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# Temporal Risk Resolution: Utility versus Probability Weighting Approaches

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► **To cite this version:**

Mohammed Abdellaoui, Enrico Diecidue, Emmanuel Kemel, Ayse Onculer. Temporal Risk Resolution: Utility versus Probability Weighting Approaches. 2021. hal-03330225

**HAL Id: hal-03330225**

**<https://hal.science/hal-03330225>**

Preprint submitted on 31 Aug 2021

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## 21 1. Introduction

22 Many real-world choices involve the resolution of uncertainty over time. Examples include such  
23 economically important decisions as consumption, savings, investment, portfolio management,  
24 and production. Temporal resolution of uncertainty also plays a role in most medical decisions  
25 such as when patients undergo genetic tests to determine the likelihood of getting a disease  
26 in the future. In all of these cases, we expect that the decision maker is not indifferent to  
27 temporal resolution of uncertainty because he assigns a value to informative signals about it. This  
28 value is instrumental when it allows taking actions conditional on information (Mossin, 1969;  
29 Spence and Zeckhauser, 1972). Alternatively, the value assigned to such information is intrinsic  
30 when it is psychological in nature, involving attitudes toward knowing (or not) about future  
31 consequences, even when it is impossible to act on these consequences (Ganguly and Tasoff,  
32 2017). For some decisions (e.g., prenatal diagnosis, whether to sell stocks during a financial  
33 crisis), delayed resolution of uncertainty may result in anxiety about the final outcome (Wu,  
34 1999; Epstein, 2008). For some others, e.g. a submission to a top journal, the decision maker  
35 may actually prefer delayed resolution in order to keep up his hope of winning under an unlikely  
36 high-stakes event (Chew and Ho, 1994).

37 Kreps and Porteus (1978), “KP” hereafter, developed the first extension of expected utility (EU),  
38 called recursive expected utility (REU), that accounts for the intrinsic value of information as  
39 related to attitudes towards risk resolution (or “temporal risk” for short)—that is, attitudes  
40 towards uncertainty resolution with known probabilities. Basically, under REU, preference for  
41 early resolution of uncertainty can be modelled as higher certainty equivalents (more risk seeking)  
42 for early lotteries than for delayed ones. Preference for late resolution is the converse. Formally,  
43 KP opted for an EU-based evaluation of lotteries and introduced a transformation function  $\varphi$   
44 that relates (recursively) the utility  $U_0$  for immediately resolved lotteries to utility  $U_T$  for delayed  
45 lotteries resolved at some future given date  $T$ , i.e.,  $U_0 = \varphi \circ U_T$ . The convexity (concavity) of  
46 the transformation function  $\varphi$  reveals preference for early (late) resolution of risk. This model  
47 and Epstein and Zin’s (1989) parametric specification, is widely used for macroeconomic and  
48 finance applications as it explains, inter alia, many asset-pricing anomalies (Epstein and Zin,  
49 1991; Bansal and Yaron, 2014; Epstein et al., 2014). Yet, from a descriptive standpoint, KP’s  
50 model may fail to accurately depict behavior when EU is violated (Gonzalez and Wu, 1999;  
51 Wakker, 2010; L’Haridon et al., 2019).

52 Assuming a rank-dependent utility framework (henceforth RDU; Quiggin, 1982), Wu (1999, Sec-  
53 tion 2) proposed an alternative model to REU in which preferences are represented by a temporal

54 RDU functional.<sup>1</sup> In this model, nonlinear probability weighting (for delayed lotteries) plays a  
55 key role with regard to attitudes towards temporal risk (Epper and Fehr-Duda, 2018). Specifi-  
56 cally, the latter is captured through the difference between the probability weighting used in the  
57 RDU-evaluation of early resolved lotteries and the probability weighting involved in the RDU-  
58 evaluation of lotteries resolved at a later date.<sup>2</sup> Wu (1999) argued that, in addition to a better  
59 descriptive accuracy (Tversky and Kahneman, 1992), this approach also accounts for experi-  
60 mental findings showing a decline in the percentage of subjects exhibiting preference for early  
61 resolution when facing small-gain probabilities than high-gain ones (Chew and Ho, 1994). Along  
62 the same lines, Epstein (2008, Section 5.3) argued that allowing for an early vs. late resolution  
63 probability weighting in his general KP’s setup could explain the anxiety (hopefulness) that  
64 results from delayed resolution when a risky favorable outcome is likely (unlikely). Descriptively,  
65 however, the issue of whether and how temporal risk affects utility or probability weighting re-  
66 quires a systematic investigation in order to provide a reliable measurement of attitudes towards  
67 temporal risk in empirical applications.

68 The present paper proposes a simple measurement method to elicit preferences for temporal risk.  
69 Two experiments are conducted to compare the descriptive power of REU and a more generalized  
70 version of it, a recursive RDU model (RRDU, Epstein 2008, Sections 4 and 5 therein). Basically  
71 we assume a RDU-evaluation of two-outcome lotteries, where both probability weighting and  
72 utility depend on the timing of uncertainty resolution. Similar to REU, RRDU implies that  
73 the utility index  $U_0$  (for early resolution lotteries) is related to the utility index  $U_T$  (for delayed  
74 resolution lotteries) through a transformation  $\varphi$ , i.e.,  $U_0 = \varphi \circ U_T$ . In the absence of probability  
75 weighting, RRDU reduces to REU.

76 We first show that, under REU, the evaluation of two-outcome lotteries using matching proba-  
77 bilities allows for a simple elicitation of the transformation function  $\varphi$ . We also show how this  
78 function can be elicited from certainty equivalents of early vs. late resolution lotteries. Second,  
79 we investigate the descriptive power of different strategies to capture attitudes towards temporal  
80 resolution under RRDU in terms of goodness of fit and prediction accuracy.

81 Overall, the elicited matching probabilities show a predominant preference for early resolution of  
82 temporal risk both at the aggregate and individual levels.<sup>3</sup> Furthermore, matching probability-  
83 based evaluations reveal a more pronounced preference for early resolution when subjects face

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<sup>1</sup>Wu (1999, Lemma 1) assumed EU for immediately resolved lotteries ( $t = 0$ ) and proposed an axiomatization that allows for a temporal risk-based probability weighting. Specifically, lotteries resolved at two different future dates ( $t_1 > t_2 > 0$ ) are evaluated using two different probability weighting functions.

<sup>2</sup>A recursive version of RDU was introduced to analyze ambiguity through two-stage lotteries in Segal (1987, 1990).

<sup>3</sup>Aggregate level analyses assume that all the choices of the different subjects in the sample can be considered as the choices of one “representative subject.”

84 moderate and high delayed-winning probabilities than small ones. Among other things, this result  
85 could explain the previous empirical findings of Chew and Ho (1994) and Lovallo and Kahneman  
86 (2000) showing that the percentage of subjects exhibiting preference for early resolution declines  
87 when the winning probability decreases (see also Masatlioglu et al., 2017). Similar model-free  
88 results are obtained when attitudes towards temporal risk is inferred from certainty equivalents.

89 We use matching probabilities to directly estimate different parametric specifications of the  
90 transformation function  $\varphi$  under REU. We observe that  $\varphi$  is convex at the aggregate level and  
91 predominantly convex at the individual level, thus showing that REU captures the previously  
92 elicited model-free preference for early resolution. On the other hand, the estimation of REU  
93 from certainty equivalents reveals a more convex  $\varphi$  than from matching probabilities. When REU  
94 is supplemented with atemporal probability weighting, i.e., we allow for a single probability  
95 weighting function under RRDU, we still observe that  $\varphi$  exhibits more convexity than when  
96 elicited from matching probabilities, but in a less pronounced manner. Furthermore, this RRDU  
97 version performs better than REU in terms of both goodness of fit and prediction accuracy.

98 Under “full force” RRDU where attitudes towards temporal risk can be revealed through both  
99 utility and probability weighting, our data cannot reject the null hypothesis of an identity  
100 transformation  $\varphi$ , be it a power, an exponential, or an expo-power function. This points to  
101 a more parsimonious version of RRDU, where attitudes towards temporal risk is exclusively  
102 revealed through a change in early vs. late probability weighting. Finally, we find that in terms  
103 of both goodness of fit and prediction accuracy, this parsimonious version of RRDU outperforms  
104 RRDU with an atemporal probability weighting.

105 The rest of our paper proceeds as follows. In section 2 we introduce the theoretical framework and  
106 explain how attitudes towards temporal resolution can be elicited under REU through matching  
107 probabilities and certainty equivalents. Section 3 describes the experimental design. Section  
108 4 reports the model-free results measuring attitudes towards temporal risk through matching  
109 probabilities (in studies A and B) and certainty equivalents (study B). Section 5 focuses on  
110 the parametric measurement of the transformation function  $\varphi$  under REU. Section 6 provides  
111 a comparative analysis of the different descriptive extensions in terms of goodness of fit and  
112 prediction accuracy. Section 7 discusses our results and concludes.

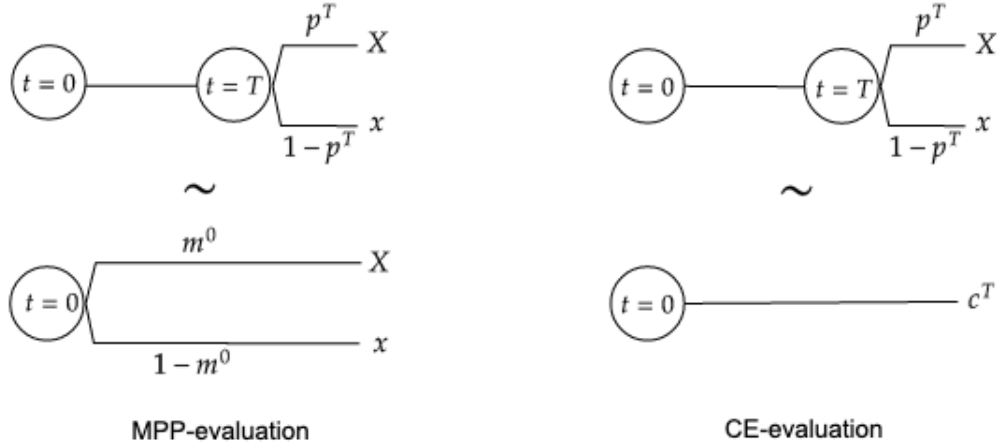


Figure 1: Matching present probability vs. certainty equivalent

## 113 2. Theoretical framework

### 114 2.1. Notation and Definitions

115 We consider both delayed and immediately resolved two-outcome lotteries. All outcomes are  
 116 nonnegative monetary amounts (i.e., gains). To avoid considerations related to discounting (when  
 117 outcomes are received at different dates), both type of lotteries pay out at a fixed future date  
 118  $T > 0$  (Ahlbrecht and Weber, 1997; von Gaudecker et al., 2011). Outcomes are elements of  
 119 an interval  $[0, M]$  of monetary amounts, with  $M > 0$ . We use  $(X, p^t, x)$  to denote a lottery,  
 120 resolved at some time  $t \in [0, T]$ , that yields outcome  $X$  with a “winning probability”  $p^t$ , and  
 121 outcome  $x \leq X$  otherwise. When the probability superscript is set at 0, it means that the lottery  
 122 is immediately resolved; otherwise  $t > 0$ , e.g.  $t = T$ , meaning that the resolution is delayed  
 123 (Figure ??). In our setup, uncertainty is resolved in one-shot through one-stage lotteries.<sup>4</sup> The  
 124 indifference between two lotteries  $l_A$  and  $l_B$  is denoted by  $l_A \sim l_B$ .

125 The *certainty equivalent* (CE)  $c^t$  of a lottery  $(X, p^t, x)$  is a monetary amount defined by  $c^t \sim$   
 126  $(X, p^t, x)$ . As all outcomes,  $c^t$  is received at time  $T$ . Similarly, for  $(X, p^t, x)$ ,  $m^0$  denotes the  
 127 probability (referring to an immediate resolution) such that  $(X, m^0, x) \sim (X, p^t, x)$ ;  $m^0$  is called  
 128 a *matching present probability* (MPP). Under standard assumptions of continuity and mono-  
 129 tonicity,  $c^t$  and  $m^0$  exist and are unique. Figure ?? illustrates the two types of evaluations used  
 130 for a lottery  $(X, p^t, x)$  with  $t = T$ .

<sup>4</sup>Ahlbrecht and Weber (1997) investigated temporal risk under REU in a setup where uncertainty can also be gradually resolved through two-stage lotteries. More recently, Nielsen (2020) reports model-free experimental results showing that attitudes towards temporal resolution may depend on whether the uncertainty is framed as a two-stage lottery or information structure.

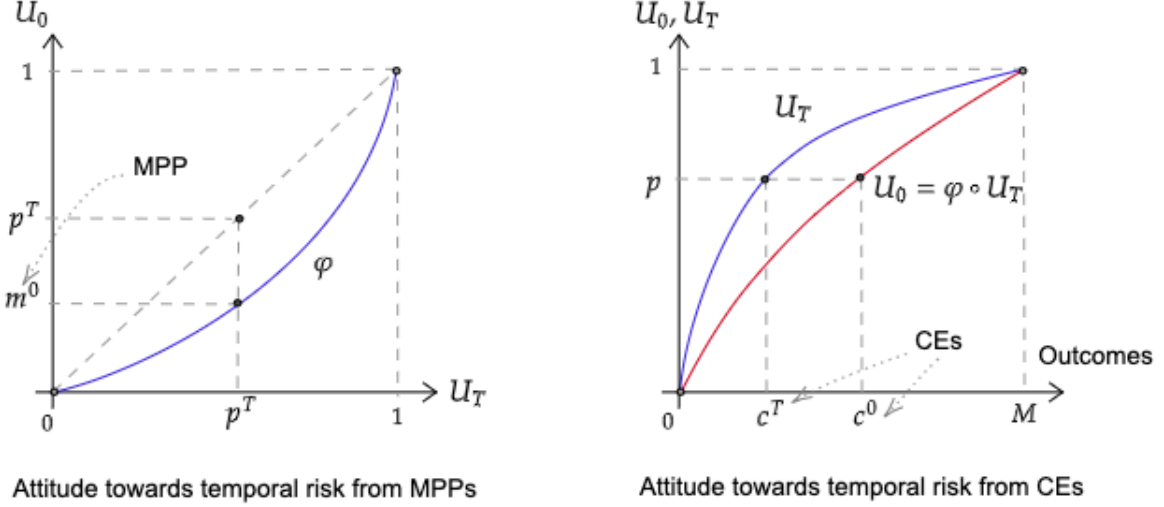


Figure 2: Eliciting attitudes towards temporal risk resolution under REU

131 **2.2. Formal setup**

132 We elicit attitudes towards temporal risk in two different ways. The first is based on the proba-  
 133 bility premium  $p^t - m^0$ . A positive (negative) probability premium implies preference for a lower  
 134 winning probability in return for an immediate (delayed) resolution of uncertainty. The second  
 135 method used to elicit attitudes towards temporal risk employs the outcome scale. Specifically,  
 136 we compare the certainty equivalents  $c^0$  and  $c^t$  of a two-outcome lottery resolved either now or  
 137 later, respectively. Here, a positive (negative) premium  $c^0 - c^t$  implies preference for early (late)  
 138 resolution. Figure ?? illustrates how  $p^t - m^0$  and  $c^0 - c^t$  affect the shape of utility under REU  
 139 (with  $t = T$ ).

