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Risk Preferences at Different Time Periods: An Experimental Investigation

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Intertemporal decision making under risk involves two dimensions: time preferences and risk preferences. This paper focuses on the impact of time on risk preferences, independent of the intertemporal trade-off of outcomes, i.e., time preferences. It reports the results of an experimental study that examines how delayed resolution and payment of risky options influence individual choice. We used a simple experimental design based on the comparison of two-outcome monetary lotteries with the same delay. Raw data clearly reveal that subjects become more risk tolerant for delayed lotteries. Assuming a prospect theory–like model under risk, we analyze the impact of time on utility and decision weights, independent of time preferences. We show that the subjective treatment of outcomes (i.e., utility) is not significantly affected by time. In fact, the impact of time is completely absorbed by the probability weighting function. The effect of time on risk preferences was found to generate probabilistic optimism resulting in a higher risk tolerance for delayed lotteries.

Key words: time preferences; risk preferences; delayed lotteries; attitude toward risk; utility; decision weights; optimism; sensitivity to probabilities
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1. Introduction

Suppose that a decision maker (DM) is indifferent between two immediately resolved and payable options: $300 for sure and a 50-50 lottery for $0 or $1,000. Does the DM exhibit the same indifference if both options are to be resolved and paid with a delay of one year from now?[1] Recent empirical findings by Noussair and Wu (2006) show that in an expected-utility setup, time does influence risk preferences and the DM may prefer the lottery to the sure amount when he or she is faced with both options in the future. This finding is also consistent with research that suggests when a risky option is delayed, individuals may perceive it differently. For instance, Baucells and Heukamp (2009) propose a probabilistic discount rate that captures the difference between the perceived value of an immediate lottery and a future one. Other studies establish the link between intertemporal choice and risk by introducing a mortality rate that depicts the belief that future outcomes may disappear (Epper et al. 2009, Halevy 2008).

Many decisions in management and economics involve risky options that are blocked for a predefined period of time (e.g., five years). The uncertainty about returns is resolved and payment made only at the end of that period. Barrier options, quite popular in financial markets, are another example. The price of the underlying security must reach a prespecified level or barrier within a given time frame $[0, T]$ before these options can be exercised. A different example is the current debate on whether there is a need to take action regarding climate change because of the severe uncertainty inherent to the situation. In this case, a higher level of risk tolerance for lotteries played out in the future can explain the reluctance of a significant segment of the population to change their behavior as regards the consumption of fossil energy. All of these examples show that a comparative analysis of risk attitudes for lotteries that are resolved and paid in the present versus in the future is needed in order to better understand the implications on markets and on policy making.

The present paper aims to contribute to the literature on risky intertemporal choice through an experimental elicitation of individual preferences at different points of time. More specifically, we use

[1] In our setup, "delay" refers to cases where a lottery is both resolved and paid at the same time in the future.

the certainty equivalents of two-outcome (delayed and nondelayed) lotteries to empirically capture the impact of time on individual choice under risk. In our experiments, lotteries are simultaneously resolved and paid in different periods, ranging from the present to 12 months in the future, including a case where the DM does not know the exact date, except that it lies within a certain interval of time. The main advantage of a simple design such as this is that it allows a straightforward model-free observation of attitude toward risk for different levels of probabilities and delays. We also use a canonical model of decision under risk to quantify changes in risk attitudes over time. In addition to its popularity as a descriptive choice model for two-outcome lotteries, our canonical model generalizes expected utility coinciding with prospect theory (PT), rank-dependent utility, and Gul's (1991) disappointment aversion theory for a given time period. It also coincides with Wu's (1999) model when applied to two-outcome lotteries with variable resolution timing but with a fixed payment time in the future.

Our canonical model also extends to lotteries more general than those in the recent experimental investigation by Baucells and Heukamp (2010). By substituting probabilities with decision weights, our model also allows for the impact of delay on risk preferences, if any, to be reflected and measured through the subjective treatment of probabilities. Moreover, our experimental design does not exclude the impact of time on the subjective treatment of outcomes from an empirical point of view. We use an elicitation technique initially proposed to efficiently elicit prospect theory (Abdellaoui et al. 2008). This technique consists of two steps. In the first step, the utility function is elicited through the determination of a series of independent certainty equivalents of two-outcome lotteries with a fixed probability. The procedure allows us to factor out the impact of probability weighting on utility; i.e., utility is elicited independently from the (above mentioned) probability. Then in the second step the decision weight assigned to a probability is directly inferred from the certainty equivalent of a two-outcome lottery corresponding to that particular probability. In addition to reducing biases in utility measurement, this elicitation procedure allows us to study the impact of time on decision weights without imposing a specific parametric form for the probability weighting function (e.g., Baucells and Heukamp 2010).

Our data reveal that individuals exhibit significantly higher levels of risk tolerance for future risky payments, compared to immediate ones. Consequently, we confirm the findings by Noussair and Wu (2006) without requiring that risk attitudes be independent from probabilities. Our individual elicitation-based findings are also consistent with the aggregated results reported by Baucells and Heukamp (2010). For the case of unknown delay (where the lottery is realized at some point in the next 12 months), the observed certainty equivalents are equal to or less than those corresponding to the deterministic delay (where the lottery is realized in exactly six months from today), implying ambiguity aversion with respect to timing uncertainty. Finally, by fitting our data to the canonical model, we elicited utility and probability weighting for different delays. We found that there is no significant evidence that utility is subject to the impact of time. In other words, the subjective treatment of outcomes does not depend on the time period in which they are evaluated. By contrast, our findings indicate that the observed effect of time is entirely absorbed into the subjective treatment of probabilities. To our knowledge, this is the first study that disentangles the effect of time on the evaluation of probability and outcomes at an individual level.

This paper proceeds as follows. Section 2 reviews the theoretical background and previous empirical findings. Section 3 introduces the experimental design, followed by the results in §§4–6. The paper ends with a discussion and concluding remarks in §§7 and 8, respectively.

2. Theory and Experimental Findings

2.1. Canonical Model

We consider a DM who has to evaluate lotteries $(x, E_p; y)$ where outcome x is received if event E_p occurs with probability p and outcome y is received otherwise. Throughout the paper, we assume that outcomes are monetary and that $x \geq y \geq 0$. Notation $L_\theta = (x, E_p^\theta; y)$ means that the lottery is resolved and paid out at θ. Two natural ways of evaluating lottery L_θ exist (for $\theta > 0$). The first consists of determining its present certainty equivalent, i.e., the sure amount payable at time 0, that the DM considers as equivalent to that particular lottery. The second, used in the present paper, consists of the assessment of its certainty equivalent at θ, denoted by CE_θ, i.e., the sure amount payable at θ and considered as equivalent to L_θ. Whereas the determination of the certainty equivalent of L_θ at time 0 involves both time preferences and risk preferences, the assessment of CE_θ involves only risk preferences at time θ. Ahlbrecht and Weber (1997) illustrated this difference through the decomposition of the assessment of the value of L_θ at time 0 into two steps. In the first step, CE_θ is determined; in the second step, the sure amount at time 0 equivalent to the delayed certainty equivalent CE_θ is assessed, which implies an intertemporal trade-off of outcomes.

