

## The Description–Experience Gap in Risky and Ambiguous Gambles

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### ABSTRACT

Recent research in decision making reported a description–experience (DE) gap: opposite risky choices when decisions are made from descriptions (gambles in which probability distributions and outcomes are explicitly stated) and when decisions are made from experience (the knowledge of the gambles is obtained by sampling outcomes from unknown probability distributions before making a choice). The DE gap has been reported in gambles commonly involving a risky option (outcomes drawn from a fixed probability distribution) and a safe option (probability of the outcome is 1), or in gambles involving two risky options. Here, we extend the study of the DE gap to gambles in which people choose between a risky option and an ambiguous option (with two nested probability distributions, where the event-generation mechanism is more opaque than that in the risky option). We report empirical evidence and show a DE gap in gambles involving risky and ambiguous options. Participants' choices are influenced by the information format and by the ambiguous option: participants are ambiguity-seeking in experience and ambiguity-averse in description in problems involving both gains and losses. In order to find reasons for our results, we investigate participants' sampling behavior, and this analysis indicates choices according to a cognitive model of experiential decisions (instance-based learning). In experience, participants have small sample sizes, and participants choose options where high outcomes are experienced more frequently than expected. We discuss the implications of our results for the psychology of decision making in complex environments. Copyright © 2013 John Wiley & Sons, Ltd.

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### THE DESCRIPTION–EXPERIENCE GAP IN CONDITIONS INVOLVING RISK AND AMBIGUITY

Benjamin Franklin famously stated that the only things certain in life are death and taxes. In many decisions we make, we face different options with varying degrees of ambiguity. While we might be able to attach specific probabilities to different outcomes in certain problems (e.g., the probability of getting a “3” when throwing a fair die; Hertwig, in press), we may encounter certain events where assessing a precise probability value is not possible (e.g., when predicting the precise probability of a future global-warming catastrophe; Dutt & Gonzalez, 2012). The economist Frank Knight (1921) made an initial conceptual distinction between decisions under *risk* (“measurable probabilities”) and decisions under *ambiguity* (“unmeasurable probabilities”) (p. 20). Therefore, risk refers to decisions where the decision maker knows with certainty the mathematical probabilities of possible outcomes for choice options; in contrast, ambiguity refers to decisions where the likelihoods (probabilities) of different outcomes are vague and cannot be expressed with any mathematical precision (Knight, 1921; Luce & Raiffa, 1957; Rakow & Newell, 2010).

For risky decisions, an increasing body of research indicates that choices between options depend on how information about probabilities and outcomes is learned. Researchers have made use of a “sampling paradigm” in decisions made from

“experience” where people first sample as many outcomes as they wish from an option with defined probability distributions (that are unknown to participants) and then decide from which option to make a single draw for real (Hertwig, Barron, Weber & Erev, 2004; Hertwig & Erev, 2009). In contrast, when decisions are made from “description,” the information about the possible outcomes from an option and their probability distribution is given to the participants, and they make a selection between different options (Hertwig et al., 2004). In both experience and description, people are asked to either choose between two risky options (each with a single probability distribution) or choose between a risky option and a safe option (where probability = 1). For descriptive decisions, people behave as if rare (low probability) outcomes receive more impact than they deserve according to their objective probability, whereas for experiential decisions, people behave as if rare outcomes receive less impact than they deserve (Gonzalez & Dutt, 2011; Hertwig et al., 2004; Hertwig & Erev, 2009; Weber, Shafir & Blais, 2004). This phenomenon has been called the description–experience (DE) gap in decisions under risk, and it seems to hold for problems involving both gains and losses.<sup>1</sup>

Like risk, decisions under ambiguity could also be presented to participants in either a descriptive or an experiential form. However, the probabilities of outcomes in the ambiguous option cannot be expressed with any mathematical precision (Rakow & Newell, 2010), and the question is how to

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<sup>1</sup>In decisions under risk, the DE gap is defined as participants' risky choices in experience minus their risky choices in description (Hertwig et al., 2004).

distinguish ambiguity from risk? One possibility proposed by Arló-Costa and colleagues (Arló-Costa & Helzner, 2009; Arló-Costa, Dutt, Gonzalez & Helzner, 2011) is to distinguish ambiguity from risk in terms of the number of random variables that determine the outcomes, that is, the number of probability distributions needed to determine the outcome of a choice.<sup>2</sup> Typically, in decisions under risk, the outcome of a choice is determined by a single random variable (one probability distribution) (Hertwig & Erev, 2009). However, one way of making the same risky option ambiguous might be to break this single random variable (one probability distribution) into equivalent two nested random variables (two probability distributions), such that the working of both these events now determines the resulting outcome. We refer to conditions in which the outcome of a choice is determined by two or more probability distributions as *ambiguous*, to distinguish it from risky conditions (one probability distribution) but also to acknowledge that this event-generation mechanism is not really an ambiguous one in the Ellsberg sense (see discussion in the following sections) but instead simply more opaque than the one probability distribution risky mechanism.

The idea of two or more nested probability distributions in decisions under ambiguity is common in many natural decision making situations (Gonzalez, Vanyukov & Martin, 2005; Gonzalez, Lerch & Lebiere, 2003). For example, when we want to collect information about a product, we first select a source (e.g., a store; the first random variable) and then get samples from this source (answers to questions; the second random variable). Similarly, when deciding between several garments (each placed in a separate rack in a store), we might first select a rack (first random variable) and then decide to get samples from the chosen rack (the second random variable). Up to now, research has paid little attention to the DE gap in gambles where the options differ in the number of random variables.

In this paper, we set two explicit goals. First, we determine the degree of people's aversion to ambiguity when people are presented simultaneously with the same option as either risky (one random variable) or ambiguous (more than one random variables) in a descriptive form. Second, we contrast this descriptive situation with a similar situation now presented in the sampling paradigm to determine people's attitude to ambiguity in decisions from experience. Thus, we test whether the additional complexity in the ambiguous option results in ambiguity aversion in decisions from description and, more importantly, whether this additional complexity can lead to ambiguity-seeking in decisions from experience. In other words, is there a DE gap when people are asked to choose between a risky option and an ambiguous option, where the options differ on the number of random variables?

<sup>2</sup>A random variable conceptually does not have a single, fixed value (even if unknown); rather, it can take on a set of possible different values, each with an associated probability. In this paper, the risky option has a single random variable; however, the ambiguous option has two random variables.

## DECISIONS UNDER RISKY AND AMBIGUOUS CONDITIONS

In contrast to a risky option, in an ambiguous option, all possible values of probability (between 0 and 1) could be assumed to be equally likely, with the midpoint of the range of possible likelihoods (e.g., .5) as the best estimate (Weber & Johnson, 2008). However, Ellsberg (1961) showed that when presented with described risky and ambiguous options, people have a clear preference for the former rather than the latter—a behavior that Ellsberg called *ambiguity aversion*. Ambiguity aversion has been observed in both laboratory experiments and in real-world health, environmental, and negotiation contexts (Camerer & Weber, 1992; Curley & Yates, 1989; Hogarth & Kunreuther, 1989; Wakker, 2010). For example, Camerer and Weber (1992) provided a thorough review of the literature on decisions under ambiguity and showed that ambiguity aversion is a very stable phenomenon observed in a large number of described problems.

