Preference Reversals Under Ambiguity *

Hela Maafi[†]

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Abstract

Preference reversals have been widely studied using risky or riskless gambles. However, little is known about preference reversals under ambiguity. We asked subjects to make a binary choice between ambiguous P-bets and ambiguous $-bets and elicited their willingness to accept. Subjects then performed the same two tasks with risky bets, where the probability of winning for a given risky bet is the center of the probability interval of the corresponding ambiguous bet. Preference reversals are not only replicated under ambiguity but are even stronger than those under risk. This is due to higher elicited prices for the $-bet and lower elicited prices for the P-bet under ambiguity than under risk. We explain this result by the shape of the probability-weighting function for different levels of uncertainty and for different elicitation modes.

JEL classification: D81, D03, C91.

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†Paris School of Economics, and University of Paris I - Panthéon Sorbonne, 106-112 Bd de l'hôpital, 75647 Paris Cedex 13, France, (Email: hela.maafi@malix.univ-paris1.fr)

1 Introduction.

Preference reversals occur when subjects provide different preference orders over two risky options under different elicitation mechanisms. A typical preference-reversal experiment involves two risky lotteries: one lottery (or "bet") featuring a high probability of winning a small amount of money, called the probability bet or "P-bet", and another lottery featuring a low probability of winning a large amount of money, called the dollar bet or "$-bet". To illustrate, consider the following bets: $-bet = ($16, 11/36; -$1.50, 25/36) and P-bet = ($4, 35/36; -$1, 1/36), taken from Lichtenstein and Slovic (1971), Table 3. Here, the $-bet offers an 11/36 chance of winning $16 and a 25/36 chance of losing $1.50, while the P-bet offers a 35/36 chance of winning $4 and a 1/36 chance of losing $1. Both bets have an expected value of approximately $3.85. Subjects are asked to make a straight choice between these two bets, and then to value them separately. Subjects of ten prefer the P-bet to the $-bet but assign a greater value to the $-bet (this is known as Standard Preference Reversal, SPR). They also sometimes choose the $-bet and assign a greater value to the P-bet (this is known as Non-Standard Preference Reversal, NSPR).

Preference reversals were first discovered by cognitive psychologists (Lichtenstein and Slovic, 1971, and Lindman, 1971). Later, in an attempt to disprove the phenomenon, Grether and Plott (1979) showed that preference reversals are resistant to economic considerations, including monetary incentives, and the possibility of expressing indifference in the choice tasks. Preference reversals were then generally accepted as a notable challenge to almost all theories of preferences, including expected utility. In ensuing work, preference reversals have been extensively replicated with small experimental variations, showing that reversals are an empirical regularity and that preferences are context-dependent (See Seidl, 2002, for an extensive survey).

To date, the numerous pieces of work that have examined preference reversals involve either *risky* options, i.e. situations in which the decision maker knows the probabilities associated with the possible outcomes, or *riskless* options (Delquié, 1993). This represents a particular case of uncertainty since in general probabilities are unknown, so that we may wonder about preference reversals when the lotteries involve only partially-known probabilities, i.e. when there is ambiguity. This is empirically relevant, as most real-life probabilities situations are unknown: for example, those associated with the future price of stocks, the outcome of a football match, or a candidate's victory in an election.

The current paper thus asks whether preference reversals hold under ambiguity. It also compares preference reversals under ambiguity, if any, to those under risk. To do so, we consider six typical paired-lotteries used in preference reversals experiments under risk and construct corresponding ambiguous lotteries by introducing ambiguity around the probability of winning for each bet using two-stage objective lotteries. We use a two-stage lotteries for three reasons. First, we assume that the implementation of "true" ambiguity in the case of classical preference reversal paired-lotteries would complicate the understanding of the task (see Section 4.5, for an extensive discussion). Second, as noted by Hey et al. (2008), it is not straightforward to implement "true" ambiguity in the laboratory, *particularly with modern practice where openness and transparency are paramount.* Third, although two-stage objective lotteries are not the correct representation of "true ambiguity", many experiments have indeed found ambiguity-aversion using this representation (Yates and Zukowski, 1976, Bernasconi and Loomes, 1992, Chow and Sarin, 2002, and Halevy, 2007).

In our experiment the ambiguous bets are constructed as follows. For a risky-bet (x, p) offering amount x with probability p, the corresponding ambiguous-bet $(x, [\underline{p}; \overline{p}])$ offers the same amount x with a probability between $\underline{p}$ and $\overline{p}$, where p=$(\underline{p} + \overline{p})/2$. To illustrate, consider the risky paired-lottery: {P-bet_R:(€5, 80%); \$-bet_R:(€20, 20%)} (this is pair I in Table 1). The corresponding ambiguous paired-lottery is {P-bet_A:(€5, [60%, 100%]); \$-bet_A:(€20, [0,40%])}, where the ambiguous P-bet offers €5 with a probability between 60% and 100% and the ambiguous \$-bet offers €20 with a probability between 0 and 40%. Subjects were asked to provide their minimum selling price for the ambiguous P-bet and the ambiguous \$-bet, and to choose between the two. They then performed the same tasks with the corresponding risky bets.

The main result here is that subjects reverse their preferences more often under ambiguity than under risk. This primarily reflects higher elicited prices for the \$-bet and lower elicited prices for the P-bet under ambiguity than under risk.

As ambiguity is directly related to probabilities, we interpret our results in terms of probability distortions under risk and ambiguity. Based on prospect theory (Kahneman and Tversky, 1979, and Tversky and Kahneman, 1992), which argues that subjects overweight small probabilities and underweight large ones, we estimate the probability-weighting function under both risk and ambiguity and show that it is more curved (more concave for small probabilities and more convex for large probabilities) under ambiguity than under risk (Tversky and Fox, 1995, Wu and Gonzalez, 1999, Kilka and Weber, 2001, Abdellaoui et al., 2005, and Abdellaoui et al., 2010). This feature, called “less sensitivity to ambiguity than to risk” (Tversky and Fox, 1995, and Wakker, 2004), is more pronounced for valuation than for choice.

The remainder of the paper is organized as follows. Section 2 reviews some existing results on preference reversals and ambiguity, and Section 3 makes predictions for preference reversals under ambiguity, based on the characteristics of the weighting function under risk and uncertainty previously found in the literature. Section 4 presents our experimental design, and Sections 5 and 6 the results. Section 7 then explains these results via the shape of the weighting function under risk and ambiguity. Section 8 contains a general discussion and Section 9 concludes.

2 A Brief Survey of Existing Results and Motivation

Preference reversals under risk pose a significant challenge to preference theories. The phenomenon is a manifest failure of invariance and its robustness has intrigued economists for the past four decades (Seidl (2002) presents an extensive review of preference reversals). Many attempts have been proposed to explain preference reversals under risk, but the phenomenon is generally attributed to the use of different heuristics across elicitation procedures (or response modes). The attractiveness of the P-bet in the choice task is induced by *the prominence effect*: the more prominent attribute looms larger in choice than in matching (Tversky et al., 1988), while the attractiveness of the $-bet in valuation is a result of *scale compatibility*: attributes of decision alternatives that are compatible with the elicitation method are weighted more heavily than those that are not (Tversky et al., 1990). This results in inconsistent preferences and raises the question of what true preferences actually are.

The distinction between risk and uncertainty in economics dates back to Knight (1921), who distinguished situations characterized by risk, where the probabilities associated with outcomes are assumed to be known, from situations characterized by uncertainty, where these probabilities are unknown. Most decisions under uncertainty lie between these two extremes, in such a way that individuals do not know the exact probabilities associated with outcomes, but they have some ambiguous notion about their occurrence. Currently, choice under ambiguity constitutes one of the most important domains of decision theory.

One notable criticism of expected utility theory under ambiguity is the Ellsberg paradox (1961), which introduced the notion of ambiguity aversion by demonstrating that people prefer to bet on known rather than unknown probabilities. The example given by Ellsberg (1961) illustrates that individuals prefer to bet on the outcome of an urn that contains 50 red and 50 black balls rather than the outcome of an urn that contains 100 red and black balls, but in an unknown proportion. The two bets have the same expected probability of winning, $E(p)$, but not the same degree of uncertainty: in the first bet, the probability of drawing a black or red ball is exactly 0.5, while in the second bet this probability is ambiguous. Further work using variations of Ellsberg's original problem has found considerable support for ambiguity aversion (see Camerer and Weber, 1992, for a survey).

As the expected probability of winning in Ellsberg's original problem is 0.5, some of this work has examined ambiguity attitudes along the probability interval. Subjects are shown to exhibit ambiguity aversion for moderate and large probabilities of winning, and ambiguity seeking for modest probabilities of winning (Einhorn and Hogarth, 1986, Kahn and Sarin, 1988, Curley and Yates, 1989, and Hogarth and Einhorn, 1990). This finding is essential to the work presented here: as the $-bets involve small probabilities of gain and the P-bets larger probabilities of gain, we expect that ambiguity will amplify the effect of risk in the case of preference reversals.

There is substantial empirical evidence of the systematic violation of normative principles of rationality under risk and ambiguity. To take into account the more realistic case of imprecision regarding probabilities, it is important to bring these two blocks of research together to consider the anomalies observed under risk in the more general case of uncertainty. The present paper relates ambiguity aversion to classical preference reversals. Two recent contributions (Trautmann et al., 2009 and Pogrebna, 2010) examine different types of preference reversals under ambiguity. Trautmann et al. (2009) investigate preference reversals under ambiguity using Ellsberg's original two-color problem. In their experiments, subjects make a straight choice between the two urns and value them jointly. They observe that a substantial proportion of subjects choose the unknown urn but place a higher value (buying price) on the known urn. The authors explain these preference reversals by loss aversion under valuation.

In Pogrebna (2010), subjects report their preferences over three ambiguous lotteries that differ in the degree of ambiguity but offer the same prize: a relatively less ambiguous lottery (LA), a relatively more ambiguous lottery (MA), and a partially ambiguous lottery (PA). Subjects report their preferences using three elicitation mechanisms: a certainty-equivalent task, a risk-equivalent task and a binary-choice task. Subjects reverse their preferences by attributing a higher certainty or risky equivalent to MA than LA or PA but then choose the alternative bets in the binary-choice task.

In Trautmann et al. (2009) and Pogrebna (2010), the options offer the same prize with the same expected probability. Thus, the type of reversals observed by these two papers are fundamentally different from classical preference reversals because they cannot be explained by context-dependent weightings of attributes. The present paper focus on classical preference reversals where the two bets have different outcomes and different probabilities of winning. The topic of the current paper is of interest because it allows us to uncover the effect of ambiguity on context-dependent preferences. Assuming that subjects use different modes of information-processing in valuation and choice under risk, and given previous results on attitudes toward ambiguity for likely and unlikely events, we look to see how subjects integrate ambiguity into each response mode.

