Theory Dec. (2016) 80:71–100
DOI 10.1007/s11238-015-9490-3

Comparing attitudes toward time and toward money in experience-based decisions

Emmanuel Kemel · Muriel Travers

Published online: 21 April 2015

Abstract This paper reports an experimental comparison of attitudes toward time and toward money in experience-based decisions. Preferences were elicited under rank-dependent utility for prospects with two or three consequences expressed either in time or in monetary units. Probabilities were unknown but learned through sampling. More specifically, time and money were compared under two conditions. In a first experiment, both consequences and probabilities of prospects were unknown and learned through sequential sampling. In a second experiment, the possible consequences were revealed after the sampling. A real incentive system was implemented for both time and money. The heterogeneity of preferences was assessed for time and for money through individual and mixed modeling estimations. We observe that the nature of consequences (time or money) modifies probability weighting in terms of elevation and sensitivity. Subjects exhibit more optimism and less sensitivity to probability changes when deciding about time than about money. Revealing the consequences impacts the shape of the utility function and leaves probability weighting unchanged. We also observe that the real incentives have no effect except for the reduction in decision errors. This effect is stronger for money than for time.

Keywords Experience-based decisions · Time · Real incentives · Mixed modeling · Errors · Probability weighting

E. Kemel (✉)
GREGHEC & Cerema, Nantes, France
e-mail: emmanuel.kemel@cerema.fr

M. Travers
UMR Granem, University of Angers, Angers, France
e-mail: muriel.travers@univ-angers.fr

1 Introduction

Most everyday life décisions involve uncertainty, at some point. In most empirical investigations of choice behavior under uncertainty, choice alternatives are risky prospects, i.e., probability distributions over a set of consequences. Aside from games of chance where probabilities are objective, decision makers hardly ever know the probabilities involved in real life decisions. Probabilities are rarely totally unknown either. Decision makers can base their choice on their experience, i.e., on previously observed frequencies. For instance, drivers planning a visit to their family may not have access to the distribution of travel time for each time period. However, they may recall from their past visits that traffic jams are more frequent in some time slots than in others and choose their departure time based on past observations of travel time. In 2004, Hertwig, Barron, Weber, and Erev (hereafter HBWE) compared decisions from *description*, where probabilities are known from description and *experience-based decisions* (EBD) where probabilities are learned from experience. In EBD, subjects had to choose between prospects whose probability distribution and possible consequences were not indicated. Instead, they had the possibility of learning about the distributions through sequential sampling, before making their decisions. EBD has engendered an important stream of empirical literature (Hertwig et al. 2006; Hau et al. 2008; Camilleri and Newell 2009, 2011; Ungemach et al. 2009; Abdellaoui et al. 2011). According to this literature, rare events receive different subjective treatments depending on whether they are described or experienced. More precisely, accumulated empirical results show that small probabilities are overweighted in decisions from description. In EBD, however, the weighting of small probabilities is smaller. This characterizes the so-called "described-versus-experienced gap."

Although one of the reasons for studying decision from experience stems from its proximity to real life decisions, most empirical investigations of the gap focus on binary prospects involving money. Hau et al. (2008) called for an exploration of EBD in a "wider range of problems." Real life situations can indeed involve more than two consequences and non-monetary attributes. One of the non-monetary attributes of particular concern in economic studies is time. Time is at stake in health economics (life duration), management and education, travel and consumer behavior (travel or waiting time). Aside from medical decision making where attitudes toward life duration are analyzed (e.g., Bleichrodt and Pinto 2000), empirical studies of decisions involving time gains are relatively rare in the decision theory literature. Attitudes toward time risk have been assessed by a sizable transportation literature, but investigations under descriptive models such as rank-dependent utility (hereafter RDU) are less common (Li and Hensher 2011). Analyzing risk attitudes toward gains and losses is not as straightforward for time as it is for money. While the current level of wealth offers a natural reference point for money prospects, there is no such equivalent for time. Abdellaoui and Kemel (2014) asked subjects to participate in a 2-h experiment. Time gains (losses) were defined as the possibility to leave the experiment earlier (later) than expected. The authors compared time and money in risky decisions in terms of utility and probability weighting. Although the main patterns of prospect theory (loss aversion and inverse S-shaped probability weighting) hold for time, utility and decisions weights differed across attributes.

This paper presents an empirical comparison of attitudes toward time and toward money in EBD. Hadar and Fox (2009) proposed the following definition of EBD: decision makers' knowledge of the possible consequences or the corresponding probabilities is incomplete and information can be collected through sampling. In the standard HBWE paradigm, both consequences and probabilities are unknown. In the framework built by Savage (1954) and adopted by most decision models, decision makers are assumed to know the state space i.e., all the aspects of the world that are relevant for the decision. If subjects do not know the state space, this may lead to asymmetries of information between them and the experimenters. For instance, when only one consequence is observed through sampling, subjects may take it as being certain although it is not, and vice versa (Hadar and Fox 2009). Several authors (e.g., Hadar and Fox 2009; Abdellaoui et al. 2011) have proposed an adaptation of the EBD paradigm, in which subjects were presented with the set of possible consequences before making their choice. According to Hadar and Fox's (2009) terminology, we call the condition where the set of possible consequences is revealed the *complete information condition* and, the other condition, in which no other information but sampling is provided the *incomplete information condition*. We ran two experiments to compare attitudes toward time and toward money at the individual level and across these two conditions. Both experiments involved experienced prospects with two or three consequences and whose probabilities were not described but learned through sampling. In the first experiment, decisions were made under the complete information condition: the consequences were revealed to the subject before the decisions (as in Abdellaoui et al. 2011). The second experiment implemented the incomplete information condition, and neither the probabilities nor the consequences were indicated (as in Hertwig et al. 2004). We measured attitudes under RDU. Two groups of 40 students participated in each of these experiments, with a real incentive system implemented for both time and money.

The distribution of RDU parameters (i.e., utility and probability weighting) in this pool was measured for each attribute using individual level and mixed modeling estimations. Mixed modeling has been increasingly used in the empirical decision literature to assess the heterogeneity of preferences. Bruhin et al. (2010) proposed a finite mixture model that captured the heterogeneity of the respondents by identifying several classes of parameters. Heterogeneity can also be assessed by models that assume continuous distributions of parameters among the population of respondents (Train 2009). Andersen et al. (2012) used a mixed model of this type to estimate the distribution of the utility parameter on a subject sample, assuming expected utility. This first attempt was made using standard likelihood maximization methods but Bayesian methods such as the expectation maximization (EM) algorithm can be more efficient, especially when more parameter are concerned (Train 2009). Toubia et al. (2013) used a Bayesian approach to estimate continuous distributions of RDU parameters. The present study builds on these recent developments to measure the heterogeneity of preferences in EBD.

To summarize, this empirical investigation estimates RDU parameters in EBD involving two or three consequences with gains expressed in monetary or time units. The objective is to test whether "preferences towards time are the same as preferences towards money, in EBD" (our H0 hypothesis). This hypothesis is tested under two conditions, when possible consequences are revealed after sampling (the complete information condition), and when they are not (the incomplete information condition). The next section introduces the theoretical background. Section 3 presents the experimental design. This section also presents also the stimuli, data collection method, and the parameter estimation procedure. Section 4 presents the results: a raw data analysis is provided followed by the results of RDU parameter estimations. These results are discussed in Sect. 5.

2 Theoretical background

2.1 Notation

We consider a decision maker who has to choose between experienced prospects involving up to three possible consequences. Consequences are non-negative and expressed in time or monetary units. Considering three consequences $x > y > z$, a prospect $P = \left(x, p_x; y, p_y; z, p_z\right)$ offers a gain x with probability p_x, a gain y with a probability p_y, and a gain z with probability $p_z = 1 - p_x - p_y$. In this study, p_x and p_z are non null and the case where $p_y = 0$ refers to a two-consequence prospect. Prospects with consequences expressed in monetary (resp. time) units are referred to as money (resp. time) prospects. The conventional notations $\succ$ and $\sim$ are used to represent strict preference and indifference over prospects.

2.2 Risk attitudes under rank-dependent utility

In order to capture attitudes toward probabilities in EBD, we measure preferences under RDU. This model measures attitudes toward outcomes with a utility function u and attitudes toward chance with a probability weighting function w. A RDU maximizer assigns a prospect $P = \left(x, p_x; y, p_y; z, p_z\right)$, the value $V(P)$ according to (1).

$$\begin{aligned} V(P) = w(p_x)\, u(x) &+ \left[w\left(p_x + p_y\right) - w(p_x)\right] u(y) \\ &+ \left[w\left(p_x + p_y + p_z\right) - w\left(p_x + p_y\right)\right] u(z), \end{aligned} \tag{1}$$

u is strictly increasing and defined up to a positive linear transformation and can be normalized so that $u(0) = 0$. The function w is uniquely defined and strictly increasing from [0, 1] to [0, 1]. It satisfies $w(0) = 0$ and $w(1) = 1$. This model includes the expected utility model as a particular case where w is linear.

