People's perception of others' risk preferences

Shari Liu (shariliu01@g.harvard.edu) and **Tomer Ullman (tullman@fas.harvard.edu)**
Department of Psychology, Harvard University
Cambridge, MA 02143 USA

John McCoy (jpmccoy@wharton.upenn.edu)
The Wharton School, University of Pennsylvania
Philadelphia, PA 19104 USA

Abstract

Our everyday decisions are driven by costs, risk, and reward. How do people take these factors into account when they predict and explain the decisions of others? In a two-part experiment, we assessed people's perceptions of other people's risk preferences, relative to their own. In Part 1, participants reported their relative preference between a guaranteed payout and lotteries with various probabilities and payouts, and made predictions about other people's preferences. In Part 2, participants estimated the lottery payout that generated a given relative preference between a guaranteed payout and a lottery, both for themselves and others. We found considerable individual variability in how people perceive the risk preferences of others relative to their own, and consistency in people's perceptions across our two measures. Future directions include formal computational models and developmental studies of how we think about our own and each other's decision-making.

Keywords: intuitive psychology; decision making; risk

Introduction

Humans are social beings, who spend much of their time attempting to predict what decisions others will make, and explain why others chose as they did. Adults, and even infants, make predictions about what another person will do based on their beliefs about the person's mental state, and also make inferences about someone's mental state after observing their behavior (Epley, 2015; Kushnir, Xu, & Wellman, 2010; Repacholi & Gopnik, 1997).

Recent computational accounts of such abilities see people as performing Bayesian inference using a model of others as rational planners or intuitive utility maximizers who take actions to maximize their expected reward relative to their incurred cost (Baker, Saxe, & Tenenbaum, 2009; Lucas et al., 2014; Jara-Ettinger, Gweon, Schulz, & Tenenbaum, 2016; Baker, Jara-Ettinger, Saxe, & Tenenbaum, 2017). Previous work has shown that such rewards and costs are early-emerging, separate targets of inference (Jara-Ettinger, Gweon, Tenenbaum, & Schulz, 2015; Liu, Ullman, Tenenbaum, & Spelke, 2017). Here, we study a related variable at the heart of other people's expected utility: the probability of the outcome. Specifically, we study how people perceive and reason about other people's risk preferences, especially compared to their own.

The central role of risk in decision making has been long appreciated (Bernoulli, 1738). For example, many people prefer a 50/50 chance of losing \$200 to losing \$100 for sure, and prefer gaining \$100 for sure over a 50/50 chance of gaining \$200, even though the expected value of the options are equal in each case. Under expected utility theory, decision makers weight probabilities linearly, and risk aversion is measured and explained by the curvature of the utility function (Pratt, 1964; Arrow, 1965). Rabin's Calibration Theorem illustrates the difficulties with this approach (Rabin, 2000). A large body of work by psychologists and behavioral economists has shown that decision making under risk involves non-linear weighting of probabilities (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992; Wakker, 2010; Dhami, 2016).

Research has also examined how people perceive the risk sensitivity of others. Some previous work finds that people perceive others as more risk-seeking than themselves (Hsee & Weber, 1997), while a different set of studies finds that, on average, people assume others are more risk-averse (Eckel & Grossman, 2008), although the focus of this study and others (Siegrist, Cvetkovich, & Gutscher, 2002) was the role of gender stereotypes in risk perception. Differences in cross-national risk perceptions have also been explored (Hsee & Weber, 1999). This paper differs from previous work in a number of ways. First, the previous literature used group-based analyses that collapsed across people and a small number of gambles, and so could not determine whether the average results reflected homogeneous perceptions across individuals, whereas we additionally consider individual level perceptions. Second, participants in past studies made predictions about binary choices between lotteries, whereas in our study participants give more fine-grained predictions about their degree of relative preferences for a lottery over a sure thing. Third, participants previously only made predictions about the decisions of others, whereas we additionally have participants estimate the monetary value of gambles that would cause a particular preference in other people.

We use a two-part experiment to study how people perceive the risk preferences of others. In Part 1, we present participants with choices between \$100 for sure and a lottery, with eight levels of payout and five levels of probability. For each choice, participants reported their own preferences and predicted the preferences of others, using a five point Likert scale. In Part 2, we ask the same participants to estimate the (unseen) payout that led others to report a specific preference, and that would lead themselves to report the same preference. We then relate the judgments of participants across the two parts of the experiment.