3 Predictions

It is arguably acknowledged that individuals' choices between risky prospects systematically violate expected utility theory because their preferences are not linear in probabilities (Kahneman and Tversky, 1979 and Machina, 1982). Many of these violations can be explained by a non-linear weighting function, $w(.)$, that overweights small probabilities and underweights large probabilities, yielding risk seeking for low-probability gains and risk aversion for moderate- and high-probability gains. Much empirical work has considered the probability-weighting function under risk, most often suggesting an inverse S-shaped function (Tversky and Kahneman, 1992, Wu and Gonzalez, 1996, Gonzalez and Wu, 1999, Abdellaoui, 2000, and Bleichrodt and Pinto, 2000). The inverse S-shaped function is relatively sensitive to changes in probability near the end points 0 and 1, but relatively insensitive to changes in probability in the middle region. This principle, called diminishing sensitivity, gives rise to a weighting function that is concave near 0 and convex near 1.

Tversky and Wakker (1995) generalized the risky inverse S-shaped weighting function to the domain of uncertainty using *bounded subadditivity*, which comprises *lower subadditivity* (LSA) and *upper subadditivity* (USA). Formally, the weighting function under uncertainty, $W(.)$, is defined on subsets of a sample space, where $W(\emptyset) = 0$ and $W(S) = 1$. W satisfies *bounded subadditivity*, if for two disjoint events A and B, there are events E and E' such that:

(i) $W(A) \geq W(A \cup B) - W(B)$, whenever $W(A \cup B) \leq W(S - E)$

and

(ii) $1 - W(S - A) \geq W(A \cup B) - W(B)$, whenever $W(B) \geq W(E')$

where E and E' are boundary events. Conditions (i) and (ii) refer to LSA and USA. LSA implies that an event A has a greater impact when it is added to the null event than when it is added to some non-null event (reflecting the *possibility effect*). USA implies that an event A has greater impact when it is subtracted from the certain event than when it is subtracted from some uncertain event $A \cup B$ (reflecting the *certainty effect*). LSA and USA correspond respectively to the concavity of unlikely events and the convexity of likely events.

Empirical work has provided support for *bounded subadditivity* (Tversky and Fox, 1995, Wu and Gonzalez, 1999, Kilka and Weber, 2001, and Abdellaoui et al., 2005), and further suggests that it is more pronounced for uncertainty than for risk: both LSA and USA are amplified when the outcome probabilities are not specified, giving a weighting function that is more concave for unlikely events, more convex for likely events and flatter in the middle. This property is called *less sensitivity* to uncertainty than to risk. Recently, Abdellaoui et al. (2010) show that subjects are less sensitive to ambiguity than to risk (in the Ellsberg experiment), but find no evidence for ambiguity seeking at low-probability gains

Less sensitivity to uncertainty than to risk is key in our work, since the \$-bets (P-bets) involve small (large) probabilities. Assuming that the difference between the probability-weighting function under ambiguity and that under risk can be ascribed to ambiguity attitudes, we conjecture that ambiguity will act on the \$-bets (P-bets) via its effect on LSA (USA). We put forward two hypotheses:

Hypothesis 1. *Ambiguity increases the attractiveness of the \$-bet as a result of greater LSA.*

Hypothesis 2. *Ambiguity decreases the attractiveness of the P-bet as a result of greater USA.*

These hypotheses show how ambiguity affects choice and valuation. In the valuation task, ambiguity will increase the gap between the prices of the $-bet and the P-bet due to less sensitivity to ambiguity than to risk: ambiguity makes the $-bet more attractive in valuation. In the binary choice task, ambiguity makes the P-bet less attractive. However, the effect of ambiguity on the prevalence of preference reversals cannot be predicted, as it depends on *less sensitivity* in each response mode. There are three possible outcomes:

Proposition 1. *Ambiguity increases preference reversals if less sensitivity is more pronounced in valuation than in choice.*

Proposition 2. *Ambiguity reduces preference reversals if less sensitivity is more pronounced in choice than in valuation.*

Proposition 3. *Ambiguity leaves preference reversals unaffected if it affects the weighting functions in valuation and choice in the same way.*

The effect of ambiguity on two normatively equivalent response modes is therefore an empirical question. We test these hypotheses in the following experiment.

4 Experimental Design

4.1 Stimuli.

The gambles used in our experiments (see Table 1) are identical to those in Grether and Plott (1979), experiment 1, so that we can compare our results. The gambles here do not involve losses, and probabilities were stated via an urn containing 100 balls. A risky urn contains winning and losing balls in known proportions; these proportions are, however, only partially known in an ambiguous urn. All of the gambles were of the same type: if you draw a winning ball, you win €x, and if you draw a losing ball you win nothing.[1] For example, consider pair 1 of Table 1. Here, the risky $-bet offers €20 if a winning ball is drawn from an urn containing exactly 20 winning balls and 80 losing balls, and the risky P-bet offers €5 if a winning ball is drawn from an urn containing exactly 80 winning balls and 20 losing balls. The corresponding ambiguous $-bet

[1] The winning (losing) balls were red- (black-) colored and refer to the positive non-zero (zero) outcome.

offers €20 if a winning ball is drawn from an urn containing between 0 and 40 winning balls among 100 balls, and nothing otherwise, and the corresponding ambiguous P-bet offers €5 if a winning ball is drawn from an urn containing between 60 and 100 winning balls, and nothing otherwise. Subjects were told that the number of winning and losing balls in an ambiguous urn is determined using a uniform distribution over the relevant range. More precisely, they were told that the composition of, say, the ambiguous urn of the $-bet in pair I is determined as follows: the computer program randomly picks one number between 0 and 40 to determine the number of winning balls in the urn. For instance, if the computer picks the number n ($0 \leq n \leq 40$), then the urn contains n winning balls and $100 - n$ losing balls.

For all ambiguous bets, the known probability p was replaced by a uniform distribution over the interval $[0, 2p]$ for $p \leq 0.5$ and $[2p - 1, 1]$ for $p > 0.5$. The resulting intervals provide the maximum ambiguity consistent while leaving the expected value unchanged. The choice of intervals bounded by 0 or 1 ensures that certainty effects associated with ambiguity aversion are captured. Using the maximum interval introduces maximum ambiguity, but does mean that the bets in Table 1 cover different ranges, which may produce different behaviors conditional on the range. The experiment was computerized using software developed under REGATE (Zeiliger, 2000).

4.2 Participants

We recruited 41 (25 males and 16 females) subjects at the University of Paris 1 (France). We ran three sessions: there were 15 subjects in sessions 1 and 2 and 11 subjects in session 3. No subject participated in more than one session.

4.3 Procedure

The experiment was divided into four rounds, and all participants completed all four rounds. We opted for a within-subject analysis as this is statistically more powerful than between-subject analysis when there is no range effect (Greenwald, 1976). We argue in the next section that our experiment is immune to range effects.

In the first round, subjects were asked to specify their minimum willingness to accept (WTA) for the twelve ambiguous bets of Table 1 (six ambiguous P-bets and six ambiguous $-bets) using

Table 1: Paired lotteries under risk and ambiguity

Pairs	Type	Probability of Winning under Risk	Probability of Winning under Ambiguity (/100)	Amount of win (€)	EV
I	$	20/100	[0, 40]	20	4
	P	80/100	[60, 100]	5	4
II	$	30/100	[0, 60]	16	4.8
	P	90/100	[80, 100]	5	4.5
III	$	20/100	[0, 40]	10	2
	P	90/100	[80, 100]	4	3.6
IV	$	40/100	[0, 80]	6	2.4
	P	90/100	[80, 100]	3	2.7
V	$	50/100	[0, 100]	12	6
	P	90/100	[80, 100]	6	5.4
VI	$	25/100	[0, 50]	27	6.75
	P	70/100	[40, 100]	8	5.6

the Becker-DeGroot-Marschak (1963) (BDM) mechanism. This mechanism is widely used in the preference reversal literature. Subjects also value two variations of the ambiguous $-bet of pair II and two variations of the ambiguous $-bet of pair IV (in which we vary the range of the probability interval). The results of these four additional valuations are given in Section 8, Table 8. In the second round, subjects were asked to choose between the ambiguous $-bet and its corresponding ambiguous P-bet for the six ambiguous paired-lotteries.

In the third round, subjects were asked to specify their minimum WTA for the twelve risky bets (6 risky P-bets and six risky $-bets) using the BDM mechanism, as in the first round. Last, in the fourth round subjects were asked to choose between the risky $-bet and its corresponding risky P-bet for the six risky paired-lotteries. Examples of the experimental design are given in the Appendix.

To control for order effects, the $-bets and the P-bets were presented to subjects randomly in rounds 1 and 3. Similarly, the paired-lotteries were presented randomly in rounds 2 and 4.

Moreover, the order in which the two bets were presented in the choice tasks was counterbalanced. However, the order of the rounds was not arbitrary: we choose to (1) run ambiguous tasks before risky tasks, and (2) run valuation before choice.

First, subjects carried out preference-reversal tasks under ambiguity before risk to prevent them from establishing a probability reference point. Had we begun with the risky task, subjects may have reduced ambiguity to risk by considering the expected probability of winning and ignoring ambiguity. In addition, we assume that the running of ambiguous tasks before risky tasks is unlikely to affect behavior. Pommerehne et al. (1982) show that the repetition of preference-reversal tasks, even in the presence of feedback, does not significantly change preference-reversal rates.

Second, we did not change the order of choice and valuation, as it has been shown that the elicitation of prices before or after binary choice does not influence the pattern of reversals under risk. Grether and Plott (1979) note that choice patterns and reversal rates appear to be the same for choices made before and after the obtention of selling prices (p. 632).[2]

4.4 Incentives

At the end of the experiment, one of the questions was played for real. The computer first randomly chose one round (1, 2, 3 or 4) and then one question from the selected round. For example, if round 1 were chosen in the first step, then the subject plays the BDM mechanism. The computer then randomly chose one question, say the ambiguous $-bet of pair I. Afterwards, an offer between €0.1 and €20 is chosen randomly. If the random offer exceeded the expressed WTA, the participant received the random offer. If the random offer was below the expressed WTA, the subject played the ticket. In the latter case, the computer program determines the number of winning balls by choosing a number between 0 and 40 (with all of the numbers being equiprobable). It then drew a ball from the urn, which is now known. The subject won €20 if the drawn ball was a winning ball and nothing otherwise. In the BDM mechanism, the maximum offer for a given bet, (€x, $E(p)$), was €x. Subjects earned on average €6.7, with a minimum of €0 and a maximum of €27. Subjects also received €5 for their participation.

[2]Although we have presumed that eliciting prices before or after choice will not significantly affect reversal rates under ambiguity, it may be that the result observed by Grether and Plott (1979) does not extend to ambiguity. This remains an open question for future research. I thank an anonymous referee for emphasizing this point.