Figure 1 **Isolating Risk Preferences in Intertemporal Choice**

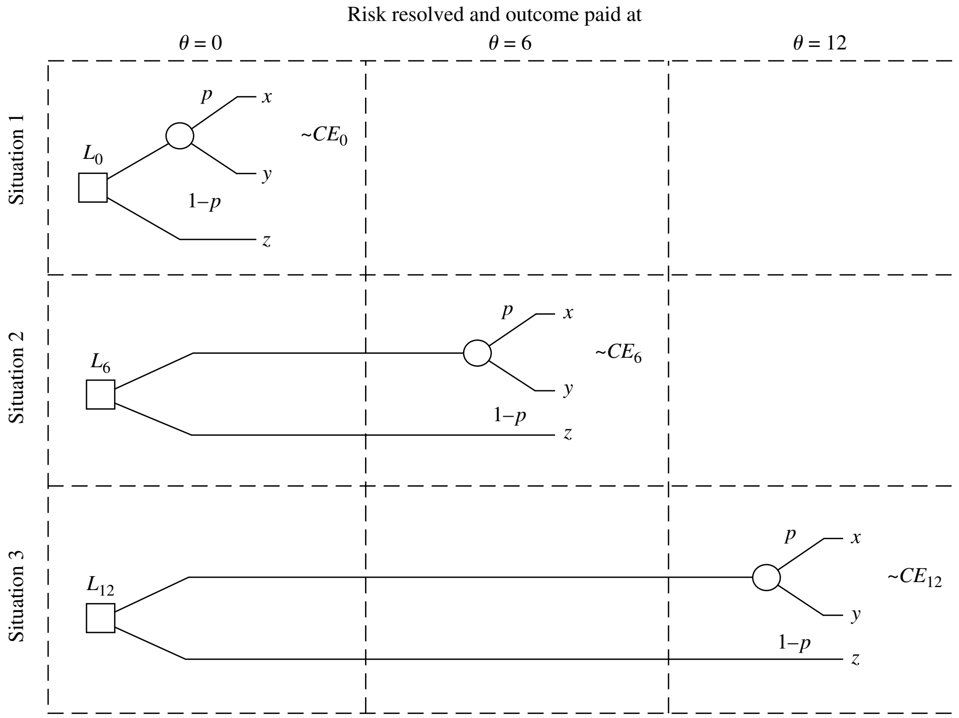


Figure 1 shows three different choice situations corresponding to a choice between a lottery giving outcome x with probability p and outcome y with probability $1-p$ and a sure amount of money z. Situation 1 corresponds to a standard risky choice without any delay. Situation 2 (3) corresponds to a risky choice where the DM has a choice between the delayed lottery L_6 (L_{12}) and the sure amount z payable at $\theta = 6$ ($\theta = 12$). To capture risk preferences in a specific situation, i.e., with a given θ, we assume that the DM evaluates the lottery L_θ as follows:

$$w^\theta(p)u^\theta(x) + (1 - w^\theta(p))u^\theta(y), \tag{1}$$

where $w^\theta(\cdot)$ is a *probability weighting function* and $u^\theta(\cdot)$ a *utility function*. The probability weighting function is increasing on the probability interval with $w^\theta(0) = 0$ and $w^\theta(1) = 1$, and the utility function is increasing on the set of outcomes. In this model, the impact of time can be captured by both the probability weighting function and the utility function.[2] For $\theta = 0$, model (1) coincides with the traditional rank-dependent utility (RDU) under risk for nondelayed lotteries (e.g., Quiggin 1982, Kahneman and Tversky 1979, Gul 1991). It serves as a benchmark for analyzing the impact of delay on individual preferences.

Noussair and Wu (2006) used a similar setup (as in Figure 1) to study risk preferences. However, they implicitly imposed expected utility; i.e., they assumed that $w^\theta(p) = p$ for all $p \in [0, 1]$ (see also Holt and Laury 2002). In their experiment, any observed change of risk attitudes due to delay θ is necessarily absorbed by the utility function. The use of an RDU representation of preferences has the advantage of avoiding the descriptive drawbacks of the standard model of expected utility (e.g., Starmer 2000). Eliciting model (1) for different values of θ allows us to take into account the possible impact of time not only on the subjective treatment of outcomes but also on the subjective treatment of probabilities.

The model we used to capture risk preferences over time is similar to two other recent models proposed by Wu (1999) and Baucells and Heukamp (2009), particularly as regards the introduction of probability weighting (i.e., the use of an RDU utility representation of preferences). More specifically, Wu (1999) studied the impact of delayed resolution of uncertainty on risk preferences over time without the interference of intertemporal trade-offs of outcomes. In his setup, all outcomes are received at a unique future date $T > 0$. Delay $\theta < T$ was used to represent resolution timing; i.e., lotteries are resolved at period θ and paid out later at a fixed date T. In terms of preference representation, Wu postulated expected utility for nondelayed lotteries and RDU for lotteries with delayed resolution.

[2] Formally, model (1) indicates that utility reflects the nature of outcomes without imposing an ad hoc discounting form such as $u^\theta(x) = \phi(\theta)u(x)$ (which can result from intertemporal trade-offs of outcomes), where $\phi(\cdot)$ is a discounting function.

There is a natural similarity between our canonical model and the probability-time trade-off model proposed by Baucells and Heukamp (2009). These authors presented a (multiplicative) RDU representation of preferences for lotteries in the form $(x, E_p^\theta; 0)$ where there is no formal disentangling of risk preferences and time preferences.[3] In their model, individuals evaluate a future lottery $(x, E_p^\theta; 0)$ by using

$$w(pe^{-r(x)\theta})u(x), \tag{2}$$

where r is the probabilistic discount rate that captures how time and probability are traded off. In this model, a lottery $(x, E_p^\theta; 0)$ is subjectively perceived as giving outcome x with the modified probability $pe^{-r(x)\theta}$. The "discounting term" $e^{-r(x)\theta}$ is also related to intertemporal trade-offs of outcomes. Note that like in our design, the decision weight $w(pe^{-r(x)\theta})$ depends on delay θ. However, uniqueness up to a power transformation of w and u for one-zero-outcome lotteries complicates the empirical interpretation of the model (see Baucells and Heukamp 2009, Theorem 1; also see Gonzalez and Wu 1999). In addition to extending the evaluation of one-nonzero-outcome lotteries to general two-outcome lotteries, our model allows us to factor out the intertemporal trade-offs of outcomes from the start.

2.2. Existing Experimental Evidence

Together with the gain-loss asymmetry, nonlinearity in probability represents one of the most robust violations of expected utility, the standard model of decision under risk (e.g., Kahneman and Tversky 1979). The accumulated experimental evidence with regard to the subjective treatment of probabilities for nondelayed lotteries $(\theta = 0)$ is in favor of an inverse S-shaped probability weighting function for gains and losses, with an overweighting of small probabilities (below 1/3) and an underweighting of moderate and high probabilities (e.g., Wu and Gonzalez 1996, Abdellaoui 2000). Most empirical studies also show that the utility function is concave for gains and predominantly convex or linear for losses (e.g., Abdellaoui et al. 2008).

To our knowledge, for delayed lotteries, there has been no attempt to elicit preferences under risk at an individual level, allowing for probability weighting as suggested by model (1). Noussair and Wu (2006) used the Holt and Laury (2002) protocol to elicit attitude toward risk in an expected utility-like environment. For a given delay θ and a set of outcomes, the protocol consisted of comparing a lottery $(x, E_p^\theta; y)$ with another lottery $(x', E_p^\theta; y')$ for 10 different and equally spaced values of their common probability p. The first lottery was considered safer because the difference between its outcomes was smaller than it was in the second lottery. The subject's risk tolerance was examined through the value of p at which there was a switch in preferences between the safe and risky lottery. This procedure implicitly considers an expected utility framework where preferences are linear in the probabilities. The authors studied a delay ranging from the present to three months in the future and observed that subjects are more risk tolerant when lotteries are realized in the future than in the present.

Baucells and Heukamp (2010) report experimental results suggesting, among other things, that the observed increase in risk tolerance for future lotteries is because of the additional uncertainty introduced by the delay. They showed that adding a common delay θ to a pair of nondelayed lotteries $(x, E_p^0; 0)$ and $(x', E_q^0; 0)$ results in an effect similar to the one we obtain when we multiply probabilities p and q by a common factor of, say, 1/10. Baucells and Heukamp (2010) also report aggregated parametric estimates for their probability time trade-off model using the compound invariance parametric probability weighting function initially suggested by Prelec (1998) and an expo-power utility function. However, the interpretation of their estimates is formally hindered by the uniqueness of utility and probability weighting up to a power transformation, as explained in §2.1.

