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Attitudes to risk and attitudes to uncertainty: experimental evidence

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In a series of experiments the interactions among individual attitudes towards risk and uncertainty, the sign of the outcome domain, and the way uncertainty is represented are tested. This is done in a unified framework, eliciting individual values by means of a second price auction. Results confirm the presence of the well-known fourfold pattern of risk attitude (risk aversion for gains and risk seeking for losses at high probability, and risk seeking for gains and risk aversion for losses at low probability) and show that this pattern can also be extended to uncertainty. In the valuation of losses the modal pattern is decreasing risk and uncertainty aversion as the probability of loss increases, while increasing risk and uncertainty aversion is observed for gains. Moreover, it is found that the size of reaction to uncertainty does not depend on the outcome domain, and that it persists in the face of an incentive-compatible mechanism to elicit preferences.

I. INTRODUCTION

One of the main features of Prospect Theory (Kahneman and Tversky, 1979), as well as one of the generally accepted empirical results of laboratory experiments in individual decision making, is the fourfold pattern of risk attitudes: risk aversion for gains and risk seeking for losses at high probability, and risk seeking for gains and risk aversion for losses at low probability (Kahneman and Tversky, 1979; Cohen *et al*., 1987; Wehrung, 1989; Tversky and Kahneman, 1992; among many others). According to Expected Utility theory (EU henceforward), risk attitudes are simply due to the shape of the utility function, since expected utility is linear in the probabilities. According to Prospect Theory, the fourfold pattern is the joint effect of a value function, which is concave for gains and convex for losses, and of the weighting function, which is a nonlinear transformation of objective probabilities. Such a pattern of risk attitudes has sometimes been called the reflection effect.

Risk attitudes are generally considered to be distinguished from attitudes towards uncertainty (Camerer and Weber, 1992; Tversky and Fox, 1995). Since Knight (1921), decision theorists have drawn a distinction between risky prospects where the probabilities of outcomes are objectively known, and uncertain prospects where these probabilities are unknown or vague. According to EU, individuals' attitude towards uncertainty should be that of neutrality. Risk and uncertainty should be equivalent in choice/valuation, provided the expected probabilities of outcomes under uncertainty coincide with the known probabilities of those same outcomes under risk. Ellsberg's (1961) experiment put empirical content to Knight's idea that risk and uncertainty are regarded as different by decision makers. Ellsberg found that, when confronted with the choice to bet on an urn containing 100 red and black balls in known proportions (the risky urn) or to bet on an urn with 100 red and black balls in unknown proportions (the ambiguous urn), the majority of subjects preferred to bet on the former, an attitude termed

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since then *uncertainty* or *ambiguity aversion*. Ellsberg also conjectured that if the probability of the event in the known urn were small (say 1%), the attitude of subjects may have been that of *ambiguity preference*. Ellsberg's experiment implied that individuals were ambiguity seeking when the probability in the known urn was small, while they were ambiguity averse when the expected probability was high, a pattern somehow analogous to the risk seeking attitude at low objective probabilities of gain and risk aversion at high objective probabilities.

In a series of experiments, we test whether a 'reflection effect' extends to decision under uncertainty as follows: for losses, ambiguity aversion prevails at low mean probabilities and ambiguity proneness at high mean probabilities; while in the domain of gains ambiguity proneness prevails at low mean probabilities and ambiguity aversion at high mean probabilities. This hypothesis has already been put forward and tested by Einhorn and Hogarth (1985) and Kahn and Sarin (1988) among others. However, the few experimental tests on this topic provide highly mixed evidence.[1]

Given the relevance of decisions under uncertainty in real-life situations, we think it is important to investigate the influence of the outcome domain on individual reaction to ambiguous probabilities. Moreover, the presence of the fourfold patterns provides a direct test of Prospect Theory under risk and of Cumulative Prospect Theory under uncertainty (Tversky and Kahneman, 1992). Besides, since many decisions under risk or uncertainty are taken in markets, it is crucial to verify whether the incentives created by the market reduce or not the impact of ambiguity by inducing valuations more in line with the predictions of EU.

This experiment tests whether reaction to uncertainty and in particular the reflection effect under uncertainty exists and is robust to the use of an incentive-compatible market institution to elicit individual preferences.[2] In addition, we investigate whether the fourfold pattern of attitudes towards uncertainty corresponds to the risk attitude pattern both at the aggregate and at the individual level. In short, given a chance and an uncertain prospect, does the fact that an individual displays risk aversion in the valuation of the chance prospect also entail that he or she will prefer the chance prospect to the uncertain one? According to theories which accept the idea that choice and valuation are guided by competence (Heath and Tversky, 1991; Keppe and Weber, 1995) this will not be the case, and so far correlation between attitudes to risk and attitudes to uncertainty has not been found in previous work (see, among others, Cohen *et al.*, 1985 and Hogarth and Einhorn, 1990).[3]

The testable hypotheses can therefore be summarized as:

(1) There is a fourfold pattern of risk attitudes: (i) risk aversion for gains and risk seeking for losses at high probability, risk seeking for gains and risk aversion for losses at low probability. This pattern extends to decision under uncertainty as follows: (ii) ambiguity aversion at low expected probabilities for losses and at moderate to high probabilities for gains, ambiguity preference at low expected probabilities for gains and at high probabilities for losses.
(2) Market mechanisms and incentives reduce non-EU behaviour. We expect a weaker reaction towards uncertainty and a higher proportion of risk-neutral and ambiguity neutral subjects with respect to other studies that have not used similar exchange institutions.

The series of experiments were organized as follows. Individual valuations were elicited using a market institution, namely a computerized second price auction, which is also incentive-compatible.[4] In order to guarantee a uniform framework for the two outcome domains, both prospects involving gains and losses are framed in terms of an 'insurance' decision. When losses are evaluated, subjects compete in the auction to buy the right to insure against a potential loss that occurs with an ambiguous probability; likewise, when ambiguous gains are evaluated, subjects compete to buy the right to assure themselves a gain. Answers are stratified according to the definition of ambiguity adopted: two typical representations of probability uncertainty are used, a 'best estimate' value of the probability, and an interval of probability (Hogarth and Kunreuther, 1989). Comparability between risky and ambiguous prospects is obtained by adopting mean ambiguous probabilities corresponding to those of the risky prospects.

The results of the experiment confirm the presence of the fourfold pattern of risk attitude and show that this pattern can also be extended to uncertainty. Moreover, it is found that the size of ambiguity reaction does not depend on the outcome domain and that ambiguity reaction persists in the face of an incentive-compatible mechanism to elicit preferences.

[1] Ambiguity preference at high probabilities for losses and at low probabilities for gains is found by Curley and Yates (1985, 1989). Erev and Wallsten (1993) find that the fourfold attitude towards risk does not extend to uncertainty or, if present, it is very weak. Cohen *et al.* (1985, 1987) and Einhorn and Hogarth (1986) find mixed evidence.

[2] See Camerer and Kunreuther (1989), Sarin and Weber (1993) and Di Mauro and Maffioletti (1996, 2001) for market experiments referring to only one outcome domain.

[3] Camerer and Weber (1992), however, warn that lack of a correlation may be due to measurement errors.

[4] The second price auction (Vickrey, 1961) is a market institution which should induce subjects' revelation of their true values (for examples of its application see Coursey *et al.* 1987; Shogren *et al.* 1994 among many others).

Table 1. *Summary of experimental design*

How much does valuation under ambiguity differ from valuation under risk?	• Risky scenarios (probability is exactly known) • Ambiguous scenarios (probability is not known exactly) *Within subject factor*
Does ambiguity reaction depend on the size of probability?	• Four probability levels 3%, 20%, 50%, 80% *Within subject factor*
What is the impact of different representations of ambiguity?	Two alternative specifications of ambiguity • Best Estimate • Interval of Probability *Between subject factor*
What is the impact of the outcome domain?	Two groups of experiments: • With gains • With losses *Between subject factor*

The plan of the article is the following: Section II explains the experimental design and the procedures used. Section III presents results and Section IV discusses implications for economic behaviour under uncertainty. Section V concludes the article.