We had two main research questions. First, we were interested in the distribution of people's perception of their own risk preferences relative to others. Second, we investigated the consistency of people's perceptions about their own and others' risk preferences across two tasks, one that asked people to make predictions about preferences, and the other that asked people to make inferences about lottery payouts given preferences.

Experiment

Participants

We recruited 205 participants on Amazon Mechanical Turk, restricted to the United States. Of these, we excluded 33 participants for (1) failing to pass an attention check, or (2) providing the same answer for all questions in Parts 1 or 2, or (3) taking less than 5 minutes to complete the experiment, or (4) giving payout judgments larger than $2000 in Part 2. These criteria were specified ahead of data analysis but not ahead of data collection. After exclusion our sample consisted of 172 participants (median age=34 years, median annual income=$47,000, 75 female, 96 male, 1 other). All participants gave informed consent prior to participating. All recruitment and study procedures were approved by the MIT Committee on the Use of Humans as Experimental Subjects.

Methods

Participants were presented with a series of hypothetical choices between lotteries and $100 for sure. Each lottery consisted of a random draw from a box of 10 balls. If a player were to enter the lottery, a ball would be drawn at random from the box, and the player would win the amount of money on the ball. For example, a lottery where a player has a 50-50 chance to win $500 would contain 5 balls worth $0 each, and 5 balls worth $500 each.

In Part 1, participants saw 40 trials, each involving a choice between $100 for sure, or a [.1, .3, .5, .7, or .9] chance of winning [$100, $150, $200, $300, $400, $600, $800, or $1000]. For each decision, participants gave their own preference, and predicted the preference of an average other player, on a 5-point Likert scale (1=$100 is a lot better, 2=$100 is somewhat better, 3=$100 and lottery are equally good, 4=lottery is somewhat better, and 5=lottery is a lot better). We note that these Likert ratings do not express participants' valuation of the lottery itself, but rather differences between the utility of the lottery and the utility of the sure reward. See Figure 1.

In Part 2, participants saw 5 trials, each involving a choice between $100 for sure, or a 50-50 lottery to win some other amount of money, this time unknown to the participant (Figure 1, bottom). On each trial, participants were informed that, on average, other players rated the lottery one of the five possible levels of the Likert scale (i.e., on the first trial participants were told that other players on average strongly preferred the $100, on the second trial that other players slightly preferred the $100, etc.). Participants were asked to estimate