3. Experimental Design

The experiment was conducted at Bogazici University (Turkey) and consisted of individual computer-based interviews of 52 undergraduate students recruited from an introductory economics course. Each subject faced a series of choice situations. In each situation, the subject had a choice between a lottery $L_\theta = (x, E_p^\theta; y)$ and a sure amount of money to be received at θ (as described in Figure 1). The objective of the choice process was to determine the certainty equivalent CE_θ. The experiment consisted of four independent sessions. Each session was devoted to the elicitation of the certainty equivalents for 10 lotteries L_θ for a given θ. One session focused on the elicitation of CEs of nondelayed lotteries, i.e., $\theta = 0$. Two sessions aimed at determining the CEs of delayed lotteries for $\theta = 6$ and 12 months, respectively; and one session elicited CEs for ambiguously delayed lotteries for which the delay θ was not known for sure, only that it was sometime between now and 12 months; i.e., $\theta \in [0, 12]$. Table 1 presents the 10 lotteries used to determine certainty equivalents $CE_\theta(i)$, $i = 1, \ldots, 10$, $\theta = 0, 6, 12$, and $\theta \in [0, 12]$. Outcomes are in Turkish liras (YTL; 1 YTL $\simeq$ €0.56).

[3] Their model does not exclude the comparison of lotteries $(x, E_p^\theta; 0)$ and $(y, E_p^t; 0)$ with $t \neq \theta$; i.e., it takes into account intertemporal trade-offs of outcomes in addition to risk preferences.

Table 1 Lotteries Used to Elicit $u^\theta(\cdot)$ and $w^\theta(\cdot)$

	Index *i*									
	1	2	3	4	5	6	7	8	9	10
x_i	2,400	2,400	1,200	2,400	1,200	2,000	2,400	2,400	2,400	2,400
p_i	1/6	2/6	2/6	2/6	2/6	2/6	2/6	3/6	4/6	5/6
y_i	0	0	0	1,200	600	800	1,800	0	0	0

Note. Amounts of money in Turkish liras.

The experiment lasted 45 minutes on average. Subjects were told at the beginning that there were no right or wrong answers and that the experimenters were interested only in their true preferences. The experiment was carried out by two experimenters through a series of individual interviews. A bisection (midpoint) method was used to elicit certainty equivalents. More specifically, for each lottery, subjects were given a choice between the lottery and its expected value for sure and were asked to state their preference for either of the two alternatives or their indifference between them. In the subsequent questions, the sure alternative was revised (upward or downward, depending on the previous response) until indifference was reached (see Appendix A).

The lotteries were presented graphically as checks in a transparent urn. For instance, the lottery (2,400, 1/6; 0) was represented as six checks in an urn containing five checks of 0 YTL and one check of 2,400 YTL (see Appendix B). Subjects were told that the lottery would be resolved by a random draw of a check from the urn. In each choice question, the subject indicated his or her preference between two lotteries and the decision was entered in the computer by the experimenter. Each experimental session started with a set of instructions. There was a two-stage computer training session before the experiment actually began. In the first stage, the randomization process (i.e., drawing a check from the urn) was explained using a simple computer program. In the second stage, subjects were presented with some sample questions in order to familiarize them with the choice task and with the difference between nondelayed and delayed options.

At the beginning of the experiment, subjects were told that once the experiment was over, a participant would be chosen randomly and one of the 10 lotteries (L_θ) would be played out for real.[4] We used the Becker-deGroot-Marschak mechanism for incentive compatibility (Becker et al. 1964). In this procedure, the experimenter draws a random number between the lowest and highest outcome of the chosen L_θ. If the drawn number is greater than the elicited certainty equivalent for that particular lottery, the subject receives the drawn number as payoff. Otherwise, he or she plays the lottery.[5] Because of the intertemporal nature of the experiment, subjects were also told that any future payment was to be made on the specific date (in 6 or 12 months). For the ambiguous case, they were told that the payment was to be made within the next 12 months (to be resolved by assuming a uniform distribution over $[0, 12]$, which was not communicated to the participants). Based on this procedure, 1,590 YTL (approximately €900) was paid to the chosen participant at $\theta = 0$, which was one of the four possible periods.

For each delay θ, the assessed certainty equivalents $CE_\theta(i)$ were used to elicit the components of the preference functional given by Equation (1): utility and decision weights. Utility, $u^\theta(\cdot)$, was elicited at the individual level using the certainty equivalents of the lotteries $(x_i, E^\theta_{2/6}; y_i)$, $i = 2, \ldots, 7$ (Table 1). Assuming a power utility function, $u^\theta(x) = x^{\rho_\theta}$, we simultaneously estimated ρ_θ and the decision weight $w^\theta(2/6)$ through the minimization of the nonlinear least squares $\|CE_\theta - \widehat{CE}_\theta\|^2$, where

$$\widehat{CE}_\theta(i) = [w^\theta(2/6)((x_i)^{\rho_\theta} - (y_i)^{\rho_\theta}) + (y_i)^{\rho_\theta}]^{1/\rho_\theta}.$$

Note that a measurement of $u^\theta(\cdot)$ assuming expected utility, as in Noussair and Wu (2006), requires that the equality $w^\theta(2/6) = 2/6$ be imposed beforehand. But for descriptive purposes, we allowed this parameter to be estimated along with the power of the utility function. Under RDU, the probability used to elicit utility has no impact on utility. Abdellaoui et al. (2008) report an empirical confirmation of this statement.[6] With utility $u^\theta(\cdot)$ available, decision weights could easily be elicited using certainty equivalents. To elicit $w^\theta(1/6)$, we used $CE_\theta(1)$ corresponding to lottery $(2{,}400, E^\theta_{1/6}; 0)$ in Table 1. Then, assuming model (1), we obtained

$$w^\theta(1/6) = \frac{u^\theta(CE_\theta(1)) - u^\theta(0)}{u^\theta(2{,}400) - u^\theta(0)}. \tag{3}$$

Decision weights $w^\theta(3/6)$, $w^\theta(4/6)$, and $w^\theta(4/6)$ were elicited in a similar way, using $CE_\theta(8)$, $CE_\theta(9)$, and $CE_\theta(10)$ instead of $CE_\theta(1)$ in Equation (3), respectively.

[4] A comparative analysis of within- and between-subject randomization in incentive designs is provided in Balthussen et al. (2010).

[5] The bisection method is an assisted choice task where subjects know that the goal of the experiment is to elicit CEs in an iterative process. Although it might appear nonstandard, we believe this procedure achieves incentive compatibility.

[6] More specifically, assuming RDU, Abdellaoui et al. (2008) did not detect significant differences between utility functions elicited with probabilities 1/3 and 2/3. The common finding $w(1/3) = 1/3$ suggests that the impact of probability weighting on utility can be minimized even when assuming expected utility.

4. Analysis of Raw Data

4.1. Reliability

As explained above and also in Appendix A, each of the certainty equivalents was constructed through a series of choices following a bisection process. For each lottery and each delay, a consistency check was performed at the end of the session in which subjects were faced once again with the choice situation corresponding to the third iteration in the corresponding bisection process. This procedure resulted in 10×4 consistency questions. In this context, reliability refers to the stability of the subject's responses when he or she faced an identical choice question twice. This allowed us to assign an across-subject rate of consistency to each lottery (i.e., the percentage of subjects for which the replication of the third iteration led to the same choice). The overall reliability was good in the four sessions. The lowest across-lottery consistency rate was 90.40%, 90.40%, 86.50%, and 88.50% for delay conditions $\theta = 0, 6$, and 12, and $\theta \in [0, 12]$, respectively.

4.2. Risk Attitudes and Delay from CEs

Certainty equivalents provide a model-free measure of risk attitude. Table 2 presents the empirical characteristics of the 10×4 elicited certainty equivalents. At an aggregated level, the comparison of means and medians to the corresponding expected values (Table 2, column 2) shows that for all lotteries and all delays, risk aversion clearly predominates. To analyze the impact of delay on attitude toward risk, we first determined the percentages of subjects who consistently exhibited risk aversion for each delay in all 10 lotteries. When lotteries are not delayed, i.e., $\theta = 0$, 77% of the subjects exhibit risk aversion. This percentage declines to 75% and 67% when the delay of lotteries is set at 6 and 12 months, respectively. When the delay is unknown to the decision maker but can take any value between now and 12 months, the percentage of risk averse subjects declines considerably to 58%. Qualitatively, this finding on attitudes toward risk reveals that CEs are sensitive to delay in a manner that deserves a more detailed analysis.

