

# Experienced vs. Described Uncertainty: Do We Need Two Prospect Theory Specifications?

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This paper reports on the results of an experimental elicitation at the individual level of all prospect theory components (i.e., utility, loss aversion, and weighting functions) in two decision contexts: situations where alternatives are described as probability distributions and situations where the decision maker must experience unknown probability distributions through sampling before choice. For description-based decisions, our results are fully consistent with prospect theory's empirical findings under risk. Furthermore, no significant differences are detected across contexts as regards utility and loss aversion. Whereas decision weights exhibit similar qualitative properties across contexts typically found under prospect theory, our data suggest that, for gains at least, the subjective treatment of uncertainty in experience-based and description-based decisions is significantly different. More specifically, we observe a less pronounced overweighting of small probabilities and a more pronounced underweighting of moderate and high probabilities for experience-based decisions. On the contrary, for losses, no significant differences were observed in the evaluation of prospects across contexts.

*Key words:* experience-based decisions; description-based decisions; rare events; risk; uncertainty; prospect theory; utility; loss aversion; decision weights; probability weighting; source of uncertainty; ambiguity

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## 1. Introduction

Thirty years after the publication of Kahneman and Tversky's (1979) famous paper, it has now become widely accepted that prospect theory (PT) is one of the most influential descriptive models for analyzing decision making under risk. In addition to the evaluation of outcomes as gains and losses relative to a reference point, with more sensitivity to losses than to gains (i.e., loss aversion), PT introduces an inverse S-shaped probability weighting function overweighting small probabilities and underweighting moderate and high probabilities (e.g., Tversky and Kahneman 1992, Gonzalez and Wu 1999). Most of the accumulated empirical findings on PT have been observed within the predominant experimental paradigm where choice situations are described in terms of probability distributions over potential outcomes. These situations are also referred to as description-based decision making (henceforth, DBDM).

Several recent experimental papers have considered another type of decision in which probabilities and outcomes for a given alternative must be learned

through sampling, i.e., repeated draws with replacement from a probability distribution unknown to the decision maker. More specifically, these papers report empirical findings that, in such experience-based decision making (henceforth, EBDM) contexts, people act as if they underweight the true objective probability of rare events (e.g., Hertwig et al. 2004, hereafter, HBWE; Weber et al. 2004; Hertwig et al. 2005; Hau et al. 2008). In these studies, the difference between DBDM and EBDM in terms of probability weighting was inferred from preference reversals at an aggregate level. For instance, 48% of the participants in the HBWE (2004) experiment preferred the prospect giving a gain of 32 points with probability 0.1 and gain 0 otherwise to a gain of 3 points for sure in DBDM. In contrast, this percentage declined to 20% when subjects were confronted with the same choice situation in an EBDM context (see Online Appendix A, Table A.1, decision problem 5; provided in the e-companion).<sup>1</sup> Many of these papers also report

<sup>1</sup> An electronic companion to this paper is available as part of the online version that can be found at <http://mansci.journal.informs.org/>.

parametric estimates of the probability weighting function and utility at the aggregate level confirming the finding that small probabilities are underweighted in experience-based choice (e.g., Ungemach et al. 2009).

Hau et al. (2008, p. 514) recognized, however, that most attempts to analyze the gap between DBDM and EBDM used limited sets of decision problems, making it necessary to fit models to the aggregate choice data (e.g., Fox and Hadar 2006, Ungemach et al. 2009). Consequently, they call for studies to examine “how robust and large the gap is across a wider range of problems, including mixed gambles, gambles with more than two outcomes, and gambles with a wider range of probabilities.” Indeed, in a recent experimental investigation, Erev et al. (2010) took steps in this direction, reporting parametric aggregated estimates of PT (in the HBWE setup) based on the choice between general two-outcome prospects and using a richer set of decision problems. Regarding aggregate choice data, Hau et al. (2008, p. 515) insist on the importance of “studying more problems in the future and, in particular, of letting the same respondent make numerous choices to arrive at reliable individual-specific parameter estimates.” The present paper aims to move further in this direction through a quantitative study of the difference between DBDM and EBDM under PT at the level of individual decision makers.

More specifically, we elicited all the different PT components, i.e., utility for gains and losses, loss aversion, and weighting functions, for both DBDM and EBDM. Our experimental setup used general two-outcome prospect certainty equivalents with significantly larger amounts of money at stake and a wider range of decision problems than in most of the aforementioned studies. For EBDM, we adapted the way sampling is performed in the HBWE paradigm to allow a consistent rank-dependent weighting of outcomes when evaluating two-outcome prospects under PT. In fact, whereas probabilities *and* outcomes for a given prospect were first obtained through sampling, as in the HBWE paradigm, our experimental setup also provides the subject with the list of the outcomes involved by this prospect at the end of the sampling process (before choice). Additional details on the above-mentioned adaptation of the HBWE setup are discussed in §2.3.

To efficiently elicit PT for described and experienced decisions, the present paper builds on a semi-parametric utility elicitation method that can work for different parametric specifications of utility, but the measurement of decision weights is parameter free. This allows a comparison of probability weighting across contexts without the interference of specific parametric forms of probability weighting. Unlike

many existing procedures, this method is significantly less time consuming and can be used for risk as well as for uncertainty (see Fox and Poldrack 2008). It is based on the assessment of certainty equivalents of two-outcome prospects, a widely used method. The different certainty equivalents are not linked and therefore not subject to error propagation (Wakker and Deneffe 1996).

In what follows, §§2.1 and 2.2 define EBDM and introduce the formal restriction of PT to binary prospects under risk. Subsection 2.3 describes the main characteristics of the HBWE paradigm and elucidates the formal requirements for a consistent PT evaluation of prospects in EBDM. Then, it interprets described and experienced uncertainty as two different sources of uncertainty and brings out the main expected prediction resulting from such an interpretation. Subsection 2.4 reviews the existing empirical evidence on utility, loss aversion, and probability/event weighting for both DBDM and EBDM. Section 3 describes our PT elicitation method for description- and experience-based decisions. Readers who are not interested in the elicitation techniques can skip this section. Section 4 describes the experimental design that allows eliciting PT for description- and experience-based decisions. The results of the study are presented and analyzed in §§5 and 6. Additional results are provided in Online Appendix D. Finally, §7 summarizes and discusses the experimental findings.

## 2. Prospect Theory: Description-Based vs. Experience-Based Decisions

### 2.1. Preliminaries

We consider a decision maker who has to make a choice between two-outcome prospects. The set of states of nature, i.e., the carriers of uncertainty, is denoted by  $\mathbb{S}$ , and the set of outcomes is denoted by  $\mathbb{R}$ . Subsets of  $\mathbb{S}$  are *events*. Let  $E_p$  denote an event of probability  $p$ , and let  $(x, E_p; y)$  denote the binary prospect that results in outcome  $x$  if  $E_p$  obtains and in outcome  $y$  otherwise. Probability  $p$  may be known or unknown to the decision maker. Outcomes are expressed as changes with respect to the status quo or *reference point*, i.e., as gains or losses. Throughout this paper, we assume that the reference point outcome is zero. A *mixed* prospect involves both a gain and a loss; otherwise, the prospect is *nonmixed*. The above notation of binary prospects assumes  $x \geq y \geq 0$  for gain prospects,  $x \leq y \leq 0$  for loss prospects, and  $x > 0 > y$  for mixed prospects.

Following Hadar and Fox (2009, p. 318), we define a decision from experience as a single decision satisfying two conditions: first, the decision maker's knowledge of possible outcomes and/or corresponding probabilities is incomplete, and second, this information is inferred, at least in part, from a sampling

process.<sup>2</sup> In the sequel,  $(x, E_p; y)$  denotes a prospect involved in an EBDM situation where the decision maker learns about  $p$ ,  $x$ , and  $y$  from a sequence of  $E_p$ -based independent random drawings. When the decision maker is provided with  $p$ ,  $x$ , and  $y$  from the outset (i.e., DBDM), the corresponding prospect is denoted by  $(x, p; y)$ .

## 2.2. PT for Description- and Experience-Based Decisions

In DBDM, the PT value of the nonmixed prospect  $(x, p; y)$  is given by

$$w^s(p)u(x) + (1 - w^s(p))u(y). \quad (1)$$

Here,  $u$  denotes utility, which is an increasing function from  $\mathbb{R}$  to  $\mathbb{R}$  satisfying  $u(0) = 0$ . Function  $w^s(\cdot)$ , called the *probability weighting function*, is strictly increasing from  $[0, 1]$  to  $[0, 1]$  and satisfies  $w^s(0) = 0$  and  $w^s(1) = 1$ , with  $s$  being positive for gains and negative for losses. Expression (1) generalizes expected utility by the replacement of probabilities  $p$  and  $1 - p$  by *decision weights*  $w^s(p)$  and  $1 - w^s(p)$ , respectively. These last coefficients reflect the rank ordering of the outcomes. Expression (2) below extends the above-mentioned generalization to mixed prospects. More specifically, the PT value of the mixed prospect  $(x, p; y)$  is

$$w^+(p)u(x) + w^-(1 - p)u(y). \quad (2)$$

When probability  $p$  is unknown (as in a standard decision under uncertainty and EBDM), and the decision maker has inferred from sampling that she is facing the nonmixed prospect  $(x, E_p; y)$ ; the value of such a prospect is given by expression (1), except that decision weights  $w^s(p)$  and  $1 - w^s(p)$  are replaced by decision weights  $W^s(E_p)$  and  $1 - W^s(E_p)$ , respectively, where  $W^s$  is an event weighting function assigning weight 0 to the vacuous event and weight 1 to the universal event, and satisfying monotonicity with respect to set inclusion. Similarly, the value of a mixed uncertain prospect is given by expression (2) in which the probability weighting functions (for gains and losses) are replaced by the corresponding event weighting functions.

