Risking the Future? Measuring Risk Attitudes towards Delayed Consequences

Emmanuel Kemel, Corina Paraschiv

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Abstract

This paper presents an experiment that investigates differences of risk attitudes in decisions with immediate versus delayed consequences. Our experimental design allows to control for the effects of discounting and timing of risk resolution. We show that individuals are more risk tolerant in situations involving delayed consequences. Investigations based on rank-dependent utility show that this finding is mainly driven by probability weighting. More precisely, probability weighting is more elevated for delayed consequences, suggesting an overall increase in decision maker's optimism regarding the chances of success associated to risks for which consequences materialize in the future.

Keywords: Risk Attitudes, Time, Rank Dependent Utility, Delay, Future Consequences.

JEL: D81, D90, C91.

*Corresponding author. CNRS & GREGHEC, HEC Paris, France, emmanuel.kemel@greg-hec.com

†LIRAES, Université de Paris, France, corina.paraschiv@u-paris.fr

1 Introduction

The literature regarding decision making under risk generally assumes immediate consequences: after making a choice, the decision maker observes risk resolution, learns the outcome of the decision, and gets it without any delay. However, real-life risky situations rarely correspond to this theoretical setting of immediate consequences. Instead, a delay often separates the moment when the decision is made from the moment when consequences materialize. This paper presents an empirical investigation of the impact that the delay in the reception of the outcomes has on risk attitudes.

The delay separating the moment of the decision from the moment of outcome materialization may have an important role in explaining the variability of risk attitudes across real-life settings. In fact, delayed consequences characterize a wide range of health, political, legal, work, or daily-consumption decisions. The outcomes of political elections are known at the end of the voting process, while the consequences for voters are, most often, experienced with delay. For instance, British citizens voting for Brexit knew that the effective Brexit would take place several years after the referendum. One may wonder if they would have made the same choice if Brexit had been announced to take place right after voting. The delay in the reception of the consequences is also important for deterrence: law offenders have different perceptions of the risk of sanction for fines received long after the reckless behavior (Howe and Brandau, 1988). In education or work domains, agents often make decisions such as applying to a new program or a job, whose effects materialize in the future (the program/job may start several months after receiving an admission letter). Situations with delayed consequences are also not uncommon in the health domain. For example, risky sexual behavior may result in diseases (e.g. cancer caused by sexually transmitted viruses) which, albeit contracted and diagnosed immediately, may have future consequences. Prenatal tests and the related possible actions entail medical decisions affecting the future development and health of the offspring. In all these examples, the moment of decision making and the moment of consequence materialization are different. These decisions therefore involve both risk and time.

Risk and time, although often intertwined in real-life decisions, have long been considered as two separate research topics in the economic literature. For preferences under risk, the rational decision-making model is expected utility (EU). More descriptive extensions account for reference dependence (i.e., consequences are perceived as changes from a reference point), and non-linear probability weighting, two aspects formalized by Prospect Theory (Tversky and Kahneman, 1992). For intertemporal preferences, the rational decision-making model is discounted utility (Samuelson, 1937), with more descriptive extensions accounting for reference dependence and non-constant impatience (e.g. Laibson 1997, Ebert and Prelec 2007). Observing preferences in decisions involving both risk and time opened new perspectives in theoretical and empirical research.

A first stream addressing the interaction between risk and time questions whether intertemporal preferences are the same when the reception of future consequences is sure or not. In particular, several papers (Weber and Chapman 2005, Gerber and Rohde 2010) have investigated whether anomalies in intertemporal choice, like present bias (i.e., tendency to overvalue present rewards and prefer a small gain today to a high gain later), persist when future outcomes become uncertain. Halevy (2008) and Baucells and Heukamp (2012) proposed models that connect decision biases observed for risky and for intertemporal choices. Andreoni and Sprenger (2012) highlighted differences between intertemporal preferences under risk and intertemporal preferences under certainty. A key insight from these studies is that people discount differently certain and uncertain future outcomes. Our empirical investigation of the interaction between risk and time does not address discounting. Contrary to these studies, our experimental design does not involve time trade-offs. By neutralizing the impact of discounting, our protocol allows to study the interaction between risk and time without making specific assumptions about the intertemporal preferences of the decision maker.

A second stream of research connects risk and time by investigating attitudes towards uncertain delays of reception of outcomes (e.g. Ebert 2020, Li et al. 2017). In this context, the outcome of the risky decision is the time that the decision maker has to wait before getting the payoff. The present study does not belong to this stream. Indeed, in our experiment, the outcomes at stake are always received at a fixed (possibly future) date.

A third stream of research, to which our study directly contributes, focuses on the impact of time on risk attitudes (e.g. Keren and Roelofsma 1995; Weber and Chapman 2005; Noussair and Wu 2006; Coble and Lusk 2010; Abdellaoui et al. 2011b). Under the rational decision-making model, EU, risk attitudes are captured by the utility function, generally characterized in empirical applications through a single parameter (reflecting utility curvature). However, empirical evidence has highlighted systematic violations of EU raising questions about this characterization of risk attitudes through a single dimension. Allais (1953) in particular identified two major phenomena that cannot be accommodated by EU: common-consequence[1] and common-ratio[2] effects. These violations of EU are accounted for by behavioral models, from which one of the most famous is Rank Dependent Utility (RDU), which takes into account probability weighting (Starmer 2000). Several authors analyzed the interaction between risk and time by questioning whether EU violations hold in situations involving delays.

Keren and Roelofsma (1995) investigate empirically whether time delays impact violations of EU. These authors considered a series of binary risky choices testing the common-consequence effect under two treatments: (1) with consequences received now, and (2) with consequences received later. Delay impacted risk preferences, but did not modify the common-consequence effect. Weber and Chapman (2005) further explored this hypothesis. They also observed no effect of time delays (neither for 1 year, nor for 25 years) on the common-consequence effect when choice alternatives were evaluated jointly.

[1]Let $(x, p_1; y, p_2; z)$ refer to the lottery that gives x with probability p_1, y with probability p_2 and z with probability $1 - p_1 - p_2$. The common-consequence effect states that the preference between two lotteries $(x, p_1; y, p_2; z)$ and $(x', p_1; y, p_2; z')$, which share a common-consequence y (with the associated probability p_2), may depend on the value of y.

[2]Let $(x, p; y)$ refer to the lottery that gives x with probability p and y with probability $1 - p$. The common-consequence effect states that the preference between two lotteries $(x, qp_1; y)$ and $(x', qp_2; y)$ with $0 < q \leq 1$, may depend on the value of q.

Nevertheless, the authors captured an effect of the time dimension (a 25 year delay in payoffs) on the common-ratio effect, when choice alternatives were evaluated separately. It is however noteworthy that these pioneer investigations did not use real incentives, which are nowadays standard in experimental procedures. Moreover and most important, in the presentation of the choice situation, the subjects were not informed about when the risk associated to the lottery would be solved (now or at payment time).

