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Sampling experience reverses preferences for ambiguity

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Abstract People often need to choose between alternatives with known probabilities (risk) and alternatives with unknown probabilities (ambiguity). Such decisions are characterized by attitudes towards ambiguity, which are distinct from risk attitudes. Most studies of ambiguity attitudes have focused on the static case of single choice, where decision makers typically prefer risky over ambiguous prospects. However, in many situations, decision makers may be able to sample outcomes of an ambiguous alternative, allowing for inferences about its probabilities. The current paper finds that such sampling experience reverses the pattern of ambiguity attitude observed in the static case. This effect can only partly be explained by the updating of probabilistic beliefs, suggesting a direct effect of sampling on attitudes toward ambiguity.

JEL Classification C91 · D81

Keywords Ambiguity aversion · Decisions from experience · Sampling · Probability estimates

In many situations, decision makers are confronted with choices between alternatives that have well-known risks, and alternatives that have uncertain, or ambiguous, risks. Consumers choose between products of well established brands and those of new brands that offer more uncertain, but potentially higher, benefits. Patients choose between known medications, and uncertain but cheaper generic drugs that contain the same active substances (Muthukrishnan et al. 2009). A large number of decisions in

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business, insurance, and finance are affected by ambiguity (e.g., Einhorn and Hogarth 1986; Kunreuther et al. 1993; Mukerji and Tallon 2001).

Experimental studies of ambiguity attitudes typically consider participants' preferences in one-shot decisions involving risky and ambiguous prospects that are equivalent under expected utility. Ambiguity aversion is typically found for modest and large likelihood events: people prefer the risky prospect, unless it is made significantly worse than the ambiguous prospect (Camerer and Weber 1992; Trautmann and van de Kuilen 2013).[1] In contrast to the experimental work that has focused on static decisions, many of the relevant decision situations outside the lab allow the decision maker to gather experience with the unknown, ambiguous risk before reaching a decision. For instance, consumers are encouraged to sample new products at a discounted price, and firms try out product prototypes on limited markets before going into full production.

Surprisingly, despite the relevance of such sampling experience in decisions under ambiguity, little is known about its potential effect on ambiguity attitudes. Trautmann and Zeckhauser (2013) find that people shy away from ambiguous alternatives in repeated settings because they do not anticipate the learning opportunities offered by these alternatives. Rode et al. (1999) show that people sometimes prefer ambiguity if their needs are higher than the mean outcome of the known-risk distribution. However, these studies do not speak to the effect of observing a short sample from the ambiguous alternative before making a choice between ambiguous and risky alternatives. Closer to our study, Baillon et al. (2013) find that people become more sensitive towards differences in likelihoods as they receive more information, but they find no effect on a motivational component in ambiguity attitude. Viscusi and Magat (1992) provide people with two probability estimates and study how these estimates are aggregated. They find evidence for pessimism in probability updating. We discuss these studies in more detail below.

The idea that ambiguity attitudes might be affected by sampling experience is motivated by the literature on decisions from experience. This literature studies situations in which the decision maker does not receive a description of some uncertain prospects in terms of outcomes and probabilities, but has to collect this information by drawing samples from these prospects. Evidence shows that such sampling experience leads to risk-taking behavior that deviates from the patterns observed when full prospect descriptions are available (Barron and Erev 2003; Hertwig et al. 2004; Rakow and Newell 2010). In particular, in decisions from experience decision makers seem to underweight rare events (low probabilities), and overweight likely events (high probabilities). Recent studies show that these experience effects also occur when, in addition to the sampling experience, a full description of the prospects is given (Jessup et al. 2008; Lejarraga and Gonzalez 2011; Newell and Rakow 2007). These findings suggest that sampling from prospects has psychological effects beyond the effect of mere information collection, motivating the current study of ambiguity attitudes.

