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Probability weighting and the ‘level’ and ‘spacing’ of outcomes:

An experimental study over losses

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Abstract: The main goal of the experimental study described in this paper is to investigate the sensitivity of probability weighting to the payoff structure of the gambling situation – namely the *level* of consequences at stake and the *spacing* between them – in the loss domain. For that purpose, three kinds of gambles are introduced: two kinds of homogeneous gambles (involving either small or large losses), and heterogeneous gambles involving both large and small losses. The findings suggest that at least for moderate/high probability of loss do both 'level' and 'spacing' effects reach significance, with the impact of 'spacing' being both opposite to and stronger than the impact of 'level'. As compared to small-loss gambles, large-loss gambles appear to enhance probabilistic optimism, while heterogeneous gambles tend to increase pessimism.

Keywords: Individual decision making under risk, Prospect theory, Losses, Probability weighting

JEL Classification: C91, D81.

A huge body of experimental as well as field evidence has demonstrated the descriptive weaknesses of the expected utility (EU) model. Among the most promising challengers to EU, the *rank-dependent* family includes rank-dependent utility – denoted RDU (Quiggin, 1982) – and (Cumulative) Prospect Theory – simply denoted PT (Tversky and Kahneman, 1992). The satisfactory descriptive power and growing popularity of these models are closely linked with their typical 'dual' structure, which is intended to mimic the intuitively 'dual' structure of risk attitude, decomposing in attitude towards probability and in attitude towards consequences (Wakker, 1994). Like EU, RDU and PT capture sensitivity towards outcomes through a utility function[1]. But unlike EU, they also model subjectivity toward probability (which can be called probabilistic risk attitude) through a probability weighting function[2]. Probability weighting has received many interpretations. It can be seen as either irrational (McFadden, 1999) or self-regulatory and adaptative (Higgins, 1997, 1998, 2000; Kluger et al., 2004). It may also capture the psychophysics of chance (Kahneman and Tversky, 1984; Gonzalez and Wu, 1999) as well as some strategic attitude towards probabilistic risk (Wakker, 2004).

The probability weighting function has been extensively investigated, both theoretically (e.g. Diecidue, Schmidt and Zank, 2007; Prelec, 1998) and empirically. Whatever the domain (either gains or losses) under investigation, the most typical and widely replicated result is the inverse-S shape of the probability weighting function at the aggregate level (Abdellaoui, 2000; Lattimore, Baker and Witte, 1992; Tversky and Kahneman, 1992). However, note that some

[1] The utility function in the PT model actually exhibits some peculiar features, and it has been given a different name (the value function). Since these features do not matter here, the usual 'utility' name will still be used throughout the paper (see Fennema and Van Assen, 1999).

[2] In both RDU and PT, the weighting function is used to build the decision weight associated to each consequence using a rank-dependent combination rule, from which the rank-dependent designation (for some details on this point, see Gonzalez and Wu, 1999, p. 135-136 and Diecidue and Wakker, 2001; for a general discussion about probability weighting, see Neilson, 2003).

recent studies found S-shaped median functions (e.g. Alarié and Dionne, 2001; Humphrey and Verschoor, 2004; Harbaugh, Krause and Vesterlund, 2002) and, above all, that huge heterogeneity prevails at the individual level. For instance, probability weighting has been shown to depend on the respondents' socio-demographic characteristics (such as gender, e.g. Fehr-Duda, de Gennaro and Schubert, 2006; or age, e.g. Harbaugh, Krause and Vesterlund, 2002) as well as on their emotional state and mood (e.g. Fehr et al., 2007). It has also been shown to be affected by some features of the gambling situation, such as the emotional content of the payoffs (e.g. Rottenstreich and Hsee, 2001) or their gain/loss nature (e.g. Abdellaoui, 2000).

Besides, there is also some suggestive evidence that, within a given payoff domain, the probability weighting function be sensitive to the payoff structure of the gambling situation. This result cannot be reconciled with either RDU or CPT[3]. As Tversky and Kahneman (1992) suggest, "*despite its greater generality, the cumulative functional is unlikely to be accurate in detail. We suspect that decision weights may be sensitive to the formulation of the prospects, as well as to the number, the spacing and the level of outcomes. In particular, there is some evidence to suggest that the curvature of the weighting function is more pronounced when the outcomes are widely spaced*" (p. 317, underlined by the author). The sensitivity of probability weighting to the payoff structure of the gambling situation has actually been indirectly shown in some laboratory studies (Allais, 1988, p. 243; Camerer, 1992, p. 237; Harless and Camerer, 1994, p. 1282; Sonsino, 2008, p. 379) and it has been documented outside the laboratory as well. For instance, probabilities seem to be all the more optimistically [resp. pessimistically] overweighted since they are associated with especially desirable consequences (Irwin, 1953;

[3] Note that some generic rank-dependent models allow probability weighting to be affected by the payoffs (Green and Jullien, 1988; Quiggin, 1989; Segal, 1989, 1993; see also Quiggin, 1993). Besides, Viscusi's prospective reference theory (Viscusi, 1989) allows probabilities to depend on the number of the payoffs, but not on the 'level' and 'spacing' of these payoffs.

Rosett, 1971; Slovic, 1966) [resp. negative consequences; Viscusi, 1995]. But I am aware of only one specifically dedicated experimental study (Etchart-Vincent, 2004, in this journal), that was designed to investigate the impact of the magnitude (i.e. the 'level') of the payoffs on probability weighting in the loss domain. Etchart-Vincent (2004)'s findings suggest that people tend to be more pessimistic when facing large losses rather than small ones. However, Tversky and Kahneman (1992)'s above-quoted passage suggests that the payoff structure of a risky gamble should not be reduced to the 'level' of the outcomes. Their 'spacing' is also likely to affect probability weighting. And my expectation is that it might result in stronger probabilistic pessimism (as well as, consequently, in more risk aversion[4]).