Equation 1 assumes that decision makers do not make errors when valuing prospects and that their choices directly derive from RDU components. A more flexible specification involves the accounting for the errors made by the decision maker. Formally, errors such as these can be introduced by adding a Fechner error i.e., a random parameter to the value function. In this paper, we assume that the value assigned to a prospect (V_{s}) contains this type of stochastic error.

$$V_{\mathrm{s}}(P) = V(P) + \varepsilon. \tag{2}$$

ε denotes a random error centered around 0 and with a variance of σ^2. Equation 2 provides a formula for the estimation of RDU components using econometric methods[1] (Wilcox 2008). A large range of parametric specifications is now available for both utilities and decision weighting functions (Stott 2006; Palma et al. 2008). For the probability weighting function, we consider the two most popular specifications, proposed by Goldstein and Einhorn (GE, 1987) and Prelec (1998), respectively.

$$\text{Prelec: } w(p) = \exp(-(-\log(p))^{\gamma})^{\delta}.$$
$$\text{GE: } w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}}.$$

The δ parameter of the GE specification (resp. Prelec) is an index (resp. anti-index) of elevation of the weighting function. The parameter γ measures the sensitivity to probability change. Each parameter received a psychological interpretation (Gonzalez and Wu 1999; Wakker 2010). The more (resp. less) elevated the weighting function, the more optimistic (resp. pessimistic) the decision maker. For the GE specification, the δ elevation parameter directly relates to the weighting of probability 0.5, with $w(0.5) = \delta/(1+\delta)$. Under this specification, δ gives information about attitudes towards the middle of the probability interval. When $\delta < 1$ (resp. $\delta > 1$) probability 0.5 is underweighted (resp. overweighted). The second dimension relates to the cognitive capability to discriminate probabilities. The smaller the γ, the weaker the sensitivity toward probability changes in the middle of the [0, 1] interval. Regarding the utility, the power (CRRA) utility function is often used in the literature, and this specification is used in the present study. The power parameter α measures the curvature of the utility function.

2.3 Source attitudes under rank-dependent utility

Most of the estimations of RDU parameters reported in the literature deal with risk and money. However, RDU can also be used under ambiguity, when probabilities are not known (Wakker 2010). Abdellaoui et al. (2010) have shown that ambiguity impacts RDU parameters. More precisely, ambiguity has an impact on the weighting function in terms of elevation and sensitivity. Probability weighting can thus vary with the source of uncertainty and its degree of ambiguity. Attitudes toward sources are captured by source functions i.e., probability weighting functions that can vary from one source to another, but are assumed to remain stable within source (see Abdellaoui et al. 2010 for a formal definition of sources and source functions). Abdellaoui et al. (2011) proposed to consider probabilities in EBD as a given source of uncertainty and show that this source generates different attitudes than risk. In the present study, we propose to explore source preference in EBD in further detail. Under the incomplete information condition, subjects receive less information than under the complete

[1] We accounted for between-subject heteroscedasticity by allowing σ to vary across individuals. However errors are assumed to be homoscedastic across choices. If this assumption is violated, standard errors may be biased. For this reason, inference relies either on bootstrap or on a comparison of individual-level parameters.

information condition. The former condition may thus constitute a source that is more ambiguous than the latter. For this reason, we allow attitudes toward uncertainty in EBD to differ between the complete and the incomplete information condition.

We also extend the concept of source in another direction. Wakker (2010, p. 327) draws a parallel between ambiguous events and non-monetary outcomes which can both generate a wide diversity of attitudes. The present study comes in the aftermath of Abdellaoui and Kemel (2014) who showed that the type of outcome at stake also impacts attitudes. From a descriptive perspective, we consider in this paper that a source is characterized not only by the process that generates the uncertainty, but also by the type of outcome at stake. Therefore, time prospect and money prospect are considered empirically as two different sources. RDU parameters are assumed to be stable within a given attribute but can vary across attributes. The behavior of a decision maker for a given source s is characterized by a vector of parameters $\beta_s = (\alpha_s, \delta_s, \gamma_s, \sigma_s)$ that measures the decision maker's utility, optimism, sensitivity, and amplitude of errors of the decision maker, for a source s. Our objective is to compare the individual parameters for money (β_{m}) and time (β_t) in EBD. Studying attitudes toward ambiguous sources (i.e., situations with unknown probabilities) requires controlling for subjective probabilities. We assume that there is no sampling bias and that subjective probabilities learned through sampling correspond to the objective probabilities. In Appendix 5, we test the stability of the results when subjective probabilities are assumed instead to fit the sampled frequencies.

3 Experiment

3.1 Experimental design

3.1.1 Decision tasks

We observed behavior in EBD under two conditions: the complete information condition and the incomplete information condition. A separate experiment was run for each condition. In both experiments, the decision task consisted of choices between an experienced prospect and a series of sure offers. The objective probabilities of the experienced prospects were not revealed to the decision makers. Instead, subjects had the possibility to observe realizations from the underlying distributions by sampling them as often as they wanted.

Figure 1 shows the sampling display of a time prospect. Panels b and c are realizations observed after each click on the sample button. For money prospect, the realizations were expressed in money units. The sampling display was the same under the two conditions. After sampling, the subjects had to make a decision between a series of sure gains and the experienced prospects.

The display used for the choices differed across conditions. Under the complete information condition, the prospect was presented by a decision tree in which consequences were displayed and probabilities were not (cf. Fig. 2a). This type of display is similar to the one used by Abdellaoui et al. (2011). Under the incomplete information condition, the set of possible consequences of the experienced prospect was

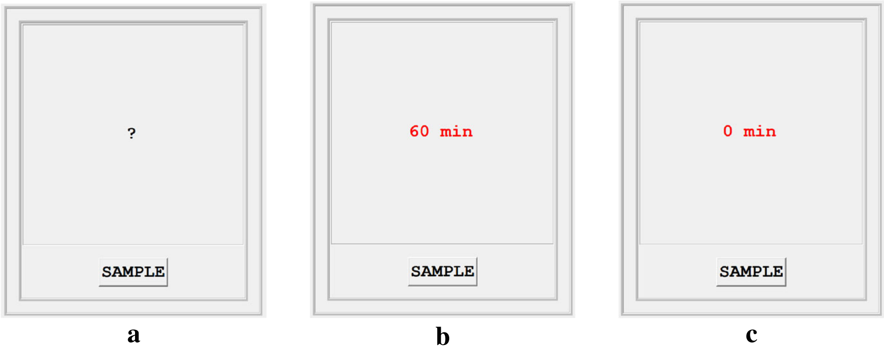

Fig. 1 Sampling display (identical in the two experiments). **a** Before sampling, **b** observation of a first realization, **c** observation of a second realization

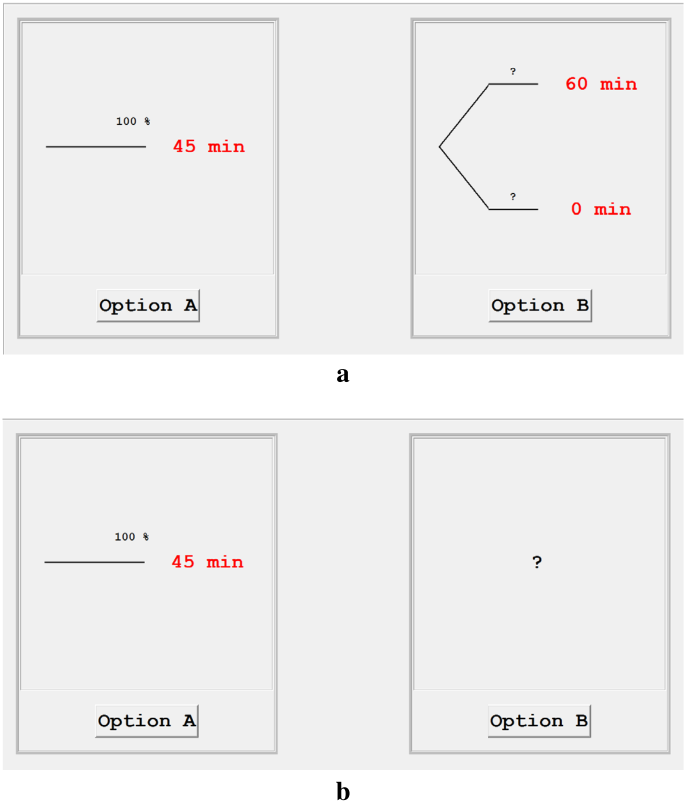

Fig. 2 Choice display. **a** Time prospect under the complete information condition. **b** Time prospect under the incomplete information condition

not revealed (cf. Fig. 2b), and a consequence that had not been observed in the sampling process would remain unknown to the subject. Note that even in the incomplete information condition, the sure consequence was presented as certain. Although the sampling display was the same for the two conditions, subjects knew whether the consequences would be displayed or not after the sampling. In both conditions, subjects faced two types of choices: choices where consequences were monetary gains and choices where gains were expressed in time units. Time consequences ranged from 0 to 60 min and money consequences from 0 to 150 €.

To summarize, two experiments were run to compare attitudes toward time and toward money in a within-subject design. The two experiments differed regarding the information condition, i.e., whether the consequences were revealed to the decision makers or not after the sampling step.

3.1.2 Procedure

The experiments were conducted through individual computer-based interviews. Each *experimental session* had a fixed duration of one hour. When subjects arrived at the experimental session, they received a 10-min presentation and answered practice questions. They were informed that there were neither right nor wrong answers and that they could not modify their decision once the choice was made. The responses were entered into the computer by the experimenter so that the subject could focus on the task. Half of the subjects started with money prospects; the other half started with time prospects. The two parts of the experiment were broken up by a ten-minute coffee break.

In each experiment, a real-incentive system was implemented for both time and money on half of the sample. Subjects assigned to a real incentive group were told that two of them could be selected to participate in a payment session a few weeks after the experiment. During the payment session, a time choice and a money choice made during the experiment session would be selected and played for real. The subjects from the hypothetical choice group only participated in the experimental session. All time and money choices were thus hypothetical. 40 subjects participated in each experiment. All of the 80 participants were students from Angers (France). All of them received a 15 € flat payment for their participation. 20 pilot sessions were run to fine tune the computer program and check that the instructions and displays were properly understood.