II. THE EXPERIMENT

Table 1 summarizes the experimental design adopted. Each of the 116 paid subjects was asked to participate in a series of $8(4 \times 2)$ auctions, four referring to a risky prospect and four concerning an ambiguous prospect with the same expected probability of occurrence as the known probability of the risky prospect. Risk and ambiguity were thus manipulated as a within-subject factor. The same within-subject treatment was adopted for probability levels: in particular, four different probability levels (3%, 20%, 50%, 80%), which ranged from low to high, were used. Scenarios framed in terms of either gains or losses were instead evaluated by different subjects, using a between person treatment.[5] The eight scenarios were auctioned in a completely random order using a table of random numbers. The discussion of the experimental design will be carried out through the description of the treatment of outcome domain, the definition of ambiguity, and the incentive mechanism used.

Outcome domain. As already mentioned, the domain of the choices was manipulated as a between-subject factor: subjects evaluated lotteries implying either potential gains or potential losses. Whatever the domain of the experiment, subjects were asked to state their willingness to pay for eight lotteries, four referring to a loss/gain occurring with a known probability (risky scenarios), and four others to a loss/gain having an uncertain probability (ambiguous scenarios). In each of the four risky lotteries the loss/gain of £10 occurred with a different probability, either 3%, or 20%, or 50%, or 80%. The equivalence between risky and ambiguous lotteries was assured by characterizing the four ambiguous lotteries by expected probabilities of loss/gain coinciding with the probabilities of the risky scenarios. Therefore, the prospects evaluated by subjects were of the following type:

$$\text{GAIN FRAME} \quad (£10,\ p; 0, (1-p))$$

$$\text{LOSS FRAME} \quad £10 + (-£10, p; 0, (1-p))$$

where £10 was both the size of the loss in the loss frame experiment and the size of the potential gain in the gain frame experiment, and p was replaced by p', the expected value of the probability distribution, in the ambiguous lotteries. In both types of experiments, in an attempt to create a common framework, subjects were asked to indicate how much they were willing to pay to insure themselves against the events of ‘losing £10’ in the loss frame and of ‘not winning £10’ in the gain frame.[6] More precisely, in the domain of gains subjects were asked to state their maximum willingness to pay in order to ‘assure themselves a gain of £10’. In the domain of losses, subjects were asked their maximum willingness to pay in order to ‘reduce the

[5] This choice was due to the fact that we wanted to observe valuation of risky and ambiguous scenarios for each individual at varying probability levels. The administration of stimuli concerning both gains and losses to the same individuals would have then made the experimental task especially long and tiresome for subjects (about 4 hours).
[6] See Appendix A for the full text of the scenarios.

potential loss of £10 to zero'. In the loss experiment subjects were initially endowed with £10 before they were asked to evaluate each scenario. This was done in the deliberate attempt to induce a sense of ownership before subjects decided whether they wanted to risk their endowment or not (Cohen *et al.*, 1985; Hogarth and Einhorn, 1990). Also, in the instructions the terms 'winning' and 'losing' the £10 were stressed. The individual willingness to pay in the gain frame (WTP_G) and in the loss frame (WTP_L) thus solved the following equations:

$$\text{GAIN FRAME} \quad U(£10 - WTP_G) = pU(£10)$$

$$\text{LOSS FRAME} \quad U(£10 - WTP_L) = (1 - p)U(£10).$$

Definition of ambiguity. In order to describe uncertainty in the probabilities, two definitions of ambiguous probabilities were used. These characterizations will be referred to as the 'best estimate probability' and the 'interval of probability' representations. Each subject evaluated ambiguous scenarios relating to only one definition of ambiguity so that the 'definition' of ambiguity was manipulated as a cross-subject factor. In the 'Best estimate' scenarios subjects were told that there was an estimate of the probability of the gain/loss provided by an expert, but that there was considerable uncertainty about it. This representation – used in most of Einhorn and Hogarth's experiments – was meant to induce subjects to anchor on the 'best estimate' value, while allowing them to simulate other possible probability values lower/higher than the best estimate. In the 'interval of probability' scenarios, subjects were told that according to the opinion of an expert the probability of the gain/loss lay anywhere within an interval, thus suggesting that any probability value within the interval was possible. To illustrate, consider the following scenarios:

Gains domain and 'Best estimate' definition of ambiguity[7]

Assume that there is a chance of the occurrence of some event. There is an estimate of the possible occurrence of this event; an expert, hired by a governmental agency, estimates that the probability of the occurrence of such an event is 3%. However, this is the first investigation ever carried out and consequently you experience considerable uncertainty about the precision of this estimate. If this event occurs, you will gain £10.

Gains domain and 'Interval of probability' definition of ambiguity

Assume that there is a chance of the occurrence of some event. There is an estimate of the possible occurrence of this event; an expert, hired by a governmental agency, estimates that the probability of the occurrence of such an event can be anywhere between 1% and 5%. If this event occurs, you will gain £10.

These two representations of ambiguity were chosen for two main reasons. First of all, they can be made operational as second-order probability distributions. This was useful since subjects in the experiment were rewarded according to the realized value of the lotteries, i.e. by actually playing the lotteries evaluated. The 'best estimate' representation was made operational as a symmetric distribution centred on the best estimate, i.e. the most likely value of probability; we interpreted the interval representation as a uniform probability distribution bounded by the extremes of the interval. Subjects in the experiment, however, did not know how uncertainty was going to be resolved until the end of the evaluation process.

For illustrative purposes, consider the risky lottery involving a gain of £10 with probability $p = 3\%$. In this case the lottery was resolved by simply asking subjects to draw a ball out of an urn containing 3 white balls and 97 black balls. To resolve the equivalent ambiguous urn, in the case of the 'best estimate' definition, subjects were asked to draw a ticket from an urn containing five tickets carrying on them either 1% or 3% or 5%. To each of the tickets was assigned a given probability as follows:

1%	3%	5%
1 ticket	3 tickets	1 ticket
1/5	3/5	1/5

Thus 3% was the most likely value of the probability of gain, although 1% and 5% were also possible. In the case of the 'interval of probability', in order to determine the exact probability of gain, a ticket was drawn out of an urn containing one ticket for every number inside the interval 1%–5% (extremes included), so that all values within the interval were equally likely.

1%	2%	3%	4%	5%
1 ticket	1 ticket	1 ticket	1 ticket	1 ticket
1/5	1/5	1/5	1/5	1/5

The second reason for choosing these two definitions of ambiguity is that some authors consider the interval of probability characterization as intrinsically 'more ambiguous' as it involves a greater variance. Hence, reaction to ambiguity in the 'interval of probability' scenario should be stronger than in the 'best estimate' one.

[7] See the Appendices for the same examples in the loss domain.

Incentive mechanism. Subjects' maximum willingness to pay was elicited by means of a computerized auction mechanism, which is a variant of the classical second-price auction.[8] The use of the second-price auction was motivated not only by the intention to study the effects of market incentives on choice under uncertainty, but also by the search for an incentive mechanism capable of inducing truthful revelation of the subjects' private values (Vickrey, 1961).

In each session of the experiment, an experimental market was built in which the right to assure oneself a gain of £10 or to reduce a loss of £10 to zero was auctioned among eight participants.[9] Subjects sat each in front of a computer screen on which one scenario at a time was visualized. Each scenario, i.e. each lottery, corresponded to an auction. At the start of each auction a clock was displayed on the screen, with a price steadily increasing from 0 British pence to 10 British pounds, 1 penny at a time. Subjects were asked to hit any key when the price reached the most that they were willing to pay, i.e. when they wanted to leave the auction. No information concerning the winner of the auction or the other participants' bids were provided during the evaluation of the eight scenarios. After all the scenarios had been evaluated one of them was chosen randomly. For that scenario, the first and the second highest bids were announced. The winner of the auction was the subject who submitted the highest bid, and she or he had to pay an insurance premium equal to the second highest bid. The player with the highest bid acquired thus the right to avoid the loss or to assure herself the gain. The other subjects had to draw eventually from the urn corresponding to that scenario: that scenario was played out for real, and gains (losses) were contingent on the outcome of the lottery.