An example derived from the insurance field may help grasp the importance of the 'spacing' hypothesis. Indeed, taking out an insurance does not only considerably reduce the magnitude of the potential loss, it also – and perhaps above all – reduces the *gap* between the most and the least serious consequences in the corresponding lottery (with probabilities being held constant). Instead of losing, say, either US$ 10 000 (in case damage occurs, with a probability of 0.01 for instance) or 0 (with a probability of 0.99), the insured individual will now lose, say, either US$ 750 if damage occurs (corresponding to the payment of an insurance premium and a deductible) or US$ 200 (corresponding to premium only) if not. Insurance purchase thus roughly induces the replacement of highly heterogeneous Lottery A = (–US$ 10 000, 0.01; 0) with rather homogeneous Lottery B = (–US$ 750, 0.01; –US$ 200). My expectation is that this significant reduction in loss heterogeneity might result in lower probability overweighting (or, if we retain the most usual interpretation of probability weighting in the PT

[4] Note that the opposite idea of 'probability neglect' (Sunstein, 2003) also predicts that individuals will be more risk averse when facing the possibility of an extremely low probability-extremely large loss event (e.g. a terrorist attack). In that case indeed, people will focus on the badness of the outcome rather than on the (low) probability with which the outcome is supposed to occur. Therefore, this event will have much stronger negative impact than would have been expected given the objective value of the risk.

framework, in weaker probabilistic pessimism). This may in turn induce a lower degree of risk aversion, or even some proneness to risk seeking, and finally explain why some people tend to take more risks when being insured (Cummins and Tennyson, 1996). Interestingly, the 'spacing and level' hypothesis allows us to regard the risk taking behaviour of insured people as cognitive and possibly unintentional, instead of deliberate and opportunistic – as usually done in the 'moral hazard' literature.

The present experimental study primarily aims at investigating whether and how probability weighting is to be affected by the payoff structure of the gamble, and at disentangling the respective effects of 'level' and 'spacing'[5]. The experimental framework we have chosen to develop for that purpose is thus similar to, but more integrating than, the one that was used in Etchart-Vincent (2004).

To be specific, the study is based on a two-stage semi-parametric choice-based procedure. In the first stage, each subject's utility function is elicited on a wide interval of losses I, using the non-parametric trade-off method (Wakker and Deneffe, 1996). In the second stage, three different loss situations are considered. The first two situations, called the 'small loss' and 'large loss' situations respectively, involve lotteries made up of either small losses (at the upper part of I) or large losses (at the lower part of I). The third situation involves heterogeneous gambles, i.e. gambles that offer both a small loss (at the upper bound of I) and a large one (at the lower bound of I). A simple certainty-equivalent method is then used to elicit, within the PT framework, the subject's probability weighting function in each of the three loss situations.

[5] As a worthwhile by-product, the experimental design also allows us to investigate the subjects' risk attitude depending on the payoff structure of the gambling situation, as well as the subjects' utility function on a wide interval of losses. For the sake of clarity, only the results concerning probability weighting will be reported here.

The main results are as follows. At least for moderate and high probability of loss, the weighting function appears to be affected by the payoff structure of the prospects. Besides, 'level' and 'spacing' appear to have rather opposite effects: as compared to small loss prospects, large loss gambles tend to induce less probability overweighting (i.e. either less pessimism or more optimism), while heterogeneous prospects tend to increase probability overweighting (i.e. to generate either more pessimism or less optimism).

The remainder of the paper is organized as follows. Section 1 is devoted to the set out of the two-stage method used to successively elicit the utility and weighting functions. The experimental design is described in Section 2. Section 3 reports the results, which are further discussed in Section 4. Section 5 concludes.

1. Method

First, just recall that the PT model introduces two different weighting functions depending on the domain of consequences. They are denoted w^+ and w^- for the gain and loss domains respectively. In the simplified framework of a two-outcome non-zero lottery $P = (x_2, p; x_1)$ with $x_2 < x_1 < 0$, the PT valuation of P is given by $V_{PT}(P) = w^-(p)U(x_2) + (1- w^-(p))U(x_1)$, where U is the utility function. Besides, the PT valuation of a mixed lottery $P = (x_2, p; x_1, 1- p)$ with $x_2 > 0 > x_1$ is given by $V_{PT}(P) = w^+(p)U(x_2) + w^-(1- p)U(x_1)$.

Now, let us present the basic principles of the two-stage semi-parametric procedure that was used to elicit the probability weighting functions at the individual level. It is basically the same as in Etchart-Vincent (2004). First, the utility function was elicited for each subject, using the now well-established non-parametric trade-off method (introduced by Wakker and Deneffe, 1996 and applied to losses by Abdellaoui, 2000; Etchart-Vincent, 2004; Fennema and Van Assen, 1999). As in Etchart-Vincent (2004), utility was individually investigated over small as

well as large losses (until around 15 000 €). But in the 2004 study, only two distinct local parts of the utility function were obtained. Here, utility was elicited on a unique and wide interval I, enabling us to work with heterogeneous lotteries within this interval. In the second stage of the procedure, a certainty-equivalent method was introduced, using some points of the previously elicited utility function as well as its parametric fitting, to build the weighting function in each of three loss situations, called the 'small loss situation' (S), 'large loss situation' (L) and 'small-large loss situation' (S/L) respectively.

Let us briefly recall the main features of the trade-off (TO) method. This method consists in eliciting a sequence of outcomes that are equally spaced in terms of utility. Using its more reliable 'outward' version (see Fennema and van Assen, 1999), the general principle of the method is the following. Given fixed outcomes x_0, r and R such that $x_0 < 0 < r < R$, the subject is asked to make successive choices allowing (through a l-iterations bisection process) to determine the outcome $x_1 < x_0$ that makes her indifferent between the (mixed) lotteries $(x_0, p; r, 1-p)$ and $(x_1, p; R, 1-p)$. Then, x_1 is used as an input, and a similar choice-based bisection process allows to determine the outcome $x_2 < x_1$ that makes the subject indifferent between $(x_1, p; r, 1-p)$ and $(x_2, p; R, 1-p)$. The procedure is implemented n times in order to obtain a sequence $x_n, \ldots, x_i, \ldots, x_0$. Under PT, indifference between $(x_i, p; r, 1-p)$ and $(x_{i+1}, p; R, 1-p)$ implies that, for $0 \leq i \leq n-1$, $w^-(p)U(x_i) + w^+(1-p)U(r) = w^-(p)U(x_{i+1}) + w^+(1-p)U(R)$. In other words:

$$U(x_i) - U(x_{i+1}) = (w^+(1-p)/ w^-(p))[U(R) - U(r)] \text{ for all } 0 \leq i \leq n-1 \qquad \text{Eq. (1)}$$

