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Overcoming Ambiguity Aversion Through Experience

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ABSTRACT

Ambiguity is often characterized with unknown probability distributions (for potential outcomes), which people avoid while making decisions. Existing literature shows that ambiguity aversion often persists even when these probability distributions are explicitly described to decision makers. We test the hypothesis that exposure to these probability distributions via sampling *experience*, rather than description, will lead to a reduction in ambiguity aversion. We used the classic two-colour Ellsberg task in which the participants were asked to choose to bet on either a risky bet (i.e. probabilities were known) or (versions of) an ambiguous bet (i.e. exact probabilities were unknown). Different probability distributions, each providing subtly different information about the underlying properties of the ambiguous bet, were either experienced through sampling or described to participants prior to choice. Overall, the results indicated that people demonstrated ambiguity-neutral attitudes when the underlying probability distributions were experienced. In contrast, when described, attitudes toward ambiguity changed as a function of the type of probability distribution. Additional analyses confirmed that decision makers were less likely to be ambiguity-averse when their individual experiences were positive during sampling trials (i.e. observing distributions with winning being more likely or more frequent). Copyright © 2014 John Wiley & Sons, Ltd.

KEY WORDS ambiguity aversion; experience; description; sampling; probability distributions

INTRODUCTION

Ambiguity aversion refers to a pattern of preferences favouring events with known probabilities for potential outcomes over those with unknown probabilities, even when the best probability estimate for the latter is more or less equal to that of the former (Budescu, Kuhn, Kramer, & Johnson, 2002; Camerer & Weber, 1992). The existence of ambiguity aversion has been primarily demonstrated and investigated in the classic two-colour Ellsberg task (Ellsberg, 1961, see Figure 1). While not demonstrating a particular colour preference, the majority of people given this task prefer to bet on the risky box rather than the ambiguous box (Charness, Karni, & Levin, 2013; Chew, Ebstein, & Zhong, 2012; Chow & Sarin, 2001; Fox & Tversky, 1995; Halevy, 2007; Keren & Gerritsen, 1999; Kramer & Budescu, 2005; see Camerer & Weber, 1992 for an extensive review). This pattern of preferences is paradoxical because it is not justifiable from a normative point of view [i.e. the risky box cannot contain a higher portion of *both yellow and black balls at the same time* (Savage, 1954)] yet intuitive from an individual decision-maker perspective.[1]

The "unknowns" in the Ellsberg task

Ambiguity aversion is often thought to result from the unknown probabilities (Frisch & Baron, 1988; Camerer & Weber, 1992). There are two different types of probabilities that could be known in the Ellsberg task: First-order probabilities (henceforth, FOPs), which correspond to the probability of obtaining a particular outcome, and second-order probabilities (henceforth, SOPs), which are the probabilities of the probability of obtaining a particular outcome. Figure 1 depicts these two different types of probabilities. For the risky box, the information regarding both FOP (i.e. 0.5) and SOP (i.e. 1) is known, but for the ambiguous box, both are unknown. The other three boxes in Figure 1 demonstrate examples in which the information regarding various SOP (distributions) is known. For the box labelled "Equal Probability", the probability of drawing any number of black balls is uniformly distributed, which indicates that all possible FOPs are equally likely. For the box labelled "Normal Distribution", the probability of drawing a black ball is normally distributed, which indicates that the FOP is more likely to be around 0.5. For the box labelled "Fifty-Fifty", the probability of drawing a black ball for sure or a nonblack ball for sure is equally likely (0.5), which implies that the FOP is either 1 or 0. As seen in Figure 1, the information regarding the SOP distributions is crucial in determining the "objective" level of ambiguity: Even though the exact FOPs remain unknown, the known SOP distribution implies some information regarding the FOPs and hence reduces the level of ambiguity (i.e. from a state of *unknown FOP and SOP* to a state of *unknown FOP but known SOP*). Therefore, ambiguity aversion should, from a normative perspective, decrease when the SOP distribution is known (Camerer & Weber, 1992).

Unlike numerous studies concerning the effect of varying FOP information on ambiguity aversion (e.g. see Becker & Brownson, 1964; Budescu et al., 2002; Curley & Yates, 1985; Du & Budescu, 2005; Einhorn & Hogarth, 1986; Kahn & Sarin, 1988; Kramer & Budescu, 2005; Kuhn & Budescu,

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[1]The adequacy of "ambiguity" (aversion) as a descriptive term has been challenged, and rather, the use of "imprecision" (avoidance) or "vagueness" (avoidance) is encouraged by some parties (e.g. Budescu, Kuhn, Kramer & Johnson, 2002; Kramer & Budescu, 2005). However, the term "ambiguity" (aversion) is preferred in this paper in order to follow the general convention in the literature (Camerer & Weber, 1992).

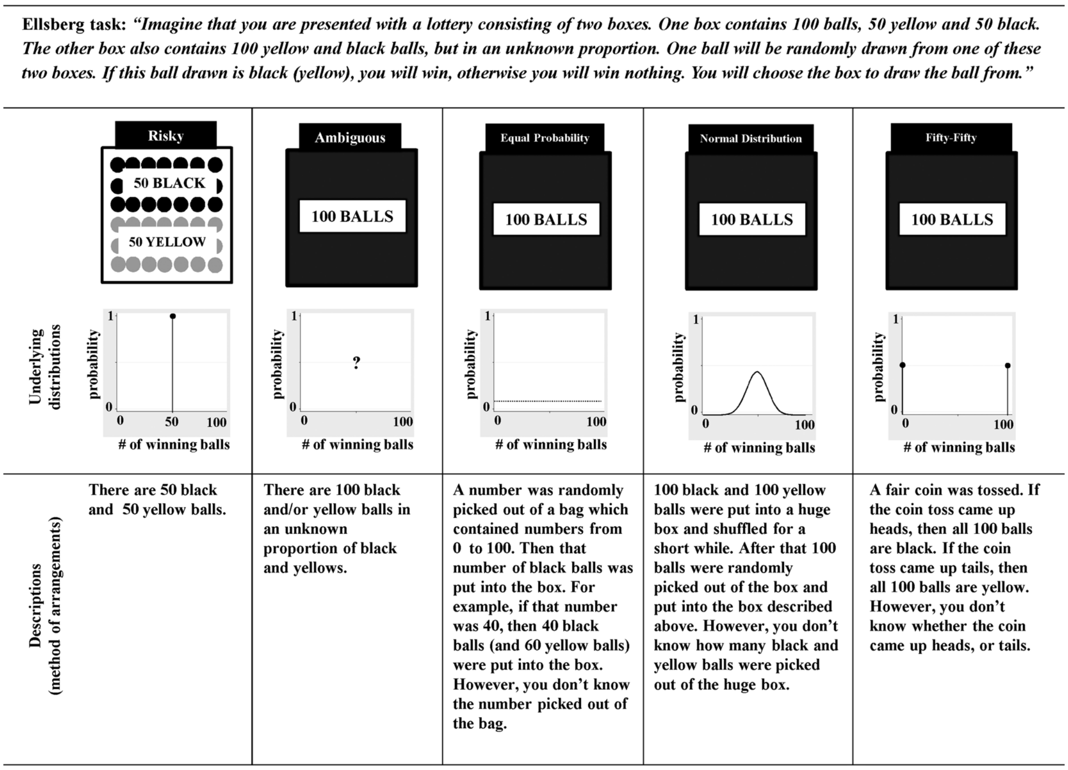

Figure 1. The two-colour Ellsberg task, underlying probability distributions in Risky, Ambiguous, Equal Probability (EP), Normal Distribution (ND) and Fifty-Fifty (FF) bets and corresponding descriptions