4.5 Ambiguity Implementation

Unlike a large body of experimental literature considering "true" ambiguity (Ellsberg's unknown urn), this paper uses two-stage objective lotteries. There are three reasons for doing so. The first is to reduce the complexity of the ambiguous task to a minimum by using probability intervals (in the spirit of Curley and Yates, 1985, and 1989). Implementing "true" ambiguity in the case of classical preference reversal may be confusing for subjects, as one bet features a small probability of winning and the other a large probability. To illustrate, consider the risky paired-lottery: {P-bet_R:(€5,80%); \$-bet_R:(€20, 20%)}. Framing this question in an Ellsberg way yields two urns (one risky and one ambiguous) and four bets (two risky and two ambiguous). For example, consider two ten-color urns each containing 100 balls. The number of balls of each color is known (exactly 10) in the risky urn (Urn 1). However, the number of balls of each color is unknown (it could be anywhere between 0 and 100) in the ambiguous urn (Urn 2). In a binary-choice task under risk (ambiguity), subjects would be asked to choose between:

- **Risky (ambiguous) P-bet**: bet on *two colors* from Urn 1 (Urn 2). If one of these corresponds to the color of the ball that is drawn, the prize is €5.

- **Risky (ambiguous) $-bet**: bet on *eight colors* from Urn 1 (Urn 2). If one of these corresponds to the color of the ball that is drawn, the prize is €20.

We believe that this formulation complicates the understanding of the task, as in the same choice subjects have to bet on different numbers of colors that result in different prizes. In addition, the different pairs used in the experiments involve different probabilities (sometimes not divisible by ten, e.g. 25%), which also complicates the task. Due to the asymmetry between the P-bet and the $-bet, framing ambiguity via probability intervals likely simplifies the task. The second reason relates to the "suspicion" caused by the unknown urn. Hey et al. (2008) point out the shortcomings of "true" ambiguity implementation. They argue that subjects may suspect the experimenter of manipulating the unknown urn in order to save money. Thus, the unknown urn becomes "suspicious", which may lead participants to report higher levels of ambiguity aversion. Some experimental evidence has indeed shown that ambiguity aversion is lower with two-stage objective lotteries than with "true" ambiguity (Halevy, 2007, Chow and Sarin, 2002, Yates and Zukowski, 1976, and Bernasconi and Loomes, 1992). Last, this experimental evidence has also shown that even when probabilities are knowable (although it is unlikely that individuals can calculate them) subjects do exhibit ambiguity aversion.

5 Results

Unless stated otherwise, all the results reported in this section are two-tailed paired t-tests.

5.1 Preference Reversals under Ambiguity

Table 2 summarizes the results of choice and valuation under ambiguity for the six paired lotteries. We focus our analysis on aggregate choices. We dropped the choices and valuations of one subject in pair IV due to a missing value in the valuation task. Thus, the number of observations in each choice task is 245 instead of 246, and the number of observations in each valuation task is 490 instead of 492.

Table 2 shows that preference reversals do occur under ambiguity: 129 choices out of 245 (53 percent) were inconsistent with the announced selling prices.[3] Specifically, 123 (78 percent) of the 158 choices of ambiguous P-bets were inconsistent with the announced selling prices, with an analogous figure of only 6 (7 percent) of the 87 choices for ambiguous $-bets. When the probability of winning is ambiguous, preference reversals continue to be systematic: the rate of standard preference reversals (78 percent) greatly exceeds that of non-standard preference reversals (7 percent).

Subjects value the ambiguous $-bets higher than the corresponding ambiguous P-bets. For each of the six pairs, the hypothesis of equal selling prices was rejected at the one percent level using a t-test (see Table 10). Subjects state a higher price for the ambiguous $-bet as compared to the ambiguous P-bet, irrespective of whether the expected value of the ambiguous $-bet is higher than, lower than or equal to the expected value of the ambiguous P-bet. Furthermore, subjects value the ambiguous $-bet higher than the corresponding ambiguous P-bet in 82 percent of cases, and lower in only 12 percent of cases (see Table 9).

Consistent with previous findings under risk, preference reversals under ambiguity come from (1) the attractiveness of the P-bet in the choice task, as subjects massively chose the bet with the high ambiguous probability of winning (the proportion choosing the ambiguous P-bet

[3] The rate of preference reversals observed here is higher than that in Trautmann et al. (2009), who identified them in only a minority of cases.

is 64 percent), and (2) the attractiveness of the $-bet in the valuation task, as subjects report a higher price for the bet with the more favorable, as compared to the less-favorable, outcome.

Table 2: Frequencies of Reversals under Risk and Ambiguity

	Bet	Choices	Selling Prices		
			Consistent	Inconsistent	Equal
Ambiguity	P	158	25	123	10
	$	87	78	6	3
Risk	P	153	48	94	11
	$	92	75	13	4
N=41					

5.2 Comparing Preference Reversals under Ambiguity and Risk

The third and fourth rounds of the experiment provide a benchmark for preference reversals under risk. As specified above, the probability of winning of a given risky bet is the center of the probability interval, $E(p)$, of its corresponding ambiguous bet. Consequently, we can compare the rate of preference reversals under ambiguity and risk.

Table 2 shows the results of choice and valuation under risk for the six risky paired-lotteries. We see that 107 (44 percent) choices out of 245 were inconsistent with the announced selling prices. The overall rate of preference reversals under risk in our experiment is consistent with that in previous work (Seidl, 2002). The rate of standard preference reversals under risk is 61 percent (of the 153 choices of P-bets, 94 were inconsistent with the announced selling price) and the rate of non-standard preference reversals is 14 percent (13 of the 92 choices of $-bets). The general pattern of reversals under risk here is similar to that in Grether and Plott's experiment 1 (with incentives): subjects reversed their preferences 33 percent of the time (91 choices out of 273), the rate of standard preference reversals was 69 percent (69 out of the 99 choices of the P-bet), and that of non-standard preference reversals was 13 percent (22 out of the 174 choices of the $-bet).

We found that subjects valued the risky $-bets higher than the corresponding risky P-bets. The hypothesis of equal selling prices was rejected at the one percent level by a t-test for four of the six bets (see Table 11 in the Appendix). Subjects thus state a higher price for the risky

$-bet as compared to the risky P-bet when the expected value of the risky $-bet was greater or equal to that of the risky P-bet, but not when it was lower. Preference reversals under risk also result from a tendency to choose the bet with the greater probability of winning, and to state a higher price for the bet yielding the higher amount to be won. As such, preference reversals under risk result from the attractiveness of the P-bet in the choice task and the attractiveness of the $-bet in the valuation task.

Table 2 shows that the rates of overall preference reversals and standard preference reversals are higher under ambiguity than under risk. We compute for each individual the proportion of overall preference reversals, standard preference reversals and non-standard preference reversals under risk and ambiguity. The t-test rejects the hypothesis that the individual proportions of preference reversal under ambiguity and risk are equal at the 5% level ($PR_A = 53\%$, $PR_R = 44\%$, $N = 41$, $t = 2.154$, $p = 0.037$). The individual proportions of standard preference reversals are significantly higher under ambiguity than under risk ($SPR_A = 79\%$, $SPR_R = 57\%$, $N = 38$, $t = 3.942$, $p = 0.000$), while the individual proportions of non-standard preference reversals under ambiguity and risk are not significantly different from each other ($NSPR_A = 9\%$, $NSPR_R = 12\%$, $N = 32$, $t = -0.435$, $p = 0.667$). Note that, by construction, the averages of the individual proportions of conditional preference reversals are different from the aggregate proportions of conditional preference reversals. Also, the number of observations (N) in the tests of standard and non-standard preference reversals is less than 41 as paired tests ignore the missing values which can occur in the standard preference reversals test when a given subject never chooses the P-bet and in the non-standard preference reversals test when a given subject never chooses the $-bet.[4]

In conclusion, we find that preference reversals are not only replicated under ambiguity, but

[4] We also computed these tests at an aggregate level and found that the overall level of PR is significantly higher under ambiguity than under risk ($PR_A = 53\%$, $PR_A = 44\%$, $N = 245$, $t = 2.195$, $p = 0.029$). The proportion of standard preference reversals is significantly higher under ambiguity than under risk ($SPR_A = 73\%$, $SPR_R = 61\%$, $N = 111$, $t = 2.721$, $p = 0.008$), while the proportions of non-standard preference reversals under ambiguity and risk are not significantly different from each other ($NSPR_A = 8\%$, $NSPR_A = 15\%$, $N = 45$, $t = -1.138$, $p = 0.261$). The paired-tests of conditional preference reversals involve only observations where subjects made the same choice under risk and ambiguity. To illustrate, consider the preferences of subject i for pair j and assume that he chose the P-bet under risk and was inconsistent, and chose the $-bet under ambiguity and was inconsistent. As the computation of SPR (NSPR) is conditional on choosing the P-bet ($-bet), the value of SPR_{ij}^R is 1, whereas that of SPR_{ij}^A is missing. Further, the the value $NSPR_{ij}^A$ of subject i is 1, whereas that of $NSPR_{ij}^R$ is missing. Thus, the paired-test ignores the observations of subject i for pair j in both tests. For this reason, and because the test on aggregate data assumes that the observations of the same subject are independent, we tested the difference between preference reversals under risk and ambiguity using individual proportions of reversals. Note however that both tests lead to the same conclusions.

are even more prevalent than under risk.

6 The Causes of the Higher rate of PR under Ambiguity

The greater rate of preference reversals under ambiguity as compared to risk can reflect either the greater attractiveness of the P-bet in choice under ambiguity, or the greater attractiveness of the \$-bet in valuation under ambiguity, or both. In the following, we consider the impact of ambiguity on choices and valuations.

6.1 Choice

At a first glance, the pattern of choice appears to be the same under risk and ambiguity. Individuals choose the ambiguous P-bet rather than the ambiguous \$-bet in 64 percent of cases (158 choices out of 245), and choose the risky P-bet rather than the risky \$-bet in 62 percent of cases (153 choices out of 245). The t-test fails to reject the hypothesis of equality here ($N = 245$, $t = 0.529$, $p = 0.597$). However, these proportions are not over-informative, as subjects may switch from one bet to another. For a given pair, there are four possible choice patterns: (1) choosing the P-bet under both ambiguity and risk, $\mathrm{P}_A\mathrm{P}_R$; (2) choosing the \$-bet under both ambiguity and risk, $\$_A\$_R$; (3) choosing the P-bet under ambiguity and the \$-bet under risk, $\mathrm{P}_A\$_R$; and (4) choosing the \$-bet under ambiguity and the P-bet under risk, $\$_A\mathrm{P}_R$. In cases (1) and (2), ambiguity does not significantly change preferences. Ambiguity increases the attractiveness of the P-bet in case (3) and that of the \$-bet in case (4). Consequently, if the greater extent of preference reversals under ambiguity is caused by an increase in the attractiveness of the P-bet under ambiguity, *ceteris paribus*, pattern (3) should clearly dominate pattern (4).