The current study compares choices between risky and ambiguous options associated with the same payoff distribution (following the approach in studies of preferences

[1] Ambiguity aversion does not typically prevail in the domain of modest likelihood losses, or for low likelihood gain events (see e.g. Viscusi and Chesson's (1999) 'Hopes and Fears,' or Trautmann and van de Kuilen (2013) for a recent review). While the evidence for ambiguity aversion for modest likelihood gains is strong, recent studies have shown its sensitivity to design issues (Charness et al. 2013), and the importance of heterogeneity of ambiguity attitudes (Conte and Hey 2013; Binmore et al. 2012).

for risk and ambiguity), with and without sampling (following the decisions from experience studies that focus on how experience affects risk taking). As such, the current study builds a bridge between these two lines of research. Interestingly, despite the commonalities that the two approaches share, they have been studied separately and have rarely informed each other. Indeed, to our knowledge the current research is the first attempt to explore the potential relation between sampling experience and ambiguity preferences.

1 Predictions

The effects of sampling experience on beliefs and on attitudes under uncertainty can be modeled by extending the expected utility approach to account for deviations from Bayesian updating and from ambiguity neutrality (Baillon et al. 2013; Viscusi 1997; Viscusi and Magat 1992). We employ the belief-based weighting account of Fox and Tversky (1998; Wakker 2004) to model the two components. Let u be a utility function over outcomes, w a probability weighting function, and $B(E)$ the subjective probability that event E occurs. The value of an ambiguous prospect $x_E y$ that pays outcome x if event E occurs, and outcome $y < x$ otherwise is given by $w(B(E))u(x)+(1-w(B(E)))u(y)$. Consequently, sampling experience can potentially affect either the belief B (E), possibly in a non-Bayesian way as in Viscusi (1997) and Viscusi and Magat (1992), or the ambiguity attitudes in form of changes in w, as in Baillon et al. (2013), or both.[2]

Based on the previous literature, we identify two mechanisms that can affect preferences in ambiguous environments with sampling opportunities. First, familiarity and competence effects may affect attitudes when ambiguous alternatives are encountered repeatedly. Repeated exposure to ambiguous alternatives may lead to feelings of higher competence/familiarity with this alternative, and therefore to more ambiguity seeking (Curley et al. 1986; Heath and Tversky 1991). Because of the motivational nature of the competence effect, it should affect the weighting function w, and therefore change ambiguity attitudes in the same direction for all levels of the underlying probabilities.

Second, research on the effect of experience on risk taking suggests that people evaluate samples of uncertain options as if they underweight rare outcomes (Erev et al. 2008; Hertwig and Erev 2009; Hertwig et al. 2004; Jessup et al. 2008; Ungemach et al. 2009). To illustrate, consider a prospect that yields a payoff of \$1 with probability 0.1, and \$0 otherwise. The rare outcome of the desired \$1 gain would show only in the minority of the samples. Thus, sampling might decrease the attractiveness of this prospect as it would emphasize that the desired outcome is unlikely. In contrast, when sampling a prospect that yields \$1 with probability 0.9, and \$0 otherwise, the rare outcome is the undesired outcome of receiving nothing. The \$1 gain will be present in the majority of the samples. Thus, sampling this prospect can increase its attractiveness.

[2] Viscusi and Magat (1992) distinguish between ambiguity effects on beliefs, and ambiguity effects on the utility function. Our approach is closer to Baillon et al. (2013) in modeling this latter effect through the weighting function.

Applying this pattern to our setting, we predict that the attractiveness of the sampled ambiguous prospect, relative to a known-probability risky prospect with equal winning probability, increases when the probability of the good outcome is high, and decreases when the probability of the good outcome is low. This effect should work directly through the belief component *B(E)*, and would vary with the underlying probabilities (low vs. high). The experienced-based account of ambiguity attitude thus predicts the opposite pattern of preference than what is commonly observed in no-sample decisions, where a high winning probability for the risky prospect leads to strong ambiguity avoidance, and a low winning probability leads to more choosing of ambiguity. With sampling, a risky prospect will be compared to an uncertain prospect of equal underlying probability, and the perception and weighting of this ambiguous probability is potentially affected by the sampling experience. We test our predictions in two studies. In the first study we consider sampling effects on choices, and in the second study we consider sampling effects on beliefs.