1996; Larson, 1980), investigation of SOPs is limited in the literature: (i) there is a lack of variation with respect to the type of SOP distributions under investigation [i.e. uniform distribution is widely used, but see Halevy (2007)], (ii) findings are inconclusive [some people avoid the known SOPs, but some do not (Chow & Sarin, 2002; Halevy, 2007; Keren & Gerritsen, 1999; Yates & Zukowski, 1976; and see Bernasconi & Loomes, 1992 for results in the three-colour Ellsberg problem], (iii) some results are inconsistent with theoretical predictions [i.e. binomially distributed SOPs are expected to decrease ambiguity aversion (Attanasi et al. 2012), but they do not (Halevy, 2007)], and more importantly, (iv) no clear underlying psychological mechanism has been proposed to explain the existing findings. Thus, unlike in the literature on decisions under risk [see Lopes (1984; 1987) for the discussion of potential psychological factors determining responses to varying distributions], there seems to be no clear evidence on the extent to which participants understand the implications of known SOP information nor the subsequent impact of the information on choice in decisions under ambiguity. Referring back to Segal's (1987) theoretical notion, the persistence of aversion to known SOP distributions could be attributed to the "inability to deduce FOPs through using information regarding SOPs" (Halevy, 2007; Bernasconi & Loomes, 1992). However, the existence of such inability does not rectify the listed limitations, and the question of where this inability stems from still remains unclear.

A large body of empirical evidence in the judgment and decision-making literature demonstrates that people are in general not good at dealing with probabilistic information under uncertainty (Kahneman & Tversky, 1984; Kahneman & Tversky, 1979; Koehler, 1996; Newell, Lagnado, & Shanks, 2007). However, many other examples show that the use of probabilistic information can be facilitated—and thus probabilistic fallacies can be eliminated—through presenting probabilities in settings or frameworks that mesh more readily with the cognitive machinery that people bring to bear when faced with such problems (Cosmides & Tooby, 1996; Gigerenzer & Hoffrage, 1995; Hertwig, Barron, Weber & Erev, 2004; Hogarth & Soyer, 2011; Krynski & Tenenbaum, 2007; Stanovich & West, 2000).

The information regarding the SOP distributions or what it implies with regards to ambiguity is relatively complex (see Figure 1), and people have been shown to make inaccurate probabilistic inferences when the distributions are explicitly described (Curley et al., 1989). However, we argue that like the other examples in the literature, the probability distributions can be expressed in a more intuitive manner, which could facilitate their use under ambiguity and thus result in a reduction in ambiguity aversion. One way to create such an intuitive context is to let people *experience* the probability distributions. Such experience allows interaction with what Hogarth has termed "kind" environments—ones in which the elements of a decision problem are made transparent thereby facilitating reasoning and choice (Hogarth, 2001; Hogarth & Soyer, 2011; Hogarth, Mukherjee & Soyer, 2013).

In the current study, we aimed to understand how people's attitudes towards SOP distributions underlying the

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ambiguous box[2] in an Ellsberg type task would change when potential distributions were experienced through sampling, instead of via descriptions. We conjecture that experience with probability distributions might lead decision makers to make more accurate inferences about the probabilities of winning with the ambiguous box and that this experience will have downstream influences on their preferences.

How to experience potential distributions under ambiguity
A recent study by Dutt, Arlo-Costa, Helzner, and Gonzalez (2013) aimed to establish a Description-Experience gap for decisions under ambiguity by using a similar sampling set-up to those used in studies of decisions under risk. Dutt et al. (2013) used a modified version of the two-colour Ellsberg task, and prior to the decision making stage, the participants were allowed to sample the possible *outcomes* (i.e. winning/losing a particular outcome) from both the risky box and the ambiguous box, with the latter being renewed in each sampling trial in order to preserve the ambiguous nature of the box. The probability of winning (FOP) was 0.5 for the risky box and uniformly distributed for the ambiguous box (i.e. corresponding to our "Equal Probability" case presented in Figure 1). Their results demonstrate that "experiencing" the win/lose outcomes from both risky and the so-called ambiguous boxes through the *outcome sampling* method decreased ambiguity aversion and resulted in an ambiguity-seeking pattern [Dutt et al., 2013; also see Ert & Trautmann (2014) for another study investigating a similar issue in an Ellsberg type task through an outcome sampling method and showing that ambiguity aversion reduces when FOP was 0.5].

However, in accordance with our aims, we took one further step in incorporating ambiguity into the sampling experience paradigm, and thus, instead of an outcome sampling method, we used a *distribution sampling* method. This method presents the distribution of winning balls in a sample of balls representing the potential underlying probability distributions for the ambiguous box. Figure 2 below depicts the differences between the *outcome sampling* (as used in Dutt et al. study) and *distribution sampling* methods (as used in our study) in terms of *what can be experienced and/or learned across sampling trials* and hence explains why the distribution sampling method is more advantageous for testing the effect of experience of ambiguity and associated probability distributions in an Ellsberg-type task.

As shown in Figure 2, while the outcome sampling method only provides "win/lose" type *outcome information*, the distribution sampling method [panels (a), (b) and (c)] provides participants with a "win with probability of X" type *probabilistic information*. Therefore, participants' overall experience is related to *uncertain outcomes* in the outcome sampling method but to *uncertain probabilities associated with uncertain outcomes* in the distribution sampling method. Note that people need to avoid uncertainty about probability distributions, not only uncertainty associated with outcomes, in order to describe that avoidant pattern of preferences as ambiguity aversion, instead of risk aversion (Camerer & Weber, 1992, p. 331). Therefore, any avoidant preferences can be confidently classified as ambiguity aversion in the distribution sampling case but not necessarily in the outcome sampling case since the experienced uncertainty is associated with probabilities in the former but not in the latter.

In order to satisfy the "ambiguity" principle in the sampling paradigm, the ambiguous box needs to be renewed in each sampling trial so that the content of the box remains unknown. Since the distribution sampling method provides participants with probabilistic information, the underlying probability distribution is still tractable even when the box is a new one in each trial. As seen in Figure 2, the overall experience in panel (c) distribution sampling case indicates that any winning likelihood is possible (therefore indicates a uniform distribution), whereas in panel (a), that winning likelihood is likely to be around 0.5 (therefore indicating a normal distribution). However, observing outcomes in the outcome sampling method does not give any information regarding a specific underlying probability distribution when the box is renewed each time. For instance, the observed outcome samples in the outcome sampling case of Figure 2 could result from a uniform distribution as well as a normal distribution or a binomial distribution. Thus, the outcome information observed in the outcome sampling method does not differentiate one distribution from another.

Therefore, we argue that the distribution sampling method (i) provides further insight into ambiguity aversion in the sampling experience paradigm and (ii) is more suitable for distinguishing one distribution from another and hence for testing the impact of various SOP distributions underlying the ambiguous box in the sampling paradigm.

THE PRESENT STUDY

The task we used in the experiment was the two-colour Ellsberg task described in Figure 1. However, we had four different versions of the ambiguous box (which was always presented along with the risky box): the original Ambiguous box with unknown SOP distributions and the other three boxes with known SOP distributions, "Equal Probability" (henceforth, EP), "Fifty-Fifty" (henceforth, FF), and "Normal Distribution" (henceforth, ND) as described in Figure 1. To the best of our knowledge, ND has never been previously used in the literature, unlike EP (Chow & Sarin, 2002; Halevy, 2007; Yates & Zukowski, 1976) and FF (Halevy, 2007).

In the *Description* condition, the participants were provided with the SOP information through descriptions of the methods used in the arrangement of coloured balls

[2]On the basis of the reasons outlined above, we acknowledge the fact that once the underlying SOP distribution is known, the ambiguous box/bet is no longer as ambiguous as the original ambiguous box/bet in the classic Ellsberg task. In order to keep the original labelling in the Ellsberg task, however, we will continue to use the label of "ambiguous" regardless of whether the SOP distribution is unknown or known.