The *payment session* (cf. Fig. 3) was introduced to implement real time and money incentives. For money, one of the choices made during the experimental session was randomly selected at the end of the payment session, played for real, and paid in cash. It was announced that the payment session would last one hour. This duration defined a reference point for time and was used to implement the real incentives

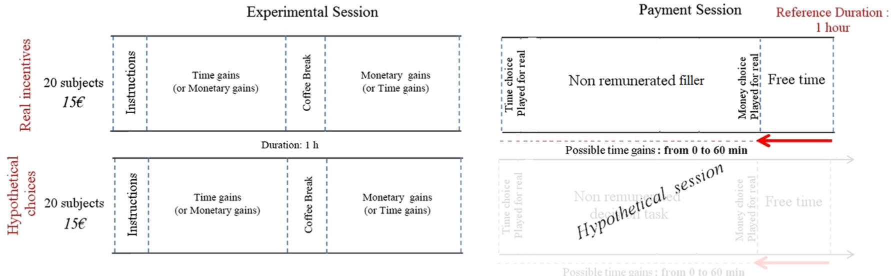

Fig. 3 Framing of the real incentive system for time and money

for time. Subjects were told that the payment session consisted in a filler task that would not be paid. Therefore, it was in their best interest to reduce the duration of the payment session in order to play the money prospect and leave as soon as possible. The possibility of reducing the duration of the payment session defined the time gains. More precisely, subjects were told that one of the time choices made during the experimental session would be randomly selected at the beginning of the payment session and played for real. The resulting time gain would determine the duration of the payment session. For instance, if the time prospect resulted in a gain of 45 min, then the duration of the payment task would be reduced so that the subject would only have to spend 15 min before playing the money prospect and leaving with the (money) payoff. In the reference case, the subject would have to spend 1 h in the payment task without receiving any money payment. In the best case scenario, they would play the money prospect at the very beginning of the payment session (thus saving one hour) and leave with 150 €. In most experiments, the money incentives are implemented at the end of the experimental session. In the present experiments, they were implemented at the end of the payment session in order to make sure that the subjects would in fact come to the payment session where the time incentives when implemented.

As pointed out by an anonymous referee, the shortening of the payment session also shortens the delay before the monetary prospect can be resolved. Therefore, in this set up, attitudes toward time theoretically interfere with attitudes toward the resolution of uncertainty. However, the payment session took place several weeks after the experiment, and the additional amount of time that the subjects had to wait (during the payment session) before the monetary prospect was resolved, can be considered negligible.

3.2 Stimuli and data collection method

The decision task consisted in choices between a sure gain and an experienced prospect involving two or three consequences. More precisely, for each of the prospects presented in Table 1, subjects were confronted with a series of sure gain offers that aimed at estimating the certainty equivalent of the prospect.

In this experiment, certainty equivalents were measured using the bisection method. This method consists in enclosing the certainty equivalent within an interval of given amplitude by iterative bisections of the intervals containing the possible values of the certainty equivalent (Abdellaoui et al. 2008). The main limitation of this method is that an error made during the bisection process will propagate and bias the final measure. In order to fix this problem, two confirmation choices were systematically added at the end of each certainty equivalent measurement. An example of bisection and the related confirmation choices is provided in Appendix 1. For each prospect, a series of certain offers were proposed according to the bisection method. The objective of this procedure was to locate the indifference area. Then, two independent choices were proposed around this area. This allowed the subjects to confirm that their indifference was within the interval. When this was not the case, two new independent choices were proposed and the process was repeated untill the indifference was located within the proposed interval. This procedure allows to measure for each prospect P, two certain offers c_{inf} and c_{sup} such that $c_{sup} \succ P \succ c_{inf}$.

Table 1 Prospects for which certainty equivalents were estimated

Prospect		Money (€)					Time (min)				
		x	p_x	**y**	p_y	**z**	**x**	p_x	**y**	p_y	**z**
1	Two consequences	150	0.50			75	60	0.50			30
2		150	0.50			25	60	0.50			10
3		100	0.50			25	40	0.50			10
4		150	0.50			0	60	0.50			0
5		100	0.50			0	40	0.50			0
6		50	0.50			0	30	0.50			0
7		150	0.33			0	60	0.33			0
8		150	0.08			0	60	0.08			0
9		150	0.66			0	60	0.66			0
10		150	0.92			0	60	0.92			0
11		150	0.17			0	60	0.17			0
12		150	0.84			0	60	0.84			0
13	Three consequences	150	0.50	50	0.25	0	60	0.50	20	0.25	0
14		125	0.50	50	0.25	25	50	0.50	20	0.25	10
15		150	0.50	75	0.25	25	60	0.50	30	0.25	10
16		100	0.50	25	0.25	0	40	0.50	10	0.25	0
17		150	0.08	50	0.25	0	60	0.08	20	0.25	0
18		150	0.17	50	0.17	0	60	0.17	20	0.17	0
19		150	0.66	50	0.17	0	60	0.66	20	0.17	0
20		150	0.84	50	0.08	0	60	0.84	20	0.08	0

3.3 Estimation strategy

In terms of our stochastic model (Eq. 2), for each prospect P, the bounds c_{inf} and c_{sup} allow to enclose the error term ε:

$$V(c_{\text{inf}}) - V(P) < \varepsilon < V(c_{\text{sup}}) - V(P). \tag{3}$$

There is one error per prospect and we assume that the distribution of errors remains the same across prospects. Consequently, assuming that $\varepsilon \sim N(0, \sigma)$, the probability for observing c_{inf} and c_{sup} is:

$$\begin{aligned} &p\left(V\left(c_{\text{inf}} - V(P)\right) < \varepsilon < V\left(c_{\text{sup}}\right) - V(P)\right) \\ &= \Phi\left[\frac{V(c_{\text{sup}}) - V(P)}{\sigma}\right] - \Phi\left[\frac{V(c_{\text{inf}}) - V(P)}{\sigma}\right], \end{aligned}$$

where Φ is the cumulative function of the normal distribution.

Assuming that for a subject i, the function V_i is specified by a vector of parameters $\beta_i = \left(\beta_{\text{m},i}, \beta_{i,j}\right)$, the likelihood of observing $c_{\text{inf}}^{i,j}$ and $c_{\text{sup}}^{i,j}$ for a prospect P_j is:

$$p_{i,j}\left(c_{\text{inf}}^{i,j}, c_{\text{sup}}^{i,j} \mid \beta_i\right) = \Phi\left[\frac{V\left(c_{\text{sup}}^{i,j} \mid \beta_i\right) - V\left(P_j \mid \beta_i\right)}{\sigma}\right] - \Phi\left[\frac{V\left(c_{\text{inf}}^{i,j} \mid \beta_i\right) - V\left(P_j \mid \beta_i\right)}{\sigma}\right].$$

At the individual level, the vector of RDU parameters β_i is assumed to be constant over all the choices, for a given condition and for a given attribute.

The likelihood (LL) of a parameter vector β_i over the K observations is

$$\text{LL}\left(\beta_i\right) = \prod_{j=1}^{K} p_{i,j}\left(c_{\text{inf}}^{i,j}, c_{\text{sup}}^{i,j} \mid \beta_i\right),$$

When enough observations are available, each likelihood LL(β_i) can be maximized. A vector of preference parameters can be estimated for each subject (Beauchamp et al. 2012; Kemel and Paraschiv 2013). We use this approach to estimate individual level parameters and derive the parameter distribution among the subject population. An alternative approach consists in assuming that the parameters are distributed among the population according to a given (multivariate) distribution, whose vector of characteristics Θ (e.g., mean and variance–covariance matrix) have to be estimated. This is the mixed model approach. This approach will also be used in this paper. Technical considerations are provided in Appendix 2. In this study, the vector β contains the RDU parameters for time and money $\beta = (\beta_{\text{m}}, \beta_t)$. The distributions of these two vectors of parameters will be compared. More precisely, analyzing preferences for time and money will consist in comparing the mean of the two distributions but also in analyzing the covariance of time and money parameters.

4 Results

We present a raw data analysis of the experiment, focusing on sampling behavior and certainty equivalents, respectively. The analysis then focuses on estimated RDU parameters. A first series of analyses relies on individual level parameters which are compared across attributes (time versus money) and conditions (complete information versus incomplete information). The last section presents the results of mixed model estimations.

4.1 Sampling behavior

Subjects were free to choose the sample size for each prospect. Table 2 reports the median and mean sample size selected by subject for each attribute in the two conditions.

The average sample size is larger for money than for time. Subjects also based their choices on larger samples under incomplete information than under complete

Table 2 Sample size for each attribute under complete information and incomplete information conditions

	Money		Time	
	Median	Mean	Median	Mean
Complete information (n = 40)	13	15.5	14	14.5
Incomplete information (n = 40)	14	16.1	15	15.0

information. A 2×2 ANOVA test, with attribute (time vs money) as a within-subject factor and condition (complete vs incomplete information) as a between-subject factor, confirmed these observations. Both factors were found to significantly impact sampling behaviors ($p = 0.01$ for condition and $p < 0.001$ for attribute). Another 2×2 ANOVA was run on sampling size with two other factors: order (starting with time choices or money) and presence of incentives (incentivized or hypothetical choices) as between-subject factors. A main effect of order was observed ($p < 0.001$). Subjects who started by time sampled 1.1 less on average for both attributes than those who started with money.

In the large majority of cases, subjects realized enough samples to observe all the consequences. Overall, situations in which a consequence with a non-zero probability was not observed through sampling were rare. This happened two times with two-outcome prospects and 13 times with three-outcomes prospects. Consequently, in the large majority of cases, subjects from the incomplete information condition discovered the complete set of possible consequences during the sampling process. In order to test the presence of sampling bias in the two-outcome prospects, a regression was run for each subject and each attribute, with sampled frequencies as a dependent variable and unknown real probability as an independent variable. The coefficient of the unknown probability was significantly different from one for three subjects in time prospects and four subjects in money prospects. This suggests that at the individual level, only a few subjects suffered from sampling bias. On the aggregated level, the figure in Appendix 4 plots the mean and standard deviation of sampled frequencies, for each unknown real probability. It can be seen that mean observed frequencies are very close to real probabilities.