For each scenario the auction was conducted only once. It was chosen not to run repeated auction periods since this would have most likely reduced the impact of ambiguity. The reduction in ambiguity due to market experience may have interfered with that induced by the acquisition of information about the second order probability distribution, making it impossible to disentangle the former effect from the latter.[10]

III. EXPERIMENTAL RESULTS

The impact of the outcome domain on the valuation of risk and ambiguity

In order to analyse the existence of the fourfold pattern of risk attitude, consider Table 2, which shows the mean risk attitude in the various treatments. For each prospect, individual risk ratios have been calculated by dividing the bid in the auction for a risky prospect, $Bid(R)$, by that prospect's expected value, EV, both for losses and gains, so that a ratio greater than one stands for risk aversion, whereas a ratio smaller than one signals risk preference.

$$Risk\ ratio = Bid(R)/EV$$

Further, in order to maintain the sample size constant and to make results relating to risk attitude directly comparable to those referring to ambiguity, summary statistics for the risk ratio have been divided according to the definition of ambiguity, although there is no theoretical motivation to expect the risk ratios to be different.[11]

Table 2 presents summary statistics for the risk ratios that confirm the fourfold pattern for risk attitude: risk aversion for gains and risk love for losses at high probability, coupled with risk love for gain and risk aversion for losses at small probability. More precisely, for losses the risk ratio decreases monotonically as the probability of loss increases, and the risk attitude is risk aversion at low probabilities (3%, 20%) and risk preference at high probabilities (50%, 80%). Exactly the opposite pattern is observed for gains, although in the Interval of Probabilities treatment there is no switch from risk preference to risk aversion but simply a risk ratio increasing with the probability.

As a measure of the differential attitude towards ambiguity *vis-à-vis* risk we use the ratio between the individual auction bid under ambiguity, $Bid(A)$, and the bid for the corresponding risky lottery, $Bid(R)$.

$$Ambiguity\ Ratio = Bid(A)/Bid(R)$$

A ratio equal to 1 indicates indifference between risk and ambiguity, as predicted by EU, whereas a ratio greater/lower than one corresponds to ambiguity aversion/preference. The data reported in Table 3 confirm that the fourfold pattern observed for risk ratios extends also to

[8] A similar type of auction was used by Harstad (1990). This kind of auction mechanism is fully explained by Di Mauro and Maffioletti (1996).
[9] A few sessions were run with six or seven participants as some of the students who had registered for the experiment did not turn up. The bidding behaviour in a second price auction, however, is robust to changes in the number of bidders. See Kagel and Levine (1993) for an experimental test of robustness.
[10] Several auction periods are generally adopted as a solution to the overbidding/underbidding problem. The repetition of trials should help subjects familiarise with the auction procedure. Even if present, overbidding or underbidding should not be considered a problem in this case. There are no reasons to think that this phenomenon may be different in the evaluation of risky and ambiguous lotteries and hence the ratios of ambiguous to risky bids should not be affected.
[11] Homogeneity was also tested for explicitly with a Mann–Whitney U test, and the null hypothesis of equality of distributions of the $Bid(R)/EV$ ratios in the Best Estimate and the Interval of Probability treatments accepted.

Table 2. *Summary statistics for ratios of risky bids to expected value*

		Risky lotteries – best estimate			
Probability levels		3%	20%	50%	80%
Losses (29)	Mean	1.26	1.22	0.86	0.85
	Median	0.50	1	0.90	0.87
	St.Dev	2.13	0.56	0.33	0.16
	Confidence Interval (95%)	(0.45–2.07)	(0.93–1.5)	(0.73–0.98)	(0.78–0.93)
Probability levels		3%	20%	50%	80%
Gains (31)	Mean	0.82	0.90	1.06	1.31
	Median	0.96	0.95	1.10	1.07
	St.Dev	0.30	0.28	0.5	1.01
	Confidence Interval (95%)	(0.71–0.93)	(0.79–1.00)	(0.93–1.2)	(−0.22–16.47)
		Risky lotteries – interval of probabilities			
Probability levels		3%	20%	50%	80%
Losses (30)	Mean	2.88	1.22	0.97	0.83
	Median	3.32	1.16	1	0.88
	St.Dev	2.4	0.61	0.33	0.24
	Confidence Interval (95%)	(1.95–3.81)	(0.99–1.44)	(0.84–1.09)	(0.74 – 0.92)
Probability levels		3%	20%	50%	80%
Gains (26)	Mean	0.58	0.65	0.86	0.97
	Median	0.65	0.69	0.90	0.98
	St.Dev	0.10	0.37	0.47	0.74
	Confidence Interval (95%)	(0.45–0.71)	(0.50–0.80)	(0.67–1.05)	(0.59–1.29)

Note: The risk ratio has been calculated as BID/EV. Hence a risk ratio >1 implies risk aversion, while a risk ratio <1 means risk loving behaviour.

Table 3. *Summary statistics for ratios of ambiguous to risky bids*

		Best estimate			
Probability levels		3%	20%	50%	80%
Losses (29)	Mean	10.55	1.07	1.21	0.89
	Median	2	1	1.06	0.92
	St.Dev	4.99	0.55	0.63	0.17
	Confidence Interval (95%)	(0.33–20.76)	(0.86–1.28)	(0.97–1.45)	(0.82–0.95)
Probability levels		3%	20%	50%	80%
Gains (31)	Mean	1.38	1.02	1.13	8.13
	Median	1	1.03	1.04	1.16
	St.Dev	1.66	0.33	0.5	22.75
	Confidence Interval (95%)	(0.77–1.99)	(0.9–1.14)	(0.97–1.45)	(0.82–0.95)
		Interval of probability			
Probability levels		3%	20%	50%	80%
Losses (30)	Mean	4.96	2.79	1.11	0.99
	Median	1.11	1.08	1	0.88
	St.Dev	10.9	8.92	0.25	1.1
	Confidence Interval (95%)	(0.89–9.03)	(−0.55–6.12)	(1.02–1.21)	(0.58–1.4)
Probability levels		3%	20%	50%	80%
Gains (26)	Mean	1.94	2.22	16.15	20.08
	Median	1.19	1.02	0.97	0.86
	St.Dev	1.75	5.95	53.75	59.46
	Confidence Interval (95%)	(1.23–2.65)	(−0.19–4.62)	(−5.56–37.86)	(−3.94–44.09)

ambiguity ratios. Table 3 shows mean, medians, and standard deviations for the ratio of the willingness to pay under ambiguity to the willingness to pay under risk under the various experimental treatments. We start discussion of the table by looking at summary statistics concerning the valuation of losses. As the table shows, both for the Best Estimate and Interval of Probability definitions of ambiguity, the sample displays ambiguity aversion when the probability of loss is low (3%) and ambiguity preference when the probability of loss is high (80%). The intermediate probabilities of 20% and 50% give rise to a moderate ambiguity aversion, which is close to ambiguity indifference if one looks at median values. In the case of the Interval of Probability, there is a clear declining pattern of the ambiguity ratio as the probability of loss increases. Worthy of notice is the fact that at low probabilities of loss, confidence intervals are very wide. This is caused by the fact that the distribution of individual ratios shows the presence of one or two outliers per treatment. However, as these extreme values may signal a very strong ambiguity aversion attitude rather than irrationality or errors, we felt reluctant to eliminate them from the calculation of the mean.

