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An Experimental Investigation of the Impact of Ambiguity on the Valuation of Self-Insurance and Self-Protection

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Abstract

We build two experimental markets to examine individual valuations of risk reductions with two risk-management tools: self-insurance and self-protection. We find no positive evidence that the risk-reducing mechanisms constitute a "frame." Ambiguity in the probability on average affects valuation only weakly, and changes in the representation of ambiguity do not alter valuation. Finally, unlike the results obtained by Hogarth and Kunreuther for the case of market insurance, our findings do not provide a strong support for the "Anchoring and Adjustment" ambiguity model.

Key words: risk, uncertainty, ambiguity, self-protection, self-insurance, framing
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Since the seminal paper by Ehrlich and Becker (1972), several theoretical contributions have analyzed the alternatives to market insurance which are available to an expected utility maximizing individual who wants to cover against the risk of a loss. An individual can purchase preventive measures that either reduce the probability of a loss (self-protection) or reduce the size of the loss (self-insurance).

Very little attention has been paid to the comparative valuation of these two risk-reduction tools in laboratory experiments or survey studies. The only such study we are aware of (Shogren, 1990) addresses the issue of whether the risk-reduction mechanism constitutes a "frame" that affects valuation. The hypothesis put forward is that, since choice and valuation are often influenced by the frame under which the decision problem is presented, individuals may evaluate self-protection and self-insurance differently simply because they perceive them as two different ways of reducing risk, even when it would be rational to value the two risk-reduction tools indifferently. In short, the value assigned to risk reduction may depend not only on *how much* risk is reduced but also on *how* risk is reduced.

To test this hypothesis Shogren uses a lottery involving a loss L in the bad state of the world and a gain G in the good state, given an initial endowment W. He finds that the valuation of self-protection is consistently higher than that of self-insurance; this is interpreted as evidence that the risk-reduction mechanism matters to evaluation. However, the use of a lottery of the type $(p, W - L; (1 - p), W + G)$ does not allow for the isolation of a framing effect due to the risk-reduction mechanism used. If the individual invests in complete self-protection, i.e., in a reduction to zero of the probability of the loss, he/she gets G with certainty, while if the individual invests in complete self-insurance, i.e., in a reduction to zero of the size of the loss, he/she gets an expected payoff of $(1 - p)G$. Hence, any rational individual should value self-protection more that self-insurance.

This article attempts to make a contribution to the understanding of how individuals value risk reduction through alternative risk-management tools. First, we modify Shogren's work in order to pick up "pure" framing effects (if any). By using a lottery that makes self-protection and self-insurance indifferent to a rational individual, we test whether the different frame provided by the two risk-reduction mechanisms really determines a difference in valuation. Secondly, we investigate how individuals value risk reduction when the probability of loss is ambiguous, and compare this valuation to that given when probabilities are exactly known.

The experimental design incorporates two markets: the market for self-insurance and the market for self-protection. In these markets we try to elicit the respondents' willingness to pay for self-insurance and for self-protection for both risky and ambiguous lotteries.

The issue of a "framing effect" due to the risk-reduction mechanism is addressed by asking subjects to evaluate lotteries of the following kind: $(W - L, p; W, (1 - p))$. With such lotteries the subject faces a loss in one state of the world but no gain in the other state of the world. Hence, self-insurance that reduces the size of the loss to zero is perfectly equivalent to self-protection that reduces the probability of the loss to zero. Any difference in the valuation of the two risk-management tools can only be ascribed to the "frame."

With respect to ambiguity, the design of the experiment is meant to capture three aspects which are of potential relevance to the valuation of risk reduction:

1. The first issue concerns whether the presence of ambiguity alters the valuation of self-protection and self-insurance, and whether self-insurance and self-protection are ranked in the same order under risk and under ambiguous probabilities. For instance, an individual may prefer to install a burglar alarm in a house (self-protection) rather than put his valuables in a safe (self-insurance). But if there is no agreement concerning the probability of a burglary, would he still value the purchase of the alarm more than the safe? To test this, subjects are asked to evaluate ambiguous lotteries and risky lotteries, where both kinds of lotteries are characterized by the same expected probability of loss for an expected utility maximizer.
2. We operationalize ambiguous probabilities in three different ways. One group of subjects is asked to evaluate scenarios in which the probability of loss is given as a point estimate, but not a precise one; a second group of subjects evaluates scenarios in which the probability of loss lies within an interval; and, finally, a third group of subjects evaluates scenarios in which there is a set of four probability measures.
3. Our third goal is to provide subjects with both low-probability and high-probability lotteries. By considering a wide range of probability measures (p=3%, 20%, 50%,

80%), we test whether the attitude to ambiguity varies with changes in the reference probability. This design allows us to test whether one of the "psychological" models of behavior under uncertainty, namely Einhorn and Hogarth's (1985) "model of anchoring and adjustment" is a good predictor of valuations of risk-reductions. This model has performed pretty well in predicting consumers' willingness to pay for market insurance (see Hogarth and Kunreuther, 1985, 1989, 1992), so that it is of interest to determine whether it properly fits individual responses to risk reduction in general.

