared to the expected time option, and lead individuals to choose the sure timing option. However, if the probability of early realization times is small, such as 20%, one would overweight that probability and the timing lottery would become relatively more attractive, compared to its expected time alternative. We will discuss the implications of these results and elaborate on our conjecture in Section 6.

4. Study 2: Pricing and Matching Tasks

In Study 1, we examined how individuals evaluate timing lotteries using choice tasks, which necessarily require a joint evaluation of the risky and certain alternatives. However, in many real-life decisions, one may need to evaluate a future payoff with risky timing without necessarily comparing it to a sure alternative, such as in the case of deciding how much to invest in an R&D project with an uncertain completion time. In addition, in the matching task of Study 1, in which we elicited the CTEs, participants may have anchored on the sure timing that was provided. To overcome such possible shortcomings, in Study 2, we elicited the present values (hereafter PV) of the timing lotteries by using a pricing task and by using a matching task in the absence of a sure timing option. Finally, we manipulated the magnitude of the payoffs to see how changes in payoff magnitudes affect the CTEs.

4.1. Method

Fifty-six first-year undergraduate economics students from Bogaziçi University, Istanbul, participated in this study. We paid all subjects a flat rate to of 5 NTL for their participation.

As in the previous study, we employed six different timing lotteries resulting from crossing two payoff levels (x = winning 1,600 NTL or x = losing 1,400 NTL) with three levels of probabilities of early realization times (p = .20, .50, .90). As before, the early and late realization times were fixed at t_1 =1 month and t_2 = 11 months. We also used the same scenarios as in the previous study, except that we did not provide the participants with any sure timing option. The questionnaire included matching and pricing tasks. In the matching task, participants provided their CTEs for the six timing lotteries. In the pricing task, they reported their PVs for the same lotteries. The matching task was given before the other tasks to be able to make a between-subject comparison of the elicited CTEs between the two studies. We also elicited participants' average monthly discount rates for the sure delays of 1, 2, 6, 9 and 11 months for $x = 1600$ NTL and $x = -1400$ NTL.

4.2 Results

Looking at the discount rates for the sure delays, all participants exhibited positive time preference. As seen in Figure 2, the mean values for average monthly discount rates decline as the delay length increases, both for gains and losses, indicating a hyperbolic discount function. Individual-level analysis shows that 96% of the subjects have decreasing discount rates consistent with hyperbolic discount functions.

INSERT FIGURE 2 HERE

Pricing Task. To provide further support for our findings in Study 1, we first compared the PVs of the timing lotteries to the PVs of the same payoffs with fixed delays. The latter set of responses was collected separately at the end of the questionnaire and was also used for eliciting time preferences under sure timing. The EDU model predicts that, in the gain (loss) domain, a timing lottery would be more (less) attractive than getting the money for sure at the expected time. This means that the PV of a timing lottery would be larger than the PV of the same payoff that occurs at the expected time. Table 6 shows the descriptive statistics for the PVs of the timing lotteries and the corresponding sure timing alternatives.

INSERT TABLE 6 HERE

We conducted a Wilcoxon test to compare the two sets of PVs. The results show that the PVs for the .90- and .50-lotteries in the gain domain are significantly lower than the PVs of their corresponding sure timing options, $z = -6.013$, $p < .001$ and $z = -2.573$, $p = .01$, respectively. The difference between the PVs for .20-lottery and the PVs for 9 months for sure is not statistically different, $z = -1.278$, $p = 0.201$. Hence, in general individuals behaved in a risk-averse manner for gains: they valued the payoffs with sure delays more than the same payoffs with risky delays with the same expected delay. However, in the loss domain, as shown by the descriptive statistics, individuals behaved more in a risk-neutral manner. The Wilcoxon tests confirm this conclusion. None of the differences between the PVs for the lotteries and the PVs for the corresponding sure timing options are significant ($-1.099 \le z < 0$ and $p \ge 0.272$ for all comparisons).

For further confirmation of the observed pattern, we analyzed the individual data using the same pricing task and we looked at the *implied* choices by comparing the PV of the timing lotteries with the PV of their corresponding sure timing options (see Tversky, Sattath and Slovic, 1988 for a discussion on choice versus implied choice). The proportion of the subjects that behaved as predicted by the EDU model is reported in Table 7. For instance, in the gain domain, only 5% of the subjects gave a PV for the .90-lottery higher than the one for the corresponding 2-month sure option. This risk-averse behavior is even more profound than what we observe in Study 1 (see Table 2). In other words, EDU predictions are poorer in the non-comparative case. On the other hand, in the loss domain, the proportion of subjects that behaved as predicted by the EDU model is higher compared to the first study, that is, individuals seem to prefer losses with sure delays to losses with risky delays, at least in non-comparative situations. Finally, in the implied choice case, the proportion of subjects that switched their preferences between the fixed and the risky delays is much lower than in the direct choice case.