4.2 Certainty equivalents

The data collection method allowed us to measure *certainty equivalents* (CE) for each prospect. Descriptive statistics on the collected CE for complete-information and incomplete-information conditions are presented in Appendix 3. In order to compare time and money CE that were not measured on the same scale, the certainty equivalents were normalized by the maximum consequence at stake in the prospect. A 2×20 ANOVA was run on normalized complete-information CE, with attribute (time vs. money) and prospect (1–20) as within-subject factors. As expected, a main effect of prospect was observed ($p < 0.001$). Despite the normalization, a main effect of attribute was also observed, as well as an interaction with prospect ($p < 0.001$). The same analysis was run on incomplete-information CE, and the same results were observed. The procedure implemented allowed for a control of order and/or incentive

Table 3 p values of order and/or incentive effects in 2 × 2 ANOVA

	Complete information		Incomplete information	
	Money	Time	Money	Time
Order	0.80	0.12	0.20	0.83
Incentives	0.27	0.05	0.31	0.32
Order × incentives	0.15	0.54	0.54	0.09

Table 4 Distribution of RDU parameters for time and money under complete and incomplete information conditions

Condition	Parameter	Time β_t			Money β_m			Correlation	
		Median	Mean	SD	Median	Mean	SD	Value	p value
Complete information $n = 40$	Utility (α)	0.91	0.95	0.25	0.91	0.88	0.21	0.24	0.120
	Errors (σ)	0.07	0.07	0.02	0.06	0.07	0.02	0.41	0.010
	Sensitivity (γ)	0.56	0.60	0.27	0.66	0.67	0.20	0.48	0.002
	Elevation (δ)	0.73	0.77	0.36	0.56	0.71	0.42	0.51	<0.001
Incomplete information $n = 40$	Utility (α)	1.03	1.04	0.30	1.00	1.07	0.49	0.17	0.280
	Errors (σ)	0.07	0.07	0.02	0.07	0.07	0.03	0.58	<0.001
	Sensitivity (γ)	0.60	0.64	0.19	0.64	0.74	0.30	0.59	<0.001
	Elevation (δ)	0.67	0.80	0.46	0.58	0.64	0.33	0.57	<0.001

effect. A series of 2×2 ANOVA was run on these factors on each of the treatments (cf. Table 3).

Four different 2×2 ANOVA tests considering order and the presence of real incentives as between-subject factors were run on complete-information time CE, complete information money CE, incomplete-information time CE, and incomplete-information money CE. The results are presented in Table 3: none of these four ANOVA tests revealed any significant effect at the 5 % level.

4.3 Individual level estimations

RDU parameters were estimated at the individual level separately for time and for money. Individual estimations allow to measure the heterogeneity of preferences without having to impose restricting assumption on the shape of the distribution (cf. Table 4). Individual level estimations also allow to measure the correlation between time and money parameters.

Individual RDU parameters were estimated using both the Prelec and the GE specifications. The two specification offered similar goodness of fit and showed similar patterns. We report the analysis of individual estimations using the GE specification because its elevation parameter is easy to interpret (cf. Sect. 2.2).

Table 5 *p* values of ANOVA tests on RDU parameters

Independent/dependent variable		Utility α	Errors σ	Sensitivity γ	Elevation δ
Between	Condition (complete information vs. incomplete information)	0.02	0.61	0.23	0.83
	Incentives (yes vs. no)	0.44	<0.01	0.99	0.07
	Condition × incentives	0.66	0.69	0.12	0.99
Within	Attribute (time vs. money)	0.68	0.03	<0.01	0.03
	Attribute × condition	0.34	0.28	0.61	0.28
	Attribute × incentives	0.96	0.03	0.57	0.56
	Attribute × condition × incentives	0.83	0.53	0.43	0.78

Mean and standard deviations of the distribution of estimated parameters among the subject sample are presented in Table 4. This analysis is completed by a correlation test in order to detect a relation between time and money parameters.

4.3.1 Utility

Under the complete-information condition, in which the consequences were revealed to the decision maker, utility shows a slight curvature for time and for money. On average, utility for time does not deviate from linearity (t test, $p = 0.18$) while the concavity is significant (t test, $p < 0.001$) for money. More specifically, 18 subjects (out of 40) exhibit a convex utility for time, while only 10 do so for money. Under incomplete information, utility curvatures do not deviate from linearity for any of the attributes, and the proportion of subjects with a concave utility is very similar for both time and money (18 vs. 19). According to the ANOVA test reported in Table 5, utility functions exhibit less curvature under complete information compared to under incomplete information ($p = 0.02$), a tendency that concerns both time and money.

Overall, the utility parameter does not significantly differ between time and money. Nonetheless, subjects did not systematically treat time consequences in the same way as they treated money consequences. Indeed, a correlation test, reported in Table 4 failed to detect any relation between time and money utility, whether it involved the complete-information condition ($p = 0.12$) or for the incomplete-information condition ($p = 0.28$).

The ANOVA reported in Table 5 also tested the impact of real incentives on utility. No overall effect of the presence of real incentives was detected ($p = 0.44$). No interaction between the presence of real incentives and the attribute was observed ($p = 0.96$).

4.3.2 Probability weighting

Under both conditions, the main difference between time and money concerns weighting parameters (Fig. 4). Whether it be for time or for money, the average parameters

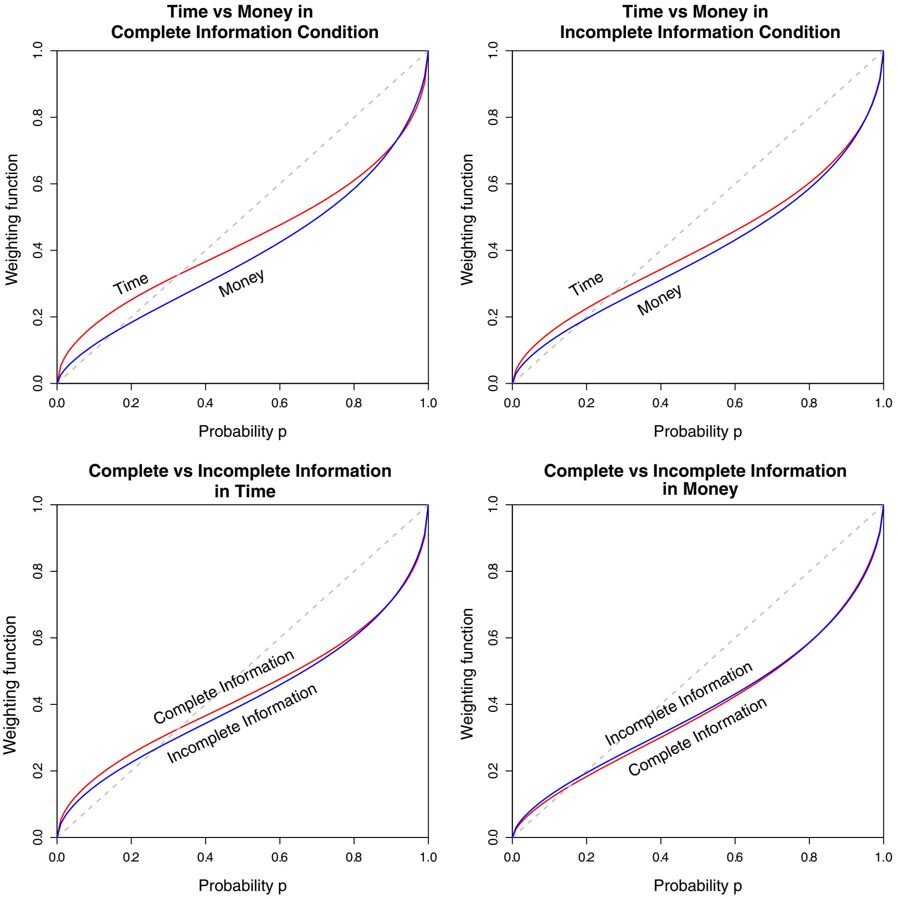

Fig. 4 Probability weighting (GE specification)

show inverse S-shaped probability weighting. Under both conditions and for the two attributes, the γ parameter was on average lower than 1 according to a series of t tests ($p < 0.001$). Probability weighting is more pronounced for time than for money. More specifically, probability weighting exhibits less sensitivity to probability changes for time than for money (cf. Table 5, $p = 0.004$). This impact of attribute on sensitivity does not interact with the conditions ($p = 0.61$). The average elevation parameter was always found to be lower than 1, at the 1 % level, according to a series of t test. This shows that probability 0.5 was generally underweighted, whatever the condition or attribute. However, elevation parameters are higher for time than for money ($p = 0.03$), suggesting that subjects were less pessimistic toward chance when time was at stake. This attribute dependence of optimism does not interact with the condition ($p = 0.28$).

Although different, the subjective treatment of probabilities for time and for money was found to be correlated. Regarding the sensitivity parameter, this observation is consistent with the interpretation of the sensitivity toward probability change as a measure of a cognitive dimension. An individual who poorly discriminates probabilities

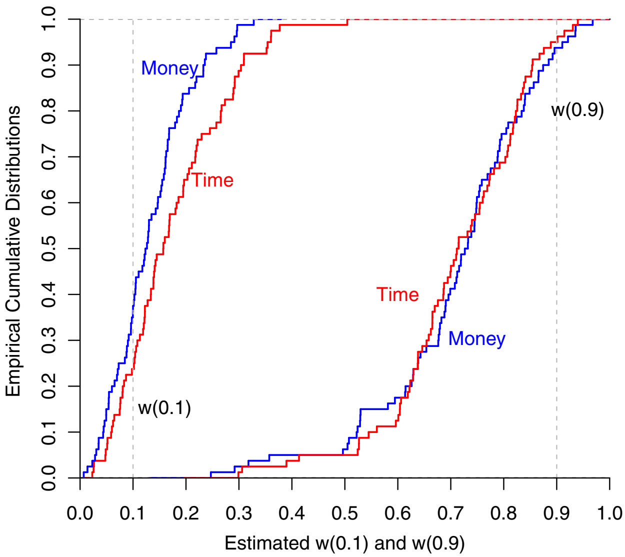

Fig. 5 Heterogeneity in the treatment of small and large probabilities

would be likely to do so whether the decision involves time or money. Elevation of the probability weighting function, namely optimism or pessimism, is also correlated between time and money. Besides the impact of attribute, this correlation suggests the existence of a common factor regarding the attitude toward chance, the so called "probabilistic risk aversion."