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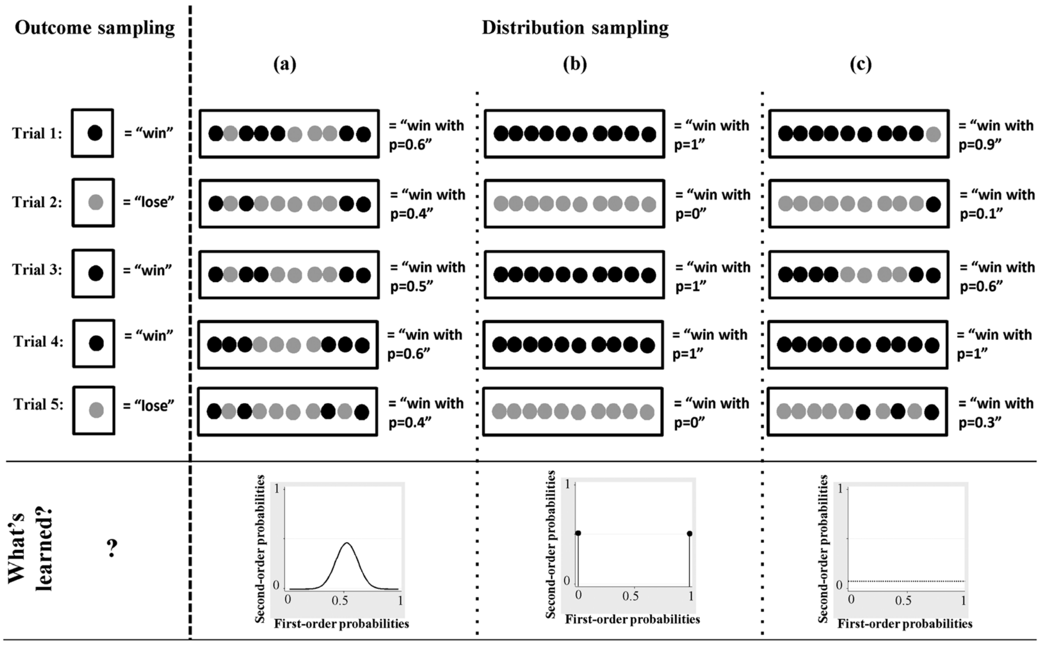

Figure 2. Difference between outcome sampling and distribution sampling methods in terms of what is experienced/learned across hypothetical sampling trials

in the ambiguous box (see Figure 1 for the corresponding descriptions in the EP, ND, and FF groups), except for those in the Ambiguous group (i.e. the original ambiguous box in the Ellsberg task was presented). In the *Experience* condition, the SOPs were experienced through distribution sampling. The participants were allowed to take a sample of 10 coloured balls (displayed all at once, as in Figure 2) in each sampling trial only from the ambiguous box before final choice stage, and each of these 10-ball samples reflected the corresponding probability distribution, either a uniform (in the EP group) or a normal (in the ND group), or a binomial (in the FF group) (see Method section for details). Note that in each sampling trial, the 10-ball sample was taken from a *new* ambiguous box, but the underlying distribution remained unchanged. For example, in the FF group, the 10-ball sample in the first trial could consist of all winning balls, but in the second trial, it could be all nonwinning balls. In this way, the decision makers still did not know the *exact* content of the ambiguous box (i.e. the number of winning balls) but only learned *what the distributions of wining balls looked like*. Otherwise, through sampling, the decision makers would know that, for instance, all balls were winning balls (or none were winning balls) rendering the ambiguous box no longer ambiguous. Importantly, the ambiguous box was renewed with a new set of balls in the final choice stage as well.

The formulation of the ambiguous box in the Ambiguous group of the Experience condition was completely different from that of the other SOP groups as well as from those in the previous literature [i.e. Dutt et al. (2013)]: There were three potential probability distributions (a uniform, a normal, or a binomial) that could underlie the ambiguous box, and in each sampling trial, one of them was randomly assigned. This formulation was in line with the theoretical definition of ambiguity, that is the inability to assign a single probability distribution to a specific outcome probability (see Camerer & Weber, 1992, p. 332) since there were multiple potential underlying distributions and it was unknown to the participants which distribution will come up in which sampling trial (and in the final choice stage).

Even though ambiguity aversion should decrease once the SOP distributions are known, we expected to obtain high levels of ambiguity aversion to the box with EP and FF in the Description condition on the basis of existing findings (Halevy, 2007; Yates & Zukowski, 1976). However, the level of ambiguity aversion could be relatively lower for the box with ND. This is mainly because ND implies that the FOP is more likely to be around 0.5, whereas EP, for example, indicates that FOP could be anything between 0 and 1 with an equal probability. Therefore, participants might be more confident in predicting/estimating the potential likelihood of winning in the former and could demonstrate less aversion (Güney & Newell, 2011).

Our predictions for the Experience condition were as follows: First, ambiguity aversion, in comparison to the Description condition, would be lower for all groups, including the Ambiguous group, because experience would facilitate the use and understanding of the SOP distributions. A secondary prediction relates to the sampling strategies adopted by participants. Recent studies suggest that participants sample differently when facing different outcomes in risky choice situations (e.g. sampling more when facing a loss than a gain; Lejarraga, Hertwig & Gonzalez, 2012). Building on these and related findings (e.g. Hills & Hertwig, 2010), we predicted that participants in the Ambiguous group and those given the Equal Probability distribution (EP) would sample *more* from the ambiguous box than participants faced with the other distributions. This prediction is based on the simple idea that

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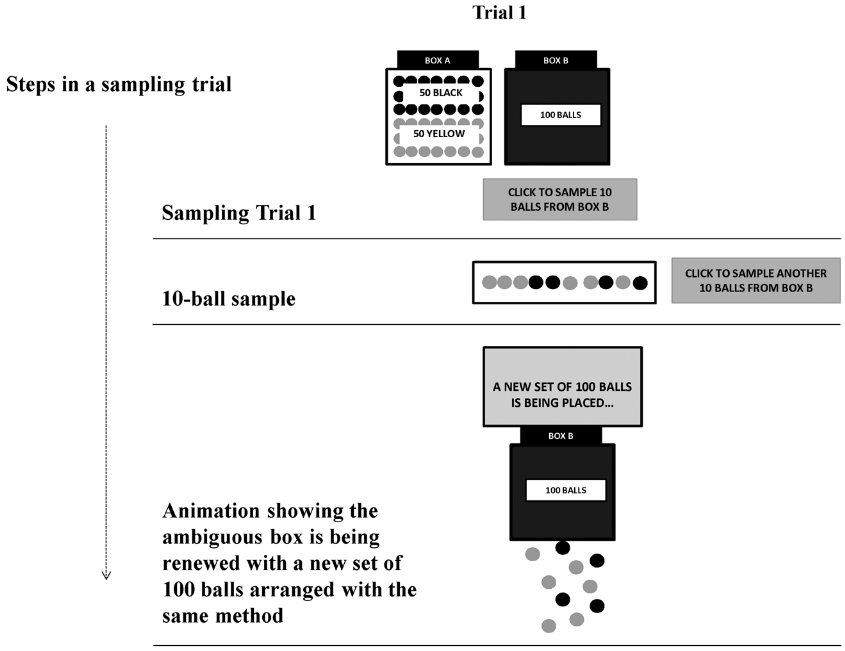

Figure 3. Steps in a sampling trial. This procedure was repeated for five trials. Then the participants were provided with the option for proceeding to the final choice stage, along with the option of sampling more. For the animation showing that the box is emptied and refilled with a new set of 100 balls, the participants were informed that the dropping balls may or may not reflect the content of the box

the less informative one's samples are about the underlying chance of winning, the more samples one will take. Finally, even though our manipulation ensures that the average number of observed winning balls would be around 5 regardless of the type of SOP distribution experienced (i.e. expected probability of winning in *all* groups is concentrated around 0.5), we predicted that the likelihood of choosing one box over another would be contingent on participants' individual experiences regarding (i) average and (ii) frequent winning probabilities observed during sampling trials (see Camilleri & Newell, 2011; Hills & Hertwig, 2010; Rakow, Demes & Newell, 2008 for similar findings in risky choice).