For the case of gains, for both operationalizations of ambiguity, the means show a consistent pattern of ambiguity aversion, which is low when the likelihood of the gain is small (3%) and becomes very strong when the gain is very likely (80%). For the Best Estimate characterization, the pattern of valuation of ambiguous gains displays a monotone increasing ambiguity aversion as one goes from low to high probabilities. Although models such as Hogarth and Einhorn (1990) and Tversky and Kahneman (1992) predict ambiguity preference at low probability of gains, the observed pattern of response agrees with what has been found in previous studies (see, for instance, Einhorn and Hogarth, 1986).

To sum up, the pattern of valuation in the case of ambiguous losses is a switch from ambiguity aversion to ambiguity preference as the probability of the loss increases. A mirror pattern is present in the domain of gains: even if the data in the gain frame do not reveal the switch from one attitude of ambiguity to the other, however, ambiguity aversion clearly increases with the probability of the gain. To check whether, keeping the domain constant, it is the reference probability that determines the size of reaction to ambiguity, a Friedman test[12] on the ambiguity ratios was implemented. The test procedure showed that, across differential treatments, the change in the reference probability has a statistically significant effect on the distribution of the ratios (Best Estimate–Gain $\chi^2 = 5.41$, $p = 0.01$; Interval of Probability–Gain $\chi^2 = 7.66$; $p = 0.05$, Best Estimate–Losses, $\chi^2 = 12.14$, $p = 0.007$; Interval of Probability–Losses $\chi^2 = 15.63$, $p = 0.0013$).

As for the fourfold pattern under risk, the intuition behind the fourfold pattern of behaviour under uncertainty lies in the over-weighting of small probabilities of outcomes and in the under-weighting of high probabilities. That is in the presence of the so-called 'possibility effect' and 'certainty effect' (Tversky and Fox, 1995). In particular, experimental evidence (for instance Fox *et al.*, 1996) has shown that under uncertainty this phenomenon might exist even when subjects display a linear value function. Under uncertainty, the absence of objective probabilities – except the values provided as 'references' – may increase the individual simulation of the possible probability weights, and consequently the over/under weighting of expected probabilities with respect to a situation of risk.

It must be highlighted that the values of the ambiguity ratios do not appear to be larger for gains than for losses. Hence, similarly to Kahn and Sarin (1988), the claim that the size of the reaction to ambiguity under the gain domain consistently differs from that for losses is rejected

To conclude, the main point we want to stress is that the fourfold pattern is confirmed under risk as well as under uncertainty. However, it must be pointed out that ambiguity aversion, wherever present, tends to be stronger than risk aversion. Usually, for small amounts of money, an approximately linear utility function has been observed. This has been found recently in Fox *et al.* (1996), Fox and Weber (1998), Kilka and Weber (2001), and Maffioletti and Santoni (2001a, 2001b), where expert or competent people are almost risk neutral but ambiguity averse or ambiguity prone. In the present experiment it is found that subjects acting under a market institution react like experts. Hence, the presence of ambiguity is likely to create a greater effect on market prices than risk.

After the aggregate analysis of data, the patterns of choice across probability levels were analysed for each

Table 4. *Summary of individual patterns of behaviour for the risky lotteries*

Behavioural pattern	Subjects in gain	Subjects in loss
Decreasing risk aversion (DRA)	1	25
Increasing risk aversion (IRA)	29	10
Risk proneness	12	5
Risk neutrality*	3	1
Risk aversion	0	4
Unclear pattern	12	14
Total	57	59

* Risk neutrality is defined as ±5% from expected value.

[12] See Siegel and Castellan (1988).

Table 5. *Summary of individual patterns of ambiguity reaction*

Behavioural Pattern	Subjects in gain	Subjects in loss
Decreasing amb.aversion (DAA)	13	38
Increasing amb.aversion (IAA)	19	2
Ambiguity proneness	7	11
Ambiguity neutrality*	3	0
Ambiguity aversion	5	0
Unclear pattern	10	8
Total	57	59

* Ambiguity neutrality is defined as ±5% from the bid for the corresponding risky lottery.

Table 6. *Number of subjects with coherent risk and uncertainty attitudes*

		AA-RA	AN-RN	AP-RP
BE Gain (31)	P = 3%	0	11	4
	P = 20%	2	4	4
	P = 50%	8	4	3
	P = 80%	4	1	1
IP Gain (26)	P = 3%	0	1	1
	P = 20%	1	0	7
	P = 50%	3	3	6
	P = 80%	6	0	7
BE Loss (29)	P = 3%	6	1	4
	P = 20%	4	4	5
	P = 50%	5	1	5
	P = 80%	0	0	14
IP Loss (30)	P = 3%	9	0	2
	P = 20%	10	5	1
	P = 50%	2	5	0
	P = 80%	0	3	12

Note: AA-RA = ambiguity averse and risk averse; AN-RN = ambiguity neutral and risk neutral; AP-RP = ambiguity prone and risk prone.

experimental subject. The results are summarized in Table 4 for risk and Table 5 for ambiguity. Table 4 shows that, as far as risk is concerned, there is no more noise in the behavioural responses across probability levels for losses with respect to gains. When looking at the pattern of risk ratios it is seen that in the gain experiment 29 out of 57 subjects displayed increasing risk aversion, whereas 25 out of 59 in the loss experiment exhibited decreasing risk aversion. The number of subjects who exhibited an unclear pattern of risk attitude was nearly the same in the two domains: 12 subjects for gains and 14 for losses.

As far as uncertainty is concerned Table 5 shows that there is a neat difference in the pattern of response to ambiguity for gains and losses. For losses, the modal response is a declining ambiguity aversion as the probability of loss increases (38 out of 59 subject). For gains, on the other hand, there is no strongly predominant pattern of valuation as probabilities of the event vary: the modal response is increasing ambiguity aversion as the probability of gain increases, but this mode corresponds to the behaviour of 19 subjects out of 57. The findings reported in Table 5 contradict those of Cohen *et al*. (1985, 1987) and Hogarth and Einhorn (1990), who report that attitudes towards ambiguity for losses are more unstable than for gains.

In order to determine if the correlation between risk attitude and uncertainty attitude holds also at the individual level, for each experimental treatment we calculated the number of subjects who displayed a consistent attitude towards risk and uncertainty, whereby consistency was indicated, for instance, by a subject being either averse or neutral or prone both to risk and uncertainty. Table 6 shows the results of this analysis: less than half of the subjects for each treatment showed a consistent attitude. That is to say people who are ambiguity averse may well be risk neutral or prone, although the pattern of average ambiguity and risk ratios tends to coincide and the modal responses tend to be the same.[13] This result is not new, although to date it has been observed only in experiments which did not use incentive-compatible elicitation procedures (see, for instance, Curley *et al*., 1986; Hogarth and Einhorn, 1990).

So far this analysis has focused on the existence of a pattern of valuation of ambiguous and risky losses and gains along the probability scale, as predicted by Einhorn and Hogarth (1985) and Tversky and Kahneman (1992) models. Next, a statistical test is carried out of whether – at each probability level – attitudes towards ambiguity and towards risk depend on the outcome domain. By means of a chi-square test, it is verified that the proportion of ambiguity averse, neutral, prone subjects differs according to whether the lottery is framed as a gain or as a loss. Evidence has been found of a statistically different proportion at extreme probabilities (at 3% chi-square = 11.27, $p < 0.01$, at 80% chi-square = 18.23, $p < 0.001$) but not at intermediate probabilities of outcomes (at 20% chi-square = 1.55, $p > 0.30$, at 50% chi-square = 0.95, $p > 0.50$). The same test was applied to the risk ratios with substantially analogous results. The proportion of risk averse, neutral, prone subjects differs according to the outcome domain at extreme probabilities (at 3% chi-square = 46.44, $p < 0.001$, at 80% chi-square = 15.85,

[13] A Spearman correlation coefficient between the risk and the ambiguity ratio was also calculated. Results of such a test, however, are likely to be biased and therefore it was preferred not to present the test. At any rate, the values of the coefficient tend to be low in most cells and it is significant only at the probability of loss and gain of 3%.