140 **2.3. Recursive expected utility**

141 In our setup, we assume REU with two dates of risk resolution:  $t = 0$  (early) and  $t = T$  (late).  
 142 The model assumes EU for both immediately and delayed lotteries with two possibly different  
 143 von Neumann and Morgenstern utility functions  $U_0$  and  $U_T$ , respectively. We assume that the  
 144 utility functions are continuous and strictly increasing over the set of monetary outcomes  $[0, M]$ .  
 145 The certainty equivalent  $c^T$  of a delayed lottery  $(X, p^T, x)$  is consequently given by

$$c^T = U_T^{-1}(p^T U_T(X) + (1 - p^T) U_T(x)). \quad (1)$$

146 Similarly, the certainty equivalent  $c^0$  of the immediately resolved lottery  $(X, p^0, x)$  is given by

$$c^0 = U_0^{-1}(p^0 U_0(X) + (1 - p^0) U_0(x)). \quad (2)$$

147 The CEs and transitivity, establish the preferences between delayed and non-delayed lotteries.

148 We next assume that the two outcomes  $X$  and  $x$  are fixed at  $M$  and  $0$ , respectively, and  
 149 adopt the normalization  $U_0(X) = U_T(X) = 1$  and  $U_0(x) = U_T(x) = 0$ . If  $m^0$  is the MPP  
 150 corresponding to lottery  $(X, p^T, x)$ , Eqs. (1) and (2) – with  $m^0$  instead of  $p^0$  – give the same CE,  
 151 implying  $U_0^{-1}(m^0) = U_T^{-1}(p^T)$ . In other words, there exists a strictly increasing transformation  
 152  $\varphi = U_0 \circ U_T^{-1} : [0, 1] \rightarrow [0, 1]$ , i.e.,  $U_0 = \varphi \circ U_T$ , such that

$$m^0 = \varphi(p^T).$$

153 Consequently, determining the matching present probability  $m^0$  allows for a direct elicitation of  
 154 the transformation function  $\varphi$ ; so there is no need to elicit the utility functions  $U_0$  and  $U_T$ . In  
 155 our setup, when the shape of  $\varphi$  is modelled by a single parameter, it can be revealed by a single  
 156 choice list. As illustrated in Figure ?? (left-hand side panel), preference for early resolution (i.e.,  
 157  $m^0 < p^T$ ) is represented by a convex transformation  $\varphi$ .

158 Note that under REU with normalized utility functions  $U_0$  and  $U_T$ , we can also elicit  $\varphi$  from  
 159 the CEs of the lottery  $(X, p, x)$  resolved at  $0$  and  $T$ , respectively. In other words, Eqs. (1) and  
 160 (2) result in

$$\begin{cases} c^0 = (\varphi \circ U_T)^{-1}(p) \\ c^T = U_T^{-1}(p), \end{cases} \quad \& \quad (3)$$

161 as illustrated in the right-hand side panel of Figure ?. In other words, the elicitation of the  
 162 transformation function  $\varphi$  requires the prior measurement of  $U_0$  and  $U_T$ .

## 163 2.4. Recursive rank-dependent utility

164 Inspired by Wu (1999) and Epstein (2008), our general model (for two-outcome lotteries), RRDU,  
 165 reveals attitudes towards temporal risk through both the utility and the probability weighting  
 166 scales. In addition to the two utility indexes  $U_0$  and  $U_T$ , RRDU supplements REU with prob-  
 167 ability weighting, based on two assumptions. The first postulates that nonlinear probability  
 168 weighting represents the main source of deviations from EU in choice settings involving two-  
 169 outcome lotteries (Tversky and Kahneman, 1992; Wakker, 2010). Note that assuming RDU-like  
 170 preferences for two-outcome lotteries also subsumes other non-EU models for risk as Gul’s (1991)  
 171 disappointment aversion and Birnbaum’s (1988) configural weight models (see also Miyamoto,  
 172 1988). The second assumption postulates that temporal risk in our early vs. late setup results  
 173 in two probability weighting functions  $w_0$  and  $w_T$  for the evaluation of immediately resolved  
 174 and delayed lotteries, respectively (Epstein, 2008, Section 4). In the sequel,  $w_0$  and  $w_T$  are



175 strictly increasing over the probability interval and satisfy  $w_i(0) = 0$  and  $w_i(1) = 1$  for  $i = 0, T$ .  
 176 In other words, RRDU assumes RDU with utility  $U_0$  ( $U_T$ ) and weighting function  $w_0$  ( $w_T$ ) for  
 177 immediately resolved (delayed) lotteries.

178 Under RRDU, the certainty equivalent  $c^T$  of a delayed lottery  $(X, p^T, x)$  is given by

$$c^T = U_T^{-1}[w_T(p^T)U_T(X) + (1 - w_T(p^T))U_T(x)]. \quad (4)$$

179 Similarly, the certainty equivalent  $c^0$  of the immediately resolved lottery  $(X, p^0, x)$  is given by

$$c^0 = U_0^{-1}[w_0(p^0)U_0(X) + (1 - w_0(p^0))U_0(x)]. \quad (5)$$

180 As under REU, the CEs and transitivity, establish the preferences between delayed and non-  
 181 delayed lotteries.

182 Taking into account the utility normalizations we introduce in the previous Section, if  $m^0$  is  
 183 the MPP corresponding to lottery  $(X, p^T, x)$ , Eqs. (4) and (5) – with  $m^0$  instead of  $p^0$  – give  
 184 the same CE, implying  $U_0^{-1}(w_0(m^0)) = U_T^{-1}(w_T(p^T))$ . In other words, there exists a strictly  
 185 increasing transformation  $\varphi = U_0 \circ U_T^{-1} : [0, 1] \rightarrow [0, 1]$ , such that

$$w_0(m^0) = \varphi[w_T(p^T)]. \quad (6)$$

186 Consequently, the attitudes towards temporal risk, as elicited through MPPs, involves the trans-  
 187 formation function  $\varphi = U_0 \circ U_T^{-1}$  on the one hand, and the two probability weighting functions  
 188  $w_0$  and  $w_T$  on the other hand. Note that in the presence of neutrality towards temporal risk,  
 189 i.e.,  $U_0 = U_T$  and  $w_0 = w_T$ , matching probabilities  $m^0$  should coincide with the corresponding  
 190  $p^T$ s.

191 Under RRDU, the determination of certainty equivalents  $c_T^0$  and  $c_T^T$  of a lottery  $(x_T, p, y_T)$  with  
 192  $p = p^0$  and  $p = p^T$ , respectively, implies the following two equations

$$\begin{cases} c^0 = (\varphi \circ U_T)^{-1}(w_0(p)) \\ c^T = U_T^{-1}(w_T(p)). \end{cases} \quad \& \quad (7)$$

193 Note that a CE-based elicitation of attitudes towards temporal risk under RRDU requires in  
 194 principle that the four components  $\varphi$ ,  $U_0$ ,  $w_0$ , and  $w_T$  of RRDU, to be elicited. In the absence  
 195 of nonlinear probability weighting, Eqs.(??) reduce to Eqs.(??).

196 In sections 4 and 5 of the present paper, we investigate the descriptive power and prediction  
 197 accuracy of RRDU and three of its restrictions. The first restriction is the standard REU, i.e.,  
 198 RRDU with no probability weighting at all. The second restriction supplements REU by an

199 atemporal probability weighting  $w_0 = w_T$ ; meaning that attitudes towards temporal resolution  
200 is exclusively revealed through the transformation  $\varphi$ . The third restriction of RRDU assumes  
201 an extension of REU where attitudes towards temporal risk is exclusively revealed through  
202 probability weighting functions  $w_0$  and  $w_T$  (with an atemporal utility  $U_0 = U_T$ , i.e.,  $\varphi$  is the  
203 identity function).

### 204 **3. Experimental setup**

205 We conducted two experiments. Study A investigates attitudes towards temporal risk through  
206 MPPs in an incentivized experiment. Study B goes one step further and uses both MPPs and  
207 CEs to elicit attitudes towards temporal risk from incentivized choices. The CEs collected in  
208 study B also allow for an investigation of the goodness of fit and prediction accuracy of the  
209 different versions of RRDU (including REU).

#### 210 **3.1. Subjects and procedure**

211 Subjects in study A were 70 undergraduate students from the University of Paris Descartes  
212 (France). Each of them received a participation fee of 1€7 for a one-hour computer-based in-  
213 terview. Instructions concerning the experiment were communicated to the subjects through a  
214 power point presentation. The experiment began with a few practice questions to familiarize the  
215 subjects with the software used to display and collect choices. Each individual interview took  
216 about one hour.

217 To test whether the presence of real incentives affected individual behavior, subjects were divided  
218 into two subsamples of 35 subjects each: the “real incentives” group and the “hypothetical  
219 choices” group. At the beginning of the individual interview, each subject in the real incentive  
220 group was informed that, at the end of the session, a random draw from an urn containing one  
221 winning ball out of a total of 20 balls would take place to decide whether he was selected to  
222 have one choice question (randomly drawn and) played out for real.

223 Two subjects in the real incentive group had one of their choices played out for real. For one, it  
224 resulted into a sure gain of 25 euros. For the other, a lottery was resolved 9 months after the  
225 experiment and resulted in no gain.

226 The subjects in study B were 68 undergraduate students from ESSEC Business School (France);  
227 each of them received a participation fee of 1€7 Upon arrival, the subjects were shown a 10-  
228 minutes video with the instructions for the experiment. This was followed by a survey with

229 comprehension questions, in order to determine whether or not the subject needed further ex-  
230 planations. The experiment began with a few practice questions to familiarize the subjects with  
231 the software used to display and collect choices. Each individual interview took about one hour.

232 Real incentives were implemented for all of the subjects, and the related procedure was explained  
233 in the instructions. Each of the subjects had one of their choices played out for real at the end  
234 of the experiment. According to the Prince principle (Johnson et al., 2020), the number of the  
235 question to be played out for real was selected before the beginning of the experiment, and  
236 only revealed at the end of it. For  $t = 0$ , lotteries were resolved the day after the experiment,  
237 producing a small front-end delay. When  $t = 6$ , lotteries were resolved 6 months after the  
238 experiment.

239 For both immediate and late resolution, uncertainty was resolved by drawing from a physical  
240 random device (a bingo cage). In order to avoid suspicion or transaction costs, it was up to  
241 the subject to choose between watching the resolution through a Skype session or coming to  
242 the lab (the day after the experiment, in the case of an immediate resolution). In the case of a  
243 gain, money was paid by Paypal transfer. Overall, the procedure systematically separates the  
244 experiment from the resolution and the payment, and ensures that the conditions “now” ( $t = 0$ )  
245 and “later” ( $t = 6$ ) do not differ in terms of transaction cost or one-vs-multiple-shot resolution  
246 of uncertainty.

247 The total payment in study B was 1€795 (excluding the show-up fees). Specifically, 36% of the  
248 subjects got an average sure gain of 1€7.54; 42% got the sooner resolution, with an average  
249 value of 1€7.43 euros; 22% got the later resolution, with an average value of 1€7.

## 250 3.2. Stimuli

251 As shown in Tables ?? and ??, both studies A and B elicited baseline risk preferences, i.e., risk  
252 preferences for immediately resolved lotteries ( $t = 0$ ). Specifically, studies A and B elicited 11  
253 CEs of each for the lotteries  $(X, p^0, x)$ , where the date of receipt of outcomes  $T$  was fixed at  
254 12 and 6 months, respectively. The elicitation of CEs with a fixed (variable) probability  $p^t$  and  
255 varying (fixed) outcomes  $X, x$  was mainly devoted to capture the utility (probability weighting)  
256 curvature.

257 To elicit attitudes towards temporal risk, both studies elicited MPPs of delayed lotteries for 5  
258 levels of the winning probability  $p^t$ . Specifically, studies A and B elicited MPPs for  $t = 3, 6, 9, 12$   
259 and  $t = 6$ , respectively (last five rows of Tables ?? and ??). Furthermore, study B elicited 11 CEs  
260 for lotteries  $(X, p^t, x)$  with  $t = 6$ . This allowed us to check whether the elicitation of attitudes

Resolution	Lottery			Task
	$X$	$x$	$p^t$	
$t = 0$	100	0	0.50	CE
	200	0	0.50	
	400	200	0.50	
	450	150	0.50	
	500	200	0.50	
	500	100	0.50	
$t = 0$	500	0	0.10	CE
	500	0	0.20	
	500	0	0.50	
	500	0	0.80	
	500	0	0.90	
$t = 3, 6, 9, 12$	500	0	0.10	MPP
	500	0	0.25	
	500	0	0.50	
	500	0	0.75	
	500	0	0.90	

(a) Study A

Resolution	Lottery			Task
	$X$	$x$	$p^t$	
$t = 0, 6$	60	0	0.25	CE
	60	0	0.75	
	80	20	0.25	
	80	20	0.75	
	90	10	0.25	
	90	10	0.75	
$t = 0, 6$	100	0	0.10	CE
	100	0	0.25	
	100	0	0.50	
	100	0	0.75	
	100	0	0.90	
$t = 6$	100	0	0.10	MPP
	100	0	0.25	
	100	0	0.50	
	100	0	0.75	
	100	0	0.90	

(b) Study B

Table 1: Stimuli

261 towards temporal risk is robust to the scale used to evaluate lotteries: the probability scale for  
262 MPPs vs. the outcome scale for CEs. The elicitation of CEs for delayed lotteries in study B  
263 also allowed us to compare the descriptive power of the utility vs. the probability weighting  
264 approach to temporal risk.

265 In both studies, CEs and MPPs were determined using an iterative bisection choice process in a  
266 first step. Then, in a second step, the subjects were presented with an already completed choice  
267 list and were asked to either validate or change it (Appendices ?? and ??). This means that  
268 any error that might have occurred during the bisection process could be fixed before validation.  
269 Both the subjects in the real incentive group of study A and the subjects in study B were  
270 informed that all the decisions made in each choice list were eligible and equally likely to be  
271 selected and played out for real. CEs were elicited with a precision of 5 euros in both studies.  
272 MPPs were elicited with a precision of 0.02 in study A and 0.05 in study B.

