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When and why do people avoid unknown probabilities in decisions under uncertainty? Testing some predictions from optimal foraging theory

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Abstract

When given a choice between two otherwise equivalent options — one in which the probability information is stated and another in which it is missing — most people avoid the option with missing probability information (Camerer & Weber, 1992). This robust, frequently replicated tendency is known as the *ambiguity effect*. It is unclear, however, why the ambiguity effect occurs. Experiments 1 and 2, which separated effects of the comparison process from those related to missing probability information, demonstrate that the ambiguity effect is elicited by missing probabilities rather than by comparison of options. Experiments 3 and 4 test predictions drawn from the literature on behavioral ecology. It is suggested that choices between two options should reflect three parameters: (1) the need of the organism, (2) the mean expected outcome of each option; and (3) the variance associated with each option's outcome. It is hypothesized that unknown probabilities are avoided because they co-occur with high outcome variability. In Experiment 3 it was found that subjects systematically avoid options with high outcome variability regardless of whether probabilities are explicitly stated or not. In Experiment 4, we reversed the ambiguity effect: when participants' need was greater than the known option's expected mean outcome, subjects preferred the ambiguous (high variance) option. From these experiments we conclude that people do not generally avoid ambiguous options. Instead, they take into account expected outcome, outcome variability, and their need in order to arrive at a decision that is most likely to satisfy this need.

Keywords: Decision making; Optomal foraging theory; Ambiguity effect

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1. Introduction

Over the course of the last 40 years, there has been an extensive and controversial debate in the psychological and economic literature over the quality of human decision making in uncertain situations (Kahneman, Slovic & Tversky, 1982; Gigerenzer, 1996; Gigerenzer & Goldstein, 1996; Kahneman & Tversky, 1996). In this debate, one of the most prominent demonstrations of allegedly irrational decision making has been the *ambiguity effect*. This occurs when people choose an option in which the probability information is explicitly stated over one in which it is either imprecise or lacking, even though both have the same expected utility. Consider, for example, the famous two color problem first proposed by Ellsberg (1961):

> You are given the opportunity to win money in a lottery. The lottery consists of two boxes. One box contains 50 black and 50 white balls, the other box also contains 100 black and white balls but in an unknown composition. Suppose a ball is randomly drawn from one box and you receive \$100 if the ball is black. Which box would you bet on? Suppose now the ball is returned to its box and another ball is drawn at random from one of these boxes. This time you would receive \$100 if the ball is white. Which box would you bet on?

Faced with a choice task like this, most people bet on the 50/50 box in both cases. Although this pattern of preferences is intuitively compelling, it violates one of the fundamental axioms of rational decision making, namely the Additivity Axiom of Subjective Expected Utility Theory (Savage, 1954).

According to this axiom, subjective probabilities assigned to white and black for a given box must sum to 1. The probability of drawing black from the 50/50 box is 0.5: you would not choose it for black unless you thought the probability of drawing black from the ambiguous box were less than 0.5. If the probability of drawing black from the ambiguous box is less than 0.5, then the probability of drawing white from it must be *greater* than 0.5 (by the Additivity axiom). By the same logic, however, preferring the 50/50 box when you want to draw *white* implies you believe the probability of drawing white from the ambiguous box is l*ess* than 0.5. The probability of drawing white from the ambiguous box can't be both greater and less than 0.5. In other words, preferring the 50/50 box for both bets — regardless of whether your goal is to draw black or white — involves a contradiction. Moreover, it commits one to the view that the subjective probabilities assigned to the ambiguous box for white and black are each less than 0.5, which means they sum to less than 1: a conclusion that violates the Additivity axiom.

The fact that people typically prefer the 50/50 box for both bets has been widely interpreted as a preference for known probabilities over unknown (ambiguous) ones. Twenty years of research have shown this response pattern to be strong and reliable, persisting even in the face of energetic attempts to eliminate it (MacCrimmon, 1968; Curley, Yates & Abrams, 1986; Bowen, Qiu & Li, 1994).

Given that many decisions in our natural environment have to be made on the basis of imprecise information about risks, the ambiguity effect is of high practical relevance. Moreover, given that people in real life sometimes deliberately choose ambiguous options, it is equally interesting to discover under what circumstances ambiguous options are preferred. A person who invests in a new technology, undergoes an experimental medical procedure, or goes to court has, in effect, chosen the ambiguous option. This means we need a theoretical explanation that allows us to predict which conditions will cause ambiguity to be avoided and which will cause it to be preferred (but see Einhorn & Hogarth, 1985 for a descriptive model of ambiguity avoidance and preference). Despite a long history of research, this basic question has not yet been answered.

In fact, a review of the literature on the ambiguity effect reveals that it is not even clear whether it is ambiguity per se that people are avoiding. There are (at least) two distinct factors that could be eliciting the ambiguity reaction: (1) the missing probability parameter itself, or (2) motivational or attributional factors that arise when one is asked to compare two options in a choice task. Before we can formulate an explanation for the ambiguity effect, we must determine which factor — missing probabilities or the task format — are eliciting it.

Therefore, this article is organized in the following way. In the first section, we present two experiments designed to test whether ambiguity avoidance is elicited primarily by unknown probabilities or task characteristics. In the second section, we propose and test a theoretical explanation that is based on the assumption that the human cognitive architecture is well-designed for making decisions in uncertain environments, and that the ambiguity effect is a byproduct of the application of an adaptive choice strategy that not only uses information about the mean payoffs of different options, but also about their variance and the organism's needs. Risk-sensitive foraging theory (as the theoretical framework is called) provides a principled basis for studying under which circumstances organisms will avoid and prefer uncertain options (e.g. Stephens & Krebs, 1986).

In this view, the system is not designed merely to maximize expected utility. It is designed to minimize the probability of an outcome that fails to satisfy one's need.

If, for example, one needs a certain amount of food to survive until tomorrow, then one should be willing to take risks to avoid falling below that baseline. When two resource patches have the same mean payoff but different payoff variance, you ought to forage on the low variance patch, *unless* the payoff you need is higher than its mean. If it is, then your best hope for surviving until tomorrow is to forage on the high variance patch. Options with known probabilities and ambiguous options are equivalent with respect to the expected mean payoff but they differ with respect to the variability of possible outcomes. Given a known probability the range of possible mean payoffs and the variance is low whereas the range of possible mean payoffs and the variance is high given an ambiguous option.

We postulate that people associate ambiguous probabilities with highly variable outcomes. Risk-sensitive foraging theory then implies that people do not avoid ambiguous options indiscriminately. When the outcome they need is higher than the mean payoff of both options, they should *prefer* the ambiguous one because the distribution of its possible outcomes is more variable and therefore it is more likely to obtain an outcome above the mean payoff. Two experiments in the second section of this article provide evidence that people use an adaptive decision rule with the properties just described.

2. Cognitive and motivational effects on ambiguity avoidance

Ambiguity or uncertainty avoidance has traditionally been approached from two different perspectives: cognitive and attributional/motivational. The descriptive or ''cognitive'' approach assumes that ambiguous probability information is transformed into a precise estimate (Ellsberg, 1961; Einhorn & Hogarth, 1985; Einhorn & Hogarth, 1986; Curley & Yates, 1989) and that this precise term is used to calculate the option's expected utility. A person thus does not compare an unambiguous to an ambiguous option, but one with a stated probability term to one with an estimated probability term. To explain biases in choice behavior, exponents of this approach posit a cognitive mechanism that systematically distorts the probability estimation. The characteristics of this distortion process will determine whether the ambiguous option will appear more or less attractive than one of known risk that has the same ''on paper'' expected utility. If the estimation rule is known for a particular subject, choices can be predicted. Different models propose different estimation processes (see Camerer & Weber, 1992 for a review). For example, the algorithm suggested by Ellsberg is a linear combination of the expected value of the probabilities, the lowest possible probability and a parameter of the confidence for those estimations.

A more recent model (Einhorn & Hogarth, 1985) proposes an anchoring and adjustment mechanism to explain ambiguity avoidance. In a state of uncertainty, a subject first assigns a value to the unknown probability parameter, which serves as an anchor. By applying a nonlinear transformation rule to this anchor, the subject arrives at the final estimation of the probability (adjustment). This adjustment process depends on the number of possible values of the probability that the subject can imagine and a differential weighing of values that are above and below the anchor. The distinctive claim of these models is that people avoid ambiguous options because the process whereby they estimate the relevant probability parameter is inappropriate: it causes them to perceive the expected utility of the ambiguous option as lower than that of the unambiguous one.

An alternative approach holds that ambiguity avoidance emerges during the choice task. According to this approach, people systematically avoid the more ambiguous option because of secondary motivational or attributional factors that arise during the comparison process. In this view, people actually compare an unambiguous option to an ambiguous one and the missing knowledge elicits processes that causes them to avoid the ambiguous option. For example, reasons for choosing the unambiguous option are more ''available'', making this choice easier to justify (Curley et al., 1986). In this view, people are reluctant to bet on inferior knowledge, but only when this inferiority is brought to mind — as in a choice task — does their reluctance result in ambiguity avoidance (Fox & Tversky, 1995; p. 599). A similar view holds that the unambiguous option makes us feel more competent; therefore a possible win can be attributed to competence whereas a possible win with an ambiguous option would have to be attributed to chance (Heath & Tversky, 1991). According to other motivational accounts, subjects suspect they are facing a hostile opponent who might take advantage of their lack of knowledge, so they favor the unambiguous option (Frisch & Baron, 1988).

Neither the cognitive nor the motivational explanations are satisfying. First, no model has yet been confirmed by coherent experimental data. Second, none of them provides a conclusive theory of the ambiguity effect. Although the cognitive models formally describe the observed behavior, they do not explain why the transformation process should be distorted in such a systematic way. The motivational/attributional explanations have similar shortcomings: they are post hoc and not theory-generated. As a result, it remains unclear why (for example) it is easier to justify choosing an unambiguous option than an ambiguous one.

Before we suggest an alternative explanation for ambiguity avoidance, we need to determine what factors elicit it. The first step is to distinguish effects of missing probability information from effects related to the choice task.

Following the practice in the literature of distinguishing between uncertainty (situations where probability information is lacking) and risk (situations where probability information is known [but $<100\%$]), for ease of exposition we will henceforth call the unambiguous option, with its explicitly stated risk, the ''known-risk option''.