This result is supported by statistical analysis. A 4×10 ANOVA test with repeated measures on the factor θ rejected the null hypothesis that certainty equivalents are not influenced by the delay ($p < 0.001$). One way ANOVA tests with repeated measures performed across lotteries detected a significant impact of delay for lotteries 2, 3, 4, 6, 8, 9, and 10 at the significance level $\alpha = 5\%$.

Two-tailed paired t-tests reveal that for a majority of lotteries and except for lottery 1 (giving 2,400 YTL with a low probability, and nothing otherwise), significant differences exist between CE_0 on the one hand and CE_6, CE_{12}, and $CE_{0,12}$ on the other hand (Table 3). This is confirmed by the observation that a majority of subjects exhibit more risk tolerance (i.e., higher CEs) for lotteries played in the future as compared to the benchmark delay $\theta = 0$ (Table 3, rows 1–3). The third row of Table 3 also confirms that for a majority of lotteries, CE_{12} is generally higher than CE_6 at an individual level. This result is consistent with the hypothesis that more delay generates more risk tolerance (initially suggested by Noussair and Wu 2006), also confirmed by one-tailed t-tests and Wilcoxon signed-rank tests at the significance level of $\alpha = 5\%$.

Table 3 (rows 4 and 5) also show that when the delay is unknown, the resulting CEs (i.e., $CE_{0,12}$) have a tendency to lie between CE_0 and CE_6 rather than between CE_6 and CE_{12}. In other words, although exhibiting more risk tolerance for lotteries played in the future, subjects confronted with the ambiguous delay $\theta \in [0, 12]$ behaved as if the resolution delay is less or equal to six months rather than above six months.

Table 2 **Certainty Equivalents for Different Delays**

		Certainty equivalents											
		CE_0			CE_6			CE_{12}			$CE_{0,12}$		
i	EV_i	Mean	Median	Std. dev.	Mean	Median	Std. dev.	Mean	Median	Std. dev.	Mean	Median	Std. dev.
1	400	272	280	111	268	280	98	269	260	105	263	260	100
2	800	500	500	159	539	560	154	560	590	163	523	530	168
3	400	250	255	68	271	260	100	270	260	88	260	260	87
4	1,600	1,469	1,555	125	1,473	1,500	114	1,489	1,500	111	1,477	1,500	95
5	800	735	750	58	751	750	52	742	750	49	744	750	52
6	1,200	1,060	1,100	103	1,088	1,100	97	1,088	1,100	97	1,088	1,100	91
7	2,000	1,919	1,925	56	1,927	1,900	53	1,927	1,900	49	1,926	1,900	49
8	1,200	748	780	185	831	860	203	891	920	204	817	820	219
9	1,600	1,040	1,040	222	1,162	1,190	226	1,235	1,220	237	1,122	1,160	249
10	2,000	1,423	1,470	260	1,568	1,570	229	1,636	1,650	227	1,482	1,520	277

Note. EV, expected value.

Table 3 **Paired t-Tests (CE_θ vs. $CE_{\theta'}$)**

	Lottery index									
	1	2	3	4	5	6	7	8	9	10
$\#(CE_0 > CE_6)$	28	5	8	12	12	14	10	2	1	2
$\#(CE_6 > CE_0)$	18	35	23	17	22	25	17	46	47	46
$t_{51}(0-6)$	0.62^{ns}	-4.16^{**}	-2.30^{**}	-0.36^{ns}	-1.82^{ns}	-2.10^{*}	-1.24^{ns}	-6.55^{**}	-6.78^{**}	-6.51^{**}
$\#(CE_0 > CE_{12})$	26	7	9	12	13	9	14	3	2	2
$\#(CE_{12} > CE_0)$	19	38	31	27	20	26	22	48	48	47
$t_{51}(0-12)$	0.31^{ns}	-5.18^{**}	-3.11^{**}	-1.83	-1.17^{ns}	-3.01^{**}	-1.05^{ns}	-8.29^{**}	-8.57^{**}	-8.08^{**}
$\#(CE_6 > CE_{12})$	14	9	8	10	11	9	11	4	5	3
$\#(CE_{12} > CE_6)$	17	31	16	23	8	15	11	41	41	39
$t_{51}(6-12)$	-0.33^{ns}	-3.67^{**}	0.16^{ns}	-2.21^{*}	1.55^{ns}	0.04^{ns}	0.03^{ns}	-5.58^{**}	-6.26^{**}	-6.23^{**}
$\#(CE_0 > CE_{0,12})$	26	13	9	15	14	11	15	7	4	9
$\#(CE_{0,12} > CE_0)$	11	30	27	17	20	23	20	36	41	35
$t_{51}(0-0,12)$	1.44^{ns}	-2.03^{*}	-1.35^{ns}	-0.73^{ns}	-1.16^{ns}	-2.50^{*}	-0.80^{ns}	-3.27^{**}	-3.56^{**}	-2.01^{*}
$\#(CE_6 > CE_{0,12})$	19	27	11	14	12	14	12	32	26	34
$\#(CE_{0,12} > CE_6)$	14	10	14	15	8	16	8	12	14	5
$t_{51}(6-0,12)$	1.20^{ns}	2.70^{*}	0.95^{ns}	-0.35^{ns}	1.02^{ns}	0.07^{ns}	0.21^{ns}	0.92^{ns}	2.60^{*}	4.26^{**}

Note. ns, nonsignificant.
$^{*}p < 0.5$; $^{**}p < 0.01$.

5. Stationarity of Utility

The interference of probabilities in the observed attitudes toward risk (because of a nonlinear subjective treatment of probabilities) should necessarily result in biased measurements of utility under expected utility (Wakker and Deneffe 1996). Taking into account probability weighting, i.e., assuming an RDU representation of preferences, model (1) allows for more consistent measurements of utility.

RDU models have successfully demonstrated that the attitude toward probabilities needs to be modeled separately from the attitude toward outcomes. Model (1) allows for this separate elicitation. In addition, it does not preclude that delay will impact utility and/or probability weighting. The impact of θ on utility is tested assuming a power utility function, the most widely used parametric form of utility under PT. The null hypothesis to be tested here corresponds to the equality of power estimates ρ_0, ρ_6, ρ_{12}, and $\rho_{0,12}$.

Table 4 reports the main characteristics of the empirical distributions of individual power estimates for the four delay contexts. Overall, the reported means and medians do not seem to reflect an impact of delay. Median estimates are also quite consistent with previous studies on utility elicitation (e.g., Tversky and Kahneman 1992, Abdellaoui et al. 2007). A one-way ANOVA test with repeated measures did not reject the null hypothesis of the stationarity of the utility function on the four delay contexts ($p = 0.6$). Paired t-tests and sign tests confirmed the absence of significant discrepancies for ρ_0 versus ρ_6, ρ_0 versus ρ_{12}, and ρ_0 versus $\rho_{0,12}$.[7] Figure 2 illustrates

Figure 2 **Empirical Distributions of Utility Powers**

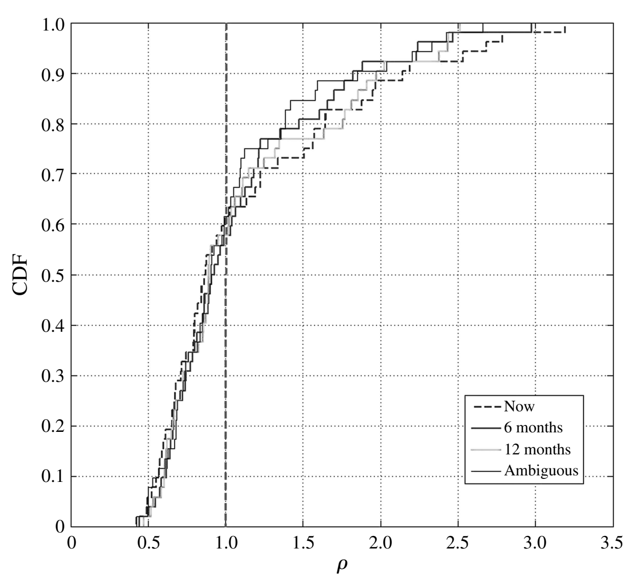


Table 4 **Power Estimates for Utility**

	Power			
	ρ_0	ρ_6	ρ_{12}	$\rho_{0,12}$
Mean	1.14	1.09	1.11	1.05
Median	0.86	0.92	0.89	0.90
Standard deviation	0.66	0.54	0.56	0.52
Concave utilities (%)	61.5	58	58	61.5

[7] The paired t-test for ρ_0 versus ρ_{12} gave $p = 0.013$, but sign and Wilcoxon signed-rank tests gave $p = 0.33$ and $p = 0.07$, respectively.