2 Study 1: the effect of sampling on choice between risk and ambiguity

Let 2_p0 denote an uncertain prospect that pays a prize of NIS2 (≈\$0.5) with probability p, and zero otherwise. In order to evaluate the effect of sampling on ambiguity attitudes, we study five decision problems with choices between risky prospects 2_p0, with $p=0.1$, 0.2, 0.5, 0.8, and 0.9, and their equivalent ambiguous prospects. For risky prospects, p is known. For ambiguous prospects, p is unknown. In all decision problems p was identical for the risky and the ambiguous prospect, but the subjects were not aware of this.[3]

2.1 Method

Fifty-six participants were randomly assigned to two experimental conditions. In the *no-sampling* condition, 24 participants made choices between risky and ambiguous prospects based on given descriptions of the two prospects. This replicates the standard procedure used in studies of ambiguity attitude. Table 1 shows the description of the five prospects under risk and ambiguity. Participants were presented with the five decision problems in a random order, indicating for each problem their choice. When they finished marking their choices, one problem was randomly selected, resolved, and paid in cash.

In the *sampling* condition, 32 participants also saw the descriptions of the prospects, but could additionally sample the ambiguous prospect before they were asked to make their choice. In particular, participants were told that before making their payoff-relevant choice, there would be a sampling stage in which they could sample the ambiguous prospect by clicking on that option as many times they wished (see Fig. A1a in the Appendix). Each click generated an independent draw from the relevant distribution (e.g., in problems with $p=0.9$ the sampled outcome was NIS2 in 90% of the draws and 0 in 10% of the draws). The draws in the sampling stage had no effect on the participant's actual payoff. When they felt they had sampled enough, participants

[3] In Study 2 we show that subjects do not anticipate that the probabilities are equal for risk and ambiguity.

Table 1 Description of risky and ambiguous prospects in Study 1

Problem	Description of the risky prospect	Description of the ambiguous prospect
0.1	You receive NIS2 with probability 0.1	You either receive NIS2 or nothing; the probability of winning the NIS2 is unknown.
0.2	You receive NIS2 with probability 0.2	
0.5	You receive NIS2 with probability 0.5	
0.8	You receive NIS2 with probability 0.8	
0.9	You receive NIS2 with probability 0.9	

proceeded to the payoff-relevant stage, by clicking a button marked as "real game." In this real-game stage they were asked to make one binding decision between the two prospects for real payoffs (see Fig. A1b in the Appendix). This procedure was repeated for all five problems shown in Table 1. The order of the prospects was randomized across participants, and the real game choices were not played out until the end of the experiment when the participants had completed all five problems. Then, one problem was selected at random and the selected lottery in the real game was played, and paid for real. In both conditions, the rewards were added to the participant's show-up fee of NIS20.

2.2 Results

The results, presented in Fig. 1, show that the choice pattern of participants who sampled the ambiguous prospect was the exact opposite of the choice pattern of participants who could not sample that prospect. The light bars, which show the results of the no-sampling condition, reveal a *negative* relationship between the probability of success and the proportion of choices of the ambiguous prospect ($Z=3.42$, $p<0.01$, probit regression controlling for repeated measures, marginal effect of 1.06% decrease per percentage point of underlying probability). This trend replicates the typical findings from previous studies where the risky lottery is preferred when it offers a 50% or larger chance of a gain, and the ambiguous lottery is more often preferred when the risky option offers increasingly lower chances.[4]

Results of the sampling condition, represented by the dark bars in Fig. 1, reveal the exact opposite pattern of preferences. This condition reveals a *positive* relationship between the probability of winning and the proportion of participants preferring the ambiguous prospect ($Z=2.18$, $p<0.05$, probit regression controlling for repeated measures, marginal effect of 0.33% increase per percentage point of underlying probability). Also noteworthy is the elimination of ambiguity aversion under the moderate probability (problem 0.5) after sampling ($p=0.86$, binomial test). Foremost these results confirm that people use relevant sampling information in their decisions (Viscusi and Magat 1992), which consequently affects their ambiguity preferences in the current setting. Moreover, the reversal in preferences shows that decision-from-experience

[4] See e.g. the typical ambiguity premia for probability matching tasks shown in Table 1 in Trautmann and van de Kuilen (2013).