INSERT TABLE 7 HERE

Matching Task. Table 8 shows the descriptive statistics for the CTEs in the gain and loss domains. The results are consistent with those from Study 1 (see Table 5). The mean CTE for the .90-lottery, both for gains and losses, is significantly higher than the expected time of 2 months ($t(55)=9.75$, $p< 0.001$ and $t(55)=8.78$, $p< 0.001$, respectively). In fact, all subjects gave a CTE higher than 2 months. This means they behave as if they are risk-averse for gains and risk-prone for losses. The mean CTE for the .50-lottery in the gain domain is not significantly different from 6 months, p=0.76, but the mean CTE in the loss domain is significantly lower than 6 months, $t(55)=-2.16$, $p=0.03$. Finally, the mean CTE for the .20-lottery is lower than the expected time of 9 months, both in the gain and in the loss domains, $t(55)=-9.26$, $p<0.001$ and $t(55)=-11.33$, $p<0.001$, respectively, indicating a risk-prone (risk-averse) behavior for gains (losses).

INSERT TABLE 8 HERE

By comparing Table 7 and Table 8, we can see that there is a discrepancy between the implied choice patterns revealed by the pricing task and the matching task, except for .50-and .90-lotteries in the gain domain. While the data revealed by the matching task are consistent with the pattern we observed in the first study (hence contradicting the predictions of the EDU model), the results from the pricing task are more mixed. In order to check for preference reversals between the pricing and matching tasks, we conducted an individual-level analysis. As seen in Table 9, even though there is no systematic pattern, the proportion of subjects that reversed their preferences in the two tasks is quite high. Such preference reversals, due to the compatibility of the response mode and the stimulus attribute, were also found in previous studies (e.g., Slovic, Griffin and Tversky, 1990).

INSERT TABLE 9 HERE

Finally, in a between-subject analysis, we compare the mean CTE values for Study 1 and Study 2 (Tables 5 and 8). Even though participants' discount rates elicited using the sure timing options were quite different in the two experiments, the CTEs for different lotteries were not statistically different, with the exception of the .50-lottery in the gain domain ($t=3.18$, $p<.002$) and the .90-lottery in the loss domain ($t=3.05$, $p=.002$). We will elaborate on the consequences of this result with respect to eliciting discount functions in the conclusion.

The two studies reported up to now focus on evaluating timing lotteries either by comparing them to a sure alternative or by eliciting the CTEs. In the next section, we present results from Study 3, where subjects had to choose between pairs of timing lotteries, in order to examine behavior in the absence of a sure realization time.

5. Study 3: Pairwise Comparisons without Sure Timing Alternative

The two previous experiments employed choice and matching tasks and joint and separate evaluation conditions. In all the choice questions, the alternatives were given as a timing lottery versus a sure option (fixed at the expected time of the timing lottery). This might create a bias, especially if there is a strong certainty effect (Tversky and Kahneman, 1981). Even though certainty effect cannot explain the changes in the proportion of risk-averse choices as the probabilities change, it can account for part of the risk aversion observed in the previous experiments. To control for this, we designed another experiment in which subjects were asked to indicate preference (or indifference) between different timing lotteries, with no sure timing alternative.

In each choice task, subjects faced two timing lotteries, which yield the same monetary payoff and which have the same expected delay. One of the two timing lotteries was *stochastically more variable* than the other. Thus, under the EDU model, we would expect any individuals with a convex discount function, exponential or hyperbolic, to choose the more variable lottery.[10]

5.1. Method

Forty-six first-year economics and management undergraduate students at Bogaziçi University, Istanbul, were recruited to participate in the study as a part of their coursework. They were paid a flat rate of 5 NTL for their participation.

[10] This follows from variability ordering. For $L_1, L_2 \geq 0$ such that $E[L_1] = E[L_2]$, L_1 is *more variable* than L_2 if and only if $E[h(L_1)] \geq E[h(L_2)]$ for all convex h (Ross, 1996).