3. Experiment 1

In the typical experiment demonstrating the ambiguity avoidance effect, subjects are given a choice task containing two options, one of which is ambiguous. This method confounds the ambiguity of probability information with the choice task format, so it cannot be used to test between the cognitive and motivational families of explanation. The purpose of Experiment 1 is to disentangle these two factors, to see whether ambiguity avoidance is elicited by missing probability information or the choice task format.

If ambiguity avoidance is caused by a cognitive mechanism that systematically distorts the estimation of an ambiguous probability term, then an ambiguous option should be less attractive than an equivalent option of known risk even when it is presented alone, without any other option to which it can be compared. But if it is elicited by a comparison process, as the motivational/attributional accounts claim, then an ambiguous option should be less attractive than the equivalent known-risk option only when both options are presented simultaneously within a choice task.

To test these predictions, subjects were asked to rate the attractiveness of experimental lotteries under three different Conditions. In Condition 1, subjects were presented only with lotteries of known risk. In Condition 2, subjects rated only ambiguous lotteries. In Condition 3, subjects were given a choice task and, after the choice, were asked to rate the attractiveness of both kinds of lotteries, following the typical procedure for ambiguity experiments (Yates & Zukowsky, 1976; Curley et al., 1986).

3.1. Method

3.1.1. Subjects

Fifty-one (17 per Condition) undergraduates from the University of California, Santa Barbara participated in this experiment (mean age: 20.7 years). They received \$5 for participating, with the possibility of earning more if they were selected to play some of the lotteries for real money (see below).

3.1.2. Materials and procedure

The task was to rate the attractiveness of experimental lotteries. Each lottery was described as involving a box that contains a total of 100 balls. Each ball is either black or white. In each lottery, the subject is given the opportunity to draw a ball (without looking) from this box. If the subject draws a black ball, then that subject wins \$10. If the subject draws a white ball, he/she wins nothing. Each subject rated five lotteries. The type of lottery presented (only ambiguous lotteries, only known-risk lotteries, or both types of lotteries) was varied between subjects, while the probability of winning a lottery was varied within subjects. The five lotteries employed five levels of probability between 0.3 and 0.7 (0.3; 0.4; 0.5; 0.6; 0.7). The experiment was administered as a paper-and-pencil test in the form of a booklet. However, the subjects were told that, after completing the questionnaire, a few of them would be randomly selected to actually play some of the lotteries for real money, according to their answers in the questionnaire. This procedure was used to ensure that subjects would think carefully about the problems.

Subjects were randomly assigned to one of the following three Conditions:

3.1.2.1. Condition 1. The five lotteries were all of known risk. Each lottery explicitly stated the probability of winning that lottery as the exact number of black balls in the box. For instance, the subject might be told that there are exactly 30 black balls and 70 white balls in the box.

3.1.2.2. Condition 2. The five lotteries were all ambiguous. In these lotteries, the probability of winning was described as an interval: e.g. the subject might be told that the exact number of black balls could be any number between 0 and 60. The center of each interval was equal to the known-risk probability for the matching lottery in Condition 1. The interval was always $\pm$ 30 balls.

3.1.2.3. Condition 3. There were five pairs of lotteries, all presented in the form of a choice task. In each choice task, they were asked to choose between a lottery of known risk and an ambiguous lottery of equivalent expected utility and next they rated both lotteries.

To measure the attractiveness of the lotteries, we used the minimum selling price (MSP) paradigm proposed by Becker, DeGroot and Marschak (1964). The minimum selling price is determined as follows. The subject owns a lottery. The MSP is the smallest amount of money for which the subject will sell her right to play the lottery. That is, if the subject gets just one cent less than this price, she would rather play the lottery. But if she is given the MSP, then she will sell the lottery to the experimenter.

Independently of the MSP, the experimenter determines a buying price by picking a pokerchip from a box that contains 101 poker chips labeled from 0 cents to $10 in 10 cent increments. If the buying price is equal to or higher than the MSP, the subject must sell the lottery in exchange for the buying price. If the buying price is lower than the subject's MSP, then the subject does not sell the lottery, and plays it instead.

Each subject was given a questionnaire that contained five lotteries and was asked to state his or her MSP for each lottery. The order of the lotteries was determined randomly for each subject. The subjects who received ambiguous lotteries were told that the exact number of black balls in the box will be determined randomly within the given interval by picking a number from a box with poker chips. In this box, each poker chip was labeled with one of the 61 possible numbers of black balls. This box, as well as the box that was used to determine the experimenter's buying price, was shown to the subjects. They were told that the actual distribution for the ambiguous lotteries and the buying prices would be determined by an independent person who draws the relevant information by using these boxes when the lotteries are played.

The experiment was conducted in group sessions and 10 percent of those participating in a session were selected after they filled out the questionnaire to play two of their lotteries for real money.

3.1.3. Predictions

If ambiguity avoidance is caused by a cognitive distortion of probability estimation, then the ambiguous lotteries should be regarded as less attractive than the known risk ones, independent of context. In other words, the difference between the MSP in Condition 1 (in which only known-risk lotteries were presented) and the MSP in Condition 2 (in which only ambiguous lotteries were presented) should be equal to the difference between the MSP between known-risk and ambiguous lotteries in the choice task in Condition 3.

In contrast, if the comparison process inherent in choice tasks produces ambiguity avoidance, then, as usual, the ambiguous lotteries should elicit a lower MSP than their matching known-risk ones in the choice tasks of Condition 3. But there should be no difference between the MSP in Conditions 1 and 2, in which lotteries were presented without an alternative option.

3.2. Results and discussion

The minimum selling prices (MSP) stated by the subjects were analyzed in two separate analyses of variance (ANOVAS). First, the MSPs of Condition 1 and Condition 2 (only known-risk vs. only ambiguous lotteries) were compared in a 2×5 (type of lottery: ambiguous or known-risk $\times$ level of probability) ANOVA. As the cognitive models — those claiming that ambiguity avoidance is elicited by the ambiguous probability parameter itself — predict, there was a significant difference between the MSP assigned to ambiguous lotteries and those assigned to known-risk lotteries ($F(1, 32) = 11.262$, $P < 0.05$, Table 1). As shown in Fig. 1, the MSPs for ambiguous lotteries are about $1 lower than the respective MSPs for known-risk lotteries over the entire range of probabilities. Hence, even in the absence of contextual information — such as the presence of a choice task — the ambiguity effect persists.

If missing probability information is the only source of the ambiguity effect, a replication of these data is expected for Condition 3, in which subjects were given a choice between a known-risk and an equivalent ambiguous lottery. To test this prediction, a within-subjects comparison was performed on the MSPs assigned to ambiguous and known-risk lotteries in Condition 3. Contrary to this prediction, the 2×5 (type of lottery $\times$ level of probability) ANOVA revealed a significant interaction between the type of lottery and the level of probability ($F(4, 64) = 2.811$, $P < 0.05$, see Table 1), in addition to a significant main effect for the type of lottery ($F(1, 16) = 23.5$). Fig. 2 shows that the difference between MSP for known-risk and ambiguous lotteries increased when probability of winning was high (see also Discussion section of Experiment 4 for a similar finding). Also, closer inspection of Fig. 2 shows that the overall level of MSP is lower in Condition 3 than in Conditions 1 and 2.

One can statistically examine the effect of the choice task on the MSPs by analyzing the known-risk lotteries in Condition 1 and Condition 3 by 2×5 (single versus choice presentation $\times$ level of probability) ANOVA. The only difference between these two sets of lotteries is that one set was evaluated singly, whereas the other set was evaluated in the context of a choice task. The same analysis was performed on the MSPs for ambiguous lotteries in Conditions 2 and 3. The purpose of this test was to see to what degree the two types of lotteries were affected by the presentation format. Both analyses revealed similar results: a significant interaction between presentation format and level of probability (known-risk lotteries: $F(4, 128) = 2.47$, $P < 0.05$; ambiguous lotteries: $F(4, 128) = 4.91$, $P < 0.01$). This indicates that the choice task affected perceived attractiveness in both types of lotteries.

To investigate the influence of presentation format on the evaluations of lotteries more thoroughly, the most appropriate statistical test would be a three-way analysis of variance comparing type of lottery (ambiguous versus known-risk), way of presentation (single versus with an alternative option) and level of probability. This analysis is not possible because of the between-subjects (Condition 1 versus Condition 2) versus within-subjects (Condition 3) comparison in the design of this experiment. Therefore the data were transformed into difference scores that were then used in a two-way ANOVA with the factors ''level of probability'' and ''type of lottery''. For each subject in Condition 3 (choice task), the difference between each minimum selling price and the mean minimum selling price of the respective lottery presented in the single presentation conditions was computed. Assume, for example, that Subject 1 stated a MSP of \$3 for the known-risk lottery with a probability of winning of 0.3. The mean MSP for the 0.3 probability lottery in Condition 1 (where subjects received only known-risk lotteries) was \$3.5. So the difference score that would enter the analysis would be -0.5. These difference scores (see Table 2) were analyzed in a 2×5 ANOVA (factors: type of lottery, level of probability). A significant main effect for level of probability ($F(4, 64) = 15.09$, $P < 0.001$) indicates that the magnitude of the difference scores increases the higher the probability of success was.

Table 1
Mean minimum selling prices in Experiment 1 (standard deviations in parentheses)

Probability of winning	Known-risk single presentation	Ambiguous single presentation	Known-risk choice	Ambiguous choice
0.3	3.88 (1.57)	3.03 (1.10)	3.78 (1.56)	3.55 (1.49)
0.4	4.82 (1.41)	3.82 (1.15)	4.28 (1.26)	3.76 (1.60)
0.5	5.53 (0.99)	4.35 (1.40)	5.38 (0.97)	4.32 (1.26)
0.6	6.41 (1.40)	5.23 (1.21)	5.70 (1.21)	4.73 (1.82)
0.7	7.67 (1.18)	6.08 (1.66)	6.29 (1.49)	4.85 (1.77)

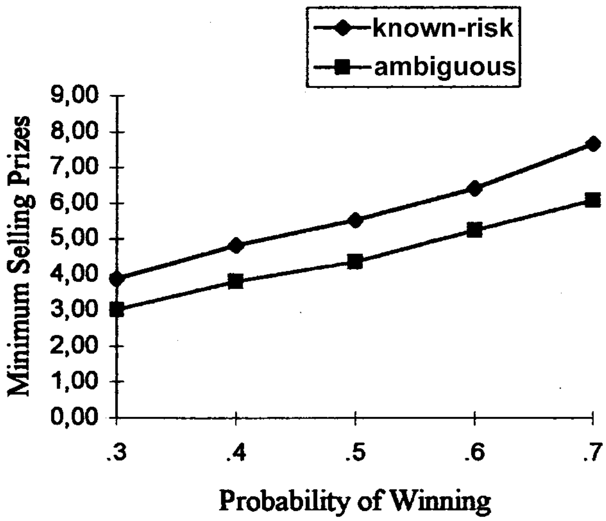

Fig. 1. Mean minimum selling prices for known-risk and ambiguous lotteries presented alone in Experiment 1.