One of the first studies investigating the impact of a delay associated to risky lotteries on risk preferences using (modern) experimental procedures, with real incentives, was provided by Noussair and Wu (2006). These authors observed that delaying the outcomes (up to three months) increased risk tolerance. However, their measurement of risk attitudes was based on the method popularized by Holt and Laury (2002). This method relies on EU, and does not allow to account for probability weighting. Coble and Lusk (2010) also used the Holt and Laury method in an empirical investigation of risk and time preferences. They observed higher risk tolerance when lotteries were delayed (up to 37 weeks). Analyzing risk preferences under EU, this higher risk tolerance for future lotteries was attributed to a less convex utility function. However, this interpretation may no longer hold when considering a more descriptive non-EU behavioral model.

Abdellaoui et al. (2011b) provided a further analysis of the impact of time on risk attitudes relying on a design which allowed to capture violations from EU related to a nonlinear probability weighting. Specifically, the study analysed the impact of delayed consequences on risk attitudes under RDU, a model accounting for probability weighting. Consistently with prior empirical evidence, the authors also observed more risk tolerance for delayed consequences. They could further identify that this effect was captured by a change in probability weighting rather than by a change in utility. In their study, probability weighting was more elevated when consequences were delayed.

Overall, prior research accords on the fact that more risk tolerance is exhibited towards delayed lotteries. However, prior research considered lotteries where both the resolution of risk and the materialization of outcomes were delayed. Indeed, in the three previouslymentioned studies, risk was solved (i.e the lottery was played to determine the outcome) at the time of payoff reception. Therefore, these experiments study the joint effect of delayed resolution of risk and delayed materialization of the payoffs, on risk attitudes, without disentangling them. The objective of the present paper is to capture the sole impact of the timing of materialization of consequences, on risk attitudes. To this aim we consider an experimental design where choices vary regarding this sole dimension, while avoiding confounds related to other time effects, such as discounting or delayed resolution of risk. Following Abdellaoui et al. (2011b), we measure preferences under RDU, a general model that accounts for probability weighting, and integrates EU as a particular case.

Our experiment investigates the impact of a time delay before the reception of the outcomes on attitudes towards risk, by comparing risk preferences in two situations: (1) consequences received "now", and (2) consequences received "later" (in one year for now). Our results show that utility of consequences incurred "now" and in "one year for now" is similar. However, the probability weighting function is different for delayed consequences, for which the decision maker exhibits more optimism. The time dependence of risk attitudes appears as the first of the seven key facts regarding risk and time listed and studied by Epper and Fehr-Duda (2018). This highlights the importance of this fact for the literature on risk and time. Nevertheless, the authors note that it "has been documented by a range of papers that do not distinguish between the effects of delay on utility and probability weights". They cite Abdellaoui et al. (2011b), in which lotteries where delayed in terms of both payment and resolution. Our study fills the gap and adds a missing piece of evidence to the understanding of the role played by probability weighting in decisions involving both risk and time.

The rest of the paper is organized as follows. Section 2 presents the theoretical background and the measurement method. The experimental procedure is presented in Section 3. Results are reported in Section 4. Section 5 concludes with a discussion of our main findings.

2 Theory

2.1 Preliminaries

We focus on a decision maker confronted to choices between risky lotteries involving non-negative monetary outcomes. In the present study, only (at most) two-outcome lotteries are considered. Therefore, the formal presentation of the model provided in this section is restricted only to such lotteries.

The decision maker chooses between risky lotteries of the type $(x_t, p; y_t)$, where t refers to the time of reception of the outcomes. More precisely, the lottery $(x_t, p; y_t)$ yields, at the corresponding time t, either x with probability p, or y with probability $1 - p$. Two different times $t \in \{0, T\}$ are considered in the study: $t = 0$ refers to immediate consequences received "now" and $t = T$ refers to delayed consequences received "later". The uncertainty associated to the lottery is always solved at time $t = 0$ (i.e., immediately after choice). The decision maker has preferences over lotteries that are captured by a preference relation $\succsim$, with $\sim$ denoting indifference and $\succ$ strict preference.

2.2 Time-dependent rank-dependent utility

We assume that decision maker's preferences follow a time-dependent RDU model. Under this model, the value associated to the lottery $(x_t, p; y_t)$ is given by

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

where $u^t(x)$ is a strictly increasing utility function, measuring the utility of receiving the monetary outcome x at time t, and $w^t(p)$ is a strictly increasing probability-weighting function mapping $[0, 1]$ to $[0, 1]$ and capturing the perception of probabilities in decisions involving outcomes received at time t. Note that EU is a particular case of the RDU model where $w^t(p) = p$ for all $p \in [0, 1]$.

For the econometric estimations of the time-dependent RDU model, we assume parametric specifications for utility and probability weighting functions. The time-dependence of the RDU model is captured by the time dependence of the (utility and probability weighting) specification parameters.

Regarding utility, an exponential function is considered. The other most commonly used utility specification in empirical literature is the power function. However, the exponential specification was preferred because it accords better with our data (see Section 4.2.2 for details). For consequences in the interval $[0, M]$, exponential utility is defined as:

$$u^t(x) = \frac{1 - e^{-\alpha_t x}}{1 - e^{-\alpha_t}}. \tag{2}$$

The parameter α_t measures the curvature of the utility, which is allowed to vary depending on the payment time t. α_t equals 0 for a linear function, and increases (decreases) with the concavity (convexity) of the function.

For probability weighting, we use the two-parameter specification axiomatized by Prelec et al. (1998):

$$w^t(p) = e^{-\beta_t(-log(p)^{\gamma_t}}. \tag{3}$$

This two-parameter specification, often employed in experimental studies, captures two different psychological phenomena related to probability weighting. Parameter β_t characterizes elevation and reflects the degree of optimism of the decision maker regarding probabilities: the lower its value, the more elevated the function, and the more optimistic the decision maker. Parameter γ_t characterizes the curvature of the function, and is generally interpreted as measuring sensitivity to changes in probabilities. In particular, when $\gamma < 1$, the function exhibits an inverse S-shape, with more sensitivity to changes in low and high probabilities and less sensitivity to changes in intermediate probabilities. The subscript t captures the fact that, in our study, these dimensions of probability-weighting can be time-dependent.

Overall, our econometric analysis consists in estimating the model parameters α_t, β_t and γ_t for each of the two times $t = 0$ and $t = T$, and comparing the estimated parameter values across payment times.

2.3 Method

Our method is based on the elicitation of certainty equivalents. A set of lotteries $(x_t, p; y_t)$ is built by fixing different values for probability $p \in]0, 1[$, and for the monetary outcomes $x > y \geq 0$, with $x, y \in [0, M]$. For each lottery, our method consists in measuring the (dated) certainty equivalent, i.e. the monetary outcome c_t such that the decision maker is indifferent between receiving this amount for sure at time t or receiving the lottery. Formally, our method consists in estimating c_t such as $c_t \sim (x_t, p; y_t)$. In the experiment, the same set of lotteries was presented twice to the subjects, once for consequences payed "now" and once for consequences payed "later".