Table 5 Decision Weights for Different Delays

		p				
		1/6	2/6	3/6	4/6	5/6
$w^0(p)$	Mean	0.13	0.22	0.32	0.43	0.58
	Median	0.17	0.27	0.38	0.48	0.63
	Std. dev.	0.08	0.11	0.13	0.15	0.16
$w^6(p)$	Mean	0.12	0.23	0.35	0.49	0.65
	Median	0.15	0.27	0.39	0.51	0.67
	Std. dev.	0.07	0.09	0.10	0.11	0.11
$w^{12}(p)$	Mean	0.13	0.24	0.37	0.51	0.68
	Median	0.14	0.25	0.41	0.54	0.70
	Std. dev.	0.07	0.10	0.11	0.12	0.11
$w^{0,12}(p)$	Mean	0.13	0.24	0.36	0.48	0.63
	Median	0.14	0.26	0.38	0.50	0.65
	Std. dev.	0.07	0.09	0.10	0.12	0.13

the absence of significant differences between power estimates across contexts. Figure 2 and Table 4 also show that the majority of subjects have concave utility functions. Another interesting observation is that the power estimates with delay are highly correlated with the power estimates without delay (Pearson correlation coefficients above 0.88).

The fact that delay has no significant impact on utility but does have a significant impact on attitudes toward risk suggests that the probability weighting function depends in some way on the parameter θ. The next section investigates this hypothesis.

6. Probability Weighting and Delay

6.1. Decision Weights for Different Delays

Table 5 reports means, medians, and standard deviations of the empirical distributions of decision weights $w^\theta(k/6)$ for $k = 1, \ldots, 6$. At the individual level, we observed a variation between subjects. Figure 3 presents examples where decision weights $w^\theta(k/6)$ are drawn against probabilities $k/6$ for six subjects. Subjects 1, 9, 27, 29, 48, and 50 have probability weighting functions for $\theta = 0$ below probability weighting functions corresponding to $\theta > 0$.

The significant discrepancies between CEs across different delays and the existence of a stationary utility suggest that the impact of time should be observed through decision weights $w^\theta(p)$. A 4×5 ANOVA test with repeated measures on delay rejected the null hypothesis that decision weights are not influenced by the delay ($p < 0.001$). A more specific testing of the same hypothesis for individual probabilities (i.e., one way ANOVA with repeated measures) detects significant discrepancies for middle to high probabilities: 3/6, 4/6, 5/6 (critical probabilities: $p < 0.001$).

Eliciting decision weights at the individual level (without assuming a specific parametric form for probability weighting) allows for the analysis of the impact of delay on decision weights for different delays and probabilities. Paired t-tests revealed that "delayed decision weights" (i.e., $\theta > 0$) exhibit significant differences from nondelayed decision weights (i.e., $\theta = 0$) for probabilities 3/6, 4/6, and 5/6 (Table 6, last three rows). More specifically, when $p \geq 3/6$, a majority of subjects satisfied $w^0(p) < w^\theta(p)$ for $\theta = 6$ and 12 and $\theta \in [0, 12]$. No significant discrepancies were detected across probabilities between $w^6(p)$ and $w^{0,12}(p)$, revealing a tendency of subjects to act as if the unknown delay $\theta \in [0, 12]$ was in the middle of the interval; i.e., $\theta = 6$. The results reported in the present subsection are consistent with the empirical distributions of individual decision weights reported by Figure 4.

6.2. Optimism and Sensitivity to Probabilities for Different Delays

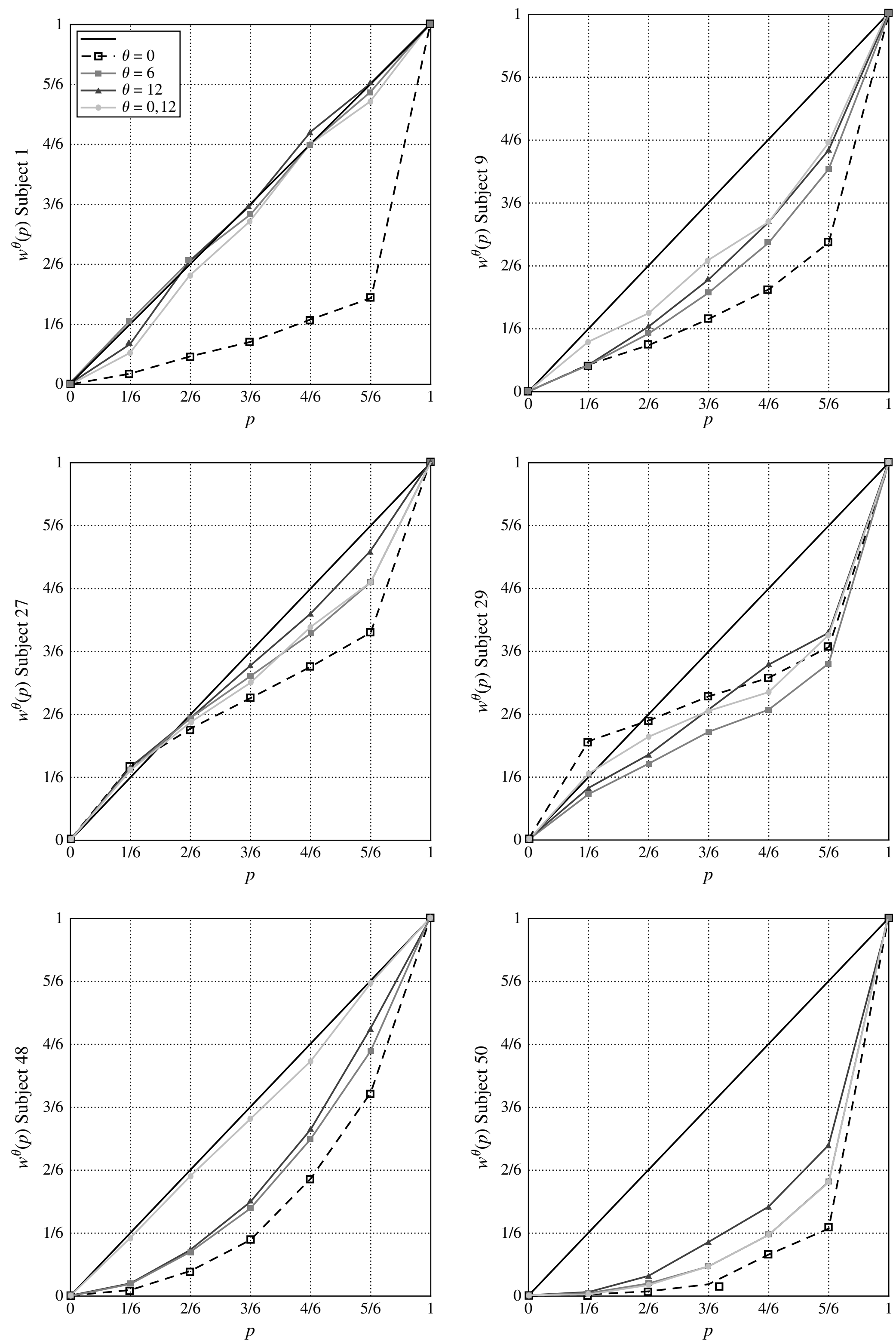
To further analyze the impact of different delays on the subjective treatment of probabilities, we chose a parametric family for the probability weighting function $w^\theta(\cdot)$. The most sophisticated parametric forms take into account two characteristics of probability weighting: *elevation* and *curvature* (Gonzalez and Wu 1999, Diecidue et al. 2009). Behaviorally, elevation reflects optimism and pessimism and curvature reflects sensitivity to probabilities. For instance, if the probability weighting function is linear, more