273 The following section reports a model-free analysis of the data. Sections 5 and 6 report econo-  
274 metric estimations from likelihood maximization of structural equations (see Appendix C).

## 275 4. Model-free measurement of attitudes towards temporal risk

276 Attitudes towards temporal risk can be measured model-free by means of MPPs of delayed  
277 lotteries in studies A and B, and by comparing CEs of lotteries resolved now and later in study

$p^t$	Study A ( $t = T = 12$ ; $n = 70$ )				Study B ( $t = T = 6$ ; $n = 68$ )			
	Median	Std	$t$ -test	$\#(m^0 < p^{12})$	Median	Std	$t$ -test	$\#(m^0 < p^6)$
0.10	0.09	0.03	2.13*	62***	0.12	0.06	4.56***	29 <sup>ns</sup>
0.25	0.21	0.05	-0.47 <sup>ns</sup>	55**	0.22	0.04	-3.85***	51***
0.50	0.45	0.08	-7.80***	63***	0.42	0.05	-10.72***	64***
0.75	0.67	0.10	-8.27***	55***	0.67	0.08	-9.80***	66***
0.90	0.79	0.12	-9.19***	63***	0.77	0.08	-11.09***	66***

*ns*: non-significant; \*:  $p < 0.05$ ; \*\*:  $p < 0.01$ ; \*\*\*:  $p < 0.001$ ;  $n$ : sample size

Table 2: Empirical distributions of MPPs

278 B. Both methods of measurement consistently point to a predominance of preference for early  
279 resolution that declines in intensity for small winning probabilities. More details about reliability  
280 and real incentives in study A are given in Appendix ???. Appendix ??? reports details about  
281 baseline risk preferences in studies A and B.

$p^t$	Lottery			$t = 0$		$t = 6$		Comparison of CEs	
	$X$	$x$	Median	Std	Median	Std	$t$ -test	$\#(c^6 \leq c^0)$	
0.25	60	0	12.50	5.80	12.50	5.00	3.82***	28/9**	
0.75	60	0	32.50	7.30	27.50	6.70	8.31***	51/4***	
0.25	80	20	32.50	4.60	32.50	3.90	4.17***	28/5***	
0.75	80	20	47.50	8.20	37.50	6.50	11.64***	59/4***	
0.25	90	10	27.50	6.50	22.50	5.80	3.42**	27/7**	
0.75	90	10	52.50	9.40	37.50	9.70	9.19***	56/4***	
0.10	100	0	15.00	8.90	7.50	7.20	4.43***	27/8**	
0.25	100	0	22.50	6.20	17.50	5.90	4.68***	29/5***	
0.50	100	0	37.50	6.10	32.50	6.60	8.92***	52/4***	
0.75	100	0	52.50	12.10	42.50	11.70	10.26***	58/2***	
0.90	100	0	65.00	11.90	57.50	13.80	7.07***	58/4***	

*ns*: non-significant; \*:  $p < 0.05$ ; \*\*:  $p < 0.01$ ; \*\*\*:  $p < 0.001$ ; sample size:  $n = 68$

Table 3: Empirical distributions of CEs in study B

#### 282 4.1. Measurement from matching present probabilities

283 Table ??? reports the medians and standard deviations of the elicited MPPs in studies A and  
284 B for  $t = T = 12$  and  $t = T = 6$  respectively (see also Table ???, Appendix ???, for interme-  
285 diary resolution dates  $t = 3, 6, 9$  in study A). At the aggregate level we observe that, in both  
286 studies, median MPPs are consistently lower than the corresponding delayed probabilities. One-  
287 sample  $t$ -tests confirm that, overall, MPPs differ from the corresponding delayed probabilities  
288 in both studies A and B. At the individual level, MPPs were below the corresponding delayed  
289 probabilities for a large majority of subjects (Table ???: columns 5 and 9 for studies A and B,  
290 respectively). This suggests a predominance of preference for early resolution.

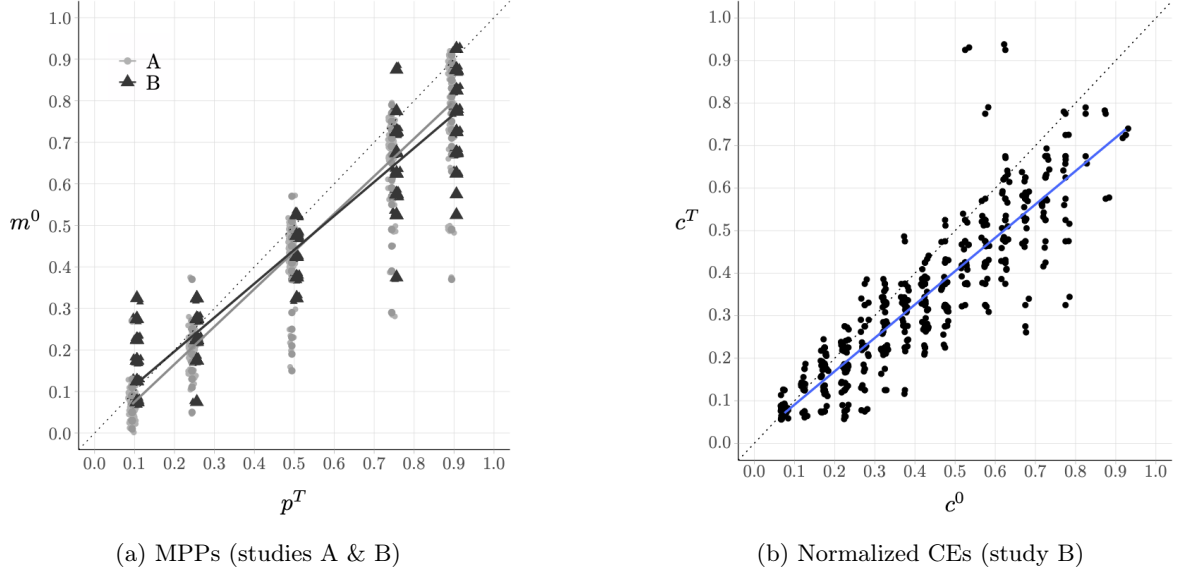


Figure 3: attitudes towards temporal risk from linear regression

291 Table ?? also shows that, in study A, the difference between delayed probabilities ( $p^t$ ) and the  
 292 corresponding MPPs ( $m^0$ ) increases from 0.01 when  $p^t = 0.10$  to 0.11 when  $p^t = 0.90$  (Page  
 293 trend test,  $p < 0.001$ ). A similar pattern of the probability premium  $p^t - m^0$  is observed in  
 294 study B (Page trend test,  $p < 0.001$ ). This is confirmed by the linear regression of MPPs on  
 295 the corresponding delayed probabilities, where the probability premium  $p^t - m^0$  is the vertical  
 296 distance between the 45-degree line, that materializes neutrality towards temporal risk ( $m^0 = p^t$ ),  
 297 and the regression line (Figure ??). In both studies A and B, the regression lines (of MPPs on  
 298 delayed probabilities) do not coincide with the 45-degree line (Fisher test:  $p < 0.01$ ). Regression  
 299 estimates show that the slopes of regression lines are similar and below the unit; furthermore, the  
 300 intercepts are close to zero. Again, this suggests a preference for early resolution of uncertainty  
 301 which declines (in terms of magnitude) when the delayed winning probability decreases.

## 302 4.2. Measurement from certainty equivalents

303 Study B also elicited CEs,  $c^0$  and  $c^6$ , of lotteries  $(100, p^0 = p, 0)$  and  $(100, p^6 = p, 0)$ , respectively,  
 304 for five different values of probability  $p$ . Here, preference for early resolution of uncertainty  
 305 corresponds to a positive difference  $c^0 - c^6$ , meaning that, lottery  $(100, p, 0)$  is assigned a higher  
 306 value (CE) when resolved now ( $p^0 = p$ ) as compared to later ( $p^t = p$ ). At the aggregate level, we  
 307 observe that the null hypothesis of equal CEs,  $c^0 = c^T$ , is rejected by paired  $t$ -tests (Table ??,  
 308 column 8). This conclusion accords with the observation that the mean CEs are systematically  
 309 lower for delayed lotteries as compared to immediately resolved ones, and this for each of the  
 310 five winning probability levels ( $p^t = 0.10, 0.25, 0.50, 0.75, 0.90$ ). At the individual level, Table ??

311 (last column) shows that a majority of subjects assign a higher value to lotteries resolved now  
 312 than the equivalent lotteries resolved later.

313 Figure ?? confirms the results obtained from MPPs, displaying that preference for early reso-  
 314 lution, as inferred from CEs, is predominant at the aggregate level. A Fisher test shows that  
 315 the regression line of  $c^0$  on  $c^6$  does not coincide with the 45-degree line materializing neutrality  
 316 towards temporal risk ( $p < 0.01$ ). Furthermore, as the regression line have a slope below the  
 317 unit and an intercept which is positive, the magnitude of the difference  $c^0 - c^6$  declines when  
 318 the delayed-winning probability is decreased (Page trend test,  $p < 0.01$ ).

Power	Exponential	Expo-power
$x^\alpha$	$(1 - e^{-\alpha x}) / (1 - e^{-\alpha})$	$(1 - e^{-\alpha_1 x^{\alpha_2}}) / (1 - e^{-\alpha_1})$

Table 4: Parametric specifications for  $\varphi$  and  $U_T$

## 319 5. Attitudes towards temporal risk under REU

320 As explained in section 2.3, REU uses two utility functions:  $U_T$  and  $U_0 = \varphi \circ U_T$ , where the  
 321 transformation  $\varphi$  reveals the impact of temporal risk. The present section elicits the transforma-  
 322 tion function using two different methods. The first directly determines  $\varphi$  from MPPs. Based  
 323 on CEs, the second method infers  $\varphi$  from the elicitation of both  $U_T$  and  $U_0 = \varphi \circ U_T$ . We use  
 324 the two-parameter expo-power family reported in Table ?? to estimate REU components. This  
 325 family has the advantage of including the power and the exponential specifications as a limiting  
 326 case ( $\alpha_1 \rightarrow 0$ ), and particular case ( $\alpha_2 = 1$ ) respectively (Peel and Zhang, 2009). In addition to  
 327 their popularity in the empirical literature, the power and the exponential specifications are used  
 328 to detect simple convex / concave shapes. The expo-power is particularly suitable for goodness  
 329 of fit comparisons when the data set is rich enough.

Component	Study A					Study B			
	Aggregate		Individual			Aggregate		Individual	
	Estimate	SE	Median	IQR	Estimate	SE	Median	IQR	
Transformation ( $\varphi$ )	$\alpha_1$	-1.86***	0.24	-0.90	[-1.99;-0.21]	-2.50***	0.02	-2.48	[-2.61;-1.10]
	$\alpha_2$	0.69***	0.04	0.96	[0.81; 1.01]	0.53***	0.01	0.62	[0.52; 0.76]

SE: standard error; \*\*\*:  $p < 0.001$

Table 5: Estimates of  $\varphi$  under REU from MPPs

330

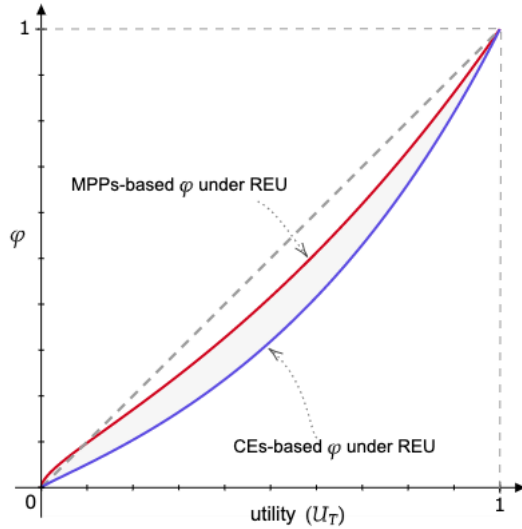


Figure 4: Aggregate estimates assuming an expo-power  $\varphi$  (Study B)

### 331 5.1. Eliciting $\varphi$ from matching present probabilities

332 Under REU, MPPs allow for a simple elicitation of the transformation function  $\varphi$ . As shown  
 333 in Section 2.3, the transformation function links MPPs  $m^0$  to the corresponding present prob-  
 334 abilities  $p^T$ . We use a maximum likelihood procedure to estimate  $\varphi$  both at the aggregate and  
 335 individual levels while assuming a normal error, that is

$$m^0 = \varphi(p^T) + \epsilon, \quad (8)$$

336 where  $\epsilon \sim N(0, \sigma)$ . Table ?? reports MPP-based estimates of  $\varphi$  assuming an expo-power spec-  
 337 ification in studies A and B for  $t = T = 12$  and  $t = T = 6$ , respectively. Additional estimates  
 338 are provided in Tables ?? and ?? in appendix ??.

339 At the aggregate level, the null hypothesis that  $\varphi$  is the identity function is rejected by a  
 340 likelihood ratio test ( $p < 0.001$  for studies A and B). This clearly means that temporal risk  
 341 affects the shape of  $\varphi$ , thereby showing that REU has more descriptive power than the standard  
 342 EU. As expected, likelihood-ratio tests show that the expo-power specification fits the data  
 343 better than both a power and an exponential  $\varphi$  ( $p < 0.001$  in studies A and B). Note that  
 344 Figure ?? shows that while  $\varphi$  (as inferred from MPPs under the expo-power specification) is  
 345 globally convex, it also exhibits a slight concavity for small values of the utility scale, i.e., when  
 346 the winning probability is small.<sup>5</sup>

347 At the individual level, Table ?? shows that the median estimates of the expo-power parameters  
 348 are close to the corresponding aggregate estimates (see also Table ??, Appendix ??) and point

<sup>5</sup>This result is consistent with the implication of Finding 4 in Masatlioglu et al. (2017) that suggests that the transformation function  $\varphi$  is S-shaped under REU.



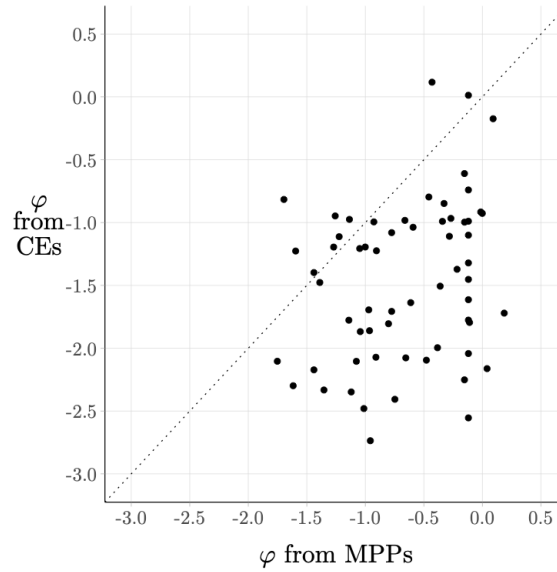


Figure 5: Individual estimates of  $\varphi$  (exponential) under REU: MPPs vs CEs

349 to a global convexity of  $\varphi$ . Binomial tests show that, under both the exponential and power  
 350 specifications, convexity of the transformation function predominates in studies A and B ( $p <$   
 351  $0.001$ ). Under the exponential specification, 63 (60) subjects out of 70 (68) exhibited a convex  $\varphi$   
 352 in study A (B). A similar pattern holds when a power transformation is assumed. These findings  
 353 are fully consistent with the model-free findings described in section 4.