Thus, the influence of the presentation mode depends on the probability of winning: all else equal, the higher the lottery's probability of success, the worse the choice task presentation makes it look relative to the alone presentation. Even more interesting is a statistical trend for the factor ''type of lottery'' ($F(1, 16) = 4.09$, $P = 0.06$), suggesting that the attractiveness of known-risk lotteries is reduced by the presence of an alternative even more than the attractiveness of ambiguous lotteries is.

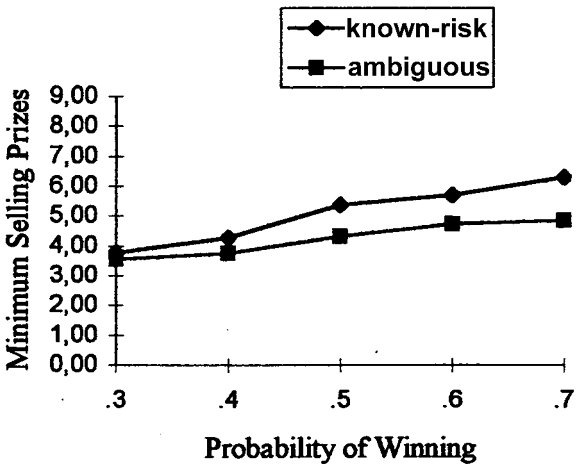

Fig. 2. Mean minimum selling prices for known-risk and ambiguous lotteries presented in a choice task in Experiment 1.

Table 2
Mean difference scores in Experiment 1 (standard deviations in parentheses)

Probability of winning	Mean difference scores for known-risk lotteries	Mean difference scores for ambiguous lotteries
0.3	−0.11 (1.25)	0.55 (1.49)
0.4	−0.54 (1.26)	−0.06 (1.60)
0.5	−0.14 (0.97)	−0.02 (1.26)
0.6	−0.70 (1.21)	−0.47 (1.78)
0.7	−1.50 (1.36)	−1.2 (1.70)

Taken together, the results of Experiment 1 reveal two important features of the ambiguity effect. First, ambiguity avoidance occurs in a non-choice situation. This result cannot be accounted for by theories that say it is caused by comparing alternative options. Of course, we cannot entirely exclude the possibility that subjects in the single presentation conditions internally generated a choice task by (for example) systematically comparing the experimental lottery to a sure amount of money. However, based on our postexperimental interviews with subjects, there is no evidence whatsoever that such a strategy was applied. Furthermore, it would be plausible to assume that if such an internal comparison were executed, the option that the experimental lottery was compared to, namely, a sure amount of money, would have been the same for the ambiguous and the known-risk option. Thus the differences between these two conditions should still be attributed to the missing probability parameter in the ambiguous condition. It can therefore be concluded that the missing probability information rather than the contrast with a known-risk option underlies subjects' aversion to ambiguous options (but see Fox and Tversky (1995), who, using a slightly different procedure (buying prizes rather than selling prizes; different contents of material, etc.) did not find ambiguity avoidance for options presented alone).

The second important finding of this experiment was that the effect of presentation mode is not specific to ambiguous options: the presence of an alternative option reduces the attractiveness of both available options. This accords with data showing that choices can be manipulated by adding and removing other options (Shafir & Tversky, 1992; Shafir, Simonson & Tversky, 1993). So even though it does not provide an explanation of the ambiguity effect, this is an interesting finding because it implies that values and desirability of options are not stable attributes, but flexible qualities or properties that are established in a given situation.

4. Experiment 2

Experiment 2 was designed primarily to replicate the findings of Experiment 1. However, a small but important change was introduced in this study. The choice task in Condition 3 of Experiment 1 was replaced by a chance process: a coin toss determined which of the two options would be played. Thus subjects in this condition received and evaluated both an ambiguous and a known-risk lottery, but they did not choose which one they would like to play. This experiment allows us to investigate whether the presentation effect found in Experiment 1 is due to the choice process or whether it is produced by the mere presence of two options with different amounts of information. This manipulation will reveal more about the nature of the presentation effect, allowing us to evaluate models that explain ambiguity aversion by either (a) a reluctance to bet on ambiguous prospects because they are difficult to justify (Curley & Yates, 1986) or (b) a general unwillingness to act on inferior knowledge (Fox & Tversky, 1995). According to these models, when an ''active choice'' is eliminated from the task, the presentation effect should be reduced.

4.1. Method

4.1.1. Subjects

Sixty undergraduate students from the University of California, Santa Barbara (20 per condition) with a mean age of 19.95 years participated in this experiment. They received $5 for participating, but this amount could be increased by winning the experimental lotteries. As in Experiment 1, the procedure was administered as a questionnaire, but 10% of the subjects were randomly selected to actually play some of the lotteries for real money.

4.1.2. Materials and procedure

Stimuli and procedure were the same as in Experiment 1 for those subjects who received only known-risk (Condition 1) or only ambiguous lotteries (Condition 2). In Condition 3, however, subjects received an ambiguous and known-risk lottery without the choice instruction. They indicated their minimum selling prices for both lotteries. The order of pricing of the two lotteries was counterbalanced. Then the experimenter's buying price was determined as in Experiment 1.

Finally, a coin was tossed to determine which of the two lotteries would be played.

4.1.3. Predictions

If the presentation effect in Experiment 1 is caused by the simultaneous presentation of two options, then all the results of Experiment 1 should be replicated in Experiment 2. In contrast, if making a choice produces the presentation effect, then this effect should be eliminated in the present experiment: MSPs in Condition 3 should not be consistently lower than in their matching alone conditions.

4.2. Results and discussion

The statistical analysis paralleled that for Experiment 1. First, the minimum selling prices of Condition 1 (known-risk lotteries only) and Condition 2 (ambiguous lotteries only) were compared in a 2×5 (type of lottery $\times$ level of probability) ANOVA. Then a within-subjects comparison on the minimum selling prices of

Condition 3 (simultaneous presentation of known-risk and ambiguous lotteries) was performed (see Table 3). As Fig. 3 shows, the pattern of results almost exactly replicated that in Experiment 1. In the analysis of Conditions 1 and 2, there was a main effect for the type of lottery ($F(1, 32) = 21.99$, $P < 0.001$) and no significant interaction ($F(4, 152) = 0.9$, $P > 0.05$). This indicates that minimum selling prices were lower for ambiguous lotteries than for the corresponding known-risk lotteries over the entire range of probabilities. This provides another demonstration that ambiguity aversion can occur in the absence of a known-risk option.

The results of the choice task Condition 3 of Experiment 1 was also replicated in Condition 3 of the present experiment (see Fig. 4). As in Experiment 1, minimum selling prices for ambiguous lotteries were lower than those for known-risk lotteries ($F(1, 19) = 25.625$, $P < 0.001$), and they interacted with the level of probability ($F(4, 76) = 4.921$, $P = 0.001$).

Closer analysis of the data revealed that there was a depressing effect of simultaneously presenting an alternative option for the known-risk lotteries (known-risk lotteries, Condition 1 versus known-risk lotteries Condition 3: $F(1, 38) = 6.08$, $P < 0.05$). The equivalent analysis for the ambiguous lotteries (ambiguous lotteries Condition 2 versus ambiguous lotteries Condition 3) failed to reach significance.

To determine the effect of presentation mode on minimum selling prices, we again examined difference scores (Table 4) between each minimum selling price in Condition 3 and the mean minimum selling price of the matching lottery presented alone (see Results section for Experiment 1). This analysis revealed a significant effect of type of lottery ($F(1, 19) = 9.86$, $P < 0.01$), where the attractiveness of known-risk lotteries was reduced by the simultaneous presentation condition more than the attractiveness of ambiguous lotteries was. Moreover, there was a significant interaction between type of lottery and level of probability ($F(4, 76) = 3.69$, $P < 0.01$). This interaction indicated that with increasing probabilities presenting another option at the same time decreased the attractiveness of known-risk lotteries more than the attractiveness of ambiguous lotteries.

Although it seems that eliminating the choice from the comparison process slightly changes the responses (e.g. ambiguous options are less affected by the simultaneous presentation than known-risk options) the overall pattern is preserved. Ambiguity avoidance was observed in single presentation and in simultaneous presentation conditions. Therefore it can be concluded that comparison processes

Table 3
Mean minimum selling prices in Experiment 2 (standard deviations in parentheses)

Probability of winning	Known-risk single presentation	Ambiguous single presentation	Known-risk simultaneous presentation	Ambiguous simultaneous presentation
0.3	4.47 (1.85)	3.21 (1.22)	3.44 (1.42)	3.04 (1.53)
0.4	5.10 (1.18)	3.85 (1.43)	4.05 (1.51)	3.36 (1.58)
0.5	6.47 (2.01)	4.42 (1.37)	5.21 (1.65)	4.36 (1.31)
0.6	6.83 (1.35)	4.98 (1.33)	6.03 (1.48)	4.85 (1.37)
0.7	7.90 (1.29)	6.13 (1.59)	7.07 (1.61)	5.16 (1.49)

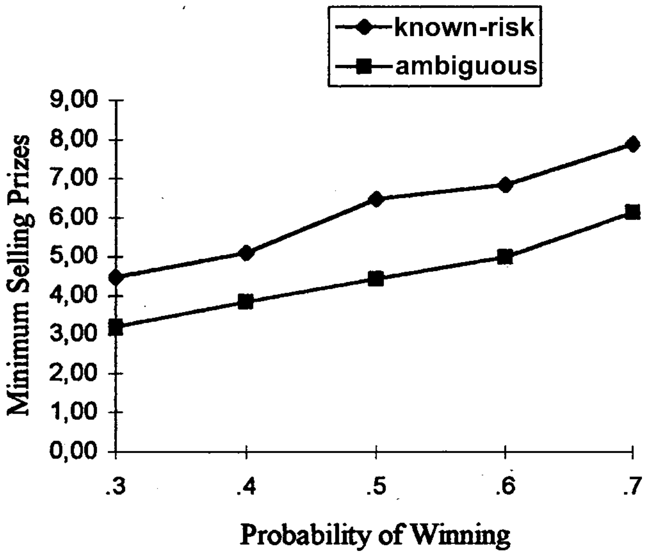

Fig. 3. Mean minimum selling prices for known-risk and ambiguous lotteries presented alone in Experiment 2.

cannot be its main causal factor. However, the effects different ways of presenting more than one option have on the evaluation of options might be worth studying.