Comparing the certainty equivalent (CE) associated to a risky lottery to its expected value (EV) allows to directly characterize the risk attitude of the decision maker, in a model-free setting. The decision maker is risk averse if CE<EV, risk seeking if CE>EV, and risk neutral if CE=EV. Moreover, the lower the CE, the higher the degree of risk aversion of the decision maker. We base our raw data analysis on the certainty equivalents in order to study risk attitudes and how they vary depending on the timing of payment.

Modelling the certainty equivalents under time-dependent RDU allows to refine the analysis by investigating which aspect of risk preferences (utility or probability weighting) is impacted by payment time. According to equation (1), under time-dependent RDU, the certainty equivalent c_t of $(x_t, p; y_t)$ follows:

$$c^t = {u_t}^{-1}[w_t(x)(u_t(x) - u_t(y)) + u_t(y)]. \tag{4}$$

Using this equation, we estimate the model parameters α_t, β_t and γ_t at each time period (the details regarding the estimation procedure are provided in Appendix C). Both aggregate and individual level estimations are performed. Aggregate level estimations assume that all respondents have the same parameters. They provide a global picture of the data. In individual level estimations, the parameters are estimated for each individual, which allows to verify that the global pattern applies to a majority of individuals and is not due to outliers.

3 Experiment

3.1 Procedure

The experiment was computer-based and took place in the laboratory. Participants were 70 undergraduate students from the University of Paris. All subjects received a flat payment of 10 euros for their participation. Upon arriving in the lab, subjects were randomly assigned to two separate groups: a real-incentive group and a non-incentivized group (e.g. Abdellaoui et al. 2011a). For the 36 respondents in the real incentive group, in addition to the fixed fee, a real-incentive scheme was implemented. Subjects were informed that, at the end of the experimental session, they would be asked to make a draw from an urn containing 20 balls. If a winning ball was selected, they would be allowed to play for real one of the choices made during the experiment. For this choice, the option indicated as preferred by the respondent during the data collection would be implemented and played to determine the final payoff. This amount of money would be received by the subject at the corresponding due time (e.g. Rohde 2019).

The data collection was based on individual interviews. Each experimental session lasted one hour on average. Upon arriving in the lab, subjects were presented the instructions, based on a 10 minutes presentation explaining the experimental tasks. A training session followed, involving several practice questions that allowed to make sure that respondents got familiar with the computer-based interface before proceeding with the experiment. Data collection was organized in two parts: one part involving decisions with immediate outcomes and a second part involving decisions with delayed outcomes. For each subject, the order of presentation of the two parts during the experiment, as well as the order of presentation of the different experimental tasks in each part were randomized.

3.2 Stimuli

Table 1 presents the lotteries used to measure risk preferences in the study. The experimental tasks corresponding to these lotteries were presented twice to the subjects, once with immediate consequences, and once with consequences delayed to "one year from now". Recall that in our experiment, risk was always solved "now", even when the payoffs were received "in one year". This difference between resolution and payment times is the main feature that distinguishes our setup from the one studied by Abdellaoui et al. (2011b).

The experimental tasks involved the elicitation of a total of 24 certainty equivalents for each subject, corresponding to 12 certainty equivalents for each condition (the 11 lotteries in Table 1 and a repetition of the task corresponding to the Lottery 7). Only positive outcomes of money were used in the study. The maximum amount was fixed to 500 euros ($M = 500$). We opted for sizeable amounts of money for two main reasons. First, a large range of monetary outcomes has to be considered for capturing the shape of the utility function (e.g. Tversky and Kahneman 1992), which is one of the components of interest in our study. Second, because the experiment involved a treatment with outcomes received one year after the date of the experiment, we wanted to make sure that subjects would be interested by the amounts at stake despite their delayed reception (Abdellaoui et al. 2019).

	x_t	p	y_t
Lottery 1	500	0.1	0
Lottery 2	500	0.2	0
Lottery 3	100	0.5	0
Lottery 4	200	0.5	0
Lottery 5	400	0.5	200
Lottery 6	450	0.5	150
Lottery 7	500	0.5	0
Lottery 8	500	0.5	100
Lottery 9	500	0.5	200
Lottery 10	500	0.8	0
Lottery 11	500	0.9	0

Table 1: Risky lotteries $(x_t, p; y_t)$ used in the experiment

The certainty equivalents were measured using choice lists with a precision of 5 euros. The list was completed according to the bisection procedure, then, all the choices from the list were reviewed and confirmed (see Appendix B). Once a list was validated it was no longer possible to modify the answers.

Regarding the implementation of real incentives, all the lotteries had the same chance to be selected for real payment. For a given lottery $(x_t, p; y_t)$ subjects were told that all the values from the list $\{y, y+5, \ldots, x-5, x\}$ where equally likely to be selected.

4 Results

4.1 Preliminary checks

Before starting the main analysis of the data with respect to our research goal, we proceed to a series of preliminary investigations regarding the consistency of the responses across the repetitions of the experimental tasks and between the incentivized and the non incentivized subgroups.

4.1.1 Consistency checks

Our experimental design included a test of the accuracy of respondents' answers. This consistency check took the form of a repetition in the measurements, by presenting twice to the subjects the experimental tasks corresponding to the Lottery 7 in Table 1. More precisely, the elicitation of the certainty equivalent for the lottery $(500, 0.5; 0)$ was performed twice for each treatment. Table 2 reports the results regarding the initial and repeated measures for the treatments "now" and "later", as well as the statistical tests assessing the consistency of the repetitions of the experimental tasks. The table confirms that the repeated measures do not differ from, and are highly correlated with the initial measures. This result holds for the two treatments (now and later).

	Init. Measure	Rep. Measure	t-test	ks test	Correlation
Now	174.75 (67.73)	174.96 (69.24)	$p = 0.95$	$p > 0.99$	0.91 ($p < 0.001$)
Later	189.25 (61.63)	186.39 (61.26)	$p = 0.51$	$p > 0.99$	0.83 ($p < 0.001$)

Notes. The table reports mean values for the initial and repeated measure of the CE corresponding to the lottery $(500, 0.5; 0)$. STDs are reported in brackets. The last column reports Person-correlation between the initial and the repeated measures, and corresponding significance levels.

Table 2: Certainty equivalents for the lottery $(500, 0.5; 0)$

Overall, the analysis of the repeated measures suggests that subjects provided consistent answer: for both treatments, the repetitions are highly correlated with the initial measures and no bias is detected. We note however that the correlation across measurements is slightly lower for delayed consequences. This suggests that, in the context of delayed outcomes, subjects' preferences are more volatile, which leads to slightly more noisy responses. In order to account for this possible effect, the econometric analysis will allow for different error sizes for the two treatments.