Although ambiguity aversion prevails robustly for described gains, the case is less clear for described losses (Wakker, 2010). For losses, some researchers found ambiguity aversion behavior (Keren & Gerritsen, 1999), some found mixed evidence (Cohen, Jaffray & Said, 1987; Dobbs, 1991; Hogarth & Kunreuther, 1989; Mangelsdorff & Weber, 1994; Viscusi & Chesson, 1999), and a number of researchers found ambiguity-seeking behavior (Abdellaoui, Vossman & Weber, 2005; Chakravarty & Roy, 2009; Davidovich & Yassour, 2009; Di Mauro & Maffioletti, 1996; Du & Budescu, 2005; Einhorn & Hogarth, 1986; Ho, Keller & Keltyka, 2002).

Ambiguity aversion is a well-known phenomenon in decisions from description. However, very little is currently known about ambiguity aversion in situations involving experiential decisions. In fact, although the study of the DE gap has been prominent for risky decisions, the existence of a similar gap for a choice between risky and ambiguous decisions has yet to be investigated. Such research that shows a DE gap becomes important because some researchers have described experiential decisions under risk to be similar to decisions involving ambiguity (Fox & Hadar, 2006; Hadar & Fox, 2009). According to Hadar and Fox (2009), decisions from experience apply to any situation in which there is ambiguity and learning through trial-and-error feedback (i.e., sampling of outcomes). However, Hadar and Fox (2009) do not say anything about what it means to have an experiential counterpart to a given description in decisions under ambiguity, an assumption that is crucial to the equivalence of descriptive and experiential decisions and to the study of the DE gap in decisions under ambiguity.

Arló-Costa and Helzner (2009) and Arló-Costa et al. (2011) have defined decisions from description and experience so that one could create equivalent experiential and descriptive counterparts for problems involving ambiguity. According to Arló-Costa et al. (2011), in risky options, people are presented with a specification of a chance mechanism, whereas in ambiguous options, people are not presented with such a specification; rather, they are allowed

to observe the behavior of the chance mechanism. In this sense, while classical descriptions under ambiguity (e.g., the Ellsberg's problem) have no experiential counterparts because the relevant ambiguities in such cases are epistemic, one can specify random variables (probability distributions) that, at least psychologically, approximate the descriptions of ambiguities and have an experiential counterpart. Having this experiential counterpart to the description in decisions under ambiguity enables us to extend the study of the DE gap in decisions under risk to decisions under ambiguity. Thus, a possibility is to make participants perceive an option as risky or ambiguous by the number of random variables that generate the outcomes: one random variable in decisions under risk and two or more nested random variables in decisions under ambiguity. The difference created between risky and ambiguous options based upon the number of random variables could be a sufficient condition to test the DE gap in decisions under ambiguity. However, one does need to note that our differentiation between risky and ambiguous options that is based upon number of random variables is different from the distinction made in the classic Ellsberg sense between risky and ambiguous options.

Given this difference, a goal of this paper is to determine choice when people are presented simultaneously with described risky and ambiguous options that differ in terms of the number of random variables. Second, we develop an experiential paradigm to extend the study of the DE gap in risky decisions to ambiguous decisions. The main questions we ask are the following: Is there a DE gap in ambiguous conditions? If so, what could be the reasons for this gap? We answer the first question by reporting an experiment where human participants make choices between risky and ambiguous options in descriptive and (approximate) experiential counterparts of the Ellsberg's problem. In order to probe the reasons for our experimental findings, we first analyze participants' trial-and-error learning (sampling) in experience. This analysis qualitatively compares experiential decisions in the ambiguous conditions to experiential decisions under risk. In past research, risky choices from experience has been explained based upon the cognitive processes proposed by the instance-based learning theory (IBLT), a theory of decisions from experience in dynamic tasks (Gonzalez et al., 2003) and a simple computational model derived from the theory for binary-choice tasks (Gonzalez & Dutt, 2011). The IBL model presents a process in which decisions are made from stored and retrieved experiences (called instances), based upon small samples and recently and frequently experienced outcomes. We expect that these cognitive processes would apply to both risky and ambiguous conditions from experience. Thus, we generate our hypotheses from the cognitive processes implemented in the IBL model as well as the literature in decisions from experience. We close this paper by drawing insights from this research effort to the psychology of complex decisions and decisions under ambiguity and on how these situations compare with decisions under risk.

## REPRESENTING EXPERIENCE IN DECISIONS UNDER AMBIGUITY

Consider the classical Ellsberg's two-color problem (Ellsberg, 1961):

*Urn A contains exactly 100 balls. 50 of these balls are solid black and the remaining 50 are solid white.*

*Urn B contains exactly 100 balls. Each of these balls is either solid black or solid white, although the ratio of black balls to white balls is unknown.*

Consider now the following questions: *How much would you be willing to pay for a ticket that pays \$25 (\$0) if the next random selection from Urn A results in black (white) ball? Repeat then the same question for Urn B.*

Urn B is ambiguous as the ratio of black to white balls is unknown, while urn A is not. It is a well-known result that a majority of participants prefer urn A to urn B and also decide to make greater payments for urn A than urn B (Ellsberg, 1961; Tversky & Fox, 1995). Tversky and Fox (1995) explained participants' ambiguity aversion in the Ellsberg's problems with the *comparative ignorance hypothesis*. Their hypothesis was that people are only ambiguity-averse when their attention is specifically brought to the ambiguity by comparing an ambiguous option (urn B) to an unambiguous option (urn A). For instance, people are willing to pay more on choosing a correct colored ball from an urn containing equal proportions of black and white balls than an urn with unknown proportions of balls when evaluating both of these urns at the same time. When evaluating them separately, however, people are willing to pay approximately the same amount on either urn. However, Arló-Costa and Helzner (2005, 2007) have recently shown that people seem to behave as ambiguity-averse even in non-comparative cases when urns A and B are not presented simultaneously. One reason for ambiguity aversion in the non-comparative cases could be that people form implicit assumptions to deal with the ambiguity resulting from the unknown information about urn B, and these assumptions might lead them to behave as ambiguity-averse (Guney & Newell, 2011).