The ANOVA tests run on probability weighting parameters (reported in Table 5) did not detect any significant difference of elevation or sensitivity between conditions ($p = 0.23$ for sensitivity and $p = 0.83$ for elevation). This suggests that deciding under complete or incomplete information did not impact probability weighting in our experiment. Regarding the presence of real incentives, no significant differences were observed between the real incentives and the hypothetical choice group ($p = 0.99$ for sensitivity and $p = 0.07$ for elevation).

According to the aggregate pattern, inverse S-shaped probability weighting prevails for time and for money. Figure 5 shows the distribution of decision weights assigned to small and large probabilities (0.1 and 0.9, respectively) so as to provide a more precise illustration of the treatment of probabilities. Among the 80 subjects, probability 0.9 is underweighted by 76 subjects for time and 75 subjects for money. Attribute difference is more important regarding the treatment of probability 0.1. This probability is overweighted by 50 subjects for money and by 61 subjects for time. In both cases, the majority of subjects overweight this small probability.

4.3.3 Errors

The econometric model used for the individual estimation introduced a normally distributed error component centered around 0 with a variance σ^2 estimated simultane-

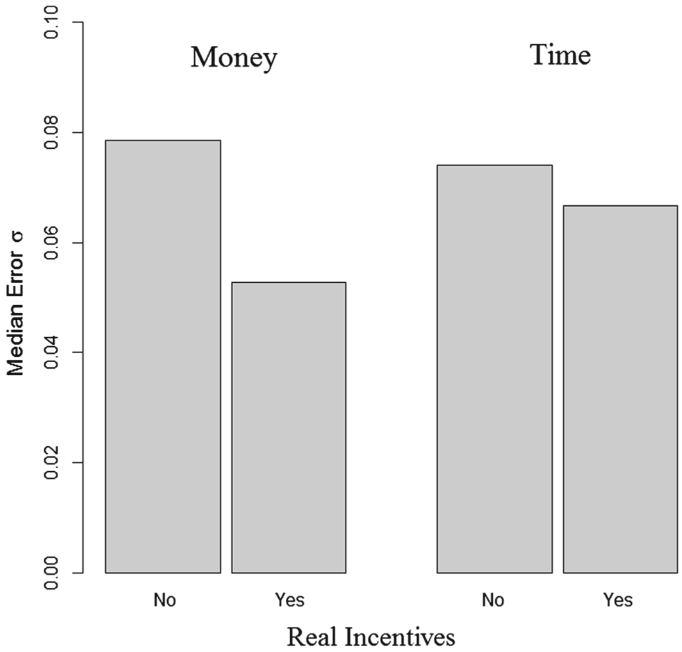

Fig. 6 Interaction between attribute and presence of real incentives on errors

ously with RDU parameters (cf. Eq. 2). This parameter is not only a by-product of the estimation method, but it also gives a measure of the amplitude of errors made by subjects in their choices.

In the complete information condition, 29 subjects (out of 40) were found to make larger errors when deciding about time than when deciding about money. This was also the case for 23 subjects in the incomplete-information condition. The ANOVA (reported in Table 5) that assessed the impact of attribute and conditions on errors confirmed the impact of attribute on errors ($p = 0.03$). Besides these differences, the error terms for time and for money are found to be significantly correlated. Globally, inconsistent subjects gave noisy responses for both time and for money choices. While no difference was captured between the two conditions, the presence of real incentives was found to impact the error term ($p < 0.001$). A significant interaction between "incentive" and "attribute" factors suggests that the impact of incentives was not the same on time as it was on money. Figure 6 represents this interaction and shows that the errors were smaller when real incentives were implemented. This trend applies to both time ($p = 0.03$) and money ($p < 0.001$) but is more important for money.

4.4 Mixed modeling estimations

A mixed model was estimated on our data in order to extend the analysis presented in the previous sections. Most mixed model estimations presented in the literature assume that the variance–covariance matrix of the parameters is diagonal. This means that parameters are generally assumed not to be correlated. In this study, measuring the correlation between preferences for time and for money is of particular interest. The estimation of the full variance–covariance matrix can be particularly difficult using standard likelihood maximization methods. Train (2009, chap. 14, p. 361) presents a procedure for estimating normal mixing distributions with full covariance, using the Expectation Maximization algorithm. This procedure was implemented under the *R* software and used for the present estimation.

The algorithm works with any transformation of a normal distribution. All the parameters of our model are non-negative. In such cases, log-normal transformations are generally considered. However, the large tails of such distributions can predict extreme behaviors. The transformation considered in this estimation was a left-truncation of the normal distribution in 0. Using the notations introduced in Sect. 3, the mixed model presented in this section assumed that

$$\begin{pmatrix}\beta_{\mathrm{m}}\\ \beta_t\end{pmatrix} \equiv N_0\left(\begin{pmatrix}\overline{\beta_{\mathrm{m}}}\\ \overline{\beta_t}\end{pmatrix}, \begin{bmatrix}\theta_{\mathrm{m}}, & \theta_{\mathrm{m},t}\\ \theta^t_{\mathrm{m},t}, & \theta_t\end{bmatrix}\right).$$

The mixed likelihood was computed by simulation with 1000 pseudo random (Halton[2]) draws. In order to avoid local maximums, 100 random values were considered as starting values for the procedure. The standard errors of the estimated distribution characteristics were calculated by the means of bootstrap over 1000 replications. Table 6 reports the estimates of the underlying multivariate normal distribution.

Standard deviations are systematically different from 0. This shows the presence of significant heterogeneity of preferences among our subject population and legitimizes the use of a mixed model.

Estimations of means of parameter distributions are similar to the one observed in the previous sections obtained by a different estimation method (cf. Table 4). The main difference between these measures and those obtained in the previous section regards the standard deviation of parameters. The variance of parameters is systematically lower than the one previously estimated. This illustrates that measuring individual heterogeneity from individual parameter estimates increases the observed variance. More interestingly for the present study, these estimations offer more statistical power for comparing attributes and conditions.

Eventually, most differences between the estimations reported in Table 4 and those in Table 6 regard correlations between time and money parameters. The sign and significance of the correlation parameters are stable across estimation methods. However, the amplitude of correlation coefficients is generally higher when estimated by mixed modeling.

5 Discussion

This experimental investigation examined individual behavior in experience-based decisions (EBD) involving two or three consequences expressed in monetary or time

[2] Halton draws were generated by the *halton* function provided by the *randomtoolbox* package, in the R software (The R development core team 2005).

Table 6 Results of mixed model estimations by the EM algorithm

Parameter	Time		Money		Correlation
	Mean	SD	Mean	SD	
Complete information $n = 40$					
Utility (α)	0.85	0.12	0.81	0.14	0.59
	(0.021)	(0.016)	(0.021)	(0.014)	(0.117)
Errors (σ)	0.09	0.02	0.07	0.02	0.72
	(0.003)	(0.002)	(0.003)	(0.003)	(0.132)
Sensitivity (γ)	0.56	0.21	0.64	0.17	0.27
	(0.039)	(0.024)	(0.028)	(0.017)	(0.156)
Elevation (δ)	0.81	0.24	0.75	0.26	0.70
	(0.039)	(0.031)	(0.040)	(0.035)	(0.105)
Incomplete information $n = 40$					
Utility (α)	0.96	0.12	0.93	0.16	0.76
	(0.020)	(0.014)	(0.029)	(0.022)	(0.104)
Errors(σ)	0.08	0.02	0.08	0.02	0.71
	(0.003)	(0.002)	(0.004)	(0.004)	(0.110)
Sensitivity (γ)	0.61	0.14	0.67	0.19	0.71
	(0.023)	(0.018)	(0.033)	(0.025)	(0.112)
Elevation (δ)	0.80	0.25	0.70	0.27	0.76
	(0.042)	(0.029)	(0.047)	(0.031)	(0.070)

The standard errors estimated by bootstrap are in brackets

units. The comparison of attitudes toward time and money in the context of EBD provided an extension of the results of Abdellaoui and Kemel (2014) who compared these two attributes under risk[3]. Considering prospects with more than two consequences and a non-monetary consequence also extends the range of applications of the EBD paradigm.

5.1 Time versus money in experience-based decisions: differences and similarities

The objective of this study was to compare the subjective treatment of consequences (utility) and probabilities (probability weighting) for time and for money in EBD. This was done in a within-subject design, under two independent conditions. The main impact of attribute on RDU components concerns probability weighting. Subjects exhibited less pessimism toward chance when time rather than money was at stake. This explains why subjects took more risk with time than with money. It was also observed that the sensitivity to probability changes were smaller for time than for money. This produced a more pronounced S-shaped probability weighting, i.e., a

[3] The range of possible time gains also varied from 0 to 1 hour as in the present study. Regarding money, the authors considered hypothetical payoffs over [0 €, 1200 €]. In the present study, smaller monetary consequences were considered (up to 150 €). This allowed for the implementing of real incentives for money as well as for time.

larger deviation from a linear treatment of probabilities. These patterns are consistent with what was observed by Abdellaoui and Kemel (2014) under risk. The present study thus replicates their findings in another decision context: EBD. These results suggest that independently from the type of uncertainty involved, subjects do not exhibit the same attitudes when consequences are expressed in time or in money units. In particular, differences between attributes were larger than differences between information conditions. From an empirical perspective, time and money can thus be considered descriptively as two different sources. This leads one to consider that a source is not only defined by the events that generate uncertainty but also by the type of outcome at stake.