4.1.2 Hypothetical choices versus real-incentives

Because our subject pool included two separate groups, one with hypothetical choices and another with real incentives (i.e., subjects knew that they were eligible for having a choice played for real), it seems important to analyze the role of the incentives by investigating the potential differences in behavior between the two groups. In order to address the impact of real incentives, we focus on the two treatments (now and later) separately. For each treatment, a 12×2 ANOVA was run, with "lottery" as a within-subject factor and "incentives" (hypothetical/real) as a between-subject factor. In both treatments, "lottery" was found to impact the certainty equivalent ($p < 0.001$), but incentives were not, neither in terms of main effect ($p = 0.35$ for "now" and $p = 0.76$ for "later"), nor in terms of interaction with "lottery" ($p = 0.66$ for "now" and $p = 0.93$ for "later"). Based on this data, we cannot reject the assumption that subjects in the two groups provided similar responses. We therefore pool the two groups together in the rest of the statistical analysis.

4.2 Raw data

This section presents a model-free analysis of the data. The main goal is to measure the impact of "treatment" (now/later) on the preferences expressed by the decision makers. The model-free analysis provides results that are insightful on their own, but it's also important because it may provide guidance for the modeling choices in the econometric analysis.

4.2.1 Investigating Between-Treatment Differences

The main results for the two treatments are summarized in Table 3 (additional statistics are reported in Appendix D). For standard risk (i.e. lotteries solved and payed now), the usual pattern of risk attitudes is observed. Risk aversion prevails, except for lotteries involving small probabilities. Indeed, we cannot reject the assumption of risk neutrality for the lottery with a winning probability of 0.1 and 0.2. Similar patterns are observed when payment is delayed. In this case, however, risk seeking is statistically significant for a winning probability of 0.1. Risk attitudes are therefore probability dependent in the two contexts.

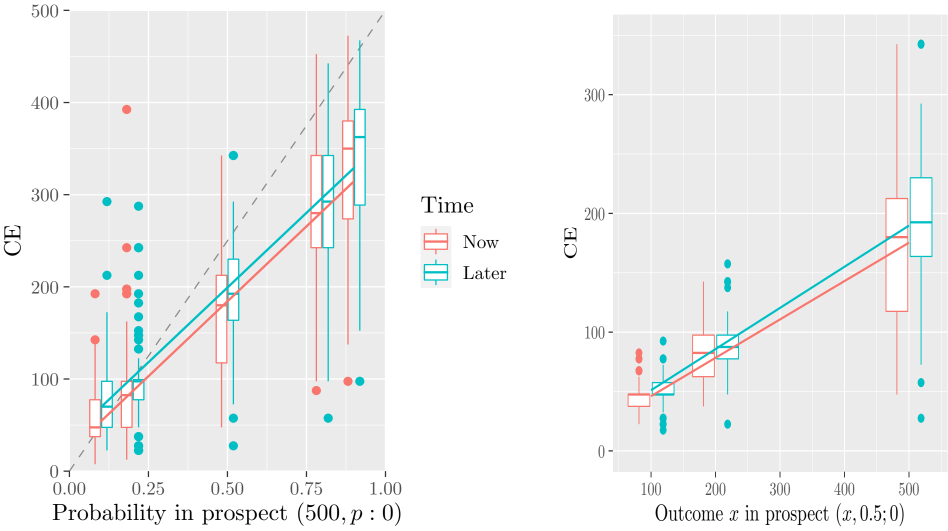
We further analyse the impact of treatment (now vs. later) on certainty equivalents. A comparison of the certainty equivalent associated to each risky lottery between the two experimental conditions shows that subjects provided higher certainty equivalents in the treatment where outcomes are delayed (see Table 3). An ANOVA with "lottery" and "treatment" (now vs later) as within-subject factors finds significant effects of "lottery" ($p < 0.001$) and "treatment" ($p < 0.001$) but no interaction between these two factors ($p = 0.23$).

Lottery	EV	Now		Later	
		Mean	Std	Mean	Std
$(500, 0.1; 0)$	50	57.86^{ns}	35.79	78.57^{***}	48.35
$(500, 0.2; 0)$	100	88.50^{ns}	58.62	98.86^{ns}	51.02
$(100, 0.5; 0)$	50	44.36^{**}	13.73	49.64^{ns}	13.71
$(200, 0.5; 0)$	100	80.71^{***}	24.15	87.68^{***}	23.42
$(400, 0.5; 200)$	300	286.71^{***}	24.30	285.21^{***}	22.77
$(450, 0.5; 150)$	300	257.43^{***}	47.54	260.14^{***}	40.84
$(500, 0.5; 0)$	250	174.75^{***}	67.73	189.25^{***}	61.63
$(500, 0.5; 100)$	300	249.86^{***}	58.56	255.36^{***}	50.25
$(500, 0.5; 200)$	350	315.43^{***}	44.66	316.14^{***}	38.83
$(500, 0.8; 0)$	400	278.07^{***}	83.77	285.71^{***}	73.45
$(500, 0.9; 0)$	450	322.29^{***}	85.01	343.79^{***}	77.62

Notes. The exponent of the mean reports significance of the difference with the EV.
$\star$: $p < 0.05$, $\star\star$: $p < 0.01$, $\star\star\star$: $p < 0.001$

Table 3: Certainty equivalents for the treatments "now" and "later"

The increase of the certainty equivalents for delayed consequences may be easily visualized when focusing on the lotteries of the type $(500, p; 0)$, by looking at the relationship between the certainty equivalents and the probability p. As explained by Bouchouicha et al. (2017), this relationship captures the overall pattern of risk preferences. Figure 1 (left) illustrates this pattern based on our experimental data. It is confirmed by an ANCOVA that detects a significant impact of the "probability" p and a main effect of time treatment ($p < 0.001$). The interaction between "probability" and treatment is not found to be significant ($p = 0.24$). Figure 1 (left) illustrates that the difference of certainty equivalents across treatments applies to all probability levels considered in the experiment. For lotteries of type $(500, p; 0)$, subjects gave larger certainty equivalents on average when outcomes were payed later.



Panel left: CEs for lotteries $(500, p; 0)$ Panel right: CEs for lotteries $(x, 0.5; 0)$

Figure 1: Impact of treatments on certainty equivalents for various probability and outcome levels

A similar analysis was run on lotteries of the type $(x, 0.5; 0)$ (see Figure 1, right). These lotteries allow to illustrate the effect of the time treatment when the consequences at stake increase. The Figure shows that the difference of certainty equivalents across treatments in confirmed for the various levels of outcomes. An ANOVA with outcome x and treatment as within-subject factors captures a significant effect of these factors ($p < 0.001$ and $p = 0.003$ respectively) but no significant effect of their interaction ($p = 0.18$). The certainty equivalents associated to these lotteries were on average larger by 9 euros when the payment occurred later.

