



HAL
open science

Risking the future? Measuring risk attitudes towards delayed consequences

Emmanuel Kemel, Corina Paraschiv

► **To cite this version:**

Emmanuel Kemel, Corina Paraschiv. Risking the future? Measuring risk attitudes towards delayed consequences. *Journal of Economic Behavior and Organization*, 2023, 208, pp.325-344. 10.1016/j.jebo.2023.02.014 . hal-04385738

HAL Id: hal-04385738

<https://hal.science/hal-04385738>

Submitted on 10 Jan 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Risking the Future? Measuring Risk Attitudes towards Delayed Consequences

Emmanuel Kemel* and Corina Paraschiv†

Abstract

This paper presents an experiment that investigates differences in 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. This suggests an overall increase in decision-makers' optimism regarding the chances of success when 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

† Université Paris Cité, LIRAES, F-75006 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 materialization 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 materialization 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 (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 of research addressing the interaction between risk and time questions whether intertemporal preferences are the same when the materialization of future consequences is sure or not. 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 certain and uncertain future outcomes differently. These studies investigate discounting by considering intertemporal tradeoffs. Contrary to these studies, our empirical investigation of the interaction between risk and time does not involve this kind of tradeoffs. Thus, 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 toward uncertain delays of materialization of outcomes (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 (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) identified two major phenomena that cannot be accommodated by EU: common-consequence¹ and common-ratio² effects. These violations of EU are accounted for by behavioral models, from which one of the most famous is Rank Dependent Utility (RDU), which considers 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

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 $(x_0, p_1; y, p_2; z_0)$, 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-ratio effect states that the preference between two lotteries $(x, qp_1; y)$ and $(x_0, qp_2; y)$ with $0 < q \leq 1$, may depend on the value of q .

when choice alternatives were evaluated jointly. 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 importantly, in the presentation of the choice situation, the subjects were not informed about when the risk associated with the lottery would be solved (now or at payment time).

One of the first studies investigating the impact of a delay associated with 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 concave 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 analyzed 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 literature accords with 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 previously mentioned studies, risk was solved (i.e. the lottery was played to determine the outcome) at the time of payoff. 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 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 materialization 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 from 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 facts³ regarding risk and time listed and studied by Epper and Fehr-Duda (2019). 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 were delayed in terms of both payment and resolution. More recently Abdellaoui et al. (2022) provide an extensive investigation of the

³ The seven key facts listed by Epper and Fehr-Duda (2019) are the following: observed risk tolerance increases with delay (fact #1), is higher for one-shot than for sequential valuation (fact #3), is characterized by intrinsic preference for timing of uncertainty resolution (fact #5), and depends on order of delay and risk discounting (fact #7), while observed patience increases with delay (fact #2), is higher for one-shot than for sequential valuation (fact #4), and is higher for risky payoffs than for certain ones (fact #6).

attitudes towards the timing of resolution of risk, testing different models on a series of experiments where the timing of payment is held constant. Therefore, the literature provides prior studies on situations where both resolution and payment are delayed, as well as on situations where resolution only is delayed, leaving cases where payment only is delayed, as an open research question. Our study fills this gap in prior literature by analyzing the role of delayed consequences on risk attitudes when the timing of risk resolution is kept constant. As such, we add 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 discusses our main findings and Section 6 concludes.

2 Theory

2.1 Preliminaries

We focus on a decision maker confronted with 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 materialization of the outcomes and the consequences are such as $x > y \geq 0$. More precisely, the lottery $(x_t, p; y_t)$ yields, at the corresponding time t , either x with probability p , or y with probability $1-p$. The uncertainty associated with the lottery is always solved at time $t=0$ (i.e. immediately after choice). Two different times of materialization of the outcomes $t \in \{0, T\}$ are considered in the study: $t=0$ refers to immediate consequences received “now” and $t=T$ refers to delayed consequences received “later”. The 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 the decision maker's preferences follow a time-dependent RDU model. Under this model, the value associated with the lottery $(x_t, p; y_t)$ is given by

$$RDU(x_t, p; y_t) = w_t(p)u_t(x) + (1 - w_t(p))u_t(y), \quad (1)$$

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 the 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:

$$u_t(x) = \frac{1 - e^{-\alpha_t x}}{1 - e^{-\alpha_t}}. \quad (2)$$

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 (1998):

$$w_t(p) = e^{-\beta_t(-\log(p))^{\gamma_t}} \quad (3)$$

This two-parameter specification, often employed in experimental studies, captures two different psychological phenomena related to probability weighting. The 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. The parameter γ_t characterizes the curvature of the function and is generally interpreted as measuring sensitivity to changes in probabilities. 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 of 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 of 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 of 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 paid “now” and once for consequences paid “later”.

The comparison of the two treatments “now” vs. “later” allows to analyze the impact of delaying outcomes on risk attitudes. Two approaches are retained in the paper. First, we analyze risk attitudes in a model-free setting. Second, we analyze risk attitudes by eliciting decision-makers' preferences under RDU. These two approaches are detailed hereafter.

2.3.1 Model-free analysis of risk attitudes

The standard definition of risk attitudes uses the choice between a lottery and its expected value. By definition, a decision-maker is risk averse if she prefers the expected value to the lottery; she is risk seeking if she prefers the lottery to the expected value, and she is risk neutral if she is indifferent between the lottery and its expected value. Our method based on the elicitation of certainty equivalents informs us directly about risk attitudes. Comparing the certainty equivalent (CE) associated with a risky lottery to its expected value (EV) allows to characterize the risk attitude of the decision maker as risk neutral, risk seeking or risk aversion, 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.

Our raw data analysis based on the elicited certainty equivalents allows to study risk attitudes and how they vary depending on the timing of payment. For example, observing higher (lower/equal) CEs for a risky lottery in the treatment “later” than in the treatment “now” denotes less (more/equal) risk aversion when consequences are delayed. Note that this definition of risk attitude is model-free, which means that the classification of a decision maker's behavior as risk averse, risk neutral or risk seeker in the raw data analysis does not depend on the RDU modeling of preferences.

2.3.2 Analyzing risk attitudes under RDU

Modeling 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. Indeed, under RDU, risk attitudes depend both on utility u , which captures attitudes towards consequences, and on probability weighting w , which captures attitudes towards probabilities (see Wakker 1994 for a detailed discussion of risk attitudes under RDU). Thus, a change in risk attitudes depending on payment time may be due to a change in utility⁴, a change in probability weighting function or a change in both.

From a methodological point of view, we face the challenge of selecting an RDU estimation procedure allowing to disentangle utility and probability weighting. To our knowledge, the tradeoff method (Wakker and Deneffe, 1996) is the only available method that allows to separately identify the utility function (independently from probability weighting). However, this method builds on chained measurements that present two disadvantages. First, they complicate the implementation of real incentives (i.e. subjects may exploit the chained nature of the stimuli and try to increase the amounts at stake in subsequent questions). Second, they create a risk of error propagation in the measurements. Therefore, in our study, we followed the standard approach in the empirical RDU literature, which consists in estimating all the parameters of the RDU specification jointly using likelihood maximization (e.g. Bruhin et al. 2010; Baillon et al. 2018). The advantage of this joint estimation method is that (1) the estimated CEs are independent one from another and can be incentivized, and (2) the quality of the identification of the parameters can be assessed by the variance-covariance matrix of the estimators.