$p < 0.001$) but not at intermediate probabilities of outcomes (at 20% chi-square = 4.2, $p > 0.10$, at 50% chi-square = 1.1, $p > 0.25$). These results support, in particular, Prospect Theory and all the other theories of behaviour under risk and uncertainty which allow for different weighting functions according to the sign of outcome. The fact that risk and ambiguity reaction diverge in the two domains at low and high probability levels supports also the hypothesis of a linear weighting function except near the endpoints (Tversky and Kahneman, 1992; Tversky and Fox, 1995; Tversky and Wakker, 1995).

The impact of the representation of ambiguity

In the present experiment, two alternative definitions of ambiguous probabilities have been adopted following Hogarth and Kunreuther (1989). The 'interval of probability' definition has been made operational as a second-order uniform distribution of probabilities inside the given interval. The 'Best Estimate' is a discrete symmetric distribution around a value of the probability that is considered the most likely one. Although the two distributions were always built so as to have the same expected value, their variance is different, and so non-expected utility agents may react to the two types of ambiguity in different ways. In particular, the Interval of Probability scenario may be perceived as intrinsically more ambiguous than the Best Estimate one. In order to test this hypothesis, a Mann–Whitney U-test was carried out for independent samples to compare the distribution of ambiguity ratios under the two representations of ambiguity. This test was carried out for each level of probability and for each of the two outcome domains. Table 7 presents the results of the test, which show that the distributions of the ambiguity ratios are never significantly different. A further test of the joint effect of the outcome domain and of the definition of ambiguity was carried out by applying a Kruskal–Wallis test for homogeneity of the ambiguity ratios in the four experimental treatments (Best Estimate–Gain, Best Estimate–Losses, Interval of Probability–Gain, Interval of Probability–Loss). Results of the test are summarized in Table 8 and show that only at the extreme mean probabilities of 3% and 80% do the distributions of ratios differ. By comparing the results of the Kruskal-Wallis test with those of the Mann–Whitney test, it appears that the difference among the ratios is due to the outcome domain, more than to the definition of ambiguity used.[14]

To conclude, the 'Interval of Probability' and the 'Best Estimate' scenarios are interpreted as equally ambiguous sources of uncertainty and experimental subjects respond to them in the same fashion.

Table 7. *Mann–Whitney U-test for independent samples between the two definitions of ambiguity*

	Gains	Losses
P = 3%	196 ($p = 0.009$)	351.5 ($p = 0.21$)
P = 20%	401 ($p = 0.97$)	332 ($p = 0.12$)
P = 50%	365.0 ($p = 0.5426$)	404 ($p = 0.64$)
P = 80%	316.5 ($p = 0.17$)	396 ($p = 0.55$)

Table 8. *Kruskall–Wallis test for homogeneity of distributions of ambiguity ratios*

Probability	3%	20%	50%	80%
Chi-square[a]	10.9537	3.1426	1.5314	13.1108
Significance	0.01	0.37	0.67	0.04

[a] chi-square values are corrected for ties.

IV. DISCUSSION

Three issues have been addressed in this paper: (i) what is the impact of the outcome domain on the valuation of ambiguous prospects; (ii) is there a correlation between individual behaviour under risk and behaviour under uncertainty; (iii) does the valuation of ambiguous prospects depend on the description of probability uncertainty. The main results of the paper can be summarized as follows:

First, it is found that there is a clear-cut difference in the behaviour under the gain frame as opposed to the loss frame. This difference is reflected in the pattern of valuation across probability levels both aggregate and individual, rather than in the size of the ambiguity premiums. In fact, under all experimental conditions, a distinct pattern of decreasing ambiguity aversion for losses going from low to high expected probabilities was observed and, in particular, a switch from ambiguity aversion to ambiguity proneness. For gains, the modal pattern is an increasing degree of ambiguity aversion, but there is much more variability of patterns, and the switch from ambiguity preference to ambiguity aversion is not so frequent. Concerning the size of the ambiguity ratio, no systematic difference has been observed in the two domains.

Therefore, the difference between the valuation of positive and negative ambiguous prospects cannot be resolved in terms of higher/lower amounts of ambiguity at each probability level, as suggested by some studies (Cohen *et al.*, 1985), but rather in terms of alternative patterns of

[14] This conclusion is further reinforced by the results of a parametric two-way ANOVA carried out on the ambiguity ratios. This analysis has shown that there is a strong significant main effect on ratios only for the outcome domain at the probability of 3% (F = 5.05, $p = 0.02$) and 80% (F = 5.4, $p = 0.02$) but not for the definition of ambiguity.

behaviour across probability levels. Similarly to Hogarth and Kunreuther (1989), in the valuation of losses the modal pattern is decreasing risk and ambiguity aversion as the probability of loss increases, while increasing ambiguity aversion is observed for gains.

These results are of economic significance as well as of policy relevance. Since most risks people take every day in markets are not precisely known, the finding that reaction to ambiguity – be it aversion or preference – persists in the face of incentive – compatible elicitation procedures of individual willingness to pay, suggests that ambiguity should be taken into account when predicting economic agents' behaviour. Consider for instance, the implications of these results for the loss domain: willingness to pay to purchase complete insurance against a potential loss shows the prevalence of aversion to ambiguity if the mean probability of loss is low, and of preference for ambiguity if the mean probability of loss is high. As highlighted by Viscusi and Chesson (1999), at low mean probabilities ambiguity determines a 'fear' of suffering the loss, whereas at high mean probabilities the 'hope' effect predominates. Knowing how people respond to the presence of ambiguity helps understand how people will self-protect or how much insurance they will buy against potential losses. For rare losses, people will express a willingness to pay to insure beyond that corresponding to the mean risk, but for highly likely losses, they will take the risk and reduce expenditure on insurance or precautions.

In order to establish whether preference for ambiguity at high mean probabilities of loss may disrupt insurance markets one should be able to observe both sides of the market. Hogarth and Kunreuther (1989),[15] for instance, have found that insurance companies increase prices in response to probability ambiguity, and this will imply that the market for insurance for highly likely losses may be thin. More specifically, increased insurance prices will not be matched by increased willingness to pay on the consumers' side and little trade will occur.

Borges and Knetch (1998) have highlighted that, in general, a lower volume of market trades than standard theory would predict can be the consequence of the differential valuation of gains and losses. This present study shows that the presence of ambiguity can exacerbate the effects of the gain/loss disparity even further.

Finally, these results may be relevant for contingent valuation studies: consider a survey in which the interviewed is faced with the alternative between paying a sum to contribute to the public acquisition of an environmental amenity, or face the risk that the amenity is purchased for private development and never made available for recreation. These results imply that if the public acquisition is considered highly likely, the interviewed will over-estimate his contribution, whereas if the private purchase is considered the most likely event his contribution will be undervalued. Thus, the presence of ambiguity may inflate or depress contingent valuation values, as the reference mean probability of the event under consideration varies.

Second, comparing mean ambiguity ratios with mean risk ratios it has been found that they reflect the same pattern of valuation. At low probabilities of loss risk aversion and ambiguity aversion prevail, whereas at high probabilities of loss there is ambiguity and risk aversion. For gains, risk and ambiguity aversion/preference prevail at high/low probability of the gain. This result suggests that if risk averse behaviour prevails in a market, ambiguity aversion should prevail in markets where the mean risk is the same although probabilities of outcomes are vague. The risk ratios tend, however, to be closer to 1 – the risk neutrality value – than the ambiguity ratios, signalling that uncertainty tends to have a stronger impact on valuation as compared to risk. Hence, the presence of ambiguity, as stated by Kahn and Sarin (1988) '... will accentuate the effects of risk aversion or risk proneness and will not cancel it out'.