5. Discussion for Experiments 1 and 2

Experiment 2 replicated the main finding of Experiment 1: even in the absence of

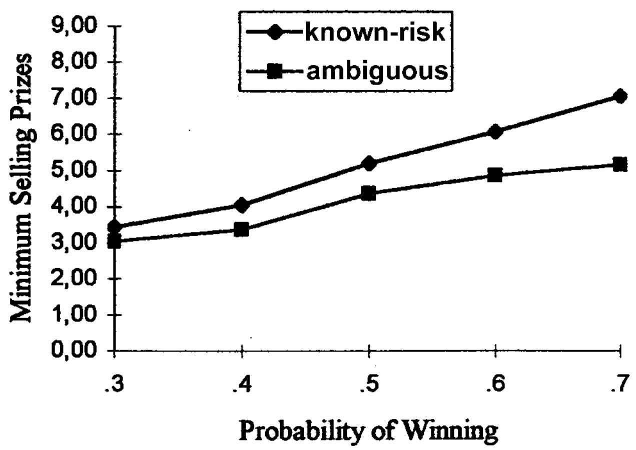

Fig. 4. Mean minimum selling prices for known-risk and ambiguous lotteries presented simultaneously in Experiment 2.

Table 4
Mean difference scores in Experiment 2 (standard deviations in parentheses)

Probability of winning	Mean difference scores for known-risk lotteries	Mean difference scores for ambiguous lotteries
0.3	− 1.02 (1.45)	− 0.16 (1.57)
0.4	− 1.05 (1.55)	− 0.48 (1.62)
0.5	− 1.26 (1.69)	− 0.67 (1.34)
0.6	− 0.77 (1.55)	− 0.12 (1.40)
0.7	− 0.82 (1.65)	− 0.98 (1.53)

an alternative option, lotteries with missing probability information are considered less desirable. Furthermore, presentation of two options — whether the subject must choose between them or not — reduces the attractiveness of each, relative to situations in which each option is presented singly. This undercuts motivational accounts of the ambiguity effect: these predict that comparison processes reduce the attractiveness of ambiguous options, not of known-risk ones. Indeed, if anything, known-risk options suffered more than ambiguous ones from the simultaneous presence of an alternative with which they could be compared. In addition, Experiment 2 showed that the attractiveness of at least known-risk options is affected by the presentation of an alternative even in the absence of an active choice task. Taken together these results provide strong evidence against explanations of ambiguity avoidance that focus on the comparison process inherent in choice tasks, such as those proposed by Curley et al., (1986); Fox and Tversky (1995).

Further evidence that people assume that missing probability information portends a bad outcome comes from Rode (1996). Her procedure provides further evidence for a ‘‘pure’’ ambiguity effect: one unadulterated by the process of assigning an MSP, by the presence of a known-risk alternative, or by any suspicions that the lottery is rigged that might arise from the fact the experimenter usually decides whether black or white is the winning color[1]. In this experiment, Rode presented subjects with the same type of ambiguous lotteries as were used in Experiments 1 and 2: the only difference was that the subjects themselves determined the color of the winning ball. This was to minimize the possibility that subjects would think the lotteries were rigged against them. (Curley et al. (1986) describe in detail the procedure used to compose ambiguous lotteries for which the winning color is determined by the subject.) After choosing black (or white) as the winning color, subjects were asked questions to reveal how many black (or white) balls they believe the box most likely contains. The results clearly revealed that although subjects decided which color would count as a win, they were consistently (across subjects and lotteries) more confident that the actual number of winning balls would fall

[1] But note that subjects in our experiments were carefully instructed that the content of ambiguous boxes was determined randomly and independently of the experimenter from a uniform probability distribution.

below the expected mean number of winning balls than above it. Moreover, note that they had no other option to which these ambiguous lotteries could be compared. Thus, this study further confirmed the hypothesis that missing probability information rather than comparison processes is responsible for the ambiguity effect.

5.1. Why do people react to missing probability information?

Based on Experiments 1 and 2, we conclude that the ambiguity effect is primarily caused by aversion to the unknown probability parameter. So the crucial question at this point is: Why does missing or imprecise probability information evoke such a reaction? In the following section we argue that ambiguous probability information elicits this behavior because, all else equal, people associate it with high outcome variance.

When asked to judge the probability of a single event, people trying to solve a simple Bayesian inference problem usually give the wrong answer (Kahneman et al., 1982). But when the same problem asks them to compute a frequency instead, most people answer correctly (Gigerenzer, 1991; Gigerenzer & Hoffrage, 1995; Cosmides & Tooby, 1996a). In a recent series of articles Gigerenzer, as well as Tooby and Cosmides (Gigerenzer, 1991; Gigerenzer, 1994; Cosmides & Tooby, 1996a; Brase, Cosmides & Tooby, 1999; Tooby & Cosmides, 1999) have argued that this is because the human mind contains decision making mechanisms that require the presentation of event frequencies to operate properly. In this spirit, it is instructive to consider an ambiguity problem that has been rephrased in a frequency format:

> You are given the opportunity to win money in a lottery. The lottery consists of two boxes. One box contains 50 black and 50 white balls; the other box also contains 100 black and white balls but in an unknown composition. To play this lottery, you randomly draw a ball from one of these two boxes: you choose which box to draw from. If the ball is black, you will receive $10; if it is white, you will receive nothing. Imagine you are given the opportunity to draw many times with replacement from one of these boxes.
>
> If you draw from the 50/50 box repeatedly with replacement, let us say 100 times, it is likely that you will end up with an amount around the expected mean payoff of $500. But if you draw from the ambiguous box, there may be 100 black balls, in which case your expected mean outcome will be $1000, there may be no blackball, in which case you will win nothing, or the number of black balls may fall anywhere in between, in which case your expected mean payoff will be somewhere between $0 and $1000.

This example shows that one can make good estimates of the expected outcome given precise knowledge of the probability of the event. However, if one lacks knowledge of the probability one cannot make good predictions about the mean outcome. The outcome depends on the (unknown) distribution of balls in the box and varies accordingly. In other words, lacking probability information implies lacking the opportunity to predict your outcome. The estimated outcome thus has a larger range and accordingly larger variance than the option with a known probability[2]. Yet outcome information — or, in other words, the consequences of behavior — is a very important variable not only for humans but also for other animals.

Animal studies on foraging strategies have repeatedly demonstrated that avoidance of high variance outcomes is a predominant behavior. Just as in a psychological decision making experiment, foraging for food in the wilderness often requires a choice between two or more options that are not completely predictable in terms of their consequences. However, in contrast to experiments in the laboratory, the quality of the animals' decision strategy in the natural world determines its survival (Sinn & Weichenrieder, 1993). Empirical studies of animal choice have demonstrated (Boneau & Cole, 1967) that under certain conditions, animals consider the mean and the variance of calories of available food options. If its mean calorie payoff is above the current need, they choose the option with the lower variance and they select higher variance options if their need is above the mean outcome (Caraco, 1981). Using this decision rule maximizes the probability of survival.

We propose that people attend to the fact that unknown probability parameters indicate that the expected payoff is highly variable, which implies that they have only uncertain predictions for the *next* possible outcome. Imagine you have to decide where to go in order to find food for tomorrow. Assume further you have to get at least 500 calories every day in order to survive. Even if — in the long run — all available options would provide you a mean calorie payoff of 600, a highly variable option would more often reveal outcomes of less than 500 calories. Therefore, in order to make it through the next day, you are better off choosing the low variability option, which will more likely provide you with the necessary amount of calories[3]. It should be noted however, that the step-function implied here is not the only possible one. The essential point is a non-linear relationship between the external currency like calorie, and some internal currency like utility or fitness. Creating a step func-

[2] To estimate the variability of outcomes one first has to calculate the probability of getting each of the 10 possible numbers of black balls (0 to 10) given 10 draws with replacement for the given probability distribution in the box. Given these probabilities one can determine the expected outcome $E = \Sigma(p_i * i)$, where p_i is the probability of getting i black balls in 10 draws with replacement provided a given distribution in the box. The variance of the distribution of the possible outcomes (provided the 10 draws) is the average square distance between the actual outcome and the expected outcome weighted by its probability.

$$s^2 = \sum_{i=0}^{10} p_i(i - E)^2 \tag{1}$$

In case of an ambiguous box, the procedure is slightly more complicated because the probabilities of obtaining a particular number of black balls would have to be calculated for each possible distribution in the ambiguous box (see footnote to Table 5). From these probabilities the overall probability of getting a particular number of black balls given 10 draws with replacement would be calculated by summing over the 101 possible distributions and dividing this value by 101. Then the expected outcomes and variance can be computed given these overall probabilities according to the formulas presented above.

[3] Please note that we are concerned with options having the same mean payoff but different outcome variability. Of course, in the natural environment people (and animals) have to deal with options differing with respect outcome variance *and* mean payoff. In this case the predictions of optimal foraging become more complex.

tion is just one form of this general situation, and death is just one obvious example of this.

Thus we think that people avoid the ambiguous lottery in ambiguity experiments without a specified need because they wish to avoid the highly variable distribution of outcomes. We assume that this adaptive rule is over generalized to single-draw ambiguity experiments[4].