, from which the following equality: +

$$U(x_0) - U(x_1) = U(x_1) - U(x_2) = \cdots = U(x_i) - U(x_{i+1}) = \cdots = U(x_{n-1}) - U(x_n) \qquad \text{Eq. (2).}$$

Eq. (2) implies that, for the subject under consideration, the x_{-i}s are equally spaced in terms of utility. Using the conventional normalization $U(x_0) = 0$ and $U(x_n) = -1$, one gets $U(x_i) = -i/n$, $i = 0, \ldots, n$. Note that, by construction, the TO method neutralizes the role of probability in the

elicitation process. It thus avoids those biases that are due to probability weighting and are known to distort traditional assessment methods (see Wakker and Deneffe, 1996 for a critical review of these methods)[6].

Now, let us present the general principle of the certainty-equivalent method that was used in the second stage of the procedure to build the weighting function under a given payoff condition: the decision maker is asked to make successive choices allowing – at the end of a m-iterations bisection process – to determine the value CE_j that makes her indifferent between two-outcome Lottery A = (x_k, p_j; x_i, 1–p_j), with x_k and x_i two elements of the former standard sequence and $x_k < x_i < 0$, and degenerate Lottery B = (CE_j, 1). In generic Lottery A = (x_k, p_j; x_i, 1–p_j), k and i can be chosen so as to make x_k and x_i eligible as bounds of the payoff condition under consideration. By construction, $x_k < CE_j < x_i$.

Under PT, and with $x_k < x_i < 0$, the indifference between (x_k, p_j; x_i, 1–p_j) and CE_j entails that $w^-(p_j)U(x_k) + (1-w^-(p_j))U(x_i) = U(CE_j)$. By construction of the TO method, $U(x_i) = -i/n$ and $U(x_k) = -k/n$. So:

$$w^-(p_j) = \frac{nU(CE_j) + i}{i - k} \qquad \text{Eq. (3)}$$

The procedure thus makes it possible to determine algebraically the 'subjective weight' $w^-(p_j)$ for any probability p_j. By applying it for different values of p_j, the whole weighting function can be obtained under the payoff condition given by [x_k; x_i].

[6] Note that the TO method may suffer from two drawbacks (see Wakker and Deneffe, 1996). First, it induces a bias toward linearity. Therefore, it should not be used to elicit the utility function over a small interval of consequences. In this study, the elicitation process involves a wide interval of losses, which prevents this problem. Second, the TO method is chained. So any early error in the elicitation process will propagate and distort subsequently elicited utility values. However, several studies have investigated this point and shown that the impact of error propagation can be considered as negligible (Abdellaoui, Vossman and Weber, 2005; Bleichrodt and Pinto, 2000).

In the present study, the weighting function had to be built under each of the S, L and S/L payoff conditions. In each case, the points (of the previously elicited standard sequence) x_k and x_i had to be properly chosen so as to be eligible as the bounds of the payoff condition under consideration. So, S was defined by $k=1$ and $i=0$, L by $k=n$ and $i=n-1$, and S/L by $k=n$ and $i=0$ (see Figure 1). Note that, even though *k* and *i* were the same for all the subjects, the *values* x_k and x_i were specific to each subject (since they were elements of her endogenously elicited utility function).

[INSERT FIGURE 1 ABOUT HERE]

The interest of the above-described procedure is that it makes it possible to roughly disentangle the 'level' effect from the 'spacing' effect[7]. Indeed:

- $\bar{w}_L$ and $\bar{w}_{S/L}$ were both obtained using the last point of the standard sequence x_n. But in the L situation, the alternative consequence was x_{n-1}, instead of x_0 in the S/L situation. The comparison between $\bar{w}_L$ and $\bar{w}_{S/L}$ thus makes it possible to investigate how probability weighting is to be affected by the 'spacing' of consequences.
- $\bar{w}_L$ and $\bar{w}_S$ were both constructed using homogeneous lotteries. Indeed, the distance (in terms of utility) between x_n and x_{n-1} is (by construction) subjectively equivalent to the distance between x_1 and x_0. By neutralizing the 'spacing' effect, the comparison between the functions $\bar{w}_L$ and $\bar{w}_S$ thus makes it possible to investigate the sole impact of the absolute level of consequences.

At this stage, an important point to make is that certainty equivalents CE_js are unlikely to be elements of the previously elicited standard sequence. So the $U(CE_j)$s and $\bar{w}(p_j)$s could not be

[7] Roughly, since it is actually impossible to completely control the way subjects perceive a loss situation that is intended by the experimenter to be 'homogeneous' (resp. 'heterogeneous').

obtained without fitting U parametrically, from which the name of 'semi-parametric' procedure[8]. Moreover, U needed be especially well fitted to allow reliable calculations using Eq. (3). This is why each individual utility function was fitted using 3 different specifications, and for each subject the best fitting specification was retained. The first two – standard – specifications are the one-parameter POWer function, with $U_{POW}(x) = -(-x)^{\alpha}$ and $\alpha>0$ (Tversky and Kahneman, 1992) and the two-parameter EXpo-POWer function, with $U_{EXPOW}(x) = [1-\exp(-\beta(-x)^{\alpha})]/(\exp(-\beta)-1)$, $\alpha>0$ and $\beta>0$ (Abdellaoui, Barrios and Wakker, 2007; Saha, 1993)[9].

The third specification is more unusual. Denoted GE (with reference to Goldstein and Einhorn, who introduced it in their 1987 paper), it is given by $U_{GE}(x) = -\frac{\delta(-x)^{\gamma}}{\delta(-x)^{\gamma} + (1+x)^{\gamma}}$, with $\delta>0$ and $\gamma>0$. Because it allows inverse-S shape, this specification has been extensively used in the literature to fit probability weighting functions. Since 25% of our individual utility functions exhibited an inverse-S shape[10], the GE specification was used for the pragmatic purpose of best fitting.