Table 3: Choice under risk and ambiguity

	Ambiguous \$-bet	Ambiguous P-bet	Total
Risky \$-bet	45	47	92
Risky P-bet	42	111	153
Total	87	158	245

Table 3 shows that ambiguity did not affect choices in 64 percent of cases (patterns (1) and

(2): 156 choices out of 245). Ambiguity does increase the attractiveness of the P-bet in 19 percent of cases (pattern (3): 47 choices out of 245) but also increases the attractiveness of the $-bet in 17 percent of cases (pattern (4): 42 choices out of 245). The Wilcoxon signed-rank test fails to reject the hypothesis that choice patterns (3) and (4) are equal ($N = 245$, $z = 0.530$, $p = 0.596$). The comparison of risky and ambiguous choices does not yield a particularly clear explanation of the increase in the attractiveness of the P-bet under ambiguity. Consequently, we can assume that the greater rate of reversals under ambiguity is not induced by an increase in the attractiveness of the P-bet under ambiguity, as subjects generally seemed to reduce ambiguity to risk.

6.2 Valuation

As noted in Section 4, subjects value the $-bet higher than the P-bet under both risk and ambiguity. To understand the effect of ambiguity on prices, we compare the selling price for the twelve ambiguous bets and their corresponding risky bets. Table 4 shows that the selling price for the ambiguous $-bet is significantly higher than that of the corresponding risky bet for all of the pairs except IV and V, where the probability of winning is respectively 0.4 and 0.5. Thus, subjects exhibit ambiguity-seeking for low probabilities of winning, which increases the selling prices the $-bets. This result is consistent with our hypothesis 1; it is also consistent with the shape of the weighting function previously observed under uncertainty. In particular, ambiguity-seeking for low probabilities ($p \leq 0.3$) is related to more *lower subadditivity* under ambiguity. Ambiguity-neutrality in pair IV can be explained by the location of the weighting function's inflection point, which has been found to lie between 0.34 and 0.4 (see Prelec, 1998 for a discussion). Concerning pair V, which corresponds to the original Ellsberg problem, we impute the absence of ambiguity-aversion here to the use of two-stage lotteries which is known to result in lower levels of ambiguity aversion than "true" ambiguity.

Table 5 shows that the selling price of the ambiguous P-bet is significantly lower than that of the corresponding risky bet for four pairs out of six. Subjects exhibit ambiguity-aversion for high winning probabilities, which reduces the selling prices of the P-bet. The lower prices of the P-bet under ambiguity than under risk reflect more *upper subadditivity* under ambiguity, as predicted by our hypothesis 2, and reinforce the previous findings on the shape of the weighting

Table 4: Prices of the \$-bet under ambiguity and risk

Pairs	N	$E(p)$	EV	$WTA_{Ambiguity}$	WTA_{Risk}	t-test
I	41	20%	4	7.59	6.29	$t = 2.629$, $p < 0.05$
II	41	30%	4.8	6.56	5.77	$t = 2.245$, $p < 0.05$
III	41	20%	2	3.79	2.91	$t = 2.613$, $p < 0.05$
IV	40	40%	2.4	2.86	2.39	$t = 1.992$, $p < 0.1$
V	41	50%	6	5.64	6.04	$t = -1.579$, ns
VI	41	25%	6.75	11.68	9.59	$t = 2.944$, $p < 0.01$
All	245			6.37	5.51	$t = 4.752$, $p < 0.01$

Notes: $E(p)$= the expected probability of winning; EV=Expected Value; ns= non significant

function under uncertainty.

Table 5: Prices of the P-bet under ambiguity and risk

Pairs	N	$E(p)$	EV	$WTA_{Ambiguity}$	WTA_{Risk}	t-test
I	41	80%	4	2.68	3.35	$t = -3.465$, $p < 0.01$
II	41	90%	4.5	3.06	3.76	$t = -2.912$, $p < 0.01$
III	41	90%	3.6	1.91	3.02	$t = -8.893$, $p < 0.01$
IV	40	90%	2.7	1.97	2.15	$t = -1.465$, ns
V	41	90%	5.4	4.16	4.50	$t = -1.372$, ns
VI	41	70%	5.6	3.97	5.17	$t = -4.634$, $p < 0.01$
All	245			2.963	3.66	$t = -8.092$, $p < 0.01$

Notes: $E(p)$= the expected probability of winning; EV=Expected Value; ns= non significant

The higher prices of the \$-bets and the lower prices of the P-bets represent clear evidence of ambiguity-seeking for low-probability gains and ambiguity-aversion for intermediate- and high-probability gains, as found in previous work (see Camerer and Weber, 1992, p. 334).

Figure 1 further shows that the average gap between the prices of ambiguous bets and their corresponding risky bets increases as the expected probability of winning, $E(p)$, falls. The correlation between *the price gap between ambiguity and risk* and *the probability of winning* for all bets is negative for \$-bets (the Pearson correlation is -0.2146 with $N = 245$ and p= 0.0007, and Spearman's ρ is -0.2386 with $N = 245$ and p= 0.0002), but *weakly* positive for P-bets (the Pearson correlation is 0.1524 with $N = 245$ and p= 0.0170, and Spearman's ρ is 0.1204 with $N = 245$ and p= 0.0599). We thus claim that ambiguity, by increasing the attractiveness of the \$-bet and reducing the attractiveness of the P-bet in the valuation task, increases the gap between the prices of the \$-bets and their corresponding P-bets, yielding a higher rate of preference reversals.

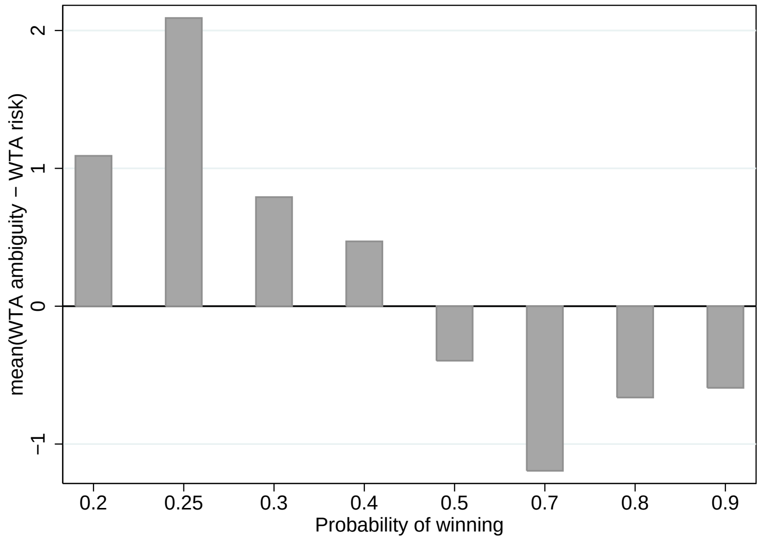


Figure 1: The average price gap between ambiguity and risk

One notable result here, although beyond the scope of this paper, is the prevalence of ambiguity-aversion, and also of ambiguity-seeking, in a "weaker" form of non-comparative context. The Ellsberg Paradox was first revealed when the two bets were evaluated jointly. Fox and Tversky (1995) showed that ambiguity-aversion disappears when subjects value the two original Ellsberg urns separately. They also found moderate ambiguity-aversion at high winning probabilities (p=2/3) in a non-comparative as compared to a comparative context, but no evidence of ambiguity-seeking at low winning probabilities in both comparative and non-comparative contexts. These conclusions were however partially invalidated by Chow and Sarin (2001), who tested the comparative hypothesis using variations of the Ellsberg problem, and found that subjects did exhibit ambiguity aversion in a non-comparative context but less so than in a comparative context for low, moderate and large probabilities of winning ($p \in \{1/3, 1/2, 2/3\}$).

The research discussed in Fox and Tversky (1995) and Chow and Sarin (2001) relies on between-subject analysis. In both papers, three groups valued the known and unknown urns.

In the comparative context, the same group valued both urns; in the non-comparative context, the known and the unknown urns were valued separately by two different groups. In the present paper, the same group of subjects valued the known and the unknown urns, but not at the same time. The unknown urns are valued in the *first round* and the known urns are valued in the *third round*[5], so that valuation takes place in a "*weak*" non-comparative context. We mean by "*weak*" that exposure to an unknown urn in round 1 may lead subjects to implicitly compare it to the corresponding risky urn in round 3, although it may seem unlikely that subjects, when pricing the risky bets in the third round, would engage in a mental process to remember each of the corresponding ambiguous bets in order to make an explicit comparison.[6].

We find that subjects exhibit ambiguity-seeking for low winning probabilities (the $-bets of pairs I, II, III and IV where $p < 0.4$) and ambiguity-aversion for high winning probabilities (the P-bets of pairs I, II, III and IV where $p > 0.5$).

This non-neutral attitude towards ambiguity shows that ambiguity has a significant effect for both less-favorable and more-favorable bets in a "weak"non-comparative context, suggesting that the ambiguity attitude is not entirely captured by an explicit comparison between bets. Our results are however inconclusive with respect to the original Ellsberg problem (the $-bet of pair V where $p = 0.5$). On average, the price of the risky bet ($WTA_{Risk} = 6.04$) is not significantly higher than that of the ambiguous bet ($WTA_{Ambiguity} = 5.64$). Although this result is consistent with Fox and Tversky (1995), it should be treated with caution as we use two-stage lotteries, which are known to yield less ambiguity aversion than "true" ambiguity. It is thus not obvious that the absence of ambiguity-aversion in the original Ellsberg problem results from the "*weak*" non-comparative context. Overall, we show that existing evidence regarding the comparative hypothesis is not conclusive and call on future research to further address this question.

Our results also question the "true" attitude toward ambiguity for low winning probabilities: Fox and Tversky (1995) found ambiguity-neutrality and Chow and Sarin (2001) ambiguity-aversion, whereas the most common conclusion is ambiguity-seeking (Einhorn and Hogarth,

[5]In our experiment, subjects never directly compare the known and the corresponding unknown urns, as valuation under ambiguity (round 1) and valuation under risk (round 3) are separated by binary choice under ambiguity (round 2).

[6]I would like to thank an anonymous referee who correctly pointed that our design does not provide a non-comparative context as in Fox and Tversky (1995) and Chow and Sarin (2001), and may induce implicit comparison.

1986, Kahn and Sarin, 1988, Curley and Yates, 1989, and Hogarth and Einhorn, 1990).

7 Prospect theory under risk and under ambiguity?

As ambiguity relates to probabilities, the inherent way of disentangling its effects is to examine the probability weighting for different uncertainty levels and response modes. To do so, we appeal to prospect theory (Kahneman and Tversky, 1979, and Tversky and Kahneman, 1992) as an alternative to expected utility theory to estimate risk-preference parameters, and extend this to capture the effect of ambiguity on preferences and therefore on preference reversals. Contrary to expected utility theory, which assumes that outcomes are framed in terms of final wealth, prospect theory suggests that decision makers frame outcomes in terms of gains and losses. The expected utility theory utility function is replaced by a value function $v(.)$ which is concave in the domain of gains (subjects are generally risk-averse over gains), and convex in the domain of losses (subjects are generally risk-seeking over losses). Further, probabilities are weighted by an inverse S-shaped function. Under uncertainty, the weighting function satisfies *bounded subadditivity* (the characteristics of the weighting function are discussed in Section 3).