Our formal analysis of risk attitudes proceeds as follows. According to equation (1), under time-dependent RDU, the certainty equivalent c_t of $(x_t, p; y_t)$ follows:

⁴ An observed change in the utility function can, for example, account for a different marginal utility of consumption in the future and in the present.

$$c_t = u_t^{-1}[w_t(x)(u_t(x) - u_t(y)) + u_t(y)]. \quad (4)$$

Using this equation, we estimate the model parameters α_t , β_t and γ_t at each time period t (the details regarding the estimation procedure are provided in Appendix A). This allows to investigate whether changes in risk attitudes when moving from $t=0$ to $t=T$ come from a change in sensitivity to outcomes (i.e. different α_t), a change in optimism (i.e. different β_t) or a change in sensitivity to probabilities (i.e. different γ_t).

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 before the beginning of the Covid crisis. The participants were 70 undergraduate students from the University of Paris. Such sample size is consistent with prior literature investigating time lotteries in the lab.⁵ 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 (Etchart-Vincent and L'Haridon, 2011; 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. The comparison of the real incentive group and hypothetical-choice group

⁵ Abdellaoui et al. (2011b) based their analysis on 52 subjects, Noussair and Wu (2006) ran their experiment on 63 subjects, and Coble and Lusk (2010) report results on 47 subjects.

allows to investigate whether the incentive mechanism impacts preferences. Indeed, the absence of incentives can create a hypothetical bias, but a complex incentive system may also distort preferences if subjects do not understand or trust it. A similar between-subject design was implemented, for example, by Abdellaoui and Kemel (2013) that did not capture a significant impact of the incentive mechanism on preferences.

Subjects in the real incentive group 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 (one ball over 20), 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 (Baillon et al., 2018). This amount of money would be received by the subject at the corresponding due time (Rohde, 2019).

Two subjects from the real incentive group played choices for real. For one subject, the real incentive procedure resulted in a sure gain of 30 euros to be received immediately (treatment now). For the other subject, it resulted in a risky lottery from the treatment later. The lottery was solved and resulted in a payment of 0.

The data collection was based on individual interviews. Each experimental session lasted one hour on average. Upon arriving in the lab, subjects received the instructions based on a 10-minute presentation of the experimental tasks (see Appendix B). 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. The 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” (see Appendix C for an illustration of the displays). 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).

	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 experimental tasks involved the elicitation of a total of 24 certainty equivalents for each subject, corresponding to 12 certainty equivalents for each condition. Among these 12 CEs, 11 dealt with the lotteries in Table 1, and one was the repetition of the task corresponding to Lottery 7. The CE of Lottery 7 was thus measured twice. This repetition was used as a consistency check. Our set of stimuli has been selected with the goal to make utility and probability weighting identifiable in joint estimations. In particular, the CEs of the prospects $(x, p; y)$ where x and y vary whereas p is fixed aim at identifying the utility curvature, while controlling for probability weighting (see Abdellaoui et al. 2008). Moreover, the CEs of the

prospects $(x, p; 0)$ where x is fixed and p varies aim to identify the sensitivity parameter of the probability weighting function.

Only positive outcomes of money were used in the study. The maximum amount was fixed at 500 euros ($M=500$). We opted for sizeable amounts of money for two main reasons. First, a large range of monetary outcomes must be considered for capturing the shape of the utility function (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 in the amounts at stake despite their delayed payment (Abdellaoui et al., 2019).

The certainty equivalents were measured using choice lists with a precision of 5 euros. To simplify the data collection process and reduce the cognitive effort of the respondents, the choice lists were filled using a bisection procedure. Respondents faced several binary choices from the choice list that allowed them to pre-fill the entire list. A validation step followed where all the choices from the list were reviewed and confirmed. Appendix D gives detailed information about these different steps of the elicitation method. Similar approaches based on a combined use of choice lists and bisection procedure were also used by Kemel and Paraschiv (2018). Once a list was validated by the respondent it was no longer possible to modify the recorded answers.

Regarding the implementation of real incentives, all the lotteries had the same chance to be selected for real payment. For a given lottery $(x, p; y_t)$ subjects were told that all the values from the list $\{y, y+5, \dots, x-5, x\}$ were 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 proceeded 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: the experimental tasks corresponding to the Lottery 7 (see Table 1) were presented twice to the subjects. 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 certainty equivalent corresponding to the lottery (500,0.5;0), as well as significance tests of the difference between the two measures. Standard deviations are reported in brackets at the right of the mean value. The last column reports Person-correlation between the initial and the repeated measures, with the corresponding significance level.

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

Overall, the analysis of the repeated measures suggests that subjects provided consistent answers: 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. 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. 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 is 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 E). For standard risk (i.e. lotteries solved and paid 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 analyze 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 ($p = 0.23$).

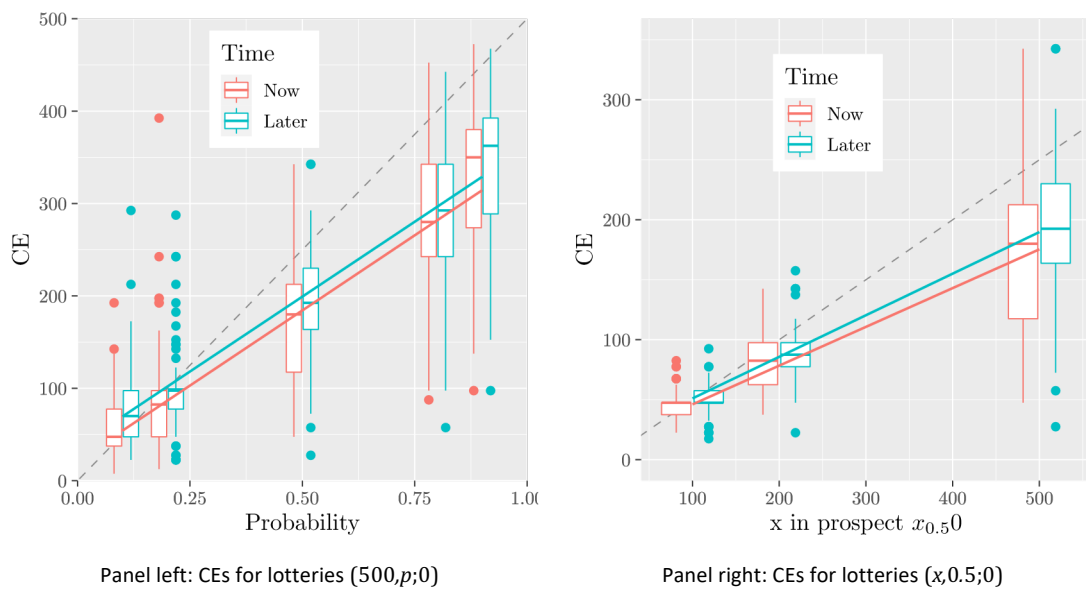
Lottery	EV	Now		Later	
		Mean	Std	Mean	Std
(500,0.1;0)	50	57.86	35.79	78.57***	48.35
(500,0.2;0)	100	88.50	58.62	98.86	51.02
(100,0.5;0)	50	44.36**	13.73	49.64	13.71
(200,0.5;0)	100	80.71***	24.15	87.68***	23.42
(400,0.5;200)	300	286.71***	24.30	285.21***	22.77
(450,0.5;150)	300	257.43***	47.54	260.14***	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 table reports means and standard deviations (std) of the elicited certainty equivalents for the treatments “now” and “later”. The exponent of the mean reports the significance of the difference with the expected value EV.