Participants answered a series of hypothetical intertemporal choice questions in which they were asked to choose between two timing lotteries. In total, there were 24 choice pairs constructed from matching 12 timing lotteries. The timing lotteries have only two possible delays and as before, three probability levels are used for the early realization times (p =.20, .50 and .90). Half of the twelve timing lotteries have an expected delay of 4 months and the other half have an expected delay of 18 months. The sure monetary payoff is fixed at 5,000 NTL for all lotteries. The lotteries and the predicted preference orderings under EDU are given on Figure 3. We paired the lotteries in all possible combinations such that one lottery is stochastically more variable than the other, and such that the expected times of the paired lotteries are the same.[11] This procedure resulted in twelve questions for each level of expected delay and 24 choice questions in total.

INSERT FIGURE 3 HERE

5.2. Results

We hypothesize that if subjects are exponential or hyperbolic discounters, regardless of their discount rates, they would choose the more variable timing lottery (see Footnotes 8 and 9). The proportion of subjects that chose the more variable lottery in each pair is shown in Table 10. On average, participants chose the more variable lottery only 30% of the time (Note that the EDU prediction for this proportion is 100%). Assuming that individuals have convex-shaped discount function, our design enables us to attribute these deviations to insensitivity to the objective probabilities. Moreover, the deviations from the predictions are more pronounced in those choice pairs where the probability of early realization is .90 for the more variable lottery and .20 for the less variable lottery (e.g., pairs such as L_6 vs. L_1 and L_6 vs. L_2) consistent with underweighting of .90 and overweighting of .20. On the other hand, the deviations from the EDU predictions are less pronounced for those pairs where both gambles

[11] If L_1 and L_2 are nonnegative random variables with distributions F and G respectively, then L_1 is *more variable* than L_2 if and only if $\int_a^{\infty}(1-F(x))dx \geq \int_a^{\infty}(1-G(x))dx$ for all $a \geq 0$ (see Ross, 1996)

had the same probability for early realization (e.g., L_4 vs. L_1, L_5 vs. L_2 and L_6 vs. L_3). This study enables us to conclude that observed aversion to timing risk can be explained only by non-linear treatment of probabilities given that individual discount functions are convex shaped.

INSERT TABLE 10 HERE

6. General Discussion

The expected utility model assumes that the sole determinant of an individual's risk attitude is the shape of her utility function. Hence, in a risky timing problem, keeping the amount of the future payoff constant and assuming that the discount function and the utility function are separable, the shape of the utility function should not play any role in determining the risk attitude. Instead, it is the shape of the discount function which determines one's attitudes toward risk, since the variation comes only from the timing of the outcomes. Under the classical assumption of convex discounting (i.e. constant or decreasing discount rates), the EDU model predicts that individuals are risk-prone for timing when the outcome is desirable and risk-averse when the outcome is undesirable. However, our results show that this framework fails to predict individuals' choices for risky timings. First, we found that a substantial number of subjects behaved as if they were risk-averse in the gain domain and risk-prone in the loss domain. Second, their risk attitude toward timing risk was sensitive to the probabilities attached to realization times. In particular, they became more risk-averse (risk-prone) in the gain domain (loss domain) as the probability of the early realization time went down. Third, for both choice and matching tasks, a significant number of participants did not switch their preferences between the risky and the sure timing option when the sign of the outcome was changed. All these observations indicate that an EDU model cannot capture the individual behavior, and that there is a need for a behaviorally more appealing model that allows for probability transformation, such as a rank-dependent model.

In rank-dependent utility models (Quiggin, 1982; Tversky and Kahneman, 1992), risk attitude is determined by the shape of the utility function (or the shape of the discount function in our case) *and* by the shape of the (cumulative) probability transformation. The rank-dependent utility of a simple lottery $(p_1, x_1;...; p_n, x_n)$, where $x_1 \geq x_2 \geq ... \geq x_n$ and $p_j > 0$ for all j, is:

$$RDU(p_1, x_1;...;p_n, x_n) = \sum_{i=1}^{n} \pi_i U(x_i) \tag{9}$$

where $\pi_i = w(p_1 + ... + p_i) - w(p_1 + ... + p_{i-1})$ and $\pi_1 = w(p_1)$, and where $w(.)$ is a probability weighting function increasing with $w(0) = 0$ and $w(1) = 1$. Applying this representation to the timing lotteries is straightforward, since in timing lotteries we have only one payoff and possible timings impose a natural order on the timed outcomes (x, t_i) given the decision maker's time preference.