The observable utility  $u(\cdot)$  implicitly takes into account loss aversion, i.e., more sensitivity to losses than to gains. To formally isolate loss aversion, we assume, as in Tversky and Kahneman (1992), that

$$u(x) = \begin{cases} x^\alpha & x \geq 0, \\ -\lambda(-x)^\beta & x < 0, \end{cases} \quad (3)$$

<sup>2</sup> In a recent paper, Hertwig and Erev (2009) proposed a more general definition of decision from experience that distinguishes between three different experimental paradigms representing decision from experience. The sampling paradigm as studied in the present paper is one of the three above-mentioned paradigms.

where the coefficient  $\lambda > 0$  represents the *loss aversion index* reflecting the different processing of gains and of losses. Paying more attention to losses than to gains, as assumed in PT, results in  $\lambda$  exceeding 1 (e.g., Zank 2010).

## 2.3. Implications of PT for Experience-Based Decisions

### 2.3.1. Adaptation of the HBWE Paradigm.

The HBWE paradigm designates the common characteristics of the various experimental setups that were recently devoted to the investigation of the difference between DBDM and EBDM under PT (e.g., HBWE 2004, Hau et al. 2008). Except for a recent study by Erev et al. (2010), the HBWE paradigm has involved only one-nonzero-outcome prospects. For instance, in DBDM for gains, the PT value of  $(x, p; 0)$  is given by the simple multiplicative expression  $w^+(p)u(x)$ . Similarly, in EBDM for gain, the value of  $(x, E_p; 0)$  under PT is given by  $W^+(E_p)u(x)$ . It turns out, however, that such multiplicative models warrant uniqueness of the utility and the weighting function only up to a power.<sup>3</sup> This suggested to us the first adaptation of the HBWE paradigm, namely, the use of general two-outcome prospects instead of one-nonzero-outcome prospects. Such an adaptation has the advantage of preserving the uniqueness properties of utility and decision weights under PT. In other terms, only the unit of the utility scale can be changed.

In the HBWE paradigm, the decision maker facing experience-based decisions learns about probabilities and outcomes through sampling, i.e., independent random drawings with replacement. In each choice situation, the decision maker sees two buttons on a computer screen and is told that each button is associated with an alternative. By clicking on a button, the decision maker samples an outcome from the corresponding prospect. Participants can sample until they are confident about which alternative they wish to play for real (e.g., HBWE 2004). For instance, a choice between prospects  $(4, E_{0.8}; 0)$  and  $(3, E_{1.0}; 0)$  may result (after sampling) in the sequences  $\{0, 0, 4, 4, 4, 0, 4, 4, 4\}$  and  $\{3, 3, 3, 3, 3, 3\}$ , respectively, and the choice of the first prospect to be played for real. One final random draw from the preferred prospect, i.e.,  $(4, E_{0.8}; 0)$ , may result in an earning of 4 (e.g., Hau et al. 2008, p. 495). Because of the presence of only one nonzero outcome, the evaluation of these prospects from sampling in the HBWE

<sup>3</sup> It can be easily observed that when comparing two prospects  $(x, p; 0)$  and  $(x', q; 0)$  with  $x, x' > 0$ ,  $u$ , and  $w^+$  can be indifferently replaced by  $u^k$  and  $(w^+)^k$  for  $k > 0$ . Formally, this means that  $u$  and  $w^+$  are unique to a power, hence the problematic interpretation of the estimated utility and probability weighting function under the above-mentioned multiplicative PT form used in the HBWE paradigm (Gonzalez and Wu 1999, p. 133).

paradigm requires less information on the rank ordering of outcomes than choice involving general two-outcome prospects.

The second adaptation of the HBWE paradigm considers the information available to the decision maker before and after sampling. In fact, to allow a consistent weighting of the consequences of a given two-outcome prospect under PT, our setup allows the decision maker to primarily learn about the number of consequences and their ranking before sampling. Then, after sampling probabilities and outcomes, as in the HBWE paradigm, the decision maker is provided with the list of outcomes corresponding to the sampled prospect. To illustrate this, assume that the decision maker has to evaluate the prospect  $P = (x, E_{0.01}; y)$ . If she samples  $P$  eight times (approximately the median number reported in HBWE 2004), one would expect her to probably end up with the sequence  $\{y, y, y, y, y, y, y, y\}$ . In this example, the decision maker does not have the information needed about outcomes to obtain a consistent PT evaluation of prospect  $P$ ; she needs to know that  $x$  is the second outcome. Similarly, if the decision maker is faced with the prospect  $(x, E_{1.0}; y)$  and has sampled the sequence  $\{x, x, x, x, x, x\}$ , she might reasonably consider that there exists at least one other unlikely outcome that she did not observe (see Hadar and Fox 2009). Note that in the HBWE paradigm, where  $y = 0$  for all prospects, subjects might guess from the previous choice situations that the second outcome is zero.

**2.3.2. Drawing a Parallel Between DBDM/EBDM and Ellsberg (1961).** The Ellsberg (1961) two-color example provides a situation similar to that of an experimental setup studying DBDM versus EBDM. In his famous example, Ellsberg (1961) suggests that people typically prefer gambling on a color from an urn containing 50 black balls and 50 red balls, i.e., the known urn, to gambling on a color from an urn containing 100 black and red balls in an unknown proportion, i.e., the unknown urn. The difference in terms of attitudes across urns can be illustrated in terms of attitudes toward different *sources of uncertainty* where one source of uncertainty (the known urn) concerns known probabilities, and the other source (the unknown urn) concerns unknown probabilities (e.g., Fox and Tversky 1998, Wakker 2004).

At least for moderate probabilities and gains (as in the Ellsberg (1961) example above), subjects are expected to weakly prefer prospect  $(x, p; y)$  over the corresponding experience-based prospect  $(x, E_p; y)$ . This is consistent with the idea of *source preference* (Tversky and Fox 1995, Tversky and Wakker 1995).<sup>4</sup> Furthermore, subjects are expected to be

more sensitive to changes in (moderate) probabilities when probability  $p$  is known than when it is determined with some residual uncertainty (e.g., Baillon and Cabantous 2009). Sensitivity to probabilities and desirability of prospects “across urns” were studied in an Ellsberg-like experiment reported in Abdellaoui et al. (2011).

**2.3.3. Beliefs in Experienced Contexts.** When evaluating a prospect  $(x, E_p; y)$  under PT, the decision weight  $W^s(E_p)$  is not a pure measure of belief; it can also reflect attitude toward uncertainty. For instance, it can reflect ambiguity aversion as in the Ellsberg (1961) two-color example.

Building on empirical findings that decision makers are less sensitive to uncertainty than to risk, Fox and Tversky (1998) proposed a two-stage model in which the decision maker first assesses the *judged* probability of an uncertain event and then transforms this value by the probability weighting function for risk. Using a different approach, Wakker (2004) showed that choice between two-outcome nonmixed prospects (uncertain versus risky prospects) allows one to find a subadditive choice-based set function  $\pi(\cdot)$  such that

$$W(E_p) = w(\pi(E_p)), \quad (4a)$$

where  $w(\cdot)$  is the probability weighting function under risk. The function  $\pi(\cdot)$  is assumed to reflect the decision maker’s choice-based beliefs (see also Abdellaoui et al. 2005). The present paper did not perform an independent elicitation of  $\pi(\cdot)$  as in Fox and Hadar (2006), where judged probabilities of events  $E_p$  were elicited. Subsection 6.2 explains how to determine  $\pi(\cdot)$  regarding events  $E_p$  assuming PT and using Equation (4a).

In the presence of different sources of uncertainty, Fox and Tversky (1998) suggested a more general and accurate specification of the model presented in Equation (4a) that can be defined by

$$W(E_p) = w_\sigma(\pi(E_p)), \quad (4b)$$

where the transformation  $w_\sigma$  of probability depends on the source of uncertainty  $\sigma$ . Abdellaoui et al. (2011) used a choice-based version of this model in which  $w_\sigma$  is called a *source function*, and  $\pi(\cdot)$  is an additive probability measure. This function reflects the subjective treatment of uncertainty for a specific source (e.g., ambiguity aversion relative to another source). Section 6 of this present paper elicits the source function corresponding to EBDM using objective and experienced probabilities.

<sup>4</sup> In Tversky and Fox (1995) and Tversky and Wakker (1995), if  $A$  and  $B$  are events related to two different sources of uncertainty,

and  $(100, A; 0)$  is weakly preferred to  $(100, B; 0)$ , and  $(100, A^c; 0)$  is weakly preferred to  $(100, B^c; 0)$ , then source preference holds for  $A$  against  $B$ .

## 2.4. Empirical Findings

### 2.4.1. Subjective Treatment of Outcomes

*Description-Based Decisions.* Measurements of utility under risk have generally confirmed PT's assumption of concave utility for gains and convex utility for losses. The available evidence is stronger, however, for gains than for losses. Tversky and Kahneman (1992) assumed power utility and found a median power coefficient of 0.88 both for gains and losses. Abdellaoui (2000) and Etchart-Vincent (2004) found slightly convex utility for losses at the aggregate level (median power coefficients varied between 0.84 and 0.97). Using a parameter-free elicitation technique, Abdellaoui et al. (2007b) found strong support for the S-shaped utility function both at the aggregate and the individual levels (see also Booij and van de Kuilen 2009).