METHODS

Participants

Four-hundred and sixty-four participants (M age = 29.7, 160 female) were recruited through Amazon Mechanical Turk and paid a flat participation fee (i.e. 30 cents) in return for their online participation. The participants were also given bonus payments (i.e. 20 cents) if they won in the two-colour Ellsberg task. All participants were located in the U.S.A. and were native English speakers. The experiment took 8 minutes for the Description condition and 14 minutes for the Experience condition, approximately.

Design and procedure

The experiment had a 2(Description versus Experience) × 4 (Ambiguous versus EP versus ND versus FF) between-subjects design, and incoming participants were randomly allocated to one of the eight conditions[3]. The two-colour Ellsberg task was explained first. The winning colour (i.e. black or yellow) in the task was pre-set and randomized across participants. The risky box was labelled as Box A and ambiguous box(es) as Box B. In the *Description* condition, except for the Ambiguous group, participants were told that Box B was arranged with a *special method* that made the proportion of black and/or yellow balls unknown. Then they were given the corresponding information regarding the method of arrangement of the coloured balls (see Figure 1).

In the *Experience* condition, the participants were given the following instructions (the information in parentheses were not given to those in the Ambiguous group):

> (Box B was arranged with a special method that made the proportion of black/yellow balls unknown). The exact proportions of black and yellow balls in Box B would never be known throughout the whole experiment. However, you would be given a chance to see what the proportion of balls would look like in Box B, prior to the actual decision making stage. This would be realized by allowing you to take a sample of 10 balls from Box B on each sampling trial. Each 10-ball-sample would reflect how the black/yellow balls could possibly be distributed in Box B or how many

[3]We ran an additional condition in which the participants were given the descriptions and then asked to think carefully about (and estimate) the probabilities and distributions prior to the final choice stage (see Appendix for post-task questionnaire). We speculated that if SOPs were effective in determining the level of ambiguity aversion but persistent aversion results from people ignoring the relevant information, then ambiguity aversion should have also decreased when people are forced to think. However, the obtained levels of ambiguity aversion in this additional condition were very similar to those found for the Description condition thus providing no support for this speculation. We do not consider data from this condition further.

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winning balls could be in a 10-ball sample from Box B. After each sampling trial, Box B would be emptied and re-filled with a new set of 100 black and/or yellow balls (which was arranged with the same special method). Once you completed the required number of sampling trials, you would be allowed to proceed to the actual decision making stage or continue to take samples for as many trials as you like. Box B would be emptied and re-filled with a new set of 100 coloured balls (with the same special method of arrangement) once again in the beginning of the actual decision making stage.

Afterwards, the participants proceeded to the sampling stage (see Figure 3 for details of a sampling trial). In the EP group, the 10-ball sample could contain any number of winning balls (either black or yellow) with equal probability (i.e. a 10-ball sample was equally likely to consist of 2 black + 8 yellow balls or 7 black + 3 yellow balls or 5 black + 5 yellow balls and so on). In the ND group, the 10-ball sample could contain any number of winning balls, which was more likely to be around 5 [i.e. a 10-ball sample was more likely to contain 5 black + 5 yellow balls than 6 black + 4 yellow balls and so on]. In the FF group, with probability of .5, the 10-ball sample either consisted of all winning balls or none (i.e. either 10 black balls or 10 yellow balls) (see Figure 2). In the Ambiguous group, the program randomly selected one of these three possible distributions first in each sampling trial, and then the above procedure was executed accordingly.

Together with the written instructions, the participants were provided with animations showing how the ambiguous box was emptied and refilled with a new set of balls in the beginning of each sampling trial (see Figure 3 for the animation). Once they completed the fifth sampling trial (i.e. which was compulsory, but unknown to the participants), the option of proceeding to the final choice stage was given along with the option of continuing the sampling trials. After relevant stages were completed, all participants were asked to choose the box that they would like to bet on. Following the choice, participants completed a post-task questionnaire, the details of which are contained in the Appendix. Then one ball was randomly chosen from the box that the participants selected. If the selected box was the ambiguous one, the underlying probabilities of probabilities of winning were contingent on the corresponding probability distributions that were generated prior to the final choice stage. If the colour of the ball drawn matched the colour of the winning ball, then the participants won a bonus payment of 20 cents, otherwise nothing.

RESULTS

Data of five participants were discarded from the analyses because they either stated that the (ambiguous) box was not a new one in the Experience condition or did not pass the attention check question (i.e. "How many black balls were in Box A?") which was presented right after the description of the Ellsberg task.

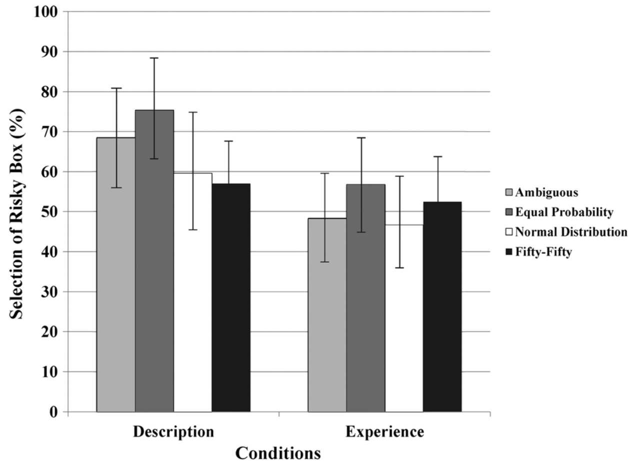

Figure 4. Selection rates of Risky box/bet for Ambiguous, Equal Probability, Normal Distribution and Fifty-fifty groups across Description and Experience conditions. Error bars correspond to 95% CI

Level of ambiguity aversion

Figure 4 shows the selection rate of the risky box—an index of ambiguity aversion—for all SOP groups (i.e. Ambiguous, EP, ND and FF) in the *Description* and *Experience* conditions. In the *Description* condition, the selection rate of the risky box was above 50% in all groups, indicating ambiguity aversion. The respective difference from 50% was statistically significant in the Ambiguous and EP groups (binomial test, two-sided—$p = .009$ and $p = .0002$, respectively). In addition, the level of ambiguity aversion was significantly higher in the EP group than in the FF group [LR χ^2 (1, $N = 109$) = 4.07, $p = .04$] and marginally higher than in the ND group [LR χ^2 (1, $N = 110$) = 3.12, $p = .07$]. In the *Experience* condition, however, none of the groups showed rates of risky box selections that significantly differed from 50%, $p > .05$. In addition, none of the groups significantly differed from each other in terms of the obtained level of ambiguity aversion (see Figure 4).

We then compared the change in levels of ambiguity aversion for each group across the Description and Experience conditions. For both the Ambiguous and EP groups, the level of ambiguity aversion was significantly lower in the Experience condition than the Description condition, LR χ^2 (1, $N = 116$) = 4.79, $p = .02$ and LR χ^2 (1, $N = 111$) = 4.24, $p = .03$, respectively. For the ND and FF groups, even though ambiguity aversion was, on average, lower in the Experience condition, the differences were not statistically significant.