Assuming that the decision maker has positive time preference, and $x \geq 0$ is a desirable payoff, we have $(x, t_i) \prec (x, t_j)$ for all $t_i > t_j$. Likewise, in the loss domain, for a payoff $x < 0$, the order of preference would reverse: $(x, t_i) \succ (x, t_j)$ for all $t_i > t_j$. Without loss of generality, for a timing lottery $(x; t_1, p_1;...;t_n, p_n)$, with $t_1 < t_2 < ... < t_n$, we would have $(x, t_1) \succ (x, t_2) \succ ... \succ (x, t_n)$. The rank-dependent discounted utility of this timing lottery would be:

$$RDDU(x; t_1, p_1;...;t_n, p_n) = \sum_{i=1}^{n} \pi_i D(t_i) u(x) \tag{10}$$

where $\pi_i = w(p_1 + ... + p_i) - w(p_1 + ... + p_{i-1})$; $\pi_1 = w(p_1)$, and $w(.)$ is the probability weighting function.

Now let us look at the simple timing lotteries used in our experiments to see how a RDDU model can explain the findings: Under the RDDU framework, preferences between the risky timing option and the sure timing option (for gains) would be determined by the following equation:

$$V(L)-V(S)=\left(w(p)D(t_1)+(1-w(p))D(t_2)-D(\bar{t})\right)\left(u(c+x)-u(c)\right) \quad (11)$$

where $\bar{t}$ is the expected time of the timing lottery L and $w(p)$ is an inverse S-shaped probability weighting function with $w(0)=0$ and $w(1)=1$ (Tversky and Kahneman, 1992; Prelec, 1998; Gonzalez and Wu, 1999).

Unlike the EDU model, the rank-dependent evaluation of timing lotteries does not require a decision maker's preference ordering between a timing lottery $(x; t_1, p; t_2, (1-p))$ and its expected timing alternative $(x; pt_1+(1-p)t_2)$ to remain the same for all $0 \le p \le 1$. An individual who is evaluating timing lotteries in a rank-dependent fashion would prefer the risky option $(x; t_1, p; t_2, (1-p))$ to its expected timing alternative $(x; pt_1+(1-p)t_2)$ whenever $w(p) \ge p$. Since $w(p)$ is an inverse S-shaped function, for small probabilities we have $w(p) > p$ and for large probabilities we have $w(p) < p$. Hence, an individual might be risk-averse for timing lotteries where the probability of early timing is large, and risk-prone whenever the probability of early timing is small. For instance, in our experiments, for the .20-lottery in the gain domain, individuals would choose the risky timing option under RDDU since $w(.20) > .20$. Likewise, for the .90-lottery, since $w(.90) < .90$, the weight of the early realization would decrease and this would, in return, reduce the attractiveness of the lottery. This is the pattern we found in both matching and choice tasks.

Looking at the loss domain, where the later realization is better than earlier realization, decision weights would be as follows:

$$V(L)-V(S)=\left(1-w(1-p))D(t_1)+w(1-p)D(t_2)-D(pt_1+(1-p)t_2)\right)\left(u(c+x)-u(c)\right) \quad (12)$$

This shows that even if the decision maker uses the same probability weighting function, the decision weights for gains and for losses would differ from each other, due to the ranking of the timed payoffs. For instance, for the .90-lottery in the loss domain, the difference in discounted utilities of risky timing and sure timing options would be:

$$V(L)-V(S)=\left((1-w(.10))D(t_1)+w(.10)D(t_2)-D(.90\,t_1+.10\,t_2)\right)\left(u(c+x)-u(c)\right)$$

and since $w(.10) > .10$, the weight of $D(t_1)$ would be smaller than .90. Thus, the risky option would become relatively more attractive given that the decision maker prefers to pay later than earlier. Likewise, for the .20 lottery we would have:

$$V(L) - V(S) = \left((1 - w(.80))D(t_1) + w(.80)D(t_2) - D(.20t_1 + .80t_2)\right)\left(u(c + x) - u(c)\right)$$

and since $w(.80) < .80$, the weight of $D(t_1)$ would be larger than .20, making the risky timing option less attractive.