In Ellsberg's problem, it is next to impossible to have an experiential counterpart for urn B because the probabilistic information is ambiguous. That is because the ratio of black to white balls is unknown, and so, one cannot simulate the process as an experience. Rakow and Newell (2010) have provided a continuum of types of ambiguity/probability, the *degrees of uncertainty*. According to these researchers, anchored at one end are risky decisions of perfect regularity where probabilities can be determined precisely, with the other extreme being ambiguous decision situations where only an estimate of the probability could be used to determine one's belief. From the decision maker's perspective, these decision extremes differ according to how easily the outcomes' probability distributions can be calculated. Considering these degrees of uncertainty, urn A is of the former risky decision type (with a precise definition of the probability), while urn B is of the latter ambiguous



decision type (with an imprecise definition of the probability). According to Rakow and Newell (2010), risky decisions from experience generally tend to occupy a middle ground between the extremes in the degrees of uncertainty. Thus, the probability of the outcomes is not precisely known in risky decisions from experience, but it could be empirically determined by observation (sampling) of outcomes. If we want to evaluate the DE gap in Ellsberg's problem, then we need to develop an experiential middle ground between urns A and B for the ambiguous information in urn B to be performed experientially. One way of doing so is to convert the single random variable (i.e., a probability distribution) that determines the probability in the risky option into two random variables (i.e., two probability distributions) that are likely to be perceived as the ambiguous option. Although this setup is different from the classical Ellsberg's problem, Arló-Costa and Helzner (2005, 2007) have used this idea to propose the following descriptive chance setup:

*B\** First, select an integer between 0 and 100 at random, and let  $n$  be the result of this selection. Second, make a random selection from an urn consisting of exactly 100 balls, where  $n$  of these balls are solid black and  $100 - n$  are solid white.

In  $B^*$ , the first selection between 0 and 100 (i.e., the first random variable) is like picking an urn with a certain distribution of black and white balls. Once the first selection is made, the second selection (i.e., the second random variable) is the act of playing the urn that was picked in the first selection. In a number of experiments, Arló-Costa and Helzner (2005, 2007) and Arló-Costa et al. (2011) have shown that participants' payments for  $B^*$  are in between those for urns A and B. For example, Arló-Costa et al. (2011) reported that payments for urn A ( $=\$7.04$ ) were greater than those for  $B^*$  ( $=\$6.36$ ), and those for  $B^*$  were greater than those for urn B ( $=\$4.93$ ). Thus, people prefer an option (A), which depends on one risky random variable, over an option ( $B^*$ ), which depends on two risky random variables. Also, people prefer an option ( $B^*$ ), which depends on two risky random variables, over an option (B), where the specification of random variables is ambiguous. Chow and Sarin (2002) and Yates and Zukowski (1976) reported similar results using  $B^*$ . These results show that people consider  $B^*$  to be of intermediate ambiguity between the ambiguous urn B and the unambiguous urn A and that one reason for these findings could be the inability to reduce the compound lottery  $B^*$  (containing two random variables) to the simple lottery A (Halevy, 2007). This line of reasoning might be plausible because  $B^*$  is mathematically equivalent to A.<sup>3</sup> Also, The pattern of preference between A,  $B^*$ , and

<sup>3</sup>The line of reasoning is roughly as follows: The random selection in the first stage of  $B^*$  entails that for each integer  $i$ , where  $0 \leq i \leq 100$ , there is a probability of  $\frac{1}{101}$  that the urn sampled in the second stage consists of  $i$  black balls and  $100 - i$  white balls. Moreover, according to this line of reasoning, the random selection in the second stage entails that if  $i$  is selected in the first stage, then the probability of selecting a black ball in the second stage is  $\frac{i}{100}$ . This line of reasoning then continues by combining the first and second stage probabilities to conclude that the probability of getting a black ball on any trial of  $B^* = \frac{1}{101} \left( \sum_{i=0}^{100} \frac{i}{100} \right) = \frac{1}{2}$ , exactly as in the case of urn A.

B suggests that part to the indication for ambiguity aversion can be related to a tendency to prefer simpler options, which have fewer or well-defined random variables.

More importantly, the perception of  $B^*$  as being more ambiguous than A is very useful, as it allows us to treat  $B^*$  as an operational approximation of urn B in experience. Again, the interest of this move is that  $B^*$  is easily implementable in experience, while it is notoriously difficult to find an experiential counterpart of urn B. The way we do in this paper is by making option B more ambiguous in option  $B^*$  by introducing two random variables that determine the outcomes.

#### EXPERIMENT: THE DE GAP IN DECISIONS UNDER RISK AND AMBIGUITY

In this section, we report an experiment that tests for the DE gap by utilizing the formulations of urns A and  $B^*$  in description and experience.

#### Hypotheses

Our goal was to compare the difference in people's ambiguity-seeking/aversive predisposition for outcomes presented as a written description or as an experience (i.e., the DE gap for ambiguity) in problems involving risky and ambiguous options. Given the overwhelming evidence of the existence of the DE gap in decisions under risk (e.g., Hertwig et al., 2004; Hertwig & Erev, 2009) where decision makers make decisions based upon recency and frequency of experienced outcomes (explained by IBLT) and the arguments earlier that risk and ambiguity are a part of a continuum of degrees of uncertainty (Rakow & Newell, 2010), we expect a similar DE gap in decisions under ambiguity. More specifically, as people are shown to be ambiguity-averse in description in a large number of studies in decisions under ambiguity (Camerer & Weber, 1992; Curley & Yates, 1989; Hogarth & Kunreuther, 1989; Wakker, 2010), we expect them to be less ambiguity-averse in experience. This expectation is based upon the assumption that decision makers can distinguish between one or more than one random variables that determine the outcomes in risky and ambiguous options in experience, respectively. Here, according to the IBL model's predictions (Gonzalez & Dutt, 2011), participants are likely to choose an option (risky or ambiguous) where participants encounter a high (maximizing) outcome more recently and frequently (based upon the IBLT assumptions of recency and frequency). Thus, if participants more frequently and recently encounter higher payoffs during their sampling in the ambiguous option, then they are likely to choose the ambiguous option during their final choice in experience. Therefore, we expect the following:

**H1:** A greater proportion of participants will be ambiguity-seeking in experience compared with description.

Furthermore, the DE gap in decisions under risk has been reported for both gains and losses (Hertwig et al.,

2004; Hertwig & Erev, 2009). Whether one considers gains or losses, the nature of the gap is driven by underweighting rare outcomes in experience and overweighting rare outcomes in description. Moreover, in decisions under ambiguity, people have been found to be ambiguity-averse for gains, and there currently exists mixed evidence for losses (Wakker, 2010). Thus, in decisions under ambiguity, we expected people to be ambiguity-averse in description and less ambiguity-averse in experience for both gains and losses. Therefore, we expect the following:

**H2:** A greater proportion of participants will be ambiguity-seeking in experience compared with description irrespective of gains and losses.