4.2.2 Characteristics of risk attitudes: CARA versus CRRA

The stimuli in our experiment were chosen such as to allow a parameter-free assessment of the type of risk preferences, checking consistency with constant absolute risk attitudes (CARA) or constant relative risk attitudes (CRRA). This assessment is based on Lotteries

4, 5, and 7. Under CRRA, the (distribution of) certainty equivalents for Lottery 7 $(500, 0.5; 0)$ should equal 2.5 times (the distribution of) the certainty equivalents for Lottery 4 $(200, 0.5; 0)$. Under CARA, the (distribution of) certainty equivalents for the Lottery 5 $(400, 0.5; 200)$ should equal 200 plus (the distribution of) the certainty equivalents for the Lottery 4 $(200, 0.5; 0)$. The empirical cumulative functions of these distributions are reported in Appendix D. A series of Kolmogorov-Smirnov tests was run to test these (equal distribution) assumptions, on each treatment. CRRA is rejected for the two treatments ($p = 0.001$ for outcomes payed now and $p < 0.001$ for outcomes payed later), whereas CARA is not rejected for any of the two treatments ($p = 0.47$ for now and $p = 0.18$ for later). Our data are therefore consistent with CARA. CARA can be captured by an exponential specification, whereas CRRA can be captured by a power specification. Consistently with these results, an exponential functional form for utility will be used in the econometric analysis.

4.3 Econometric estimations

Overall, the raw data analysis revealed a clear impact of time treatment on the measured certainty equivalents. Subjects exhibited higher certainty equivalents, reflecting more risk seeking, when the reception of outcomes was delayed. However, the analysis based on raw data did not allow to test whether this change of attitudes derives from a change in probability weighting, a change in utility, or both. This aspect will be further investigated hereafter based on the econometric analysis.

According to the series of model-free tests performed in the previous sections, the responses were consistent across repetitions and did not differ between the incentivized and the non-incentivized groups. All these data can therefore be pooled in the econometric analysis. The preliminary tests also recommend the use of a CARA utility specification, which was therefore retained for the econometric analysis. Table 4 reports the results of the estimations at aggregate and individual level based on the exponential utility function and the Prelec probability weighting function. Estimations using the alternative probability weighting specification proposed by Goldstein and Einhorn provided similar results, reported in Appendix E.

Parameter	Aggregate-Level Estimates		Individual-Level Estimates	
	Now	Later	Now	Later
Utility α_t	1.197 (0.097)	1.257 (0.131)	1.096 [0.433, 2.190]	1.233 [0.631, 2.102]
Elevation β_t	0.941 (0.036)	0.859 (0.035)	0.978 [0.781, 1.144]	0.865 [0.719, 1.073]
Sensitivity γ_t	0.609 (0.025)	0.621 (0.025)	0.645 [0.496, 0.836]	0.671 [0.546, 0.877]
LL	-5878.904		-4568.743	

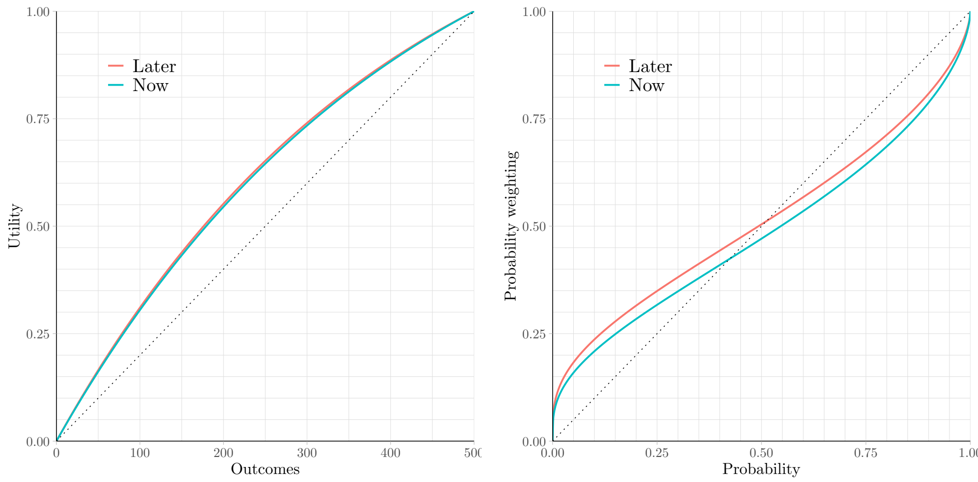
Notes. For aggregate-level estimations, standard errors clustered at individual level are reported between brackets, below the parameter value. For individual estimations, median values of individual parameters are reported, with the interquartile range between square brackets.

Table 4: Aggregate and Individual Estimations with Prelec

4.3.1 Aggregate-level estimations

Regarding immediate risk (i.e., corresponding to the treatment with consequences payed now), our results are consistent with the usual findings reported in the literature. The average subject exhibits a concave utility function which contributes to risk aversion, and an inverse S-shaped probability weighting, which entails less risk aversion for small probabilities than for medium and large probabilities. Similar patterns are captured when outcomes are payed later, albeit with different parameter-values.

A series of Wald tests are run to compare the aggregate parameters across the treatments "now" and "later". No between-treatment difference is captured regarding the utility parameter α_t ($p = 0.77$) and the sensitivity parameter γ_t ($p = 0.72$). However, a significant difference between the two time treatments is captured regarding the elevation parameter β_t ($p = 0.047$): the probability weighting function is more elevated when consequences are received with delay. This higher elevation can be interpreted as more optimism. Indeed, a higher value of this parameter contributes to more risk seeking, consistent with what was observed in the raw data analysis. To illustrate this pattern, we picture in Figure 2 the average utility and probability weighting functions deriving from aggregate-level estimations. Panel A shows that the utility function is similar when consequences are immediate and when they are delayed. Panel B illustrates the differences in probability weighting between the two conditions. We observe that the probability weighting function for delayed consequences is above the probability weighting function for immediate consequences, consistent with more optimism.



Panel Left. Utility functions. Panel Right. Probability weighting functions.

Figure 2: Aggregate-Level Estimations: Utility and Probability Weighting

4.3.2 Individual-level estimations

Individual level estimations confirm the aggregate patterns. The median and IQR values of the individual elevation parameter are lower when consequences are paid now (see Table 4). The difference is significant according to a Wilcoxon test ($p < 0.004$). The individual values of the elevation parameter across payment times are scatter plotted in Figure 3. Lower parameters for delayed payment are observed for 45 subjects (out of 70, binomial test, p=0.02). For the other two parameters (utility and sensitivity), neither Wilcoxon, nor binomial test captures significant differences.