*: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$

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) displays the distribution of CEs for each probability levels, using the expected value of the prospect (materialized by the dashed line) as a benchmark. It shows that, for lotteries of type $(500, p; 0)$, subjects gave larger certainty equivalents on average when outcomes were paid later. This result is confirmed by an ANCOVA that detects a significant impact of probability p and a main effect of time treatment ($p < 0.001$). The interaction between “probability” and treatment is not found to be significant ($p = 0.24$). These effects are displayed by the regression lines of the ANCOVA (cf. plain lines on Figure 1).



Note. The dashed lines show the expected value of the prospects. The plain lines correspond to the regression lines of the ANCOVAS.

Figure 1: Impact of time treatment 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 is confirmed for the various levels of outcomes. An ANCOVA 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 Lottery 4 (200,0.5;0). One can note that all these lotteries involve a probability of 0.5. Therefore, our test of utility (CARA vs. CRRA) holds independently of the probability weighting function.

The empirical cumulative functions of the distributions corresponding to the Lotteries 4, 5 and 7 are reported in Appendix E. 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 paid now and $p<0.001$ for outcomes paid 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 payment 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 F.

Parameter	Aggregate-Level Estimates		Individual-Level Estimates	
	Now	Later	Now	Later
Utility α_t	1.160 (0.129)	1.112 (0.115)	0.985 [0.490, 2.203]	1.144 [0.511 1.962]
Elevation β_t	0.944 (0.041)	0.890 (0.034)	0.989 [0.799 1.128]	0.873 [0.760 1.019]
Sensitivity γ_t	0.605 (0.026)	0.607 (0.025)	0.637 [0.490 0.858]	0.655 [0.525 0.797]
LL	-6070.103		-4739.714	

Notes. The table reports aggregated and individual estimations of the parameters for utility and probability weighting using Prelec specification. 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 paid 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 paid later, albeit with different parameter values.

To derive robust inference on the estimators despite the moderate sample size, we estimated the variance-covariance matrix of the estimators from 10,000 bootstrap replications. The diagonal elements of this matrix provide (the squared) standard errors, and the off-diagonal elements inform on the correlation of estimators. For each of the two time periods, the correlations between the utility parameter and the weighting function parameters are lower than 0.5 (in absolute value), which corresponds to an acceptable level of correlation⁶.

A series of Wald tests are run to compare the aggregate parameters across the treatments “now” and “later”. No between-treatment difference (immediate versus delayed payment) is captured regarding the utility parameter α_t ($p=0.75$) and the sensitivity parameter γ_t ($p=0.93$). However, results point to a difference between the two time-treatments regarding the elevation parameter β_t ($p=0.077$): 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.

⁶ For example, in linear regressions, the usual threshold for multicollinearity among two regressors is a VIF of 5, corresponding to a correlation of 0.9.

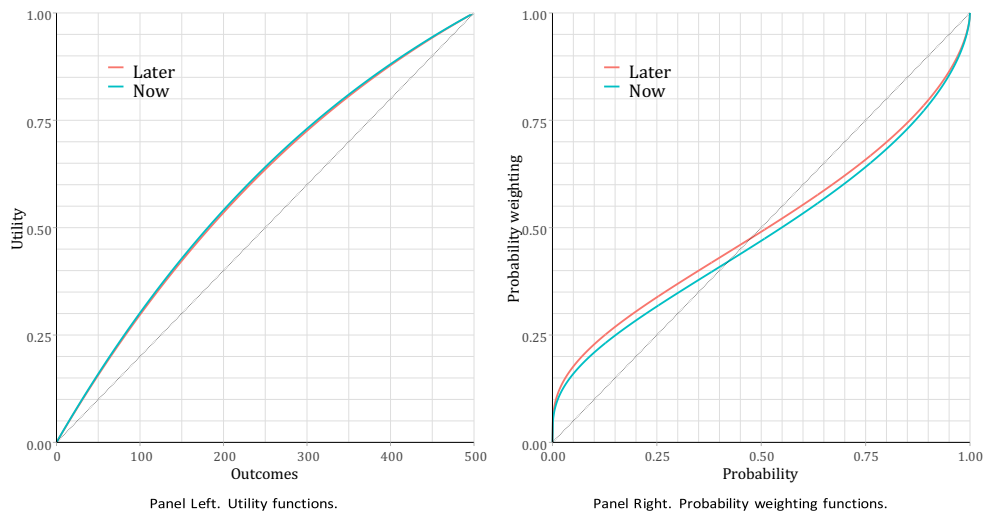


Figure 2: Aggregate-Level Estimations: Utility and Probability Weighting

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 ($p=0.02$). The individual values of the elevation parameter across payment times are scatter plotted in Figure 3. Lower parameters for delayed payment are observed for 42 subjects (out of 70, binomial test, $p=0.11$). For the other two parameters (utility and sensitivity), neither Wilcoxon, nor binomial test captures significant differences.

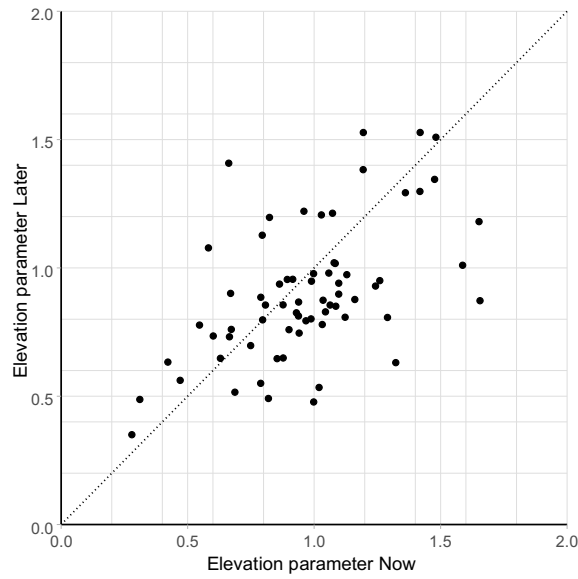


Figure 3: Individual-Level Estimations: Elevation Parameter

Overall, the econometric analysis recovers the usual patterns observed under the RDU model in the condition when consequences are paid now and captures a more elevated probability weighting function in the condition when consequences are paid 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.