In addition, we derive predictions for another model of behavior under uncertainty, namely Gardenfors and Sahlin's (1982,1983) "model of unreliable probabilities." This latter has been interpreted as a maximin rule and applied to a case in which the set of possible probability distributions and their reliability is exogenously given. We do realize that this procedure is a simplification of the original model. However, our aim is to check for the percentage of respondents in an insurance/protection context who apply a maximin rule in choosing their buying price.[1]

This article is organized as follows. Section 1 presents the predictions of the Einhorn and Hogarth and of the Gardenfors and Sahlin models, while section 2 discusses the experimental design. The experimental results and the conclusions are outlined in sections 3 and 4 respectively.

1. Ambiguity in the probability and the valuation of self-insurance and self-protection: the predictions of two theories

1.1. Einhorn and Hogarth's model of anchoring and adjustment

Consider an expected utility maximizer with initial wealth W who faces the risk of a loss L if the bad state of the world prevails. Let p be the probability of the loss occurring. If there is no gain in the good state of the world, then he/she should give the same valuation to a reduction to zero of the loss and to a reduction to zero of the probability of the loss. Consider the lottery $(W - L, p; W, (1 - p))$. The maximum willingness to pay in order to eliminate the risk (either through insurance or protection), P, is identified by:

$$U(W - P) = pU(W - L) + (1 - p)U(W) \tag{1}$$

Assume now that the probability of loss p is not known exactly, but is ambiguous. If the individual is an expected utility maximizer, since the expected utility is linear in the probabilities, ambiguity should not affect premium setting by consumers who want to self-protect or self-insure themselves. This holds as long as the mean of the probability distribution coincides with the probability of the risky lottery.

The anchoring and adjustment model assumes that individuals evaluate an ambiguous lottery by forming a subjective assessment of the true probability, $S(p)$, according to the following functional:

$$S(p) = p + \vartheta[(1-p) - p^{\beta}], \tag{2}$$

where p is the *anchor*, i.e., the starting value of probability which is adjusted upwards or downwards according to people's perception of ambiguity and according to their attitude to ambiguity. The anchor value of the probability, p, is established according to the individual's experience and information set. ϑ $(0 \leq \vartheta \leq 1)$ is a parameter that indicates the amount of ambiguity perceived, and β is the parameter that indicates the attitude to ambiguity. In particular, $\beta = 1$ means that the individual gives equal weight to adjustments below or above the anchor. $\beta > 1$ implies that individuals attach more weight to adjustments above the anchor, and the opposite if $\beta < 1$. $\beta = 0$ implies that adjustment takes place only below the anchor.

If individuals assess probabilities according to the anchoring model, the premium for self-protection or self-insurance is identified by:

$$U(W - AP) = S(p)U(W - L) + S(1-p)U(W), \tag{3}$$

where AP is the ambiguity premium, and $S(1-p)$ is given by:

$$S(1-p) = (1-p) + \vartheta[p - (1-p)^{\beta}]. \tag{4}$$

Assuming that the anchor used in forming the value of $S(p)$ coincides with the probability of loss in the risky lottery, and normalizing so that $U(W - L) = 0$, we can divide (3) by (1) and obtain:

$$\boldsymbol{R}_c = R_c(p,\vartheta,\beta) = \frac{U(W-AP)}{U(W-P)} = \frac{S(1-p)}{(1-p)} \tag{5}$$

If the individual is averse to ambiguity, he will be willing to pay a higher premium to self-protect or self-insure against the uncertain lottery, i.e., $AP > P$. If utility is monotonically related to wealth states, this implies that $\boldsymbol{Rc} < 1$, and in turn that $S(1-p) < (1-p)$. For each positive value of β, $\boldsymbol{Rc}$ increases as the value of p rises, and the individual will eventually switch from ambiguity aversion to ambiguity preference. Each value of β, in fact, identifies a unique crossover point from ambiguity aversion to ambiguity proneness.[2]

Hypothesis 1. As the probability of a loss increases from low to high values, individuals will switch from ambiguity aversion ($\boldsymbol{Rc} < 1$) to ambiguity preference ($\boldsymbol{Rc} > 1$). The switching point depends on the individual's β.