354

## 355 5.2. Eliciting $\varphi$ from certainty equivalents

356 A traditional method for eliciting the transformation  $\varphi$  under KP's REU model consists in  
 357 determining the CEs of a lottery  $(X, p, x)$  in an early vs. late setup (e.g. von Gaudecker et al.,  
 358 2011). In addition to its more demanding nature, CE-based elicitation of  $\varphi$  under REU may be  
 359 biased in the presence of nonlinear probability weighting. In particular, the certainty effect (as  
 360 represented by a steeper inverse S-shaped probability weighting function near certainty) would  
 361 result in discrepancies between a CE-based and a MPP-based  $\varphi$ s, as MPPs exclusively result  
 362 from a comparison between non-degenerate lotteries.

363 We use a maximum likelihood procedure to estimate the components of REU in Eqs.(??) at  
 364 both the aggregate and individual levels. Table ?? reports the estimates of the parameters of  
 365  $U_T$  and  $\varphi$  assuming expo-power parametric forms. The estimates of the power and exponential  
 366 families are reported in Table ?? (Appendix ??).

Components	Aggregate		Individual		
	Estimate	SE	Median	IQR	
Utility ( $U_T$ )	$\alpha_1$	0.0003***	0.0005	0.004	[ 0.001; 0.007]
	$\alpha_2$	1.66***	0.15	1.59	[1.38; 1.83]
Transformation ( $\varphi$ )	$\alpha_1$	-1.97***	0.32	-2.42	[-2.67;-0.74]
	$\alpha_2$	0.86***	0.10	0.71	[ 0.55; 1.29]

\*\*\*:  $p < 0.001$

Table 6: Estimates of  $U_T$  and  $\varphi$  under REU from CEs

367

368 At the aggregate level, likelihood ratio tests reject the null hypothesis that  $\varphi$  is the identity  
369 function ( $p < 0.001$ ). The estimates suggest a (globally) convex transformation  $\varphi$ , be it power  
370 or exponential. Figure ?? shows an exaggerated convexity when  $\varphi$  is inferred from CEs rather  
371 than from the certainty-effect-free MPPs under the exponential specification.

372 As for the individual level, the estimates point to a predominance of convex  $\varphi$ s, thus showing a  
373 prevalence of preference for early resolution. For instance, under the exponential specification,  
374 61 subjects out of 68 exhibit a convex  $\varphi$ . Even so, the median estimate of the exponential  
375 parameter from CEs is almost the double of the corresponding median estimate from MPPs.  
376 Furthermore, Figure ?? shows that a majority of subjects exhibit a more convex  $\varphi$  when elicited  
377 from CEs than when elicited from MPPs.

## 378 6. Attitudes under recursive rank-dependent utility

379 This section analyzes temporal risk under recursive rank-dependent utility using the CEs ob-  
380 tained in study B. Specifically, REU is supplemented with two probability weighting functions  
381  $w_0$  and  $w_T$  that could possibly capture the impact of temporal risk on probability weighting.  
382 We first show that RRDU outperforms REU in terms of descriptive accuracy. Then, we inves-  
383 tigate whether temporal risk impacts both the utility and probability weighting scales or just  
384 one of them, i.e., either  $U_0 = U_T$  or  $w_0 = w_T$ . The results of the present section suggest that  
385 RRDU with an atemporal utility scale performs better than RRDU with atemporal probability  
386 weighting, in terms of goodness of fit and predictive power.

### 387 6.1. Eliciting RRDU components

388 As explained in section 2.4 (Eq. ??), under RRDU, the certainty equivalents  $c^0$  and  $c^T$  of a  
389 given lottery  $(X, p, x)$  are predicted by  $(U_T^{-1} \circ \varphi^{-1} \circ w_0)(p)$  and  $(U_T^{-1} \circ w_T)(p)$ , respectively. In

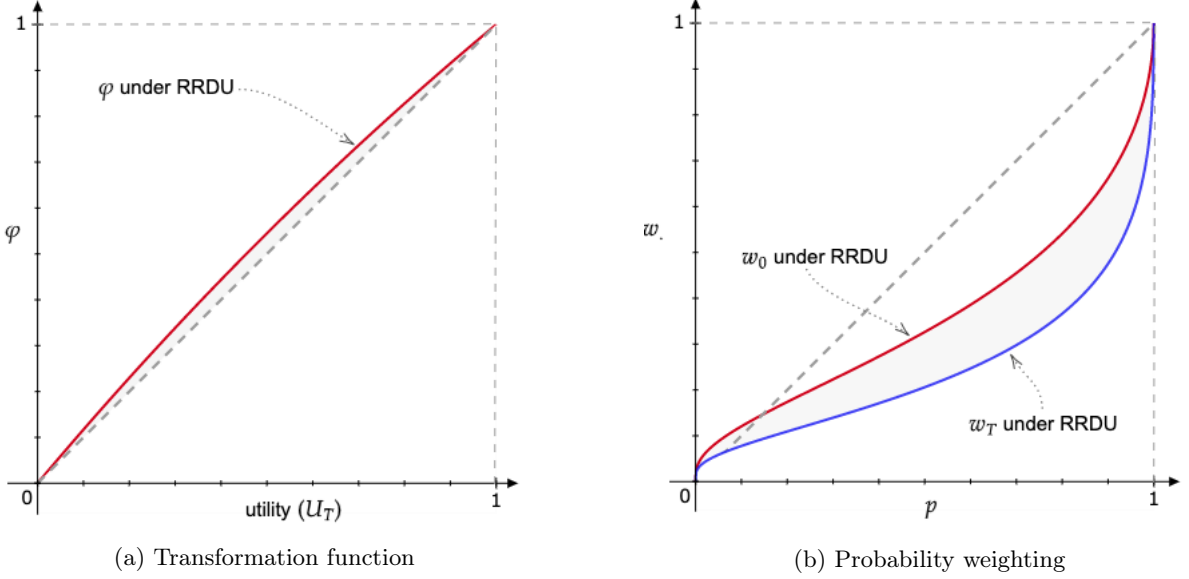


Figure 6: Aggregate estimates of  $\varphi$ ,  $w_0$  and  $w_T$  under RRDU

390 the sequel, we assume the Prelec’s (1998) two-parameter specification for  $w$ , i.e.,

$$w(p) = e^{-\delta(-\ln(p))^\gamma}, \quad (9)$$

391 where parameter  $\delta$  is an index of optimism / pessimism towards probability, and  $\gamma$  reflects sen-  
 392 sitivity to probabilities. When  $\delta = \gamma = 1$ ,  $w$  reduces to the identity function, i.e. no probability  
 393 weighting. The accumulated experimental evidence shows that, when facing risky gains, people  
 394 exhibit an inverse S-shaped  $w$ , overweighting small probabilities, and underweighting moderate  
 395 and high probabilities. In terms of the Prelec specification, this generally results in  $\delta > 1$  and  
 396  $\gamma < 1$  (Wakker, 2010). As for utility scales, we assign an expo-power specifications to both  $U_T$   
 397 and  $\varphi$ . Appendix ?? reports estimates assuming power and exponential specifications for  $\varphi$ .

398 We use maximum likelihood procedures to estimate the parameters of RRDU. The corresponding  
 399 estimates are reported in Table ?. Figure ?? suggests that, at the aggregate level, probability  
 400 weighting captures most of the impact of temporal risk on preferences. This is confirmed by  
 401 likelihood ratio tests. Specifically, while we could not reject the hypothesis of identical utility  
 402 functions  $U_0$  and  $U_T$  ( $p = 0.46$  under an expo-power  $\varphi$ ), the hypothesis of identical probability  
 403 weighting functions  $w_0$  and  $w_T$  is clearly rejected by our observations ( $p < 0.001$ ).<sup>6</sup>

404 At the individual level, Table ?? shows that median estimates for the parameters of  $U_T$ ,  $\varphi$ ,  
 405  $w_0$  and  $w_T$  are very similar to aggregate estimates. Table ?? in Appendix ?? confirm this  
 406 observation when a power (or an exponential) specification is assigned to  $\varphi$  as well. When  $\varphi$  is

<sup>6</sup>Note that, in both cases, we test a restricted RRDU model (6 parameters) against the “full force” RRDU model (8 parameters). The statistics of each test has (asymptotically) a  $\chi^2$  distribution with  $2 = 8 - 6$  degrees of freedom.

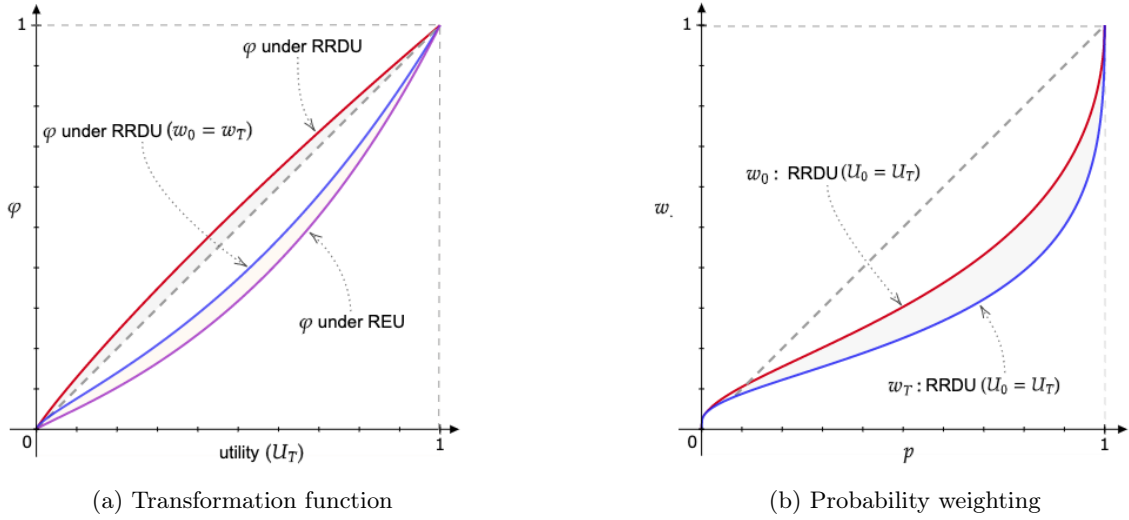


Figure 7: Aggregate estimates of restricted versions of RRDU

407 assigned a power parametric form, 28 (40) subjects exhibit a convex (concave) shape (binomial  
 408 test,  $p = 0.18$ ).

Component	Aggregate		Individual		
	Estimate	SE	Median	IQR	
Expo-power utility ( $U_T$ )	$\alpha_1$	0.0007**	0.0002	0.00004	[-0.018; 0.0009]
	$\alpha_2$	1.43***	0.06	1.32	[0.96; 1.76]
Expo-power ( $\varphi$ )	$\alpha_1$	0.16 <sup>ns</sup>	0.29	0.19	[-2.23; 1.59]
	$\alpha_2$	0.92***	0.06	0.91	[0.60; 1.35]
Probability weighting ( $w_0$ )	$\delta$	1.36***	0.07	1.68	[1.24; 2.00]
	$\gamma$	0.53***	0.02	0.58	[0.44; 0.69]
Probability weighting ( $w_T$ )	$\delta$	1.83***	0.08	1.91	[0.32; 0.70]
	$\gamma$	0.40***	0.02	0.40	[0.28; 0.48]

*ns*: non-significant; \*:  $p < 0.05$ ; \*\*:  $p < 0.01$ ; \*\*\*:  $p < 0.001$

Table 7: Estimates of  $U_T$ ,  $\varphi$ ,  $w_0$ , and  $w_T$  under RRDU

409

410 To sum up, both the aggregate and individual-level estimates of RRDU point to a more parsi-  
 411 monious version of RRDU where  $\varphi$  is linear, i.e.,  $U_0 = U_T$ . This implies that attitudes towards  
 412 temporal risk is captured by probability weighting rather than by the utility scale. This also  
 413 accords with the aggregate estimates for study A assuming RRDU with a linear  $\varphi$  (see Appendix  
 414 ??).

## 415 6.2. Goodness of fit and prediction accuracy

416 The present section compares three restrictions of RRDU both in terms of goodness of fit and  
417 prediction accuracy assuming expo-power parametric forms for  $U_T$  and  $\varphi$ , and Prelec parametric  
418 specifications for  $w_0$  and  $w_T$ . The first consists of REU, the second supplements the latter  
419 with atemporal probability weighting ( $w_0 = w_T$ ), and the third assumes an atemporal utility  
420 ( $U_0 = U_T$ ).

421 Table ?? reports the the Akaike information criterion (AIC) values corresponding to each of the  
422 three aforementioned restrictions of RRDU. It allows the comparison of goodness of fit while  
423 accounting for the difference of the number of involved parameters. In particular, it shows  
424 that the goodness of fit of REU improves with atemporal probability weighting. This result  
425 is consistent with the less pronounced curvature of the MPP-based transformation function as  
426 compared to that inferred from CEs under REU (Figure ??). In contrast to CEs, MPPs avoid  
427 the certainty effect (one of the major causes of probability weighting), which results in a less  
428 biased measurement of the transformation function under REU.

429 We also compare REU to RRDU with atemporal probability weighting in terms of prediction  
430 accuracy as measured by the root mean square error (RMSE), an estimator of the standard  
431 deviation of prediction errors regarding MPPs. Specifically, in study B, we used the models esti-  
432 mated from CEs to measure the RMSE-based discrepancy between the observed and predicted  
433 MPPs (Appendix ??). Table ?? reports aggregate and individual level MPP-based RMSE values  
434 and shows that, in terms of prediction accuracy, RRDU with atemporal probability weighting  
435 performs slightly better than REU.