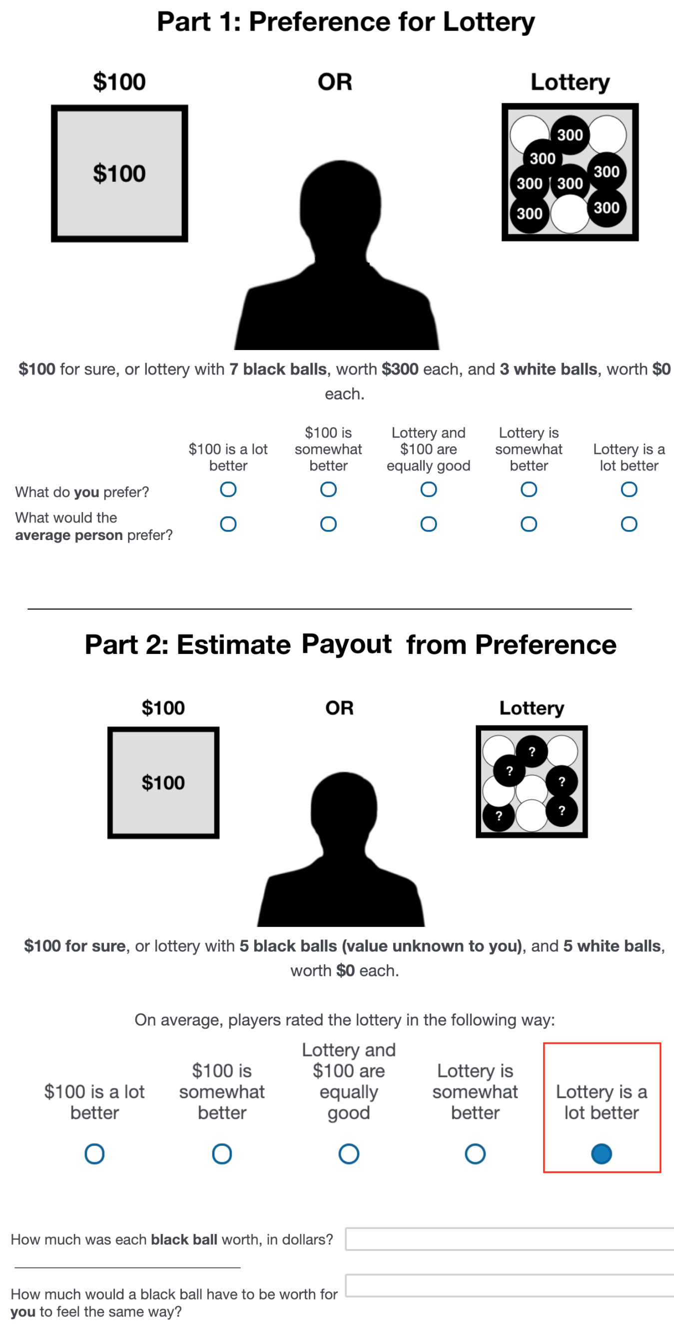

Figure 1: Example trials from the experiment. In Part 1, participants rated their own preferences between $100 for sure and a lottery, and predicted the preference of others. In Part 2, participants were told the preference of another person and both estimated the payout of the lottery, and judged how much money would have to be at stake for them to feel the same way.

how much money was at stake in the lottery given this preference, and gave their response using a freeform text field.

Figure 2: Participant Likert ratings indicating preference for lottery or guaranteed $100, and their predictions for the average other player, across all probabilities and payouts. Opaque points indicate mean Likert ratings with bootstrapped 95% confidence intervals. Translucent points indicate raw data plotted with vertical jitter.

Participants then estimated how much money would have to be at stake in the lottery for they themselves to give the same rating. See Figure 1.

In Parts 1 and 2, trials were presented in a random order, and the left-right orientation of the lottery vs $100 and the anchors for the Likert scale were consistent within participants, but randomized across participants.

Results

The data were analyzed using mixed effects linear models (Bates, Mächler, Bolker, & Walker, 2015; Team, 2015), unless noted otherwise. All models included random intercepts for participant identity (i.e. responses are nested within participants), and for trial number (i.e. responses are nested within linear trial order). We report coefficients from modeling the Likert rating as continuous for ease of interpretation, but fitting a Cumulative Link Model yields similar results. Bracketed values indicate 95% confidence intervals of unstandardized coefficients (e.g. the effect of increasing the stake of the lottery by $1 on preferences for the lottery in Likert ratings), and p-values are all two-tailed. Participant gender and annual household income are included as regressors.

Part 1: Preferences between a lottery and sure thing

People's own risk preferences. Before turning to our first question concerning how people perceive the risk sensitivity of others compared to their own risk sensitivity, we conducted a basic analysis of the data to confirm that 1) people more strongly preferred the lottery as its probability and payout increased, and 2) whether people, on average, were risk averse. As expected, across all 40 trials, participants' preference for the lottery increased as the payout increased ([1.2e-3,1.4e-3], $p<.001$), and as the probability of winning increased ([3.456,3.637], $p<.001$), see Figure 2.[1]. To measure participants' level of risk aversion, we examined the two trials that included lotteries equal in expected value to receiving a guaranteed $100 (i.e. the 50-50 lottery with $200 payout, and the 10-90 lottery with $1000 payout). In both of these trials, people preferred the guaranteed $100 over the lottery (Likert mean=2.56, median=2 for 50-50 lottery, $p<.001$; mean rating=1.67, median=1 for 10-90 lottery, $p<.001$, one-sample t-test against $\mu=3$).

Perceptions of risk preferences of others. We repeated the same basic analyses as reported above, this time on people's judgments of others. Across all 40 trials, participants' estimates of others' Likert ratings increased as the payout increased ([1.3e-3,1.5e-3], $p<.001$), and as the probability of winning increased ([3.171, 3.353], $p<.001$). We again analyzed the two trials that included lotteries with an expected value of $100. In the trial with the 50-50 lottery, participants predicted that others would be indifferent between the

[1]Model formula: `response ~ payout + probability + gender + log(income) + (1|participant) + (1|trial)`