4.4 Modeling the interaction between risk and time

The decisions studied in this paper involve either risk (when $t=0$) or risk and time (when $t>0$). When risk and time are considered jointly, the question of discounting may arise. Our previous analysis was based on the assumption of a multiplicatively separable discount factor diminishing the utility of future consequences, which corresponds to the standard approach in the intertemporal literature. In this section, we discuss in detail this assumption and its implications, and investigate alternative approaches to modeling the impact of time, and how they may affect the interpretation of our results.

4.4.1 The Assumption of Multiplicatively Separable Discounting

Experimental studies involving intertemporal choices generally assume that people are rational in the sense that they prefer (1) to gain more rather than less (i.e. strictly increasing utility) and (2) to receive desirable consequences sooner rather than later (especially when consequences are monetary and can be saved). This last rule, called preference for present, entails that future consequences are discounted. The standard approach to model discounting is based on a (multiplicatively) separable discount factor that reduces the utility of a future consequence. Formally, the utility of a consequence x received at time t is evaluated as $\delta_t u(x)$, where u is a stationary utility and δ_t is the discount factor corresponding to time t . The discount factor δ_t captures intertemporal tradeoffs, like, for instance, preferences between a smaller sooner and a larger later outcome. The preference for present implies that $\delta_t < 1$ for any future time $t > 0$. The assumption of multiplicatively separable discounting is standard in economic models such as discounted utility or discounted expected utility. It is also common in behavioral models of intertemporal preferences (Laibson, 1997; Ebert and Prelec, 2007) and in recent models of risk and time preferences (e.g. discounted rank dependent utility model used by Abdellaoui et al. 2019).

Our experiment avoided intertemporal tradeoffs as all choices involved consequences received at the same time period (either now, or later). Under the assumption of multiplicatively separable discounting, this design neutralizes discounting, meaning that the discount factor does not impact the preferences over future lotteries. Indeed, our method relied on the elicitation of certainty equivalents c_t for lotteries of the type $(x, p; y)$. With multiplicatively separable discounting, the value of the lottery $(x, p; y)$ is $w_t(p)\delta_t u_t(x) + (1 - w_t(p))\delta_t u_t(y)$ and the value of its certainty equivalent c_t is $\delta_t u_t(c)$. As the decision maker is indifferent between the two, this yields:

$$w_t(p)\delta_t u_t(x) + (1 - w_t(p))\delta_t u_t(y) = \delta_t u_t(c). \quad (5)$$

One can observe that the discount factor cancels out from the equation of the certainty equivalent. This means that the utility estimated for the treatment “later” in our experiment corresponds to a stationary utility (not affected by discounting).⁷ Therefore, discounting cannot explain the difference of risk attitudes observed in our study if the standard approach to discounting based on a multiplicative discount factor is retained.

4.4.2 Complementary Analysis: Utility vs. Probability Approach

A recent research stream in decision-making literature questions the standard approach to discounting, proposing alternative models to capture intertemporal risky choice behavior. In this section, we complete our results by considering two recently developed models by DeJarnette et al. (2020) and Epper and Fehr-Duda (2019). These two models adopt different approaches to integrate risk and time. The first model, called Generalized Expected Discounted Utility, is an extension of Discounted Expected Utility that models utility under risk as a transformation of intertemporal utility. This utility-based model does not allow for probability weighting. The second model is a generalization of RDU where the impact of time is captured by probability weighting. Within this probability-based model, time affects the weighting function, rather than utility. The technical details regarding the two models and their estimation methods are reported in Appendix G.

The results show that, for aggregated-level estimations, the probability-based model offers a better log likelihood than the utility-based model, which indicates a better fit to our data. This is confirmed by the individual level analysis: the probability-based model offers a better goodness of fit for 50 subjects (out of 70, binomial test, $p < 0.001$). These findings provide support to the idea that the increase in risk tolerance for delayed outcomes is best captured

⁷ One can note that our model is a more general version of the discounted RDU model used by Abdellaoui et al. (2019). The discounted RDU model considers that the value of the lottery $(x_t, p; y_t)$ is $w(p)\delta_t u(x) + (1-w(p))\delta_t u(y)$. Our model is a generalization that assumes that the probability weighting function and the curvature of the utility can vary over time. Under both models the discount factor cancels out from the equation of choices considered in our design.

by a change of the probability weighing function. This is in line with our main results reported in Section 4.3.

5 Discussion

Our paper analyzed interactions between risk and time in decision-making by investigating the impact of a delay in the materialization of the consequences on risk attitudes. We used an experimental design that allowed to neutralize both the effects of discounting and risk resolution, to focus on the sole effect of a delayed materialization 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 allowed for a model free analysis of risk attitudes, based on CEs. 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 paid now” than for lotteries “solved later and paid later”. This pattern could be explained through a preference for later resolution of risk (Coble and Lusk, 2010). However, this interpretation is in contradiction with empirical findings suggesting that preference for early resolution prevails (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.

A recent study by Abdellaoui et al. (2022) gives support to this intuition. Investigating attitudes towards the timing of risk resolution, these authors observe that preference towards early resolution prevails, except for small probabilities. In other words, the CEs of lotteries “solved later and paid later” are lower than the CEs of lotteries “solved now and paid later”. Comparing our results to those of Abdellaoui et al. (2022) suggests that delaying resolution and delaying payment have indeed opposite effects on CEs. The two studies are thus complementary, allowing to isolate and clarify two different phenomena (delayed resolution and delayed outcomes), often intertwined in prior research.

5.2 Delayed consequences lead to more optimism towards probabilities

Our model-free analysis of risk attitudes captured more risk tolerance when consequences were delayed. The complementary analysis under RDU allowed us to investigate whether this change was driven by different attitudes towards probabilities or by different attitudes towards outcomes. More precisely, a time-dependent version of RDU 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. Our findings regarding utility suggest that the marginal utility of consumption does not depend on the timing of materialization of consequences, even though subjects facing delayed consequences have the possibility to better plan their future consumption.

The main contribution of our study to behavioral decision-making is to show that interactions between risk and time in the context of a delayed materialization of outcomes are captured by probability weighting. This finding is consistent with the results reported by Abdellaoui et al. (2011b) and Abdellaoui et al. (2022). Like in our research, in both these studies, an exploratory approach was used, simply allowing probability weighting functions to be time dependent. Yet, the observation that the probability weighting changes over time highlights the need for models connecting these probability weighting functions across (resolution and payment) time periods.

Regarding probability weighting, the two-parameter Prelec specification allowed to investigate which aspect, optimism/pessimism or sensitivity to probabilities, is responsible for the observed behavioral change. We observed more elevation of the probability weighting 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; Abdellaoui et al., 2022). 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 of outcomes and timing of risk resolution. Our subjects behaved as if they became more optimistic about risk for consequences materializing in the future. The analysis based on the model proposed by Epper and Fehr-Duda (2019) provides a behavioral explanation to this pattern. The increase in optimism may come from the fact that the future is intrinsically uncertain. This uncertainty is captured by a survival probability (that discounts the probability of future consequences). When introduced in the model, this survival probability accounts for the optimism observed towards future risks.