436 We now consider the comparison of RRDU with atemporal probability weighting vs. RRDU  
437 with atemporal utility in terms of both goodness of fit and prediction accuracy. Note that each  
438 of these two models involves the same number of parameters to estimate, i.e. 6 parameters. This  
439 is illustrated in Figure ?? where delayed resolution clearly impacts the discrepancy between  $w_0$   
440 and  $w_T$  more strongly than the discrepancy between  $U_0$  and  $U_T$  as measured by the curvature  
441 of  $\varphi$  (under RRDU). As for goodness of fit, measured by AIC, the assumption of RRDU with  
442 atemporal utility performs better than RRDU with atemporal probability weighting.<sup>7</sup> Under  
443 RRDU, our results also point to a better predictive performance of the assumption  $U_0 = U_T$

---

<sup>7</sup>Although the full force RRDU has a better predictive performance than RRDU with atemporal utility at the aggregate level (RMSE: 0.071 vs. 0.09), it does not outperform the latter in terms of AIC (AIC: 5750.92 vs. 5748.47). This conclusion is reminiscent of the likelihood ratio test performed in Section 6.2 showing that the full force RRDU does not improve significantly goodness of fit as compared to (the nested assumption of) RRDU with atemporal utility.

	Restriction	AIC	MPP-based RMSE	
			Aggregate	Individual (median)
	REU	6097.69	0.104	0.115
RRDU	$w_0 = w_T$	5766.28	0.103	0.111
	$U_0 = U_T$	5748.47	0.090	0.102

Table 8: Goodness of fit and prediction accuracy

444 as compared to the assumption  $w_0 = w_T$ , both at the both aggregate and individual levels.  
445 Specifically, the null hypothesis of equal RMSEs across these two models is rejected (paired  $t$ -test,  
446  $p < 0.001$ ). Further, the RMSE is smaller under RRDU with atemporal probability weighting  
447 than under RRDU with atemporal utility for 55 subjects out of 68 (Binomial,  $p < 0.001$ ).

## 448 7. Discussion and conclusion

449 We have analyzed attitudes towards temporal risk in a discounting-free setup through a general-  
450 ization of recursive expected utility (REU) where preference for early resolution could affect both  
451 utility and probability weighting. Our contribution is twofold: (i) Proposing a simple method  
452 (Matching present probabilities, MPPs) to elicit the transformation function under REU; (ii)  
453 Conducting a “horse race” between two approaches to temporal risk, i.e., utility vs. probability  
454 weighting, which confirms and extends the early (qualitative) empirical findings that attribute  
455 temporal risk to probability weighting.

456 We show that using MPPs to measure attitudes towards temporal risk is less demanding than  
457 using certainty equivalents under REU (e.g., Ahlbrecht and Weber, 1997; von Gaudecker et al.,  
458 2011; Brown and Kim, 2014) and it allows for a simple elicitation of the transformation function  
459  $\varphi$ . To our knowledge, this method represents the simplest way of eliciting attitudes towards  
460 temporal risk under REU. We also show that, in contrast to the use of certainty equivalents  
461 (CEs), the comparison of non-degenerate lotteries involved in MPP elicitation circumvents the  
462 certainty effect, one of the major sources of probability weighting.

463 The paper also proposes and implements two ways of measuring attitudes towards temporal risk  
464 under recursive rank-dependent utility (RRDU): the first uses MPPs while the second is based  
465 on CEs. Studies A and B perform a simple probability scale-based measurement of attitudes  
466 towards temporal risk, using MPPs. Our findings point to a predominance of preference for  
467 early resolution. Furthermore, this preference declines as the winning probability decreases. In  
468 study B, where we use both MPPs and CEs, most of the subjects prefer early resolution when

469 the winning delayed probability is moderate or high, but only a minority of them exhibit such  
470 a preference when the winning probability is low, i.e.,  $p^T = 0.10$  (Table 2). This result is in line  
471 with the previous findings by Chew et Ho (1994) and Lovallo and Kahneman (2000) suggesting  
472 that attitudes towards temporal risk may depend on the magnitude of the winning probability  
473 (see also the more recent contributions of van Winden et al., 2011; Masatlioglu et al., 2017,  
474 experiment 3). Descriptively, these findings support adopting the general model proposed in the  
475 present paper, i.e., RRDU, to investigate attitudes towards temporal risk without committing  
476 a priori to a utility or a probability weighting-based approach. Under RRDU, our data suggest  
477 that the attitudes towards temporal risk is carried by temporal probability weighting as initially  
478 suggested in Wu (1999) and subsequently exploited in Epstein (2008), meaning that capturing  
479 temporal risk in terms of probability weighting descriptively outperforms the traditional utility-  
480 driven REU approach.

481 Empirical investigations on one-shot resolution of uncertainty (e.g. Ahlbrecht and Weber, 1997;  
482 von Gaudecker et al., 2011; Brown and Kim, 2014), did not investigate whether the decision-  
483 makers view the value of information as intrinsic (exhibiting an aversion to prolonged uncer-  
484 tainty) or instrumental (preferring an early resolution of uncertainty regarding monetary rewards  
485 to plan future consumption; Ganguly and Tasoff, 2017). This issue is particularly relevant under  
486 Kreps and Porteus' (1978) REU where the transformation function  $\varphi$  is assumed to capture the  
487 intrinsic value of information. The risk resolution in our setup presents the question of whether  
488 the decision-makers consider the instrumental or the intrinsic value of information. While we  
489 cannot directly answer such a question, we think that an instrumental value of information would  
490 affect both probability weighting and utility transformation ( $\varphi$ ). Furthermore, study A suggests  
491 that the fully informative signals we use in our setup were likely to be assigned an intrinsic  
492 value. In fact, our subjects exhibit a systematically more pronounced aversion to temporally  
493 prolonged uncertainty as the delay of resolution is increased. For instance, under REU, table 16  
494 (Appendix E) shows that the convexity of the transformation function  $\varphi$  gets more pronounced  
495 when the delay of resolution increases from 3 to 12 months. This is consistent with the idea of  
496 a temporally increasing psychological cost of waiting for uncertainty resolution.

497 When individual decision-making involves both time and risk dimensions, a lottery can be either:  
498 (i) resolved and paid now; (ii) both resolved and paid later; or (iii) resolved now and paid later.  
499 As compared to the standard case (i), case (ii) involves two additional psychological dimensions.  
500 The first is related to the delayed receipt of outcomes, and the second has to do with delayed  
501 resolution of risk, i.e., temporal risk. Noussair and Wu (2006) and Abdellaoui et al. (2011),  
502 assuming EU and RDU respectively, reported consistent findings pointing to more risk tolerance  
503 in case (ii) than in case (i). It is however, noteworthy to observe that Abdellaoui et al. (2011)  
504 found that the increase in risk tolerance was due to a shift in terms of probability weighting

505 rather than in terms of utility. While this is consistent with the findings of the present paper  
506 focusing on the difference between cases (ii) and (iii), it should also be observed that the impact  
507 on probability weighting in these studies goes in opposite directions, i.e., more risk tolerance  
508 between (i) and (ii) and more risk aversion between (ii) and (iii). This suggests a more complex  
509 interaction between intertemporal tradeoff of outcomes and risk resolution in case (i) vs. case  
510 (ii) where the overall observed optimism outweighs the pessimism involved by the sole delayed  
511 risk resolution. We think that further investigation is desirable to understand the factors that  
512 influence risk attitudes when intertemporal tradeoffs of outcomes are intertwined with delayed  
513 resolution.



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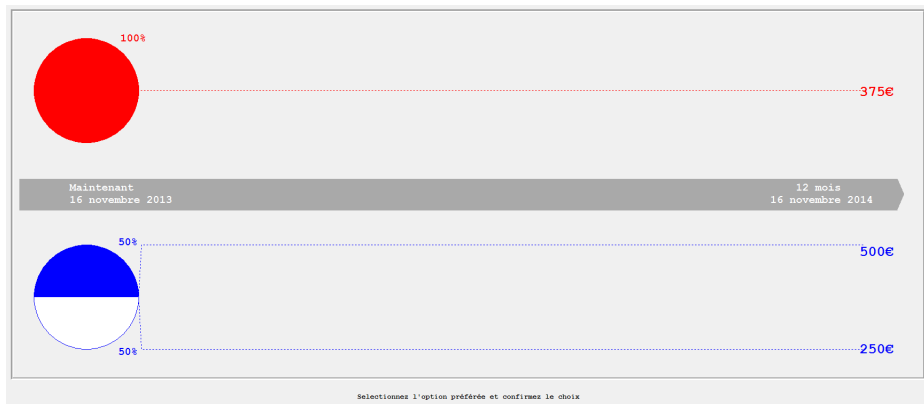
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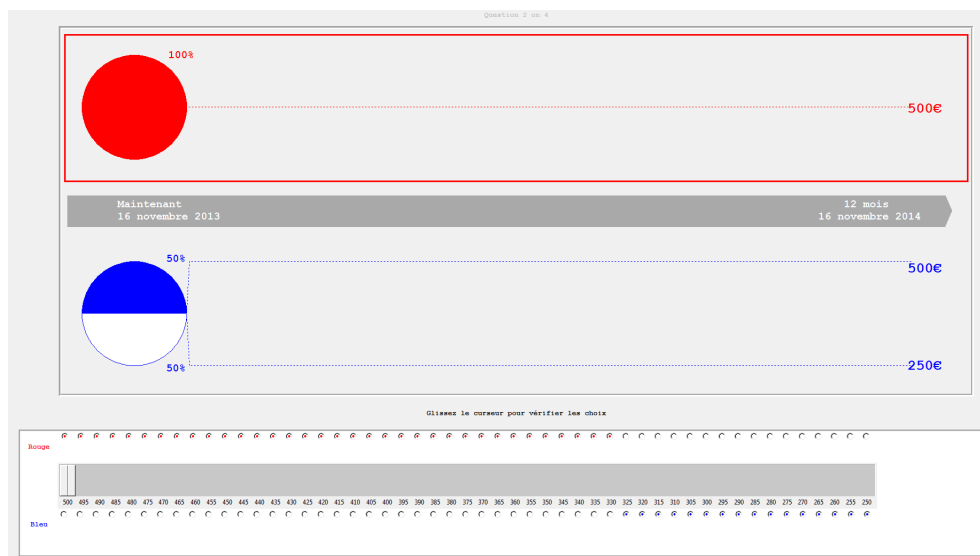
## 594 A. Displays

## 595 A.1. Study A



(a) Binary choice during the bisection step

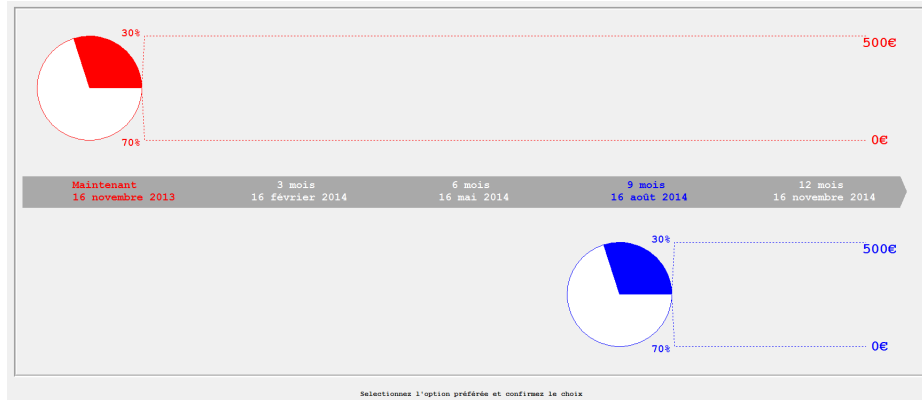
During the bisection step, subjects report their preferences by clicking on the preferred lottery in each iteration.



(b) Choice list for confirmation

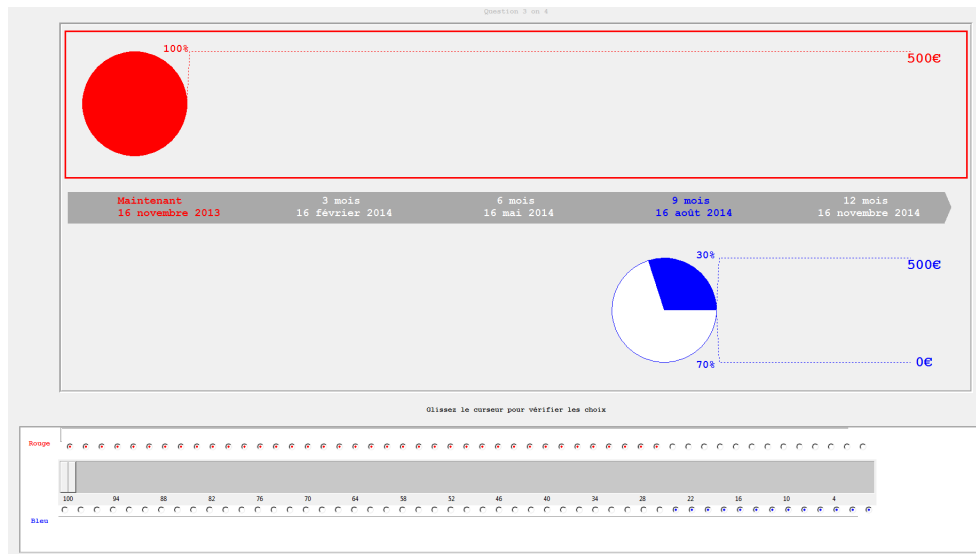
In this example, the subject shifted from option  $A$  to option  $B$  for  $z \in [\text{€}325, \text{€}330]$  during the bisection process (step 1); so in step 2, the corresponding choice list was presented. The subject was then asked to scroll the bar from left to right and thereby to check whether he still preferred to shift between options  $A$  and  $B$  for  $z \in [\text{€}325, \text{€}330]$ . Otherwise, he could change the “shifting value”.

Figure 8: Steps for eliciting CEs in study A



(a) Binary choice during the bisection step

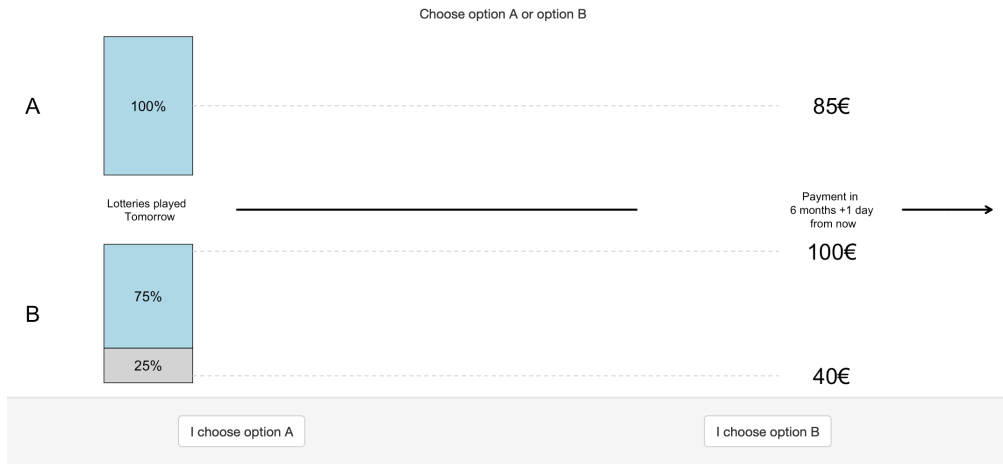
During the bisection step, subjects reported their preferences by clicking on the preferred lottery in each iteration.