Eliciting loss aversion requires that the utility be measured both for gains and for losses (e.g., Tversky and Kahneman 1992, Schmidt and Zank 2005). Numerous quantitative elicitations of loss aversion for decision under risk have been presented in the literature recently. Bleichrodt et al. (2007) estimated six loss aversion coefficients and found a median coefficient of 2.54. Abdellaoui et al. (2008) found a median coefficient of 2.61. Booij and van de Kuilen (2009) estimated separate loss aversion coefficients for high and low monetary amounts and reported an average coefficient of 1.87.

*Experience-Based Decisions.* Although a major part of behavioral research on PT has been on the measurement of utility and loss aversion for DBDM, only a few studies exist on the measurement of these components under uncertainty (Wu and Gonzalez 1999). Considering that the HBWE paradigm is relatively recent, we are aware of only a few attempts that estimated utility for experienced contexts at an aggregate level for gains and losses (Hau et al. 2008, Erev et al. 2010) and at an individual level for gains (Jessup et al. 2008). Most attempts, however, were characterized by the use of limited sets of choice problems per subject and small amounts of money at stake. For gains, no strong evidence for a concave utility was obtained. In contrast, Hau et al. (2008) reported evidence in favor of convexity of the utility function for losses. To our knowledge, except for the present study, no study has elicited loss aversion for EBDM at an individual level.

### 2.4.2. Subjective Treatment of Uncertainty

*Description-Based Decisions.* Most empirical studies on probability weighting observed inverse S-shaped probability weighting both for gains and for losses (Tversky and Kahneman 1992, Tversky and Fox 1995, Wu and Gonzalez 1996, Gonzalez and Wu 1999,

Abdellaoui 2000, Bleichrodt and Pinto 2000).<sup>5</sup> The point where the probability weighting changes from overweighting probabilities to underweighting probabilities generally lies between 1/4 and 1/3.

*Experience-Based Decisions.* For decision under uncertainty, and following Schmeidler (1989), the convexity of the weighting function  $W^s(\cdot)$  has been used to formalize ambiguity aversion. Subsequently, convexity was shown to reflect pessimism under uncertainty (Wakker 2001), where pessimism means that events receive more attention as their corresponding outcomes are ranked lower. However most experimental studies have shown that the weighting function tends to reflect diminishing sensitivity, resulting in an overweighting of unlikely events and an underweighting of likely events (e.g., Tversky and Fox 1995, Wu and Gonzalez 1999, Kilka and Weber 2001, Abdellaoui et al. 2005).

Paraphrasing Fox and Hadar (2006, p. 159), the most influential study on the difference between DBDM and EBDM was presented by HBWE (2004). The experiment consisted of six decision problems (described in Online Appendix A, Table A.1) used either in a description-based context or in an experience-based context. The observed preference reversals across contexts in the six choice problems suggested a context-dependent subjective treatment of probabilities. More specifically, HBWE (2004) focused on the conclusion that people act in experienced contexts as if they underweight the (objective) probability of rare events. The authors of the study provided two explanations for the difference between DBDM and EBDM. The first explanation stipulates that, because of the binomial distribution underlying sampling, the observed small size samples (per decision problem) result in an undersampling of low-probability events. The second explanation, called the *recency effect*, suggests that "observations made late in the sequence of  $n$  observations had more impact on the choice process than they deserved" (Hau et al. 2008, p. 495). The recency effect was considered as a factor that aggravates undersampling of low-probability events.

Fox and Hadar (2006) replicated the HBWE (2004) experiment for experience-based decisions and added an elicitation of judged probabilities for the events used in the six choice problems. The elicitation of judged probabilities aimed to test if the observed reversal should be attributed to sampling error or to incorrect judgement regarding experienced occurrence of rare events. Then, assuming PT and using Tversky and Kahneman's (1992) median utility and weighting function parameter estimates, they found

<sup>5</sup> See Birnbaum (2004, 2006) for different findings regarding probability weighting.

that assigning either experienced (i.e., observed relative frequencies) or judged probabilities to events instead of objective probabilities (unknown to the decision maker) allows for a better consistency of experienced choices with PT.<sup>6</sup>

Subsequently, Hau et al. (2008) tested the robustness of Fox and Hadar's (2006) "one-factor" (sampling error) explanation using two new experimental protocols in which subjects drew on large samples of experience to make a choice, i.e., reducing the gap between experienced and objective probabilities. Although confirming that more experience reduces the description–experience gap, the observations of Hau et al. (2008) are not consistent with the disappearance of such a gap. Furthermore, the authors did not find evidence in favor of a recency effect as initially conjectured by HBWE (2004). The absence of a significant impact of the recency effect was confirmed by Rakow et al. (2008).

Taking into account the above-mentioned results, we conjecture that, in the absence of sampling error, the residual gap between description and experience could be investigated in terms of attitudes toward ambiguity across DBDM and EBDM contexts (see §7.1).

### 3. Elicitation of PT in Experienced and Described Contexts

This section presents the procedure we used to elicit all of the PT components: utility, loss aversion, and (probability) weighting functions. The procedure consists of three stages, each one involving the measurement of a different component. Our measurements are based on the comparison of a sure outcome with a binary prospect. Except for loss aversion elicitation, all measurements consist of the determination of certainty equivalents (see also Abdellaoui et al. 2008).

#### 3.1. Elicitation of Utility and Weighting Functions

We begin with the elicitation of utility for non-mixed prospects in an experience-based context. We first select a probability  $p^*$  and  $k$  pairs of outcomes  $\{(x_i^s, y_i^s) : i = 1, \dots, k, s = +, -\}$ , that are kept fixed throughout the elicitation process. Then, we determine  $k$  certainty equivalents  $z_1^s, \dots, z_k^s$  such that

$$z_i^s \sim (x_i^s, E_{p^*}; y_i^s), \tag{5}$$

with  $i = 1, \dots, k$  and  $s = +$  ( $s = -$ ) in the gain (loss) domain. The advantage of keeping the probability  $p^*$  fixed is that only one additional parameter,  $W^s(E_{p^*})$ ,

<sup>6</sup>The formal link between decision weights and judged probabilities was based on Fox and Tversky's (1998) two-stage model. Fox and Hadar (2006) found a high correlation (0.97) between experienced and judged probabilities.

has to be estimated besides the parameter(s) of the utility function. If we adopt a parametric specification for utility, then the utility parameter can be obtained from minimization of the nonlinear least squares  $\|z^s - \hat{z}^s\|^2$  with  $\hat{z}_i^s = u^{-1}[W^s(E_{p^*})[u(x_i^s) - u(y_i^s)] + u(y_i^s)]$ , where  $s = +$  ( $s = -$ ) for gains (losses), and  $i = 1, \dots, k$ .

With utility available, decision weights can easily be elicited using certainty equivalents. To determine decision weights  $W^s(E_{p_1}), \dots, W^s(E_{p_m})$ , we need  $m$  certainty equivalents  $z_1^s, \dots, z_m^s$  and a fixed outcome  $x_*^s$  in the (elicited) utility domain such that

$$z_j^s \sim (x_*^s, E_{p_j}; 0) \tag{6}$$

or, equivalently,  $W^s(E_{p_j}) = u(z_j^s)/u(x_*^s)$  for  $j = 1, \dots, m$ .

For description-based decisions, utility and probability weighting functions are elicited in the same way. The difference with the elicitation for experience-based decisions lies in the fact that the probabilities and outcomes are known to the decision maker from the outset. Formally,  $W^s(E_{p_j})$  is replaced by  $w^s(p_j)$  in the relevant equations.

#### 3.2. Measuring Loss Aversion

For experience-based decisions, if a gain  $g_*$  and a probability  $r$  are fixed beforehand, the elicitation of the loss aversion coefficient  $\lambda$  requires a determination of the loss  $l$  such that

$$(g_*, E_r; l) \sim 0. \tag{7}$$

Using the analogue of expressions (2) under uncertainty and Equation (3), we obtain  $\lambda = [W^+(E_r)/W^-(E_{1-r})][g_*^\alpha/(-l)^\beta]$ , where  $\alpha, \beta, W^+(E_r)$  and  $W^-(E_{1-r})$  are assumed to be known. The elicitation process of  $\lambda$  for description-based decisions is similar except that the event weighting function is replaced by the probability weighting function in the (PT) equation corresponding to indifference (9).<sup>7</sup>

## 4. Experiment

### 4.1. Subjects

Subjects were 61 (45 female) undergraduate students in management at the Institut Universitaire de Technologie of Paris. We divided the set of subjects into two subsets to investigate whether real incentives

<sup>7</sup>Köbberling and Wakker (2005, pp. 121–122) and Wakker (2010, pp. 267–271) reported analytical difficulties of power utility for analyzing loss aversion. Among other things, they noted that the scaling convention  $\lambda = -u(-1)/u(1)$  depends on the unit of payment. Although the present paper is not meant to be a systematic study of loss aversion, it will be shown that our results regarding loss aversion are consistent with those reported in recent experimental studies, including Tversky and Kahneman (1992). It will be also shown that the use of an exponential utility (as suggested in results in Köbberling and Wakker 2005) gave similar measurements for  $\lambda$ .