If this interpretation is true, then what people prefer in most ambiguity experiments is not the known probability per se, but the predictability of the mean outcome (or at least the knowledge that the range of possible outcomes will be comparatively small). In Experiments 3 and 4 we test several hypotheses which follow from this view.

6. Experiment 3

To test the hypothesis that it is high outcome variance rather than unknown probability information that is avoided, we designed the following experiment in which subjects choose between a known-risk option with high outcome variance and an ambiguous option with low outcome variance. The problems had a frequency format: each lottery allows one to draw 10 balls, rather than just one.

6.1. Method

6.1.1. Subjects

Thirty-four (mean age 18.5; 23 female and 11 male) students at a Gymnasium (high-school) in Potsdam, Germany, served as subjects in this experiment. In a questionnaire, they received a number of decision tasks involving urns and balls. They indicated their answers by circling their preferred option. They knew, however, that 10% of the subjects would be randomly selected to play some of the lotteries presented in the questionnaire for real money.

6.1.2. Materials and procedure

Along with some unrelated questions, the subjects were asked to choose or express indifference between two options that differed with respect to knowledge about probabilities and outcome variability in the following way: one option had a known-risk of 0.5 to win but high outcome variance, whereas the other option was ambiguous but had lower outcome variance. The order of presentation of the two

[4] In the typical ambiguity experiment with one draw of one ball options do not differ with respect to outcome variability. Our point is that people use missing probability information as a cue for high outcome variance. And this cue is used in the single-draw situation as well. There are many examples of adaptive strategies that are generalized to situations to which the strategy does not actually apply. Probability matching, for instance, is a good strategy if an animal competes with conspecifics for resources. However, in the absence of competing conspecifics the probability matching rule is suboptimal yet shown by the animal. Any strategy is only optimal in certain environments; however, one cannot have as many optimal strategies as there are environments. As a consequence, most strategies that are functional in certain environments can be shown to be used in suboptimal environments as well.

options was counterbalanced. The specific wording of the problem was (translated from German):

> Imagine the following situation: you are given the opportunity to choose between the following two options: Option 1 offers you two boxes. One box contains 100 black balls, one box contains 100 white balls. You are allowed to pick 10 balls with replacement from one of these boxes. For each black ball that you draw you will receive DM 10. Option 2 offers you one box that contains 100 black and white balls in an unknown composition. The exact number of black and white balls in this box will be determined randomly from all 101 possible distributions. You are allowed to pick ten balls with replacement from this box. [After each draw a new composition of black and white balls will be determined at random by picking one of the 101 possible distributions]. For each black ball that you draw you will get DM 10.

In this scenario, the ambiguous option has lower outcome variability than the known-risk option has (see footnote 2). We are aware that the wording of Option 1 is somewhat odd because the participant will know her payoff after the first draw as soon as she realizes from which box she picked. However, for methodological reasons we kept the wording of the options as similar as possible.

To make sure that the findings are not caused by a perceived difference in the range of the possible outcomes or the fact that the content of the ambiguous box is changed after each draw, the same subjects also received a version of the problem in which the ambiguous box remains the same throughout the ten draws [the sentence in parentheses was eliminated]. This change increased the variance of Option 2, but it was still lower than in Option 1. The order of the problems, along with several other unrelated decision tasks, was determined randomly. In a control condition, 20 subjects from the same population (high school students in Potsdam, Germany) chose between a known-risk and an ambiguous option, both of which had a frequency format:

> Imagine the following situation: you are given the opportunity to choose between the following two options: Option 1 offers a box that contains 50 black and 50 white balls. You are allowed to pick 10 balls with replacement from this box. For each black ball that you draw you will receive DM 10. Option 2 offers you one box that contains 100 black and white balls in an unknown composition. The exact number of black and white balls in this box will be determined randomly from all 101 possible distributions. You are allowed to pick 10 balls with replacement from this box. For each black ball you will get DM 10.

6.1.3. Predictions

We predict that subjects do not avoid unknown probability information per se: they avoid ambiguous problems only when the ambiguity is interpreted as indicating high outcome variability. If this is correct, then in Experiment 3, they should avoid the high outcome variability option even though it is of known-risk, and prefer the low outcome variability option, even though it is ambiguous.

6.2. Results and discussion

The choice pattern for these two problems was clear-cut. Consistently the majority of subjects chose the option with lower outcome variability even though it lacked probability information. In the version of the problem in which the ambiguous box remained the same throughout the ten draws, 67.6% (23 subjects) chose the ambiguous box, 26.4% (9 subjects) chose the known-risk box and only 5% (2 subjects) were indifferent ($\chi^2 = 4.23$, $P < 0.05$). In the version in which the ambiguous box was replaced by a new, randomly determined box after each draw, the result was even more pronounced. Seventy-three percent (25 subjects) chose the ambiguous box, 23% (8 subjects) selected the known-risk box and only 1 subject was indifferent ($\chi^2 = 7.53$, $P < 0.05$). This result cannot be accounted for by positing that these particular subjects have a general preference for ambiguity because in the control condition 70% of them (14 subjects) chose the known-risk option, 20% (4 subjects) chose the ambiguous option and 10% (2 subjects) were indifferent ($\chi^2 = 3.2$, $P < 0.10$). This control condition further shows that frequency versions of an ambiguity problem elicit the same pattern of results as single event versions do.

In choosing between known-risk and ambiguous lotteries, subjects in Experiment 3 treated outcome variability as an important variable. They preferred low variance in outcomes, even when it meant choosing an ambiguous option.

An evolutionary-functional analysis, which is based on a task analysis of an ancestral problem and aimed to discover and understand adaptations, expected this choice pattern, on the grounds that a well-engineered system for making decisions under uncertainty should be sensitive to the variance of probability distributions.

However, choosing the lower variance option when faced with the prospect of a gain, as subjects did in this experiment, is also consistent with the cumulative prospect theory of Tversky and Kahneman (1992). Cumulative Prospect theory is an algebraic model of decision making in which the consequences of alternatives are judged relative to a reference point. A value function attaches a subjective worth to each outcome. The value function is s-shaped and concave in the winning section and steeper and convex in the losing section. Given the appropriate choice of parameters, this model also allows for preference of the lower variance option. The explanation, however, would be different from an evolutionary-functional one. According to an evolutionary-functional approach, subjects were risk averse because human decision-making systems are sensitive to probability distributions: i.e. the system is designed to embody certain *rational* principles. But according to prospect theory, subjects were just risk averse because (1) there was an opportunity for gain, and (2) they have a concave utility function in the domain of gains.

Experiment 4 was designed to see whether the decision-making system has further design features suggested by the evolutionary-functional approach. In particular, we wanted to see whether the system is designed to switch from being risk averse to risk taking, depending on the individual's level of need.

To accomplish these goals, the lotteries in Experiment 4 had two stages, which allowed us to create a situation in which the subject's choice of a probability distribution (made in stage 1) was not related to the size of the reward (won by a separate lottery in stage 2). In fact, the amount of money to be won was held constant across conditions. The lotteries also introduced a need variable, creating a baseline that subjects would have to exceed in stage 1 in order to be in a position to win money in stage 2. By doing so, we were able to create situations in which *the same gain and probability distribution* should elicit different levels of risk-taking, depending on the subjects' need. Such a result is suggested by an evolutionary-functional approach.

7. Experiment 4

7.1. Decision making in uncertain environments

The results of Experiment 3 indicate that people — like other animals — attend to a variable that is highly relevant from the perspective of adaptive choice behavior: outcome variance. But do they take other relevant variables into account? We assume that cognitive structures and problem solving systems in humans and other animals evolved to deal with the daily tasks of surviving and reproducing. To arrive at a decision that maximizes the probability of survival (or, more generally, the probability of getting what one wants), an animal's decision-making system should be designed to take into account its current state as well — more specifically, its desires and goals or needs in a particular situation. The cognitive architecture of a number of foraging animals is designed to do so (Caraco, 1981; Stephens & Krebs, 1986). What about the cognitive architecture of humans?

Three parameters are relevant for maximizing the probability of getting what you want: (1) your personal goal or need in a given situation, (2) the mean outcome of the available options, and (3) the variability of the mean outcome of the options. In situations where one must choose between options that have the same expected utility, the decision rule that follows from this is to choose the lower variance as long as the mean outcome of this option satisfies the need. Otherwise, switching to the higher variance option is the best rule. Although Experiment 3 shows that ambiguity and variance can be experimentally dissociated, in the typical ambiguity experiment the ambiguous lottery might be perceived as having higher variance than the known-risk lottery. Hence, one would expect subjects following this decision rule to choose the known-risk lottery *unless* they require a payoff that exceeds the lottery's expected utility.

The following experiment was designed to test the hypothesis that people have decision rules designed to satisfy a need (or achieve a certain goal) by considering the means and the variances of the available options and then choosing the option most likely to satisfy their need. In this study, subjects were given a series of problems in which they were asked to choose between two boxes. Each problem specified the exact number of black and white balls in one of the two boxes, but left the distribution of black and white balls in the other box unknown. In addition to this information, the subject was told that he or she needs a certain number of black balls to proceed to a second stage of the lottery. To attempt to get the required number of blackballs, the subject is allowed to draw ten times with replacement from one of the boxes, and therefore has to decide which of the two boxes is more likely to provide him or her with the required number of black balls.

7.2. Method

7.2.1. Subjects

Thirty-one undergraduates (mean age 18.7 years) at the University of California, Santa Barbara served as subjects in this experiment. Each subject was paid \$5 for participation but could increase this amount by winning the experimental lotteries.

7.2.2. Material and procedure

Subjects were tested in small groups of up to five people.

All lotteries were presented in a questionnaire, but subjects were informed that after the completion of the questionnaire some of them would be randomly selected to play some of the lotteries, based on the preferences they expressed in their questionnaire.

To test the hypotheses, we conducted a within-subjects experiment that involved a two-stage lottery. The instruction part of the questionnaire familiarized the subjects with the following general procedure: There are two boxes (box A and box B), each filled with 100 black and white balls. Box A contains a specified number of black and white balls, whereas the composition of box B remains unknown. However, the subject is informed that the actual distribution in box B will be determined randomly by picking one of 101 poker chips that are labeled with each possible distribution. Thus, the expected value of Box B was always 0.5. The subject's task is to pick a certain number of black balls from one of the two boxes. To do that, the subject (blindly) draws 10 times consecutively from one box, replacing the picked ball after each draw. If she draws the required number (or more) of blackballs, she proceeds to the second stage of the lottery.