Table 6 Paired t-Tests for Differences Between Decision Weights

	$w^0(p) - w^6(p)$			$w^0(p) - w^{12}(p)$			$w^0(p) - w^{0,12}(p)$		
p	#(> 0)	#(< 0)	t_{51}	#(> 0)	#(< 0)	t_{51}	#(> 0)	#(< 0)	t_{51}
1/6	28	24	0.99^{ns}	28	24	0.91^{ns}	25	27	0.08^{ns}
2/6	20	32	-1.27^{ns}	23	29	-1.83^{ns}	21	31	-1.54^{ns}
3/6	17	35	-2.64^{*}	13	39	-4.72^{**}	22	30	-2.91^{**}
4/6	10	42	-3.58^{**}	6	46	-5.92^{**}	17	35	-3.26^{**}
5/6	9	43	-4.34^{**}	5	47	-6.19^{**}	15	37	-2.59^{*}

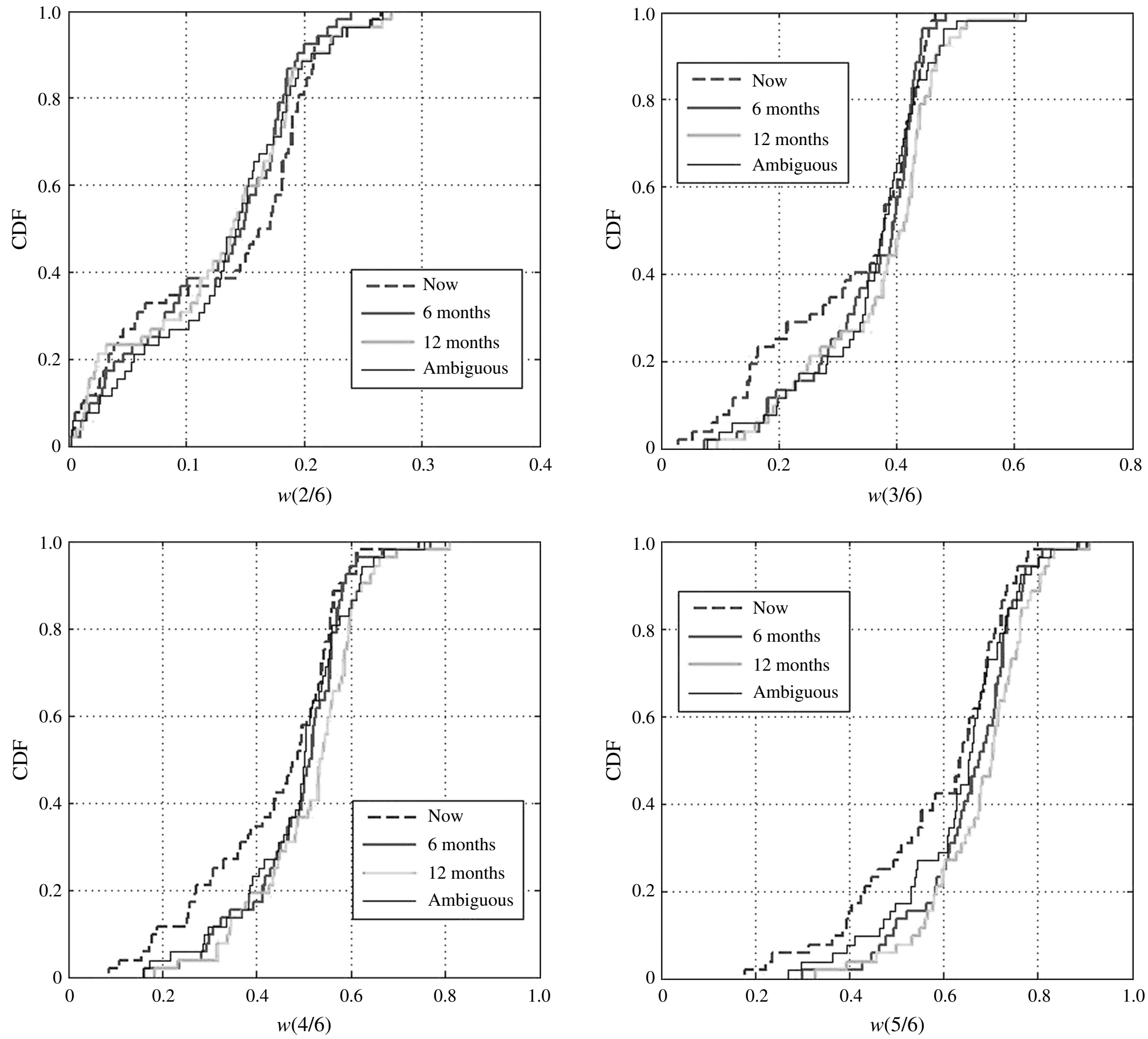
Note. ns, nonsignificant.
$^{*}p < 0.05$; $^{**}p < 0.01$.

Figure 3 Examples of Elicited Weighting Functions in Different Contexts



elevation is reflected by a higher intercept and more sensitivity, by a higher slope (e.g., Abdellaoui et al. 2011). However, it should be noted that elevation is not totally independent from curvature. For instance, a more sensitive linear probability weighting function with a "fixed point" around $p = 0.3$, i.e., $w(0.3) = 0.3$, generates more elevation and consequently more optimism for probabilities higher than 0.3.

Figure 4 Empirical Distributions of Decision Weights



In the present experimental investigation, we employ the compound invariance probability weighting family suggested by Prelec (1998). The corresponding equation is given by

$$w^{\theta}(p) = (\exp(-(-\ln(p))^{\alpha_\theta}))^{\beta_\theta},$$

where parameter β_θ mainly controls *elevation* and parameter α_θ mainly controls *curvature*. Taking the linear probability weighting function as a benchmark, i.e., $\alpha_\theta = \beta_\theta = 1$, $\beta_\theta > 1$ and $\alpha_\theta = 1$ correspond to a less elevated curve exhibiting more pessimism; $\beta_\theta = 1$ and $\alpha_\theta < 1$ correspond to a less sensitive probability weighting function.

Table 7 reports mean and median estimates of parameters β_θ and α_θ. An ANOVA test with repeated measures rejects the hypothesis of constant elevation (H_0: $\beta_0 = \beta_6 = \beta_{12} = \beta_{0,12}$, $p < 0.01$). Table 8 reports paired t-tests corroborating this conclusion. At an individual level, and for all delays, a majority of probability weighting functions exhibited $\beta_0 > \beta_\theta$, revealing a higher level of optimism for delayed than

Table 7 Parametric Estimates for Probability Weighting Functions

	$w^{\theta}(p) = (\exp(-(-\ln(p))^{\alpha_\theta}))^{\beta_\theta}$							
	β_0	α_0	β_6	α_6	β_{12}	α_{12}	$\beta_{0,12}$	$\alpha_{0,12}$
Mean	1.61	0.63	1.45	0.72	1.42	0.80	1.43	0.68
Median	1.20	0.62	1.22	0.72	1.21	0.78	1.27	0.66
Std. dev.	0.75	0.17	0.49	0.14	0.50	0.16	0.50	0.18

Table 8 Paired t-Tests for Elevation and Curvature

	Elevation: β_0 vs. β_θ			Curvature: α_0 vs. α_θ		
	$\theta=6$	$\theta=12$	$\theta\in[0,12]$	$\theta=6$	$\theta=12$	$\theta\in[0,12]$
$\#(\beta_0>\beta_\theta)$	33	32	32	—	—	—
$\#(\beta_\theta>\beta_0)$	19	20	20	—	—	—
$\#(\alpha_0>\alpha_\theta)$	—	—	—	6	3	12
$\#(\alpha_\theta>\alpha_0)$	—	—	—	46	49	37
t_{51}	2.45*	3.69**	3.27**	−5.99**	−6.97**	−2.43*

*$p<0.05$; **$p<0.01$.

for nondelayed lotteries, including the ambiguous delay (Table 8, row 1). No significant difference was detected between the elevation for the ambiguous delay and the elevation for $\theta=6$ (two-tailed paired t-test; $p=0.693$).