(b) Choice list for confirmation

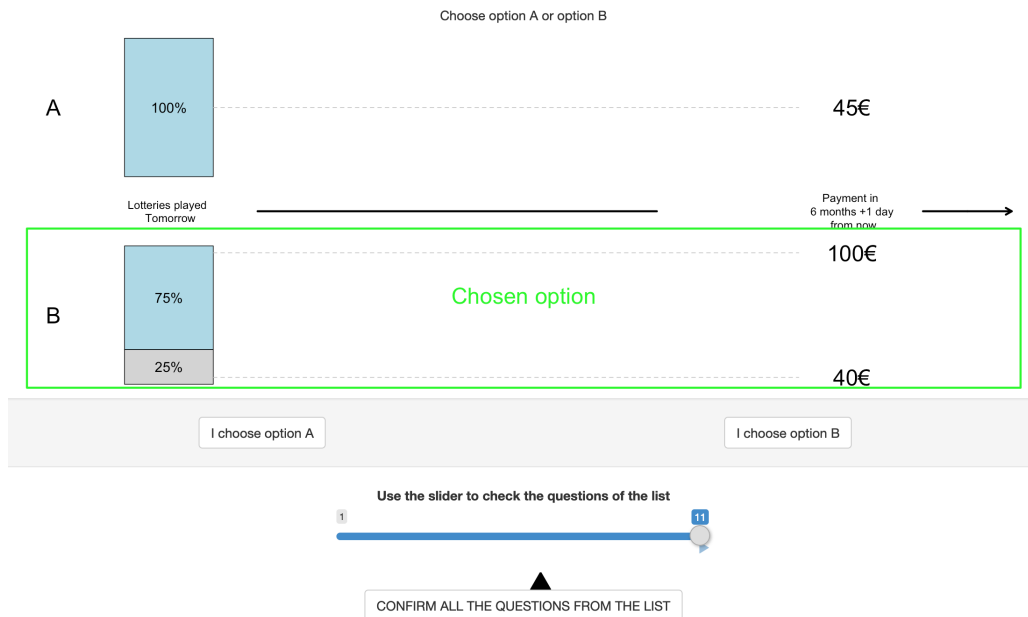
In this example, the subject shifted from option  $A$  to option  $B$  for  $q_0 \in [0.23, 0.24]$  during the bisection process (step 1); so in step 2, the corresponding choice list was presented. The subject was then asked to scroll the bar from the left to the right in order to check whether she still preferred to shift between options  $A$  and  $B$  for  $q_0 \in [0.23, 0.24]$ . Otherwise, she could change the “shifting value”.

Figure 9: Steps for eliciting MPPs in study A



(a) Binary choice during the bisection step

During the bisection step, subjects reported their preferences by clicking on the preferred lottery in each iteration. The process aims at determining the CE  $c^0$  of  $(X = 100, p^0 = 0.75, x = 40)$ .



(b) Choice list for confirmation

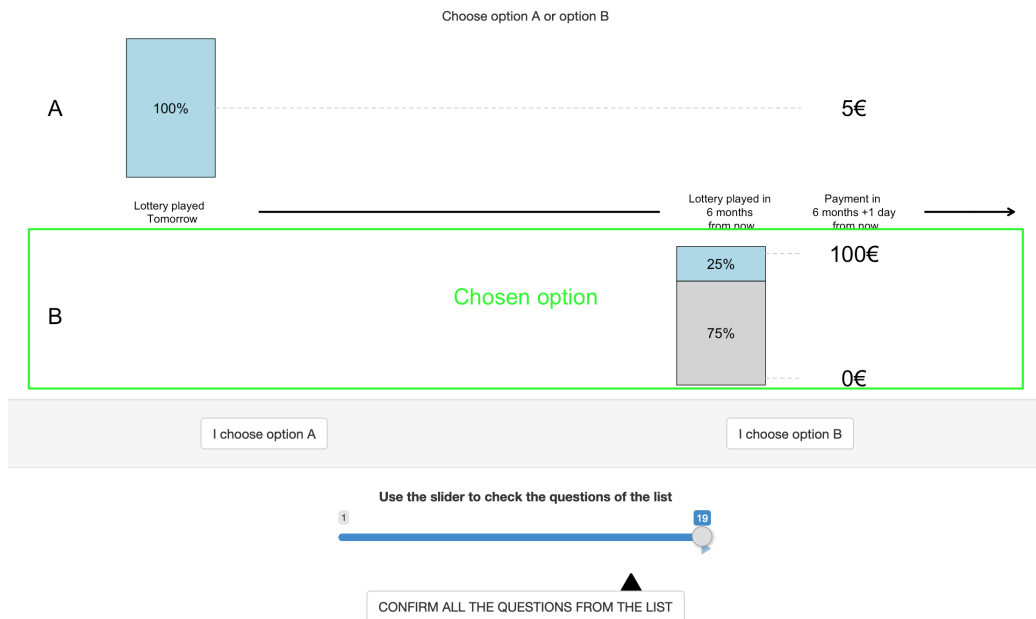
In this example, the subject is presented with the completed choice list corresponding to his CE as inferred from the bisection process. The arrowhead below the slider indicates the position of the latter where the subject is supposed to shift from option B to the risk-free option A given his choices during the bisection step. The slider can take on 11 positions from “1” to “11” corresponding to the sure amounts of money €95 to €45 (with a step-size of €5) respectively.

Figure 10: Elicitation of CEs  $c^0$  in study B



(a) Binary choice during the bisection step

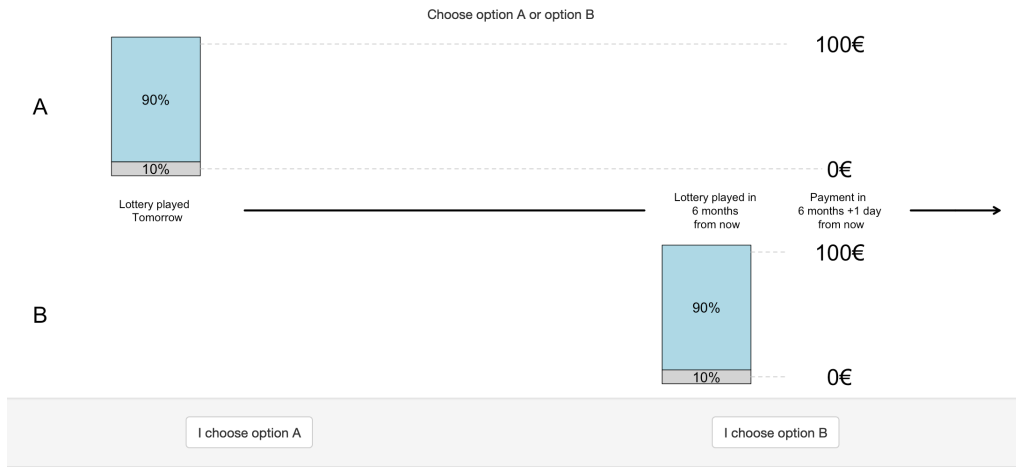
During the bisection step, subjects reported their preferences by clicking on the preferred lottery in each iteration. The process aims at determining the CE  $c^6$  of  $(X = 100, p^6 = 0.25, x = 0)$ .



(b) Choice list for confirmation

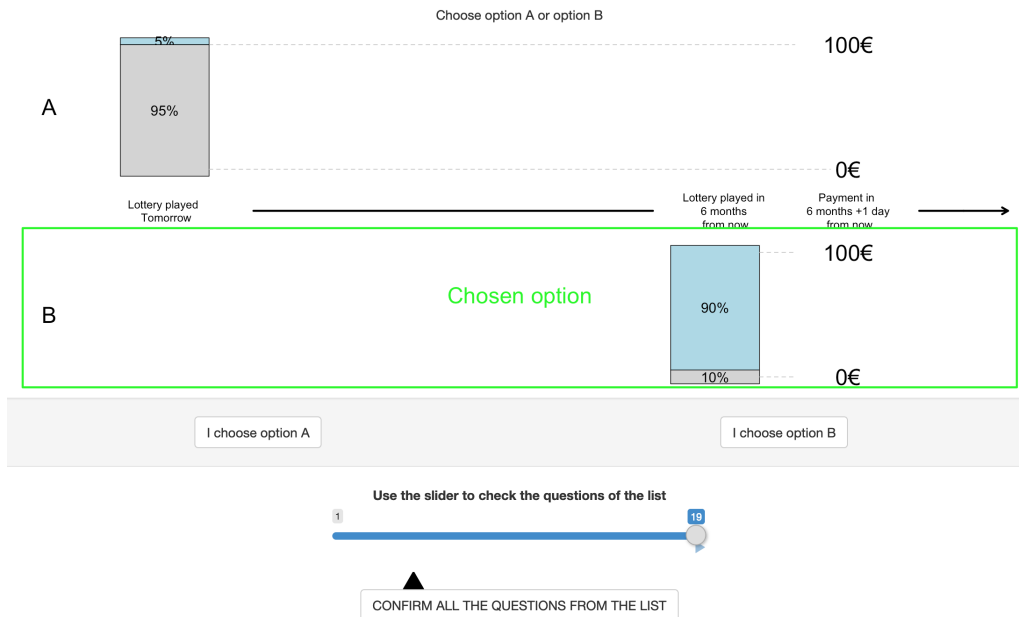
In this example, the subject was presented with the completed choice list corresponding to his CE as inferred from the bisection process. The arrowhead below the slider indicates the choice at which the subject was supposed to shift from option B to the risk-free option A given his choices during the bisection step. The slider can take on 19 positions from “1” to “19” corresponding to the sure amounts of money €95 to €5 (with a step-size of €5) respectively.

Figure 11: Elicitation of CEs  $c^6$  in study B



(a) Binary choice during the bisection step

During the bisection step, subjects reported their preferences by clicking on the preferred lottery in each iteration. The process aims at determining the MPP  $m^0$  of  $(X = 100, p^6 = 0.90, x = 0)$ .



(b) Choice list for confirmation

In this example, the subject was presented with the completed choice list corresponding to his MPP as inferred from the bisection process. The arrowhead below the slider indicates the choice at which the subject was supposed to shift from option *A* to option *B* given his choices during the bisection step. The slider can take on 19 positions from “1” to “19” corresponding to the winning probabilities 95% to 5% (with a step-size of 5%) respectively.

Figure 12: Elicitation of MPPs  $m^0$  in study B



## 597 B. Additional results

### 598 B.1. Reliability and real incentives in study A

599 **Reliability.** In order to verify the reliability of these MPP elicitations, we presented each  
600 subject in study A with the choice lists corresponding to lotteries  $(X, p^6, x) = (500, 0.90, 0)$  and  
601  $(X, p^{12}, x) = (500, 0.90, 0)$  twice. No difference was detected between the corresponding MPPs  
602 (paired  $t$ -tests, respectively  $p = 0.08$  and  $p = 0.92$ ). Furthermore, the elicited probabilities were  
603 highly correlated (Pearson's  $r = 0.80$  for  $t = 6$  and  $r = 0.83$  for  $t = 12$ ).

604 **Real incentives for MPPs.** To assess the effect of real incentives on subjects' behavior in  
605 study A, we performed a  $2 \times 16$  ANOVA test in which presence/absence of incentives was the  
606 between-subjects factor and the 16 lotteries served as the within-subjects factor. In line with  
607 our expectation, the MPPs varied across lotteries ( $p < 0.001$ ). Real incentives had no significant  
608 effect on MPPs ( $p = 0.67$ ) and did not interact with the lotteries ( $p = 0.98$ ).

609 **Real incentives for CEs.** A  $2 \times 11$  ANOVA test, where lotteries (11) were considered as  
610 a within-subject factor and presence of real incentives (yes / no) as a between-subject factor,  
611 shows that CEs are not affected by real incentives ( $p = 0.93$ ). The presence of real incentives  
612 (yes / no) do not interact with the lotteries ( $p = 0.76$ ).

### 613 B.2. Baseline risk preferences from CEs

614 Tables ?? and ?? report the main characteristics of the empirical distributions of CEs of imme-  
615 diately resolved lotteries in studies A and B, respectively. At the aggregate level, we observe a  
616 predominance of risk seeking (aversion) for  $p^0 = 0.10$  ( $p^0 > 0.10$ ), i.e., the mean CEs are above  
617 (below) the corresponding expected values. In other words, risk attitude for immediately resolved  
618 lotteries is probability-dependent as found in many studies (Bruhin et al., 2010; Wakker, 2010  
619 and references therein). This dependence accords with an inverse S-shaped baseline probability  
620 weighting function  $w_0$ .