We estimate the parameters of prospect theory under risk and ambiguity for both choice and valuation. Note that when lotteries involve one non-zero outcome, which is the case here, the two generations of prospect theory (1979 and 1992) are equivalent. For a risky-bet $L_R = (x, p)$ that offers an amount x with probability p, we use a CRRA utility function, $v(x) = x^{\sigma}$, as is common in this literature. Probabilities are distorted according to Prelec's (1998) one-parameter weighting function:[7]

$$w(p) = exp[-(-lnp)^{\alpha}]$$

The probability-weighting function is linear if $\alpha = 1$, as under expected utility. The weighting function is inverse S-shaped if $\alpha < 1$. It is, however, S-shaped if $\alpha > 1$: individuals underweight small probabilities and overweight large probabilities. In the last two cases, the weighting function has an invariant inflection point at 1/e = 0.37.

Using these parametric forms, the value of this risky-bet is:

[7]The bets used in this paper have only one non-zero outcome, which in general leaves the power of probability weighting and utility unspecified. In our analysis the power is specified by our choice of Prelec's (1998) one-parameter family, where the power is determined primarily by the diagonal concavity axiom.

$$V(L_R) = w(p)v(x) \text{ , with } w(p) = exp[-(-lnp)^{\alpha_R}]$$

For an ambiguous bet $L_A = (x, [\underline{p}; \overline{p}])$ that offers x with a probability between $\underline{p}$ and $\overline{p}$, we consider $W(.)$ as the probability-weighting function under ambiguity such that:

$$W(E(p)) = exp[-(-lnE(p))^{\alpha_A}]$$

where $E(p) = (\underline{p} + \overline{p})/2 = p$. The value of this ambiguous bet is:

$$V(L_A) = W(E(p))v(x)$$

We treat $E(p)$ as a proxy to estimate the weighting-function parameters under ambiguity for two reasons. First, the comparison between risk and ambiguity in the Ellsberg problem is carried out, under some assumptions, at the center of the interval. Second, as the present paper uses a two-stage lotteries, subjects should theoretically consider the center of the interval. It is however conceivable that subjects use any other probability in the interval, or a combination between the boundaries and the center of the interval. Absent such information, it is almost "natural" to consider the center of the interval as a plausible approximation.

We impute the gap between the price of a risky bet (x, p) and that of the corresponding ambiguous bet $(x, [\underline{p}; \overline{p}])$ to probability distortion under ambiguity. In fact, the only difference between these two bets is the degree of uncertainty over the probability of winning. We hence have no reason to think that the curvature of the value function is affected by ambiguity. However, the shapes of the weighting and value functions under risk and ambiguity in the choice task are not very clear, as subjects often reduce ambiguity to risk, but sometimes switch to the \$-bet or to the P-bet under ambiguity.

Valuation. For the two valuation tasks, we assume that:

$$WTA(L) = V(L),$$

and estimate the parameters of prospect theory under risk and ambiguity via non-linear techniques.

Table 6 reports the estimation results. Under both risk and ambiguity, the value function estimate is slightly larger than one. This does not necessarily imply risk-seeking. The convexity of the value functions can be explained by two factors. The first is the formulation of the elicited prices. As these were elicited via selling prices, it could be that the endowment effect is behind the high reported prices. Halevy (2007) found that reservation prices were no longer above the expected value when the former were not framed in terms of selling prices. The second explanation of convexity comes from the nature of bets in questions. Tversky et al. (1990) showed that preference reversals are primarily due to the "overpricing" of \$-bets. It is thus not absurd to find a convex value function if the overpricing of the \$-bet is large enough.

The fourth column of Table 6 also shows that the value-function estimates under risk and ambiguity are roughly equal: $\sigma_{Risk} \approx \sigma_{Ambiguity}$. Ambiguity therefore does not affect the curvature of the value function (similar results were obtained by Abdellaoui et al., 2010). As the effect of ambiguity is totally captured by the weighting, the following analysis focuses on decision weights under risk and ambiguity.

From the third column of Table 6, we see that $0 < \alpha_R < 1$, which implies that the weighting function under risk satisfies the principle of diminishing sensitivity (Tversky and Kahneman, 1992, Wu and Gonzalez, 1996, Gonzalez and Wu, 1999, Abdellaoui, 2000, and Bleichrodt and Pinto, 2000). Similarly, $0 < \alpha_A < 1$, so that the weighting function under ambiguity satisfies *bounded subadditivity*.

Table 6: Valuation preferences under risk and ambiguity

	No. of obs	α	σ	R-squared
Risk	490	0.461	1.128	0.8160
		(0.040)	(0.013)	
Ambiguity	490	0.213	1.165	0.7999
		(0.038)	(0.013)	

Note: Standard errors in parentheses.

We also find that $\alpha_A < \alpha_R$. This implies that the probability-weighting function is more curved under ambiguity than under risk, i.e. it is relatively more sensitive to changes in probability near the end points 0 and 1, and is relatively more insensitive to changes in probability in the middle region under ambiguity as compared to risk. Formally:

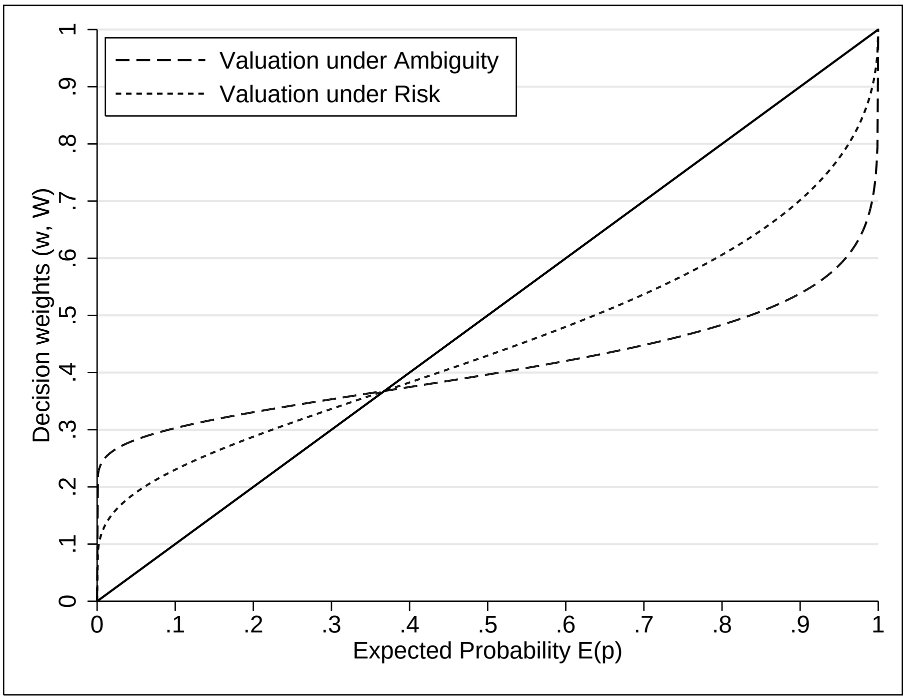


Figure 2: Probability-weighting functions under ambiguity and risk for valuation

$$\begin{cases} w(p) < W(p) & \text{if } p < 1/e \\ w(p) > W(p) & \text{if } p > 1/e \end{cases}$$

This result is consistent with previous literature on the decision weights under uncertainty (Tversky and Fox, 1995, Wu and Gonzalez, 1999, Kilka and Weber, 2001, and Abdellaoui et al., 2005), and had previously been suggested by Kahneman and Tversky (1979), who noted that the probability distortion may be more pronounced for uncertainty than for risk (p. 281). Machina (1982) also subscribes to this idea (p. 292), and Wakker (2004) notes that "For uncertain events, the decision maker is less sensitive to changes in the middle of the region than she is for known probabilities".

When probabilities are unknown, decision weights can not be described as simple transformations of the probability scale (Tversky and Fox, 1995). Building on empirical evidence suggesting less sensitivity to uncertainty than to risk, Tversky and Fox (1995), Fox and Tversky (1998) and Wakker (2004) decomposed decision weights under uncertainty into two components: a belief component that satisfies *bounded subadditivity* and a component reflecting decision attitudes. For an uncertain prospect, (x, A), that offers x when event A occurs, the decision weight is decomposed as:

$$W(A) = w(F(A))$$

where $F(A)$ is the belief component and $w(.)$ the probability-weighting function under risk.

Two different approaches to decomposing decision weights under uncertainty were followed by Tversky and Fox (1995) and Fox and Tversky (1998) on the one hand, and by Wakker (2004) on the other. In Tversky and Fox's model, the belief component is a judged probability, i.e. it is directly captured by judgment of degrees of belief, while in Wakker's model, it is a choice-based probability, i.e. subjects are indifferent between an uncertain prospect, (x, A), that offers x when event A occurs, and a risky prospect, (x, p), that offers the same prize with a known probability p, such that $F(A) = p$.

Following this decomposition, our results demonstrate that the belief component under ambiguity in the valuation task satisfies *bounded subadditivity*. If we assume that the weighting function under ambiguity is $W(A) = w(F(A))$, where A is the event "draw a winning ball from the unknown (or partially known) urn", the belief component is subadditive (i.e. it satisfies both *lower subadditivity* and *upper subadditivity*) as $W(.)$ is more curved than $w(.)$.[8]

Consistent with our hypotheses 1 and 2, less sensitivity to ambiguity as compared to risk results in higher elicited prices for the \$-bets under ambiguity as compared to risk, and lower elicited prices for the P-bets under ambiguity as compared to risk.

Choice. For the choice tasks, we use the same parametric forms, $w(.)$, $W(.)$ and $v(.)$, and determine, as above, the values of the \$-bets, $V(\$)$, and the P-bets, $V(P)$, under risk and ambiguity. The probability that the subject choose the P-bet rather than the \$-bet is given by the logit formula:

$$\begin{aligned}\text{Prob(Subject chooses P-bet)} &= \text{Prob}(V(P){>}V(\$)) \\ &= 1/(1 + exp\{-\xi(V(P) - V(\$))\})\end{aligned}$$

where ξ is the sensitivity of the choice probability to the value difference $(V(P) - V(\$))$, or the amount of "randomness" in the subject's choices ($\xi = 0$ implies that choices are random). We

[8]Further applications of the decomposition of decision weights under uncertainty can be found in Wu and Gonzalez (1999), Kilka and Weber (2001), and Abdellaoui et al. (2005).

denote the choice of the subject in paired choice i by y_i, where $y_i = 1$ if the subject chooses the P-bet, and 0 if the \$-bet is chosen. We fit the data using maximum likelihood, with the following log-likelihood function:

$$\sum_{i}^{n} y_i \ \log\{\text{Prob}(V(P) > V(\$))\} + (1 - y_i) \ \log\{1 - \text{Prob}(V(P) > V(\$))\}$$

where n is the number of observations. As this is a non-linear optimization problem, we use the Newton-Raphson routine in SAS.