**Table 1** Nonmixed Prospects Used to Elicit Utility and Weighting Functions (DBDM and EBDM)

	Index $i$											
	Utility							Decision weights				
	1	2	3	4	5	6	7	8	9	10	11	12
$ x_i^s $	100	200	200	50	150	200	200	200	200	200	200	200
$p_i$	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.05	0.25	0.50	0.75	0.95
$ y_i^s $	0	50	100	0	100	150	0	0	0	0	0	0

influenced the subjects' behavior. The first subset (30 subjects) received only a flat payment of €10 for their participation and then faced hypothetical choices. Subjects in the second subset (31 subjects) received €10 for their participation and were told that two of them will be randomly selected to play out one of the gain questions for real. Selected subjects could therefore win a maximum of €200 depending on their responses and won €75 on average. In what follows, we refer to the former as the hypothetical subset and to the latter as the real incentive subset. For ethical reasons we could not play out a loss question or a mixed question for real. More than 20 pilot sessions (i.e., individual interviews) with undergraduate students were performed to test and fine-tune the experimental protocol.

The experiment was conducted in the form of computer-based individual interview sessions. Special software was developed for use in the experiment. Subjects were told that there were no right or wrong answers, and they were allowed to take a break at any time during the session. The responses were systematically entered in the computer by the interviewer so that the subjects could focus on the choice questions. In experience-based choice situations, sampling was made by the subject. The experiment lasted 45 minutes, on average, including 10 minutes for task explanation and practice questions before the experiment began.

#### 4.2. Stimuli

**4.2.1. Utility.** We used 14 certainty equivalence questions (7 described and 7 experienced) to elicit the utility function for gains and 14 similar questions to elicit the utility function for losses (see Equation (5)). The prospects for which we determined certainty equivalents are displayed in Table 1 ( $i = 1, \dots, 7$ ). The measurements were not chained and therefore not vulnerable to error propagation. Given the fact that we aimed to elicit utility under PT, the impact of the choice of probability  $p^*$  (in Equation (5)) should be immaterial (compared to when assuming expected utility). The probability used to elicit utility in our study was  $p^* = 0.25$ . For description-based decisions and using the same elicitation method, Abdellaoui

et al. (2008) reported experimental results showing that the elicited utility is robust to the level at which probability  $p^*$  is fixed.<sup>8</sup>

**4.2.2. Decision Weights.** For decision weight elicitation, we used 10 certainty equivalence questions (5 described and 5 experienced) for gains and 10 similar questions for losses (see Equation (6)). We elicited decision weights for  $p = 0.05, 0.25, 0.50, 0.75$ , and  $0.95$  using  $|x_*^s| = €200$  in experienced and described contexts (Table 1,  $i = 8, \dots, 12$ ).

**4.2.3. Loss Aversion.** To determine loss aversion coefficients in the described and experienced contexts, we fixed gains  $g_*^1 = €90$  and  $g_*^2 = €200$  and a probability  $r = 0.50$ , and then determined  $l^1$  and  $l^2$  such that  $(g_*^i, E_{0.5}; l^i) \sim 0$ ,  $i = 1, 2$ . This resulted in two loss aversion coefficients,  $\lambda^1$  and  $\lambda^2$ , for each context. The assessment was choice based and similar to the determination of certainty equivalents (see Online Appendix B, Table B.1).

#### 4.3. Experimental Methods

**4.3.1. Choice Questions.** All indifferences were constructed through a series of binary choice questions. Each choice situation corresponded to an iteration in a bisection process (see Online Appendix B). A prospect was represented by a chance tree, i.e., a chance node (circle) with two branches. The upper (lower) branch gave the higher (lower) outcome. In description-based choice questions, the subject faced a risky prospect called "alternative A" and a sure prospect called "alternative B" (Online Appendix C, Display C.1). For experience-based situations, the subject saw alternative A as an unlabeled chance tree and had access to a sampling button located below the alternative's frame before actually choosing. By clicking on the button, the subject could sample an outcome with replacement from a binomial probability

<sup>8</sup> For gains (losses), they did not detect significant differences between elicited utilities for  $p^* = 0.50$  (0.50) and  $p^* = 0.66$  (0.33) (see also Wakker and Deneffe 1996). Abdellaoui et al. (2007a) showed that for description-based decisions, probability weighting explains the distortions in utility measurement initially detected by McCord and de Neufville (1986) under expected utility. In other words, factoring out probability/event weighting (as performed by our elicitation method) allowed us to obtain a utility function that does not depend on the probability used to elicit it.

distribution unknown to the subject. Before sampling, the subject could see that the unlabeled prospect has two nonspecified outcomes and that the upper branch of the chance tree gave the higher outcome (in absolute value). During sampling, the subject saw either the upper branch or the lower branch (along with the corresponding outcome). In accord with HBWE (2004), subjects were encouraged to sample until they felt sufficiently confident about the “value” of the corresponding unlabeled prospect. Then, the iterative process for determining the certainty equivalent of prospect *A* started (as for described decisions). In this case, the subject saw a sure prospect *B* and the sampled prospect *A* with a disabled sampling button on the computer screen, indicating that no more sampling was allowed (see Online Appendix C, Display C.2). The construction of each indifference was preceded by an independent sampling process.

**4.3.2. Reliability Checks.** Reliability of subjects' answers can be checked by a special bisection process that consists of asking them to choose again between two prospects corresponding to a given iteration. Similar reliability checks were performed in numerous studies (e.g., Abdellaoui 2000). For consistent subjects, the rate of preference reversals between equivalent alternatives *A* and *B* should be close to 50–50, i.e., it is equally likely that the subject chooses either *A* or *B* near indifference at the end of the bisection process. Away from indifference, in the middle of the bisection process for instance, a consistent subject should confirm her initial choice, i.e., the rate of preference reversal should be lower.

In the present experimental study, we repeated the third iteration for 16 indifferences: 8 for gains (4 described and 4 experienced) and 8 for losses (4 described and 4 experienced). The third iteration corresponds approximately to the middle of the bisection process, i.e., at least two or three additional iterations were required to end up with a certainty equivalent (see Online Appendices B and D).

**4.3.3. Choice Task Ordering.** Because choice tasks were cognitively less demanding in the context of DBDM, we always began the experiment with description-based choice questions. In fact, few preliminary individual interviews showed that starting with DBDM delivers a better understanding of choice questions than when the subject began with EBDM. Evidence from the main pilot study, which was identical to the final study except that we began with experience-based choice questions, did not reveal any order effect (see Online Appendix E).

We also learned from pilot sessions that subjects found it easier to start with questions involving only gains than with questions involving only losses (e.g., Abdellaoui et al. 2005). The order in which the 24 certainty equivalents were elicited in each of the two

contexts was as follows: seven certainty equivalents to determine utility, and then five certainty equivalents to determine decision weights successively for gains and losses. For each context, the series of choice questions that allowed the elicitation of loss aversion coefficients  $\lambda^1$  and  $\lambda^2$  (successively) came after the determination of the 24 certainty equivalents. Before completing the series of choice tasks in a context, subjects were given practice questions.

## 5. Results for Description-Based Decisions Under PT

This section reports the results of the elicitation of PT components for DBDM, i.e., decision under risk. It shows that our observations are globally consistent with typical empirical PT findings (e.g., Tversky and Kahneman 1992, Abdellaoui 2000, Bleichrodt and Pinto 2000).

### 5.1. Utility for Gains and Losses

We used a power parametric specification for utility. Other parametric specifications such as exponential and expo-power are also feasible. Recent works have shown, however, that under PT, using the power function is a good compromise (e.g., Abdellaoui et al. 2008). The power family is defined by  $x^\alpha$  for gains and  $-(-x)^\beta$  for losses with  $\alpha, \beta > 0$ . For gains (losses), the power function is concave if  $\alpha < 1$  ( $\beta > 1$ ), linear if  $\alpha = 1$  ( $\beta = 1$ ), and convex if  $\alpha > 1$  ( $\beta < 1$ ).

Table 2 reports utility estimates for gains and losses (the corresponding histograms are given in Online Appendix F, Figure 1). For gains, the median power coefficient of 0.79 differed significantly from 1 (Wilcoxon,  $p < 0.001$ ). The interquartile range (IQR) for the power coefficient indicated considerable variation at the individual level (e.g., Gonzalez and Wu 1999). For losses, the median power estimate of 0.96 was not significantly different from 1 (Wilcoxon,  $p = 0.87$ ). Real incentives had no significant effect on the utility function coefficients for gains (Mann-Whitney test,  $p = 0.681$ ).

Concavity was the most common pattern for gains for description-based decisions (49 out of 61). Although not as predominant as concavity, there are significantly more convex utility functions for losses than there are concave ones (35 out of 61). The proportion of subjects with an everywhere concave utility

**Table 2** Median Estimates for Utility and Loss Aversion for DBDM

	Power		Loss aversion	
	Gains ( $\alpha$ )	Losses ( $\beta$ )	$\lambda^1$	$\lambda^2$
Median	0.79	0.96	2.47	2.62
Std. dev.	0.30	0.39	5.93	4.81
IQR	0.65–0.95	0.76–1.22	1.17–4.48	1.75–4.08



(21 out of 61) was not significantly different from the proportion of subjects with an S-shaped utility function (binomial,  $p = 0.19$ ). This finding corroborates many recent results suggesting that the PT hypothesis of an S-shaped utility (i.e., hypothesis of diminishing sensitivity for gains and losses) is not fully consistent with observations (e.g., Abdellaoui et al. 2008, Abdellaoui 2000).