1.2. Gardenfors and Sahlin's maximin model

According to Gardenfors and Sahlin's model (1982, 1983), individuals facing uncertainty can form subjective probabilities over the occurrence of an event that carry different degrees of *epistemic reliability*. Given a set of states of the world $S = (s_1, s_2, \ldots, s_j, \ldots, s_m)$, beliefs about the occurrence of each state s_j may be represented by a set of n probability measures, $P(s_j) = (p_{1j}, \ldots, p_{ij}, \ldots, p_{nj})$. Even if several probability distributions are possible, only some of them will be considered *epistemically reliable* by the individual. The set $P(s_j)$ includes only those probability measures held to be sufficiently reliable. Let us consider two lotteries f and g. Let $x_{jf} = f(s_j)$ be the outcome associated to the occurrence of state of the world s_j if lottery f is chosen, and $x_{jg} = g(s_j)$ be the outcome associated to state s_j if g is chosen. The utility of each outcome is denoted by $U(\cdot)$. If lotteries are evaluated according to the maximin criterion, lottery f will be preferred to lottery g when the minimum expected utility of f is higher than the minimum expected utility of g:

$$f > g \text{ if } \min \textstyle\sum_j U(f(s_j))p_{ij} > \min \sum_j U(g(s_j))p_{ij} \tag{6}$$

Where i = 1,..., n.

In choosing the premium for self-insurance or self-protection, subjects are asked to evaluate the lottery $L = P(s_1)U(W - L) + P(s_2)U(W)$ where s_1, (loss occurs), and s_2, (loss does not occur), are the two states of the world. $P(s_1)$ denotes the vector of n probability measures that are assigned a sufficient degree of epistemic reliability, while $P(s_2)$ is the vector of complementary probability measures. We will consider the case in which the set $P(s_1)$ is exogenously given by the experimenter. In particular, we assume that $n = 4$ and that $p_1 < p_2 < p_3 < p_4$. If self-protection (or self-insurance) completely eliminates risk, the best course of action will always be to invest a positive amount. The maximum willingness to pay for complete risk reduction, AP, is determined by:

$$p_4\, U(W - L) + (1 - p_4)U(W) = U(W - AP). \tag{7}$$

This is equivalent to saying that, when choosing the maximum premium they are willing to pay to self-protect or self-insure themselves, individuals give more weight to the highest probability of loss in the set $P(s_1)$.

Hypothesis 2. Individuals who apply a Gardenfors and Sahlin maximin rule will always be ambiguity averse, whatever the probability level.

2. The experimental design

2.1. The scenarios and the auction mechanism

In order to test the hypotheses put forward above, we ran 12 experiments, with 6–8 subjects per session. In six experiments, we simulated a market for self-protection, and, in the remaining six, a market for self-insurance. In each experiment, each subject was asked to evaluate eight scenarios, four referring to a risky prospect, and the remaining four to an ambiguous prospect. The four risky scenarios were characterized by four different probabilities of loss, namely, 3%, 20%, 50%, and 80%. The four ambiguous scenarios were characterized by the same four levels of "ambiguous" probabilities. In order to maintain the same level of probability at any representation of ambiguity we adopted, the means of the second-order probability distributions were 3%, 20%, 50%, and 80%.[3]

To elicit the subject's preferences we adopted a computerized auction mechanism which is a variant of the classical second-price auction. This auction was chosen in order to provide subjects with an incentive mechanism capable of inducing truthful revelation of their subjective valuations. For each market, subjects were asked to place a bid to purchase the right to self-insure (or to self-protect). Before each bid, each subject was endowed with £10 and was told that he/she faced the risk of a loss of £10 with probability p. In the market for self-protection, each subject was asked to quote his/her maximum willingness to pay to reduce the probability of loss to zero, given the size of the loss. In the market for self-insurance, subjects were asked to quote their maximum willingness to pay to reduce the loss to zero, given the probability of the loss.

One scenario at a time was visualized on the computer screen. At the start of each auction, a clock was displayed on the screen, with a price steadily increasing from zero British pence to 10 British pounds. Subjects were asked to press any key when the clock hit the most that they were willing to pay, i.e., when they wanted to leave the auction.[4] No information concerning the winner of the auction and the individual bids were provided to the participants at the end of each auction. When all the eight bids had been placed, one out the eight scenarios was chosen at random. For that scenario, the first and second highest bids were announced. The player who had made the highest bid acquired the right to self-protection (or self-insurance) and was obliged to pay the second highest bid. The rest of the participants played the lottery for real to determine whether the loss of £10 took place or not. Subjects were paid £10 if the loss did not occur and zero if the loss occurred.

Before starting the experiment proper, subjects were given a hypothetical risky scenario to help them familiarize with the problem and the auction procedure. This hypothetical lottery was then resolved in order to show subjects how payoffs would be determined. In this phase a risky scenario was deliberately chosen instead of an ambiguous one. If an ambiguous scenario had in fact been chosen in order to show subjects how the lottery would be played out, we would have been compelled to resolve the ambiguity, which would have most probably generated a sort of learning effect such as to reduce the amount of ambiguity perceived by the subjects. Since our interest concerned the relation between ambiguous and risky lotteries with a one-shot Ellsberg type of uncertainty, we wanted to make sure that the description of the type of uncertainty given to the subjects remained as vague as possible, and that subjects did not learn about the resolution of the ambiguous lotteries until after they had completed the evaluation of the eight scenarios.