As pointed out by an anonymous reviewer, we may observe a difference of attitudes toward time and money because subjects assigned higher values to monetary payoffs. Subjects indeed sampled more on average for monetary than for time prospects and made lower errors when deciding about money. This suggests that they generally assigned higher values to money than to time prospects. Several studies including Etchart-Vincent (2004) and Fehr-Duda et al. (2010) showed that the magnitude of the stakes impacts probability weighting. The gap observed in this study between time and money may thus be a matter of magnitude (in the subjective value) of the stakes. However, a recent study by Krawczyk (2015) showed, that probability weighting can depend on the type of consequences at stake, even when the consequences are of similar magnitude and have similar subjective values. A further investigation of the gap between time and money may consist in selecting outcome ranges of similar subjective value for the two attributes.

The present study also measured correlation between RDU components for time and money. Significant correlations were measured across attributes for the probability weighting parameters and for the error term. This suggests that, besides attribute dependence, there is a common component of decision making whatever the attribute at stake. This common component can relate to subjects' attitudes and/or cognitive capabilities. Attitude toward chance, i.e., optimism or pessimism may explain why elevations of the decision weighting function were correlated for time and for money. Similarly, the correlation between error terms that was observed for time and for money may derive from a common personality factor. Subjects who completed time choices carefully also paid close attention to the money choices. The correlation of errors for time and for money may also derive from a cognitive factor. For instance, if some subjects made noisy choices for an attribute because of limited numeracy, the choices they made for the other attribute would also be expected to be noisy. Individual numeracy skills can also explain why sensitivity parameters of probability weighting functions were correlated across attributes. Subjects with low numeracy are expected to exhibited weak sensitivity to probability changes (i.e., weak discrimination of probabilities) whether the consequences are expressed in time or money units.

5.2 Experience-based decisions: S or inverse-S shape?

In both experiments and for both attributes, the majority of subjects exhibited inverse S-shaped probability weighting functions. For money, the sensitivity parameters are close to those generally observed in the literature. For time, however, deviation from a linear probability weighting is weaker than previously observed by Abdellaoui and Kemel (2014). For time gains, the authors measured a median value of 0.26 for the sensitivity parameter of the GE weighting function. The median values measured in the present study are, respectively, 0.56 and 0.60 under complete and incomplete information conditions although time gains were of similar amplitude (cf. Table 4). This pattern is consistent with the results reported by Abdellaoui et al. (2011) who also observed that under EBD, inverse S-shaped probability weighting prevails, even if the deviation from linearity is weaker than under risk. Why does EBD induce higher sensitivity to probability changes than decisions from description? Following the suggestion made by an anonymous reviewer, we speculate that observing realizations of uncertainty offers a more accurate representation of likelihood than simply receiving description in terms of probabilities. Gigerenzer and Hoffrage (1995) showed that dealing with frequencies instead of probabilities improves statistical reasoning. Our result suggests that representing uncertainty in terms of observed frequencies rather than probabilities also improves decision making (by improving sensitivity to likelihood changes).

A sizable literature reports stronger effects. The increase in sensitivity to probability change is such that probability weighting becomes S-shaped. Several methodological differences can explain this heterogeneity of results. The first type of difference regards the experimental set up. While most EBD experiments involve low stakes, the present experiment, as well as the one run by Abdellaoui et al. (2011) involve substantial monetary amounts. A more important difference probably regards the decision task. While most EBD experiments consist in binary choices, the present experiment, as well as the one run by Abdellaoui et al. (2011), relies on certainty equivalents. Certainty equivalents allow finer measures of preferences than binary choices. They also consist in choices between a sure offer and an uncertain prospect. The presence of a sure offer in each choice may help to better capture the certainty effect, which contributes to inverse-S-shaped probability weighting. Regarding the statistical treatment of experimental data, probability weighting was measured using two-parameter weighting functions which offer more flexibility in capturing attitudes toward probabilities.

5.3 Experience-based decisions: risk, ambiguity and ignorance

The pioneering work on EBD considered this context as a type of risk, following Knight (1921) who proposed a distinction between *a priori* probabilities and *statistical* probabilities, both considered as risk. As pointed out by an anonymous referee, according to the current categorization of uncertainty, EBD cannot be considered as risk because the probabilities are unknown [4]. EBD should instead be considered as a source of ambiguity, as proposed by Abdellaoui et al. (2011).

Under ambiguity, probabilities are unknown and analyzing behavior in this context requires that a subject's subjective probabilities be accounted for. As in most EBD experiments, we assumed that subjective probabilities matched with the probabilities

[4] A case of risk was considered under EBD by Barron and Ursino (2013). Subjects could sample without replacement, which allowed them to learn the objective probabilities.

characterizing the prospects. The analysis run on sampling behavior showed that, due to the large sample sizes, there was virtually no sampling bias at the aggregated level. In order to account for possible sampling bias at the individual level, the results of individual estimations and the results of the mixed model were reconsidered assuming that probability weighting applied to observed frequencies. The results of the estimations are reported in Appendix 5. One can see that measuring source functions as transformation of observed frequencies does not change the results.

According to the literature on ambiguity, the pessimism induced by ambiguity aversion is captured by less elevated probability weighting. Consequently it was expected that subjects would exhibit more pessimism under EBD than under risk. This was observed in the data. In our experiment, whether choices involved time or money, subjects exhibited more pessimism toward chance than was generally observed for risk. For time, the median optimism indexes observed in these experiments are 0.73 and 0.67 for complete and incomplete-information conditions respectively (cf. Table 4) and are lower than the value reported by Abdellaoui and Kemel (2014). For money, our measures of elevation are also lower than those reported in the literature (e.g., Bruhin et al. 2010). The less pronounced possibility effect, associated with the overall pessimism toward chance explains why small probabilities were less overweighted when learned from sampling than when known from description. This pattern is consistent with the described-versus-experienced gap and can be explained by ambiguity aversion.

The complete information condition was a replication of the decision task proposed by Abdellaoui et al. (2011) and was consistent with the Savagian framework: the state space was known. Under the incomplete information, however, the state space was unknown and a consequence that would not be observed through sampling would remain ignored. Situations where decision makers ignore some of the possible consequences are called *ignorance*. In this experiment, the degree of ignorance was moderate because the subjects knew the range of the possible consequences (from 0 to 150 euros for money prospects and from 0 to 60 min for time prospects). From a theoretical perspective, situations with unknown state spaces preclude the use of rank-dependent models. Under these models, probability weighting depends on the ranking of the consequences. Therefore, if some of the consequences are unknown, the consequences cannot be ranked and decision weights cannot be computed. We are grateful to an anonymous reviewer for raising this point. The between-subject comparison did not detect differences in terms of probability weighting between the complete and the incomplete information condition. This suggests that in this experiment, subjects had enough sampling information to rank the relevant consequences. In a similar comparison between complete and incomplete information conditions, Hadar and Fox (2009) observed that behaviors differed only when some consequences were not sampled. In the incomplete information condition implemented in this experiment, such sampling bias was rare (cf. Sect. 4.1). Seeing that the treatment of probabilities does not vary across conditions is thus consistent with the observation of these authors. We noted, however, that regarding the utility, a difference was observed. Subjects were generally willing to take more risks under the incomplete-information condition, i.e., when the possible consequences were not revealed. The concavity for money was less pronounced under the incomplete information condition where the consequences were not known. This suggests that the subjective treatment of consequences was closer to linearity when the consequences were not indicated. As pointed out by an anonymous reviewer, this pattern reminds that utility can also be impacted by the quantity of information available, as assumed by models in which utility carries ambiguity attitudes (e.g., Klibanoff et al. 2005).

Aside from rank dependence, unknown state space also raises difficulties regarding statistical learning. A common assumption in economics is that people learn about probabilities through Bayesian updating. This process requires that the number of possible outcomes be known. How do decision makers react when they are informed of the existence of a consequence that was not observed through sampling? Do they ignore it or do they update their beliefs in light of this new prior? The estimations reported in Appendix 5 from observed frequencies assume that non-observed consequences are ignored, even when revealed from description after sampling and before the choice. In this experiment, this type of situation was too rare for the impact of such an assumption to be analyzed. Therefore, other experimental data would be needed to address this issue. This type of data could consist of situations where subjects are systematically informed that a consequence that was not sampled can also obtain.

5.4 Other findings

Real incentives were implemented for both time and money on half of the subject sample. Our comparison of attitudes between these groups did not detect any impact of the presence of real incentive for any attribute, neither in the model free analysis nor on parametric RDU estimations. The error terms deriving from the econometric estimations were found to be impacted by the presence of real incentives. It was observed that subjects made smaller errors when their choices were eligible for real payment. According to these results, implementing real incentive systems did not distort the observed behavior. It may rather in fact help subjects to better focus on the task and provide cleaner responses. However, the impact of real incentives was smaller for time than for money. One explanation is that the value that was assigned to the monetary stakes was higher than the one assigned to the time stakes. Another explanation may be that people are more used to making decisions involving money than time, and that focusing more on the task does not really help compensate for this difference. All in all, this observation illustrates how the use of a non-monetary attribute for a real incentives system may improve our understanding of the impact of incentives on behavior.