2. Experimental design

30 subjects participated in the final experiment. All of them were undergraduate wage-earning students at the Department of Economics and Management at ENS de Cachan (France). They all had some background in probabilities, but none of them had followed any specific

[8] Linear interpolation could not be used here, neither for replacing estimation as in Abdellaoui, Attema and Bleichrodt (2008), nor for checking estimation reliability as in Bleichrodt and Pinto (2000). Indeed, the rather big distance between two successive points of the standard sequence made it impossible to assume linearity between them (see Wakker and Deneffe, 1996).

[9] Note that EXPOW reduces to POW when β tends to 0.

[10] The results as regards the utility function are reported in Etchart-Vincent (2008).

course on decision theory. They were paid for participation (they received a flat-rate of 15 €, around US$ 20) but no performance-based payment was used. The reason for this is twofold. First, subjecting volunteers to the possibility of losing 'for real' is both ethically questionable and practically impossible (Mason et al., 2005, p. 189 note 4), *a fortiori* when losses at stake are large. Second, the most widely used alternative option, namely the 'initial endowment' strategy[11], may give rise to several detrimental biases, among which the famous 'house money effect' (Boylan and Sprinkle, 2001; Keasy and Moon, 1996; Thaler and Johnson, 1990; Weber and Zuchel, 2005). Fortunately, there is some suggestive evidence that the use of real monetary incentives does not significantly affect the findings when the subject's task consists in choosing between simple lotteries (Beattie and Loomes, 1997; Bonner et al., 2000; Bonner and Sprinkle, 2002; Camerer and Hogarth, 1999; Etchart-Vincent and L'Haridon, 2008; Hertwig and Ortmann, 2001).

Now, the experiment consisted in two successive computerized sessions. Each subject was individually interviewed in the presence of the experimenter. The utility (resp. probability weighting) function was elicited in the first (resp. second) session. A break separated the sessions. Each interview lasted between 45 and 75 minutes. All along the experiment, the subject was only asked to make choices between lotteries, displayed as pie charts on a computer screen (both consequences and probabilities were stated explicitly; see Etchart-Vincent, 2004, Appendix A for a typical computer screen[12]). Indeed, choice-based procedures have proven to be easier for the subjects and to produce more reliable data than direct matching (Bostic, Herrnstein and Luce; 1990; Tversky, Sattah and Slovic, 1988). A 6-iterations bisection process was used to obtain all the indifference points.

[11] This strategy consists in providing the subjects with an initial endowment from which they can lose some money during the experiment. The idea is to make them suffer real losses, but not from their own pockets.

[12] The experimental display used in this study is mostly identical to that developed in Etchart-Vincent (2004).

In the first stage of the procedure, p = 0.33 was chosen to elicit the utility function at the individual level, in accordance with Wakker and Deneffe (1996, p. 1144)'s suggestion. In former studies, p was given either the value 0.5 (Bleichrodt and Pinto, 2000), 0.33 (Fennema and Van Assen, 1999) or 0.67 (Abdellaoui, 2000). The pilot experiment was used to calibrate the starting point of the standard sequence x_0, the reference outcomes r and R (with x_0, r and R being fixed and common to all subjects), and the number of points n, so as to get for x_1 (resp. x_n) a *mean* value around a month earnings (resp. around the price of a medium-sized car). n = 6 was finally chosen, as well as x_0 = –150 € (–US$ 200), r = 300 € (US$ 400) and R = 1500 € (US$ 2 000). Finally, the calibration process was rather successful, since the mean values obtained for x_1 and x_6 on our 30-subject sample were –1265 € (–US$ 1 750) and –12 850 € (–US$ 17 700) respectively. Of course, huge heterogeneity prevailed at the individual level, resulting in lower median values: median x_1 was around – 800 € (–US$ 1 100, while median x_6 was around –7 600 € (–US$ 10 500).

In the second stage of the experiment, the three payoff conditions S, L and S/L were defined by the intervals [x_1; x_0], [x_6; x_4][13] and [x_6; x_0] respectively (see Section 1 and Figure 1 *supra*)[14]. In each payoff condition, the same 6 probabilities p_j = 0.01, 0.1, 0.25, 0.5, 0.75, and 0.9 were chosen for the probability weighting elicitation work. The order in which the S, L and S/L loss situations were shown to the subjects, as well as the order in which probabilities were displayed within each situation, were randomized to prevent any order effects. As usual, a practice session was introduced prior to the experiment, as well as consistency checks after it. Since loss situations have proven to be psychologically and cognitively hard to deal with, the

[13] The pilot experiment showed that the theoretically appropriate interval [x_6; x_5] was actually too small to allow the subjects to reliably determine several certainty equivalents within its bounds.

[14] Remember that the three values x_1, x_4 and x_6 were endogenously determined using the TO method, thus specific to each subject. This means that each subject was faced with specific S, L and S/L loss situations.

practice session and the break during the experiment also aimed to make the task more comfortable for the subjects.

Now, as regards the subjects' internal consistency, it was checked through the systematic repetition of the ith (out of 6) iteration in each choice situation, with $i = 4$ for the elicitation of both the utility function and the probability weighting function in the S and L situations, and $i = 5$ for the elicitation of the probability weighting function in the S/L situation (because of the greater width of the interval of consequences in this case). The 6 points of the standard sequence thus provided 6 individual internal consistency checks for utility. Similarly, the 6 certainty equivalents obtained in S (resp. L, S/L) provided 6 individual consistency checks for probability weighting in S (resp. L, S/L). The percentage of consistent choices among our subjects was then computed to obtain four average consistency rates – 80% for S, 71% for S/L, 72% for both utility and L – which appear to be in line with those obtained in similar previous studies (see for instance Abdellaoui, 2000; Abdellaoui, Bleichrodt and L'Haridon, 2008; Camerer, 1992).