For the same reason, we decided to set up the experiment as a one-shot second-price auction run for eight different scenarios, rather than use repeated auction periods for each scenario. If auction periods have to exercise market discipline, the lotteries should be resolved at the end of each period. This implies that, at each round, the subject learns more about the second-order distribution, which reduces the effect of ambiguity. At the same time, as noted by Camerer and Kunreuther (1989), this learning about the nature of uncertainty could be confused with other types of learning, for instance, that concerning the dominant strategy in second-price auctions, so that it would have been impossible to distinguish the effects of market discipline on each of the two types of learning.

Several auction periods are generally adopted in the experimental literature as a solution to the problem of overbidding/underbidding in auctions. Repeated trials should help subjects become familiar with the auction procedure and so learn the dominant strategy.[5] In our experiment, however, the auction procedure is used to elicit subjects' valuations of both risky and ambiguous lotteries. These valuations, in turn, are used to calculate the ratio of ambiguous to risky bids. Given this objective, underbidding/overbidding, even if present, should not be a problem. There is in fact no reason why overbidding/underbidding should be stronger/weaker or more/less frequent in a risky scenario than in an ambiguous one. Therefore the ratios of ambiguous to risky prices should not be affected.

The next section explains how the ambiguous lotteries were played. The instructions and examples of the scenarios are given in the appendix.

2.2. The definitions of ambiguity and making ambiguity operational

The design considers three representations of ambiguous probabilities:

1. "best estimate" probability, where the probability of loss is given as a point estimate, but not a precise one; this is the original way of representing ambiguity used in Einhorn and Hogarth (1985, 1986);
2. a set of four probability measures, which is the original way of representing Gardenfors and Sahlin (1982);
3. an interval of probability having as extreme points the extreme values of the set of probability measures in case (2) and as mean of the interval the "best estimate" in case (1); this is one of the operationalizations of ambiguity used to test the "anchoring and adjustment" model in Hogarth and Kunreuther (1989).

In all three cases it was possible to make ambiguity operational by specifying a second-order probability distribution. This was useful when we had to resolve one of the eight scenarios in the experiment, in order to determine payoffs. The problem we faced was in fact twofold: on the one hand, we had to describe an ambiguous situation in the scenario; on the other, we had to make it possible to play the scenario for real. We tried to maintain a certain uniformity, both in the description of the scenarios and in the way in which ambiguity was resolved. In the description of the scenarios, we were careful to always use the same words, and we always referred to the probability estimate (or interval or set) as given by some expert hired by a governmental agency.[6] Similarly, when we had to play the ambiguous lottery for real, ambiguity was always made operational as a second-order probability distribution for the probability of loss, although in each of the three cases this second-order distribution had different characteristics. The "best estimate" ambiguity corresponds to a second-order distribution centered on the "best estimate" value. The interval of probability corresponds to a uniform distribution of the probability measures inside the interval. The set of probabilities corresponds to a situation where various second-order distributions are possible, but the subject does not know ex ante which particular one will apply. Hereunder, we provide a brief description of how the three types of ambiguity were made operational:

Best estimate probability. Subjects were told that p was the most reliable estimate of the likelihood of the loss but that the expert who had provided the value was not 100% certain. By doing this we tried to induce the subjects to anchor on the value of p. We made this definition of ambiguity operative by asking one of the subjects to draw a ticket out of a bag containing five tickets, three with the probability estimate given in the scenario and two with values corresponding the the extremes of the intervals in case (3). The ticket drawn determined the combination of black and white balls from which subjects were asked to draw a ball. The anchors provided were 3%, 20%, 50%, and 80%.

Probability interval. Subjects were given a range (p_L, p_H) within which the true probability lay. The probability intervals provided were:

(1%, 5%), (5%, 35%), (35%, 65%), (65%, 95%)

The average values of these intervals coincide with the probabilities in the best estimate scenarios. To resolve lotteries characterized by this type of ambiguity, we asked subjects to first draw a ticket from a bag containing as many tickets as there are integers inside the interval. The ticket drawn corresponded to the combination of black and white balls put in the bag from which subjects had to pick a ball.

Set of probability measures. Subjects were given four probability estimates of the possible loss, (p_1, p_2, p_3, p_4), for each scenario. However, the reliability of each of these estimates was not known. This is equivalent to saying that the second-order distribution of probability was unknown. The sets of probability measures chosen were:

(1%, 2%, 4%, 5%), (5%, 15%, 25%, 35%), (35%, 45%, 55%, 65%), (65%, 75%, 85%, 95%)

Again, the mean value for each set corresponds to the "best estimate" provided in the first type of ambiguous lottery described. To make ambiguity operational we told subjects that loss could occur with four different probabilities (p_1, p_2, p_3, p_4) but that the experimenter did not know which probability measure was the most reliable. We then asked one subject to draw a six-face die from a bag containing 10 biased dice.[7] The die was played and the number drawn corresponded to a bag with a combination of black and white balls reflecting one of the p_i's. One of the subjects was then asked to draw a ball to resolve the lottery.