## Method

### Participants

One hundred and fifty-three participants were randomly assigned to one of two conditions, description ( $N=61$ ) and experience ( $N=92$ ).<sup>4</sup> Seventy-six participants were male and the rest were female. The mean age was 26 years ( $SD=8$ ), and ages ranged from 18 to 63 years. All participants received a base payment of \$5 for participating in the experiment, which lasted for less than 20 minutes. In addition, participants could earn performance bonuses based upon the outcomes they received in the gain and loss problems. Participants could win \$25 or \$0 in the gain problem, and they could lose \$25 or \$0 in the loss problem. The final earnings across the two problems were added up into a total, and the total was scaled in the ratio 10:1 to pay participants their performance bonuses. For example, total earnings of \$25 across the two problems (i.e., \$25 in the gain problem and \$0 in the loss problem) would give a participant \$2.50 as performance bonus in addition to their \$5 base pay. Thus, in the worst case, a participant would get \$2.50 from the study (i.e., \$5 base payment + \$0 in the gain problem \$2.50 in the loss problem).

### Experimental design

We operationalized the definition of urns A and B\* by employing the following descriptions for gain and loss problems in terms of fair chance setups (or random variables).

*A: A fair chance setup with possible outcomes {1, 2, ..., 99, 100} has been constructed. If the outcome on the next run of this setup is less than or equal to 50, then you win (lose) \$25. Otherwise, you get \$0. (risky option)*

*B\* Two fair chance setups, I and II, have been constructed. Setup I has possible outcomes {0, 2, ..., 99, 100}. Setup II has possible outcomes {1, 2, ..., 99, 100}. The game is played by first running setup I and then running setup II. If the outcome of the run of setup II is less than or equal to the outcome from the run of setup I, then you win (lose) \$25. Otherwise, you get \$0. (ambiguous option)*

A is the *risky* option, and B\* is the *ambiguous* option based upon the specification of one or two random variables, respectively (hereafter, A will be referred to as risky and B\* as ambiguous option). Both risky and ambiguous options are either framed as a win in one problem (gain problem) or as a loss in the other problem (loss problem). We use the two earlier descriptions of the risky and ambiguous options as part of the description condition in the experiment. In the experience condition, the text for the risky and ambiguous options is replaced by button options that can be sampled repeatedly before making a final choice as is done in the traditional sampling paradigm (see Hertwig & Erev, 2009, for example). The proportion of ambiguous (B\*) choices indicated the degree of ambiguity-seeking across description and experience, and this proportion served as the main dependent variable for the purposes of statistical analysis.

### Description condition

Each participant assigned to this condition was presented with two problems in a random order. One of the problems was a gain problem (win \$25 or \$0), while the other was a loss problem (lose \$25 or \$0). In each problem, participants faced a computer window with two large buttons (representing the two games or options) that were labeled with text descriptions for the risky (A) and ambiguous (B\*) options earlier. Figure 1A provides an example of the setup that participants faced in the gain problem in the description condition. The assignment of descriptions to buttons on the left or right side of the window was randomized for each participant in both problems. Centered just below the two buttons, participants were asked the following question: *Which one out of the two games will you choose to play?* Participants made their final choice for one of the two games by clicking on one of the two buttons. After participants gave their final choice in a problem, they were asked to choose one of these button options in a following window:

*Left Button: You were indifferent between the two alternatives (L)*

*Middle Button: You had a strict preference for one of the alternatives (M)*

*Right Button: Neither (L) nor (M) reflected my attitudes*

These three button options were presented immediately after participants made their final choice in each of the two problems. As can be seen, the middle button represents a *strict preference* for the option (risky or ambiguous) that the participant chose as her final choice. The left or right buttons show either *indifference* between the options (risky or ambiguous) or a preference that was *in-between* a strict

<sup>4</sup>Both the description and experience conditions contained a large number of participants ( $>50$ ). The data in the two conditions were collected at the same time, where participants could only participate once in the study. The difference in number of participants between the two conditions was due to participants signing-up but not turning-up for the study on a particular day. The difference in the number of participants between the two conditions does not create a problem because in our results, we found that the distributions of different preference strengths were similar across the two conditions.

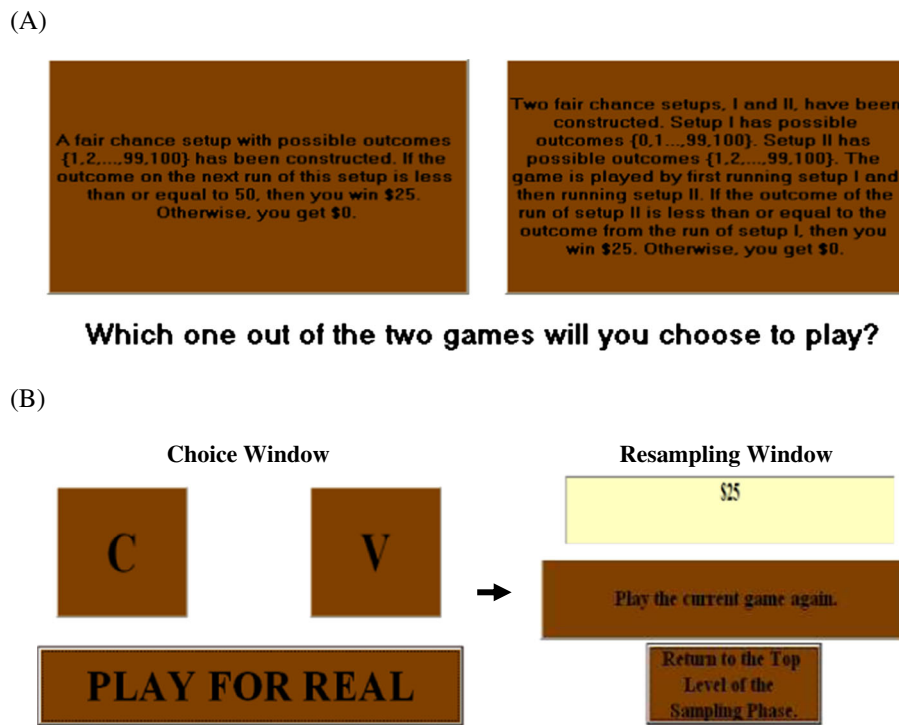


Figure 1. (A) The gain problem in the description condition. Participants had to choose one of the two options (games), one time, by clicking on one of the two buttons. (B) The gain problem in the experience condition. Option V is ambiguous (B\*) and option C is risky (A). During sampling, a participant clicks button V (choice window) and is shown the outcome (\$25) (resampling window). The participant has now the option to either resample V (by clicking on “Play the current game again”) or exit from this window (participants exited the resampling window by clicking on the button labeled “Return to the top level of the sampling phase”). To make a final choice, participants had to click the “play for real” button followed by their final choice. Sampling of options did not cost any money; only the final choice affected earnings

preference and an indifference between these options, respectively. As the difference between the risky and ambiguous options is based upon the number of random variables or probability distributions (one in the risky option and two in the ambiguous option), we kept the three preference strengths to account for any perceived difference between the ambiguous and risky options after a choice was made in the description condition.<sup>5</sup>