A rank-dependent DU model can also explain why a considerable number of subjects did not switch their preferences when the sign of the payoff was changed. When the payoff sign changes, the ranking of the best and worst timings reverse, leading to a change in decision weights, even if the probability weighting function remains the same across domains. To explain why individuals may not switch their preferences between the sure option and the risky option with a change in payoff sign, we need to impose some extra conditions on the probability weighting function known in the literature as *subcertainty* and *supercertainty* (Gonzalez and Wu, 1999; Wakker, 1994). Suppose that a decision maker prefers the risky timing option in both domains. If the individual prefers the timing lottery to the sure timing option in the gain domain, this would imply the following inequality:

$$V(L) > V(S) \Leftrightarrow w(p)D(t_1) + (1 - w(p))D(t_2) > D(pt_1 + (1 - p)t_2) \tag{13}$$

Likewise, if she prefers the timing lottery also in the loss domain, this would imply:

$$V(L) > V(S) \Leftrightarrow (1 - w(1 - p)D(t_1) + w(1 - p)D(t_2) < D(pt_1 + (1 - p)t_2) \tag{14}$$

Inequalities (13) and (14) together would imply:

$$(w(p) + w(1 - p) - 1)D(t_1) + (1 - w(p) - w(1 - p))D(t_2) > 0$$

$$\Leftrightarrow (w(p) + w(1 - p) - 1)(D(t_1) - D(t_2)) > 0 \tag{15}$$

Since $D(t_1) - D(t_2) \geq 0$, to satisfy Inequality (15), the probability weighting function of the decision maker should have the supercertainty property, that is, $w(p) + w(1 - p) > 1$, i.e., the sum of the weights for complementary probabilities should be more than 1. In a similar manner, one can show that if the decision maker prefers the sure timing option in both domains, her probability weighting function should have the subcertainty property (i.e., the sum of the weights for complementary probabilities is less than 1), that is, $w(p)+w(1-p)<1$. Previous research showed that the subcertainty and supercertainty properties of the probability weighting function are related to the elevation of $w(.)$ (Gonzalez and Wu, 1999). In this case, subcertainty would imply a probabilistic risk aversion, whereas supercertainty would mean risk-prone behavior (Wakker, 1994).

6. Conclusion and Future Research Directions

The main contribution of this paper is that it shows that it is not possible to capture individuals' risk attitudes for timing lotteries only through the shape of their discount function which are found to be convex in our studies. A convex-shaped discount function would predict one to be risk-prone for the risks generated by the variability in the delay of a payoff. However, we found that individuals can actually exhibit risk aversion for timing lotteries. We argue that the main source of the observed risk aversion is that they use decision weights rather than objective probabilities and that they evaluate risky delays in a rank-dependent fashion. Therefore, an individual's risk attitude in the time domain is determined by the shape of her (cumulative) probability distortion function together with the discount function. To sum up, in the absence of planning disadvantages due to risky realization times, aversion to timing risk is nothing but probabilistic risk aversion. Hence, by replicating and extending the limited past research on timing risk, we provide a possible explanation for the timing risk aversion.

Despite the fact that we mainly focused on the probabilities and risk attitudes in evaluating timing lotteries, taking the discount functions as given, the evaluation of a timing lottery and choices between a timing lottery and a sure timing alternative is strongly related to pure time preferences. Actually, as we argued under the EDU model, an individual's time preference, captured by her discount function, is the only factor that determines her evaluation of risky delays and her choice between a timing lottery and a sure timing alternative. This means that timing lotteries can be fruitfully used to elicit individuals' time preferences (Chesson and Viscusi, 2000). However, as we have shown, one needs to take probability distortions into consideration when calculating the implied discount rates using timing lotteries.

Even though it requires an extra step in the elicitation process, we think that eliciting discount functions using timing lotteries is a promising research direction. This is due to the fact that the conventional way of eliciting discount rates (i.e., calculating the implied discount rates from the present values of delayed amounts) can be sensitive to the sign and magnitude of the payoffs. However, in the studies that we have conducted, the certain timing equivalents, elicited under different conditions, were quite stable, meaning that the implied discount rate calculated by using timing lotteries is not sensitive to the magnitude or the sign of the payoff. This means that the sign effect (gains are discounted more than losses) and the magnitude effect (small outcomes are discounted more than large ones) that are documented in the empirical intertemporal choice literature (e.g., Benzion, Rapoport and Yagil, 1989; Thaler, 1981) might be just an artifact of the particular elicitation method chosen.