3. Results

3.1. Non-parametric and parametric tools

Probability weighting functions can be first investigated in terms of underweighting/overweighting. Following the usual interpretation of probability weighting in terms of optimism/pessimism, a decision maker is said to be optimistic (resp. pessimistic) if her weighting function over losses exhibits under (resp. over)-weighting, i.e. if $w^-(p) < p$ (resp. $w^-(p) > p$) for all p (e.g. Cohen, 1994).

Weighting functions can also be described through their main two physical features, namely curvature and elevation, which underlie the psychological and cognitive interpretation of

probability weighting (Gonzalez and Wu, 1999; Starmer, 2000; Tversky and Kahneman, 1992; Tversky and Wakker, 1995). On the one hand, elevation captures the 'attractiveness' of the gamble for the subject under consideration: her weighting function w^- will be all the higher (resp. lower) since she considers the gamble as more repulsive (resp. attractive). Note that the concepts of attractiveness/repulsiveness are close to those of optimism /pessimism.

On the other hand, curvature reflects 'discriminability' (between probabilities). The most usual interpretation of discriminability is a cognitive one. It is meant to capture the decision maker's limited ability to discriminate between probabilities: the higher this ability, the more linear the weighting function. Ability to discriminate is closely related to the 'diminishing sensitivity' principle; it is all the lower since probability is remote from the natural bounds 0 and 1 (Tversky and Kahneman, 1992). It is also connected with the decision maker's familiarity with the risky situation under consideration. High familiarity/competence may counterbalance or even prevent diminishing sensitivity. However, discriminability may also be viewed as strategic. In this approach, the decision maker will deliberately give the same weight to different probabilities, because she needs not differentiate between them in order to take a satisfactory decision. The strategic approach thus assumes that the subject adapts her cognitive effort to her needs at the end of a kind of implicit cost-benefit analysis. The comments made by our subjects during the experiment suggest that the cognitive and strategic interpretations should be viewed as complementary rather than exclusive. Still, in order to avoid ambiguity, only the descriptive term 'discriminability' will be retained here when reporting the results.

Some two-parameter specifications allow to capture both curvature and elevation, each parameter governing (as independently as possible) one feature. The most popular specification, denoted GE and such that $w_{GE}(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma}+(1-p)^{\gamma}}$, was first suggested by Goldstein and Einhorn (1987) and then used by Lattimore, Bakker and Witte (1992), Tversky and Fox (1995) and Abdellaoui (2000) among others. From a different (axiomatic) viewpoint, Prelec (1998) derived

the specification denoted PREL and such that $w_{PREL}(p) = \exp(-\delta(-\log(p))^{\gamma}$, where parameters get the same interpretation as in GE. In both GE and PREL, δ governs elevation. Under PT over losses, $\delta < 1$ (resp. $\delta > 1$) implies absolute attractiveness (resp. repulsiveness). γ governs curvature and gives some information about discriminability: the nearer to 1 γ is, the flatter the curve and the higher discriminability. Besides, $\gamma < 1$ generates the usual inverse-S shape. The comparison between two weighting functions w^{-}_{1} and w^{-}_{2} is thus reducible to the comparison between parameters γ_1 and γ_2 on the one hand, and between δ_1 and δ_2 on the other hand.

Note that some single-parameter specifications have also been used in the literature. Tversky and Kahneman (1992)'s specification, denoted TK and such that $w_{TK}(p) = \frac{p^{\delta}}{[p^{\delta}+(1-p)^{\delta}]^{1/\delta}}$, is the most popular one. However, unless discriminability and attractiveness covary so that they can be encapsulated in a single parameter – which unfortunately is unlikely to happen (Gonzalez and Wu, 1999) – the descriptive power of such specifications appears to be questionable, especially on individual data. In the following, parametric fitting of the *median* probability weighting functions using TK will nevertheless be reported, for the purpose of comparison with previous studies.

3.2. The 'level' and 'spacing' effects

Both two-tailed paired t_{29}-tests and Wilcoxon tests were run to analyse the data. Since they always give similar results, only the former will be presented here.

The left part of Table 1 reports the results of two-tailed paired t_{29}-tests as regards basic probability weighting (H_0: $w^{-}(p) = p$). Unsurprisingly, the usual inverse-S shape is replicated. Still, the S/L situation induces some specific features, with both stronger and more 'persisting'

probability overweighting than in S and L: in S/L, the only underweighted probability is 0.9 and 'low' probabilities until 0.5 are significantly overweighted.

[INSERT TABLE 1 ABOUT HERE]

Now, as regards the comparison between w^-_S, w^-_L and $w^-_{S/L}$, only for high probabilities does the difference between w^-_S and w^-_L reach significance, with large losses inducing more underweighting than small ones (right part of Table 1). This suggests that, when the 'spacing' effect is controlled, only near certainty does the absolute level of consequences markedly affect probability weighting.

The 'spacing' effect appears to be both stronger than and opposite to the 'level' one. First, only for low probability of loss ($p \leq 0.25$) does the distance ('spacing') between consequences seem *not* to affect probability weighting. Second, as probability grows, the fact that a large loss be associated with a small one (S/L) rather than with another large one (L) leads to significant probability overweighting, instead of significant underweighting.

Now, what about parametric estimates? Two-tailed paired t_{29}-tests suggest that the elevation parameter δ is not significantly different from 1 in both S and L situations, while $\delta_{S/L}$ appears to be significantly superior to 1, confirming the repulsive status of heterogeneous gambles (Table 2, left part).

[INSERT TABLE 2 ABOUT HERE]

As regards curvature, γ is dramatically inferior to 1 in both S and L, indicating very low discriminability between probabilities when only homogeneous losses are involved. By contrast, S/L-type heterogeneous prospects appear to increase discriminability, with $\gamma_{S/L}$ being only slightly inferior to 1. This finding is confirmed through direct comparison between the three loss situations (Table 2, right part). First, neither curvature nor elevation appears to significantly depend on the 'level' of consequences. Second, the data suggest that a genuine 'spacing' effect is

at play: both elevation and curvature are significantly higher when the prospects are heterogeneous rather than homogeneous.