In addition to the aforementioned empirical results, this study proposes a methodological contribution for the econometric estimation of preference parameters. Likelihood maximization was used to estimate RDU parameters at the individual level. This approach was used by Hey and Orme (1994), Stott (2006), Abdellaoui et al. (2008, 2011), Abdellaoui and Kemel (2014) and gave satisfactory results regarding the capturing of the distribution of parameters among respondents. Our analysis was completed by another approach using a recently developed estimation method: mixed modeling. This approach consists in assuming the shape of the distribution of parameters. Its characteristics (namely mean and standard deviation) are estimated. Both methods produced the same results regarding the mean of the distribution. By using the

EM algorithm we were able to measure the full variance–covariance matrix of RDU parameters. This output was particularly useful for assessing the correlation between attitudes toward time and money. Econometric methods, and more specifically, mixed modeling, whether discrete (finite likelihood mixture) or continuous (simulated likelihood) is thus a powerful and promising tool for estimating psychometric models. The capacity of these models to make robust estimations relies on a careful selection of the stimuli. In this study, indifferences were collected by bisection. A large quantity of choices was collected, and future research is needed to help select more efficient designs for mixed model estimations.

Acknowledgments This project was part of a Ph.D dissertation, entitled "Attitudes towards Uncertainty with Monetary and Time Consequences: Experimental Investigations". The Ph.D program was funded by MEDDE/DRI. The paper benefited from the valuable suggestions of the Ph.D committee. The authors thank Anisa Shyti and Corina Paraschiv for their reading and helpful remarks. They are also grateful to an anonymous reviewer and the associate editor for their constructive comments.

Appendix

Appendix 1: Modified bisection method

The bisection method was implemented as follows. For a given prospect $\left(x, p_x, y, p_y, z\right)$, the $[z, x]$ interval was bisected in order to locate its certainty equivalent c^*. The procedure began with a certain offer c_1 such as $c_1 = \mathrm{EV}(P) \pm 10$. If c_1 was preferred, then the certainty equivalent c^* stood in the $[z, c_1]$ interval. In this case, a second certain offer c_2 was proposed, where c_2 was the midpoint of the $[z, c_1]$ interval. Otherwise, c^* was in the $[c_1, x]$, and $c_2 = c_1 + 0.5\,(x - c_1)$ was proposed.

The procedure was iterated until the certainty equivalent was restrained to an interval $[c_{\inf}, c_{\sup}]$, with $c_{\sup} - c_{\inf} < 5$ (for money, 2 for time). While the standard bisection method would stop here, the adapted method introduced two last choices that allowed us to confirm that the certainty equivalent c^* was in the interval. The two last choices involving $c_{\sup}$ and $c_{\inf}$ were repeated. In Table 7, we consider a decision maker who experienced the prospect (60, 0.25; 30, 0.25, 0) and is indifferent between saving 28 min for sure and receiving this prospect.

Table 7 Illustration of the modified bisection method

	Step	A	B
Locating the certainty equivalent	1	20	(60, 0.25; 30, 0.25, 0)
	2	40	(60, 0.25; 30, 0.25, 0)
	3	30	(60, 0.25; 30, 0.25, 0)
	4	25	(60, 0.25; 30, 0.25, 0)
	5	27	(60, 0.25; 30, 0.25, 0)
	c* is in [27, 30]		
Confirmation	6	30	(60, 0.25; 30, 0.25, 0)
	7	27	(60, 0.25; 30, 0.25, 0)

Appendix 2: Mixed modeling

The likelihood of a series of choices observed by a subject i writes

$$\mathrm{LL}\left(\beta_i\right) = \prod_{j=1}^{K} p_{i,j}\left(c_{\inf}^{i,j}, c_{\sup}^{i,j} \mid \beta_i\right)$$

Assuming that $\begin{pmatrix}\beta_{\mathrm{m}}\\ \beta_t\end{pmatrix} \equiv N\left(\begin{pmatrix}\overline{\beta_{\mathrm{m}}}\\ \overline{\beta_t}\end{pmatrix}\begin{bmatrix}\theta_{\mathrm{m}}, & \theta_{\mathrm{m},t}\\ \theta_{\mathrm{m},t}^{t}, & \theta_t\end{bmatrix}\right) \equiv N\left(\Theta\right)$ this likelihood becomes:

$$L_i\left(\Theta\right) = \int \prod_{j=1}^{K} p\left(c_{\inf}^{i,j}, c_{\sup}^{i,j}, \beta\right)\varphi\left(\beta, \Theta\right)\mathrm{d}\beta \tag{4}$$

.

The total likelihood writes

$$L\left(\Theta\right) = \prod_{i=1}^{N} L_i\left(\Theta\right)$$

.

The integral of equation (4) does not have a closed form. Therefore, it has has to be simulated.

Considering R draws β_r such that $\beta_r \sim N\left(\Theta\right)$, the likelihood $L_i\left(\Theta\right)$ can be approximated by its simulated value

$$L_{s,i}\left(\Theta\right) = \frac{1}{R}\sum_{r=1}^{R}\left(\prod_{j=1}^{K} p_{i,j}\left(c_{\inf}^{i,j}, c_{\sup}^{i,j} \mid \beta_r\right)\right).$$

Then, the total likelihood can be estimated as

$$L_s\left(\Theta\right) = \prod_{i=1}^{N} L_{s,i}\left(\Theta\right)$$

If the number of draws is large enough, the simulated likelihood $L_s\left(\Theta\right)$ converges to $L\left(\Theta\right)$ and the parameters Θ that maximize the $L\left(\Theta\right)$ can be obtained by maximizing $L_s\left(\Theta\right)$.

Appendix 3: Descriptive statistics on certainty equivalents

See Tables 8, 9

Table 8 CE under complete information condition

Prospect	Money			Time		
	EV	Median CE	IQR	EV	Median CE	IQR
1	112.5	98.50	[93.50 ; 108.50]	45	43.50	[38.50 ; 43.50]
2	87.5	61.00	[48.50 ; 73.50]	35	28.50	[23.50 ; 33.50]
3	62.5	49.75	[43.50 ; 58.50]	25	23.50	[18.50 ; 24.125]
4	75	52.25	[42.25 ; 62.87]	30	26.00	[18.50 ; 28.50]
5	50	38.50	[28.50 ; 48.50]	20	18.50	[13.50 ; 18.50]
6	25	21.00	[18.50 ; 23.50]	10	8.50	[8.50 ; 13.50]
7	49.5	38.50	[23.50 ; 53.50]	19.8	18.50	[13.50 ; 19.125]
8	12	13.50	[8.50 ; 19.75]	4.8	8.50	[3.50 ; 11.00]
9	99	66.00	[47.87 ; 76.00]	39.6	26.00	[23.50 ; 31.00]
10	138	102.25	[90.37 ; 119.75]	55.2	43.50	[36.00 ; 48.50]
11	25.5	18.50	[12.87 ; 28.50]	10.2	8.50	[6.00 ; 13.50]
12	124.5	98.50	[75.37 ; 108.50]	49.8	41.00	[32.87 ; 48.50]
13	87.5	61.00	[48.50 ; 73.50]	35	26.00	[21.00 ; 28.50]
14	81.25	62.25	[56.00 ; 68.50]	32.5	26.00	[21.00 ; 28.50]
15	100	78.50	[71.00 ; 88.50]	40	33.50	[27.87 ; 38.50]
16	56.25	38.50	[28.50 ; 48.50]	22.5	8.50	[13.50 ; 23.50]
17	24.5	21.00	[13.50 ; 31.62]	9.8	13.50	[8.50 ; 16.00]
18	34	27.25	[18.50 ; 36.00]	13.6	13.50	[8.50 ; 16.00]
19	107.5	77.25	[63.50 ; 88.50]	43	28.50	[23.50 ; 33.50]
20	128.5	98.50	[76.0 ; 103.50]	51.4	38.50	[31.00 ; 44.125]

EV expected value, CE certainty equivalent, IQR inter quartile range

Table 9 CE under incomplete information condition

Prospect	Money			Time		
	EV	Median CE	IQR	EV	Median CE	IQR
1	112.5	98.50	[88.50 ; 108.50]	45	42.25	[38.50 ; 43.50]
2	87.5	68.50	[58.50 ; 78.50]	35	28.50	[23.50 ; 33.50]
3	62.5	49.75	[42.25 ; 59.125]	25	23.50	[18.50 ; 26.00]
4	75	58.50	[38.50 ; 73.50]	30	23.50	[18.50 ; 28.50]
5	50	43.50	[36.00 ; 48.50]	20	18.50	[16.00 ; 21.00]
6	25	23.50	[18.50 ; 23.50]	10	8.50	[8.50 ; 11.625]
7	49.5	38.50	[25.375 ; 48.50]	19.8	18.50	[13.50 ; 23.50]

Table 9 continued

Prospect	Money			Time		
	EV	Median CE	IQR	EV	Median CE	IQR
8	12	4.75	[8.50 ; 18.50]	4.8	8.50	[6.00 ; 13.50]
9	99	77.25	[67.25 ; 88.50]	39.6	28.50	[28.50 ; 38.50]
10	138	118.50	[104.12 ; 129.75]	55.2	46.00	[38.50 ; 48.50]
11	25.5	26.00	[12.875 ; 31.625]	10.2	13.50	[8.50 ; 13.50]
12	124.5	98.50	[76.00 ; 116.00]	49.8	42.25	[38.50 ; 43.50]
13	87.5	68.50	[50.375 ; 81.00]	35	28.50	[23.50 ; 33.50]
14	81.25	63.50	[50.375 ; 68.50]	32.5	28.50	[22.875 ; 28.50]
15	100	74.75	[72.875 ; 84.75]	40	33.50	[28.50 ; 36.625]
16	56.25	38.50	[28.50 ; 48.50]	22.5	18.50	[16.00 ; 26.00]
17	24.5	23.50	[16.00 ; 31.00]	9.8	13.50	[11.00 ; 18.50]
18	34	31.00	[17.875 ; 43.50]	13.6	13.50	[11.00 ; 18.50]
19	107.5	73.50	[62.25 ; 88.50]	43	31.00	[28.50 ; 36.625]
20	128.5	98.50	[82.25 ; 109.75]	51.4	42.25	[37.875 ; 43.50]

EV expected value, CE certainty equivalent, IQR interquartile range

Appendix 4: Distributions of observed frequencies

See Fig. 7.