*Experience condition*

Each participant assigned to this condition was presented with two problems in a random order. One of the problems was a gain problem (outcomes \$25 or \$0), while the other was a loss problem (outcomes -\$25 or \$0). In each problem, participants faced two large buttons containing the labels “C” and “V.” These labels were randomly assigned to the left or right button for each participant in both problems. Figure 1B provides an example of the setup that participants faced in the gain problem in the experience condition. Unbeknownst to participants, option C corresponded to option A (risky) in description, and option V corresponded to option B\* (ambiguous) in description. In the experience condition, before the start of experiment, through instructions,

participants were told that clicking the risky option activates a fixed game, whereas clicking the ambiguous option results in the selection of a possibly new game each time that it is pressed (and after clicking the ambiguous option, they will be offered the option of activating the game that was selected). Participants could sample either of the two options one at a time by clicking on them as many times they wanted to as well as in any order they wanted to. Sampling these two options did not cost any money to participants; only the final choice made after sampling was consequential. Clicking the risky option triggered a random selection of a number  $m$  from the set  $\{1, 2, \dots, 99, 100\}$  with replacement. If  $m$  was less than or equal to 50, then the participant was told that he got \$25 (-\$25); otherwise, he was told that he got \$0. Similarly, clicking the ambiguous option yielded an output that was obtained by triggering the double sampling (i.e., two random variable) procedure. After clicking the ambiguous option, a random selection of a number  $n$  was made from the set  $\{0, 1, \dots, 99, 100\}$  with replacement, and this selection was followed by a second random selection of a number  $k$  from the set  $\{1, 2, \dots, 99, 100\}$ , again with replacement. If  $k$  was less than or equal to  $n$ , then the participant was told that he got \$25 (-\$25); otherwise, he got \$0 (the randomly generated values of  $n$  and  $k$  were not revealed to participants). As can be seen in Figure 1B, upon clicking the ambiguous option (button V), an outcome was shown in the resampling window, and participants had the option of either resampling the same button for the same  $n$  value but a different randomly

<sup>5</sup>As shown above, the two options A and B\* were mathematically identical. Thus, the three preference strengths accounted for any perceived deviation from the mathematical similarity between A and B\*.



selected  $k$  value, or going back to the choice window to be able to choose between the ambiguous and risky buttons again. Thus, every subsequent resampling of the ambiguous option in the resampling window caused the random generation of only  $k$  from its set  $\{1, 2, \dots, 99, 100\}$  with replacement for its comparison with an existing  $n$  (this existing  $n$  was generated when the ambiguous button was clicked in the choice window to enter the resampling window). A new  $n$  was selected from its set  $\{0, 1, \dots, 99, 100\}$  only in cases when the ambiguous button was chosen for the first time in a problem or when  $V$  was chosen again in the choice window after subsequently exiting from the resampling window. The provision of resampling ambiguous button in the resampling window was provided to portray the existence of two random variables (or probability distributions) in  $B^*$ . The  $n$  was not changed for every subsequent resampling of the ambiguous option in the resampling window because the participant was given a choice to “play the current game again.”

In order to keep the sampling process identical for both option buttons, the resampling and exit options were also made available to participants for the risky button in its resampling window. In the case of the risky button, every subsequent resampling of this button without choosing to exit from the resampling window caused a new  $m$  to be randomly generated from its set  $\{1, 2, \dots, 99, 100\}$  with replacement, and then this  $m$  was compared with 50 to generate an outcome (the randomly generated value of  $m$  was not revealed to participants). Therefore, the process of generating  $m$  in the risky option was the same whether this option was chosen for the first time in a problem, whether this option was sampled again after exiting from the resampling window, or whether this option was resampled without exiting from the resampling window.

Once participants were satisfied with their sampling, they gave their final choice for one of the two option buttons by clicking on the “Play for Real” button following their choice. As shown in Figure 1B, the “Play for Real” button was located in the choice window, so if a participant was in the resampling window, then she needed to exit from that window to be able to make a final choice. Like in the description condition, they were asked to choose one of the button options among strict preference, indifference preference, and in-between preference in a following window after submitting their final choice in each problem. Just like in description, for a problem, we treat the proportion of ambiguous button choices as a measure of ambiguity-seeking behavior. Although participants were told about the differences between the risky and ambiguous options through instructions before starting their experiment, they might not perceive any difference between these two options based upon their sampling (as the actual sampling process and the generation of random numbers were kept hidden from participants under both options in experience). Thus, keeping the three preference strengths allows us to account for any differences that our participants might perceive between the two options in the experience condition.

## Procedure

Participants were randomly assigned to one of the two conditions, experience or description. Within each condition, they were given two problems, gain and loss, in a random order. Participants read the instructions about the task and how they would be paid. Questions were answered at the time they read these instructions, but none were answered while participants performed the problems. In the experience condition, participants did not know about the random numbers being generated behind the two buttons, and they only saw the resulting outcomes \$25, \$0, or -\$25, depending upon the problem they were playing. Participants were shown their final choices’ outcomes in each problem only after they finished playing both problems. Participants’ earnings were scaled, handed their base and performance payments, and thanked for their participation.

## RESULTS

Table 1 shows the proportion of ambiguity-seeking choices for the different preference strengths in the experience and description conditions for both loss and gain problems, respectively. In experience, there were 43 participants who expressed a strict preference for one of the two options (47%), 33 participants who expressed indifferences between the two options (36%), and 16 participants who expressed strength of preferences in-between a strict preference and an indifference (17%). In the description condition, there were 29 participants who expressed a strict preference for one of the two options (48%), 21 participants who expressed indifferences between the two options (34%), and 11 participants who expressed strength of preferences in-between a strict preference and an indifference (18%). Thus, across the description and experience conditions, the proportion of participants expressing the different preference strengths was similar. This result shows that participants perceived the two options, risky and ambiguous, similarly across the experience and description conditions.

Furthermore, as shown in the table, there exists a DE gap for strict preferences in both the gain and loss problems. The nature of the gap and its valence in both gain and loss problems is according to expectations stated in H1 and H2: A greater proportion of choices are ambiguity-seeking in experience compared with in description, and this effect is similar in gain and loss problems. Furthermore, there is an absence of a gap among people who did not have a strict preference for their final choice (i.e., those with indifference or in-between preferences). Thus, people who did not perceive differences between options based upon their sampling exhibited similar preferences across the description and experience conditions. Overall, these results are in agreement with our expectation of a DE gap existing in decisions under ambiguity.