Since economic situations often involve decisions with consequences materializing in a more or less distant time horizon, our results may explain why individuals sometimes suffer from an optimism bias, even though risk aversion generally prevails when measured in an atemporal setting. Further investigations in this direction may be of particular interest in situations where individuals are found to make sub-optimal decisions because of too much optimism, such as entrepreneurship or the health domain, two contexts involving delayed consequences.

Our results suggest that this optimism bias may arise from the perception of future consequences as uncertain. Thus, public or private actions that aim at reducing this uncertainty should reduce this bias. Examples of such actions include providing more information or more guaranties about the fact that future outcomes will be effective.

5.3 Directions for further research

Our analysis focused on non-negative outcomes only. 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, while our investigation was limited to gains, 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 procedures would thus be needed for future investigations of the impact of delaying losses on risk preferences.

Further research is also needed for the development of new models capturing the richness of interactions between risk and time. The classical DEU model captures intertemporal preferences by two dimensions, utility and discounting. Yet, it inherits the descriptive limitations of EU. Discounted RDU (Abdellaoui et al., 2019) accounts for these limitations by introducing probability weighting, thereby introducing a third dimension. Nevertheless, interactions between risk and time concern many other aspects of preferences: attitudes towards the timing of resolution (von Gaudecker et al., 2011), attitudes towards the time correlation of outcome (Rohde and Yu, 2022), different discounting of risky and riskless future consequences, or attitudes towards the timing of payment, like in the present study. For the moment, these dimensions are mostly studied separately to isolate behavioral patterns. The present study followed this approach, avoiding intertemporal tradeoffs and neutralizing the impact of discounting. Combining in one study several of these dimensions involves a complexity that can hardly be addressed as new (1) methods and/or (2) models are needed.

Regarding (1), the models of DeJarnette et al. (2020) and Epper and Fehr-Duda (2019) explain higher risk tolerance towards future risks through a discounting or survival probability parameter. Further research would consist in measuring these parameters from other choice contexts and test how they predict attitudes towards future risks. Concerning the model proposed by DeJarnette et al. (2020), this would imply a complete elicitation of attitudes towards riskless intertemporal choices (to identify discounting and inter-temporal utility), coupled with an elicitation of risk attitudes (to identify the utility under risk), which would require a longer experiment. Regarding the model proposed by Epper and Fehr-Duda (2019), this would imply an independent elicitation of the survival probability, but no such elicitation

method has been proposed yet. Eventually, these two models make predictions regarding decision contexts that are not treated in this paper: for example, DeJarnette et al. (2020) address attitudes towards time lotteries, and Epper and Fehr-Duda (2019) address several different patterns related to risk and time. Thus, a complete elicitation and assessment of these models would involve an investigation of several additional dimensions of risk and time interactions, which is beyond the scope of our study.

Regarding (2), in our study, we observed that delaying payment increases the elevation of probability weighting, while Abdellaoui et al. (2022) observed that delaying resolution decreases both the elevation and the sensitivity of probability weighting. These opposite effects raise the question of how to model, with a single probability weighting function, attitudes towards cases where the timing of both resolution and payment vary. To our knowledge, no model has yet been published to separately account for attitudes towards delayed resolution and delayed payment of risk. These examples illustrate that the research about risk and time still faces a lot of challenges and has a lot of complex issues to solve.

6 Conclusion

This paper reported an experiment that investigated 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 piece 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 for real-life decisions.

References

- M. Abdellaoui and E. Kemel. Eliciting prospect theory when consequences are measured in time units: “time is not money”. *Management Science*, 60(7):1844–1859, 2013.
- M. Abdellaoui, H. Bleichrodt, and O. l’Haridon. A tractable method to measure utility and loss aversion under prospect theory. *Journal of Risk and Uncertainty*, 36(3):245, 2008.
- M. Abdellaoui, A. Baillon, L. Placido, and P. P. Wakker. The rich domain of uncertainty: Source functions and their experimental implementation. *American Economic Review*, 101(2):695–723, 2011a.
- M. Abdellaoui, E. Diecidue, and A. Öncüler. Risk preferences at different time periods: An experimental investigation. *Management Science*, 57(5):975–987, 2011b.
- M. Abdellaoui, E. Kemel, A. Panin, and F. M. Vieider. Measuring time and risk preferences in an integrated framework. *Games and Economic Behavior*, 115:459–469, 2019.
- M. Abdellaoui, E. Diecidue, E. Kemel, and A. Onculer. Temporal risk: Utility vs. probability weighting. *Management Science*, 68(7):5162-5186, 2022.
- M. Allais. Le comportement de l’homme rationnel devant le risque: critique des postulats et axiomes de l’école américaine. *Econometrica*, 21: 503–546, 1953.
- J. Andreoni and C. Sprenger. Risk preferences are not time preferences. *American Economic Review*, 102(7):3357–76, 2012.
- A. Baillon, H. Bleichrodt, U. Keskin, O. l’Haridon, and C. Li. The effect of learning on ambiguity attitudes. *Management Science*, 64(5):2181–2198, 2018.
- M. Baucells and F. H. Heukamp. Probability and time trade-off. *Management Science*, 58(4):831–842, 2012.
- R. Bouchouicha, P. Martinsson, H. Medhin, and F. M. Vieider. Stake effects on ambiguity attitudes for gains and losses. *Theory and Decision*, 83(1):19–35, 2017.

- A. Bruhin, H. Fehr-Duda, and T. Epper. Risk and rationality: Uncovering heterogeneity in probability distortion. *Econometrica*, 78(4):1375–1412, 2010.
- S. H. Chew and J. L. Ho. Hope: An empirical study of attitude toward the timing of uncertainty resolution. *Journal of Risk and Uncertainty*, 8(3):267–288, 1994.
- K. H. Coble and J. L. Lusk. At the nexus of risk and time preferences: An experimental investigation. *Journal of Risk and Uncertainty*, 41(1):67–79, 2010.
- P. DeJarnette, D. Dillenberger, D. Gottlieb, and P. Ortoleva. Time lotteries and stochastic impatience. *Econometrica*, 88(2):619–656, 2020.
- J. E. Ebert and D. Prelec. The fragility of time: Time-insensitivity and valuation of the near and far future. *Management Science*, 53(9):1423–1438, 2007.
- S. Ebert. Decision making when things are only a matter of time. *Operations Research*, 68(5):1564-1575, 2020.
- T. Epper and H. Fehr-Duda. Risk in time: The intertwined nature of risk taking and time discounting. *Technical report*, Working Paper at the University of St. Gallen, 2019.
- N. Etchart-Vincent and O. l’Haridon. Monetary incentives in the loss domain and behavior toward risk: An experimental comparison of three reward schemes including real losses. *Journal of Risk and Uncertainty*, 42(1):61–83, 2011.
- A. Gerber and K. I. Rohde. Risk and preference reversals in intertemporal choice. *Journal of Economic Behavior & Organization*, 76(3):654–668, 2010.
- Y. Halevy. Strotz meets Allais: Diminishing impatience and the certainty effect. *American Economic Review*, 98(3):1145–62, 2008.
- C. A. Holt and S. K. Laury. Risk aversion and incentive effects. *American Economic Review*, 92(5):1644–1655, 2002.