We found clear evidence of loss aversion for description-based decisions. Table 2 (last two columns) reports very similar median loss aversion coefficients resulting from two different indifferences (see Online Appendix D, Table D3). Standard deviations and interquartile ranges reflect considerable variability at the individual level. Individual loss aversion coefficients  $\lambda^1$  and  $\lambda^2$  differed significantly from 1 (Wilcoxon,  $p < 0.001$ ) and did not exhibit significant discrepancies (paired  $t$ -test,  $p = 0.38$ ). This finding is consistent with the results reported by Tversky and Kahneman (1992) and Abdellaoui et al. (2007b). It is also consistent with the findings of Abdellaoui et al. (2008) using the same utility elicitation method (for DBDM). Loss aversion was clearly the dominant pattern at the individual level: for  $g_*^1 = 90$  ( $g_*^2 = 200$ ), 49 (55) subjects (80% (90%)) had a loss aversion coefficient that exceeded 1 and were classified as loss averse.<sup>9</sup>

### 5.2. Decision Weights

Table 3 gives median decision weights for gains and losses along with the corresponding interquartile ranges. The median results (combined with the corresponding IQRs) are fully consistent with an inverse-S-shaped probability weighting function for gains and losses. Paired (one-tailed)  $t$ -tests confirm that probability 0.05 is overweighted for gains and losses, and that probabilities 0.50, 0.75, and 0.95 are underweighted. The hypothesis  $w^s(0.25) = 0.25$  cannot be rejected by our data, both for gains and for losses.

We detect a significant difference between probability weighting for gains and losses only for probability 0.05. A Friedman test adjusting for probability differences found no significant overall sign effect ( $p = 0.58$ ).

To compare our results on probability weighting with those reported recently in the literature, we estimated the linear-in-log-odds probability weighting function  $w(p) = \delta p^\gamma / [\delta p^\gamma + (1 - p)^\gamma]$  for gains and for losses (e.g., Gonzalez and Wu 1999). In

<sup>9</sup>When assuming a linear utility around the reference point 0, the median loss aversion  $\lambda^1$  ( $\lambda^2$ ) is 2.25 (2.85) with a standard deviation of 4.16 (4.61). The use of an exponential utility function as suggested by Köbberling and Wakker (2005, p. 128) gave a median loss aversion coefficient  $\lambda^1$  ( $\lambda^2$ ) of 2.73 (3.75) with a standard deviation of 3.55 (4.50). This finding is similar to that resulting from the use of a power utility function.

**Table 3** Median Decision Weights and Paired  $t$ -Tests ( $w^s(p)$  vs.  $p$ ) for DBDM

Probability $p$	Gains ( $w^+(p)$ )			Losses ( $w^-(p)$ )		
	Median	IQR	$t_{60}$	Median	IQR	$t_{60}$
0.05	0.11	0.05–0.16	7.70**	0.07	0.03–0.13	4.12**
0.25	0.26	0.17–0.32	0.14 <sup>ns</sup>	0.26	0.19–0.34	0.70 <sup>ns</sup>
0.50	0.42	0.35–0.50	−4.87**	0.44	0.36–0.54	−3.39**
0.75	0.63	0.52–0.75	−5.85**	0.65	0.54–0.73	−6.15**
0.95	0.79	0.63–0.89	−8.75**	0.82	0.74–0.90	−7.77**

Note. ns, nonsignificant for  $\alpha = 0.05$ .

\*\* $p < 0.001$ .

this parametric form,  $\delta$  reflects elevation (i.e., optimism/pessimism), and  $\gamma$  represents curvature (i.e., sensitivity to probabilities).

For gains, the median elevation,  $\delta = 0.70$ , did not differ from the median estimates of Tversky and Fox (1995), Wu and Gonzalez (1996), and Gonzalez and Wu (1999), but was slightly higher than the median elevation in Abdellaoui (2000). The median curvature,  $\gamma = 0.65$ , was in the range of parameters found in the literature.

For losses, the median elevation,  $\delta = 0.78$ , did not differ from the results reported in Abdellaoui (2000) or Lattimore et al. (1992) but was significantly different from the estimate of Etchart-Vincent (2004). The median curvature,  $\gamma = 0.73$ , revealed a higher sensitivity to loss probabilities than that in the above-mentioned studies.

## 6. Results for Experience-Based Decisions Under PT

The study of probability weighting in EBDM requires the assigning of “likelihoods” to events  $E_p$ . In the present study, we can assign to an event either its objective (true) probability, as in the HBWE paradigm, or its experienced probability, i.e., observed frequency (e.g., Fox and Hadar 2006, Hadar and Fox 2009). Below, after presenting the elicitation results regarding utility and loss aversion, we focus on the weighting function first as a function of objective probabilities and as a function of experienced probabilities. We then compare the resulting decision weights.

### 6.1. Utility for Gains and Losses

Table 4 gives median power estimates for utility from experience-based decisions (the corresponding histograms are given in Online Appendix F, Figure 1). Whereas the median estimate for gains reflects concavity (as for description-based decisions), the median estimate for losses also reflects a slight concavity in contrast with description-based context. The median power estimates for both gains and losses both significantly differed from 1 (Wilcoxon,  $p < 0.001$ ). We

**Table 4** Median Estimates for Utility and Loss Aversion for EBDM

	Power		Loss aversion	
	Gains ( $\alpha$ )	Losses ( $\beta$ )	$\lambda^1$	$\lambda^2$
Median	0.82	1.14	2.44	2.24
Std. dev.	0.31	0.41	7.51	5.39
IQR	0.65–0.96	0.92–1.39	1.19–6.63	1.49–6.38

found no significant difference for the power coefficient for gains between the described and the experienced contexts (paired  $t$ -test,  $p = 0.95$ ). For losses, we found, in contrast, significant discrepancies between the power coefficients across contexts (paired  $t$ -test,  $p = 0.015$ ). Likewise, whereas the number of concave utilities for gains was similar for experience-based decisions and description-based decisions (49 and 50 respectively), the number of convex utility functions for losses decreased (across contexts) from 35 to 21. It should be added, however, that across contexts, utilities for losses are closer to linearity than utilities for gains. As for the described context, real incentives had no significant effect on the utility function coefficients for experience-based decisions (Mann–Whitney test,  $p = 0.40$ ).

Table 4 also reports median loss aversion coefficients of 2.44 and 2.24. As in decisions from description, no significant discrepancies were detected between  $\lambda^1$  and  $\lambda^2$  (paired  $t$ -test,  $p = 0.92$ ). The reported standard deviations reflected slightly more variation than in the described context. As in description-based context, loss aversion for experience-based decisions was clearly the dominant pattern at the individual level: for  $g_*^1 = 90$  ( $g_*^2 = 200$ ), 48 (53) subjects (79% (87%)) had a loss aversion coefficient that exceeded 1 and were classified as loss averse.<sup>10</sup> A one-way analysis of variance (ANOVA) did not detect any significant differences between (the four) loss aversion coefficients across contexts ( $p = 0.38$ ).

**6.2. Decision Weights for Experience-Based Decisions**

This subsection focuses on elicited decision weights in EBDM and their decomposition as suggested by the model presented in Equation (4b). We first consider the decision weight attached to an event  $E_p$  as a function of the true (objective) probability  $p$  and denote it by  $w_{tr}^s(p)$ . In this case, the probabilities are unknown to the decision maker. Then, we consider the alternative situation where the decision weight attached to event  $E_p$  is a function of the observed

<sup>10</sup> Assuming a linear utility around the reference point 0, the median loss aversion  $\lambda^1$  ( $\lambda^2$ ) is 1.87 (2.12) with a standard deviation of 2.94 (3.35). The use of an exponential utility function gave a median loss aversion coefficient  $\lambda^1$  ( $\lambda^2$ ) of 2.61 (2.87) with a standard deviation of 4.31 (4.55).

**Table 5** Median Decision Weights and Paired  $t$ -Tests ( $w_{tr}^s(p)$  vs.  $p$ ) for EBDM

True probability $p$	Gains ( $w_{tr}^+(p)$ )			Losses ( $w_{tr}^-(p)$ )		
	Median	IQR	$t_{60}$	Median	IQR	$t_{60}$
0.05	0.11	0.05–0.18	6.38**	0.08	0.03–0.16	4.51**
0.25	0.19	0.12–0.25	−3.67**	0.28	0.18–0.39	1.95 <sup>ns</sup>
0.50	0.38	0.28–0.49	−4.81**	0.47	0.35–0.60	−2.13*
0.75	0.57	0.42–0.75	−7.02**	0.63	0.49–0.80	−4.92**
0.95	0.77	0.68–0.92	−7.68**	0.87	0.73–0.93	−6.97**

Note. ns, nonsignificant for  $\alpha = 0.05$ .  
\* $p < 0.05$ ; \*\* $p < 0.001$ .

frequency  $f_p^s = f^s(E_p)$ , called experienced probability, and denoted by  $w_{ex}^s(\cdot)$ .<sup>11</sup> Note that for a given event  $E_p$ , each subject faced a specific sample of drawings, and hence a specific experienced probability, i.e.,  $f_p^s$  was not necessarily the same across subjects. Consequently, we used a linear interpolation of the corresponding weighting function at the individual level because it allowed us to draw decision weights against the same experienced probabilities  $f = 0.05, 0.25, 0.50, 0.75$ , and  $0.95$  for all subjects.