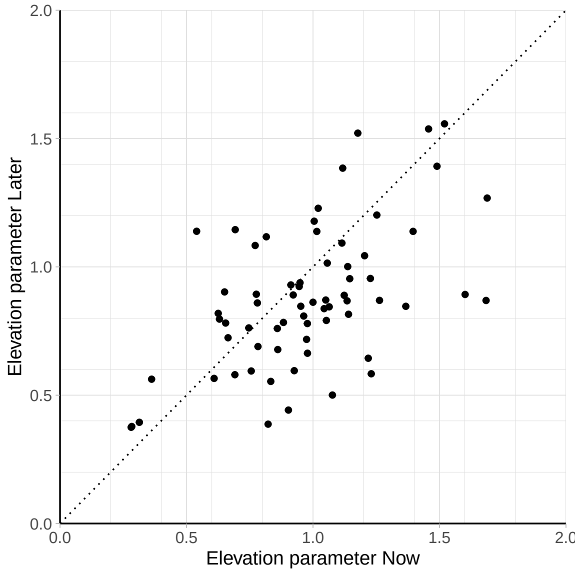


Figure 3: Individual-Level Estimations: Elevation Parameter

Overall, the econometric analysis recovers the usual patterns observed under the RDU model in the condition when consequences are payed now, and captures a more elevated probability weighting function in the condition when consequences are payed later. Under time-dependent RDU, the increase in risk taking observed when consequences are delayed is thus captured by a change in probability weighting, reflecting a higher level of optimism of the decision maker.

5 Discussion

Our paper analyzed interactions between risk and time in decision-making by investigating the impact of a delay in the reception of the consequences on risk attitudes. We used an experimental design that allowed to neutralize both the effects of discounting and risk resolution, in order to isolate the sole effect of a delayed reception of consequences. While prior research focused either on the impact of delaying both payment and resolution, or on the effect of delaying resolution only, our study provides a missing piece of evidence allowing to complete the current understanding of attitudes towards delayed lotteries.

Hereafter, we summarize the main results of our study, discussing their contribution to prior literature.

5.1 Delayed consequences are associated to more risk tolerance

Our experimental method was based on certainty equivalents, which were used to evaluate lotteries solved immediately but paid either immediately or one year later. Descriptive statistics showed that CEs were systematically higher in the condition with delay. This result is consistent with the idea that risk tolerance increases when consequences are delayed. Higher risk tolerance for delayed lotteries has been already reported in previous experiments. However, in these experiments, delayed lotteries involved both delayed payment and delayed resolution. Our results showed that delaying the payment only, while keeping the resolution of the risk immediate was enough to increase risk tolerance.

Because previous studies did not isolate the timing of payment from the timing of risk resolution, possibilities of direct comparisons with previous studies are limited. We can however discuss the direction of the effect that we captured, in relation to other effects previously investigated in the literature. The studies analyzing risk attitudes towards present versus future risks (Noussair and Wu 2006; Coble and Lusk 2010; Abdellaoui et al. 2011b) report less risk aversion for future lotteries: lower certainty equivalents should be observed for lotteries "solved now and payed now" than for lotteries "solved later and payed later". This pattern could be explained through a preference for later resolution of risk (e.g. Coble and Lusk 2010). However, this interpretation is in contradiction with empirical findings suggesting that preference for early resolution prevails (e.g. von Gaudecker et al. 2011). Our results solve this contradiction by showing that risk tolerance increases even when future lotteries do not imply delayed resolution of risk. It is thus possible that the relative impacts of delayed payment and of delayed resolution on certainty equivalents go in opposite directions: delaying resolution decreases the certainty equivalents, whereas delaying payment increases them. If the latter effect is larger than the former, delayed lotteries may have higher certainty equivalents despite a preference for early resolution.

5.2 Delayed consequences lead to more optimism towards probabilities

Our econometric analysis was based on RDU. More precisely, a time-dependent version of the model was considered, allowing for utility and probability weighting to change depending on payment time. Our study highlighted a significant change regarding probability weighting, and no significant change regarding utility when moving from the treatment "now" to "later". The assumption of a stationary utility when delaying consequences is therefore not rejected. At first sight, our finding may be seen as conflicting evidence with respect to the results provided by Noussair and Wu (2006) and Coble and Lusk (2010), who report a change in utility for future risky lotteries. However, it is important to note that their modeling under EU did not provide any other parameter (except utility curvature) for capturing differences in risk attitudes. Our result is, instead, consistent with Abdellaoui et al. (2011b) who also observed stationary utility under a RDU modeling of decision-making regarding future risks.

Regarding probability weighting, we observed more elevation when outcomes were delayed. According to these results, the increase in risk tolerance induced by time delays can be explained by more optimism for delayed consequences. Our analysis did not capture a difference regarding the sensitivity parameter of the probability weighting function. This suggests that the impact of time on risk attitudes is not likelihood-dependent. In contrast, previous studies focusing on attitudes towards delayed resolution of risk have reported evidence for likelihood dependence (Chew and Ho 1994, Lovallo and Kahneman 2000). For medium and large winning probabilities, people prefer sooner resolution, but for small probabilities, the preference may change in favor of later resolution (a behavior consistent with hopefulness).

Our findings showed that time interacts with risk attitudes beyond the impact of discounting and timing of risk resolution. Our subjects behaved as if they became more optimistic about risk for consequences materializing in the future. Since economic situations often involve decisions with consequences materializing in a more or less future time horizon, these results may explain why individuals sometimes suffer from an optimism bias, even though risk aversion generally prevails when measured in atemporal setting. Further investigations in this direction may be of particular interest in the field, in situation where individuals are found to make sub-optimal decisions because of too much optimism, such as entrepreneurship or health domain, two contexts involving delayed consequences.

5.3 Directions for further research

The main contribution of our study to behavioral decision making is to show that probability weighting can capture interactions between risk and time. This finding is consistent with the results repported by Abdellaoui et al. (2011b). In both studies, an exploratory approach was used, simply allowing probability weighting functions to be time-dependent. Further theoretical research is needed to develop models connecting these probability weighting functions across (resolution and payment) time periods. Epper and Fehr-Duda (2018) proposed a model explaining the impact of time on probability weighting. Their model assumes that future consequences are intrinsically risky and might not materialize in the future, an idea captured through a survival probability. Decision makers are assumed to edit delayed lotteries accounting for this survival probability. Under RDU, the survival probability implies that decision weights related to winning events are more elevated when consequences are delayed. With two outcome lotteries, higher decision weights for winning events are consistent with a more elevated probability weighting function. Our results are therefore consistent with the pattern predicted by Epper and Fehr-Duda (2018).

A natural question arising from our study is whether the same pattern, with an increase of risk tolerance for delayed consequences may be expected in the loss domain. Indeed, our investigation was limited to gains only, while losses are of particular interest in a lot of real-life settings including insurance and investment decisions. Based on current empirical research, little is known about the impact of time on risk preferences in the loss domain. The main difficulty with such investigations is that there is no perfect real-incentive mechanism, an aspect particularly true in the loss domain. Ingenious experimental procedure would thus be needed for future investigations of the impact of delaying losses on risk preferences.

6 Conclusion

This paper reported an experiment that showed the impact of payment delays on risk attitudes, while neutralizing the effect of discounting and delayed resolution of risk: subjects exhibited higher risk tolerance when payoffs were delayed. Econometric analysis under RDU showed that the observed difference in risk attitudes was due to a change in probability weighting, which was more elevated when consequences were delayed. These results, which isolate the effect of delaying the sole materialization of the consequences add a missing peace of evidence to the current understanding of risk attitudes for lotteries with future consequences. They may contribute to explain variations of risk attitudes across contexts of real-life decisions.