- E. S. Howe and C. J. Brandau. Additive effects of certainty, severity, and celerity of punishment on judgments of crime deterrence scale value. *Journal of Applied Social Psychology*, 18(9):796–812, 1988.
- E. Kemel and C. Paraschiv. Deciding about human lives: an experimental measure of risk attitudes under prospect theory. *Social Choice and Welfare*, 51(1):163–192, 2018.
- G. Keren and P. Roelofsma. Immediacy and certainty in intertemporal choice. *Organizational Behavior and Human Decision Processes*, 63(3):287–297, 1995.
- D. Laibson. Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics*, 112(2):443–478, 1997.
- Z. Li, J. Müller, P. P. Wakker, and T. V. Wang. The rich domain of ambiguity explored. *Management Science*, 64(7):3227–3240, 2017.
- D. Lovallo and D. Kahneman. Living with uncertainty: Attractiveness and resolution timing. *Journal of Behavioral Decision Making*, 13(2):179–190, 2000.
- C. Noussair and P. Wu. Risk tolerance in the present and the future: An experimental study. *Managerial and Decision Economics*, 27(6):401–412, 2006.
- D. Prelec. The probability weighting function. *Econometrica*, 66:497–528, 1998.
- K. I. Rohde. Measuring decreasing and increasing impatience. *Management Science*, 65(4):1700–1716, 2019.
- K. I. Rohde and X. Yu. Intertemporal correlation aversion—a model-free measurement. *Available at SSRN 4079812*, 2022.
- A. Saha. Expo-power utility: A ‘flexible’ form for absolute and relative risk aversion. *American Journal of Agricultural Economics*, 75(4):905–913, 1993.
- P. A. Samuelson. A note on measurement of utility. *The Review of Economic Studies*, 4(2):155–161, 1937.

- C. Starmer. Developments in non-expected utility theory: The hunt for a descriptive theory of choice under risk. *Journal of Economic Literature*, 38(2):332–382, 2000.
- A. Tversky and D. Kahneman. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5(4):297–323, 1992.
- H.-M. von Gaudecker, A. van Soest, and E. Wengström. Heterogeneity in risky choice behavior in a broad population. *The American Economic Review*, 101(2):664–694, 2011.
- P. Wakker. Separating marginal utility and probabilistic risk aversion. *Theory and Decision*, 36(1):1–44, 1994.
- P. Wakker and D. Deneffe. Eliciting von Neumann-Morgenstern utilities when probabilities are distorted or unknown. *Management Science*, 42(8):1131–1150, 1996.
- B. J. Weber and G. B. Chapman. The combined effects of risk and time on choice: Does uncertainty eliminate the immediacy effect? does delay eliminate the certainty effect? *Organizational Behavior and Human Decision Processes*, 96(2):104–118, 2005.

A 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 of 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 $\epsilon_{i,k} \sim N(0, \sigma^2)$. With this error specification, the likelihood of a given individual observation writes:

$$\begin{aligned} l(c_{i,k}^-, c_{i,k}^+) &= p(c_{i,k}^- < c_{i,k} < c_{i,k}^+) = p(c_{i,k}^- - \hat{c}_{i,k} < \epsilon_{i,k} < c_{i,k}^+ - \hat{c}_{i,k}) \\ &= \Phi\left(\frac{c_{i,k}^+ - \hat{c}_{i,k}}{\sigma_i}\right) - \Phi\left(\frac{c_{i,k}^- - \hat{c}_{i,k}}{\sigma_i}\right) \end{aligned} \quad (6)$$

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 log of the likelihood given by equation (6) is summed over all the stimuli (including the repeated ones) and over all the individuals. The standard errors are computed using bootstrap over 10,000 replications. For each replication, a new sample of subjects is drawn, with replacement from the initial one. For individual-level estimations, the log of the likelihood given by equation (6) is summed over all the stimuli (including the repeated ones) and the maximization is run for each individual separately. Because individual estimations do not involve a large number of observations, 50 different starting values are considered for each individual. Maximization is run using the BFGS algorithm.

B 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 these two parts in detail.

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 of a series of binary choice questions. Each question implied a choice between two options, Option A and Option B. The experimental task consisted of 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 paid immediately (like in Figure 4) and (2) with options played immediately and paid 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 payment time (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 paid immediately”, the subject would play the lottery and receive right away the corresponding payoff. If the option was of the type “played immediately and paid 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, 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, 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, to attract subject’s 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.

C 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 timeline 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”

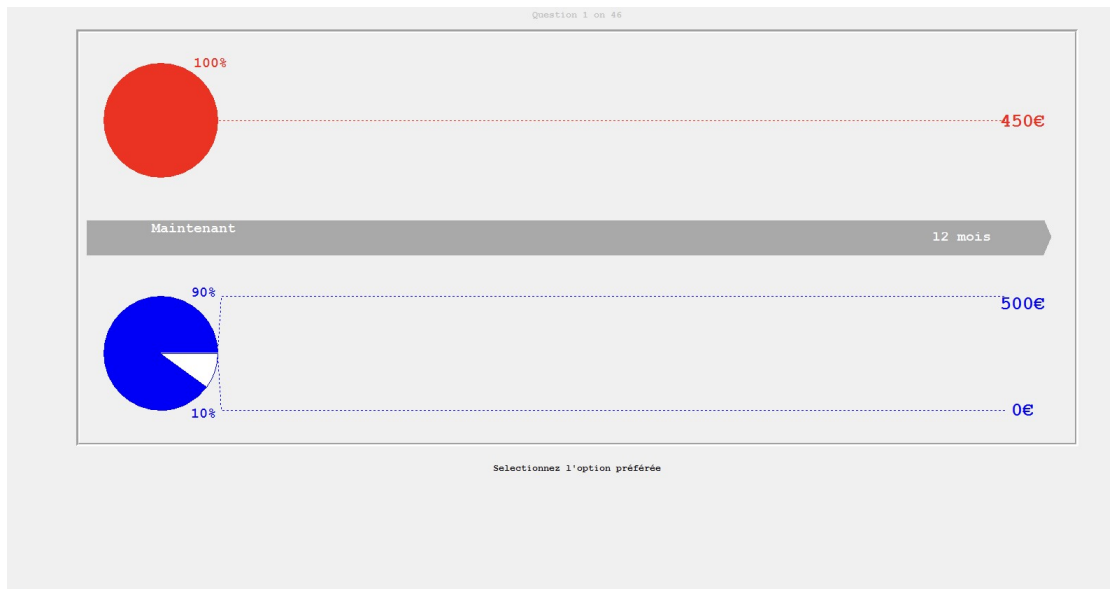


Figure 5: Example of choice question for the treatment “later”

In Figure 4, the lottery and the amounts of money are all presented at the left side of the timeline, 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 timeline, corresponding to the moment “now”, but the payoffs appear at the right side of the timeline 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 choose between Option A and Option B by clicking on the preferred lottery.

D 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 $y, y+5, \dots, x-5, x$. This choice list was used to estimate the certainty equivalent of the lottery with a precision of 5 euros.

To fasten the completion of the list and 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 the 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.