Lottery						Lottery					
$X$	$x$	$p^0$	Mean	Std	$\#(CE \leq EV)$	$X$	$x$	$p^0$	Mean	Std	$\#(CE \leq EV)$
100	0	0.50	49.64	13.71	47/23***	60	0	0.25	16.10	5.80	41/27 <sup>ns</sup>
200	0	0.50	87.67	23.42	60/10***	60	0	0.75	33.80	7.30	62/6***
400	200	0.50	285.21	22.77	58/12***	80	20	0.25	33.50	4.60	55/13***
450	150	0.50	260.14	40.84	63/7***	80	20	0.75	48.10	8.20	66/2***
500	200	0.50	316.14	38.83	61/9***	90	10	0.25	27.40	6.50	51/17***
500	100	0.50	255.36	50.25	64/6***	90	10	0.75	50.30	9.40	66/2***
500	0	0.10	78.57	48.35	31/39 <sup>ns</sup>	100	0	0.10	16.10	8.90	29/39 <sup>ns</sup>
500	0	0.20	98.86	51.02	52/18***	100	0	0.25	21.50	22.50	53/15***
500	0	0.50	189.25	61.63	63/7***	100	0	0.50	37.20	6.10	68/0***
500	0	0.80	285.71	73.45	67/3***	100	0	0.75	53.60	12.10	66/2***
500	0	0.90	343.79	77.62	67/3***	100	0	0.90	65.20	11.90	66/2***

*ns*: non-significant; \*:  $p < 0.05$ ; \*\*:  $p < 0.01$ ; \*\*\*:  $p < 0.001$

(a) Study A

(b) Study B

Table 9: Empirical distributions of CEs for immediately resolved lotteries

### 621 B.3. Model-free measurement of attitude towards temporal risk

$p^t$	$t$	Study A ( $T = 12, n = 70$ )				Study B ( $T = 6, n = 68$ )			
		Mean	Median	Std	$\#(m^0 < p^t)$	Mean	Median	Std	$\#(m^0 < p^6)$
0.10	3	0.08	0.09	0.03	64***	-	-	-	-
	6	0.14	0.09	0.14	65***	0.14	0.12	0.065	29 <sup>ns</sup>
	9	0.07	0.07	0.03	65***	-	-	-	-
	12	0.13	0.09	0.14	62***	-	-	-	-
0.25	3	0.22	0.23	0.04	48**	-	-	-	-
	6	0.26	0.23	0.10	50 <sup>ns</sup>	0.23	0.22	0.042	51***
	9	0.21	0.21	0.05	55***	-	-	-	-
	12	0.24	0.21	0.11	55***	-	-	-	-
0.50	3	0.45	0.47	0.06	65***	-	-	-	-
	6	0.44	0.45	0.07	65***	0.43	0.42	0.052	64***
	9	0.44	0.45	0.07	65***	-	-	-	-
	12	0.43	0.45	0.08	62***	-	-	-	-
0.75	3	0.69	0.71	0.08	54***	-	-	-	-
	6	0.64	0.69	0.13	54***	0.65	0.67	0.081	66***
	9	0.67	0.69	0.10	59***	-	-	-	-
	12	0.62	0.67	0.14	67***	-	-	-	-
0.90	3	0.83	0.87	0.10	65***	-	-	-	-
	6	0.74	0.83	0.17	66***	0.78	0.77	0.089	66***
	9	0.80	0.83	0.11	65***	-	-	-	-
	12	0.72	0.79	0.19	63***	-	-	-	-

*ns*: non-significant; \*:  $p < 0.05$ ; \*\*:  $p < 0.01$ ; \*\*\*:  $p < 0.001$

Table 10: Empirical distributions of MPPs

622 We denote  $m_t^0$  the MPP such that  $(X, m_t^0, x) \sim (X, p^t, x)$ . For each probability level  $p^t \in$   
623  $\{0.1, 0.25, 0.5, 0.75, 0.9\}$ , we ran a Page test, with the null  $H_0 : m_{12}^0 = m_9^0 = m_6^0 = m_3^0$  against  
624 the alternative  $H_1 : m_{12}^0 \leq m_9^0 \leq m_6^0 \leq m_3^0$  or  $H_2 : m_{12}^0 \geq m_9^0 \geq m_6^0 \geq m_3^0$  with at least one strict  
625 inequality. The null was rejected for probability 0.1 ( $p = 0.003$ ) as well as for other probability  
626 levels ( $p < 0.001$ ). Median MPPs reported in Table ?? suggest that  $H_1$  is more likely to be

627 satisfied for a winning probability  $p^t \geq 0.25$ .

## 628 C. Econometric implementation

629 We used maximum likelihood methods to estimate each model—REU and different restrictions  
630 of RRDU,—at both the individual level and the aggregate level.

631 For each subject  $i$ , a choice list  $j$ , involving a vector of stimuli  $X_j$  (choice characteristics),  
632 consisted in the elicitation of an indifference value  $y_{i,j}^*$  (MPP or CE). Assuming a specific model  
633 of choice results in a theoretical prediction of  $y_{i,j}^*$  given by the equation  $\hat{y}_{i,j} = f(X_j, \beta_i)$ , where  
634  $\beta_i$  represents the vector of unknown parameters of the given model. We also assume that the  
635 random variable  $y_{i,j}$  is related to the theoretical value  $\hat{y}_{i,j}$  through a normally distributed random  
636 error  $\epsilon_{i,j}$  with mean 0 and Std  $\sigma_i$ , i.e.  $y_{i,j}^*$  is a realization of the random variable  $y_{i,j} = \hat{y}_{i,j} + \epsilon_{i,j}$ .

637 Observed indifference values were taken as the midpoint of an interval  $[y_{i,j}^* - k/2, y_{i,j}^* + k/2]$ ,  
638 where  $k$  represents the precision with which  $y$  was measured ( 101€7for CEs and 1% for MPPs  
639 in study A; 51€7for CEs and 5% for MPPs in study B). This means that the likelihood of each  
640 observation  $y_{i,j}^*$  corresponding to subject  $i$  and choice list  $j$  is given by

$$\begin{aligned} \pi_{i,j} &= p\left(y_{i,j}^* - \frac{k}{2} < y_{i,j} < y_{i,j}^* + \frac{k}{2}\right) \\ &= p\left(y_{i,j}^* - \frac{k}{2} - f(X_j, \beta_i) < \epsilon_{i,j} < y_{i,j}^* + \frac{k}{2} - f(X_j, \beta_i)\right) \\ &= F\left(\frac{y_{i,j}^* + \frac{k}{2} - f(X_j, \beta_i)}{\sigma_i}\right) - F\left(\frac{y_{i,j}^* - \frac{k}{2} - f(X_j, \beta_i)}{\sigma_i}\right), \end{aligned}$$

641 where  $F$  denotes the CDF of the normal distribution. The likelihood of a series of choice lists  
642 completed by a subject  $i$  is therefore

$$l_i(\beta_i) = \prod_j \pi_{i,j}.$$

643 The function  $f$  depends on the dependent variable considered: MPPs or CEs; it also depends  
644 on the model assumed: REU, RRDU ( $w_0 = w_T$ ), RRDU ( $U_0 = U_T$ ) or “full force” RRDU;  
645 and the parametric forms assigned to the components of each model. Consequently, a specific  
646 likelihood function  $l_i$  is defined and maximized for the estimation of the parameters under each  
647 configuration.

648 For individual-level estimations, the logarithm of each likelihood  $l_i$  is maximized separately,  
649 leading to individual estimations  $\hat{\beta}_i$  for each configuration. For aggregate-level estimations, we  
650 assume that all subjects have the same (representative agent's) parameters  $\beta$  and  $\sigma$  such that  
651  $l(\beta) = \prod_i l_i(\beta)$ .

652 Each (individual or aggregate-level) likelihood maximization use the BFGS algorithm with 50  
653 different starting values. For aggregate-level estimations, standard errors are computed from  
654 the crossproduct of individual scores, thus accounting for the clustering of responses within  
655 individuals. For both aggregate and individual estimations, we report the sum of individual log  
656 likelihoods:  $LL = \sum_i \log(l_i)$ .

657 The log-likelihood of estimations are used to assess the goodness of fit and compare models.  
658 When comparing two nested models, likelihood ratio test are used. When comparing non-  
659 nested models, the most commonly-used indexes are the Bayesian Information Criterion,  $BIC =$   
660  $-2LL+k\log(n)$ ; and the Akaike Information Criterion,  $AIC = -2LL+2k$ , where  $n$  is the number  
661 of observations and  $k$ , the number of parameters. It is worth noting that when comparing two  
662 non-nested models involving the same number of parameters, and estimated on the same sample,  
663 the model with the best (i.e., lowest) BIC and AIC is the model with the highest  $LL$ .

664 We also compare models in terms of prediction accuracy. In study B, estimates  $\hat{\beta}_i$  derived from  
665 CEs are used to make predictions  $f(\hat{\beta}_i, X)$  of the 5 MPPs. For a subject  $i$ , the accuracy of  
666 predictions is measured by the commonly-used root mean squared error  $RMSE_i = \sqrt{\frac{SSE_i}{5}}$ ,  
667 where  $SSE_i$  is the sum of squared errors:  $SSE_i = \sum_{k=1}^5 (f(\hat{\beta}_i, X_k) - y_{i,k})^2$ . For aggregate  
668 (individual) estimations, the mean (median) individual  $RMSE$  is used to measure the prediction  
669 accuracy.

670 **D. Additional parametric results**

671 **D.1. Attitudes towards temporal risk under REU from MPPs**

		Study A				Study B			
		Aggregate		Individual		Aggregate		Individual	
		Estimate	SE	Median	IQR	Estimate	SE	Median	IQR
Power	$\alpha$	1.27***	0.04	1.22	[1.08; 1.42]	1.20***	0.02	1.21	[1.01; 1.36]
Error	$\sigma$	0.10***	0.01	0.03	[0.01; 0.06]	0.09***	0.01	0.07	[0.03; 0.10]
Log-likelihood		-1043.15		-596.14		-694.46		-528.14	
Exponential	$\alpha$	-0.79***	0.10	-0.63	[-1.14;-0.23]	-0.68***	0.06	-0.66	[-1.09;-0.15]
Error	$\sigma$	0.09***	0.01	0.03	[0.01; 0.05]	0.09***	0.005	0.06	[0.03; 0.09]
Log-likelihood		-1029.32		-557.16		-669.61		-496.43	
Expo-power	$\alpha_1$	-1.86***	0.24	-0.90	[-1.99;-0.21]	-2.50***	0.02	-2.48	[-2.61;-1.10]
	$\alpha_2$	0.69***	0.04	0.96	[0.81; 1.01]	0.53***	0.01	0.62	[0.52; 0.76]
Error	$\sigma$	0.09***	0.01	0.03	[0.01; 0.05]	0.08***	0.005	0.05	[0.03; 0.08]
Log-likelihood		-1025.27		-531.12		-645.76		-454.25	

*ns*: non-significant; \*:  $p < 0.05$ ; \*\*:  $p < 0.01$ ; \*\*\*:  $p < 0.001$

Table 11: Estimates of  $\varphi$  under REU from MPPs

672

673 Table ?? reports information about aggregate and individual estimates of the transformation  
674 function  $\varphi$  under REU. At the aggregate level, a likelihood ratio test shows that the null hy-  
675 pothesis of a constant  $\varphi$  across resolution delays (3, 6, 9, 12) is rejected ( $p = 0.002$ ). An ANOVA  
676 test with repeated measures based on individual estimates confirms that the delay of resolution  
677 affects  $\varphi$  ( $p < 0.05$ ).

Parameter	$t$	Aggregate		Individual		
		Estimate	SE	Median	Mean	Std
$\alpha$	3	-0.49***	0.07	-0.41	-0.53	0.68
	6	-0.64***	0.09	-0.52	-0.71	0.92
	9	-0.70***	0.09	-0.63	-0.76	0.90
	12	-0.79***	0.10	-0.62	-0.89	1.13
Error ( $\sigma$ )		0.08	0.01	0.03	0.04	0.04
Log-likelihood		-3951.92		-2280.97		

*ns*: non-significant; \*:  $p < 0.05$ ; \*\*:  $p < 0.01$ ; \*\*\*:  $p < 0.001$

Table 12: Estimates of an exponential  $\varphi$  from MPPs in study A

678 **D.2. Attitudes towards temporal risk under REU from CEs**

Component		Aggregate		Individual	
		Estimate	SE	Median	IQR
Expo-power utility ( $U_T$ )	$\alpha_1$	0.004***	0.0007	0.004	[ 0.002; 0.009]
	$\alpha_2$	1.58***	0.05	1.57	[ 1.32; 1.77]
Power ( $\varphi$ )	$\alpha$	1.70***	0.05	1.68	[1.41; 2.07]
Error (now)	$\sigma_0$	9.06***	0.36	5.82	[4.92; 7.42]
Error (later)	$\sigma_6$	9.33***	0.35	6.81	[5.69; 8.17]
Log-likelihood		-3052.77		-2512.76	
Expo-power utility ( $U_T$ )	$\alpha_1$	0.003***	0.0006	0.004	[ 0.001; 0.008]
	$\alpha_2$	1.65***	0.05	1.74	[ 1.50; 2.62]
Exponential ( $\varphi$ )	$\alpha$	-1.53***	0.08	-1.22	[-2.10;-0.75]
Error (now)	$\sigma_0$	9.04***	0.36	6.69	[4.77; 7.28]
Error (later)	$\sigma_6$	9.24***	0.36	6.72	[5.64; 7.80]
Log-likelihood		-3043.06		-2487.44	
Expo-power utility ( $U_T$ )	$\alpha_1$	0.0003***	0.0005	0.004	[ 0.001; 0.007]
	$\alpha_2$	1.66***	0/05	1.59	[1.38; 1.83]
Expo-power ( $\varphi$ )	$\alpha_1$	-1.97***	0.32	-2.42	[-2.67;-0.74]
	$\alpha_2$	0.86***	0.10	0.71	[ 0.55; 1.29]
Error (now)	$\sigma_0$	9.04***	0.36	5.59	[4.54; 7.25]
Error (later)	$\sigma_6$	9.23***	0.36	6.74	[5.63; 7.92]
Log-likelihood		-3042.85		-2470.57	

*ns*: non-significant; \*:  $p < 0.05$ ; \*\*:  $p < 0.01$ ; \*\*\*:  $p < 0.001$