In this paper, we argue that individuals use non-linear decision weights when they are evaluating risky timing options. However, we still do not know if the exact shape of the probability weighting function in this framework is the same as those given by the previous parametric specifications (e.g., Tversky and Kahneman, 1992; Prelec, 1998). Eliciting the probability weighting function and the discount function simultaneously seems to be another promising research direction, which would contribute to our knowledge of both probability transformation and discounting behavior. In short, understanding how people think about risky time horizons is important, and our current state of understanding of the issue is far from complete.

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Table 1: Preferences between the risky and sure timing options

	Gain Domain ($x > 0$)	**Loss Domain ($x < 0$)**
$pD(t_1) + (1 - p)D(t_2) > D(s)$	Risky timing is preferred to sure timing	Sure timing is preferred to risky timing
$pD(t_1) + (1 - p)D(t_2) = D(s)$	Indifference	Indifference
$pD(t_1) + (1 - p)D(t_2) < D(\tilde{t})$	Sure timing is preferred to risky timing	Risky timing is preferred to sure timing

Table 2: Proportion of subjects that behaved as predicted by EDU in Study 1 (n = 55)

	Choice problems		
	.90-lottery vs. 2 months	.50-lottery vs. 6 months	.20-lottery vs. 9 months
Gain domain	25%	38%	78%
Loss Domain	7%	60%	91%
Switch rate	65%	60%	84%

Table 3: Distribution of responses in the attractiveness scale for gains in Study 1 (n = 55)

	Choice pairs		
	.90-lottery vs. 2 months	.50-lottery vs. 6 months	.20-lottery vs. 9 months
Prefers sure timing option (response ≤ 3)	75%	62%	2%
Indifferent (response = 4)	25%	25%	25%
Prefers timing lottery (response ≥ 5)	0%	13%	73%

Table 4: Distribution of responses in the attractiveness scale for losses in Study 1 (n = 55)

	Choice pairs		
	.90-lottery vs. 2 months	.50-lottery vs. 6 months	.20-lottery vs. 9 months
Prefers sure timing option (response ≤ 3)	0%	33%	73%
Indifferent (response = 4)	7%	42%	22%
Prefers timing lottery (response ≥ 5)	93%	25%	5%

Table 5: Descriptive statistics for elicited CTEs in Study 1 (n = 55)

	Timing lotteries		
	.90-lottery	.50-lottery	.20-lottery
Gain Domain			
Mean (Std. Dev.)	3.236 (.961)	6.582 (.975)	7.910 (.928)
Median	3	7	8
% subjects for which CTE< $\bar{t}$	0%	13%	71%
Loss domain			
Mean (Std. Dev.)	3.7 (.825)	5.87 (.883)	7.8 (.925)
Median	4	6	8
% subjects for which CTE< $\bar{t}$	0%	32%	72%
Expected Time	2	6	9

Table 6: Mean PVs of timing lotteries and of expected timing options in Study 2 (n = 56)

	Delay Lengths					
	.90-lottery	2 months	.50-lottery	6 months	.20-lottery	9 months
GAINS						
Mean	1,111.52	1,305.45	975.36	1,020.62	857.5	872.77
(Std. Dev.)	(199.84)	(118.25)	(153.14)	(117.26)	(106.31)	(84.99)
Median	1,100	1,300	927.5	1,000	835	870
LOSSES						
Mean	1039.91	1016.25	921.16	914.73	821.87	805.18
(Std. Dev.)	(163.56)	(117.01)	(146.22)	(123.92)	(114.45)	(93.73)
Median	1000	1000	900	900	800	800

Table 7: Proportion of subjects that behaved as predicted by EDU in Study 2 (n = 56)

	Implied choices			
	.90-lottery vs. 2 months	.50-lottery vs. 6 months	.20-lottery vs. 9 months	All lotteries
Gain domain	5%	27%	34%	2%
Loss Domain	71%	68%	63%	41%
Switch rate	27%	34%	32%	2%

Table 8: Descriptive statistics for elicited CTEs in Study 2 (n = 56)

	Timing lotteries		
	.90-lottery	.50-lottery	.20-lottery
Gain Domain			
Mean (Std. Dev.)	3.34 (1.03)	5.95 (1.09)	7.51 (1.20)
Median	3	6	8
% subjects for which CTE< $\bar{t}$	0%	34%	75%
Loss domain			
Mean (Std. Dev.)	3.17 (.99)	5.71 (.98)	7.56 (.95)
Median	3	6	8
% subjects for which CTE< $\bar{t}$	0%	38%	82%
Expected Time	2	6	9

Table 9: Proportion of the preference reversals for each item in Study 2 (n = 56)