Median results may help summarize those obtained at the individual level. The median values of individual subjective weights, obtained for each probability and loss situation, were used to build the three *median* weighting functions w^-_S, w^-_L and $w^-_{S/L}$. These three functions appear to exhibit the expected shape, with significant overweighting of low probabilities and underweighting of high probabilities (see Figure 2). Moreover, $w^-_{S/L}$ (resp. w^-_L) globally appears to exhibit the highest (resp. lowest) curve. But only for intermediate and high probabilities does the difference between the curves look significant.

[INSERT FIGURE 2 ABOUT HERE]

Parametric fitting of the three median weighting functions was achieved using TK, GE and PREL specifications (see Table 3). For the sake of comparison with previous studies, Table 4 presents both the estimates obtained on our median weighting functions using the one-parameter TK and two-parameter GE specifications and those obtained with the same specifications by Abdellaoui (2000), Abdellaoui, Vossman and Weber (2005), Etchart-Vincent (2004) and Lattimore, Baker and Witte (1992).

[INSERT TABLE 3 ABOUT HERE]

[INSERT TABLE 4 ABOUT HERE]

It is interesting to note that our TK estimates are very similar to Tversky and Kahneman (1992)'s and Abdellaoui (2000)'s, except for S/L. This finding suggests that something specific happens when the prospects are heterogeneous. It is also worth noticing that, as compared to those obtained in Etchart-Vincent (2004), the present fitting results for w^-_S and w^-_L look more standard. It retrospectively appears that the S and L payoff conditions introduced in our 2004 study actually incorporated some heterogeneity. This may contribute to explain the apparent

contradiction between both series of results, as well as the remarkable similarity between previous fitting results for w^-_L and present fitting results for $w^-_{S/L}$.

Now, what about GE estimates? First, as regards elevation, S and S/L (resp. L) appear to be considered by the median subject as absolutely repulsive (resp. attractive), and S/L as the most repulsive situation ($\delta_{S/L} > \delta_S > 1 > \delta_L$). Besides, the degree of elevation is significantly higher than in Abdellaoui (2000) and Lattimore, Bakker and Witte (1992), but it is rather similar to that found by Abdellaoui, Vossman and Weber (2005) and Etchart-Vincent (2004).

Now, as regards discriminability, $\gamma < 1$ in all cases, which confirms the inverse-S shape of the three curves. Moreover, $\gamma_L < \gamma_S << \gamma_{S/L} < 1$, which suggests that discriminability is much higher in risky situations with widely spaced consequences (S/L) than in situations with homogeneous consequences, especially when those are large (L). Still, the fact that parameter γ remains quite low in the three situations indicates that discriminability in the loss domain is rather poor. Though lower than those found by Etchart-Vincent (2004), the values taken by parameter γ in this study are rather close to Abdellaoui (2000)'s and Lattimore, Baker and Witte (1992)'s.

4. Discussion

4.1. Discussion of the method

The method used in this paper may suffer from two main drawbacks. The first potential difficulty concerns the utility elicitation process. Indeed, the TO method requires that probability weighting be constant all along the elicitation process, so that $(1–w^+(p))/w^-(p)$ be constant. Otherwise, it is no longer possible to get Eq. (2) from Eq. (1) and to use Eq. (2) to build the utility function properly (see Wakker and Deneffe, 1996, p. 1147). The fact that the 'reference'

outcomes *r* and *R* remain the same all along the process while the x_is are getting more and more negative implies that the distance between the consequences at stake increases during the elicitation process. So, if probability weighting appears to be affected by a 'spacing' effect, then the standard sequence obtained using Eq. (2) is likely to be biased.

To control this problem, a multifaceted strategy was adopted. A first precautionary measure was to choose a relatively neutral probability for utility elicitation. 0.33 is usually considered as such: on aggregate data at least, w(0.33) has empirically been shown to be very close to 0.33 (see Prelec, 1998 for instance), and there is also some evidence that $w^-(0.33)$ is not affected by the payoff structure of the prospects (Etchart-Vincent, 2004). Second, the pilot experiment gave us some insight into the way the subjects were making their decisions during the utility elicitation process: it seems that, since the probability *p* was held constant throughout the process, the subjects integrated it at first and did not reconsider it later. Such an attitude is consistent with the intuition that the trade-off method focuses attention on utility and makes probability a rather secondary choice dimension (see Wakker and Deneffe, 1996, p. 1148). Thirdly, some subjects took part in both this study and the 2004 one. The remarkable similarity between the utility functions they produced on these occasions[15] suggests that the present procedure did not suffer from substantial biases[16].

The second potential drawback of the method originates from the fact that each $w^-(p_j)$ was calculated from a unique certainty equivalent CE_j – and more precisely from its utility $U(CE_j)$. Thus, any error in the evaluation of $U(CE_j)$, be it due to the poor parametric fitting of the utility function U or to some bias in the determination of CE_j, would directly result in a biased w^-

[15] Note that two years elapsed between the first and the second studies, so that no memory effect can be suspected to have affected the second set of data.

[16] The procedure used in the 2004 study was not concerned with the problem under discussion here. This is why it could be used as a benchmark for the evaluation of the reliability of the present procedure.

(p_j). I was highly aware of this potential difficulty and took special care to collect high-quality data and make good parametric fitting (see Section 1, *supra*).

4.2. Discussion of the results

The findings suggest that, at least for moderate/high probability of loss, the 'level' and 'spacing' effects do reach significance, with the impact of 'spacing' being both opposite to and stronger than the impact of 'level'. In Etchart-Vincent (2004), large-loss gambles appeared to increase pessimism as compared to small-loss ones, suggesting a pessimistically-oriented 'level' effect. So the 'level' effect found in the present study appears to be somewhat contradictory to that obtained in our previous study. This may be due to the fact that, even though Etchart-Vincent (2004) intended to investigate the sole impact of 'level', the gambles involved in that study were probably not homogeneous enough to prevent any 'spacing' effect. So the observed 'level' effect was actually a mix of genuine 'level' and 'spacing' effects, which the present study precisely shows to be both conflicting and of unequal intensity[17].