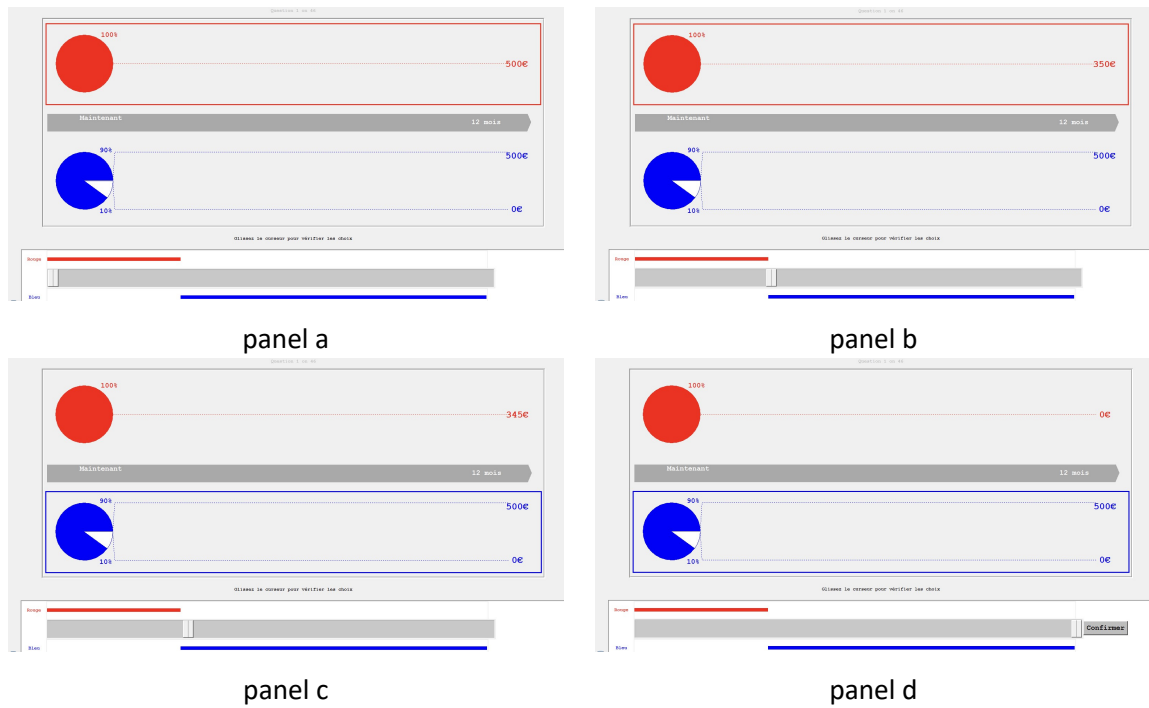


Figure 6: Validation step of a choice list

E Additional descriptive statistics

Lottery	Now		Later		Now vs. Later		
	Median	IQR	Median	IQR	Wilcoxon	<i>t</i>	Binomial
(500,0.1; 0)	47.5	[37.50, 77.50]	70.00	[47.50, 97.50]	0.000	0.000	0.000
(500,0.2; 0)	82.5	[47.50, 97.50]	97.50	[77.50, 99.37]	0.041	0.106	0.067
(100,0.5; 0)	47.5	[37.50, 47.50]	47.50	[47.50, 57.50]	0.000	0.000	0.001
(200,0.5; 0)	82.5	[62.50, 97.50]	87.50	[77.50, 97.50]	0.001	0.002	0.000
(400,0.5; 200)	292.5	[273.75, 297.50]	292.50	[272.50, 296.25]	0.696	0.611	1.000
(450,0.5; 150)	262.5	[217.50, 292.50]	257.50	[237.50, 292.50]	0.454	0.452	0.603
(500,0.5; 0)	180.0	[117.50, 212.50]	192.50	[163.75, 230.00]	0.062	0.029	0.098
(500,0.5; 100)	250.0	[203.75, 290.00]	252.50	[218.75, 292.50]	0.408	0.283	0.603
(500,0.5; 200)	307.5	[288.75, 342.50]	315.00	[292.50, 342.50]	0.486	0.872	0.427
(500,0.8; 0)	280.0	[242.50, 342.50]	292.50	[242.50, 342.50]	0.182	0.315	0.169
(500,0.9; 0)	350.0	[273.75, 380.00]	362.50	[288.75, 392.50]	0.005	0.012	0.011

Notes. IQR stands for interquartile range. The last column reports the p-value for the comparison of the certainty equivalents for the treatments “now” and “later” based on Wilcoxon, *t* and Binomial tests.

Table 5: Nonparametric statistics and p values of comparison tests of CEs Now and Later

F 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:

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

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 β . Both aggregate and individual estimates confirm an increase in elevation. This is consistent with the results based on the Prelec specification, reported in the paper.

Parameter	Aggregate-Level Estimates		Individual-Level Estimates	
	Now	Later	Now	Later
Utility α_t	1.056 (0.129)	0.993 (0.113)	0.990 [0.411; 2.184]	1.067 [0.467; 1.836]
Elevation β_t	0.868 (0.056)	0.939 (0.050)	0.863 [0.691; 1.228]	0.989 [0.751; 1.259]
Sensitivity γ_t	0.612 (0.026)	0.605 (0.025)	0.631 [0.504; 0.857]	0.639 [0.505; 0.808]
LL	-6069.866		-4725.430	

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

G Details of the Complementary Analysis

As a complementary investigation, we re-analyze our data building on the approaches proposed by DeJarnette et al. (2020) and Epper and Fehr-Duda (2019). These two approaches accommodate our findings according to two different explanations. The model of DeJarnette et al. (2020) models the increase in risk tolerance by the impact of discounting on utility. We call this model ‘utility-based’. The model of Epper and Fehr-Duda (2019) models the increase in risk tolerance by the impact of a survival probability (that outcomes are indeed received in the future) on the weighting function. We call this model ‘probability-based’. Hereafter, we present how we implement these models and show how their parametric specifications were fitted on our data.

DeJarnette et al. (2020) distinguish the utility of a consequence x in a riskless and in a risky intertemporal context. The two utility scales are mapped by an increasing function φ , such that the utility of a risky consequence x received at t is $\varphi[\delta_t v(x)]$ where v is the standard riskless intertemporal utility and δ_t is a discount factor. Under this model, the value of a lottery

$(x_t, p; y_t)$ is $p\varphi[\delta_t v(x)] + (1-p)\varphi[\delta_t v(y)]$ and the value of its certainty equivalent c_t at time t is $\varphi[\delta_t v(c)]$. This yields

$$c = v^{-1}\left[\frac{1}{\delta_t}\phi^{-1}[p\phi[\delta_t v(x)] + (1-p)\phi[\delta_t v(y)]]\right] \quad (7)$$

One can note that equation (7) is a particular case of equation (4) where $u_0(x) = \varphi \circ v(x)$ and $u_t(x) = \varphi[\delta_t v(x)]$, and $w_0(p) = w_t(p) = p$. To estimate the model, we assume that φ follows an exponential specification with parameter α , and v a power specification with parameter θ . This leads to a utility for present risky outcomes $\varphi[v]$ following the expo-power specification, popular in applied economics (Saha, 1993). Under the utility-based model of DeJarnette et al. (2020), the time dependence of risk attitudes is captured by the utility, which is $\varphi[v]$ when $t=0$ and $\varphi[\delta_T v]$ when $t=T$. The parameters to be estimated are thus α , θ , and δ_T . The latter is interpreted as a discount factor, even though its estimation does not involve intertemporal tradeoffs.