	Preference reversals in implied choices		
	.90-lottery vs. 2 months	.50-lottery vs. 6 months	.20-lottery vs. 9 months
Gain domain	29%	43%	71%
Loss Domain	77%	86%	57%

Table 10: Proportion of subjects that behaved as predicted by EDU in Study 3

Near Future, Exp Time = 4 months		Far Future, Exp Time = 18 months	
Choice question	% choosing more variable	Choice question	% choosing more variable
L_2(.50, 2; 6) > L_1(.20, 2; 4.5)	41%	**L_8(.50, 14; 22)** >. L_7(.20, 14; 19)	46%
L_3(.90, 2; 22) > L_2(.50, 2; 6)	30%	**L_9(.90, 14; 54)** > L_8(.50, 14; 22)	22%
L_3(.90, 2; 22) > L_1(.20, 2; 4.5)	20%	**L_9(.90, 14; 54)** > L_7(.20, 14; 19)	7%
L_5(.50, 0; 8) > L_4(.20, 0; 5)	48%	**L_{11}(.50, 10; 26)** > L_{10}(.20, 10; 20)	52%
L_6(.90, 0; 40) > L_5(.50, 0; 8)	39%	**L_{12}(.90, 10; 90)** > L_{11}(.50, 10; 26)	11%
L_6(.90, 0; 40) > L_4(.20, 0; 5)	22%	**L_{12}(.90, 10; 90)** > L_{10}(.20, 10; 26)	9%
L_4(.20, 0; 5) > L_1(.20, 2; 4.5)	76%	**L_{10}(.20, 10; 20)** > L_7(.20, 14; 19)	65%
L_5(.50, 0; 8) > L_2(.50, 2; 6)	57%	**L_{11}(.50, 10; 26)** > L_8(.50, 14; 22)	63%
L_6(.90, 0; 40) > L_3(.90, 2; 22)	17%	**L_{12}(.90, 10; 90)** > L_9(.90, 14; 54)	30%
L_6(.90, 0; 40) > L_2(.50, 2; 6)	0%	**L_{12}(.90, 10; 90)** > L_8(.50, 14; 22)	7%
L_5(.50, 0; 8) > L_1(.20, 2; 4.5)	37%	**L_{11}(.50, 10; 26)** > L_7(.20, 14; 19)	11%
L_6(.90, 0; 40) > L_1(.20, 2; 4.5)	0%	**L_{12}(.90, 10; 90)**> L_7(.20, 14; 19)	4%

Figure 1: Mean Values for Average Monthly Discount Rates in Study 1 (n = 55)

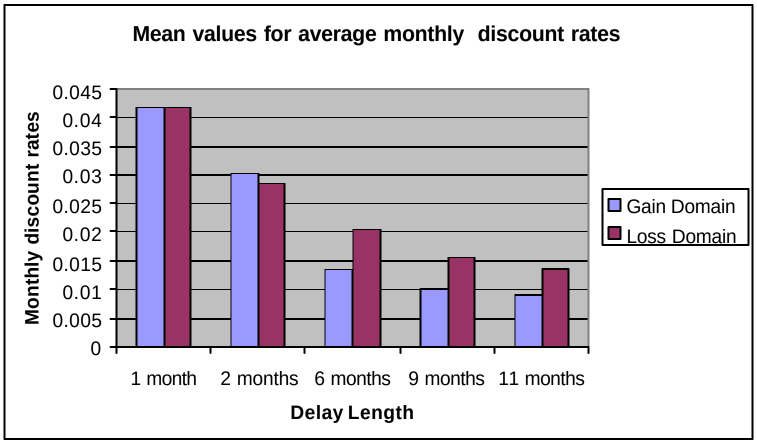


Figure 2: Mean Values for Average Monthly Discount Rates in Study 2 (n = 56)