3. Experimental evidence

The data presented in this section was obtained by running the experiment with 82 students of the University of York in May 1994. Each subject was asked to evaluate eight scenarios relating to the same risk-management tool (self-insurance or self-protection) and to only one type of ambiguity (either "best estimate" or "interval" or "set of probability measures"). Each subject provided his/her valuation at each probability level. For each experimental session, the scenarios were arranged in random order using the table of random numbers. On the whole, four factors were manipulated in the experiment: two of them were *between* subjects factors (risk-reduction mechanism, type of ambiguity), and the other two were *within* subjects factors (risky versus ambiguous lottery, probability levels). Table 1 presents the mean, median, and standard error for the various experimental markets. For each risk-reduction tool summary statistics are provided at each probability level for risky lotteries, and for each definition of ambiguity.

3.1. *Sensitivity of valuations to the risk-reduction tool*

Table 1 allows for a first check of whether, on average, self-protection is valued more than self-insurance, as assumed by Shogren. As the table shows, there is no positive evidence of a "framing effect" due to the risk-reduction mechanism used: a cursory look shows that the ratios of mean and median prices for self-protection to those for self-insurance are in the majority of cases not very different from one.

The Mann–Whitney *U*-test for independent samples was used to check whether the valuation of self-protection was stochastically larger than that for self-insurance. The results of the test (see table 2) show that self-protection is significantly larger than self-insurance in few experimental conditions. In the valuation of the risky lotteries, there is evidence of a framing effect due to the risk-reduction mechanism at the probability levels of 3% and 50%. When ambiguous lotteries are compared, there are two definitions of ambiguity in which we find some evidence of framing–namely, the "best estimate" and the "interval of probability" type of ambiguity. For the former, the ratio of mean and median prices for self-protection to those for self-insurance is always strictly greater than one, and self-protection is significantly higher than self-insurance at the probability level of 3%. In the latter, self-protection is significantly higher than self-insurance at the probabilities of 50% and 80%.

The risk-reduction mechanism was also manipulated as a within-subject factor for 12 subjects who participated in both experimental markets. This procedure provided us with a control group for whom we could observe matched pairs of prices for the two risk-reduction tools (see table 3).[8] There was no evidence in the control group suggesting a framing effect due to the risk-management tool: mean and median values for self-insurance and self-protection are fairly similar, regardless of whether self-protection was the first or the second experiment in which the subject participated. For each respondent in the control group we also calculated the ratio of the bid for self-protection to the bid for self-insurance. We found that two subjects out of 12 valued self-protection consistently

Table 1. Summary statistics of individual bids

Asset market	Probability of loss	Mean	Median	Standard deviation	Number of subjects
Self-insurance (risky lotteries)	3%	66	34	75	38
	20%	255	202	127	
	50%	434	500	162	
	80%	650	709	222	
Self-protection (risky lotteries)	3%	61	51	50	32
	20%	250	205	178	
	50%	517	521	136	
	80%	637	737	242	
Self-insurance (Best estimate)	3%	40	31	33	8
	20%	216	181	112	
	50%	376	452	135	
	80%	583	700	216	
Self-protection (Best estimate)	3%	116	46	161	8
	20%	228	227	170	
	50%	528	500	196	
	80%	745	812	230	
Self-Insurance (Intervals of probability)	3%	106	101	62	15
	20%	292	264	96	
	50%	488	561	94	
	80%	538	511	228	
Self-protection (Intervals of probability)	3%	70	49	61	12
	20%	279	214	135	
	50%	543	521	86	
	80%	833	824	40	
Self-insurance (Set of probabilities)	3%	61	31	62	15
	20%	272	205	140	
	50%	482	500	216	
	80%	630	501	242	
Self-protection (Set of probabilities)	3%	67	65	33	12
	20%	312	300	100	
	50%	495	516	107	
	80%	692	775	189	

more than self-insurance, and thus were clearly prey to the "frame" suggested by Shogren.[9] For the control group we carried out a Wilcoxon rank-sum test, but the value of the test statistic T was always above the critical value, so that we could not reject the hypothesis that the two samples were drawn from the same parental distribution.