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A Displays

Figures 4 and 5 illustrate the displays used during the experiment, based on questions involving Lottery 11 in Table 1. Figure 4 shows an example of display for the treatment now, and Figure 5 for the treatment later. In both cases, Option A (in red) corresponds to a lottery giving 450 euros for sure and Option B (in blue) corresponds to the risky lottery (500,0.9;0) allowing to win either 500 euros with 90% chances or 0 euro. The grey arrow separating the two options represents time, from "now" to "one year from now". The time line allows to see when the lottery is played and when the subject receives the payoffs.

Figure 4: Example of choice question for the treatment now

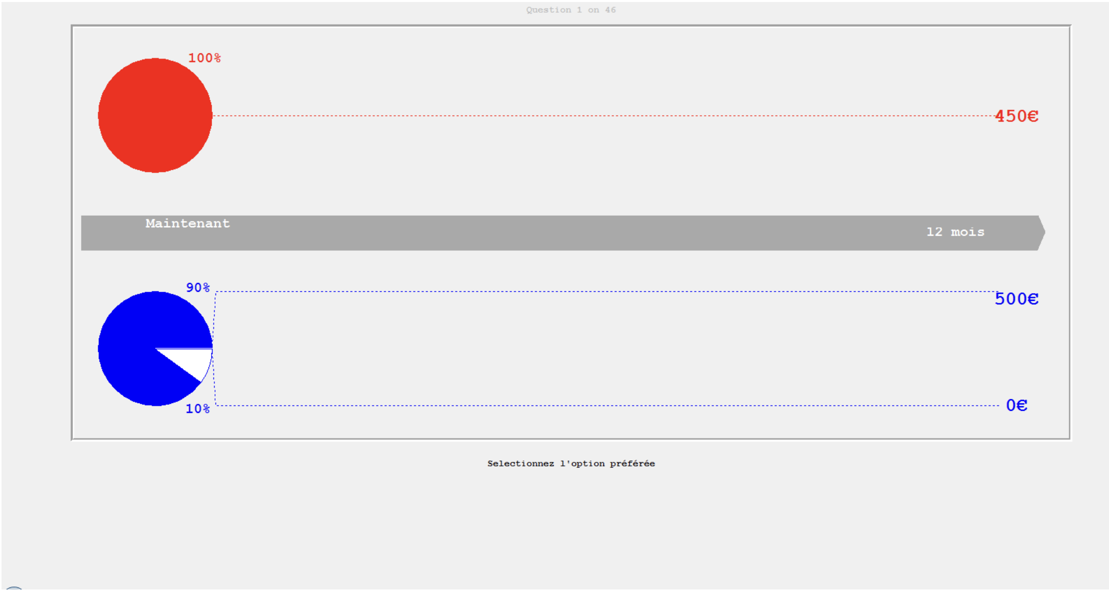

Figure 5: Example of choice question for the treatment later

In Figure 4, the lottery and the amounts of money are all presented at the left-side of the time line, corresponding to the moment "now". This means that the subject receives the payoffs immediately. More precisely, the subject choosing Option A gets 450 euros immediately and the subject choosing Option B plays immediately the lottery, and receives either 0 or 500 euros, depending on chance.

In Figure 5, the lotteries A and B are presented at the left-side of the time line, corresponding to the moment "now", but the payoffs appear at the right-side of the time line corresponding to "one year from now". This means that the choice between Option A and Option B and risk resolution take place immediately. However, the subject choosing Option A receives the corresponding payoff of 450 euros with a delay of one year. The subject choosing Option B learns immediately the payoff (either 0 or 500 euros depending on chance), but receives it with a delay of one year.

The subject is invited to chose between Option A and Option B by clicking on the preferred lottery.

B Use of Choice Lists to Elicit Certainty Equivalents

The questions corresponding to the lotteries in Table 1 were organized in choice lists. For a given lottery $(x, p; y)$ (presented as Option B), the choice list included questions where the sure amount presented as Option A varied from y to x with a step of 5. More precisely, the sure amounts in the choice list were $y, y + 5, ..., x - 5, x$. This choice list was used to estimate the certainty equivalent of the lottery with a precision of 5 euros. In order to fasten the completion of the list and to avoid order effects in the completion process, the choice list was filled using the bisection procedure.

The procedure was initiated with a choice between the lottery $(x, p; y)$ (Option B) and a sure value corresponding to the expected value of the lottery (Option A). For example, the bisection process for the lottery $(500, 0.9; 0)$ started with a first choice where Option A offered 450 euros (see Figure 5). If the subject indicated a preference for Option A (B), all the choices from the choice list corresponding to values higher than 450 (lower than 450) were pre-filled with a preference for Option A (B), and the subject faced as next choice the middle of the remaining - not yet completed - choices in the list. The second choice presented to the subject was thus the one where Option A was equal to 225 (475). The process was iterated until all the choices from the list were completed. When the list was completed, the subject proceeded to the validation step.

In the validation step, the entire choice list was presented to the subject for validation. Figure 6 shows an example of validation step. A scrollbar allowed to navigate through all the choices of the list (panels a to c). For each choice, the choice made by the subject was indicated, and could be modified, if needed. When the subject had reviewed all the choices from the list, a button appeared, allowing to confirm the entire list and to move to the next choice list (panel d). In the example illustrated in Figure 6, the respondent indicated a preference for Option A for all the choices where this option offered a sure amount larger or equal to 350 euros. For the other choices, the respondent indicated a preference for Option B. In this case, the recorded certainty equivalent was the midpoint of the interval [345, 350], i.e. 347.5 euros.

Figure 6: Validation step of a choice list

C Estimation method

For each lottery k and individual i, the elicitation of the certainty equivalent, denoted $c_{i,k}$, was made with a precision of 5 euros. Therefore, our elicitation method produces two (multiple of 5 euros) bounds $c^-_{i,k}$ and $c^+_{i,k}$, such that $c^-_{i,k} < c_{i,k} < c^+_{i,k}$ and $c^+_{i,k} - c^-_{i,k} = 5$. More precisely, each certainty equivalent elicitation task consists in building an interval $(c^-_{i,k}, c^+_{i,k})$ including $c_{i,k}$. We assume that the measured certainty equivalents, denoted $\hat{c_{i,k}}$, depart from the theoretical ones, according to a normal error: $c_{i,k} = \hat{c_{i,k}} + \epsilon_{i,k}$ with $\epsilon_k \sim N(0, \sigma^2)$. With this error specification, the likelihood of a given individual observation writes:

$$\begin{aligned} l(c^-_{i,k}, c^+_{i,k}) &= p(c^-_{i,k} < c_{i,k} < c^+_{i,k}) \\ &= p(c^-_{i,k} - \hat{c_{i,k}} < \epsilon_{i,k} < c^+_{i,k} - \hat{c_{i,k}}) \\ &= \Phi(\frac{c^+_{i,k} - \hat{c_{i,k}}}{\mu_i}) - \Phi(\frac{c^-_{i,k} - \hat{c_{i,k}}}{\mu_i}) \end{aligned} \tag{5}$$

where Φ is the cumulative function of the normal distribution.