## Sampling behavior

Given that the DE gap under ambiguity is similar to a gap under risk, we expect that the psychological mechanisms under

Table 1. Proportion of ambiguity-seeking choices for different preference strengths in the experience and description conditions for the loss and gain problems

Preference strength <sup>a</sup>	Experience	Description	Description–Experience gap
Gain problem			
Indifferent	42% (14/33)	48% (10/21)	–06% ( $Z = -.371$ , <i>ns</i> , $r = -.04$ )
<b>Strict</b>	<b>65% (28/43)</b>	<b>38% (11/29)</b>	<b>+27% (<math>Z = -2.255</math>, <math>p &lt; .05</math>, <math>r^b = -.27</math>)</b>
In-between	44% (07/16)	55% (06/11)	–11% ( $Z = -.541$ , <i>ns</i> , $r = -.10$ )
Loss problem			
Indifferent	63% (22/35)	53% (08/15)	+10% ( $Z = -.624$ , <i>ns</i> , $r = -.09$ )
<b>Strict</b>	<b>66% (27/41)</b>	<b>41% (14/34)</b>	<b>+25% (<math>Z = -2.123</math>, <math>p &lt; .05</math>, <math>r = -.25</math>)</b>
In-between	44% (07/16)	58% (07/12)	–14% ( $Z = -.750$ , <i>ns</i> , $r = -.14$ )

Note: The bolded text indicates results that are significant at  $p < .05$ .

<sup>a</sup>Preference strengths account for any perceived difference between the ambiguous and risky options after a choice is made for one of them.

<sup>b</sup>The  $r$  is the effect size.

risk would also be relevant for decisions under ambiguity. Based upon predictions from the IBL model and decisions from experience literature, we expected reliance on small samples, frequency, and recency to be the driving psychological mechanisms of the behavior in the experience condition of our experiment (Gonzalez & Dutt, 2011; Hertwig & Erev, 2009). Here, we systematically investigate these psychological mechanisms by analyzing the sampling behavior from participants in the experience condition.

### Sample size

In experiential decisions under risk, the leading cognitive explanation of the DE gap has been a “reliance on small samples” (Hertwig & Erev, 2009). Across a number of studies, participants have sampled options relatively few times (median number of samples often vary between 11 and 19) (Hau et al., 2008; Hertwig & Erev, 2009). In our experiment, the median number of samples was 20 in the loss problem and 26 in the gain problem. These numbers of samples are larger than those found in decisions under risk experiments. This finding might be due to the dynamics of the probabilities that participants encountered with our experimental paradigm. In our experiment, based upon the first random variable in the ambiguous option, participants may encounter problems of different probabilities across their sampling; some may involve rare outcomes and frequent outcomes in one single sampling of the ambiguous button. That is unlike decisions under risk, where the probability of the risky option remains fixed across samples and one expects to observe outcomes consistently with this fixed probability. It is possible that given the consistency of the probabilities in decisions under risk, people might be satisfied with their samples sooner.

### Frequency and recency of experienced outcomes

Gonzalez and Dutt (2011), Hertwig et al. (2004), and Weber (2006) documented that participants’ final choices (i.e., post sampling) were a function of the recency and frequency of experienced outcomes during sampling in experiential decisions under risk. The reliance on recency

and frequency of experienced outcomes follows directly from IBLT (Gonzalez et al., 2003).

In order to understand the role of frequency of experienced outcomes in our dataset, we analyzed the proportion of ambiguity-seeking final choices among participants who encountered the non-zero outcome (\$25 or –\$25) more or less frequently than expected during sampling of the ambiguous option (the latter being determined by the probabilities in the problems encountered during sampling). Table 2 shows this frequency analysis for different problems and preference strengths. In the gain problem, the proportion of ambiguity-seeking choices was higher for those who saw \$25 as or more frequently than expected compared with those who saw \$25 less frequently than expected for both indifference and strict preferences. A similar but reversed pattern for the loss problem was found: The proportion of ambiguity-seeking preferences was lower for those that saw –\$25 as or more frequently than expected compared with those who saw –\$25 less frequently than expected (88%) for both indifference and strict preferences. In the case of in-between preferences, this pattern was weaker in both the gain and loss problems (in fact, there are very few data points to conclude either way). These findings taken together reveal that frequency of experienced outcomes did influence participants’ final choices in both problems.

We also analyzed participants’ sampling for the role of recency in their final choices using the method suggested in Hertwig et al. (2004). For this analysis, we split the sequence of draws (samples) from each option into two halves for each problem and each participant giving different preference strengths. Then, we computed the options’ average payoffs obtained for the first and second halves of the samples, predicted each person’s choice on the basis of the average payoffs (the option with the higher average payoff was predicted to be chosen), and analyzed how many of the actual final choices coincided with the predicted choices. If recency plays a role in decisions from ambiguity (as suggested by IBLT), then the second half of samples should predict a greater proportion of actual choices compared with the first half of samples. Table 3 shows the analysis of recency for different problems and preference strengths. Overall, the proportion of actual choices correctly predicted



Table 2. The proportion of ambiguity-seeking final choices based upon the frequency of observing \$25 or -\$25 in the ambiguous option during sampling for different problems and preference strengths

Preference strength	Proportion of ambiguous option final choices	
	Observed \$25 on ambiguous option as or more frequently than expected during sampling	Observed \$25 on ambiguous option always less frequently than expected during sampling
Gain problem		
Indifferent	52% (13/25)	0% (0/6)
Strict	81% (22/27)	45% (5/11)
In-between	50% (4/8)	60% (3/5)
Loss problem		
	Observed -\$25 on ambiguous option as or more frequently than expected during sampling	Observed -\$25 on ambiguous option always less frequently than expected during sampling
Indifferent	60% (18/30)	100% (3/3)
Strict	59% (19/32)	88% (7/8)
In-between	50% (6/12)	33% (1/3)

Table 3. The proportion of actual choices correctly predicted based upon first or second half of sampling for different problems and preference strengths

Preference strength	Proportion of actual choices correctly predicted	
	By first-half samples	By second-half samples
Gain problem		
Indifferent	59% (19/32)	44% (14/32)
Strict	31% (12/39)	51% (20/39)
In-between	33% (4/12)	42% (5/12)
Loss problem		
	Sampling first half	Sampling second half
Indifferent	52% (17/33)	48% (16/33)
Strict	55% (22/40)	48% (19/40)
In-between	53% (8/15)	80% (12/15)
Overall (across different preference strengths and problems)	48% (82/171)	50% (86/171)

by the first or second sample halves show small effects of recency: The second half of samples explained 50% of actual choices, whereas the first half of samples explained 48% of the same choices. The effects of recency were particularly stronger in gain problems for strict and in-between preferences and for in-between preferences in loss problems. However, recency did not play a role for strict preferences in the loss problem and for indifference preferences in the loss and gain problems. Overall, these results show a lack of systematic pattern for recency's role across problems and preference strengths. In fact, like in our experiment, the role of recency in explaining final choices has not been consistently found. Unlike Gonzalez and Dutt (2011), Hertwig et al. (2004), and Weber (2006), Hau et al. (2008) and Rakow, Demes and Newell (2008) found its impact on final choices to be quite limited. Even Gonzalez and Dutt (2011), who used different datasets for their analyses, found that the recency's role was not consistent across all datasets.