However, results which are valid at the aggregate level do not seem to hold at the individual level: crossing individual risk attitudes with uncertainty attitudes indicate that a strongly ambiguity averse subject is not necessarily also strongly risk averse. Hence, knowledge of a trader's behaviour in a market with known risks will not help predict her/his behaviour in a 'more volatile' market.

Finally, the way uncertainty is portrayed, either by means of the 'Best Estimate' representation or through the 'Interval of Probability', does not affect the distribution of ambiguity ratios. This implies that even if the variance of the two distributions is different, subjects do not perceive any difference in the degree of ambiguity.

V. CONCLUDING REMARKS

This experiment has considered in a comprehensive framework the interactions among the sign of the outcome domain, individual attitudes towards risk and ambiguity, and the way ambiguity is represented. Moreover, with respect to previous studies in the area, individual values are elicited using an incentive-compatible market institution, namely a variant of the second price auction.

The results of the experiment show that the fourfold pattern is a robust phenomenon both under risk and under uncertainty, even when market institutions are used to elicit individual preferences. More specifically, it is found that:

[15] Results of this paper show that ambiguity aversion for firms is greater than ambiguity aversion of consumers in the insurance market.

(a) There is a clear-cut difference in the behaviour under the gain frame as opposed to the loss frame across probability levels under risk and under uncertainty. This difference is reflected in the mean valuations across probability levels, and in the modal patterns of behaviour, rather than in the absolute size of the risk or ambiguity premia.
(b) Reaction to ambiguity is stronger than reaction to risk.
(c) Ambiguity averse/prone individuals are not necessarily also risk averse/prone. The correlation between risk and ambiguity attitudes for each individual is very low. This result confirms what has been found in previous experiments that did not use incentive-compatible elicitation mechanisms.

The implications of these results are of some relevance for research into individual decision making under uncertainty and for the functioning of markets. First, rather than the existence of 'looser' categories of valuation of losses with respect to gains as suggested by Cohen *et al.* (1985, 1987), our study supports those theories of behaviour under risk and uncertainty which allow for different weighting functions according to the sign of outcome. The 'fourfold pattern' is consistent with the existence of an S-inverse probability weighting function under risk as well as under uncertainty, as suggested by Prospect Theory and Cumulative Prospect Theory. Most subjects displayed a smaller amount of ambiguity aversion at intermediate probabilities of the gain/loss, while exhibiting stronger ambiguity reaction at low and high probability levels. This supports also the hypothesis of a linear weighting function except near the endpoints (Tversky and Kahneman, 1992; Tversky and Fox, 1995; Tversky and Wakker, 1995).

Second, the fact that ambiguity aversion/preference persists in the face of incentive- compatible elicitation methods such as the one used here, suggests that ambiguity may be a relevant factor which affects market prices and allocations.

As part of our future research agenda, we intend to investigate how much reaction to ambiguity and the shape of the weighting function are dependent on the one hand, on the nature of uncertainty, and on the other, on the type of incentive mechanism used to elicit individual values. In fact, it may be crucial to establish whether uncertainty reaction is a marginal phenomenon when market institutions are involved.

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REFERENCES

Borges, B. and Knetch, J. (1998) Tests of market outcomes with asymmetric valuations of gains and losses: smaller gains, fewer trades, and less value, *Journal of Economic Behaviour and Organization*, **33**, 185–93.

Camerer, C. and Kunreuther, H. (1989) Experimental markets for insurance, *Journal of Risk and Uncertainty*, **2**, 265–300.

Camerer, C. and Weber, M. (1992) Recent development in modelling preferences: uncertainty and ambiguity, *Journal of Risk and Uncertainty*, **5**, 325–70.

Cohen, M., Jaffray. J. Y. and Said, T. (1985) Individual behaviour under risk and under uncertainty: an experimental study, *Theory and Decision*, **18**, 203–28.

Cohen, M., Jaffray, J. Y. and Said, T. (1987) Experimental comparison of individual behaviour under risk and under uncertainty for gains and for losses, *Organizational Behaviour and Human Decision Processes*, **39**, 1–22.

Coursey, D., Hovis, J. and Schultze, W. (1987) On the supposed disparity between willingness to accept and willingness to pay measures of value, *Quarterly Journal of Economics*, **102**, 679–90.

Curley, S. and Yates, F. (1985) The centre and range of the probability interval as factor affecting ambiguity preferences, *Organizational Behaviour and Human Decision Processes*, **36**, 272–87.

Curley, S. and Yates, F. (1989) An empirical evaluation of descriptive models of ambiguity reactions in choice situations, *Journal of Mathematical Psychology*, **33**, 397–427.

Curley, S., Yates, F. and Abrams, R. (1986) Psychological sources of ambiguity avoidance, *Organizational Behaviour and Human Decision Processes*, **38**, 230–56.

Di Mauro, C. and Maffioletti, A. (1996) An experimental investigation of the impact of ambiguity on the evaluation of self-insurance and self-protection, *Journal of Risk and Uncertainty*, **12**, 359–77.

Di Mauro, C. and Maffioletti, A. (2001) The valuation of insurance under uncertainty: does information about probability matter?, *Geneva Papers On Risk and Insurance Theory*, **26**(3), 195–223.

Einhorn, H. and Hogarth, R. (1985) Ambiguity uncertainty in probabilistic inference, *Psychological Review*, **92**, 433–9.

Einhorn, H. and Hogarth, R. (1986) Decision making under ambiguity, *Journal of Business*, **59**, 225–50.

Ellsberg, D. (1961) Risk, ambiguity, and the savage axiom, *Quarterly Journal of Economics*, **75**, 643–9.

Erev, I. and Wallsten, T. S. (1993) The effect of explicit probabilities on decision weights and on the reflection effect, *Journal of Behavioural Decision Making*, **6**, 221–1.

Fox, C., Rogers, B. and Tversky, A. (1996) Option traders exhibit subadditive decision weights, *Journal of Risk and Uncertainty*, **13**, 5–7.

Fox, C. and Weber, M. (1998) Ambiguity aversion, comparative ignorance and the role of context, SFB504, Universität Mannheim, WP 99-47.

Harstad, R. (1990) Dominant Strategy adoption. Efficiency and bidders experiences with pricing rules, Mimeo, Virginia Commonwealth University, VA.

Heath, F. and Tvesky. A. (1991) Preference and belief: ambiguity competence in choice under uncertainty, *Journal of Risk and Uncertainty*, **4**, 5–28.
Hogarth, R. and Einhorn, H. (1990) Venture theory: a model of decision weights, *Management Science*, **36**, 780–803.
Hogarth, R. and Kunreuther, H. (1989) Risk, ambiguity, and insurance, *Journal of Risk and Uncertainty*, **2**, 5–35.
Kagel, J. and Levin, D. (1993) Independent private value auctions: bidder behavior in first- second- and third-price auctions with varying numbers of bidders, *Economic Journal*, **103**, 868–79.
Kahn, B. and Sarin, R. (1988) Modelling ambiguity in decision under uncertainty, *Journal of Consumer Research*, **17**, 508–22.
Kahneman D. and Tversky, A. (1979) Prospect theory. An analysis of decision under risk, *Econometrica*, **47**, 263–91.
Keppe H. and Weber, M. (1995) Judged knowledge and ambiguity aversion, *Theory and Decision*, **39**, 51–77
Kilka, M. and Weber, M. (2001) What determines the shape of the probability weighting function?, *Management Science*, **47**, 1712–26.
Knight, F. H. (1921) *Risk Uncertainty and Profit*, Houghton Mifflin, Boston.
Maffioletti, A. and Santoni, M. (2001a) Do trade union leaders violate subjective expected utility? Some insights from experimental data. SFB504, Universität Mannheim, WP 01-43.
Maffioletti, A. and Santoni, M. (2001b) Emotions and competence, Unpublished Manuscript, SFB504, Universität Mannheim.
Sarin, R. and Weber, M. (1993) Effects of ambiguity in market experiments, *Management Science*, **39**, 602–15.
Shogren, J., Shin, S. Hayes, D. and Kliebenstein, J. (1994) Resolving differences in willingness to pay and willingness to accept, *American Economic Review*, **84**, 255–70.
Siegel, S. and Castellan, J. (1988) *Non Parametric Statistic for Behavioural Science*, McGraw Hill International Edition, New York.
Tversky, A. and Fox, C. (1995) Weighing risk and uncertainty, *Psychological Review*, **102**, 269–83.
Tversky, A. and Kahneman, D. (1992) Advances in Prospect Theory: cumulative representation of uncertainty, *Journal of Risk and Uncertainty*, **5**, 297–323.
Tversky, A. and Wakker, P. (1995) Risk attitudes and decision weights, *Econometrica*, **63**, 1255–80.
Vickrey, W. (1961) Counterspeculation, auctions, and competitive sealed tenders, *Journal of Finance*, **16**, 8–37
Viscusi, K. and Chesson, H. (1999) Hopes and fears: the conflicting effects of risk ambiguity, *Theory and Decision*, **47**, 153–78.
Wehrung, D. (1989) Risk taking over gains and losses: a study of oil executives, *Annals of Operational Research*, **19**, 15–139.