The hypothesis of constant curvature for $\theta = 0, 6, 12$ was rejected by an ANOVA test with repeated measures ($p<0.001$) and the corresponding paired comparisons (t-tests, Table 8). Furthermore, a majority of probability weighting functions exhibited a higher curvature parameter α in the future, meaning that sensitivity to probabilities is higher for delayed than for nondelayed lotteries (Table 8). In addition, and in contrast to what was observed for elevation, a paired t-test rejected the null hypothesis H_0: $\alpha_6=\alpha_{0,12}$. In fact, a majority of probability weighting functions (38 of 52) revealed a higher sensitivity to probabilities for $\theta=6$ than for $\theta\in[0,12]$; i.e., $\alpha_6>\alpha_{0,12}$.

To sum up, delay has a significant and clear impact on elevation and sensitivity (when assuming a parametric probability weighting function). In addition to a direct increase in optimism with delay, the observed increase in sensitivity to probabilities also results in an increase in optimism for probabilities higher than 1/3. Such a result is consistent with our parameter-free results on decision weights reported in §6.1 and with the observation of higher risk tolerance for lotteries played out in the future.

7. Discussion and Conclusion

In §§1 and 2.1 we referred to a series of theoretical works that generalized expected utility to take into account time preferences and/or risk preferences. We noted that the accumulated evidence against expected utility prevents this model from being used for descriptively valid representation of risk preferences at different points in time. This explains why the present paper follows the recent tendency of the intertemporal choice literature to take into account probability transformation as one of the most robust empirical violations of expected utility (e.g., Baucells and Heukamp 2009, Epper et al. 2009, Halevy 2008, Wu 1999).

Before assuming any preference for functional form, our experimental findings reveal that the certainty equivalent of a lottery is significantly influenced by the delay θ. Data reveal that a majority of subjects exhibit more risk tolerance for delayed lotteries as compared to nondelayed lotteries. When the delay is unknown to the DM, i.e., $\theta\in[0,12]$, elicited CEs did not exceed those for the midpoint delay in the interval $[0,12]$.[8] In other words, when confronted with the ambiguous delay, subjects were at most as risk tolerant as when $\theta=6$ (meaning that a lottery with the ambiguous delay in $[0,12]$ is at most as preferable as the corresponding lottery with a delay of six months). For nonambiguous delays, our observations (i.e., CEs) are consistent with the empirical results reported by Noussair and Wu (2006), which used a different experimental procedure based on the comparison of two-outcome nondegenerate lotteries with shorter (deterministic) delays, i.e., θ less than three months. When assuming model (1), our data reveal two things. First, delay has no significant impact on the subjective treatment of outcomes. In other words, utility seems stationary for different delays, including when this delay is unknown to the DM. This elicitation-based finding represents a clear confirmation of the qualitative experimental results reported by Keren and Roelofsma (1995) and Baucells and Heukamp (2009, 2010).[9]

Second, our data show that the whole impact of delay is reflected by the probability weighting function. Probability weighting (usually studied for nondelayed lotteries) is driven mainly by two phenomena: the possibility effect and the certainty effect. The possibility (certainty) effect stipulates that an increase of probability from 0 (near 1) has more impact than the same increase in the middle of the probability interval. The combination of both effects results in an inverse-S shaped probability weighting function. Our data confirm this shape for nondelayed lotteries, as was similarly observed in the literature on probability weighting under risk (e.g., Tversky and Kahneman 1992, Abdellaoui 2000). Although exhibiting a shape similar to that for nondelayed lotteries, the elicited weighting functions for delayed lotteries show significant discrepancies with it. It

[8] If θ is uniformly distributed on the interval $[0,12]$, its mean is equal to 6.

[9] More specifically, Baucells and Heukamp (2009) report aggregated results stipulating that the evaluation $V(x,E_p^\theta,0)=w(p)u^\theta(x)$ is not consistent with observed choice.

seems that the introduction of a delay makes lotteries more attractive, i.e., it makes subjects more optimistic as regards chance. The observed optimism is driven mainly by the increase of elevation and curvature/sensitivity, as explained in the previous section. Furthermore, the comparison of the impact of the ambiguous delay with the impact of the midpoint deterministic delay (six months) reveals an equal elevation in the two treatments but less sensitivity to probabilities in the first treatment than in the second one.

How can we explain the decline in probability transformation for risk preferences (resulting from the increase of sensitivity) when the delay increases? An affect-based reasoning may provide one possible explanation. Some recent studies look at an affective deconstruction of the probability weighting function (Rottenstreich and Hsee 2001, Brandstaetter et al. 2002). Rottenstreich and Hsee (2001) argue that the inverse-S shape pattern is moderated by the affective nature of the stimulus. The more affect-rich a lottery is (such as kissing your favorite movie star), the higher the sensitivity is toward changes in probabilities near certainty and impossibility. For affect-poor prospects, individuals use valuation by calculus, which leads to a more linear treatment of probabilities. It would be interesting to explore whether the individuals will act more like expected-utility maximizers for future events. The more lotteries are put off to the future, the more the strength of anticipated emotional reaction (joy or disappointment) will decrease, leading to a more linear probability transformation. This suggests that fine-tuning prospect theory models to accommodate the experimental findings and other choice irregularities is a potentially rich vein for future research.

To sum up, the contribution of this paper is threefold. First, we use a new and descriptively plausible model of decision making under risk that takes into account delay. The second contribution of the paper lies in the implementation of a simple elicitation technique for investigating the impact of delay on the subjective treatment of outcomes and probabilities that is not hampered by specific parametric forms for probability weighting. Third, our empirical results provide a connection with the recent and thought-provoking theoretical results on intertemporal choice in Baucells and Heukamp (2009, 2010), Epper et al. (2009), and Halevy (2008). The present paper clearly shows that individuals are more optimistic about future lotteries than they are about the ones taking place in the present. This optimism can only be explained through a temporal change in probability weighting because the utility function remains stationary for future prospects.