## GENERAL DISCUSSION

We found a DE gap for decisions under ambiguity. When people are simultaneously presented with risky and ambiguous

options, people are ambiguity-averse in description (as has been classically documented in ambiguity literature by Ellsberg, 1961, and others), while they are ambiguity-seeking in experience. The DE gap appears for people who express a strict preference for their final choice, and it is weaker for those that express an indifference preference or an in-between preference. This latter finding is reasonable, considering the fact that people who exhibit a strict preference are likely those that are able to distinguish between the two options, risky and ambiguous, based upon their sampling of outcomes (in experience) or based upon the descriptive ambiguity of the random variables in description. From an IBL perspective, the DE gap for participants expressing a strict preference is revealed in the effects of frequency for these participants. When these participants see \$25 in the ambiguous option as or more frequently than expected, a greater proportion choose it at final choice compared with those that see it less frequently than expected. However, when these participants see -\$25 in the ambiguous option as or more frequently than expected, a smaller proportion choose it at final choice compared with those that see it less frequently than expected. In addition, the DE gap for participants with a strict preference is also exhibited by the role of recency in

the gain problem: A greater proportion of final choices seem to agree with the second sample half compared with the first sample half. However, similar recency effects were weaker for the loss problem. We can only speculate, but perhaps, the negative (−\$25) outcome is more salient when it occurs in the first half of samples compared with when it occurs in the second half of samples. This saliency of early negative outcomes is consistent with hyperbolic discounting literature (Thaler, 1981), where early losses are more impacting and painful compared with delayed losses.

Furthermore, although decisions under risk and ambiguity seem similar and both these decisions involve similar cognitive processes as suggested by IBLT, there are important differences between the ambiguous experiential decisions (as in our experiment) and those under risk. In experiential decisions under ambiguity, the frequency of the ambiguous option's outcomes changes stochastically across samples (because of the two random variables involved). Therefore, the experienced frequency of outcomes for the ambiguous option is essentially unknown to the participants, and the likelihood of different outcomes cannot be expressed with any mathematical precision across samples. However, in experiential decisions under risk, the frequency of observed outcomes for an option remains the same and can be expressed with mathematical precision. Perhaps, it is due to these differences between risk and ambiguity that we find some peculiarities in human sampling behavior in our experiment. For example, although the observed median sample size in our experiment was small, this median sample size was larger than that of decisions under risk (Hertwig et al. 2004).

Despite these differences, we also found overlaps between our results and those known for experiential decisions under risk. For example, the influence of recency on participants' choices in decisions under risk has been somewhat inconsistent, and our results for decisions under ambiguity seem to agree with this inconsistency: Recency had little role to play in our results, as the first and second halves of samples seem to explain the final choices equally well in both gain and loss problems. Given that recency is an integral part of IBLT and its role is inconsistent, it seems that frequency is a stronger driving mechanism compared with recency to explain final choices based upon sampling.

Our results on the consistency of the DE gap in experiential decisions under ambiguity support similar findings in experiential decisions under risk (e.g., Hertwig et al., 2004; Hertwig & Erev, 2009). For decisions under ambiguity, people are ambiguity-averse only when decisions are made from description, and they become ambiguity-seeking when decisions are made from experience. One plausible reason for this finding could be that, in experience, participants are unable to perceive the complexity of two random variables in the ambiguous option during their sampling, and this causes them to prefer the ambiguous option. However, in description, participants get to read the description of the extra random variable, and the complexity of the random process makes them move away from the ambiguous option. In fact, an extra random variable in the ambiguous option compared with the risky option is sufficient to observe a

gap between choices in description and experience. This observation is the main contribution of our experiment.

In addition, as shown in our results, participants choose the option that gives them the high payoff more frequently than expected in the experience condition. This observation would suggest that a second factor for the DE gap observed in our study is sampling error (Hau et al., 2010; Ungemach et al., 2009). Thus, in the near future, we plan to do an additional study where one reduces or eliminates sampling error either via increased sample sizes (e.g., Hau et al., 2010) or via a constrained-sampling technique (Ungemach et al., 2009). In general, future research is likely to benefit by drawing upon the documented similarities and differences for experiential decisions under risk and under ambiguity, and in further investigating the reasons for the presence of a DE gap in decisions under ambiguity due to ambiguity differences created in other possible ways.

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#### REFERENCES

- Abdellaoui, M., Vossman, F., & Weber, M. (2005). Choice-based elicitation and decomposition of decision weights for gains and losses under uncertainty. *Management Science*, *51*, 1384–1399. DOI: 10.1287/mnsc.1050.0388.
- Arló-Costa, H., & Helzner, J. (2005). Comparative ignorance and the Ellsberg phenomenon. In F. Cozman, R. Nau, & T. Seidenfeld (Eds.), *Proceedings of the fourth international symposium on imprecise probabilities and their applications*. Pittsburgh, PA: SIPTA.
- Arló-Costa, H., & Helzner, J. (2007). On the explanatory value of indeterminate probabilities. In G. De Cooman, J. Vejnarova, & M. Zaffalon (Eds.), *Proceedings of the fifth international symposium on imprecise probabilities and their applications* (pp. 117–125). Prague, Czech Republic: SIPTA.
- Arló-Costa, H., & Helzner, J. (2009). Iterated random selection as intermediate between risk and uncertainty. In T. Augustin, F. P. A. Coolen, S. Moral, & M. C. M. Troas (Eds.), *Proceedings of the sixth international symposium on imprecise probabilities and their applications* (pp. 1–9). Durham, UK: SIPTA.
- Arló-Costa, H., Dutt, V., Gonzalez, C., & Helzner, J. (2011). The description/experience gap in the case of uncertainty. In F. Coolen, G. de Cooman, T. Fetz, & M. Oberguggenberger (Eds.), *Proceedings of the seventh international symposium on imprecise probability: Theories and applications* (pp. 31–39). Innsbruck, Austria: SIPTA.
- Camerer, C., & Weber, M. (1992). Recent developments in modeling preferences: Uncertainty and ambiguity. *Journal of Risk and Uncertainty*, *5*(4), 325–370. DOI: 10.1007/BF00122575.