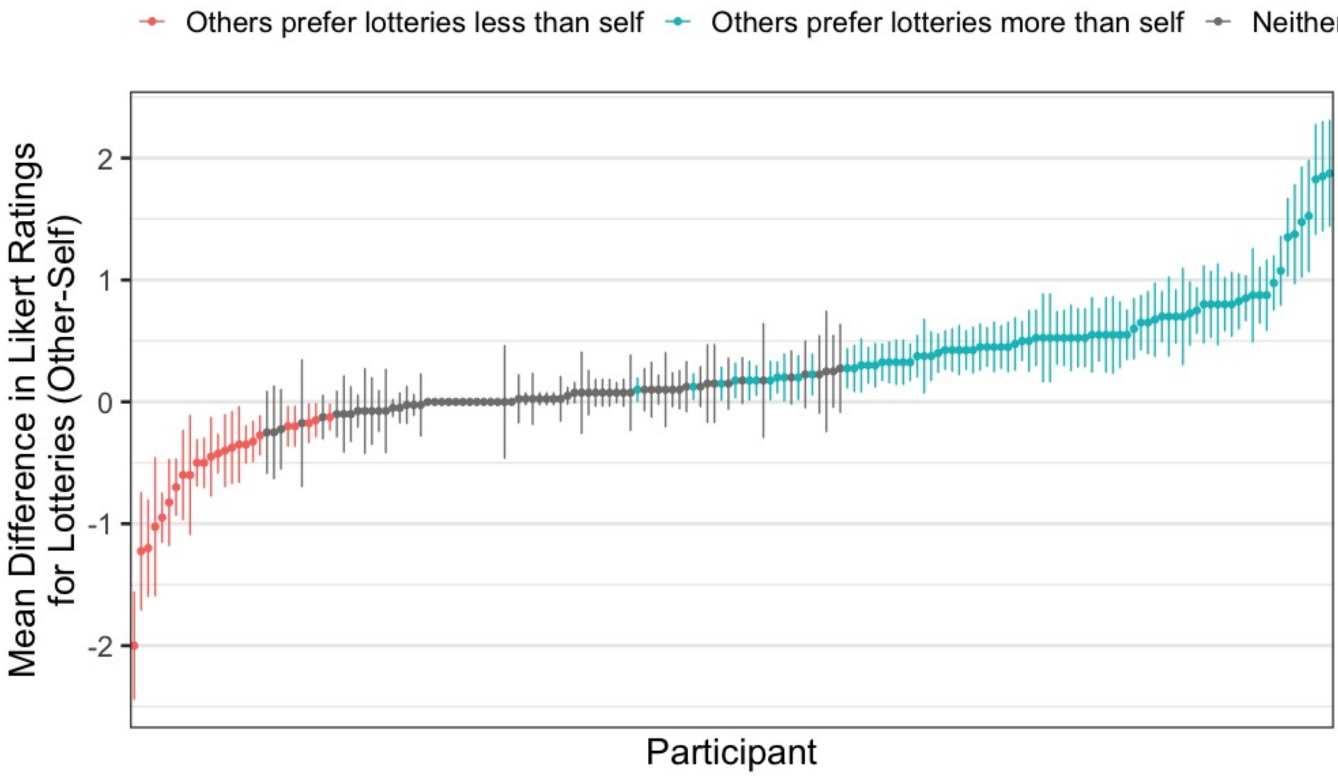

Figure 3: Differences in people's own preference for the lottery and their prediction of the preference of others, shown for each participant and averaged across trials. Each point indicates the mean difference between a single participant's Likert ratings for themselves and predicted ratings for others (40 pairs per participant), estimated by a paired-samples t test. Error bars indicate 95% confidence intervals around the mean. Participants without confidence intervals gave the same rating for themselves and others on every trial (but different ratings across trials). Of 172 participants, 81 (47%, blue) judged that others were significantly more risk-seeking than themselves, 24 (14%, red) judged that others were significantly more risk-averse than themselves, and 67 (39%, gray) gave similar ratings for themselves and others as discussed in the text.

50-50 lottery and the guaranteed \$100 (mean rating=2.96, median=3, p=.602, one-sample t-test against μ=3). In the trial with the 10-90 lottery, participants predicted that others would slightly prefer the \$100 (mean rating=2.05, median=2, $p<0.001$, one-sample t-test against μ=3).

Comparing risk preferences for self and other. Our first main question is how people perceive the risk preferences of other people, relative to their own. A group level analysis indicated that participants predicted other people to be more risk-seeking than themselves. That is, they expected others to prefer the lottery (rather than the guaranteed \$100) more than themselves, across payout amounts and lottery probabilities ([0.086,0.123], $p<.001$)[2]. See Figure 2.