We account for heteroscedasticity by assuming that $\sigma = \rho(x - y)$. For aggregate level estimations, parameters are assumed to be constant across individuals, and are estimated by likelihood maximization. The standard errors are computed using the sandwich estimator with individual clustering. For individual-level estimations, the maximization is run for each individual separately. Maximization is run using the BFGS algorithm.

D Additional descriptive statistics

Lottery	Now		Later	
	Median	IQI	Median	IQI
(500,0.1; 0)	47.5	[37.50, 77.50]	70.00	[47.50, 97.50]
(500,0.2; 0)	82.5	[47.50, 97.50]	97.50	[77.50, 99.37]
(100,0.5; 0)	47.5	[37.50, 47.50]	47.50	[47.50, 57.50]
(200,0.5; 0)	82.5	[62.50, 97.50]	87.50	[77.50, 97.50]
(400,0.5; 200)	292.5	[273.75, 297.50]	292.50	[272.50, 296.25]
(450,0.5; 150)	262.5	[217.50, 292.50]	257.50	[237.50, 292.50]
(500,0.5; 0)	180.0	[117.50, 212.50]	192.50	[163.75, 230.00]
(500,0.5; 100)	250.0	[203.75, 290.00]	252.50	[218.75, 292.50]
(500,0.5; 200)	307.5	[288.75, 342.50]	315.00	[292.50, 342.50]
(500,0.8; 0)	280.0	[242.50, 342.50]	292.50	[242.50, 342.50]
(500,0.9; 0)	350.0	[273.75, 380.00]	362.50	[288.75, 392.50]

IQI stands for inquartile interval.

Table 5: Non parametric distribution characteristics and tests on CEs

E Econometric results with Goldstein–Einhorn specification

The Goldstein–Einhorn (GE) specification for the probability weighting is also a two parameter function where δ captures elevation and γ captures sensitivity. Formally, it corresponds to the equation:

$$w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}}$$

Table 6 reports the results of the aggregate and individual estimations based on our data under the GE specification. Note that, contrary to the Prelec specification, for the GE specification, the elevation of the probability weighting function increases with δ. Both aggregate and individual estimates confirm an increase in elevation, similar with the results reported in the paper based on the Prelec specification of the probability weighting function.

Parameter	Aggregate-Level Estimates		Individual-Level Estimates	
	Now	Later	Now	Later
Utility α_t	1.093 (0.052)	1.138 (0.122)	1.108 [0.399; 2.048]	1.119 [0.597; 1.965]
Elevation δ_t	0.876 (0.045)	0.996 (0.056)	0.889 [0.658; 1.211]	1.030 [0.752; 1.445]
Sensitivity γ_t	0.615 (0.028)	0.611 (0.026)	0.631 [0.512; 0.864]	0.650 [0.522; 0.823]
LL	-5879.299		-4555.642	

Notes. For aggregate-level estimations, standard errors clustered at the individual level are reported between brackets, below parameter values. For individual estimations, medians of individual parameters are reported, as well as interquartile range between square brackets.

Table 6: Aggregate and Individual Estimations with GE

Description of the experimental procedure

The experiment was run through individual interviews. Upon arrival in the lab, subjects received instructions individually from the experimenter. The instructions consisted in two parts: (1) a 10 minute presentation with a beamer and (2) practice questions on the software used to collect the answers. This appendix presents in detail these two parts.

Presentation of the experimental instruction -Slides

The 10 minute presentation of the experiment covered the following points: general presentation of the study, experimental tasks, payment information, and real incentives.

General presentation of the study: Subjects were informed that they were going to participate in a decision-making experiment lasting about an hour on average. The experiment was computer-based. The objective of the study was to observe their choices between risky options. There were no right or wrong answers. We were only interested in their own preferences regarding the different options presented during the experiment.

Experimental tasks: The experiment consisted in a series of binary choice questions. Each question implied a choice between two options, Option A and Option B. The experimental task consisted in indicating the preferred option between the two. The different choice situations presented during the experiment were independent from one other.

The displays in Figure 4 and Figure 5 were used as supports to illustrate this part of the instructions. Subjects were explained that the Options A and B involved monetary consequences, which could be either sure, or uncertain. They only concerned gains (no losses). More precisely, Option A was always a sure amount of money and Option B was always a risky lottery that gave the possibility to gain different amounts of money based on chance. Option B always involved two possible outcomes with the corresponding probabilities (graphically represented by the surfaces in blue and in white). For Option A, the red surface was always 100% (consistent with a sure amount).

Two types of choice situations appeared in the study: (1) with options played and payed immediately (like in Figure 4) and (2) with options played immediately and payed in one year (like in Figure 5). In the experimental instructions, we insisted on the fact that the lotteries included in the study were always played immediately, meaning that after making a choice the subject would learn right away the payoff. However, we also insisted on the moment of money reception (now or one year later) that could vary depending on the experimental task.

Payment: Subjects were informed that they would receive a compensation of 10 euros for their participation in the study.

Real incentives: This part of the instruction, only concerned subjects in the group with real-incentives. Subjects in this group, were informed that they could be selected (1 chance over 20) to play for real one of the choice situations presented during the experiment. For this situation, the Option A or B chosen during the study would be implemented for real payoff. If the option was of the type "played and payed immediately", the subject would play the lottery and receive right away the corresponding payoff. If the option was of the type "played immediately and payed later", the subject would play the lottery and learn immediately the payoff, but would receive the money at the same date in one year time. In this latter case, the payment would take place in the presence of the experimenter, who would contact the respondent in advance to fix an appointment on the due date.

At the end of the instructions, subjects were invited to ask any additional question, and then proceeded to the practice questions, that also included an illustration of the implementation of the incentives for the group with real incentives.

Practice questions

The practice questions were designed to illustrate the different types of experimental tasks used in the study. They included two tasks, one for the treatment "now" and one for the treatment "in one year from now". For the treatment "now", the practice questions were based on the lottery $(250, 0.5; 0)$. For the treatment "later", the practice questions were based on the lottery $(500, 0.5; 250)$. We preferred to use lotteries that were not used in the experiment, in order to avoid repetitions of the same tasks that could affect the quality of respondents' answers in the main tasks.

The practice questions for the treatment "now" were always presented first, in order to allow the subjects to get familiar with the visual presentation of the lotteries before insisting on the delayed consequences. Moreover, the two lotteries in the practice questions involved different minimum and maximum outcomes, in order to attract subjects attention on the fact that these amounts could both vary and that the minimum outcome was not always zero. The answers provided to the practice questions were not recorded.