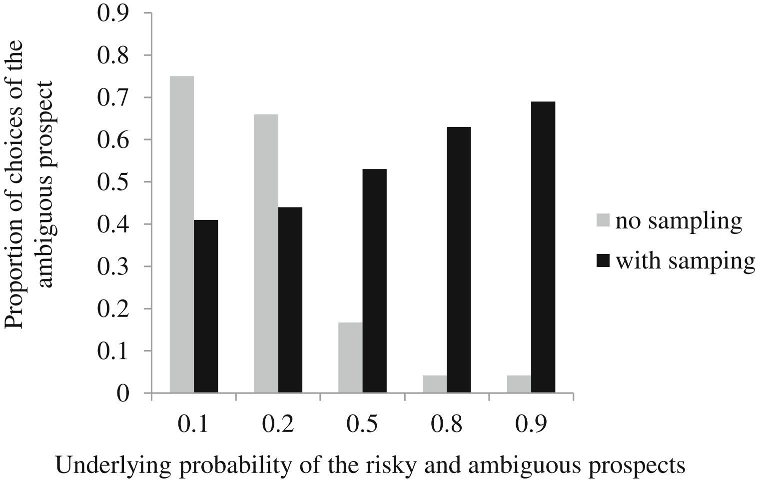

Fig. 1 The proportion of choices favoring the ambiguous prospect over the risky prospect in Study 1

effects are relevant. Interestingly, the strongly increased ambiguity preference for the 0.5 prospect seems inconsistent with Baillon et al.'s (2013) finding in the rank-dependent framework that more information leads to increased likelihood sensitivity, but not to a reduction in pessimism (i.e., ambiguity aversion). In the next section we will test whether this result can be explained by skewed prior beliefs and updating.

Despite the fact that participants could sample unlimitedly, the median number of samples was only 15, 12.5, 12, 11, and 11 in problems 0.1, 0.2, 0.5, 0.8, and 0.9 respectively.[5] Consequently, most participants experienced probabilities that were more extreme than the underlying probabilities. In problems 0.1 and 0.2 the observed probability was *lower* than the true underlying probability for most participants (59% and 66%, respectively). In problems 0.8 and 0.9, in contrast, the experienced probabilities were *higher* than the true ones for most participants (56% and 59%, respectively). Thus, if participants in the sampling condition chose the ambiguous prospect whenever the experienced probability from sampling is higher than the probability of the matched risky prospect, the observed positive correlation would emerge. To test this proposition, we created a continuous "experienced difference" variable for each participant and each choice problem that is defined as the difference between the observed success probability for the sampled prospect and the known probability of the risky prospect. Adding this variable to the probit regression alongside the underlying probability shows that the larger experienced difference indeed increases the likelihood that the ambiguous prospect is chosen ($Z=4.58$, $p<0.01$, marginal effect of 1.95% increase per percentage point experienced difference). However, the effect of the underlying probability is unaffected by the inclusion of the observed difference ($Z=2.14$, $p<0.05$, marginal effect of 0.31% increase in likelihood to choose the ambiguous lottery per percentage point of underlying probability). Consistent with Viscusi and Magat (1992) and Baillon et al. (2013), subjects use the sampling information to update their beliefs and choose accordingly. However, there remains a significant unexplained portion in the reversal. Sampling experience seems to influence attitudes beyond its effect on the

[5] These are typical sample sizes in decision from experience tasks (see Hertwig and Erev 2009).

probability update. Interestingly, we also find that the length of a participant's sampling experience does not lead to more consistency between the observed frequency and the choice.

Study 1 showed that sampling experience leads to small and somewhat skewed samples when the decision makers can decide on how many samples to take. These biased samples subsequently affect choices. However, there is a significant unexplained portion in the reversal of the preferences for the ambiguous alternative, suggesting changes in motivational components of ambiguity attitude. Because in Study 1 we did not observe subjects' beliefs directly, only their observed samples, we cannot distinguish such motivational changes from inaccurate beliefs. For example, Viscusi and Magat (1992) and Viscusi (1997) find evidence that people are pessimistic when they aggregate multiple sources of probability information. In the current experiment, the observed reversal could derive from optimism for high probability prospects and pessimism for low probability prospects. The second experiment studies beliefs directly.

