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VARUN DUTT[1,4*], HORACIO ARLÓ-COSTA[2], JEFFREY HELZNER[3] and CLEOTILDE GONZALEZ[4]
[1]

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 in 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 process proD('1(ow)trf.d5deD[nuu655t)2.5(-6-5.9(u).)lantygnora

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 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.[5]

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 fro339.3(69.4(.u(y)-77(sc)-f.97.a)"Tj-2842019an

wasc69ltes than

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, … , 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, … , 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."

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

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