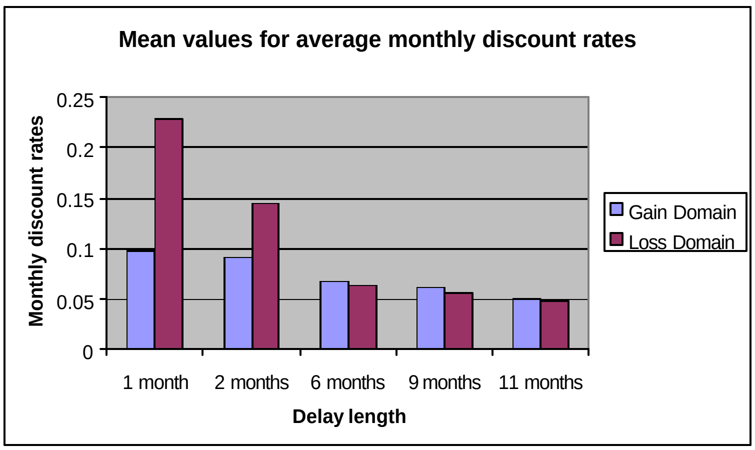
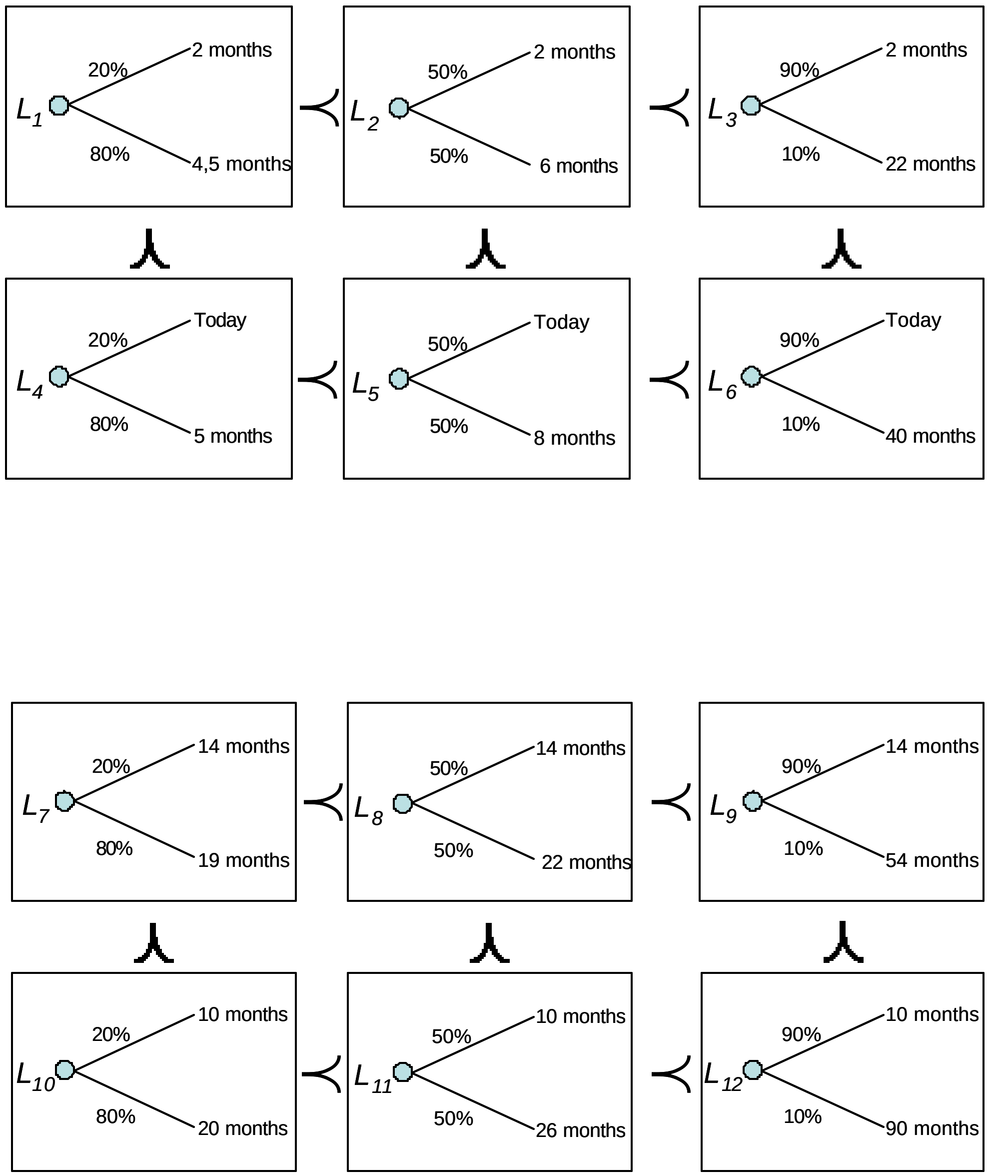


Figure 3: Experimental Design and Preference Predictions in Study 3



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