3 Study 2: does sampling experience lead to extreme beliefs about the underlying event probability?

To distinguish between motivational factors and overly extreme probability updates of the underlying probabilities of the ambiguous prospect, Study 2 examines the role of beliefs about these probabilities more directly. Specifically, it examines the possibility that the unexplained portion of the preference reversal observed in Study 1 is mostly driven by biased, overly extreme, probability judgments after sampling. If this is the case, we expect overly optimistic beliefs under high probability of success (p=0.8 and p=0.9), and overly pessimistic beliefs for low probability of success (p=0.1 and p= 0.2). Such extreme judgments could explain the effect of the underlying probability over and above the effect of the observed (objective) probability sample shown in Study 1.

3.1 Method

Thirty-two new participants were recruited for this study. Each participant was presented with the five decision problems described in Table 1. Because people are usually better in making frequency judgments than in making probability judgments (Hoffrage et al. 2000), we chose to describe the two prospects as two decks of cards and derived the probability estimations in terms of card frequencies. For example, in problem 0.9 participants saw two card decks on the screen: a (risky) deck that contained 90 green cards and 10 white cards, and another (ambiguous) deck that contained 100 green or white cards, with the exact numbers of each color unknown. The participants were then asked to estimate the frequency of the green cards in the ambiguous deck twice: once before they sampled the deck, and once after they finished sampling the deck. The elicited estimates before sampling were collected to measure whether prior beliefs of the ambiguous deck were (1) influenced by the known probability of the risky deck, and (2) if participants' beliefs about the ambiguous option were generally biased away from 50% in an optimistic or pessimistic way. The estimates elicited after sampling indicate the updated beliefs on which decisions are based after a short sampling experience. Participants were paid according to their accuracy in their estimations using the quadratic deviation rule *payment= 4*[1–(true probability–estimated probability)^2]*. At the end of the study one of the 10 estimations was randomly selected to determine the final compensation.

3.2 Results

The true (objective) probabilities, the observed frequencies, and the estimated probabilities of drawing a green card in each problem are depicted in Fig. 2. The average estimated probability before sampling was 0.52 (Sd=0.072), and did not differ between problems, F (4, 159)=1.07, p=0.37, or deviate from 0.5, t(160)=1.21, p=0.22. Thus, there was no effect of the underlying probability on the prior, and, importantly, there was no probability-based pessimism in the priors. Within the Fox and Tversky (1998) framework laid out in Section 1, this suggests that the ambiguity attitudes observed in the description condition of Study 1 are driven by pessimistic event weighting of unbiased probability estimates (at least before sampling experience).

After the sampling experience, the estimated probabilities shift toward the observed frequencies (proportion of green cards observed during sampling), which were slightly more extreme than the underlying probabilities. To formally test whether estimates are more or less extreme than the observed samples, we subtracted the former from the latter, creating a "correspondence score." Positive scores imply overestimation of the experienced probability and negative scores imply underestimation. The correspondence scores were 0.21 in problem 0.1, t(31)=3.14, p=0.0037; 0.15 in problem 0.2, t(31)=2.69, p=0.0115; −0.01 in problem 0.5, t<1; −0.08 in problem 0.8, t(31)=−3.13, p=0.0037; and -0.13 in problem 0.9, t(31)=−2.65, p=0.0126. Those values imply