APPENDIX A. TEXTS OF THE SCENARIOS USED IN THE EXPERIMENT

GAINS

RISKY SCENARIO

Assume that there is a chance of 3% that some event occurs. If this event occurs you will gain £10.

You are now asked to state what is the maximum amount of money that you would be willing to pay to assure yourself a gain of £10.

You will be asked to press any key when the price reaches the most that you are willing to pay; that is, when you want to leave the auction.

AMBIGUOUS SCENARIO – BEST ESTIMATE

Assume that there is a potential chance of the occurrence of some event. There is an estimate of the occurrence of this event; an expert, hired by a governmental agency, estimates that the probability of the occurrence of such an event is 3%. However, this is the first investigation ever carried out and consequently you experience considerable uncertainty about the precision of this estimate. If this event occurs, you will gain £10.

AMBIGUOUS SCENARIO – INTERVAL PROBABILITIES

Assume that there is a chance of the occurrence of some event. There is an estimate of the possible occurrence of this event; an expert, hired by a governmental agency, estimates that the probability of the occurrence of such an event can be anywhere between 1% and 5%. If this event occurs, you will gain £10.

LOSSES

RISKY SCENARIO

Assume that there is a chance of 3% that some event occurs. If this event occurs you will suffer a loss of £10.

You are now asked to state which is the maximum amount of money that you would be willing to pay to reduce this potential loss to zero.

You will be asked to press any key when the price reaches the most that you are willing to pay; that is, when you want to leave the auction.

AMBIGUOUS SCENARIO – BEST ESTIMATE

Assume that there is a potential chance of the occurrence of some event. There is an estimate of the occurrence of this event; an expert, hired by a governmental agency, estimates that the probability of the occurrence of such an event is 3%. However, this is the first investigation ever carried out and consequently you experience considerable uncertainty about the precision of this estimate. If this event occurs, you will suffer a loss of £10.

AMBIGUOUS SCENARIO – INTERVAL PROBABILITIES

Assume that there is a chance of the occurrence of some event. There is an estimate of the possible occurrence of this event; an expert, hired by a governmental agency, estimates that the probability of the occurrence of such an event can be anywhere between 1% and 5%. If this event occurs, you will suffer a loss of £10.

APPENDIX B

GENERAL INSTRUCTIONS: 'GAIN' EXPERIMENT

You are about to participate in an experiment about decision making under risk and uncertainty. The purpose of the experiment is to gain insight into certain features of economic behaviour. If you follow the instructions carefully you can earn money, but you may end up not earning anything other than the participation fee. You will be paid in cash at the end of the experiment. The mechanism according to which you will be paid will be explained at the end of these instructions.

During the experiment you are not allowed to communicate with the other participants. Communication between participants will lead to the automatic end of the session.

You will be presented with 8 different scenarios regarding the same kind of problem.

Imagine that you are concerned about the occurrence of some event. If this event does occur you will gain some amount of money. However, you have the opportunity to take some action at some monetary cost. If you take this action, you will gain the amount of money for sure. Each scenario considers a different probability of the potential gain of £10.

Try to think of each scenario as of a real situation.

For each scenario you will be asked to state the maximum amount you are willing to pay to gain £10 for sure.

For each scenario, you will indicate your maximum willingness to pay through the following auction mechanism. On the screen you will see a description of the scenario. Below the description, at the bottom of the screen, will be displayed a price which will steadily increase. You will indicate your willingness to pay by pressing any key when the price reaches the most that you are willing to pay; that is, when you want to leave the auction. The last person to drop out will acquire the right to obtain £10 for sure and he or she will pay the price at which the second-to-last person dropped out.

At the end of the experiment, after you have revealed your price for all the eight scenarios, one of the scenarios will be selected with a random device and that scenario will be played out for real. The player who dropped out last in that scenario pays the price of the second to last person to drop out and hence she or he will be paid £10 less that amount. The other participants will play the selected scenario out and will be paid according to the outcome.

The experiment is organized as follows:

Step 1
At the beginning of the experiment, you will be given one hypothetical example in order to help you become familiar with the problem and the auction procedure.

Step 2
You will be given the first scenario. You will be allowed a few minutes to think about it.

Step 3
The auction will take place. You will be asked to press a key when the price reaches the most that you are willing to pay; that is to say when you want to leave the auction.

Step 4
You will be presented with the other seven situations.

Step 5
At the end of the eight sessions a scenario will be selected at random and played out for real. A person will be asked to pick a number from a bag containing eight tickets numbered from 1 to 8. Each number corresponds to one of the scenarios. If, say, number 5 is picked, then the experimenter will enter that number into the control computer. At this point, the screen will show all the prices at which each subject dropped out from the auction. If you are the last person to have dropped out for the selected scenario you will have to pay the price at which the second-to-last person dropped out and in this way you will acquire the right to obtain £10 for sure. Hence the last person to have dropped out from the auction for the selected scenario will receive £10 minus the price paid, irrespective of the outcome of the played scenario.

Then the selected scenario will be played out for real.

Step 6
The scenario selected will be played in the following way: there will be an opaque bag containing 100 balls. The number of black balls corresponds to the chances of gain, while the number of white balls corresponds to the chances of no gain. The proportion of white and black balls will correspond to the various probabilities of the occurrence of the event. The selected scenario will be played out for each subject separately. Each one of the participants will be asked to draw a ball from the bag. After every draw, the ball will be replaced before the next subject draws another ball. A white ball results in no gain, i.e. in a payoff of £0 for the participant who drew the ball. A black ball results in a gain of £10, i.e. a payoff of £10 for the participant who drew the ball.

The mechanism whereby the lotteries will be played in the different scenarios will be explained in greater detail at the end of the practice scenarios. Please notice that, after the selected lottery has been played, you will be free to check whether the stated probability corresponds to the combination of white and black balls inside the opaque bag.

GENERAL INSTRUCTIONS: 'LOSS' EXPERIMENT

You are about to participate in an experiment about decision making under risk and uncertainty. The purpose of the experiment is to gain insight into certain features of economic behaviour. If you follow the instructions carefully you can earn money, but you may end up not earning anything other than the participation fee. You will be paid in cash at the end of the experiment. The mechanism according to which you will be paid will be explained at the end of these instructions.

During the experiment you are not allowed to communicate with the other participants. Communication between participants will lead to the automatic end of the session.

You will be presented with 8 different scenarios regarding the same kind of problem.

Imagine that you are concerned about the occurrence of some event. If this event does occur you will suffer a loss of money. However, you have the opportunity to take some action at some monetary cost. If you take this action, should the event occur, the loss will be reduced to zero. Each scenario considers a different probability of the potential loss of £10.

Try to think of each scenario as of a real situation.