Sampling data (Experience condition only)

Number of sampling trials

Table 1 (left column) shows the *average number of sampling trials* for each group. Note that the minimum number of sampling trials was fixed at 5, so all cells in Table 1a must be equal to or higher than 5. The average numbers of sampling trials significantly differed as a function of the group, $F(3, 235) = 22.11$, $p < .0001$. Tukey HSD test revealed that the number of sampling trials in

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Table 1. (a) Mean number of sampling trials taken during sampling stage across Ambiguous, Equal Probability (EP), Normal Distribution (ND) and Fifty-Fifty (FF) groups, and (b) each group's (mean) experience for winning in a 10-ball sample

Groups	(a) Average number of sampling trials taken [95% CI]	(b) Average group experience for winning in a 10-ball sample
Ambiguous	6.27 [5.9–6.5]	5.04
EP	6.67 [5.9–6.5]	4.99
ND	5.20 [4.8–5.5]	5.00
FF	5.10 [4.7–5.4]	4.48

both the Ambiguous and EP groups was significantly higher than that of the ND and FF groups $p < .05$ (the EP and Ambiguous groups did not differ significantly), as expected.

Overall group experience

To confirm our manipulation that all groups, on average, had the same experience for the number of winning balls in a 10-ball distribution, we examined the *average number of winning balls experienced in each SOP group* across sampling trials (Table 1 right column). For instance, if the number of winning balls was 7, 5, 3, 6, 1 in each 10-ball sample over five sampling trials, the *average number of winning balls experienced* is $(7 + 5 + 3 + 6 + 1) / 5 = 4.4$ (i.e. total number of winning balls is divided by the number of samples taken). The results show that none of the groups significantly differed in terms of the average number of winning balls experienced. Note that the expected probability of winning also did not deviate from 0.5 in any group, indicating that the overall information presented in the Experience condition is indeed equivalent to that of the Description condition.

Individual "winning" experience and box selection

We then analyzed whether two different types of individual experience for winning probabilities in the ambiguous box that participants could observe through sampling influenced their corresponding box selection: *Average winning experience* and *frequent winning experience* (see Hills & Hertwig, 2010 for a similar distinction in sampling from risky bets).

Note that in a 10-ball sample, observing more than five winning balls implies a higher probability of winning for the ambiguous box, less than five winning balls implies a lower probability of winning and exactly five balls indicates that winning and not winning are equally likely. Thus, we calculated a participant's *average winning experience* by subtracting 5 from the average number of winning balls each individual participant experienced (see above). For example, if the average number of winning balls that Participant X experienced was 4.4, then that participant's average winning experience was -0.6 ($4.4 - 5 = -0.6$). If the experience was playing a role in box selection, then this particular average winning experience (-0.6) indicates that the probability of winning in the ambiguous box was less likely, and Participant X was therefore expected to select the risky box. In

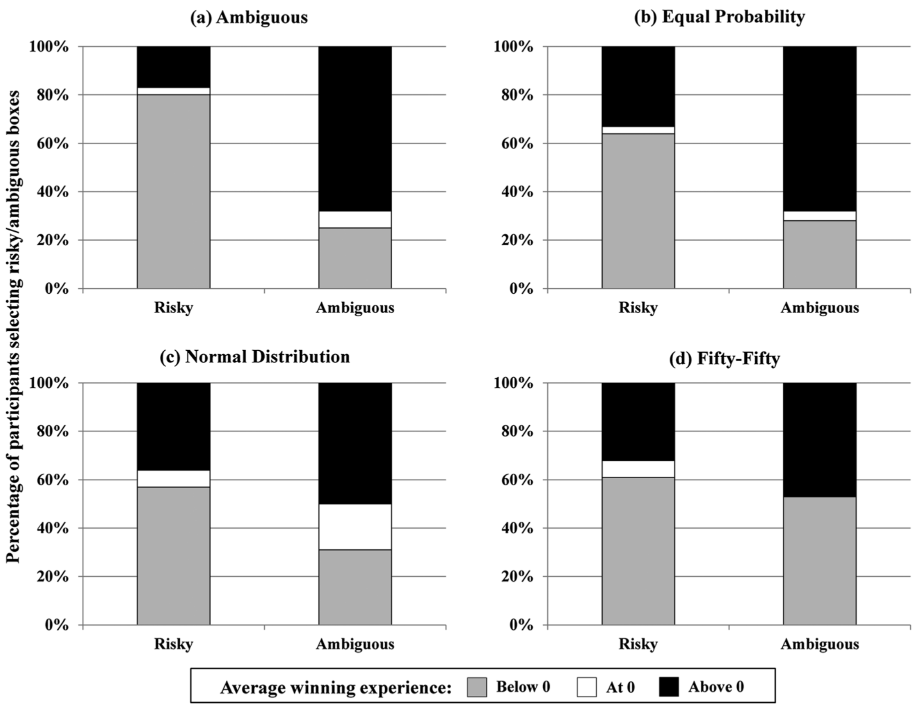

Figure 5. Percentage of participants selecting risky/ambiguous boxes in accordance with participants' average winning experience in Ambiguous, Equal Probability, Normal Distribution and Fifty-fifty groups. Average winning experience is calculated by subtracting 5 from the average number of winning balls each participant experienced during the sampling trials (see text for details)

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summary, the risky box is more likely to be selected if the participant's average winning experience is (−), the ambiguous box is more likely to be selected if (+) and both boxes are equally likely to be selected if 0. Figure 5 plots participant's box selections in accordance with their individual average winning experiences in all groups. As predicted, the majority of participants whose average winning experience was (−, below 0) selected the risky box, and those whose average winning experience was (+, above 0) selected the ambiguous box, except for participants in the FF group.

We analyzed this relationship between (+) average winning experience and the likelihood of selecting the risky box through probit regression (i.e. if a specific participant had an average winning experience that indicated that the probability of winning in the ambiguous box was more likely, is he or she less likely to choose the risky box?). Table 2 shows marginal effects, Z scores and corresponding *p*-values for Ambiguous, EP, ND and FF groups. The analyses revealed that (+) average winning experience overall decreased the likelihood of choosing the risky box by 8% ($p < .0001$). When the average winning experience was (+), the probability of choosing the risky box significantly decreased by 45% percent in the Ambiguous group ($p < .0001$), by 18% in EP ($p = .002$) and by 19% in ND ($p = .044$). Even though the likelihood of selecting the risky box decreased by 0.9% in the FF group as well, the difference was not significant ($p = .73$). So except for the FF group, the participants were less likely to be ambiguity-averse if they experienced a favourable probability of winning in the ambiguous box.

We then analyzed if *frequent winning experience* of participants affected their box selection. We examined whether observing *more* 10-ball samples with more winning balls across sampling trials influenced box selection (i.e. over six sampling trials, if a participant experienced four 10-ball samples with more winning balls and two 10-ball samples with fewer winning balls, is he or she less likely to choose the risky box?). We again conducted a probit regression analysis for the relationship between the frequency of experiencing more 10-ball samples with more winning balls and the selection of the risky box. Table 3 shows marginal effects, Z scores and corresponding *p*-values for Ambiguous, EP, ND and FF groups. The analysis revealed that observing more 10-ball samples with more winning balls decreased the overall likelihood of choosing the risky box by 11% ($p < .0001$). The likelihood of choosing the risky box decreased by 15% in the Ambiguous group ($p = .001$), by 14% in EP ($p = .004$) and by 17% in ND ($p = .009$). However, no significant decrease was found for the FF group ($p = .606$). These findings indicate that when participants more frequently experience that winning was more likely with the ambiguous box over trials, they tended to be less ambiguity-averse in the Ambiguous, EP and ND groups.