Table 7 shows the results of choice estimations under risk and ambiguity for the first five pairs of Table 1.[9] The estimated value function is concave under risk and ambiguity, contrary to the valuation task where $\sigma > 1$. This confirms that the convexity of the value function in valuation is due to other factors that do not reflect risk attitudes, such as the use of the selling price and the overpricing of \$-bets. We note that σ_R is slightly higher than σ_A. This result is surprising, first because the proportions choosing the P-bet under risk and ambiguity are not significantly different from each other, and also because previous results (e.g. Abdellaoui et al., 2010) confirm our hypothesis that ambiguity does not affect the curvature of the utility function. This can however result from the use of non-parametric estimation, which is sensitive to the number of observations.

Table 7: Estimation of prospect theory parameters for choices

	No. of obs	α	σ	ξ	Log likelihood
Risk	205	0.918	0.866	2.393	-123.647
		(0.065)	(0.036)	(0.545)	
Ambiguity	205	0.822	0.674	1.636	-'125.605
		(0.214)	(0.286)	(0.881)	

Note: Standard errors in parentheses.

The third column of Table 7 shows that the weighting function satisfies *bounded subadditivity*

[9] We restrict the analysis here to the first five pairs in Table 1 as the programs fail to converge for the full set of data. This restriction does not affect the comparison of prospect theory parameters for choice and valuation, as the estimations of the prospect theory parameters in valuation for pairs I to V yield almost exactly the same results as for the six pairs. In valuation, the estimates of prospect theory for pairs I to V are $\alpha_R = 0.528$, $\alpha_A = 0.284$, $\sigma_R = 1.061$ and $\sigma_A = 1.093$. Consistent with the estimation results with the six pairs, we found $\sigma_R \approx \sigma_A$ and $\alpha_A - \alpha_R = 0.24$.

for both risk and ambiguity ($0 < \alpha_R < 1$ and $0 < \alpha_A < 1$), as was the case for valuation. We also see that the weighting function is more curved for ambiguity than for risk, ($\alpha_A = 0.822 < \alpha_R = 0.918$). Again, as in valuation, subjects seem to be less sensitive to ambiguity than to risk. This result implies that, in choice, ambiguity increases to some extent the attractiveness of the $-bet (due to more *lower subadditivity*), and reduces the attractiveness of the P-bet (due to more *upper subadditivity*), but not enough to make subjects prefer the ambiguous $-bets to the ambiguous P-bets. Figure 3 shows clearly that ambiguity results in a more-curved weighting function for both choice and valuation, but does not affect the choice weighting function enough to produce a choice pattern that is different from that under risk. Consistent with our proposition 1, Figure 3 shows that subjects are less sensitive to ambiguity than to risk for both tasks, but that this lower sensitivity is more pronounced for valuation than for choice, which results in more preference reversals under ambiguity than under risk.

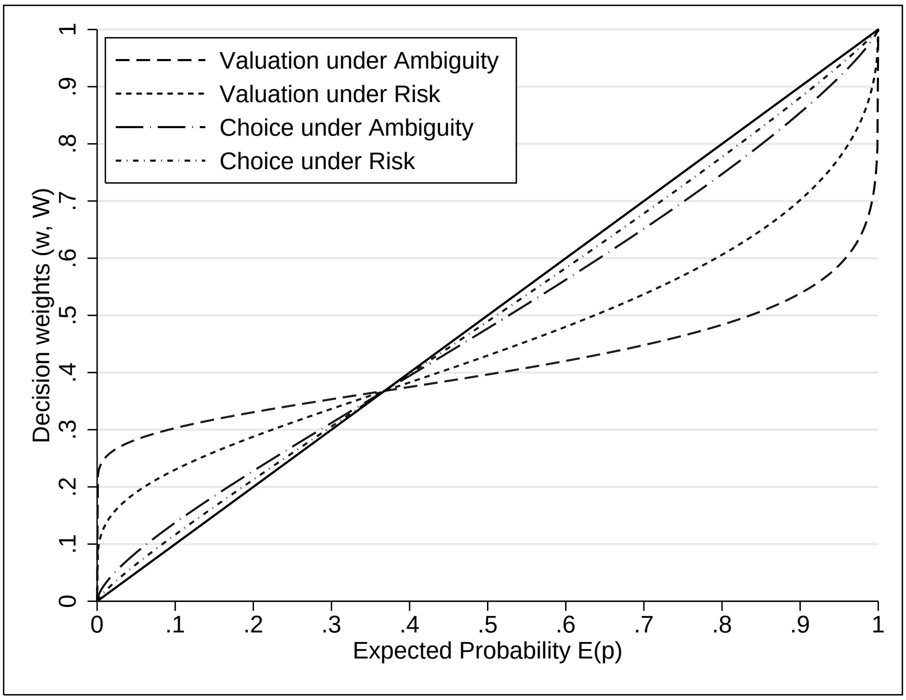


Figure 3: Probability-weighting functions under ambiguity and risk for choice and valuation

The comparison of the weighting functions shows that the weighting function is more curved for valuation than for choice under both risk ($\alpha_R^{valuation} < \alpha_R^{choice}$) and ambiguity ($\alpha_A^{valuation} < \alpha_A^{choice}$). This confirms that choice and valuation are not empirically equivalent: more empirical research is needed to determine which method better elicits true preferences.

Based on the literature on decision weights under uncertainty, the extension of prospect theory to ambiguity disentangles the greater extent of preference reversals under ambiguity. This shows that the larger gap between prices for the $-bets and their corresponding P-bets under ambiguity as compared to risk results from a more curved probability-weighting function under ambiguity than under risk in the valuation task. In the choice task, the weighting function under ambiguity is also more curved than under risk, but not enough as to change the preference of subjects for the P-bet.

8 General discussion

Ambiguity implementation. It is common in experiments testing the distinction between risk and uncertainty to consider situations where uncertainty is known or unknown (Camerer and Weber, 1992). Known uncertainty refers to the case where the probability is precisely known (Ellsberg's risky urn). Unknown uncertainty refers to the case where subjects do not know the probability that others might know (Ellsberg's ambiguous urn). The intermediate case refers to situations where uncertainty is knowable:[10] when the distribution of the probability is known in advance (two-stage objective lotteries). Although knowable uncertainty is theoretically equivalent to risk because subjects can calculate the probabilities of compound lotteries, a great deal of empirical evidence suggests that subjects exhibit ambiguity aversion in the case of two-stage lotteries (Halevy, 2007, Chow and Sarin, 2002, Yates and Zukowski, 1976, and Bernasconi and Loomes, 1992). The results here are consistent with these findings. It is known that knowable uncertainty (i.e. two-stage lotteries) entails lower levels of ambiguity aversion than unknown uncertainty. We thus presume that the rate of classical preference reversals under unknown uncertainty will be different from that under knowable uncertainty. Pogrebna (2010) used three different methods of ambiguity implementation to examine preference reversals among bets involving different degrees of ambiguity. She distinguished between one-stage non-transparent ambiguity (unknown uncertainty), two-stage transparent ambiguity (knowable uncertainty using two-stage objective lotteries) and one-stage transparent ambiguity (knowable uncertainty using a variation of Hey et al.'s (2008) Bingo Blower procedure). Preference rever-

[10] Chow and Sarin, 2002 call this uncertainty unknowable

sals were observed for the three implementation methods, but unknown uncertainty produced more severe reversals than did the two knowable uncertainties.

In the case of classical preference reversals, we have shown that knowable uncertainty affects valuation and choice differently. The comparison of weighting functions under risk and knowable uncertainty shows less sensitivity to ambiguity than to risk for both response modes. However, less sensitivity in choice is not strong enough to produce different choice patterns to those under risk, which results in more preference reversals under ambiguity. If unknown uncertainty amplifies this effect, we presume that it would increase the rate of reversals even further. Unknown uncertainty may nonetheless result in fewer reversals than under knowable ambiguity and possibly even than under risk. For instance, it could be the case that, in the binary choice task, unknown uncertainty results in sufficiently more *lower subadditivity* and *upper subadditivity* to increase the proportion of *choosing* the $-bet as compared to knowable uncertainly or risk. In this case, given more *bounded subadditivity* in valuation, we may observe fewer reversals under unknown uncertainty than under knowable uncertainty or risk. The effect of "true" ambiguity on the choice pattern, and thus on the rate of reversals remains an empirical question.

WTA/WTP. As in the majority of preference-reversal experiments, the current paper elicited reservation prices using WTA techniques. Preference reversals have also been observed when prices are elicited using willingness-to-pay (WTP) techniques (e.g. Lichtenstein and Slovic, 1971, and Schmidt and Hey, 2004). The overall rate of reversals is however lower with WTP than with WTA. Lichtenstein and Slovic (1971) showed that WTP results in fewer standard preference reversals and more non-standard preference reversals than WTA. In Schmidt and Hey (2004), WTP reduces the proportion of standard preference reversals but has no effect on the proportion of non-standard preference reversals. The lower proportion of reversals in the case of WTP results from lower elicited prices, especially for the $-bet (Lichtenstein and Slovic, 1971, page 50). This suggests that, under risk, the weighting function for buying prices is less curved than that of the selling prices. Based on the shapes of the above weighting functions, we conjecture that, using WTP, preference reversals under ambiguity would also be more frequent than under risk. The size of the increase in reversals under ambiguity as compared to risk will depend on the effect of ambiguity on both *lower subadditivity* and *upper subadditivity* in valuation, i.e. how much ambiguity increases the buying prices of the $-bets, and reduces the buying prices of the P-bets.

Design. Our experimental design is based on a within-subject analysis. Though we believe that preference reversals are immune from order effects (ambiguity/risk and valuation/choice), the results reported in this paper may be questioned. We should note that almost all of the results reported here are consistent with previous finding. First, remember that our lotteries were constructed as in Grether and Plott, 1979 to enable comparisons. Under risk, our reversal rates are similar to those theirs, although the risky tasks were performed after ambiguous tasks. This rules out criticisms regarding potential learning. Second, we have assumed that the order of the valuation and choice tasks under ambiguity has no effect on preference reversals. We indeed believe that ambiguity acts to amplify the effect of risk, and as there are no order effects for risk our assumption of no order effects under ambiguity seems plausible. Nevertheless, task order (ambiguity/risk, on the one hand, and valuation/choice on the other) should be addressed in future research to confirm our hypotheses using a between-subject design.

Further, we implemented ambiguity using probability intervals. Although this procedure is not new (Curley and Yates, 1985 and Curley and Yates, 1989), it is not frequently used in the literature. It may be thought that our design is complicated for participants, because they have to reason in terms of intervals. This is unlikely for two reasons. First, no participants were uncomfortable with the design during the instruction phase or during the experiment. Second, the ambiguity attitudes in the valuation task are consistent with the large body of empirical finding showing ambiguity-seeking for unlikely events and ambiguity-aversion for likely events.