**6.2.1. Weighting as a Function of True Probabilities.** For gains, the decision weights resulting from true (objective) probabilities were always significantly different from the corresponding probabilities (paired  $t$ -tests; Table 5). More specifically,  $w_{tr}^+(\cdot)$  exhibited overweighting for  $p = 0.05$  and underweighting for the remaining probabilities, including the relatively low probability  $p = 0.25$ . As shown later, the underweighting of relatively low probabilities is a consequence of the less pronounced elevation of the probability weighting function  $w_{tr}^+(\cdot)$  than the one found for description-based decisions.<sup>12</sup>

For losses, we could not reject the null hypothesis  $w_{tr}^-(p) = p$  for  $p = 0.25$  (Table 5, last column). A paired  $t$ -test shows that we also cannot reject the above null hypothesis for  $p = 0.5$  ( $p = 0.036$ , after Bonferroni correction). Furthermore, the comparison of median decision weights, interquartile ranges, and  $t$ -values between gains and losses suggests a less pronounced tendency to transform objective probabilities for losses than for gains.

As for sign dependence of decision weights resulting from true objective probabilities, a paired  $t$ -test cannot reject the null hypothesis that  $w_{tr}^+(p) = w_{tr}^-(p)$  for  $p = 0.05$  ( $p = 0.63$ ). This hypothesis is, however,

<sup>11</sup> For the sake of simplicity, we use the notation  $w_{tr}^s(p)$  instead of  $W_{tr}^s(E_p)$  and the notation  $w_{ex}^s(f_p^s)$  instead of  $W_{ex}^s(E_p)$ .

<sup>12</sup> Multiple comparison might call for Bonferroni corrections. To allow for direct comparison with previous studies on probability weighting, we mention Bonferroni corrections only when they have an impact on the results.

**Table 6** Median Number of Draws and Experienced Probabilities

True probability $p$	Number of draws				Experienced probability			
	Gains		Losses		Gains ( $f_p^+$ )		Losses ( $f_p^-$ )	
	Median	IQR	Median	IQR	Median	IQR	Median	IQR
0.05	21	14–27	17	12–23	0.047	0–0.095	0.055	0–0.092
0.25	20	15–24	17	11–24	0.20	0.164–0.264	0.266	0.178–0.355
0.5	18	13–25	18	13–22	0.50	0.436–0.574	0.50	0.452–0.596
0.75	15	13–21	18	13–27	0.76	0.684–0.857	0.75	0.680–0.823
0.95	17	13–21	17	13–22	0.952	0.928–0.952	0.933	0.908–1.00

**Table 7** Median Decision Weights for Experienced Probabilities and Paired  $t$ -Tests ( $w_{ex}^s(f)$  vs.  $f$ )

Experienced probability $f$	Decision weights (EBDM: $w_{ex}^s(f)$ )					
	Gains			Losses		
	Median	IQR	$t_{60}$	Median	IQR	$t_{60}$
0.05	0.08	0.05–0.12	5.08**	0.09	0.04–0.13	4.48**
0.25	0.19	0.16–0.28	–2.29*	0.27	0.19–0.36	1.60 <sup>ns</sup>
0.50	0.37	0.28–0.46	–6.84**	0.45	0.34–0.57	–2.68*
0.75	0.57	0.46–0.69	–9.22**	0.65	0.53–0.75	–5.72**
0.95	0.80	0.71–0.90	–8.66**	0.89	0.78–0.94	–6.17**

Note. ns, nonsignificant for  $\alpha = 0.05$ .  
 \* $p < 0.05$ ; \*\* $p < 0.001$ .

rejected in favor of  $w_{ir}^-(p) > w_{ir}^+(p)$  by one-tailed  $t$ -tests at the level of significance of 5% for  $p = 0.25, 0.50, 0.75$ , and  $0.95$ , and only for  $p = 0.25$  with a Bonferroni correction. Real incentives did not affect the elicited decision weights (Mann–Whitney tests, non significant at the level of 5%).

**6.2.2. Weighting as a Function of Experienced Probabilities.** Table 6 displays the median number of draws and the median experienced probabilities for experienced decisions. The median number of draws per prospect was between 15 and 21 for gains and between 17 and 18 for losses. HBWE (2004, p. 538, Figure 1) observed a lower median number of draws in their six choice problems. For similar choice problems, i.e., based on the comparison of a binary prospect and a sure amount of money, the subjects in the HBWE (2004) experiment sampled less frequently than our subjects did, with a median number of draws that did not exceed 10. We can reasonably speculate that the considerably lower amounts of money at stake in the HBWE (2004) experiment could explain why their subjects tended to sample less frequently than our subjects.<sup>13</sup> Statistically, experienced probabilities in the present study are expected to be closer to objective probabilities than in studies where subjects

sampled less frequently.<sup>14</sup> One-sample  $t$ -tests detected significant discrepancies between objective probabilities and experienced probabilities only for  $p = 0.25$  in the gain domain.

Table 7 reports median decision weights based on experienced probabilities for gains and losses. For gains, decision weights were always significantly different from the corresponding experienced probabilities. One-tailed paired  $t$ -tests show that the null hypothesis  $w_{ex}^+(f) = f$  is rejected in favor of  $w_{ex}^+(f) < f$  (at the significance level of 5%), i.e., underweighting, for  $f = 0.25, 0.50, 0.75$ , and  $0.95$ , and for  $f = 0.50, 0.75$ , and  $0.95$  with a Bonferroni correction. Likewise, a similar  $t$ -test rejected the null hypothesis  $w_{ex}^+(0.05) = 0.05$  in favor of  $w_{ex}^+(0.05) > 0.05$  corresponding to an overweighting of small probabilities. For losses, except for  $f = 0.25$ , significant differences were detected between  $w_{ex}^-(f)$  and  $f$  for  $f = 0.05, 0.50, 0.75$ , and  $0.95$ . Our observations reveal that  $w_{ex}^-(\cdot)$  is inverse-S shaped (with a less pronounced probability weighting for losses than for gains).

<sup>14</sup> As explained in §2.1, the decision maker facing a prospect  $(x, E_p; y)$  learns about  $p, x$ , and  $y$  from a sequence of  $n - E_p$  independent random trials from a binomial distribution. For a small  $n$ , the resulting empirical distribution is skewed. Consequently, it is more likely to have rare events occurring in small samples less frequently than expected.

<sup>13</sup> The highest amount at stake in the HBWE (2004) experiment was 64¢. Hau et al. (2008, p. 500, Figure 2) report results showing that people search more when stakes are higher.

**Table 8 Revealed vs. Experienced Probabilities (EBDM)**

True probability $p$	Revealed probabilities ( $\pi_p^s$ )				Pearson correlation	
	Gains		Losses		Gains	Losses
	Median	IQR	Median	IQR	$\pi_p^+ \text{ vs. } f_p^+$	$\pi_p^- \text{ vs. } f_p^-$
0.05	0.055	0.028–0.130	0.051	0.029–0.140	-0.04 <sup>ns</sup>	0.39*
0.25	0.147	0.060–0.290	0.260	0.160–0.144	0.23 <sup>ns</sup>	0.33*
0.5	0.462	0.240–0.600	0.534	0.320–0.710	0.39*	0.30*
0.75	0.663	0.540–0.840	0.750	0.580–0.920	0.30*	0.53**
0.95	0.943	0.760–0.980	0.964	0.820–0.980	0.45**	0.18 <sup>ns</sup>

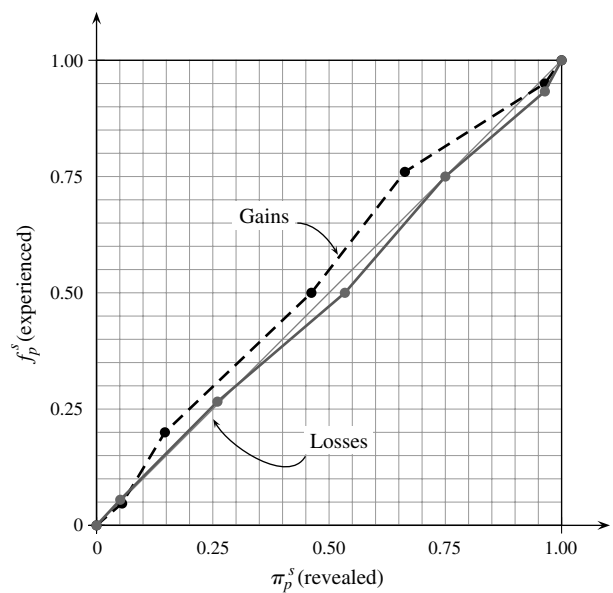
Note. ns, nonsignificant for  $\alpha = 0.05$ .  
\* $p < 0.05$ ; \*\* $p < 0.001$ .

**6.2.3. Revealed Beliefs vs. Experienced Probabilities.** As explained in §2.3, theoretical and experimental arguments suggest that a decision weight  $W^s(E)$  results from a subjective transformation of the likelihood the decision maker assigns to event  $E$  (Fox and Tversky 1998, Wakker 2004). Using Equation (4a), we inferred the likelihood assigned by the subject to event  $E_p$  through  $\pi_p^s = (w^s)^{-1}[w_{ex}^s(f_p^s)]$ .<sup>15</sup> Below, inverse images  $(w^s)^{-1}[w_{ex}^s(f_p^s)]$  were obtained using elicited  $w^s(\cdot)$  based on the linear-in-log-odds parametric form at the level of individual subjects.