Table 2. Relationship between (+) average winning experience and box selection in Ambiguous, Equal Probability (EP), Normal Distribution (ND) and Fifty-Fifty (FF) groups

	Marginal effects	Z scores	*p*-values
Ambiguous	−0.45**	−4.06	.000
EP	−0.18**	−3.09	.002
ND	−0.19*	−2.02	.044
FF	−0.009	−0.35	.730
Overall	−0.08**	−3.5	.000

Note: The marginal effects are from probit regressions in which the independent variable was (+) individual average winning experience in a 10-ball sample from ambiguous box, and the dependent variable was the likelihood of choosing the risky box (Box A). A separate probit regression was run for each group. For example, if a participant's average winning experience (+) in Ambiguous group, then the likelihood of him or her choosing the risky box decreases by 45% (intersection of column 1 and row 1).

Table 3. Relationship between frequent winning experience and box selection in Ambiguous, Equal Probability (EP), Normal Distribution (ND) and Fifty-Fifty (FF) groups

	Marginal effects	Z scores	*p*-values
Ambiguous	−0.15**	−3.38	.001
EP	−0.14**	−2.89	.004
ND	−0.17**	−2.62	.009
FF	−0.03	−0.52	.606
Overall	−0.11**	−4.61	.000

Note: The marginal effects are from probit regressions in which the independent variable was the number of sampling trials in which the participant observed more winning balls in a 10-ball sample and the dependent variable was the likelihood of choosing the risky box (Box A). A separate probit regression was run for each group. For example, if a participant observed more 10-ball samples with more winning balls in ND group, then the likelihood of him/her choosing the risky box decreases by 17% (intersection of column 1 and row 3).

DISCUSSION

Experience of distributions reduces ambiguity aversion

Participants demonstrated more neutral attitudes toward ambiguity when they experienced potential underlying probability distributions than when they were provided with descriptions of those distributions. This difference can be seen most clearly in the comparison of the Ambiguous group across the Experience and Description conditions (see Figure 4). The results also demonstrated the individual experience of winning being more likely on average or that of winning being more frequent decreased the likelihood of being ambiguity-averse (see Tables 2 and 3, respectively).

At one level, these results may seem unsurprising: giving participants some experience of the potential for winning probabilities with the ambiguous box reduces their aversion to it. At another level, however, the results belie some potentially important insights into the way *distribution sampling* (in contrast to outcome sampling) influences attitudes to ambiguity. Our principal contention is that sampling facilitates understanding the information contained within the SOP distribution descriptions. Thus, in much the same way as experiencing draws from the posterior distribution facilitates reasoning in a base-rate neglect problem (Hogarth & Soyer, 2011), our participants were "helped" by experiencing the implications of an ambiguous or EP and to a lesser extent ND distribution. Notably though, experiencing the Fifty-Fifty distribution had little impact on preferences.

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One way of explaining the results is simply that experience makes the underlying random process generating the observed samples more transparent (Hogarth & Soyer, 2011; Lejarraga, 2010). In addition to the observed reduction in ambiguity aversion in some of the Experience groups, this explanation is supported by data from the post-task questionnaire (see the Appendix). Only 24% of participants given the EP distribution in the Description condition were able to identify the correct underlying probability distribution graph (see Figure 1 for examples) compared to 69% in the EP Experience condition. A similar but less extreme benefit was seen for the ND groups (58% correct identifications in Description, 77% in Experience).

This elucidation of the process cannot be the complete story, however, because predictably, participants given the ambiguous distribution were equally poor at selecting the correct underlying probability distribution graph irrespective of presentation format (both groups approximately 50% correct). And yet preference for the ambiguous box in these two groups was highly divergent. At the other extreme, the clear majority of participants given the Fifty-Fifty distribution in the Description and Experience conditions chose the correct underlying probability distribution graph (78% and 86%, respectively) and showed similar levels of ambiguity-neutrality.

This pattern of results suggests a relatively subtle interplay between the information contained in the samples and the nature of the described SOP distribution. The relative impact of sampling on ambiguity attitudes appears to be a function of how straightforward it is for participants to intuit the underlying distribution. When the description contains no information (i.e. the Ambiguous group), sampling "possibilities of winning" has a large impact on preference—not because it allows participants to infer the functional form of the distribution but simply because it allows them to see that the chances of winning are at least as good as they are with the risky box. When the description contains readily intuited distributional information (i.e. Fifty-Fifty), samples confer little additional information and choices are similar. Whether a participant reads about a coin toss or observes samples in which either all or none of the balls were winning ones, it allows her to realize that winning for sure and losing for sure is equally likely and thus that selecting the corresponding ambiguous box is highly risky (see Lejarraga et al., 2012; Rode et al., 1999 for the impact of highly variant outcomes on choices). When the distributional information is more complex (i.e. EP), sampling confers a similar impact to that seen in the Ambiguous group *and* allows for correct inferences to be drawn about the functional form. Participants given the ND distribution lie somewhere between these extremes by showing modest improvements in identifying the underlying probability distribution and a modest reduction in ambiguity aversion.

The analysis of sampling patterns for the three different SOPs supports this general explanation. The relationship between the individual experiences and the likelihood of being ambiguity-averse was strongest for the EP group, played a lesser role in predicting choice in the ND group and no role in the FF group. Note that the average number of samples taken in the EP group was significantly higher than that of the ND group—a pattern that indicates that the participants in the EP group needed to sample more from the ambiguous box in order to gain insight about the underlying distributions than those in the ND group. This finding supports the idea that the implication of the EP distribution was relatively more difficult for participants to intuit (Güney & Newell, 2011). A similar relationship between the "informativeness" and the level of ambiguity aversion is observed for the (known) FOPs (Becker & Brownson, 1964; Budescu et al., 2002; Curley & Yates, 1985; Kramer & Budescu, 2005)—more precisely defined FOPs lead to less ambiguity aversion.

Relationship to the findings of Dutt et al. (2013)

Our findings regarding the level of ambiguity aversion are broadly consistent with the conclusion of Dutt et al. (2013)—experience reduces ambiguity aversion—but our reasons for reaching this conclusion are different. First of all, we characterized ambiguity with multiple and unknown probability distributions (i.e. in our ambiguous group) instead of a single uniform distribution (i.e. their ambiguous bet). Therefore, the reduced ambiguity aversion observed in our study provides further insights into how experience impacts decisions under (a closer approximation of) ambiguity[4]. Second, Dutt et al. found an ambiguity-seeking pattern, whereas we found ambiguity neutrality for the EP bet (the only one common to both studies). However, such a difference in the magnitude of the levels of ambiguity aversion is not unexpected because of the difference in sampling methods (outcome sampling versus distribution sampling) and hence the information experienced. Experiencing *uncertainty about both probabilities and outcomes* (as in our study) rather than *only uncertain outcomes* [as in Dutt et al. (2013) study] might lead some people to be more cautious about the ambiguous box in our study, resulting in an ambiguity neutral pattern (i.e. around half of participants selecting the ambiguous box) instead of ambiguity-seeking.

In addition, our findings differed from the Dutt et al.'s in terms of the type of samples participants took in the Experience conditions. While the median number of samples was 26 in their study, the average number of

[4]An alternative explanation for the reduction in ambiguity aversion through experience could be that experiencing only from the ambiguous box might make people more familiar with the ambiguous box and (positively) bias them towards it. Such familiarity or feelings of being more knowledgeable about an event have been shown to lead people to favour that particular event (i.e. "comparative ignorance hypothesis"; Fox & Tversky, 1995; Fox & Weber, 2002; Heath & Tversky, 1991). However, we tried to eliminate such a potential confound in our manipulation by assuring the decision makers that the ambiguous box is *renewed* each time they take a sample and would be a *different* one in the choice stage. Therefore, the decision was made between the risky box and a *new* ambiguous box, which the decision maker had no (warranted) familiarity with.