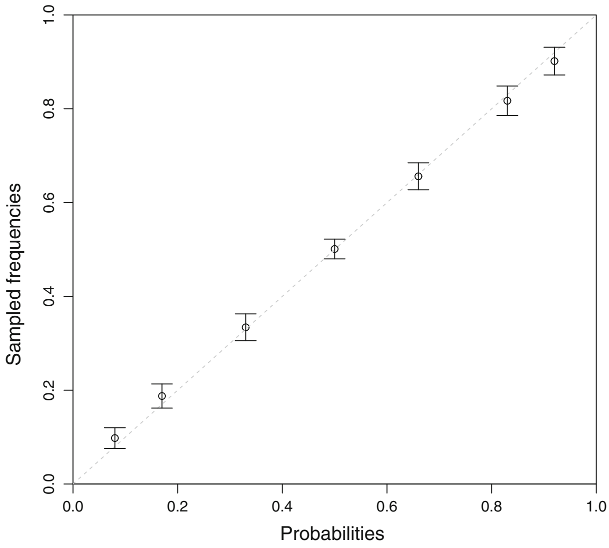

Fig. 7 Mean and standard deviations of observed frequencies

Appendix 5: Estimations based on observed frequencies

Tables 10, 11.

Table 10 Distribution of RDU parameters for time and money under complete and incomplete information conditions, based on observed frequencies

Condition	Parameter	Time β_t			Money β_m			Correlation	
		Median	Mean	SD	Median	Mean	SD	Value	p value
Complete information $n = 40$	Utility (α)	0.92	0.92	0.24	0.90	0.89	0.21	0.29	0.071
	Errors (σ)	0.07	0.07	0.02	0.06	0.07	0.02	0.43	0.005
	Sensitivity (γ)	0.57	0.62	0.29	0.68	0.71	0.22	0.51	<0.001
	Elevation (δ)	0.75	0.80	0.39	0.57	0.69	0.34	0.29	0.067
Incomplete information $n = 40$	Utility (α)	1.07	1.05	0.31	0.99	1.06	0.52	0.18	0.256
	Errors (σ)	0.07	0.07	0.02	0.07	0.07	0.03	0.56	<0.001
	Sensitivity (γ)	0.66	0.69	0.22	0.70	0.79	0.32	0.63	<0.001
	Elevation (δ)	0.66	0.81	0.50	0.60	0.65	0.33	0.57	<0.001

Table 11 Results of mixed model estimations by the EM algorithm, based on observed frequencies

Parameter	Time		Money		Correlation
	Mean	SD	Mean	SD	
Complete information $n = 40$					
Utility (α)	0.87	0.11	0.85	0.11	0.35
	(0.019)	(0.015)	(0.020)	(0.015)	(0.196)
Errors (σ)	0.08	0.02	0.08	0.02	0.56
	(0.003)	(0.003)	(0.003)	(0.003)	(0.117)
Sensitivity (γ)	0.59	0.23	0.68	0.17	0.65
	(0.040)	(0.026)	(0.027)	(0.017)	(0.100)
Elevation (δ)	0.78	0.19	0.68	0.18	0.80
	(0.037)	(0.023)	(0.033)	(0.023)	(0.076)
Incomplete information $n = 40$					
Utility (α)	0.94	0.15	0.96	0.14	0.64
	(0.028)	(0.024)	(0.029)	(0.022)	(0.092)
Errors(σ)	0.09	0.02	0.08	0.02	0.52
	(0.003)	(0.003)	(0.004)	(0.005)	(0.174)
Sensitivity (γ)	0.63	0.14	0.74	0.21	0.63
	(0.024)	(0.020)	(0.036)	(0.028)	(0.125)
Elevation (δ)	0.83	0.27	0.66	0.24	0.68
	(0.049)	(0.033)	(0.040)	(0.028)	(0.082)

The standard errors estimated by bootstrap are in brackets

References

Abdellaoui, M., Baillon, A., Placido, L., & Wakker, P. (2010). The rich domain of uncertainty: Source functions and their experimental implementation. *American Economic Review*, *101*(2), 695–723.

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

Abdellaoui, M., & Kemel, E. (2014). Eliciting prospect theory when consequences are measured in time units: Time is not money. *Management Sciences*, *60*(7), 1844–1859.

Abdellaoui, M., L'Haridon, O., & Praschiv, C. (2011). Experience-based versus description-based decision making: Do we need two different prospect theory specification? *Management Science*, *57*, 1879–1895.

Andersen, S., Harrison, G., Hole, A., Lau, M., & Rutstrm, E. (2012). Non-linear mixed logit. *Theory and Decision*, *73*(1), 77–96.

Barron, G., & Ursino, G. (2013). Underweighting rare events in experience based decisions: Beyond sample error. *Journal of Economic Psychology*, *39*, 278–286.

Bleichrodt, H., & Pinto, J. (2000). A parameter-free elicitation of the probability weighting function in medical decision analysis. *Management Science*, *46*, 1485–1496.

Beauchamp, J., Benjamin, D., Chabris, C., & Laibson, D. (2012). How malleable are risk preferences and loss aversion, Harvard University mimeo.

Bruhin, A., Fehr-Duda, H., & Epper, T. (2010). Risk and rationality : Uncovering heterogeneity in probability distortion. *Econometrica*, *78*(4), 1375–1412.

Camilleri, A., & Newell, B. (2011). When and why rare events are underweighted: A direct comparison of the sampling, partial feedback, full feedback and description choice paradigms. *Psychonomic Bulletin and Review*, *18*, 377–384.

Camilleri, A., & Newell, B. (2009). The role of mental representations in experience-based choice. *Judgment and Decision Making*, *4*, 518–529.

De Palma, A., Ben-Akiva, M., Brownstone, D., Holt, C., Magnac, T., McFadden, D., et al. (2008). Risk, uncertainty and discrete choice models. *Marketing Letters*, *19*, 269–285.

Etchart-Vincent, N. (2004). Is probability weighting sensitive to the magnitude of consequences? An experimental investigation on losses. *Journal of Risk and Uncertainty*, *28*(3), 217–235.

Fehr-Duda, H., Bruhin, A., & Epper, T. (2010). Rationality on the rise: Why relative risk aversion increases with stake size. *Journal of Risk and Uncertainty*, *40*(2), 147–180.

Gigerenzer, G., & Hoffrage, U. (1995). How to improve Bayesian reasoning without instruction: Frequency formats. *Psychological Review*, *102*(4), 684–704.

Goldstein, W.M., & Einhorn, H.J. (1987). Expression theory and the preference reversal phenomena. *Psychological Review*, *94*(2), 236.

Gonzalez, R., & Wu, G. (1999). On the shape of the probability weighting function. *Cognitive Psychology*, *38*, 29–166.

Hadar, L., & Fox, C. (2009). Information asymmetry in decision from description versus decision from experience. *Judgment and Decision Making*, *4*(4), 317325.

Hau, R., Pleskac, T., Kiefer, J., & Hertwig, R. (2008). The description-experience gap in risky choice: The role of sample size and experienced probabilities. *Journal of Behavioral Decision Making*, *21*, 493518.

Hertwig, R., Barron, G., Weber, E., & Erev, I. (2004). Decisions from experience and the weighting of rare events. *Psychological Science*, *15*(8), 534–539.

Hertwig, R., Barron, G., Weber, E., & Erev, I. (2006). The role of information sampling in risky choice. In K. Fiedler & P. Juslin (Eds.), *Information sampling and adaptive cognition* (pp. 72–91). New York: Cambridge University Press.

Hey, J., & Orme, C. (1994). Investigating generalizations of expected utility theory using experimental data. *Econometrica*, *62*(6), 1291–1326.

Kemel, E., & Paraschiv, C. (2013). Prospect theory for joint time and money consequences in risk and ambiguity. *Transportation Research Part B*, *56*, 81–95.

Klibanoff, P., Marinacci, M., & Mukerji, S. (2005). A smooth model of decision making under ambiguity. *Econometrica*, *73*(6), 1849–1892.

Knight, F. (1921). *Risk, uncertainty and profit*. New York: Augustus Kelley.

Krawczyk, M. (2015). Probability weighting in different domains: The role of stakes, fungibility, and affect, working paper 15/2015(132), University of Warsaw.

Li, Z., & Hensher, D. (2011). Prospect theoretic contributions in understanding traveller behaviour: A review and some comments. *Transport Reviews*, *31*(1), 97–115.

Prelec, D. (1998). The probability weighting function. *Econometrica*, *66*, 497–527.
R Development Core Team. (2005). R: A language and environment for statistical computing, Vienna: R Foundation for Statistical Computing. http://www.Rproject.org
Stott, H. (2006). Cumulative prospect theorys functional menagerie. *Journal of Risk and Uncertainty*, *32*(2), 101–130.
Savage, L. (1954). *The foundations of statistics*. New York: Wiley. Dover edition, 1972.
Toubia, O., Johnson, E., Evgeniou, T., & Delqui, P. (2013). Dynamic experiments for estimating preferences: An adaptive method of eliciting time and risk parameters. *Management Science*, *59*(3), 613–640.
Train, K. (2009). *Discrete choice methods with simulation*. New York: Cambridge University Press.
Ungemach, C., Chater, N., & Stewart, N. (2009). Are probabilities overweighted or underweighted when rare outcomes are experienced (rarely)? *Psychological Science*, *20*, 473–479.
Wakker, P. (2010). *Prospect theory: For risk and ambiguity*. New York: Cambridge University Press.
Wilcox, N. (2008). Stochastic models for binary discrete choice under risk: A critical primer and econometric comparison. *Research in Experimental Economics*, *12*, 197–292.