Table 8 reports medians of revealed probabilities and the corresponding interquartile ranges. Its last two columns give Pearson correlations between revealed and experienced probabilities. A  $3 \times 5$  ANOVA with repeated measures (barely) rejected the null hypothesis of the equality of true, experienced, and revealed probabilities for gains, i.e.,  $p = f_p^+ = \pi_p^+$  ( $p = 0.01$ ). For losses, in contrast, the same test clearly suggests the absence of significant discrepancies between objectives probabilities, experienced probabilities ( $f_p^-$ ), and revealed beliefs ( $\pi_p^-$ ). When attention is focused on  $f_p^s$  and  $\pi_p^s$ , paired  $t$ -tests reject (at the level of 5%) the null hypothesis  $f_p^+ = \pi_p^+$  for three of five probabilities in the gain domain, and for only two of five probabilities in the loss domain. However this hypothesis is systematically rejected for extreme probabilities (0.05 and 0.95) for gains as well as for losses. Pearson correlations confirm the overall impression that revealed beliefs (assuming Equation 4(a)) are closely tied to experienced probabilities (see Figure 1).

The possibility of a greater impact of observations having been made late in the sequence of trials (during sampling) can be explored using the revealed probabilities and experienced probabilities

**Figure 1 Revealed vs. Experienced Probabilities**



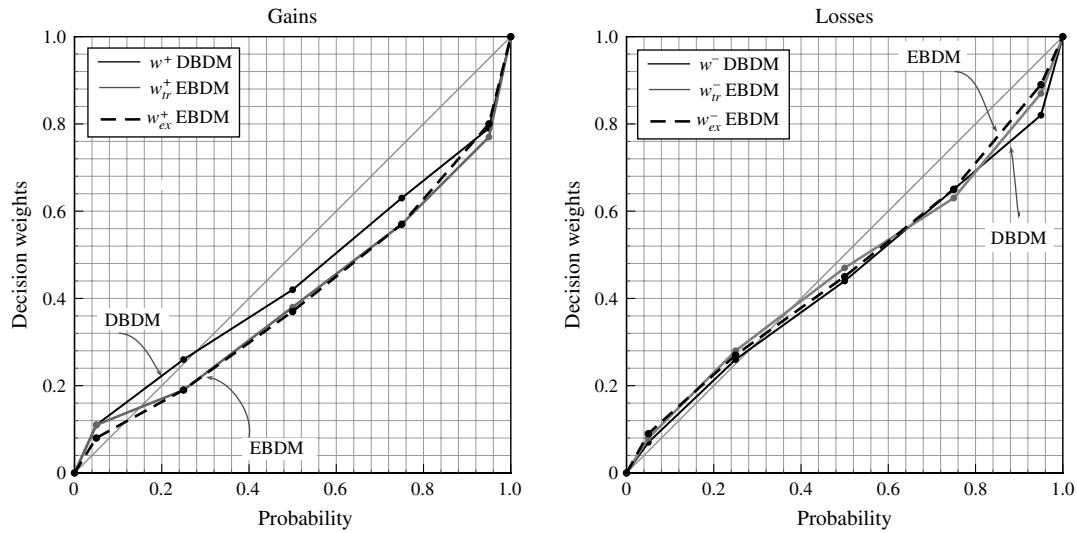
inferred from the first and second halves of each set of observations. For that purpose, we calculated for each subject the absolute differences between revealed probabilities and experienced probabilities inferred from the first/second half of each sample. For gains (losses) and across all five events, the median absolute difference was 0.128 (0.119) for the first half and 0.116 (0.118) for the second half. A  $2 \times 5$  ANOVA with repeated measures on the first and second halves of the observations did not detect significant discrepancies between the two parts of the samples ( $p = 0.22$  for gains and  $p = 0.90$  for losses). In other words, no significant recency effect was detected for either gains or losses.

**6.3. Probability Weighting Across Contexts**

The present subsection focuses on the comparison of probability weighting for description-based decisions ( $w^s(\cdot)$ ) on the one hand to probability weighting for experience-based decisions ( $w_{ir}^s(\cdot)$  and  $w_{ex}^s(\cdot)$ ) on the other hand. The absence of significant discrepancies

<sup>15</sup> Note that it is plausible that if subjects determine likelihoods of events  $E_p$  from their respective experienced frequencies ( $f_p^s$ ), then the “degree of ambiguity” (due to residual uncertainty related to sampling) reflected by the decision weight  $w_{ex}^s(f_p^s) = W_{ex}^s(E_p)$  may depend on the size of the sample.

Figure 2 Probability Weighting in Different Contexts



between experienced and true objective probabilities (except for gains with  $p = 0.25$ ) suggests a similar pattern as regards the corresponding decision weights  $w_{tr}^s(p)$  and  $w_{ex}^s(f = p)$ . Furthermore, as explained in §2.3 when DBDM and EBDM were characterized by two different sources of uncertainty, the existence of residual uncertainty in EBDM should be reflected, for gains, through a more elevated probability weighting function for risk than for experience-based decisions (i.e., some sort of ambiguity aversion). It is also plausible to observe more sensitivity to probabilities for risk than in EBDM (e.g., Abdellaoui et al. 2011).

Figure 2 plots median decision weights for (gain and loss) probabilities 0.05, 0.25, 0.50, 0.75, and 0.95. Although exhibiting a similar inverse-S-shaped pattern, the resulting curves for gains seem to reflect two categories of probability weighting: a probability weighting function for DBDM ( $w^+(\cdot)$ ) on the one hand, and two close probability weighting functions for EBDM ( $w_{tr}^+(\cdot)$  and  $w_{ex}^+(\cdot)$ ) on the other. In fact, the null hypothesis  $w^+(p) = w_{tr}^+(p) = w_{ex}^+(p)$  is rejected for  $p = 0.05, 0.25,$  and  $0.75$  ( $p < 0.05$ ) by one-way ANOVAs with repeated measures. Paired  $t$ -tests (barely) reject the null hypothesis  $w_{tr}^+(p) = w_{ex}^+(p)$  only for  $p = 0.05,$  and  $0.25$  ( $p < 0.05$ ). After Bonferroni correction, the null hypothesis is not rejected at the level of significance of 5%. This confirms the visual impression that the three probability weighting functions do not coincide for gains (Figure 2, left panel). For losses, the picture is different: the hypothesis of coincidence of the three curves is rejected only for  $p = 0.95$  (one-way ANOVA,  $p = 0.03$ ).

If we take into account the “perceived likelihoods” in described and experienced contexts, i.e., known probabilities and experienced probabilities, respectively, we detect significant differences in terms of

probability weighting. More specifically, one-tailed paired  $t$ -tests reject the null hypothesis of decision weights equality for described and experienced probabilities in favor of  $w^+(p) > w_{ex}^+(p)$  for  $p = 0.05, 0.25, 0.50,$  and  $0.75$  ( $p < 0.05$ ).<sup>16</sup> This clearly suggests a tendency to less overweighting of small probabilities (around  $p = 0.05$ ) and a more pronounced underweighting of moderate probabilities (specifically between 0.50 and 0.75) for experienced decisions compared to described decisions. This observation is confirmed by the parametric fittings reported in Table 9. In fact, although no significant differences in terms of curvature were detected between  $w^+(\cdot)$  and  $w_{ex}^+(\cdot)$ , a one-tailed  $t$ -test detected a more significant elevation of the former function compared to the latter ( $p < 0.01$ ). Furthermore, no significant differences were detected between  $w_{tr}^+(\cdot)$  and  $w_{ex}^+(\cdot)$  in terms of elevation as well as of curvature.

For losses, a one-tailed paired  $t$ -test rejected the hypothesis  $w^-(0.95) = w_{ex}^-(0.95)$  in favor of  $w^-(0.95) < w_{ex}^-(0.95)$  at the level of significance of 5%. However, no significant discrepancies were detected between  $w^-(p)$  and  $w_{ex}^-(p)$  for  $p \neq 0.95$  (paired  $t$ -tests). This result fits in with the absence of significant differences in terms of elevation and curvature between  $w^-(\cdot)$  and  $w_{ex}^-(\cdot)$ . Finally, it should also be added that, as in the gain domain, no significant differences were detected between  $w_{tr}^-(\cdot)$  and  $w_{ex}^-(\cdot)$  in terms of parameters  $\delta$  and  $\gamma$ .

<sup>16</sup> The equality  $w^+(0.05) = w_{ex}^+(0.05)$  is rejected in favor of  $w^+(0.05) > w_{ex}^+(0.05)$  by a one-tailed Wilcoxon test ( $p = 0.02$ ). The corresponding one-tailed paired  $t$ -test gave a  $p$  value slightly above 0.05 ( $p = 0.06$ ).

**Table 9** Weighting Function  $\delta p^\gamma / (\delta p^\gamma + (1-p)^\gamma)$ 

Function	Gains				Losses			
	Elevation ( $\delta$ )		Curvature ( $\gamma$ )		Elevation ( $\delta$ )		Curvature ( $\gamma$ )	
	Median	IQR	Median	IQR	Median	IQR	Median	IQR
DBDM: $w^s(\cdot)$	0.70	0.53–1	0.65	0.45–0.78	0.78	0.57–1.09	0.73	0.51–0.92
EBDM: $w_{ir}^s(\cdot)$	0.63	0.40–0.85	0.67	0.46–0.94	0.83	0.51–1.34	0.65	0.45–0.78
EBDM: $w_{ex}^s(\cdot)$	0.59	0.36–0.83	0.66	0.44–0.94	0.67	0.48–1.11	0.74	0.52–1.04

Note. The function  $w_{ex}^s(\cdot)$  was fitted using the actual individual experienced frequencies.