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Appendix A. Bisection

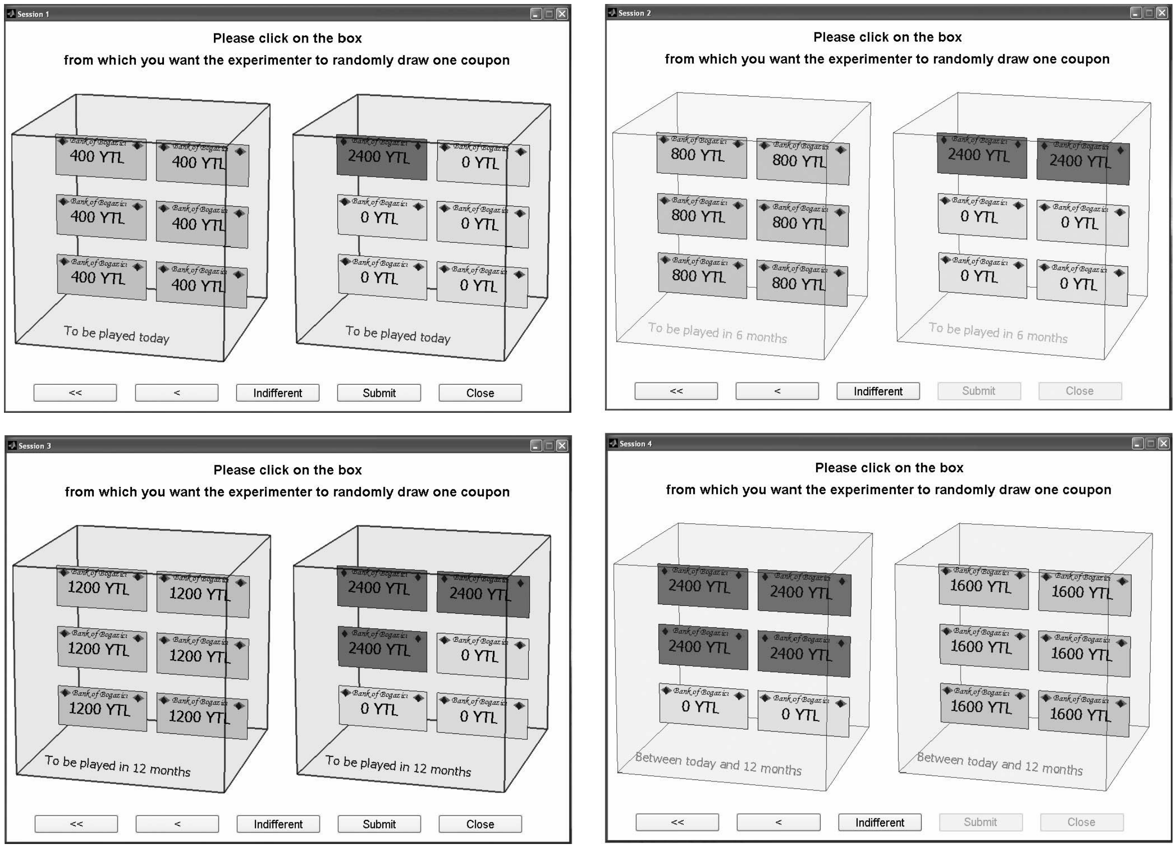
The bisection method used to determine the outcome that makes the subject indifferent between two binary lotteries A and B is described in Table A.1. It consists of a series of successive iterations, i.e., choice questions. The chosen lottery is printed in bold. Each bisection process started with a choice question in which the subject faced lotteries with the same expected value.

The second column of the table describes the bisection process that allowed us to determine the certainty equivalent of $A = (200, 0.33; 0)$. In the first iteration (i.e., choice question), the subject had a choice between lottery A and its expected value $B = 66$ for sure. At this stage, choosing B meant that the certainty equivalent of A belonged to the interval $[0, 66]$, otherwise (i.e., choosing A), the certainty equivalent would be in $[66, 200]$. Taking into account the previous choice, the subject faced a choice between lottery A and the sure amount $B = 33$ (the midpoint of the interval $[0, 66]$). Choosing A, as in the table, implied that the certainty equivalent belonged to the interval $[33, 66]$. In the following iteration, the subject faced a choice between lottery A and the sure amount $B = 49$ (the approximate midpoint of the interval $[33, 66]$). At the fifth iteration, the choice of A meant that the certainty equivalent would lie between 41 and 45. We then took 43, the midpoint of the interval $[41, 45]$, as the certainty equivalent.

Table A.1 **An Illustration of the Bisection Method**

	Choice questions	
Iteration	Alternative A	Alternative B
1	(200, 0.33; 0)	**66**
2	**(200, 0.33; 0)**	33
3	(200,0.33; 0)	**49**
4	**(200, 0.33; 0)**	41
5	(200,0.33; 0)	**45**
6		
Indifference value		43

Appendix B. Illustrations of Described Choice Questions



References

Abdellaoui, M. 2000. Parameter-free elicitation of utilities and probability weighting functions. *Management Sci.* **46**(11) 1497–1512.

Abdellaoui, M., C. Barrios, P. P. Wakker. 2007. Reconciling introspective utility with revealed preference: Experimental arguments based on prospect theory. *J. Econometrics* **138**(1) 336–378.

Abdellaoui, M., H. Bleichrodt, O. L'Haridon. 2008. A tractable method to measure utility and loss aversion under prospect theory. *J. Risk Uncertainty* **36**(3) 245–266.

Abdellaoui, M., A. Baillon, L. Placido, P. Wakker. 2011. The rich domain of uncertainty: Source functions and their experimental implementation, *Amer. Econom. Rev.* Forthcoming.

Ahlbrecht, M., M. Weber. 1997. An empirical study on intertemporal decision making under risk. *Management Sci.* **43**(6) 813–826.

Balthussen, G., T. Post, M. J. van den Assem, P. P. Wakker. 2010. Random incentive systems in a dynamic choice experiment. Working paper, Department of Economics, Erasmus University, Rotterdam.

Baucells, M., F. H. Heukamp. 2009. Probability and time tradeoff. Working paper, IESE Business School, Barcelona.

Baucells, M., F. H. Heukamp. 2010. Common ratio using delay. *Theory Decision*. **68**(1–2) 149–158.

Becker, G. M., M. H. DeGroot, J. Marschak. 1964. Measuring utility by a single-response sequential method. *Behav. Sci.* **9**(2) 226–232.

Brandstaetter, E., A. Kuhberger, F. Schneider. 2002. A cognitive-emotional account of the shape of the probability weighting function. *J. Behavioral Decision Making* **15**(2) 79–100.

Diecidue, E., U. Schmidt, H. Zank. 2009. Parametric weighting functions. *J. Econom. Theory* **144**(3) 1102–1118.

Epper, T., H. Fehr-Duda, A. Bruhin. 2009. Uncertainty breeds decreasing impatience: The role of risk preferences in time discounting. Working paper, Institute for Empirical Research in Economics, University of Zurich, Zurich.

Gonzalez, R., G. Wu. 1999. On the shape of the probability weighting function. *Cognitive Psych.* **38**(1) 129–166.

Gul, F. 1991. A theory of disappointment aversion. *Econometrica* **59**(3) 667–686.

Halevy, Y. 2008. Strotz meets Allais: Diminishing impatience and the certainty effect. *Amer. Econom. Rev.* **98**(3) 1145–1162.

Holt, C. A., S. K. Laury. 2002. Risk aversion and incentive effects. *Amer. Econom. Rev.* **92**(5) 1644–1655.

Kahneman, D., A. Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica* **47**(2) 263–291.

Keren, G., P. Roelofsma. 1995. Immediacy and certainty in intertemporal choice. *Organ. Behav. Human Decision Processes* **63**(3) 287–297.

Noussair, C., P. Wu. 2006. Risk tolerance in the present and the future: An experimental study. *Managerial Decision Econom.* **27**(6) 401–412.

Prelec, D. 1998. The probability weighting function. *Econometrica* **66**(3) 497–528.

Quiggin, J. 1982. A theory of anticipated utility. *J. Econom. Behav. Organ.* **3**(4) 323–343.

Rottenstreich, Y., C. K. Hsee. 2001. Money, kisses, and electric shocks: An affective psychology of risk. *Psych. Sci.* **12**(3) 185–190.

Starmer, C. 2000. Developments in non-expected utility theory: The hunt for a descriptive theory of choice under risk. *J. Econom. Literature* **38**(2) 332–382.

Tversky, A., D. Kahneman. 1992. Advances in prospect theory: Cumulative representation of uncertainty. *J. Risk Uncertainty* **5**(4) 297–323.

Wakker, P. P., D. Deneffe. 1996. Eliciting von Neumann-Morgenstern utilities when probabilities are distorted or unknown. *Management Sci.* **42**(8) 1131–1150.

Wu, G. 1999. Anxiety and decision making with delayed resolution of uncertainty. *Theory Decision* **46**(2) 159–198.

Wu, G., R. Gonzalez. 1996. Curvature of the probability weighting function. *Management Sci.* **42**(12) 1676–1690.