3.2. *Valuation of risky versus ambiguous lotteries*

To determine whether subjects valued risk-reduction in the presence of ambiguous probabilities more or less than risk-reduction with known probabilities, we calculated ratios of bids in "ambiguous" lotteries to bids in risky lotteries. Table 4 presents the mean ratios of

Table 2. Mann–Whitney test between risk-reduction mechanisms (one-tail test): values of U

	3%	20%	50%	80%
Risky lotteries[a]	1.78*	.2	2.64*	.058
Ambiguous lotteries				
Best estimate	27	8*	16	16.5
Interval of probability	61.5	68	27*	16*
Set of probabilities	79	67.5	89.5	79

*Significant at the 95% level in that self-protection is stochastically larger than self-insurance.
[a]For risky lotteries, the standardized normal variable Z is given instead of U, since for large samples the sampling distribution of U approaches the normal distribution.

ambiguous to risky bids for each of the two markets and for each type of ambiguity. The table format allows us to observe whether on average ambiguity aversion (a ratio greater than one) or ambiguity preference (a ratio less than one) prevails in our sample of respondents. Also, the table allows a direct test of the anchoring and adjustment model. If individuals behave according to the Einhorn and Hogarth model, we should observe ambiguity aversion with low probabilities of loss and ambiguity preference with high probabilities; moreover, the ratio of ambiguous to risky bids should decline monotonically as the probability of loss rises.[10]

The first result that emerges from the data is that the mean ratios are, in the majority of cases, different from one. The mean ratios, however, do not provide support for the model of Einhorn and Hogarth. Nowhere do we find a monotonically decreasing ratio of am-

Table 3. Summary statistics of individual bids for the control group (risky lotteries only)

Asset market	Probability of loss	Mean	Median	Standard deviation	Number of subjects
Self-insurance*	3%	83	91	70	7
(1st experiment)	20%	240	209	77	
	50%	418	413	148	
	80%	666	765	226	
Self-protection	3%	103	104	102	7
(2nd experiment)	20%	260	252	131	
	50%	497	513	174	
	80%	723	801	135	
Self-insurance	3%	58	24	73	5
(2nd experiment)	20%	196	195	92	
	50%	414	455	207	
	80%	610	601	157	
Self-protection	3%	61	24	66	5
(1st experiment)	20%	176	195	73	
	50%	436	455	169	
	80%	517	601	268	

*The first section of the table reports results for seven subjects who participated in the self-insurance experiment first and then in the self-protection experiment. The second section of the table presents results for five subjects who played in a self-protection experiment first.

Table 4. Means of individual ratios of ambiguous to risky bids

	Probability of loss			
	.03	.20	.50	.8
Self-insurance				
Best estimate	2.24	.90	.90	.90
Interval of probability	3.74	1.10	1.10	1.15
Set of probabilities	2.5	1.12	1.32	0.87
Self-protection				
Best estimate	1.62	1.47	1.20	2.25
Interval of probability	1.18	1.17	1.01	1.35
Set of probabilities	1.11	1.93	1.01	1.25

biguous to nonambiguous bids as predicted by that model, whatever the specification of ambiguity. Hence there does not seem to be on average any evidence of anchoring and adjustment, not even in the scenarios that should encourage anchoring to the probability measure provided, namely, the "best estimate" definition of ambiguity. The mean ratios are always greater than one with low probability of loss (3%), which indicates ambiguity aversion, but only in two instances do we find ambiguity preference with high probability levels (self-insurance, best estimate scenario, and set of probabilities scenario). In the other scenarios the mean ratios are strictly greater than one, as predicted by the model by Gardenfors and Sahlin. To test the statistical significance of the difference between ambiguous and risky bids, we use a Wilcoxon rank-sum test. We find that the impact of ambiguity is quite weak: as table 5 reports, the value of the test statistic T indicates that in the majority of experimental conditions ambiguous and risky bids were derived from the same parental distribution. These results parallel those obtained in two other experimental papers in which ambiguous lotteries involve losses: Camerer and Kunreuther (1989), which uses a double oral auction mechanism, and Cohen, Jaffray, and Said (1985), with one-shot choices.[11]

Table 5. Wilcoxon rank-sum test between risky and ambiguous bids (T values)

Asset market	Probability of loss			
	3%	20%	50%	80%
Self-insurance				
Best estimate	$T = 10$	10	7	13
Interval of probability	35	21*	34.5	18*
Set of probabilities	19.5	9*	30	39
Self-protection				
Best estimate	3	10	14	1*
Interval of probability	15	4*	37	4*
Set of probabilities	31.5	4*	30	22

*Significant in that risky and ambiguous bids were derived from the same parental distribution.

To explore further which model best fitted the data, we proceeded to analyze the pattern of the individual ratios of ambiguous to risky bids at varying probability levels. This approach was justified by the fact that the sample size for some of our experiments was quite small so that the presence of outliers could distort the value of the means.[12] Table 6 gives the number of subjects who behaved according to the predictions of expected utility, the anchoring model, the maximin model, and the number of those who were consistently ambiguity prone/averse. Results are given for the pooled experimental sessions. The behavioral model that receives more support from the analysis of individual data is the anchoring and adjustment one. This model of behavior fits particularly well the valuations for self-insurance, while it receives less support from the self-protection experiments, regardless of the definition of ambiguity. About 33% of the whole sample behaved according to the predictions of the model. Some of the subjects behaved according to a "weak" version of the anchoring rule: although the ratio between ambiguity prices and risky prices did not decrease monotonically, subjects always displayed ambiguity aversion at low probability levels and ambiguity preference at high probability levels. Sixteen subjects, however, displayed exactly the decreasing monotonic relation between ratios of bids and probability of loss predicted by Einhorn and Hogarth. Seventeen subjects behaved according to expected utility: the majority of them were students of economics. Only two of our subjects adopted a clear maximin strategy, since their bids for the ambiguous lotteries were close to the highest expected loss.