Table 8: The effect of the range of the probability interval of winning on the $-bet's selling price

Pair	$E(p)$	EV	N	Probability Interval	WTA_A	WTA_R	T-test
			41	[0,60]	6.56	5.77	$t = 2.245$, $p < 0.05$
II	30%	4.8	41	[10,50]	6.06	5.77	$t = 0.702$, ns
			41	[20,40]	5.89	5.77	$t = 0.313$, ns
			40	[0,80]	2.86	2.39	$t = 1.992$, $p < 0.1$
IV	40%	2.4	40	[20,60]	2.43	2.39	$t = 0.227$, ns
			40	[35,45]	2.36	2.39	$t = -0.164$, ns

In addition, we varied the range of two bets and noted that reservation prices decrease with the range of the interval (see Table 8). This result is consistent with previous findings (e.g. Becker and Brownson, 1964, and Curley and Yates, 1985) and shows that subjects did not have problems in understanding the experimental procedure.

Table 8 also confirms our hypothesis that small ranges do not do a good job in capturing attitudes toward ambiguity. This strengthens our case for using maximum range to examine the effect of ambiguity on preference reversals.

Possible explanations of the higher rate of reversals under ambiguity. Classical preference reversals under risk are commonly explained by different weightings of attributes in different response modes. For instance, the "anchoring and adjustment" model proposed by Slovic and Lichtenstein (1983) is based on this assumption. In this model, a subject who is asked to choose between two lotteries first "anchors" on the relative probabilities of winning but then makes insufficient "adjustments" for differences in the amounts to be won. On the contrary, subjects who are asked to place values on bets first "anchor" on the relative amounts to be won and then make insufficient "adjustments" for differences in the probabilities of winning. This model can be extended to ambiguity by examining the possible heuristics that are used in dealing with ambiguity in each response mode. Such a model would have the advantage of capturing the psychological components that underlie behavior under ambiguity. Nevertheless, this model is particular to one type of preference reversals and cannot account for the preference reversals observed by Trautmann et al. (2009) and Pogrebna (2010), where the options have the same prize and the same expected probabilities.

Butler and Loomes (2007) provided a model of imprecision to explain classical preference reversals. Here, subjects are imprecise in reporting their reservation prices. This model is based on MacCrimmon and Maxwell's (1986) proposition that the imprecision interval is likely to rise as a bet becomes more dissimilar to a certainty. Thus, the imprecision interval is greater for the $-bet than for the P-bet which explains the higher reported prices for the $-bets as compared to the P-bets. Since it has been shown that subjects report their preferences noisily (e.g. Camerer, 1989, Starmer and Sugden, 1989, Hey and Orme, 1994, Ballinger and Wilcox, 1997, and Loomes and Sugden, 1998), this model is appealing because it accommodates this stochastic component. It is intuitively plausible to conjecture that ambiguity increases imprecision, which results in more preference reversals as compared to risk. The generalization of Butler and Loomes's model to ambiguity is however not straightforward. First, our design cannot provide a measure of the strength of preferences and thus cannot capture the imprecision towards the $-bets and P-bets under risk and ambiguity. Consequently, we cannot determine whether Butler and Loomes's model accounts for the higher rate of reversals under ambiguity. Second, plotting the ambiguous $-bet and P-bet in the "rectangle" in order to make predictions (see Butler and Loomes (2007), page 280) is far from obvious. Third, if we assume that ambiguity increases the imprecision interval, then how can we explain the higher prices of the $-bet and the lower prices of the P-bet under ambiguity as compared to risk? For all of these reasons, the superiority of the imprecision model is not obvious, unless demonstrated with appropriate tools (see Butler and Loomes, 2007) which is not the case for prospect theory.

Therefore, prospect theory under ambiguity is the most plausible explanation for the higher rates of preference reversals under ambiguity. The advantage of our approach is that it can account for preference reversals when we allow for a random reference point in the formulation of prospect theory (Schmidt et al., 2008). We thus corroborate that prospect theory is a tractable and psychologically realistic model that has the advantage of explaining many anomalies under risk and ambiguity (Wakker, 2010).

9 Conclusion

This paper provides evidence for classical preference reversals in one of the most important domains of decision theory: ambiguity. When $-bets and P-bets are both ambiguous, subjects do indeed reverse their preferences, and these reversals are both substantial and systematic. Preference reversals are notably stronger under ambiguity than under risk. The greater extent of preference reversals under ambiguity as compared to risk is not due to an increase the attractiveness of the P-bet in choice under ambiguity, but rather to a greater gap between the prices of the ambiguous $-bets and their corresponding ambiguous P-bets. Our results are consistent with findings of less sensitivity to uncertainty than to risk (e.g. Tversky and Fox, 1995, Wu and Gonzalez, 1999, Kilka and Weber, 2001, Wakker, 2004, and Abdellaoui et al., 2005) and show that less sensitivity to ambiguity is more pronounced in the valuation task than in the choice task.

In situations involving options similar to those in classical preference reversals, preferences under ambiguity are more problematic than those under risk. In particular, preferences elicited from choices are more inconsistent with preferences elicited from pricing (WTA) under ambiguity than under risk.

References

Abdellaoui, Mohammed, "Parameter-Free Elicitation of Utility and Probability Weighting Functions," *Management Science*, 2000, *46* (11), 1497–1512.

_ , **Aurélien Baillon, Laetitia Placido, and Peter P. Wakker**, "The Rich Domain of Uncertainty: Source Functions and Their Experimental Implementation," *American Economic Review*, 2010, *forthcoming.*

_ , **Frank Vossman, and Martin Weber**, "Choice-Based Elicitation and Decomposition of Decision Weights for Gains and Losses Under Uncertainty," *Management Science*, 2005, *51* (9), 1384–1399.

Ballinger, T. Parker and Nathaniel T. Wilcox, "Decisions, Error and Heterogeneity," *Economic Journal*, July 1997, *107* (443), 1090–1105.

Becker, Gordon M., Morris H. Degroot, and Jacob Marschak, "Measuring Utility by a Single-Response Sequential Method," *Behavioral Science*, 1964, *9* (3), 226–232.

Becker, Selwyn W. and Fred O. Brownson, "What Price Ambiguity? or the Role of Ambiguity in Decision-Making," *Journal of Political Economy*, 1964, *72* (1), 62–73.

Bernasconi, Michele and Graham Loomes, "Failures of the reduction principle in an Ellsberg-type problem," *Theory and Decision*, 1992, *32* (1), 77–100.

Bleichrodt, Han and Jose Luis Pinto, "A Parameter-Free Elicitation of the Probability Weighting Function in Medical Decision Analysis," *Management Science*, 2000, *46* (11), 1485–1496.

Butler, David J. and Graham Loomes, "Imprecision as an Account of the Preference Reversal Phenomenon," *American Economic Review*, 2007, *97* (1), 277–297.

Camerer, Colin and Martin Weber, "Recent Developments in Modeling Preferences: Uncertainty and Ambiguity," *Journal of Risk and Uncertainty*, 1992, *5* (4), 325–370.

Camerer, Colin F., "An Experimental Test of Several Generalized Utility Theories," *Journal of Risk and Uncertainty*, April 1989, *2* (1), 61–104.

Chow, Clare Chua and Rakesh K Sarin, "Comparative Ignorance and the Ellsberg Paradox," *Journal of Risk and Uncertainty*, 2001, *22* (2), 129–139.

_ **and Rakesh Sarin**, "Known, Unknown, and Unknowable Uncertainties," *Theory and Decision*, 2002, *52* (2), 127–138.

Curley, Shawn P. and Frank J. Yates, "The Center and Range of the Probability Interval as Factors Affecting Ambiguity Preferences," *Organizational Behavior and Human Decision Processes*, 1985, *36* (2), 273–287.

_ **and** _ , "An Empirical Evaluation of Descriptive Models of Ambiguity Reactions in Choice Situations," *Journal of Mathematical Psychology*, 1989, *33* (4), 397–427.

Delquié, Philippe, "Inconsistent Trade-Offs Between Attributes: New Evidence in Preference Assessment Biases," *Management Science*, 1993, *39* (11), 1382–1395.

Einhorn, Hillel J. and Robin M Hogarth, "Decision Making under Ambiguity," *Journal of Business*, 1986, *59* (4), S225–S250.

Ellsberg, Daniel, "Risk, Ambiguity, and the Savage Axioms," *Quarterly Journal of Economics*, 1961, *75* (4), 585–603.

Fox, Craig R. and Amos Tversky, "Ambiguity Aversion and Comparative Ignorance," *Quarterly Journal of Economics*, 1995, *110* (3), 585–603.

_ **and** _ , "A Belief-Based Account of Decision Under Uncertainty," *Management Science*, 1998, *44* (7), 879–895.

Gonzalez, Richard and George Wu, "On the Shape of the Probability Weighting Function," *Cognitive Psychology*, 1999, *38* (1), 129–166.

Greenwald, Anthony G., "Within-Subjects Designs: To Use or Not To Use?," *Psychological Bulletin*, 1976, *83*, 216–229.

Grether, David M. and Charles R. Plott, "Economic Theory of Choice and the Preference Reversal Phenomenon," *American Economic Review*, 1979, *69* (2), 623–638.

Halevy, Yoram, "Ellsberg Revisited: An Experimental Study," *Econometrica*, 2007, *75* (2), 503–536.

Hey, John D. and Chris Orme, "Investigating Generalizations of Expected Utility Theory Using Experimental Data," *Econometrica*, November 1994, *62* (6), 1291–1326.

Hey, John D, Gianna Lotito, and Anna Maffioletti, "The Descriptive and Predictive Adequacy of Theories of Decision Making Under Uncertainty/Ambiguity," *Working Paper, University of York*, 2008.

Hogarth, Robin M. and Hillel J. Einhorn, "Venture Theory: A Model of Decision Weights," *Management Science*, 1990, *36* (7), 780–803.

Kahn, Barbara E. and Rakesh K. Sarin, "Modelling Ambiguity in Decisions under Uncertainty," *Journal of Consumer Research*, 1988, *15*, 265Ű272.

Kahneman, Daniel and Amos Tversky, "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 1979, *47* (2), 263–291.

Kilka, Michael and Martin Weber, "What Determines the Shape of the Probability Weighting Function Under Uncertainty?," *Management Science*, December 2001, *47* (12), 1712–1726.

Knight, F., *Risk, Uncertainty, and Profit*, Boston, MA: Houghton-Mifflin, 1921.

Lichtenstein, Sarah and Paul Slovic, "Reversals of Preference between Bids and Choices in Gambling Decisions," *Journal of Experimental Psychology*, 1971, *89* (1), 46–55.

Lindman, Harold R., "Inconsistent Preferences among Gambles," *Journal of Experimental Psychology*, 1971, *89* (2), 390–397.

Loomes, Graham and Robert Sugden, "Testing Different Stochastic Specifications of Risky Choice," *Economica*, November 1998, *65* (260), 581–98.

MacCrimmon, Kenneth and Smith Maxwell, "Imprecise Equivalence: Preference Reversals in Money and Probability," 1986. University of British Columbia Working Paper 1211.

Machina, Mark J., "'Expected Utility' Analysis without the Independence Axiom," *Econometrica*, 1982, *50* (2), 277–323.