A group level analysis, however, can obscure important individual heterogeneity. Figure 3 shows, for each participant, the average difference between the participant's prediction of how much other people prefer the lottery and how much they themselves prefer the lottery. While these differences clearly fall on a continuum, we were interested in what proportion of participants judged that others were more risk averse or risk seeking, relative to themselves. By this measure, 47% of participants believed that others were more risk-seeking than themselves (by a paired sample t-test on each participant, the estimated average difference for these participants had confidence intervals strictly above 0), 14% believed others were less risk-seeking (confidence intervals strictly below 0), and 39% did not show a significant difference between their preferences and those they predicted for others (confidence intervals crossed 0). These results are consistent with a paired sample sign test on each participant, which identifies 43% of participants who believe that others are more risk-seeking, 9% who believe that others are more risk-averse, and 48% who do not show a significant difference between the ratings of themselves and others (all at the $p<.001$ level).

Part 2: Estimating the payout of lotteries given a preference

[2] Model formula: `response ~ probability + payout + agent + gender + log(income) + (1|participant) + (1|trial)`

As a reminder, in Part 2 we asked participants what payout of a 50-50 lottery would cause themselves and others to have a given preference for the lottery (from much preferring the guaranteed \$100, to much preferring the lottery).

Estimates of lottery payouts for self. As in our analysis of the data from Part 1, we first conducted a basic analysis to examine people's inferences about the lottery conditional on choices for themselves. Across all trials, participants reasonably believed that a greater preference for the lottery meant that the payout of the lottery was higher ([112.65,131.60], $p<.001$)[3]. When the Likert rating was 3 (indifferent between the lottery and guaranteed \$100), participants judged that the 50-50 lottery payout must exceed \$200 for them to have given this rating (mean=\$267, median=\$200, $p<.001$, one-sample t-test against μ=\$200), indicating risk aversion.

Estimates of lottery payouts for others. We repeated the same analyses as reported above, this time on people's judgments of others. Across all five trials, participants judged that other people having a greater preference for the lottery was caused by a higher lottery payout ([110.15,127.90], $p<.001$). When the average Likert rating reported by others was 3 (indifferent between the lottery and guaranteed \$100), participants estimated that the 50-50 lottery payout for other people was no different than the risk-neutral value of \$200 (mean=\$210, median=\$200, p=.384, one-sample t-test against μ=\$200).

Comparing payout estimates for self and other. Our first main research question concerns differences in participant's estimates for the lottery payment for themselves and others. Across all participants and trials, for a given Likert rating participants judged that the estimated lottery payout was lower for other people than for themselves (agent coefficient was significantly negative, [-24.983,-6.939], p=0.001)[4].

Since there are only five trials per participant in Part 2 (5 paired estimates for self and other), to assess individual level differences, we computed for each participant the mean difference between the payout that they believed would be required to make the lottery equally attractive to themselves and other people: 51% of participants gave higher estimates, on average, for themselves than others (i.e. believed that others were more risk-seeking), 29% gave lower estimates, on average, for themselves compared to others (i.e. believed that others were more risk-averse), and 20% gave, on average, equal estimates for themselves and others (i.e. believed that they and others had the same risk preference).

Predictions of preferences and estimates of lottery payouts given a preference Our second main research question was whether people's judgments were consistent across our two tasks. We found that participants' average difference in Part 1 between their own preferences and their ratings of the preferences of others corresponded to the average difference between their payout estimates for themselves and others in Part 2 ([46.2, 102.1], $p<.001$).[5]. That is, the more a participant judged that others would prefer the lottery more than themselves in Part 1, the more lottery payout that participant needed to give the same rating as others in Part 2.[6]. See Figure 4.