For each scenario you will be asked to state the maximum amount you are willing to pay to reduce the potential loss to zero.

For each scenario, you will indicate your maximum willingness to pay through the following auction mechanism.

On the screen you will see the description of the scenario. Below the description, at the bottom of the screen, will be displayed a price which will steadily increase. You will indicate your willingness to pay by pressing any key when the price reaches the most that you are willing to pay; that is, when you want to leave the auction. The last person to drop out will acquire the right to reduce the loss to zero and he or she will pay the price at which the second-to-last person dropped out.

At the beginning of the experiment you will be given an endowment of £10 for each scenario. At the end of the experiment, after you have revealed your price for all the eight scenarios, one of the scenarios will be selected with a random device and that scenario will be played out for real. The player who dropped out last in that scenario pays the price of the second to last person to drop out and hence she or he will be paid £10 less that amount. The other participants will play the selected scenario out and will be paid according to the outcome.

The experiment is organized as follows:

Step 1
At the beginning of the experiment, you will be given one hypothetical example in order to help you become familiar with the problem and the auction procedure.

Step 2
You will be given the first two scenarios. You will be allowed a few minutes to think about them.

Step 3
The auction for the first scenario will take place. You will be asked to press a key when the price reaches the most that you are willing to pay; that is to say when you want to leave the auction. The auction for the second scenario will take place in the same fashion as the first one.

Step 4
You will be presented with the other six scenarios.

Step 5
At the end of the eight sessions a scenario will be selected at random and played out for real. A person will be asked to pick a number from a bag containing eight tickets numbered from 1 to 8. Each number corresponds to one of the scenarios. If, say, number 5 is picked, then the experimenter will enter that number into the control computer. At this point, the screen will show all the prices at which each subject dropped out from the auction. If you are the last person to have dropped out for the selected scenario you will have to pay the price at which the second-to-last person dropped out and in this way you will acquire the right to reduce your loss to zero. Hence the last person to have dropped out from the auction for the selected scenario will receive £10 minus the price paid to reduce the loss to zero irrespective of the outcome of the played scenario.

Then the selected scenario will be played out for real.

Step 6
The scenario selected will be played in the following way: there will be an opaque bag containing 100 balls. The number of black balls corresponds to the chances of loss, while the number of white balls corresponds to the chances of no loss. The proportion of white and black balls will correspond to the various probabilities of the occurrence of the event. The selected scenario will be played out for each subject separately. Each one of the participants will be asked to draw a ball from the bag. After every draw, the ball will be replaced before the next subject draws another ball. A white ball results in no loss, i.e. in a payoff of £10

for the participant who drew the ball. A black ball results in a loss of £10, i.e. a payoff of £0 for the participant who drew the ball.

The mechanism whereby the lotteries will be played in the different scenarios will be explained in greater detail at the end of the practice scenarios. Please notice that, after the selected lottery has been played, you will be free to check whether the stated probability corresponds to the combination of white and black balls inside the opaque bag.

APPENDIX C. INFORMATION ABOUT THE RESOLUTION OF AMBIGUOUS LOTTERIES PROVIDED TO THE SUBJECTS

GAINS

'Best Estimate' scenarios

Scenarios *,*,*,* will be played in the following way: one of the participants will be asked to draw a ticket from a bag. The bag contains five tickets. Three out of the five tickets will bear on them the number given in the scenario as the Governmental Agency's best estimate. The remaining two tickets will bear one, a number above the best estimate, and one, a number below the best estimate. The numbers above and below the best estimate will be symmetrically distributed around it. If, say the best estimate given in the scenario is 80%, the bag will contain five tickets, three bearing the number 80 on them, one with the number 65, and the other with the number 95. Since three tickets out of five bear the number corresponding to the best estimate, the best estimate is the most likely probability of gain

The experimenter will then prepare one bag containing 100 balls.

One ball will be drawn from the bag with black representing gain and white representing no gain. The proportion of black balls is the probability of gaining £10 and the proportion of white balls is the probability of no gain.

The selected scenario will be played out for each subject separately. Each one of the participants will be asked to draw a ball from the bag. After every draw the ball will be replaced before the next subject draws another ball. A white ball results in no gain, i.e. a payoff of £0 for the participant who drew the ball. A black ball results in a gain of £10, i.e. a payoff of £10 for the participant who drew the ball.

After the lottery has been played out, you will be free to check whether the tickets in the bag and the combination of white and black balls in the bag correspond to the explanations given above.

'Interval of probability' scenarios

Scenarios *,*,*,* will be played in the following way: one of the participants will be asked to draw a ticket from a bag. The bag contains a number of tickets corresponding to the integers within the interval provided in the scenario (including the extremes of the interval). Numbers on the tickets are integers that go from the lower bound of the interval to the upper bound. So, if the interval presented in the scenario goes from 0.65 to 0 .95, the bag will contain 31 tickets, numbered from 65 to 95.

Each number represents a value of the probability of the gain that lies in the probability interval given in the scenario.

The experimenter will then prepare one bag containing 100 balls. One ball will be drawn from the bag with black representing gain and white representing no gain. The proportion of black balls is the probability of gain and the proportion of white balls is the probability of no gain.

After every draw the ball will be replaced before the next subject draws another ball. A white ball results in no gain, i.e. a payoff of £0 for the participant who drew the ball. A black ball results in a gain of £10, i.e. a payoff of £10 for the participant who drew the ball.

After the lottery has been played out, you will be free to check whether the tickets in the bag and the combination of white and black balls in the bag correspond to the explanations given above.

Losses

'Best Estimate' scenarios

Scenarios *,*,*,* will be played in the following way: one of the participants will be asked to draw a ticket from a bag. The bag contains five tickets. Three out of the five tickets will bear on them the number given in the scenario as the Governmental Agency's best estimate. The remaining two tickets will bear one a number above the best estimate, and one a number below the best estimate. The numbers above and below the best estimate will be symmetrically distributed around it. If, say the best estimate given in the scenario is 80%, the bag will contain five tickets, three bearing the number 80 on them, one with the number 65, and the other with the number 95. Since three tickets out of five bear the number corresponding to the best estimate, the best estimate is the most likely probability of loss.

The experimenter will then prepare one bag containing 100 balls.

One ball will be drawn from the bag with black representing loss and white representing no loss. The proportion of black balls is the probability of the loss and the proportion of white balls is the probability of no loss.

The selected scenario will be played out for each subject separately. Each one of the participants will be asked to draw a ball from the bag. After every draw the ball will be replaced before the next subject draws another ball. A white ball results in no loss, i.e. a payoff of £10 for the participant who drew the ball. A black ball results in a loss of £10, i.e. a payoff of £0 for the participant who drew the ball.

After the lottery has been played out, you will be free to check whether the tickets in the bag and the combination of white and black balls in the bag correspond to the explanations given above.

'Interval of probability' scenarios

Scenarios *,*,*,* will be played in the following way: one of the participants will be asked to draw a ticket from a bag. The bag contains a number of tickets corresponding to the integers within the interval provided in the scenario (including the extremes of the interval). Numbers on the tickets are integers that go from the lower bound of the interval to the upper bound. So, if the interval presented in the scenario goes from 0.65 to 0.95, the bag will contain 31 tickets, numbered from 65 to 95.

Each number represents a value of the probability of the loss that lies in the probability interval given in the scenario.

The experimenter will then prepare one bag containing 100 balls. One ball will be drawn from the bag with black representing loss and white representing no loss. The proportion of black balls is the probability of the loss and the proportion of white balls is the probability of no loss.

After every draw the ball will be replaced before the next subject draws another ball. A white ball results in no loss, i.e. a payoff of £10 for the participant who drew the ball. A black ball results in a loss of £10, i.e. a payoff of £0 for the participant who drew the ball.

After the lottery has been played out, you will be free to check whether the tickets in the bag and the combination of white and black balls in the bag correspond to the explanations given above.

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