In stage 2, a third box, filled with 50 black and 50 white balls, is presented and the subject is required to pick a black ball. If she is successful, she will win \$20. If the subject does not get the necessary number of black balls in the first stage, she will not proceed to the second stage of the experiment and therefore will not win any money. This third box was used so there would be no connection between the gain and the actual distribution of black balls in the first and critical part of the experiment.

While the participants were working through the questionnaire they could see the three boxes to be used to actually play some of the lotteries. The entire procedure was explained twice: once by the experimenter who demonstrated with the boxes how the content of the boxes would be determined and once in the questionnaire. Any participants' questions about the procedure were answered.

The effects of two independent variables on choices under uncertainty were investigated in this study: ''need'' and ''level of probability of winning''. To operationalize and manipulate the need of the subject in this experiment, for each lottery the number of black balls that have to be drawn in ten draws with replacement is specified. The number of required balls could either match the expected value (EV) of box A or be above or below this EV by one or two balls. This independent variable — ''need'' — was tested on four different probability distributions of black to white balls in box A: 30:70, 50:50, 60:40 or 70:30. For example, for the probability distribution 30:70 black to white balls in box A, the number of black balls required to move to stage 2 was either (a) at least one black ball (two balls below the expected value), (b) at least two black balls (one below the expected value), (c) at least three black balls (exactly the expected value), (d) at least four black balls (one above the expected value), or (e) at least five black balls (two above the expected value). In this way, five levels of need were constructed for each of the four probability levels. This resulted in a final questionnaire of 20 decision situations, which were presented to each subject in a new random order. The subject had to indicate which of the two boxes she would prefer for the ten draws for each situation separately. Subjects were required to choose one of the two boxes: neither indifference nor moving back and forth in the questionnaire were allowed. In this experiment, the order of box A and B was not counterbalanced because (a) our pilot studies never revealed any order effects and (b) using different orders caused confusion and many inconsistent answers.

After the subjects completed the questionnaire, some were randomly selected to play some of the lotteries according to their answers. If the subject drew the required number of black balls in the played lottery, and also drew a black ball in the second stage of the lottery, she was paid $20.

7.2.3. Predictions

Based on optimal foraging theory, we predict that people will consider the mean outcomes and the distributions of the two boxes and select the one that is most likely to deliver the required number of balls. Specifically, the hypotheses and predictions are:

1. People choose on the basis of subjective needs. If their need in a particular situation is lower than the mean outcome of the known-risk box, subjects will choose the known-risk box. If their need is higher than the mean outcome of the known-risk box, the ambiguous box will be chosen.
2. The pattern of preferences will not depend on the probability of the known-risk option. Even if the probability of success in the known-risk box is very high, subjects will choose the ambiguous box if it is more likely to satisfy their need.

7.3. Results and discussion

The dependent variable was the choice of either the known-risk option (box A) or the unknown option (box B) for each person and each decision situation. Fig. 5

shows the relative frequencies of ambiguity-avoiding choices (preference for box A) given a need above or below the expected outcome of the known-risk box.

Subjects' choices followed a very consistent pattern. As predicted, their need in a given situation had a strong effect on their preference for a known-risk versus an ambiguous option. If the required number of balls was less than the expected value of the known-risk option, most subjects selected the known risk. But if the required number of balls exceeded the expected mean outcome, most subjects switched to the ambiguous option. In other words, we both predicted in advance, and found, a condition in which people systematically prefer the ambiguous option. This should not be possible on existing cognitive or motivational theories of the ambiguity effect.

In addition to this predicted effect, the data seem to indicate an effect of the level of probability of the known-risk option. Subjects appear more reluctant to choose the ambiguous option if the probability of winning with the known-risk option is high.

To test these effects statistically, a score was constructed to indicate the strength of ambiguity aversion. For each person and each decision, the choice of box A was coded with 1 and the choice of box B was coded with 0. Thus the more a person avoided ambiguity, the higher that person's score. Next, the data for each person were averaged over the four probability levels, resulting in one data point per need condition for each person. These scores were analyzed by a within-subjects-ANOVA with need as the repeated variable. As expected, the effect of need was highly significant ($F(4, 120) = 40.65$, $P < 0.001$). A similar procedure was applied to investigate the effect of the probability level of the known-risk option. Here, the scores were averaged over the different conditions of need, resulting in one data point per probability level for each subject. Again, a within-subjects ANOVA with probability level as repeated variable showed a significant effect ($F(3, 90) = 34.20$, $P < 0.001$), indicating that ambiguity avoidance increased with probability of the known-risk option. This increase in ambiguity avoiding choices may not be a ''bias''. Instead, it may reflect the actual differences in probabilities of winning with one or the other option. If so, then this would indicate the operation of an exceptionally well-designed system for making decisions under uncertainty, one that satisfies various principles of rationality. The crucial criterion of rationality in this context is whether the subjects' choice pattern reflects differences in the actual probabilities of satisfying their needs, given the two different boxes. To investigate this question, the actual probabilities of getting the required number of balls with each of the two boxes were calculated for the 20 conditions (Table 5, third and fourth columns). The actual probabilities in column 3 were generated as follows: For the given binomial distribution in the known-risk box, the cumulative probabilities from drawing the least number of black balls to drawing 10 black balls were computed. In case of the ambiguous box, basically the same procedure was used, but the probability of getting at least the required number of black balls is calculated for each of the 101 possible distribution of black and white balls in the box. These probabilities are summed up and divided by 101 to get the expected probability of getting at least the required number of black balls by drawing from the ambiguous box (see footnote to Table 5 for formula).

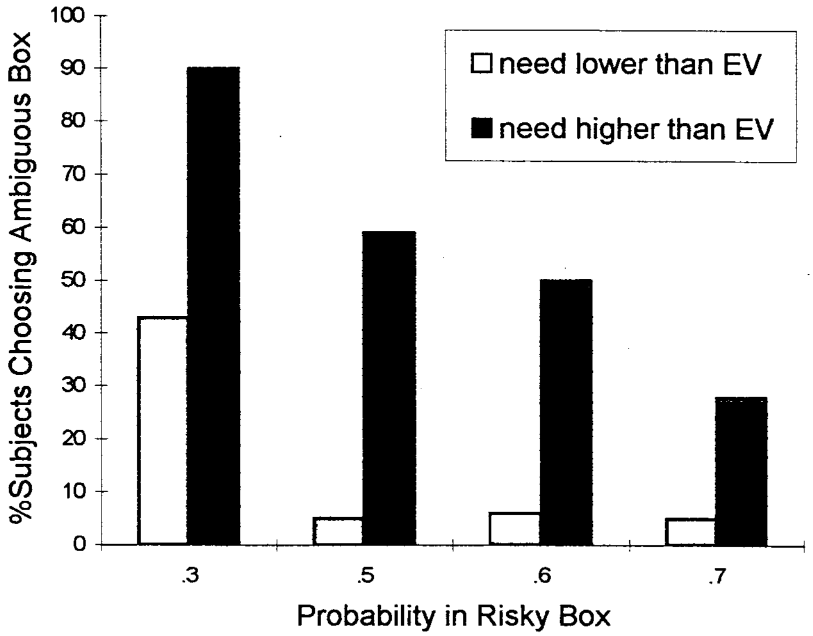

Fig. 5. Percent subjects choosing the ambiguous box.

From these probabilities one can infer which option had the higher probability of winning and therefore should have been selected in each decision problem. As a measure of the relative probability of winning, the difference between the probability of winning with box A and box B was obtained (Table 5, fifth column). These differences were then used in a regression analysis to predict the choice of the subjects. To make an overall ambiguity effect visible, the relative frequencies of ambiguity aversion decisions minus 50% were used as the criterion (this is because 50% would indicate indifference between the two options). Thus, a positive value indicates an aversion to ambiguity and a negative value indicates a preference for ambiguity (Table 5, last two columns).

From Fig. 6 it is clear that people consider actual differences in the probabilities of ambiguous and known-risk options ($r^2 = 0.91; b = 1.207; t(18) = 13.48; P < 0.01$). In other words, subjects in this experiment were behaving in an exceptionally rational manner. Somehow their answers were reflecting true probabil-ities, even though using mathematics to calculate these out is rather complex. We are not, of course, suggesting that our subjects were performing these calculations in any conscious or deliberate manner; rather, that their decision systems are designed to produce the same answers that one would were one to do the calculations.

So people are willing to select an ambiguous option if this option is more likely to satisfy their current need. However, as indicated by a significant intercept ($a = 0.08$; $P < 0.01$), there is still a minor, residual ambiguity aversion effect. More specifi-

Table 5
Choices of known-risk and ambiguous boxes and actual probabilities of getting the required number of balls[a]

Probability of winning in known-risk box	Number of balls required	Probability of getting the required number of balls from the known-risk box	Probability of getting the required number of balls from ambiguous box	Difference in probabilities	Relative frequency of ambiguity avoidance	Decision tendency
0.3	1	0.97	0.906	0.064	0.68	0.18
	2	0.85	0.816	0.034	0.64	0.14
	3	0.62	0.727	−0.107	0.36	-0.14
	4	0.35	0.638	−0.288	0.1	-0.4
	5	0.15	0.548	−0.398	0.1	-0.4
0.5	3	0.92	0.727	0.223	0.97	0.47
	4	0.83	0.638	0.192	0.94	0.44
	5	0.62	0.548	0.072	0.78	0.28
	6	0.38	0.458	−0.078	0.49	−0.01
	7	0.17	0.365	−0.195	0.33	−0.17
0.6	4	0.95	0.638	0.312	0.94	0.44
	5	0.83	0.548	0.282	0.94	0.44
	6	0.63	0.458	0.172	0.78	0.28
	7	0.38	0.365	0.015	0.51	0.01
	8	0.17	0.275	−0.105	0.49	-0.01
0.7	5	0.95	0.548	0.402	1	0.5
	6	0.85	0.458	0.392	0.91	0.41
	7	0.65	0.365	0.285	0.84	0.34
	8	0.38	0.275	0.105	0.82	0.32
	9	0.15	0.186	−0.036	0.62	0.12

[a] The formula to calculate the probability of obtaining at least a particular number of black balls from an ambiguous box is the following:

$$p = \frac{\sum_{k=0}^{100} \sum_{j=x}^{10} \binom{10}{j} \left(\frac{k}{100}\right)^{j} \left(\frac{100-k}{100}\right)^{10-j}}{101} \quad (2)$$

where p is the probability of getting at least the number of required black balls from the ambiguous box, X is the least number of black balls to be picked, and k is the number of white balls in the box.