Table 13: Estimates of  $U_T$  and  $\varphi$  under REU

Component	Aggregate			Individual	
		Estimate	SE	Median	IQR
Expo-power Utility ( $U_T$ )	$\alpha_1$	0.0007***	0.0002	0.0001	[-0.4827;0.0012]
	$\alpha_2$	1.45***	0.06	1.35	[0.46;1.80]
Power ( $\varphi$ )	$\alpha$	0.90***	0.04	0.91	[0.71;1.21]
Probability weighting ( $w_0$ )	$\delta$	1.38***	0.06	1.53	[1.26;1.82]
	$\gamma$	0.53***	0.02	0.57	[0.44;0.68]
Probability weighting ( $w_T$ )	$\delta$	1.82***	0.08	1.92	[1.49;2.28]
	$\gamma$	0.41***	0.02	0.43	[0.29;0.50]
Error (now)	$\sigma_0$	8.16***	0.38	3.96	[3.12; 4.79]
Error (later)	$\sigma_6$	8.02***	0.39	4.28	[0.39; 5.80]
Log-likelihood		-2865.52			-1911.95
Expo-power utility ( $U_T$ )	$\alpha_1$	0.0007*	0.0003	0.00004	[-0.078;0.001]
	$\alpha_2$	1.38***	0.04	1.25	[0.76;1.52]
Exponential ( $\varphi$ )	$\alpha$	0.36 <sup>ns</sup>	0.21	0.57	[-0.62;1.58]
Probability weighting ( $w_0$ )	$\delta$	1.39***	0.07	1.62	[1.08;1.94]
	$\gamma$	0.54***	0.02	0.57	[0.44;0.69]
Probability weighting ( $w_T$ )	$\delta$	1.79***	0.08	1.87	[1.46;2.36]
	$\gamma$	0.40***	0.02	0.39	[0.27;0.48]
Error (now)	$\sigma_0$	8.16***	0.38	3.76	[3.08; 4.65]
Error (later)	$\sigma_6$	8.02***	0.39	4.35	[3.31; 5.71]
Log-likelihood		-2865.76			-1893.59
Expo-power utility ( $U_T$ )	$\alpha_1$	0.0007**	0.0002	0.00004	[-0.018; 0.0009]
	$\alpha_2$	1.43***	0.06	1.32	[0.96; 1.76]
Expo-power ( $\varphi$ )	$\alpha_1$	0.16 <sup>ns</sup>	0.29	0.19	[-2.23;1.59]
	$\alpha_2$	0.92***	0.06	0.91	[0.60;1.35]
Probability weighting ( $w_0$ )	$\delta$	1.36***	0.07	1.68	[1.24; 2.00]
	$\gamma$	0.53***	0.02	0.58	[ 0.44; 0.69]
Probability weighting ( $w_T$ )	$\delta$	1.83***	0.08	1.91	[0.32;0.70]
	$\gamma$	0.40***	0.02	0.40	[0.28;0.48]
Error (now)	$\sigma_0$	8.16***	0.38	3.70	[3.01; 4.57]
Error (later)	$\sigma_6$	8.02***	0.39	4.29	[3.31; 5.68]
Log-likelihood		-2865.46			-1858.70
Expo-power utility ( $U_T = U_0$ )	$\alpha_1$	0.001***	0.0002	0.0003	[-0.311; 0.002]
	$\alpha_2$	1.38***	0.04	1.29	[0.64; 1.50]
Probability weighting ( $w_0$ )	$\delta$	1.45***	0.06	1.56	[1.27; 1.79]
	$\gamma$	0.53***	0.02	0.56	[0.43; 0.68]
Probability weighting ( $w_T$ )	$\delta$	1.73***	0.07	1.90	[1.45; 2.12]
	$\gamma$	0.41***	0.02	0.43	[0.30; 0.50]
Error (now)	$\sigma_0$	8.16***	0.38	4.01	[3.15; 4.95]
Error (later)	$\sigma_6$	8.03***	0.39	4.35	[3.35; 5.83]
Log-likelihood		-2866.23			-1939.67

ns: non-significant; \*:  $p < 0.05$ ; \*\*:  $p < 0.01$ ; \*\*\*:  $p < 0.001$

Table 14: Estimates of  $U_T$ ,  $\varphi$ ,  $w_0$ , and  $w_T$  under RRDU

682 **D.4. Attitudes towards temporal risk under RRDU with  $w_0 = w_T$**

Component		Aggregate		Individual	
		Estimate	SE	Median	IQR
Expo-power utility ( $U_T$ )	$\alpha_1$	0.0018***	0.0003	0.0006	[-0.0001; 0.003]
	$\alpha_2$	1.39***	0.04	1.33	[ 1.05; 1.56]
Exponential ( $\varphi$ )	$\alpha$	-0.98***	0.06	-1.00	[-1.39;0.74]
Probability weighting ( $w$ )	$\delta$	1.62***	0.06	1.71	[ 1.30; 2.03]
	$\gamma$	0.48***	0.02	0.49	[ 0.34; 0.59]
Error (now)	$\sigma_0$	8.22***	0.38	4.29	[3.38; 5.27]
Error (later)	$\sigma_6$	8.11***	0.38	4.73	[3.77; 6.17]
Log-likelihood		-2879.78		-2043.45	
Expo-power utility ( $U_T$ )	$\alpha_1$	0.0014***	0.0003	0.0005	[0.0001; 0.0023]
	$\alpha_2$	1.50***	0.05	1.41	[ 1.20; 1.68]
Expo-power ( $\varphi$ )	$\alpha_1$	-2.33***	0.52	-2.44	[-3.29;-0.93]
	$\alpha_2$	0.64***	0.10	0.63	[ 0.52; 0.95]
Probability weighting ( $w$ )	$\delta$	1.65***	0.07	1.66	[ 1.25; 2.11]
	$\gamma$	0.48***	0.02	0.49	[ 0.32; 0.58]
Error (now)	$\sigma_0$	8.19***	0.38	4.08	[3.27; 4.96]
Error (later)	$\sigma_6$	8.10***	0.38	4.72	[3.68; 6.03]
Log-likelihood		-2875.14		-1991.20	

*ns*: non-significant; \*:  $p < 0.05$ ; \*\*:  $p < 0.01$ ; \*\*\*:  $p < 0.001$

Table 15: Estimates of  $U_T$ ,  $\varphi$  and  $w = w_0 = w_T$  under RRDU

683

684 **E. Attitudes towards temporal risk in study A**

685 **E.1. Attitudes towards temporal risk under REU**

686 Table ?? reports information about aggregate and individual estimates of the transformation  
687 function  $\varphi$  under REU. At the aggregate level, a likelihood ratio test shows that the null hy-  
688 pothesis of a constant  $\varphi$  across resolution delays (3, 6, 9, 12) is rejected ( $p = 0.002$ ). An ANOVA  
689 test with repeated measures based on individual estimates confirms that the delay of resolution  
690 affects  $\varphi$  ( $p < 0.05$ ).



Parameter	$t$	Aggregate		Individual		
		Estimate	SE	Median	Mean	Std
$\varphi$	3	-0.49***	0.07	-0.41	-0.53	0.68
	6	-0.64***	0.09	-0.52	-0.71	0.92
	9	-0.70***	0.09	-0.63	-0.76	0.90
	12	-0.79***	0.10	-0.62	-0.89	1.13
Error ( $\sigma$ )		0.08	0.01	0.03	0.04	0.04
Log-likelihood		-3951.92		-2280.97		

*ns*: non-significant; \*:  $p < 0.05$ ; \*\*:  $p < 0.01$ ; \*\*\*:  $p < 0.001$

Table 16: Estimates of an exponential  $\varphi$  from MPPs in study A

## 691 E.2. Attitudes towards temporal risk under RRDU

692 Table ?? reports aggregate and individual estimates of the probability weighting function  $w_t$   
693 under RRDU (see also Figure ??). We assume Prelec and power specifications for  $w_t$  (elevation  
694  $\delta_t$ ; sensitivity  $\gamma_t$ ) and  $U_0 = U_T$ , respectively. Note that we cannot estimate the full-force RRDU  
695 because we only elicited CEs for immediately resolved lotteries.

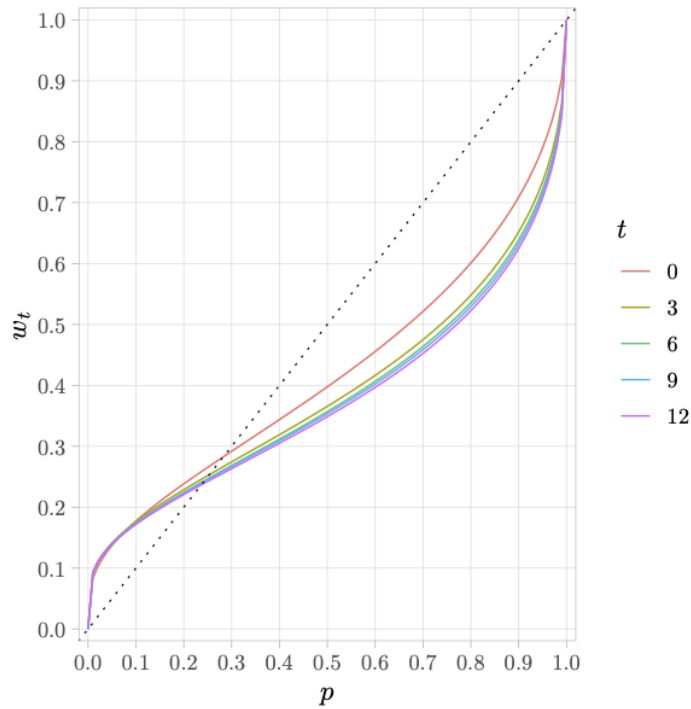


Figure 13:  $w_t$  for the mean parameter estimates

696 At the aggregate level, a likelihood ratio test shows that the null hypothesis of an invariant  $w_t$   
697 across resolution delays ( $\delta_0 = \delta_3 = \delta_6 = \delta_9 = \delta_{12}$  and  $\gamma_0 = \gamma_3 = \gamma_6 = \gamma_9 = \gamma_{12}$ ) is rejected  
698 ( $p < 0.001$ ). An ANOVA test with repeated measures based on individual estimates confirms  
699 that the delay of resolution  $t$  affects the log of both the elevation parameter  $\delta_t$  ( $p < 0.001$ ) and

700 the sensitivity parameter  $\gamma_t$  ( $p < 0.001$ ).

701 Three subjects have outlying estimates for  $t = 12$  ( $\delta_{12} > 5$  or  $\gamma_{12} > 5$ ), hence the large standard  
702 deviations for these individual parameters. The results of the ANOVA tests are unchanged when  
703 these subjects are excluded from the analysis.

Parameter	$t$	Aggregate		Individual		
		Estimate	SE	Median	Mean	Std
Power utility	12	0.931 ***	0.036	0.924	1.006	0.383
$\delta_t$	0	1.118 ***	0.049	1.104	1.277	0.565
	3	1.189 ***	0.055	1.237	1.401	0.623
	6	1.212 ***	0.057	1.240	1.445	0.617
	9	1.220 ***	0.057	1.266	1.454	0.629
	12	1.233 ***	0.058	1.289	1.957	2.799
$\gamma_t$	0	0.524 ***	0.025	0.525	0.559	0.215
	3	0.454 ***	0.027	0.446	0.484	0.223
	6	0.442 ***	0.025	0.422	0.465	0.212
	9	0.434 ***	0.026	0.441	0.452	0.209
	12	0.428 ***	0.026	0.447	0.653	1.194
Error CE		49.811 ***	0.131	19.831	20.762	4.565
Error MP		0.076 ***	0.008	0.029	0.034	0.023
Log-likelihood		-5466.589		-3607.882		

*ns*: non-significant; \*:  $p < 0.05$ ; \*\*:  $p < 0.01$ ; \*\*\*:  $p < 0.001$

Table 17: Estimates of  $U_0 = U_T$  and  $w_t$  from CE ( $t = 0$ ) and MPPs ( $t > 0$ ) in study A

## 704 F. Data recovery analysis

705 We focus on the “full force” RRDU that was estimated using the CEs collected in study B  
706 (see Table 1). We assume expo-power specifications for  $U_T$  and  $\varphi$ , and a two-parameter Prelec  
707 weighting functions  $w_0$  and  $w_T$ . Specifically, in order to check that our stimuli warrant reliable  
708 estimates of the resulting vector  $\beta$  of 8 parameters, we used our econometric procedures to  
709 estimate RRDU from simulated CEs provided by a virtual sample of 68 subjects. We used the  
710 vector of RRDU parameters  $\hat{\beta}_i$  that was estimated for subject  $i$  in our experimental sample  
711 to generate the CEs of lotteries reported in Table 1 for subject  $i$  in the simulated sample.  
712 Further, in order to reproduce response errors, we add a random noise to the simulated CEs,  
713 with a variance  $\sigma_i^s$  corresponding to the estimated individual variances in the experimental data  
714 ( $\sigma_i^s = \hat{\sigma}_i$ ). Finally, for the CEs of prospects  $x_p y$ , we censor the simulated values that are outside  
715 the interval  $(y, x)$  and we round the values to multiples of 5 euros, in order to simulate values with  
716 the same (im)precision as our experimental measures. We denote  $\hat{\beta}_i^s$  the vector of parameters  
717 of the virtual subject  $i$  estimated from the simulated CEs.

718 Aggregate level analyses compare the vectors  $\hat{\beta}^s$  and  $\hat{\beta}$  of the representative subjects in the

719 simulated and experimental samples, respectively (Table ??). Individual level analyses compare  
 720  $\hat{\beta}_i^s$  and  $\hat{\beta}_i$  the vectors of estimated parameters for the experimental and simulated subject,  
 721 respectively (Table ??).

Parameter		Experimental data		Simulated data	
		Estimate	Std Error	Estimate	Std Error
Expo-power utility ( $U_T$ )	$\alpha_1$	0.0007	0.0002	0.000	0.001
	$\alpha_2$	1.43	0.06	1.30	0.070
Expo-power ( $\varphi$ )	$\alpha_1$	0.16	0.29	0.89	0.317
	$\alpha_2$	0.92	0.06	1.05	0.079
Probability weighting ( $w_0$ )	$\delta$	1.36	0.07	1.32	0.084
	$\gamma$	0.53	0.02	0.54	0.027
Probability weighting ( $w_T$ )	$\delta$	1.83	0.08	1.83	0.107
	$\gamma$	0.40	0.02	0.38	0.021
LL		-2865.46		-2842.86	

Table 18: Aggregate estimates on experimental and simulated data

722 A likelihood ratio test does not reject the assumption that  $\hat{\beta}^s = \hat{\beta}$  ( $p = 0.69$ ). This suggests that  
 723 there is no statistically significant difference between the simulated values and the experimental  
 724 ones.

725 Table ?? reports the main characteristics of the empirical distributions of parameters estimated  
 726 (at the individual level) from experimental vs. simulated CEs. A series of paired  $t$ -tests do  
 727 not reject the null hypotheses  $\hat{\beta}^s[j] = \hat{\beta}[j]$  for  $j = 1, \dots, 8$ . Similarly, Kolmogorov-Smirnov tests  
 728 cannot reject the equality of empirical distributions of parameters for experimental vs. simulated  
 729 data. Table ?? also reports Spearman correlation coefficients.

Parameter		Experimental data		Simulated data		Comparison		
		Median	IQR	Median	IQR	$t$ -test (p)	Spearman	KS-test (p)
Expo-power utility ( $U_T$ )	$\alpha_1$	0.000	[-0.018; 0.001]	-0.000	[-0.072; 0.002]	0.760	0.072	0.457
	$\alpha_2$	1.316	[0.960; 1.756]	1.198	[0.748; 1.664]	0.914	0.352	0.594
Expo-power utility ( $\varphi$ )	$\alpha_1$	0.189	[-2.229; 1.589]	0.857	[-0.235; 2.516]	0.252	0.939	0.112
	$\alpha_2$	0.911	[0.596; 1.346]	1.066	[0.719; 1.495]	0.080	0.729	0.112
Probability weighting ( $w_0$ )	$\delta$	1.681	[1.236; 2.001]	1.618	[1.039; 2.338]	0.117	0.538	0.457
	$\gamma$	0.580	[0.441; 0.689]	0.576	[0.413; 0.755]	0.605	0.649	0.338
Probability weighting ( $w_T$ )	$\delta$	1.905	[1.524; 2.434]	1.980	[1.322; 2.926]	0.135	0.711	0.241
	$\gamma$	0.400	[0.284; 0.480]	0.406	[0.298; 0.504]	0.553	0.471	0.994

Table 19: Individual estimates on experimental and simulated data