## 7. General Discussion

### 7.1. Across Context Differences in Terms of PT

The present paper deals with the issue of the gap between DBDM and EBDM under PT, focusing on an elicitation of each of the different PT components at the individual level. The investigation of the difference between these two contexts was not restricted to probability weighting. For description-based decisions, our results were fully consistent with the accumulated empirical findings regarding utility, loss aversion, and probability weighting (Booij et al. 2010). The difference between contexts was analyzed in terms of utility and loss aversion on the one hand, and in terms of probability weighting on the other.

#### 7.1.1. Utility and Loss Aversion Across Contexts.

We did not detect important discrepancies between DBDM and EBDM in terms of utility and loss aversion. More specifically, our data do not reveal significant differences in terms of utility across contexts, except for losses where the power estimates for experience-based decisions turn out to be (somewhat) higher than for description-based decisions. Nevertheless, power estimates for losses are very close to exhibiting linearity in both contexts (Etchart-Vincent 2004). No significant differences were detected between loss aversion coefficients across contexts, reinforcing the general impression that the subjective treatment of outcomes is approximately the same for description-based and experience-based decisions.

#### 7.1.2. Decision Weights Across Contexts.

Across contexts, the situation is clearly different for decision weights than for utility. Although decision weights exhibit similar qualitative properties across contexts (as in Hadar and Fox 2009), our observations suggest that, at least for gains, the subjective treatment of uncertainty in experience-based and description-based contexts is significantly different. For description-based decisions, our findings clearly confirm that the probability weighting function is inverse-S shaped for gains and for losses. For experience-based decisions, the decision weight assigned to an event can be considered either as a

function of its true objective probability (unknown to the decision maker) as in the HBWE paradigm or as a function of its experienced probability (e.g., Fox and Hadar 2006). Roughly speaking, our data reveal the existence of two categories of probability weighting (for gains): one probability weighting function for description-based decisions on the one hand, and two very similar probability weighting functions for experience-based decisions on the other. Although inverse-S shaped, the two latter probability weighting functions are less elevated for gains than the probability weighting for described decisions. More specifically, these two functions exhibit a clear, though less pronounced, overweighting of small (true objective and experienced) probabilities.

According to our observations, the difference between DBDM and EBDM cannot be fully justified by sampling error (e.g., Fox and Hadar 2006). In fact, at the aggregate level, our subjects' sampling ended up with a rather good approximation of objective probabilities by experienced probabilities, but the corresponding decision weights were still globally lower than for described decisions. Furthermore, as in Hau et al. (2008) and Rakow et al. (2008), no clear recency effect was detected. When focusing on the very existence of a gap between contexts, these results are consistent with those reported by Hau et al. (2008) where the boosting of the size of sampling (by providing higher stakes and directing people's search) reduced the gap magnitude (between DBDM and EBDM) but did not suppress it (Hau et al. 2008, p. 513). It should also be added that our results are not inconsistent with the possibility that small samples and recency effect can result in an underweighting of rare events relative to objective probabilities (as in HBWE 2004).

For gains, subjects seemed to exhibit more optimism when facing description-based decisions than when facing experience-based decisions (for similar results, see Kilka and Weber 2001, Tversky and Fox 1995). Decision makers might be less confident when they are confronted with partial information resulting from sampling than when they are provided with a full description of prospects. In other words, the "residual uncertainty" as regards

probabilities in experience-based decisions generates pessimism. This situation is similar to the two-color Ellsberg (1961) paradox in which gambling on known probabilities is preferred to gambling on unknown probabilities. In terms of attitudes toward ambiguity across contexts, description-based and experience-based decision contexts can be assimilated to two different sources of uncertainty. Although it seems reasonable to take frequencies for the experienced source into account, subjects appeared to assign less confidence to these (partially unknown) probabilities than to objective probabilities. This is reflected in the present paper through a more elevated function in DBDM than in EBDM with experienced probabilities. Following Tversky and Wakker (1995), attitudes toward ambiguity across contexts can be captured through the difference between these two functions. We should add, however, that because of comparative ignorance effect, our within-subject design might have inflated ambiguity aversion (Fox and Tversky 1995).

The picture was different for losses. Except for probability 0.95, the probability weighting function from described decisions was not significantly different from the two probability weighting functions for experienced decisions. The three probability weighting functions were inverse-S shaped. Clearly, the overweighting of small probability events was identical across contexts (Fox and Hadar 2006, Hadar and Fox 2009).

## 7.2. Methodological Differences with the HBWE Paradigm

The investigation of the description–experience gap under PT reported in the present paper required that a few changes be made to the HBWE paradigm. In contrast to the HBWE paradigm, which is also fundamentally related to decision under uncertainty, our experimental setup provided the subject with the exhaustive list of outcomes immediately after sampling and just before the choice task(s). The purpose of this additional information was to allow a consistent rank-dependent evaluation of the two-outcome prospect faced by the subject (§2.3). In the HBWE paradigm, the absence of such information (list of outcomes) is expected to generate less inconsistencies because prospects involve only one nonzero outcome (and need only one decision weight). One might object that the access to the exhaustive list of outcomes of a prospect can turn experience-based choices into description-based choices (Erev et al. 2008). In fact, our results clearly show that, for gains at least, the gap between EBDM and DBDM is persistent.<sup>17</sup>

Another methodological difference with the HBWE paradigm in our setup lies in restricting choice tasks to comparisons of a sure amount of money and a prospect. In fact, most choice tasks in our experiment were devoted to the determination of certainty equivalents, i.e., the deterministic pricing of prospects. Whereas sure outcomes are always sampled in the HBWE setup, they are not in our experiment. Although deterministic pricing of unlabeled prospects is cognitively less demanding than comparing two unlabeled prospects, it might be argued that, after sampling, a sure outcome (in the HBWE setup) might not be treated by the decision maker as certain.<sup>18</sup> In our setup, however, it was essential that the decision maker know the number of outcomes and their ranking before evaluating a prospect. Consequently, no sampling of sure outcomes was allowed.<sup>19</sup>

In a recent study, Erev et al. (2008, p. 171) suggested that certainty equivalents (CEs) and, by extension, conclusions regarding the weighting of events derived from them are strongly affected by the comparison stimuli, i.e., the list of alternatives to which the prospect is compared (see also Birnbaum 1992). Although the present experiment makes a systematic use of CEs, it should be noted that the bisection procedure used to obtain CEs is based exclusively on one-shot comparisons between a binary prospect and a single (sure) amount of money. In other words, no subject in our experiment was offered the possibility of comparing a prospect with a list/menu of outcomes. It should also be added that for description-based decisions, our results as regards probability weighting are clearly consistent with those obtained using different CE elicitation processes (e.g., Tversky and Kahneman 1992, Fox and Tversky 1998, Wu and Gonzalez 1999). Our results are also in accord with those resulting from elicitation/estimation methods based mainly on the comparison of nondegenerate prospects (e.g., Wu and Gonzalez 1996, Bleichrodt and Pinto 2000).<sup>20</sup>

obtained by a between-context comparison of certainty equivalents. The average gap of 33% (31% for gains and 36% for losses) obtained in our study is consistent with previous measures of the description–experience gap.

<sup>18</sup> As mentioned by a referee and an associate editor, if a decision maker samples the prospects  $(100, E_{0.9}, 0)$  and  $90 = (90, E_1, 0)$  but then believes the 90 outcome to be a little less than certain, then it is possible that she will choose  $(100, E_{0.9}, 0)$  over  $(90, E_1, 0)$ . Within HBWE paradigm, this might be interpreted as evidence of “overweighting of high probability gains.”

<sup>19</sup> Hadar and Fox (2009) found that participants do not always believe that single-outcome buttons represent sure outcomes in an experience-based choice.

<sup>20</sup> Similarly, Abdellaoui et al. (2008) and Abdellaoui et al. (2011) obtained very close results in terms of probability weighting while using two different methods to elicit CEs: bisection for the former, and “choice lists” for the latter.

<sup>17</sup> A measure of the description–experience gap, similar to the one used in previous studies (e.g., Hau et al. 2010, Table 1), can be

### 7.3. Future Research

This study confirms the existence of a gap between DBDM and EBDM at least for gains. However, except for the relatively lower weighting of small probability events observed in EBDM, results in our experience-based setup are events. Obviously, this result should take the two main methodological differences with the HBWE paradigm into account, namely, the fact that outcomes were explicitly presented (after sampling), and there was no sampling for uncertainty-free prospects (i.e., choice options with sure amounts of money were not sampled). Although the absence of sampling for sure options was meant to facilitate PT elicitation, the explicit presentation of outcomes at the end of sampling was imposed by the consistent evaluation of prospects (as explained in §2.3). In fact, Hadar and Fox (2009) report qualitative results suggesting that the experience–description gap appears in EBDM situations when never-experienced outcomes are presented as possibilities. Hence, a next step would be to quantitatively study the impact of each of the differences between our setup and the HBWE paradigm on the gap between DBDM and EBDM.

## 8. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at <http://mansci.journal.informs.org/>.

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