Pogrebna, Ganna, "Ambiguity Preference Reversals," *Working paper, Columbia University*, 2010.

Pommerehne, Werner W, Friedrich Schneider, and Peter Zweifel, "Economic Theory of Choice and the Preference Reversal Phenomenon: A Reexamination," *American Economic Review*, 1982, *72* (3), 569–74.

Prelec, Drazen, "The Probability Weighting Function," *Econometrica*, 1998, *66* (3), 497–528.

Schmidt, Ulrich and John D. Hey, "Are Preference Reversals Errors? An Experimental Investigation," *Journal of Risk and Uncertainty*, December 2004, *29* (3), 207–218.

_ , Chris Starmer, and Robert Sugden, "Third-Generation Prospect Theory," *Journal of Risk and Uncertainty*, 2008, *36*, 203–223.

Seidl, Christian, "Preference Reversal," *Journal of Economic Surveys*, 2002, *16* (5), 621–655.

Slovic, Paul and Sarah Lichtenstein, "Preference Reversals: A Broader Perspective," *American Economic Review*, 1983, *73* (4), 596–605.

Starmer, Chris and Robert Sugden, "Probability and Juxtaposition Effects: An Experimental Investigation of the Common Ratio Effect," *Journal of Risk and Uncertainty*, June 1989, *2* (2), 159–78.

Trautmann, Stefan T., Ferdinand M. Vieider, and Peter P. Wakker, "Preference Reversals to Explain Ambiguity Aversion," *Working Paper, Erasmus University Rotterdam*, 2009.

Tversky, Amos and Craig R. Fox, "Weighting Risk and Uncertainty," *Psychological Review*, 1995, *102* (2), 269–283.

_ **and Daniel Kahneman**, "Advances in Prospect Theory: Cumulative Representation of Uncertainty," *Journal of Risk and Uncertainty*, 1992, *5* (4), 297–323.

_ **and Peter P. Wakker**, "Risk Attitudes and Decision Weights," *Econometrica*, November 1995, *63* (6), 1255–80.

_ **, Paul Slovic, and Daniel Kahneman**, "The Causes of Preference Reversal," *American Economic Review*, 1990, *80* (1), 204–217.

_ **, Shmuel Sattath, and Paul Slovic**, "Contingent Weighting in Judgment and Choice," *Psychological Review*, 1988, *95* (3), 371–384.

Wakker, Peter P., "On the Composition of Risk Preference and Belief," *Psychological Review*, 2004, *111*, 236–241.

_ , *Prospect Theory: For Risk and Ambiguity*, Cambridge University Press; 1 edition, 2010.

Wu, George and Richard Gonzalez, "Curvature of the Probability Weighting Function," *Management Science*, 1996, *42* (12), 1676–1690.

_ **and** _ , "Nonlinear Decision Weights in Choice Under Uncertainty," *Management Science*, 1999, *45* (1), 74–85.

Yates, J. Frank and Lisa G. Zukowski, "Characterization of Ambiguity in Decision Making," *Behavioral Science*, 1976, *21* (1), 19–25.

Zeiliger, Romain, "A presentation of Regate, Internet based Software for Experimental Economics. http://www.gate.cnrs.fr/ zeiliger/regate/RegateIntro.ppt," *GATE*, 2000.

Experimental design:

Figure 4: Illustration of round 1: valuation of the ambiguous $-bet of pair I

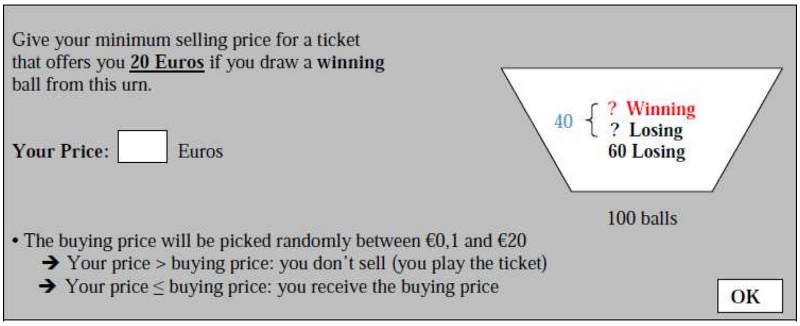


Figure 5: Illustration of round 1: valuation of the ambiguous P-bet of pair I

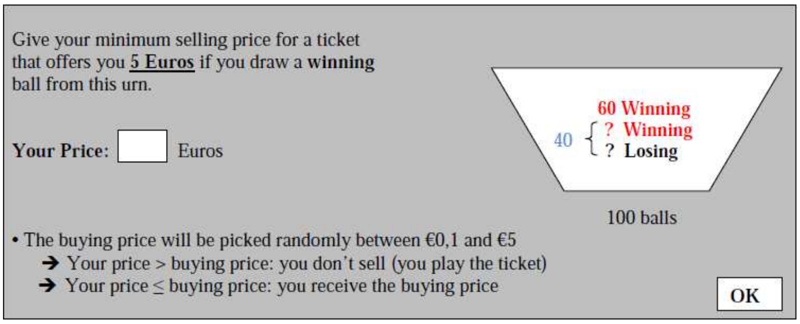


Figure 6: Illustration of round 2: Choice under ambiguity (pair I)

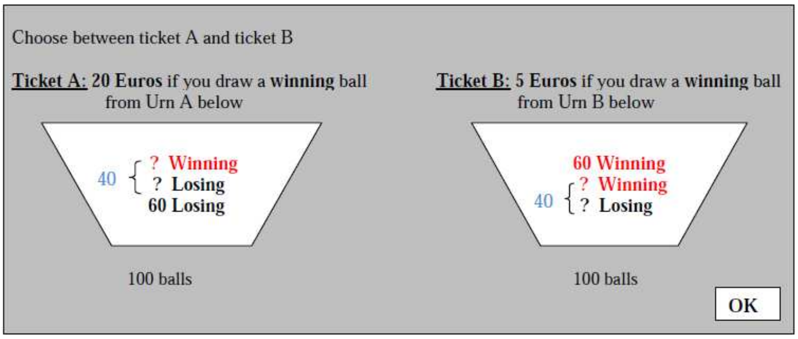


Figure 7: Illustration of round 3: valuation of the risky $-bet of pair I

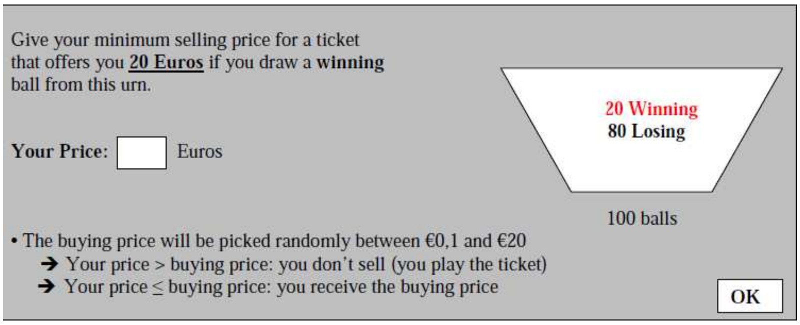


Figure 8: Illustration of the screen in round 3: valuation of the risky P-bet of pair I

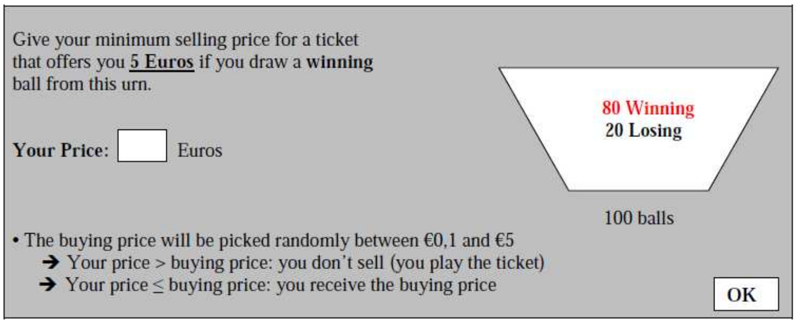
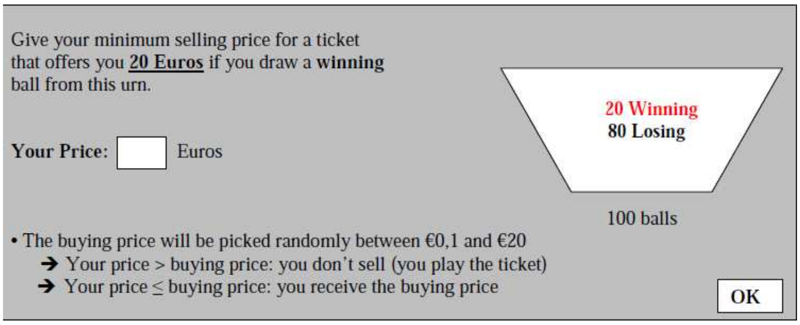


Figure 9: Illustration of round 4: Choice under ambiguity (pair I)



Tables:

Table 9: Percentage of higher selling price under risk and under ambiguity

Higher WTA	Ambiguity	Risk
P	12.65	24.90
$	82.04	68.98
Equal	5.31	6.12

Table 10: Prices for $-bets and P-bet under ambiguity

Pair	N	$WTA(\$)$	$WTA(P)$	T-test
I	41	7.59	2.68	$t = 8.861$,
		(0.54)	(0.17)	p<0.01
II	41	6.56	3.07	$t = 7.374$,
		(0.45)	(0.2)	$p < 0.01$
III	41	3.79	1.91	$t = 6.494$,
		(0.28)	(0.12)	$p < 0.01$
IV	40	2.86	1.96	$t = 4.300$,
		(0.21)	(0.11)	$p < 0.01$
V	41	5.64	4.16	$t = 4.433$,
		(0.29)	(0.22)	$p < 0.01$
VI	41	11.68	3.97	$t = 10.024$,
		(0 .83)	(0.23)	$p < 0.01$
All	245	6.37	2.96	$t = 13.915$,
		(0.27)	(0 .09)	$p < 0.01$

(i) Standard errors in parentheses, (ii) N= number of observations.

Table 11: Prices for $-bets and P-bet under risk

Pair	N	$WTA(\$)$	$WTA(P)$	T-test
I	41	6.29	3.35	$t = 5.367$,
		(0.51)	(0.17)	$p < 0.01$
II	41	5.77	3.76	$t = 4.494$
		(0.35)	(0.20)	$p < 0.01$
III	41	2.90	3.02	$t = -0.334$
		(0.28)	(0.14)	ns
IV	40	2.39	2.15	$t = 1.476$
		(0.16)	(0 .13)	ns
V	41	6.04	4.50	$t = 5.000$
		(0.29)	(0 .23)	$p < 0.01$
VI	41	9.59	5.17	$t = 5.509$
		(0.77)	(0.22)	$p < 0.01$
All	245	5.51	3.66	$t = 8.441$
		(0.23)	(0.1)	$p < 0.01$

(i) Standard errors in parentheses, (ii) N= number of observations.