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samples was around 6 in our study [see Table 1(a)]. One reason for the respective gap in the obtained sample sizes might again be relevant to the difference in the sampling methodologies used: The participants in our study were sampling "distributions of balls", which consists of 10 *balls* drawn from the box at once, whereas participants in the Dutt et al. study were sampling an "outcome" in which only 1 *ball* was drawn at a time. Therefore, the participants in our study obtained samples that gave them an overall chance of observing 60 winning/losing balls approximately, rather more than Dutt et al.'s participants. Alternatively, the different sampling patterns seen in the Dutt et al. study might be due to the fact that their participants were allowed to sample from *both* risky and ambiguous options. Therefore, the participants may have needed to sample more in order to identify if/whether the two "unknown" options were any different from each other (i.e. whether they were yielding different outcomes, with different likelihoods, etc.). Our participants did not need to do this because one option (the risky box) was clearly labelled (and could not be sampled from).

Conclusion

These results extend recent literature investigating the impact of sampling on risky choice (e.g. Lejarraga et al., 2012; Rakow et al., 2008; Hadar & Fox, 2009; Hertwig & Erev, 2009; Rakow & Newell, 2010) and probability judgment (e.g. Hogarth & Soyer, 2011) to choice under ambiguity. Consistent with findings in these other kinds of tasks, this experiment highlighted that when information regarding potential probability distributions is presented to the decision maker in a "kind" or "transparent" manner (Hogarth, 2001), judgments and choices are affected. Our findings indicate that one way of making ambiguous second-order probability (SOP) distributions more readily intuited is to allow decision makers to *experience* them. This experience, in turn, can lead to reductions in ambiguity aversion. Future studies could investigate the impact of experiencing potential unknown probability distributions for negative outcomes (i.e. loss domain) on decisions under ambiguity. When the outcomes are framed as losses experience of, for instance, a more likely or a more frequent loss might reverse the pattern observed with gains and lead to a strict avoidance of the ambiguous bet since the probabilistic information yields a highly varying and hence unpredictable loss.

APPENDIX

In the post-task questionnaire, the participants in all groups were asked the following questions: (i) how many winning balls they think the ambiguous box contains (i.e. *point estimation*) (if they stated 50, they were additionally asked whether they would be indifferent between the risky box and the ambiguous box if they were allowed to do so), (ii) what the minimum and maximum numbers of winning balls could be in the ambiguous box (i.e. *range estimation*), (iii) how confident they are in their estimations on a scale from −3 (not confident) to 3 (confident) (i.e. *confidence level*), and (iv) which of the graphical representations (out of the four SOP distribution graphs displayed in Figure 1) best represents the probability distributions of winning balls in the ambiguous box in their corresponding group (i.e. *distribution fit*).

Table A1 summarizes the results from the post-task questionnaire in the Description (Desc.) and Experience (Exp.) conditions. The mean number of winning balls estimated [panel (a)] by the participants for the ambiguous box was significantly lower than 50 in the Description condition whereas not different from 50 in the Experience for Ambiguous (p = .006 and p = .77), Equal P. (p = .0001 and p = .47), Normal D. (p = .02 and p = .97) and Fifty-Fifty (p = .001 and p = .86, respectively). Since the expected probability of winning is centred around 0.5, which corresponds to 50 winning balls for the ambiguous box for all groups, these findings indicate that participants in the Experience condition more accurately estimated the number of winning balls than those in the Description condition.

Panel (b) shows the mean ranges of winning balls for the ambiguous box estimated by participants in all groups across the Description and Experience conditions. Range estimations were calculated by subtracting participant's estimation for the minimum possible numbers of winning balls from that of the maximum. For the Ambiguous and the Normal D. groups, the mean range was significantly larger in the Description condition than the Experience condition, $F(1, 114) = 10.02$, p = .001, and $F(1, 115) = 19.16$, p = .000, respectively. This pattern indicates that these participants were less uncertain about the possible number of winning balls in the Experience condition as they gave narrower range estimations (on average). For the Fifty-fifty group, an opposite pattern was obtained, the mean range in the Experience group is larger than that of the Description group, $F(1, 113) = 9.02$, p = .002. This pattern indicates that participants in the Experience condition made a more accurate range estimation for their SOP group (i.e. the

Table A1. Responses to post-task estimation questions in each group of Description (Desc.) and Experience (Exp.) conditions

	Estimations							
	(a) Mean Point Estimations		(b) Mean Range Estimations		(c) Confidence Levels		(d) Distribution Fit	
Groups	Desc.	Exp.	Desc.	Exp.	Desc.	Exp.	Desc.	Exp.
Ambiguous	42.9	50.6	64.2	45.3	−1.74	−0.64	50%	53%
Equal P.	40.6	51.8	70.4	63.6	−1.54	−0.98	24%	69%
Normal D.	45.2	49.9	63.2	38.8	−1.68	−0.75	58%	77%
Fifty-Fifty	25.8	50.9	83.2	98.4	−0.26	−0.05	78%	86%

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larger the range, the more accurate the estimation for Fifty-fifty group). For the Equal P. group, the mean ranges did not significantly differ between conditions, $F(1, 109) = 1.28$, $p = .13$—a pattern of results that is not surprising because the participants in the Experience condition would have been inaccurate if they had given narrow range estimation (i.e. a uniform distribution yields any number of equally possible winning balls between 0 and 100).

Participants' confidence levels [see panel (c)] are also in line with our expectations (and the above interpretation): The participants in the Experience condition were much more confident than those in the Description condition in their estimations for Ambiguous, Normal D. and Equal P. groups, $F(1, 114) = 10.99$, $p = .0006$; $F(1, 115) = 11.00$, $p = .0006$; and $F(1, 109) = 3.00$, $p = .043$, respectively. For the Fifty-Fifty group, the participants' confidence levels did not significantly differ depending on the condition, $F(1, 113) = 0.24$, $p = .32$. This pattern for the Fifty-fifty group is understandable since the participants' experience told them the number of winning ball was either 100 or 0; therefore, they would think they could be completely wrong if their estimation was 0 (or 100).

Finally, the percentage of participants who correctly identified the graphical representation of the corresponding probability distribution in their groups was higher for all groups in the Experience condition than the Description condition, especially those in the Equal Probability group [see panel (d) for the respective percentages and the main text for further discussion of this result].

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REFERENCES

Attanasi, G., Gollier, C., Montesano, A., & Pace, N. (2012). Eliciting ambiguity aversion in unknown and in compound lotteries: A KMM experimental approach. Ca'Foscari University of Venice Department of Economics Working Paper No, 23.

Becker, S., & Brownson, F. O. (1964). What price ambiguity? Or the role of ambiguity in decision making. *Journal of Political Economy*, *72*(1), 62–73.

Bernasconi, M., & Loomes, G. (1992). Failures of the reduction principle in an Ellsberg type problem. *Theory and Decision*, *32*, 77–100.

Budescu, D. V., Kuhn, K. M., Kramer, K. M., & Johnson, T. R. (2002). Modeling certainty equivalents for imprecise gambles. *Organizational Behavior and Human Decision Processes*, *88*, 748–768.

Camerer, C., & Weber, M. (1992). Recent developments in modeling preferences: Uncertainty and ambiguity. *Journal of Risk and Uncertainty*, *5*, 325–370.

Camilleri, A. R. & Newell, B. R. (2011). When and why rare events are underweighted: A direct comparison of the sampling, partial feedback, full feedback and description choice paradigms. *Psychonomic Bulletin & Review*, *18*, 377–384.

Charness, G., Karni, E., & Levin, D. (2013). Ambiguity attitudes and social interactions: An experimental investigation. *Journal of Risk and Uncertainty*, *46*, 1–25.