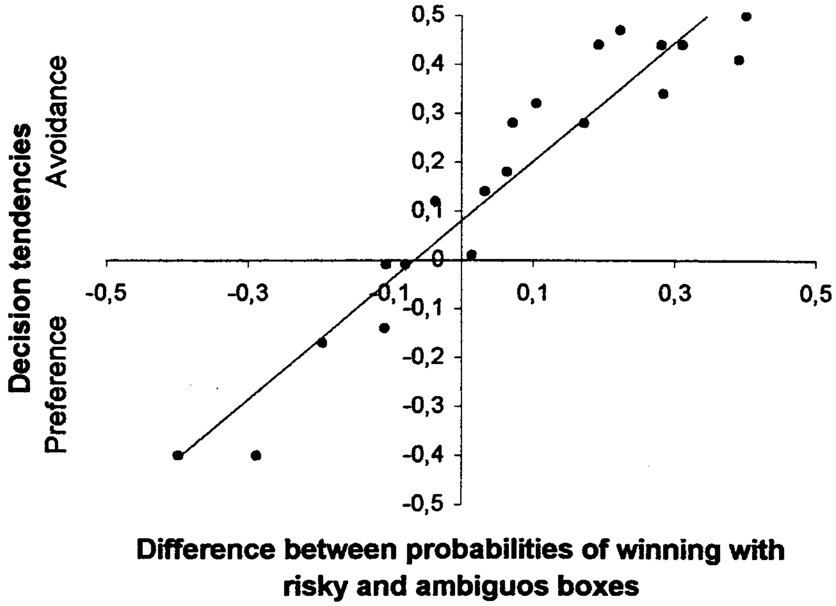

Fig. 6. Decision tendency as a function of the actual probability of winning.

cally, if the *actual* difference between the probability of winning with an ambiguous box versus a known-risk box were zero, people would prefer the known-risk option instead of being indifferent.

At this point we can only speculate about the origins of this residual ambiguity effect. One possibility is that people do not believe there is a symmetrical distribution of probabilities in the unknown box. There is evidence in support of this interpretation. In two studies, Rode (1996) asked subjects to rate the likelihood of each possible probability distribution in the unknown box. Very consistently, subjects assigned a left-skewed probability distribution to the unknown box, and this pattern did not change when subjects themselves determined the color of the winning balls (see Discussion section for Experiments 1 and 2). These results, however, do not tell us whether this belief in a skewed distribution is caused by the artificial tasks and stimuli used in these experiments or whether it reflects another interesting feature of the decision making mechanism.

According to risk-sensitive foraging theory, organisms are not irrationally risk averse, nor are they irrationally risk seeking. Instead, the organism's choice is rationally related to its level of need. Given two resource pools with the same expected utility but different outcome variance, organisms will choose to forage in the low variance pool when their need is less than or equal to the expected utility. They will choose to forage in the high variance pool when their need is greater than the expected utility. That is how human subjects behaved in Experiment 4. Taken together, the results of Experiment 4 indicate that people apply a decision rule that takes into account the three parameters specified by risk-sensitive foraging theory:

the organism's need, the mean payoff of the options, and their variance. The importance of the need factor becomes clearer when one considers the following:

1. Subjects did not avoid ambiguity in an indiscriminate manner. If they had had a *general* aversion to ambiguity, they would have chosen the known-risk box independently of their need. They did not.
2. The expected value of the boxes was not the only variable upon which subjects based their decisions. If it had been, they would have chosen the known-risk box in the 0.6 and 0.7 conditions and the ambiguous box (which has an expected value of 0.5 in the 0.3 condition) whether the number of black balls they needed was above or below the expected value. Instead, for each probability level, their box choice was determined by the relationship between the expected value and their need level.
3. Subjects did not avoid high outcome variability in an indiscriminate manner. If they had had a *general* aversion to high variance, they would have selected the known-risk box in all experimental conditions. They did not. When need dictated, they preferred the high variance box to the known-risk box.

The pattern of results obtained in this experiment deviates from all of these hypothetical alternative explanations. Moreover, there is a close fit between subjects' responses and those one would expect if they had combined information about means, variance, and need in a way that satisfies the strictures of risk-sensitive foraging theory. Thus, we conclude that the subjects took into account all three factors in a way that maximizes the probability of fulfilling their needs.

8. General discussion

Three families of theories have been put forth to explain why people avoid options with missing or imprecise probability information — the so-called ambiguity effect. Experiments 1 and 2 were designed to test between the cognitive and motivational accounts by seeing which factor elicited ambiguity avoidance: missing probability information or the comparison process inherent in the choice task format. The results showed that missing probability information is the decisive factor.

Inspired by optimal foraging theory, we proposed that people are not avoiding ambiguity per se: instead, they are avoiding the high variance of outcomes of ambiguous options. We provided evidence for this claim in Experiment 3. By using a frequency format, we were able to create a problem in which the variance of the ambiguous option was low, and the variance of the known-risk option was high. The results were clear: people preferred the low variance option, even though it was ambiguous.

Experiment 4 tested hypotheses drawn from the branch of optimal foraging theory dealing with risk-sensitive foraging. The results revealed that people integrate three parameters, their current need, the mean outcome and the variance of this mean outcome, generating a decision that maximizes the probability of getting what they need. They chose high variance options when they needed more than the mean payoff of the resource pools, and low variance options when they needed less.

The results of Experiments 1–4 converge in demonstrating that humans apply a functionally adaptive decision rule when making decisions under uncertainty. For this empirical argument we drew on the assumption that the human mind is designed to solve adaptive problems well (Cosmides, 1989; Cosmides & Tooby, 1989; Cosmides & Tooby, 1994; Tooby & Cosmides, 1992; Tooby & Cosmides., 1999; Wang, 1996), on findings showing that the human cognitive architecture has statistical inference mechanisms that operate on frequency input (Cosmides & Tooby, 1996a; Gigerenzer, 1991; Gigerenzer, 1999; Gigerenzer & Hoffrage, 1995), and on evidence for similar adaptive decision rules in other animal species (Stephens & Krebs, 1986).

These findings suggest a perspective on ambiguity avoidance that is different from other currently discussed theories. In contrast to these theories, our approach starts from the assumption that choices under ambiguity reflect a rational decision making strategy rather than a fallacy or shortcoming in the cognitive processes that generate human judgments. This approach has several advantages. First, ambiguity avoidance is theoretically explained by an existing normative theory that applies across species and has already been validated on some nonhuman species. Thus it has parsimony on its side. The approach is parsimonious in another way as well: it applies not only to the specific case of decision under ambiguity but to the more general case of decision under uncertainty. Thus once the relevant information (state of being, need, mean payoff and variability) is specified, choices can be predicted whether the subject is deciding between a known-risk and an ambiguous prospect, a known-riskand a sure prospect, or two known-risk prospects. Moreover, because all decision-types are made by the same algorithm, choices can be predicted regardless of the level of probability.

This is not true for alternative theories, such as the motivational or cognitive models introduced in the beginning of this article. For example, previous research on the ambiguity effect sometimes replicated the finding that people prefer ambiguity if the probability of winning is low (Curley & Yates, 1985; Einhorn & Hogarth, 1985). This result is difficult for all prior models to account for, especially for those proposing that a comparison process is the underlying source of systematic ambiguity avoidance. For instance, if people avoid ambiguous options because they feel less competent reasoning about uncertain probabilities, as competence theory claims (Heath & Tversky, 1991; Fox & Tversky, 1995), then there is no obvious reason why this process should favor ambiguous options when the probability of winning is small anyway. The same problem applies to Curley's argument that known-risk options are easier to justify to other people. Why should there be a difference when the probabilities at stake are low? Both models, as well as the anchoring and adjustment theory, need additional theoretical assumptions to account for these data that fundamentally differ from the general explanation of the ambiguity. As a result, they have to posit different mechanisms to account for the various empirical findings. In contrast, our approach can account for these data by suggesting that decisions are based on assumptions regarding the probability distributions (see Discussion section of Experiment 4) and *one* generally applicable decision rule.

This rule has three major components, none of which is entirely new in the decision making literature. Expected utility has been the core concept of decision making under uncertainty since its invention by Bernoulli. But outcome variability and aspiration level have also been acknowledged as important features of decision making processes. For example, outcome variability has been studied by Coombs and Pruitt (1960), who found ''a preference for certain amounts of variance'' (p. 276), and by Lichtenstein (1965), who, contrary to the Coombs and Pruitt results, found variance avoidance.

Similarly, aspiration level has been mentioned as a relevant factor for decision making (Payne, Laughlunn & Crum, 1980; Lopes, 1996), but ''subjects' goals and aspirations have not played a prominent part either practically or theoretically in the development of decision theory'' (Lopes, 1983, p. 143). In contrast to our studies, these previous attempts to study variance and aspiration level were motivated by a conviction that they were intuitively plausible, rather than by a normative theory according to which these variables are important.

This lack of theory might have led to the inconsistent results of prior experiments. In those studies, the relevant variables were not investigated in a context in which their effects could be observed. In our experiments, we intentionally combined aspiration and variance factors in a way that would be meaningful to the subjects if the theory were correct. Thus, these experiments were, in principle, capable of yielding consistent findings that can be interpreted in terms of an adaptive algorithm that works if given the appropriate input.

Our results are not necessarily inconsistent with certain aspects of other theories of decision making. Tversky and Kahneman (1992), for example, have proposed Cumulative Prospect Theory, which is explicitly considered to be merely descriptive by the authors. Insofar as Cumulative Prospect Theory is just an empirical generalization about how subjects behave, it can partly account for the pattern of data found in our experiments. If it is merely descriptive, however, then it provides no explanation. Our aim is to explain *why* subjects choose in a certain manner, not just *how* they choose. Thus, even if the data of Experiments 1–4 *were* fully consistent with some other descriptive model, our approach would be theoretically preferable because it provides an explanation.