The last row of table 6 gives the number of subjects whose behavior is not consistent with any of the two considered theoretical models of ambiguity, and who, on the other hand, are not either consistently ambiguity averse or ambiguity prone. However, even in this group we find some regularities in behavior, which suggest that these 26 subjects cannot simply be dismissed as white noise. Table 7 tries to give a detailed breakdown of their behavior. Several subjects (7) displayed ambiguity proneness with the low probability (3%) and with the high probability (80%), as well as ambiguity aversion in between. Four subjects displayed a pattern of behavior exactly opposite to that predicted by Einhorn and Hogarth model, i.e., they exhibited ambiguity proneness with the probabilities of 3% and 20% and ambiguity aversion at the probabilities of 50% and 80%. Nine other subjects were defined as "ambiguity averse/prone with error", since they behaved as ambiguity averse/prone at all probability levels except one.[13] If we keep these consistencies into account, then we end up with only 6 subjects whose behaviour cannot be explained. However, we feel very cautious in attributing these regularities in the subjects' behaviour

Table 6. Number and percentage of subjects whose behavior is consistent with a theoretical model of behavior under uncertainty

Model	Number of subjects	%
Expected Utility	17	20.6
Anchoring and Adjustment	27	33
Maximin	2	2.5
Ambiguity Proneness	2	2.5
Ambiguity Aversion	9	9.7
Others	26	31.7

Table 7. Disaggregation of the group "Others" in table 6.

Pattern of behavior	Number of subjects	%
Ambiguity adverse with error	5	6
Ambiguity prone with error	4	4.9
Ambiguity prone at $p \leq .20$ and averse at $p \geq .5$	7	8.5
Ambiguity averse at $p = .03$ and $p = .80$, ambiguity prone at $p = .20$ and $p = .50$	4	4.9
Unexplained behavior	6	7.3

to any particular model of ambiguity. A direct test of other models (e.g., Segal (1987), or Tversky and Kahneman (1992)), would have required a different design of the experiment.

Worthy of notice, finally, is the fact that, as in previous studies, (see, for instance, Shoemaker, 1991), no correspondence is found between attitude to risk and attitude to ambiguity: ambiguity aversion or preference were completely independent of risk aversion or preference.

4. Conclusions

This article has considered experimental markets for two risk-reduction mechanisms in order to obtain individual valuations of risk reductions.

We do not find any positive evidence of a "framing effect" due to the risk-reduction tool, as assumed in Shogren (1990). With our experimental design, the two risk-management tools provided exactly the same payoff. Under these circumstances the frame was created simply by a difference in the words used. The significance of the "framing effect" could, however, be affected by the context used. Therefore, in view of the importance that protection and insurance against environmental risks, product failure and workplace risk have assumed in policy making, we think that the issue of the comparative valuation of risk-reduction tools deserves to be explored further.

Concerning the valuation of risky versus ambiguous lotteries, although we find that mean ratios of ambiguous to risky bids are always different from one, comparison of the bids for ambiguous lotteries with those for risky lotteries through a non-parametric test, shows a weak effect for ambiguity. This result is in line with those obtained by Cohen, Jaffray, and Said (1985) and Camerer and Kunreuther (1989). Also, no significant difference results from the particular definition of ambiguity used.

Finally, given the similarities between the self-insurance and self-protection contexts and market insurance, we have tested whether the model of "anchoring and adjustment"—which has performed well in the insurance frame—was a good predictor of behavior in our sample. We do not find any evidence to this end when we look at mean ratios, which do not show the monotonically decreasing pattern predicted by that model and found by

Hogarth and Kunreuther (1989). However, the analysis of individual responses shows that some 33% of the sample behaved according to the predictions of the theory. Hogarth and Kunreuther's study did not use a market incentive to reward subjects (a flat payment was adopted), while in our work we chose a one-shot auction. Further research should therefore consider the sensitivity of the performance of the model to the incentive mechanism used.

Appendix: Instructions for self-protection experiment

You are about to participate in an experiment concerning decision making under risk and uncertainty. The purpose of the experiment is to gain insight into certain features of economic behavior. 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 eight 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 would suffer a loss of money. However, you have the opportunity to take some action at some monetary cost. If you take this action you will be able to reduce the probability of the occurrence of such an event to zero. Each scenario differs according to the probability of the occurrence of such an event.