Another noticeable result of the paper is the quite low degree of curvature (discriminability) exhibited by individual weighting functions. It may be due to the fact that both cognitive ability and strategic effort to discriminate be lower in the loss domain than in the gain domain. First, the subjects are likely to be less familiar with losses than with gains, which may lessen their ability to discriminate. In this respect, if we admit that probability processing is facilitated when the gamble situation itself is cognitively easier to deal with (which is the case when gambles are heterogeneous rather than homogeneous) the somewhat higher level of

[17] In this respect, the fact that the value taken by the elevation parameter δ_L in the 2004 study was intermediate between the values taken by δ_L and $\delta_{S/L}$ in the present study suggests that the former L situation was actually a mix of genuine L and S/L situations.

discriminability observed in the S/L situation may receive a cognitive interpretation. Second, a decision maker may be tempted to make lower mental effort when facing a loss situation: she may content herself with a qualitative answer to two simple questions, namely: ‘can I get into trouble, and if so, can I reasonably hope to avoid it?’. In that case, she will only consider three basic ranges of probability, corresponding to the ideas of ‘no trouble’, ‘potential trouble’, and ‘trouble with certainty’ respectively. The data collected by Cohen, Jaffray and Saïd (1987) bring some support to this view. In the gain domain indeed, intermediate probabilities 1/3 and 1/4 were subjectively weighted differently. But in the loss domain, they were subjectively confounded. This suggests that, for a decision maker facing a loss gamble, intermediate probabilities actually belong to the same (‘potential trouble’) category. In the present study, the higher level of discriminability observed in the S/L situation may receive a similar strategic interpretation: when facing both the opportunity not to lose much and the risk of losing very much, the subject may have a strong incentive to make some additional cognitive effort toward discriminability.

Emotions can have also played a role in our findings. For instance, Kunreuther, Novemsky and Kahneman (2001) and Sunstein (2003) show that discriminability tends to decrease as the emotional content of consequences grows. In our study, the L situation can be viewed as emotionally richer than the S one, and discriminability actually appears to be lower in L than in S. However, while the S/L situation can be considered as the most heavily charged with emotions, it exhibits the highest level of discriminability. This may be due to the fact that the connection between emotions and cognitive limitations/strategic motives is not trivial: emotions may exacerbate cognitive limitations, but they may also enhance the decision maker’s mental arousal.

Now, as curvature, elevation appears to be higher in the S/L situation than in both the S and L situations. Indeed, a gamble that offers both the opportunity not to lose much and the risk of losing very much may be found particularly repulsive. As shown by Rottenstreich and Hsee

(2001), elevation is likely to increase with the affective and emotional content of consequences at stake (see also Brandstätter, Kühberger and Schneider, 2002 for a similar approach). In the present study, the fact that heterogeneous gambles be heavier with negative emotions than homogeneous ones may have contributed to induce especially strong feelings of repulsiveness and pessimism. Besides, S/L-type situations can be expected to induce strong regret (resp. disappointment) feelings in case the decision maker takes the wrong decision (resp. in case the bad state of nature obtains) (see for instance Weber and Chapman, 2005). This is why she may have a strong *ex ante* motive to make the decision that is most likely to avoid such *ex post* unpleasant feelings and pain (cf. the related literature on security needs and prevention vs. promotion focus; see Higgins, 1997, 1998 and Kluger et al., 2004).

5. Conclusion

The present study aimed at investigating Tversky and Kahneman (1992)'s suggestion that "*decision weights may be sensitive to […] the spacing and the level of outcomes"*. Our data suggest that i) only for moderate and high probability does the payoff structure of the gamble actually affect probability weighting, ii) 'spacing' has more impact than 'level', and iii) their effects are opposite: as compared to (homogeneous) small-loss gambles, heterogeneous loss situations tend to enhance (probabilistic) pessimism, while (homogeneous) high-loss gambles are shown to increase optimism. Even though the small size of our sample obviously calls for more systematic investigation to ensure the robustness of our findings, it is worth mentioning the potential theoretical and prescriptive implications of the present results.

First, from a theoretical point of view, the fact that probability weighting be not *systematically* sensitive to consequences is rather good news for the RDU and PT models, which assume that probability weighting is a basic personal feature and should not be affected by any

incidental element (such as the payoff structure of the prospects or even the mood of the decision maker). Nevertheless, further experimental research is required to systematically investigate whether and to what extent such incidental ingredients may actually influence probability weighting. Only if systematic dependency of probability weighting on incidental ingredients was to be found, should some new descriptive models be developed (Currim and Sarin, 1989, p. 39) – provided such new specifications remain parsimonious and tractable enough.

Second, from a prescriptive point of view, the present study can be considered as an attempt to gather some information about how people behave, and how they deal with outcomes and probabilities, depending on whether the loss situation involves either high or low stakes. This may help understand individuals' tendency to exhibit some unexpected as well as undesirable behaviour. Let us come back to the insurance example given in the introduction: once insured people are shown to take more risks than they should, the question remains whether this risk taking behaviour is due to either probabilistic optimism (probability underweighting) or 'moral hazard'. Discriminating between those two hypotheses is not only a rhetoric point; it is likely to redirect the design of contracts and/or the communication and prevention effort. Specifically insurance-oriented experiments may help identify which behavioural hypothesis works, or to what degree each of them works.