Chew, S. H., Ebstein, R. P., & Zhong, S. (2012). Ambiguity aversion and familiarity bias: Evidence from behavioral and gene association studies. *Journal of Risk and Uncertainty*, *44*, 1–18.

Chow, C. C., & Sarin, R. K. (2001). Comparative ignorance and the Ellsberg paradox. *Journal of Risk and Uncertainty*, *22*, 129–139.

Chow, C. C., & Sarin, R. K. (2002). Known, unknown, and unknowable uncertainties. *Theory and Decision*, *52*(2), 127–138.

Cosmides, L., & Tooby, J. (1996). Are humans good intuitive statisticians after all? Rethinking some conclusions from the literature on judgment under uncertainty. *Cognition*, *58*, 1–73.

Curley, S. P., & Yates, J. F. (1985). The center and range of the probability interval as factors affecting ambiguity preferences. *Organizational Behavior and Human Decision Processes*, *36*, 273–287.

Curley, S. P., Young, M. J., & Yates, J. F. (1989). Characterizing physicians' perceptions of ambiguity. *Medical Decision Making*, *9*, 116–124.

Du, N., & Budescu, D. V. (2005). The effects of imprecise probabilities and outcomes in evaluating investment options. *Management Science*, *51*, 1791–1803.

Dutt, V., Arlo-Costa, H., Helzner, J., & Gonzalez, C. (2013). The Description–Experience gap in risky and ambiguous gambles. *Journal of Behavioral Decision Making*. DOI: 10.1002/bdm.1808

Einhorn, H. J., & Hogarth, R. M. (1986). Decision making under ambiguity. *Journal of Business*, *59*, 225–250.

Ellsberg, D. (1961). Risk, ambiguity and the Savage axioms. *Quarterly Journal of Economics*, *75*, 643–669.

Ert, E., & Trautmann, S. T. (2014). Sampling experience reverses preferences for ambiguity. *Journal of Risk and Uncertainty*. DOI: 10.1007/s11166-014-9197-9.

Fox, C. R., & Tversky, A. (1995). Ambiguity aversion and comparative ignorance. *Quarterly Journal of Economics*, *110*, 585–603.

Fox, C. R., & Weber, M. (2002). Ambiguity aversion, comparative ignorance, and decision context. *Organizational Behavior and Human Decision Processes*, *88*, 476–498.

Frisch, D., & Baron, J. (1988). Ambiguity and rationality. *Journal of Behavioral Decision Making*, *1*, 146–157.

Gigerenzer, G., & Hoffrage, U. (1995). How to improve Bayesian reasoning without instruction: Frequency formats. *Psychological Review*, *102*, 684–704.

Güney, Ş., & Newell, B. R. (2011). The Ellsberg "problem" and implicit assumptions under ambiguity. In L. Carlson, C. Hoelscher, & T. F. Shipley (Eds.), Proceedings of the 33rd Annual Conference of the Cognitive Science Society (pp. 2323–2328). Austin, TX: Cognitive Science Society.

Hadar, L., & Fox, C. R. (2009). Information asymmetry in decision from description versus decision from experience. *Judgment and Decision Making*, *4*(4), 317–325.

Halevy, Y. (2007). Ellsberg revisited: An experimental study. *American Economic Review*, *75*(2), 503–536.

Heath, C., & Tversky, A. (1991). Preference and belief: Ambiguity and competence in choice under uncertainty. *Journal of Risk and Uncertainty*, *4*, 5–28.

Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science*, *15*(8), 534–539.

Hertwig, R., & Erev, I. (2009). The Description–Experience gap in risky choice. *Trends in Cognitive Sciences*, *13*(12), 517–523.

Hills, T. T., & Hertwig, R. (2010). Information search in decisions from experience: Do our patterns of sampling foreshadow our decisions? *Psychological Science*, *21*, 1787–1792.

Hogarth, R. M. (2001). Educating intuition. Chicago, IL: University of Chicago Press.

Hogarth, R. R., Mukherjee, K., & Soyer, E. (2013). Assessing the chances of success: Naïve statistics versus kind experience. *Journal of Experimental Psychology: Learning, Memory, Cognition*, *39*(1), 14–32.

Hogarth, R. R., & Soyer, E. (2011). Sequentially simulated outcomes: Kind experience vs. nontransparent description. *Journal of Experimental Psychology: General*, *140*, 434–463.

Kahn, B. E., & Sarin, R. K. (1988). Modelling ambiguity in decisions under uncertainty. *Journal of Consumer Research*, *15*, 265–272.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*, 263–291.

Kahneman, D., & Tversky, A. (1984). Choices, values, and frames. *American Psychologist*, *39*, 341–350.

Keren, G. B., & Gerritsen, L. E. M. (1999). On the robustness and possible accounts for ambiguity aversion. *Acta Psychologica*, *103*, 149–172.

Koehler, J. J. (1996). The base rate fallacy reconsidered: Descriptive, normative, and methodological challenges. *Behavioral and Brain Sciences*, *19*, 1–53.

Kramer, K. M., & Budescu, D. V. (2005). Exploring Ellsberg's paradox in vague-vague cases. In Zwick, R., & Rapoport, A. (Eds.), Experimental business research volume III (pp. 131–154). Norwell, MA and Dordrecht, The Netherlands: Kluwer Academic Publishers.

Krynski, T. R., & Tenenbaum, J. B. (2007). The role of causality in judgment under uncertainty. *Journal of Experimental Psychology: General*, *136*, 430–450.

Kuhn, K. M., & Budescu, D. V. (1996). The relative importance of probabilities, outcomes, and vagueness in hazard risk decisions. *Organizational Behavior and Human Decision Processes*, *68*, 301–317.

Larson, J. R., Jr. (1980). Exploring the external validity of a subjectively weighted utility model of decision Making. *Organizational Behavior and Human Performance*, *26*, 293–304.

Lejarraga, T. (2010). When experience is better than description: Time delays and complexity. *Journal of Behavioral Decision Making*, *23*, 100–116.

Lejarraga, T., Hertwig, R., & Gonzalez, C. (2012). How choice ecology influences search in decisions from experience. *Cognition*, *124*, 334–342.

Lopes, L. L. (1984). Risk and distributional inequality. *Journal of Experimental Psychology: Human Perception and Performance*, *10*, 465–485.

Lopes, L. L. (1987). Between hope and fear: The psychology of risk. *Advances in Experimental Social Psychology*, *20*, 255–295.

Newell, B. R., Lagnado, D. A., & Shanks, D. R. (2007). Straight choices: The psychology of decision making. Hove, UK: Psychology Press.

Rakow, T. R., Demes, K., & Newell, B. R. (2008). Biased samples not mode of presentation: Re-examining the apparent underweighting of rare events in experience-based choice. *Organizational Behavior and Human Decision Processes*, *106*, 168–179.

Rakow, T. R., & Newell, B. R. (2010). Degrees of uncertainty: An overview and framework for future research on experience-based choice. *Journal of Behavioral Decision Making*, *23*(1), 1–14.

Rode, C., Cosmides, L., Hell, W., & Tooby, J. (1999). When and why do people avoid unknown probabilities in decisions under uncertainty? Testing some predictions from optimal foraging theory. *Cognition*, *72*, 269–304.

Savage, L. J. (1954). The foundation of statistics. New York: John Wiley and Sons.

Segal, U. (1987). The Ellsberg paradox and risk aversion: An anticipated utility approach. *International Economic Review*, *28*, 175–202.

Stanovich, K. E., & West, R. F. (2000). Individual differences in reasoning: Implications for the rationality debate? *Behavioral and Brain Sciences*, *23*, 645–665.

Yates, J. F., & Zukowski, L. G. (1976). Characterization of ambiguity in decision-making. *Behavioral Science*, *21*, 19–21.

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