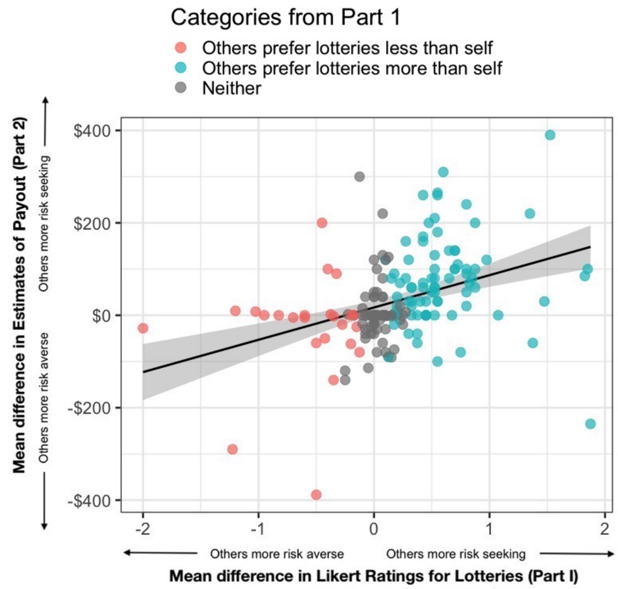

Figure 4: Relating individual differences in relative risk preference as measured in Part 1 and Part 2 of the experiment. Each point indicates one person's mean difference in preferences for 40 lotteries for themselves vs others (x-axis), and the mean difference in their estimated payout for themselves vs. others over 5 preferences for a 50-50 lottery vs a guaranteed \$100 (y-axis). Solid line indicates regression between these values with 95% confidence interval. Colors of points indicate classification of participants based on Part 1, as in Figure 3 and the main text.

Discussion

Risk matters, both for our own decisions, and in our reasoning about the decisions of others. We presented participants with choices between lotteries and guaranteed payouts, and used prediction and estimation measures to explore individual variability in people's beliefs about the risk preferences of others. Across both measures, we found two large subsets of participants: participants who believed that others were more risk seeking than themselves, and participants who believed that other people exhibited roughly the same degree of risk sensitivity as themselves. People's beliefs about how their

[3]Model formula: `response ~ likert + gender + log(income) + (1|participant) + (1|trial)`

[4]Model formula: `response ~ probability + payout + agent + gender + log(income) + (1|participant) + (1|trial)`

[5]Model formula: `diffpart2 ~ diffpart1 + gender + log(income)`

[6]Performing the same comparison using Spearman's rank correlation yielded similar results, ρ=0.472, $p<.001$

own risk sensitivity compared to other people were fairly stable across the two parts of the experiment.

Our findings are consistent with, but also complicate, the framework of Bayesian Theory of Mind. This framework models people's reasoning about others by assuming that others are carrying out a rational planning procedure to achieve goals given constraints (Baker et al., 2009, 2017; Jara-Ettinger et al., 2016). While most previous work in this literature assumed, for simplicity, that people reason about others as maximizing expected value, behavioral economics has long highlighted how people deviate from simple expected value (for example, by being risk-averse) (Dhami, 2016). Recent work has investigated deviations from optimal rational planning and the use of bounded agents in Bayesian Theory of Mind and Inverse Reinforcement Learning, for example by replacing the ideal rational planner with an agent that has false beliefs and exhibited temporal inconsistency (Evans, Stuhlmüller, & Goodman, 2016). Along the same lines, one could replace the rational planner with an agent that displayed either risk-seeking or risk-averse behavior, for example either by manipulating the agent's utility function or its probability weighting function. We are currently pursuing this direction so as to explore the cognitive processes underlying the results presented in this paper.

Another future direction suggested by the results in this paper are the downstream consequences of differences in people's own risk sensitivity and their perception of the risk sensitivity of others. For example, do people use their own or their perception of others' risk preference when making decisions on behalf of others? What do people expect others to do, when others are assigned to make decisions on their behalf?

Our experiment focused on risk of a specific kind, but risk may not be a unified concept (Loewenstein, Weber, Hsee, & Welch, 2001; Wallach & Wing, 1968). Moreover, most situations are ambiguous rather than simply risky - people are not confronted with explicit, known probabilities, but must instead act in the face of uncertainty given their beliefs. Similar experiments could examine how people perceive the degree to which other people exhibit ambiguity aversion, relative to their own ambiguity preferences.

While all our participants were adults, it is interesting to consider perceptions of other's risk sensitivity through the lens of development. Infants and children are sensitive to other people's preferences (Woodward, 1998; Jara-Ettinger et al., 2015), and the probabilities of events (Téglás et al., 2011; Xu & Garcia, 2008, 2008). Recent studies suggest that children use probability (Denison & Xu, 2010, 2014) and reward (Feigenson, Carey, & Hauser, 2002) to make decisions and analyze the decisions of others (Wellman, Kushnir, Xu, & Brink, 2016; Lucas et al., 2014). But these experiments leave open when children become sensitive to risk in their own decisions, and when they understand others as risk-sensitive.

In this paper, we examined risk in the context of a series of simple lotteries. This is a common laboratory paradigm, but is less common in real life. Outside the lab, risk is a major force in consequential decisions, from starting wars, to developing new technologies, to making medical decisions for ourselves and our loved ones. Such decisions are not made in isolation, but in consultation, collaboration, and competition with other people. Thus, studies of risk—a fundamental component of our decisions and social lives—bear on all of these situations, by revealing the nature of how we represent other people's decisions, and our own.

Acknowledgments

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