Epper and Fehr-Duda (2019) consider that receiving a consequence at a future time $t > 0$ is intrinsically uncertain. The effect of time is to reduce the probability of getting the outcomes. This is captured through a survival probability parameter $\delta_t < 1$. Assuming that the survival probability is integrated with the future lottery, the value of a lottery $(x_t, p; y_t)$ becomes $w(\delta_t p)[u(x) - u(y)] + w(\delta_t)u(y)$ and the value of its CE c received at time t becomes $w(\delta_t)u(c)$. Under these assumptions, we have

$$c = u^{-1}\left[\frac{w(\delta_t p)}{w(\delta_t)}(u(x) - u(y)) + u(y)\right] \quad (8)$$

One can note that equation (8) is a particular case of equation (4) where $w_t = \frac{w(\delta_t p)}{w(\delta_t)}$ and $u_0 = u_t$. For estimation purposes, we assume that the function u follows an exponential specification with parameter α , and w follows a one-parameter Prelec specification with parameter γ . The parameters to be estimated are thus α , γ , and δ_T .

Taken together, the models by DeJarnette et al. (2020) and Epper and Fehr-Duda (2019) can be used as a robustness check to test whether the difference in risk attitudes observed for delayed outcomes in our study may be attributed to utility vs. probability. To do so, we estimate the two models both at the aggregated and at the individual level, using likelihood maximization. One can note that the parametric specifications of the two models by DeJarnette et al. (2020) and Epper and Fehr-Duda (2019) involve the same number of parameters (three). This allows for a fair comparison of their goodness of fit on our data.

Model	Aggregated level		Individual level	
	Utility-based model	Probability-based model	Utility-based model	Probability-based model
α	2.212 (0.098)	0.902 (0.132)	2.231 [1.248; 3.222]	0.986 [0.344; 1.537]
θ	1.160 (0.035)		1.149 [0.985 1.317]	
γ		0.569 (0.022)		0.641 [0.524 0.865]
δ_T	0.982 (0.013)	0.993 (0.003)	0.976 [0.910 1.000]	0.984 [0.913; 0.998]
LL	-6188.354	-6074.23	-5256.062	-5026.106

Notes. The table reports aggregated and individual estimations of the parameters corresponding to the utility-based model by DeJarnette et al. (2020) and to the probability-based model by Epper and Fehr-Duda (2019). For aggregate-level estimations, standard errors clustered at the 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 7: Utility-based versus probability-based approach

The results of the estimations are reported in Table 7. For aggregated-level estimations, we can see that the model of Epper and Fehr-Duda (2019) offers a better log-likelihood than the model of DeJarnette et al. (2020), indicating a better fit for our data. This is confirmed by the individual estimations. The individual log-likelihoods of the two models are plotted in Figure 7. The probability-based model offers a better goodness of fit for 50 subjects (out of 70,

binomial test, $p < 0.001$). This result reinforces the idea that the increase in risk tolerance is best captured by a change in the probability weighing function.

The utility-based and probability-based models considered in this complementary analysis are specific cases of the main model⁸ (time-dependent RDU) introduced in Section 2.2. Therefore, the two models necessarily offer a lower log-likelihood than our main model. They nevertheless feature the following advantages. First, they provide a behavioral interpretation of the increase of risk tolerance between time periods: for the utility-based model, the increased risk tolerance is driven by the discounting of outcomes; for the probability-based model it is driven by the survival probability. Second, comparing these two models offers a direct test of which approach best accounts for our data. Third, the probability-based model may provide a parsimonious version of the main model. Indeed, the model captures the difference between w_0 and w_t through a single parameter δ_t whereas this difference is captured by two parameters in the original model ($\beta_0 \neq \beta_t$ and $\gamma_0 \neq \gamma_t$). It is thus noteworthy that the goodness of fit of the probability-based model is very close to the one of the original model (-6069.866 vs. -6074.23) although it involves fewer parameters. The BIC, which allows to compare models with different numbers of parameters, is lower for the probability-based model than for the main model (6111.363 vs. 6129.278), suggesting that the former is indeed a suitable parsimonious version of the latter.

⁸ Recall that the utility-based model imposes that $u_t(x) = \varphi[\delta_t v(x)]$, and $w_0(p) = w_t(p) = p$ and the probability-based model imposes that $u_t(x) = u_0(x)$, and $w_t = \frac{w(\delta_t p)}{w(\delta_t)}$ in equation (4).

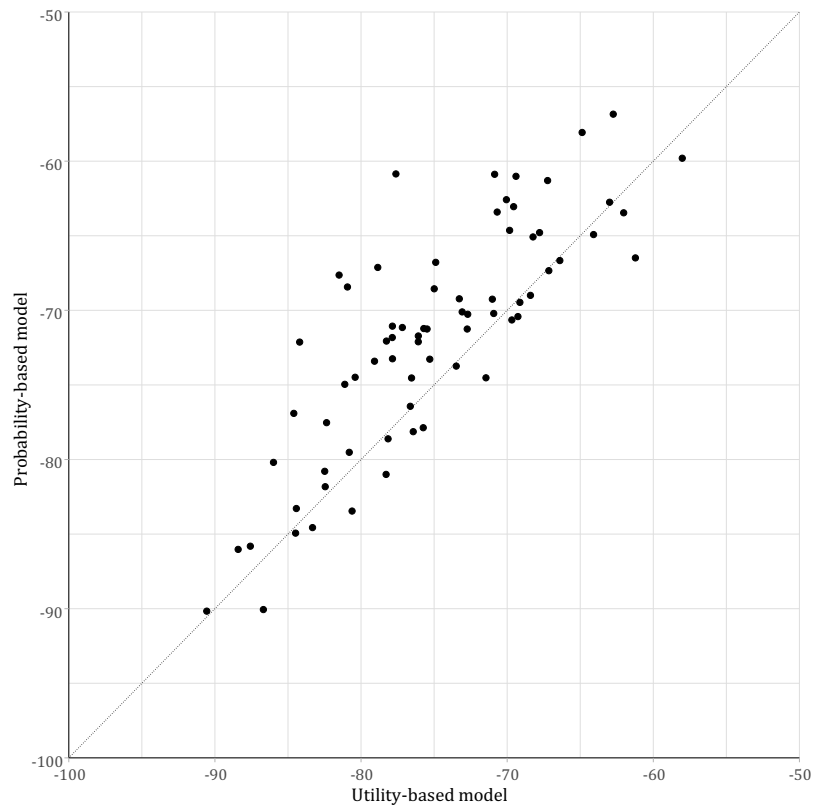


Figure 7: Individual log-likelihoods