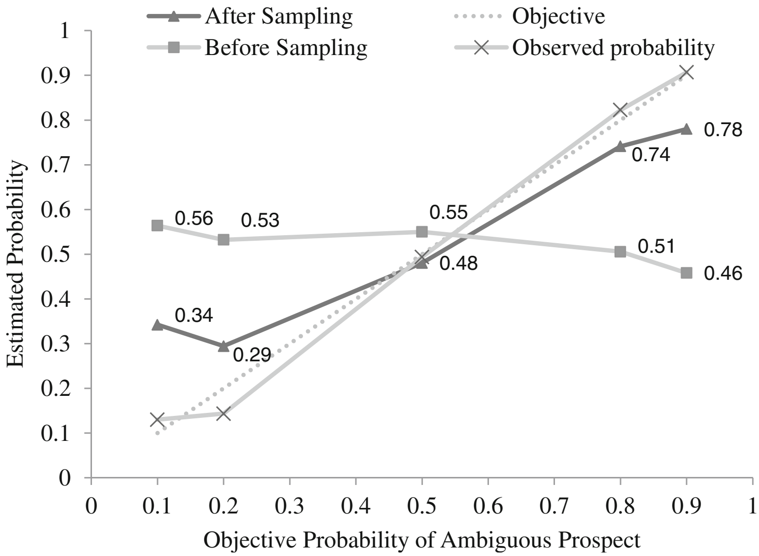

Fig. 2 Subjective estimates of the probability of drawing a green card from the ambiguous deck before and after sampling

overestimation of the low probabilities, an accurate estimation of the 0.5 probability, and underestimation of the high probabilities. In other words, we find that subjective probabilities were significantly *less extreme* than the observed probabilities. As Fig. 2 shows, they are also less extreme than the objective probabilities.

These results show that, based on the description of the ambiguous prospects with two possible outcomes, the average participant holds prior probability estimates close to 50%. These estimates are not affected by the probability of the matched risky prospect. After sampling, people update their beliefs in a way that is consistent with Bayesian updating. Given prior beliefs around 0.5, a Bayesian model based on the beta distribution, as assumed for example in Viscusi and Magat (1992, p.376), predicts that the posterior is a weighted average of the prior and the sample. This is what we observe in the current data.[6] This pattern of overestimating rare events and underestimating likely events is consistent with patterns of beliefs about frequencies of events outside the lab, such as health hazards (e.g. Lichtenstein et al. 1978). Similarly, Baillon et al. (2013, their Figure 9) find that with more information, subjective probability estimates recovered from their rank-dependent utility model move monotonically from a biased prior toward a well calibrated posterior.

These probability estimates show that the unexplained portion of the reversal in ambiguity attitudes in Study 1 for small and for large underlying probabilities is not due to overly extreme updates after sampling. People are conservative in their estimates, rather than too extreme. This suggests that the reversal is driven by motivational components of the weighting function. When experiencing samples from low probability prospects (high probability prospects), the decision maker predominantly encounters failures (successes). This might affect their attitudes toward these prospects in a way that enforces the observed effect of oversampling successes in high and undersampling successes in low probability prospects. Another indication for the role of a motivational component in sampling comes from the observation that in the no-sampling condition of Study 1, ambiguity aversion under high probabilities is stronger than ambiguity seeking under low probabilities ($t(23)=2.94$, $p=0.007$; for the differences in deviation from neutrality in problems 0.1 and 0.2 versus in their reflected problems 0.8 and 0.9). As Fig. 1 shows, for the high probability prospects sampling leads to a large shift in preference, while for the low probability prospects the shift is more modest; for the 0.5 prospect we have seen that ambiguity aversion is completely eliminated. Thus, the sampling experience increases the overall preference for ambiguity.[7]

4 Concluding discussion

Allowing decision makers to have a short sampling experience, we found a complete reversal of the pattern of ambiguity preference observed in decisions from description (the classic design of studies of ambiguity preferences). Eliciting subjective beliefs after

[6] We cannot distinguish 'appropriate' weighting from risk aversion in learning in the spirit of Viscusi and Magat (1992). However, given that the prior is basically based on zero observations, the posteriors are very conservative.

[7] Barron and Yechiam (2009) observe a similar pattern of overestimation and underweighting for the case of rare events in a decision from experience task.

sampling, we find that the subjects update their probability beliefs in a Bayesian way, and that the reversal of ambiguity preferences cannot be explained by too extreme updating of probability judgments after short samples. That is, while the composition of the observed sample adds to the reversal as predicted on the basis of overweighting of rare events, it cannot explain the full effect, which includes a direct effect of sampling on attitude toward ambiguity. In terms of the belief-based weighting account (Fox and Tversky 1998; Wakker 2004), sampling experience seems to affect the belief updating component *B(E)*, but also the motivational ambiguity attitude component in *w*. We propose two processes to explain the latter effect, one based on motivational changes and one based on the effect of biases in the processing of random samples.