- Chakravarty, S., & Roy, J. (2009). Recursive expected utility and the separation of attitudes towards risk and ambiguity: An experimental study. *Theory and Decision*, *66*(3), 199–228. DOI: 10.1007/s11238-008-9112-4
- Chow, C. & Sarin, R. (2002). Known, unknown and unknowable uncertainties. *Theory and Decision*, *52*(2), 127–138. DOI: 10.1023/A:1015544715608
- Cohen, M., Jaffray, J. Y., & Said, T. (1987). Experimental comparisons of individual behavior under risk and under uncertainty for gains and for losses. *Organizational Behavior and Human Decision Processes*, *39*(1), 1–22. DOI: 10.1016/0749-5978(87)90043-4.
- Curley, S. P., & Yates, J. F. (1989). An empirical evaluation of descriptive models of ambiguity reactions in choice situations. *Journal of Mathematical Psychology*, *33*(4), 397–427. DOI: 10.1016/0022-2496(89)90019-9.
- Davidovich, L. & Yassour, Y. (2009). Ambiguity preference. Emek Hefer, Israel: Ruppin Academic Center.
- Di Mauro, C., & Maffioletti, A. (1996). An experimental investigation of the impact of ambiguity on the valuation of self-insurance and self-protection. *Journal of Risk and Uncertainty*, *13*(1), 53–71. DOI: 10.1007/BF00055338.
- Dobbs, I. M. (1991). A Bayesian approach to decision-making under ambiguity. *Economica*, *58*(232), 417–440. DOI: 10.2307/2554690.
- Du, N., & Budescu, D. (2005). The effects of imprecise probabilities and outcomes in evaluating investment options. *Management Science*, *51*(12), 1791–1803.
- Dutt, V., & Gonzalez, C. (2012). Why do we want to delay actions on climate change? Effects of probability and timing of climate consequences. *Journal of Behavioral Decision Making*, *25*(2), 154–164. DOI: 10.1002/bdm.721.
- Einhorn, H. J., & Hogarth, R. M. (1986). Decision making under ambiguity. *Journal of Business*, *59*(4), S225–S250.
- Ellsberg, D. (1961). Risk, ambiguity, and the savage axioms. *Quarterly Journal of Economics*, *75*(4), 643–669. DOI: 10.2307/1884324.
- Fox, C. R., & Hadar, L. (2006). “Decisions from experience” = sampling error + prospect theory: Reconsidering Hertwig, Barron, Weber & Erev (2004). *Judgment and Decision Making*, *1*(2), 159–161.
- Gonzalez, C., & Dutt, V. (2011). Instance-based learning: Integrating sampling and repeated decisions from experience. *Psychological Review*, *118*(4), 523–551. DOI: 10.1037/a0024558.
- Gonzalez, C., Lerch, F. J., & Lebiere, C. (2003). Instance-based learning in real-time dynamic decision making. *Cognitive Science*, *27*(4), 591–635. DOI: 10.1016/S0364-0213(03)00031-4.
- Gonzalez, C., Vanyukov, P., & Martin, M. K. (2005). The use of microworlds to study dynamic decision making. *Computers in Human Behavior*, *21*(4), 273–286.
- Guney, S., & 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 meeting 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. *Econometrica*, *75*(2), 503–536. DOI: 10.1111/j.1468-0262.2006.00755.x.
- Hau, R., Pleskac, T. J., & Hertwig, R. (2010). Decisions from experience and statistical probabilities: Why they trigger different choices than a priori probabilities. *Journal of Behavioral Decision Making*, *23*(1), 48–68. DOI: 10.1002/bdm.665.
- Hau, R., Pleskac, T. J., Kiefer, J., & Hertwig, R. (2008). The description–experience gap in risky choice: The role of sample size and experienced probabilities. *Journal of Behavioral Decision Making*, *21*(5), 493–518. DOI: 10.1002/bdm.598.
- Hertwig, R. (in press). The psychology and rationality of decisions from experience. *Synthese*. DOI: 10.1007/s11229-011-0024-4.
- Hertwig, R., & Erev, I. (2009). The description–experience gap in risky choice. *Trends in Cognitive Sciences*, *13*(12), 517–523. DOI: 10.1016/j.tics.2009.09.004.
- 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. DOI: 10.1111/j.0956-7976.2004.00715.x.
- Ho, J. L. Y., Keller, L. R., & Keltyka, P. (2002). Effects of outcome and probabilistic ambiguity on managerial choices. *Journal of Risk and Uncertainty*, *24*(1), 47–74. DOI: 10.1023/A:1013277310399.
- Hogarth, R. M., & Kunreuther, H. (1989). Risk, ambiguity, and insurance. *Journal of Risk and Uncertainty*, *2*(1), 5–35. DOI: 10.1007/BF00055709.
- Keren, G. B., & Gerritsen, L. E. M. (1999). On the robustness and possible accounts of ambiguity aversion. *Acta Psychologica*, *103*(1–2), 149–172. DOI: 10.1016/S0001-6918(99)00034-7.
- Knight, F. H. (1921). *Risk, uncertainty and profit*. Boston: Houghton Mifflin.
- Luce, R. D., & Raiffa, H. (1957). *Games and decisions: Introduction and critical survey*. Dover, NY: Wiley.
- Mangelsdorff, L., & Weber, M. (1994). Testing choquet expected utility. *Journal of Economic Behavior and Organization*, *25*(3), 437–457. DOI: 10.1016/0167-2681(94)90109-0.
- Rakow, T., & 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. DOI: 10.1002/bdm.681.
- Rakow, T., Demes, K., & Newell, B. (2008). Biased samples not mode of presentation: Reexamining the apparent underweighting of rare events in experience-based choice. *Organizational Behavior and Human Decision Processes*, *106*(2), 168–179. DOI: 10.1016/j.obhdp.2008.02.001.
- Thaler, R. H. (1981). Some empirical evidence on dynamic inconsistency. *Economic Letters*, *8*(3), 201–207. DOI: 10.1016/0165-1765(81)90067-7.
- Tversky, A., & Fox, C. R. (1995). Weighing risk and uncertainty. *Psychological Review*, *102*(2), 269–283. DOI: 10.1037/0033-295X.102.2.269.
- Ungemach, C., Chater, N., & Stewart, N. (2009). Are probabilities overweighted or underweighted when rare outcomes are experienced (rarely)? *Psychological Science*, *20*(4), 473–479. DOI: 10.1111/j.1467-9280.2009.02319.x.
- Viscusi, W. K., & Chesson, H. (1999). Hopes and fears: The conflicting effects of risk ambiguity. *Theory and Decision*, *47*(2), 157–184. DOI: 10.1023/A:1005173013606.
- Wakker, P. P. (2010). *Prospect theory for risk and ambiguity*. Cambridge, UK: Cambridge University Press.
- Weber, E. U. (2006). Experience based and description based perceptions of long term risk: Why global-warming does not scare us (yet). *Climatic Change*, *77*(1–2), 103–120. DOI: 10.1007/s10584-006-9060-3.
- Weber, E. U., & Johnson, E. J. (2008). Decisions under uncertainty: Psychological, economic, and neuroeconomic explanations of risk preference. In P. Glimcher, C. Camerer, E. Fehr, & R. Poldrack (Eds.), *Neuroeconomics: Decision making and the brain* (pp. 127–144). New York: Elsevier.
- Weber, E. U., Shafir, S., & Blais, A.-R. (2004). Predicting risk sensitivity in humans and lower animals: Risk as variance or coefficient of variation. *Psychological Review*, *111*(2), 430–445. DOI: 10.1037/0033-295X.111.2.430.
- Yates, J. F., & Zukowski, L.G. (1976). Characterization of ambiguity in decision making. *Behavioral Science*, *21*(1), 19–25. DOI: 10.1002/bs.3830210104.



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