The purpose of our experiments was to probe the design features of human computational mechanisms and not to prove that people ''are'' either rational or irrational. Because our goal was to elucidate design features, Experiments 3 and 4 — in contrast to most decision-making studies — asked about lotteries in which subjects have the opportunity to draw more than one time. This deviation from the traditional method was necessary because of accumulating evidence that the statistical inference mechanisms activated in this kind of study operate on frequency input. In other words, if we want to study how such decision making mechanisms work, we need to provide the appropriate input. Because of this methodological change, we cannot unequivocally conclude that people apply the same cognitive algorithm to the single-draw situations commonly used in ambiguity experiments.

So strictly speaking, our results should be constrained to decision-making problems in which participants draw repeatedly. We would like, however, to conclude by reconsidering, from a functional perspective, the classical Ellsberg task introduced in the beginning of this article.

Assume a subject may choose between one box that is filled with 50 black and 50 white balls and another box that is also filled with 100 black and white balls but in an unknown composition. The subject is first given the opportunity to win $100 by drawing a black ball from one of these two boxes. Most subjects prefer the box that is filled with 50 black and 50 white balls. Next the subject is offered the opportunity to win another $100, but this time she must draw a white ball to win. Again, most subjects prefer the 50/50 box. Failing to switch which box she draws from is usually interpreted as an irrational choice because it violates the Additivity axiom, as discussed previously. But considering the subject's needs might lead to a different conclusion.

Typically an ambiguous option would be the higher variance one for the reasons discussed. But in the Ellsberg problem, the variance in winning outcomes is higher for the 50/50 box. This difference arises because, whereas black was always the winning color in the other problems, what counts as a win changes from black to white in the Ellsberg problem — a winning outcome for the first draw is a losing outcome for the second. Now suppose your goal (or self-defined need) in the above situation is to win the $100 in both draws: in other words to maximize the probability of winning $200. If this is the case, it is rational to prefer the high variance, 50/50 box for both bets. In contrast, if your goal is to avoid winning nothing — i.e. to win at least $100 — then it is rational to prefer the low variance unknown box for both bets. The reason is as follows:

The probability of winning with the unknown box varies depending on the distribution of balls it ends up having. If the unknown box contains more black than white balls, then one is more likely to win the first bet but less likely to win the second, and vice versa if white outnumbers black. In other words, 100 out of 101 distributions are more likely to produce one winning outcome than two. The only distribution that does not stack the odds against two wins is a 50/50 distribution, which can be expected to yield two wins $\sim$ 25% of the time. The known-risk box definitely has a 50/50 distribution, whereas there is only 1 chance in 101 of a 50/50 distribution in the unknown box. Because a 50/50 distribution will produce two wins more often than other distributions, the 50/50 box should be chosen if your goal is to win both times.

By the same logic, you should choose the unknown box for both draws if your goal is to win at least one bet (i.e. to avoid winning nothing). The unknown box is unlikely to produce zero wins for the same reason it is unlikely to produce two wins: for 100 out of 101 distributions, the most frequent outcome will be one win. In contrast, the 50/50 box will yield no wins 25% of the time.

In other words, the decision rule we have been testing applies: if you need the mean payoff, "forage" in the low variance box; if you need more, forage in high variance box. The only difference between this situation and ordinary lotteries —

ones in which what counts as a win stays constant — is that the unknown box in the Ellsberg lottery has lower outcome variability than the known-risk box.

Within this paradigm goal state has not been experimentally controlled and also it is not yet clear whether people view the two steps of the task as one gamble or as two different gambles. However, the typical choice pattern observed is either selecting the known box for both bets or selecting the unknown box for both bets. Given that the instructions for the Ellsberg problem do not specify a goal, clearly distinguish between the steps, or clearly frame it as one single problem, it may be speculated that subjects determine their needs individually without the experimenter's knowledge and act in accordance with the theoretical framework presented in this article.

The results of these experiments indicate that subjects take both mean, variance, and need level into account in making decisions under uncertainty. Moreover, in Experiment 4, their answers reflected the true probabilities of each box satisfying their need level, suggesting the operation of a very well-designed system.

Given these results, a reasonable person might ask, Are these judgments the output of an evolved system? Or do people learn the relevant pieces of information and the equations for combining them through experience?

Before addressing this question, let us pose it more precisely. Optimal foraging theory is an explicit account of some of the selection pressures that should have shaped mechanisms for making judgments under uncertainty in foraging animals. Based on this theory, animal behavior researchers have found evidence of mechanisms in nonhuman animals that generate the judgments one would expect if these mechanisms were functionally specialized for solving the adaptive problems described by optimal foraging theory. Based on both considerations — the selection pressures and the evidence from the literature on risk-sensitive foraging in other animals — we predicted that humans, who were also shaped by a selective history of foraging, would also have evolved mechanisms that are functionally specialized for making such decisions. Just as your retina can compute the second derivative of the local distribution of light intensity (regardless of whether you have ever taken a course in calculus; Gallistel, 1990), we predicted that the mechanisms that generate these judgements are designed to combine data about means, variances, and need level in the mathematically appropriate ways to generate a well-calibrated judgment (regardless of whether the subject has ever had explicit instruction in probability theory). Our hypothesis is that the mechanism is functionally specialized for this purpose, in the same way that the language faculty is thought to be functionally specialized for the acquisition of language (Pinker, 1994).

Every evolved mechanism (including the language faculty) requires certain environmental conditions to develop properly, and we assume the mechanisms we have hypothesized are no exception. We frame no specific hypotheses about what role experience might have in the development of these mechanisms; we do note, however, that they appear to reliably develop within the boundaries of (ancestrally) normal variations in environmental conditions, and in the absence of explicit instruction.

The alternative ''learning'' view makes two claims: (1) people lack a mechanism functionally specialized for risk-sensitive foraging, and (2) using other mechanisms (ones not specialized for this purpose), people somehow learn that means, variances, and need levels (and not other kinds of data) are relevant, and they learn how to combine these variables in the mathematically appropriate ways, incidentally and without conscious deliberation. The primary difference is that the learning view posits an mechanism that is not specialized for making this kind of judgment under uncertainty. Also, there is not just one learning view, but many: many different algorithms can cause learning (compare those that cause the acquisition of syntax to those that cause the acquisition of food aversions). Without knowing exactly which learning algorithm is being proposed, one cannot say with certainty whether it is, or is not, capable of acquiring the knowledge of which variables are relevant and how they should be combined.

Nevertheless, the plausibility of the learning view(s) can be evaluated in a qualitative sense by asking whether subjects are good at learning simpler probability relations. To do this, consider the literature on how people reason about frequencies versus the probability of single events (e.g. Gigerenzer, 1991; Gigerenzer & Hoffrage, 1995; Cosmides & Tooby, 1996). In experiment after experiment, subjects given problems in which they are asked to compute the probability of a single event fail miserably (see also Kahneman et al., 1982).

Yet a simple way to solve these problems is to translate them into a frequency format; indeed, if the experimenter makes this translation for the subject, the subject will perform very well (Gigerenzer & Hoffrage, 1995; Cosmides & Tooby, 1996a). But there are data indicating that only 12–36% of college students spontaneously learn to make this translation (see Cosmides & Tooby, 1996). If 66–88% of people fail to learn such a simple translation function through incidental learning, then how likely is it that a similar process would cause the majority of subjects to induce the solution to the vastly more complicated problems that we gave them? Footnote 2 shows the formula that the experimenters needed to use to calculate the true probabilities: the calculations were complex and laborious, even though we knew what the relevant variables were. According to the learning view, the subject would first have to segregate out all and only means, variances, and need levels as the relevant variables, then induce the formula in footnote 2, and then carry out the calculations — all using mechanisms that are not specialized for this purpose, and that do not have the relevant formulas or calculatory machinery built into their design.

Given the difficulty of the task and the inability of subjects to solve simpler tasks within the same domain, we find the learning view implausible. The data are, after all, surprising: this is not the kind of calculation that one would expect untutored subjects to routinely make with ease. When a prior prediction, derived from a well-formulated theory, is confirmed by surprising data, the hypothesis that gave rise to that prediction deserves careful consideration. Future data may, of course, change our conclusion. But until such data emerges, we think it is more parsimonious to assume that a mechanism specialized for making risk-sensitive judgments has evolved in humans, just as it has in other animals, and that our subjects' judgments were generated by this functionally specialized mechanism.

9. Conclusion

The people who participated in our experiments executed complex decision strategies, ones that take into account three parameters — mean, variance, and need level — rather than just the single parameter (mean) emphasized by some normative theories. Their intuitions were so on target, that their decisions very closely tracked the actual probabilities of each box satisfying their needs. This was true even though explicitly deriving these probabilities is a nontrivial mathematical calculation.

Indeed, the people in our experiments did something quite sophisticated: they used *meta-probability information*. They were given information about the population of possible probability distributions and the process that would be used to determine which one the unknown box would contain. From this, they appear to estimate the variability of possible outcomes and use this estimate to make a rational decision.

If one considers the kinds of adaptive problems that foraging animals encountered during their evolutionary history, people's ability to estimate the variance of both outcomes and probability distributions may seem less surprising. Consider two groves of fruit trees. Neither the expected outcome of a foraging trip nor the probability of a given outcome is likely to stay constant. Many factors — fluctuations in wind conditions, season, your own state of health, the population of tree-dwelling predators, and so on — can affect the probability that you will be able to harvest a given amount from a grove. Some days there will be a high probability of getting a certain take, on others there will be a low probability, but one does not always know in advance what probability will pertain today. Rather than collapsing all the outcomes and probabilities of outcomes that obtain under different conditions into an omnibus expected value, risk-sensitive foraging theory says that an animal is better off if it can use information about the variance associated with these outcomes and probability distributions.

Like many optimality models from evolutionary biology, risk-sensitive foraging theory includes parameters such as the organism's current state and its level of need — values rarely considered in the normative theories popular in cognitive psychology. One should not expect the cognitive architectures of evolved organisms to be ''rational'' when rationality is defined as adherence to a normative theory drawn from mathematics or logic. One should expect their cognitive architectures to be *ecologically rational*: well-designed for solving the adaptive problems their ancestors faced during their evolutionary history (Cosmides & Tooby, 1996b; [Tooby & Cosmides., 1999]).

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