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Table 1. Probability Weighting on Individual Data (Two-Tailed Paired t_{29}-Tests)

	Probability weighting in each loss situation			Comparison between the three loss situations		
H_0	$w^-_S(p) = p$	$w^-_L(p) = p$	$w^-_{S/L}(p) = p$	$w^-_S(p) = w^-_L(p)$	$w^-_S(p) = w^-_{S/L}(p)$	$w^-_{S/L}(p) = w^-_L(p)$
0.01	-6.797***	-5.496***	-5.564***	-0.929 ^{ns}	-0.157 ^{ns}	-0.654 ^{ns}
0.1	-5.347***	-4.757***	-4.897**	-1.256 ^{ns}	-0.625 ^{ns}	-0.899 ^{ns}
0.25	-3.441***	-2.992**	-3.49**	-0.695 ^{ns}	-0.624 ^{ns}	-0.887 ^{ns}
0.5	0.023^{ns}	1.882^{ns}	-2.857**	-1.179^{ns}	2.184*	-3.378**
0.75	2.930**	4.297***	-0.516^{ns}	-2.047*	2.754**	-4.306***
0.9	4.718***	6.323***	4.642***	-2.414*	2.158*	-4.822***

^{ns}: non significant at the 5% level; *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$

Table 2. Elevation and Curvature on Individual Data (Two-tailed Paired t_{29}-Tests)

		Elevation and Curvature in each loss situation			Comparison between the three loss situations		
Elevation	H_0	$\delta_S = 1$	$\delta_L = 1$	$\delta_{S/L} = 1$	$\delta_S = \delta_L$	$\delta_S = \delta_{S/L}$	$\delta_{S/L} = \delta_L$
	δ	-1.962*	0.525^{ns}	-3.458**	-1.928^{ns}	2.3*	-3.440**
Curvature	H_0	$\gamma_S = 1$	$\gamma_L = 1$	$\gamma_{S/L} = 1$	$\gamma_S = \gamma_L$	$\gamma_S = \gamma_{S/L}$	$\gamma_{S/L} = \gamma_L$
	γ	6.471***	9.523***	0.270^{ns}	1.126^{ns}	2.317*	-2.474*

^{ns}: non significant; *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$

Table 3. Parametric Fitting of Median Weighting Functions

	S	L	S/L
TK	$\gamma = 0.748$	$\gamma = 0.672$	$\gamma = 0.861$
	(0.072)	(0.025)	(0.115)
GE	$\delta = 1.170$	$\delta = 0.894$	$\delta = 1.355$
	(0.061)	(0.034)	(0.121)
	$\gamma = 0.572$	$\gamma = 0.561$	$\gamma = 0.746$
	(0.035)	(0.026)	(0.067)
PREL	$\delta = 0.812$	$\delta = 0.965$	$\delta = 0.767$
	(0.018)	(0.027)	(0.049)
	$\gamma = 0.639$	$\gamma = 0.581$	$\gamma = 0.819$
	(0.023)	(0.027)	(0.075)

Standard errors are in parentheses.

Table 4. Parametric Fitting of Median Weighting Functions: A Comparison with the Literature

		TK	LBW	
		γ	δ	γ
Abdellaoui (2000)		0.7	0.84	0.65
Abdellaoui, Vossman and Weber (2005)		-	1.182[a]	0.848[a]
			1.209[b]	0.809[b]
Etchart-Vincent (2004)[a]	S	0.869	1.020	0.836
	L	0.908	1.179	0.853
This study[d]	S	0.748	1.170	0.572
	L	0.672	0.894	0.561
	S/L	0.861	1.355	0.746
Lattimore, Baker and Witte (1992)		-	0.713[c]	0.522[c]
Tversky and Kahneman (1992)		0.69	-	-

a: utility was estimated using the two-parameter EXPOW specification

b: utility was estimated using the one-parameter POW specification

c: this figure is actually the mean of four individual estimations (the only ones provided by the authors). It thus has to be considered with cautiousness.

d: utility was estimated using a two-parameter specification (either EXPOW or GE)

Figure 1. The Standard Sequence and its Three Sub-Intervals

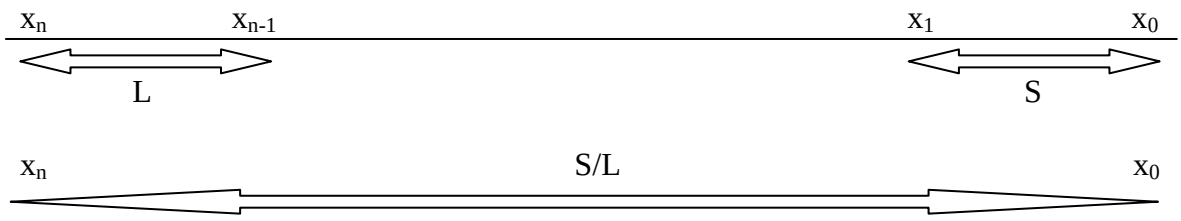
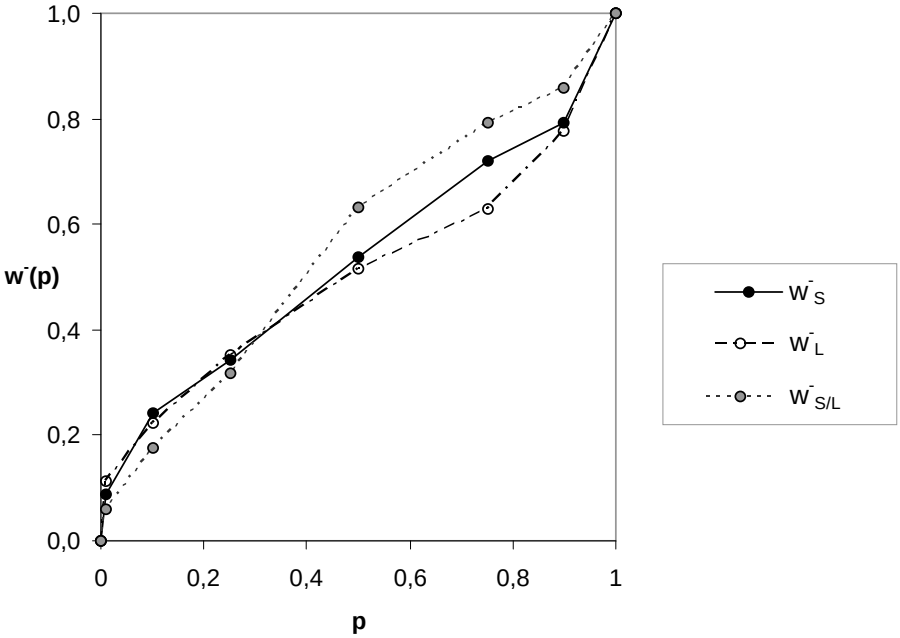
Figure 2. Median Weighting Functions w^-_S, w^-_L and $w^-_{S/L}$