Although a sample may reduce the ambiguity of the unknown-probability option to some extent, this option will always remain ambiguous relative to the known-probability risk. The general upward shift for ambiguity preference therefore suggests motivational changes which are caused by sampling experience. This shift can be modeled in a prospect theory framework through changes in the weighting *w* of probabilistic beliefs in the ambiguous event as described in Section 1 (Fox and Tversky 1998; Wakker 2004; see also Wakker 2010). In particular, while ambiguous prospects are typically associated with *pessimistic* weighting, sampling might induce more *optimistic* weighting and thus an overall upward shift in ambiguity preference. Additionally, while ambiguity is typically associated with likelihood *insensitivity*, sampling might increase likelihood *(over)sensitivity*, and could lead to decision weights that are more extreme than the observed beliefs. Jointly, these two effects can explain the general upward shift of ambiguity preference under sampling, and the reversal in preference between low and high probabilities.

Another potential explanation for the findings in our studies could relate to a processing effect. Asparouhova et al. (2009) found that gambler's and hot-hand fallacies often jointly exist in the processing of random sequences. In the current study, people made a decision based on a sequence of random samples from the ambiguous prospect's distribution. Thus, while their explicit probability estimates in Study 2 may reflect their consideration of the whole observed sample, their choices in Study 1 may reflect their expectations for the *next* draw from the random process. Here hot hand effects may be strong even after larger samples, explaining why larger samples did not lead to stronger correlation between observed frequency and choice behavior. Obviously, longer streaks are more common in the extreme probability events, leading to ambiguity preference for high probability events and ambiguity avoidance for low probability events. Another type of potential processing effect may relate to the assertion that agents might consider only a subset of the samples they experienced (e.g., Erev et al. 2010). It is possible that the size of the subset is influenced by the nature of the task: if choosing is a simpler task than estimating probabilities, then choice tasks might facilitate the consideration of smaller samples, and thus be more sensitive to underrepresentation of rare events.

Both the motivational and the processing effects are consistent with recent research in the domain of risky choice that shows that different process models are necessary to explain decisions from description and from experience (Erev et al. 2010). One of the interesting features of choice between ambiguous and risky alternatives is that it combines aspects from description based choice (some information is available), and from experienced based choice (other information is absent and could be learned).

While such a "mixed domain" seems ecologically valid in many decisions we make, and implies an interesting set of theoretical questions, it has not received as much attention yet as the "pure domains" of description or experience. The current study provides a step in this direction: it shows that experience does have a large impact on ambiguity preferences and provides a first look into the process, showing how the observed outcomes during sampling affect people's choices between risk and ambiguity.

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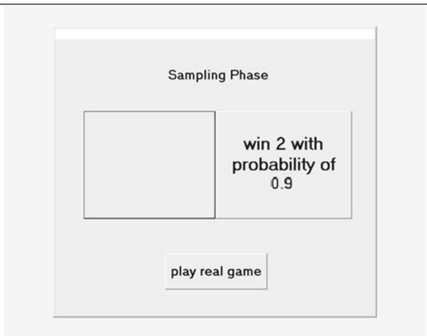
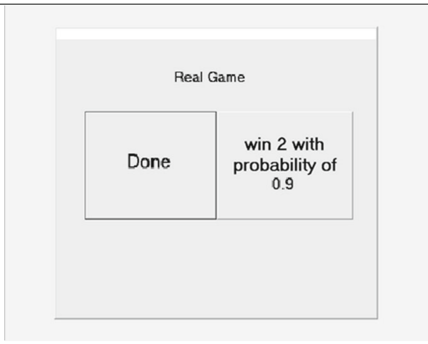
Appendix

a. "Sampling" stage	b. "Real game" stage
	
The left key represents the ambiguous prospect (identical to the described prospect on the right key). Each click on this key initiates an independent draw from its distribution. The bottom key ends the sampling stage, starting the decision (real game) stage.	In this example the participant selected the ambiguous (blank) key. The computer marks this choice by writing "Done" on the selected key so the participant knows that her choice was recorded. At the end of the study one problem was selected randomly and paid according to the participant's choice and its realization.

Note: The decision problem presented in this example is problem 0.9.

Fig. A1 Experimental screens for Study 1. The decision problem presented in this example is problem 0.9

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