Try to think of each scenario as a real situation.

For each scenario you will be asked to state the maximum amount you are willing to pay to reduce the probability of the occurrence of such an event to zero.

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 reduce the probability of the loss to zero and she or he 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. 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 pounds 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 a 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, 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 number 5 is picked, the experimenter will enter that number into the control computer. At this point, the screen will display 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. In this way you will acquire the right to reduce the probability of the occurrence of the event 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 probability of the occurrence of the event 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 £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 question. Please notice that after a 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.

Examples of self-protection scenarios

Best estimate. Assume that there is a potential risk of the occurrence of some event; an expert, hired by a governmental agency, estimates that the probability of the occurrence of such an event is 20%. However, this is the first investigation ever carried out; consequently, you experience considerable uncertainty about the precision of this estimate. If this event occurs, you will suffer a loss of £10.

You are now asked to state the maximum amount of money that you would be willing to pay to reduce the probability of such an event to zero.

Interval of probability. Assume that there is a potential risk 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 5% and 35%. If this event occurs you will suffer a loss of £10.

Set of probabilities. Assume that there is a potential risk of the occurrence of some event. There is an estimate of the possible occurrence of this event; four experts, hired by a governmental agency, have each provided estimates of the probability of the occurrence of such an event. These four estimates of probability are 5%, 15%, 25%, and 35%. All these estimate carry some reliability, although you do not know if any of them is more reliable than the others. If this event occurs, you will suffer a loss of £10.

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Notes

1. In an experiment in which individuals were asked to evaluate several ambiguous lotteries, Maffioletti (1995) found that half of the subjects applied the maximin rule. In this experiment, however, only gains were involved.
2. It can be easily verified that a necessary condition for the individual to remain persistently ambiguity averse, whatever the value of the anchor, is that $\beta = 0$. For each positive value of β, as the value of p rises, Rc increases. If $\beta \leq 1$, the switching point from ambiguity aversion to ambiguity preference will take place at a value of the anchor such that $(1 - p) < .5$. If $\beta \leq 1$, in fact, the individual will give more weight to adjustments below the anchor $(1 - p)$, and hence will deem the state of the world involving a loss more probable. If $\beta > 1$, the individual can only be ambiguity averse for $(1 - p) > .5$.
3. As will be explained in detail in section 2.2., ambiguity was always operationalized as a second-order probability distribution.
4. For reference to this type of clock auction, see Harstad (1990). On the preference revealing properties of the Vickrey auction in the presence of ambiguity, see Karni and Safra (1986) and Salo and Weber (1994).
5. Cf. Coppinger, Smith, and Titus (1980) and Coursey, Hovis, and Schultze (1986). However, there is no conclusive evidence of the existence of a learning process that eliminates over/underbidding (see Kagel,

Harstad, and Levin, 1987; Kagel and Levin, 1993). Moreover, Gregory and Furby (1987) argue that the use of hypothetical lotteries that are not resolved could, rather than lead to learning, induce the building of bargaining positions to be used in the non-hypothetical auction period.

6. By doing this, we meant to avoid problems tied to source reliability which might affect the valuations of the scenarios used in Hogarth and Kunreuther (1989).
7. Numbers on the die go from 1 to 4 and stand for the number of probability measures in each set. The number of times a number corresponding to a probability measure figures on a die gives the weight attached to that probability measure. Given the 10 dice:

A 1,1,1,2,3,4
B 2,2,2,1,3,4
C 3,3,3,1,2,4
D 4,4,4,1,2,3
E 1,1,2,2,3,4
F 1,1,3,3,2,4
G 1,1,4,4,2,3
H 2,2,3,3,1,4
I 2,2,4,4,1,3
J 3,3,4,4,1,2.

Die A gives a weight of 1/2 to p_1, and 1/6 to each of p_2,p_3, and p_4, Each set of weights is equally probable.

8. More precisely, five subjects took part in the self-insurance experiment first and then in the self-protection experiment, while seven subjects participated in the two experiments in the reverse order.
9. One of them played the self-protection experiment as his/her second experiment, while the other played self-protection before self-insurance.
10. Also, this table format allows a direct comparison with the results obtained in Hogarth and Kunreuther (1989), who use the same type of table and obtain strong support for the Einhorn and Hogarth model.
11. Eisenberger and Weber (1995) find a slightly stronger ambiguity effect in a experiment using a one-shot design.
12. Tables 1 and 4 were also constructed eliminating the highest bid from each auction that we run. However, in table 1 this did not eliminate the disparity between mean self-protection and mean self-insurance prices wherever this difference existed. Likewise, elimination of the highest bid did not eliminate the presence of ratios greater than one in table 4, which were due to the presence of extremely ambiguity averse individuals.
13. Provided the ratio of ambiguous to risky bid at that probability is not sensibly different from one.

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