

Electronic Companion

Regression results

Experiment 1. We used logistic regression models to estimate, first, the effect of participants' choices in the individual stage on dyadic choices and, second, whether the effect of the participant who had learned from experience depended on how large a sample he or she had drawn in the individual stage. Tables A.1A and A.1B include both the mixed-effect models described in the text and basic logistic regression models without random effects (that yield virtually identical results). The mixed-effect models were estimated using the `glmer` function in the `lme4` package in R (Bates, Maechler, Bolker, & Walker, 2014).

As detailed in the main text, the dependent variable in all regression models for Experiment 1 was whether a dyad chose the risky option or not (1 = risky, 0 = safe). Models 1 and 2 included two independent variables that captured whether each individual in the dyad (description vs. experience) chose the risky option or not (1 = risky, 0 = safe). Models 3 and 4 examined the effect of sampling, and further included a continuous variable "sample size," and an interaction term between this variable and the variable that captured whether the individual who had learned from experience chose the risky option or not.

As further detailed in the text, the hypothesis that dyads rely on both sources of information predicts positive coefficients for the two independent variables capturing individual choices. The hypothesis that sample size affects the influence of the individual who learned from experience on the dyadic decision further predicts a negative coefficient on sample size, and a positive coefficient (at least as large, in absolute value) on the interaction term.

The rationale behind the latter prediction is that if the experiential learner chooses the safe option, the interaction term is zero, and only the coefficient on "sample size" affects the regression model. In this case, larger samples should reduce the probability that a dyad chooses "risky," which leads to the prediction that the coefficient on "sample size" should be negative. If, on the other hand, the experiential learner chooses the risky option, the interaction term is equal to the sample size, and the sum of the

coefficient on sample size and the interaction term affects the regression model. Larger samples should then increase the probability that a dyad chooses “risky,” which leads to the prediction that the coefficient on the interaction term should be positive, and at least as large (in absolute value) as the coefficient on “sample size.”

Experiment 2. We used regression analysis to examine the effect of the sample size on the influence of the experiential learner in the dyadic decision. We adopted a slightly different modeling strategy that takes advantage of the continuous response measure in this study (although we also analyzed models analogous to those for Experiment 1; these yielded the same pattern of results).

The (continuous) dependent variable in the regression models in Table A.2 was the implied weight on experience $1-w_d$ (see Equation 1), and the independent variable was the continuous variable “sample size.” The table includes the mixed-effect model described in the text (Model 2), a basic linear regression model without random effects that yields similar results (Model 1), and the regression models that separately analyze dyads that adopted the view of one of their members, (Model 2.a), compromised (Model 2.c), or polarized (Model 1.p), as described in Footnote 11. Note that the regression model for polarizing dyads did not include mixed effects—there were so few cases of polarization that the simpler modeling approach seemed more adequate. As detailed in the text, the hypothesis that sample size affects the influence of the individual who learned from experience on the dyadic decision predicts a positive coefficient on “sample size” in these models. (The mixed-effect models were estimated using the `lmer` function in the `lme4` package in R; Bates et al., 2014.)

Cumulative prospect theory

According to cumulative prospect theory (CPT, Tversky & Kahneman, 1992), the value v of an outcome x is

$$v(x) = \begin{cases} x_i^\alpha, & \text{if } x \geq 0 \\ -\lambda(-x_i)^\beta, & \text{if } x < 0 \end{cases} \quad \text{Eq. A1.}$$

Parameters $\alpha \in [0,1]$ and $\beta \in [0,1]$ reflect the sensitivity to differences in gain and loss outcomes, respectively; and λ reflects the relative weight of gains and losses, with $\lambda > 1$ indicating loss aversion. For small amounts such as those studied here, the value function has been found to be relatively linear (see Diecidue & Wakker, 2002; Luce, 2000), so we assume $\alpha = \beta = \lambda = 1$. In so doing, we interpret the resulting probability-weighting functions as indicating whether the choices are in the direction of over- or underweighting of rare events.

The probabilities associated with each outcome are transformed into decision weights π . For two-outcome gambles, as we used here, π is calculated as follows. With outcomes X and x occurring with probabilities p and $1 - p$, respectively, the decision weights are:

$$\pi_X = w(p) \text{ and } \pi_x = 1 - w(p) \quad \text{for } X > x \geq 0, \quad \text{Eqs. A2}$$

$$\pi_X = w(p) \text{ and } \pi_x = w(1 - p) \quad \text{for } X > 0 > x,$$

$$\pi_X = w(p) \text{ and } \pi_x = 1 - w(p) \quad \text{for } 0 \geq x > X,$$

where w is a probability-weighting function. We use a functional form with two parameters proposed by Prelec (1998) that can accommodate both over- and underweighting of small probabilities (see below):

$$w(p) = e^{-s(-\ln p)^r} \quad \text{Eq. A3}$$

where r indicates the curvature of the weighting function (i.e., how curvilinear it is) and s indicates the elevation of that curvature.

The value V of an option A is given by weight-adding outcomes j and their associated decision weight:

$$V(A) = \sum_{j=1}^k v(x_j) \pi_j(p) \quad \text{Eq. A4}$$

Cumulative prospect theory predicts that the option with the higher V is chosen. To capture variability in choice behavior, it is usually implemented in combination with a probabilistic choice rule. We employed the logit choice rule advocated by Stott (2006). The probability of choosing option A over B $p(A, B)$ is

$$p(A, B) = \frac{1}{1 + e^{-(V(A) - V(B))}} \quad \text{Eq. A5}$$

Fitting procedure for Experiment 1. We fitted the model to decisions from description, decisions from experience, and decisions by dyads, separately. For each condition, we derived predictions from different values of r and s , and then evaluated each prediction against the observed choices. The best-fitting parameters were those that minimized the discrepancy measure G^2 ,

$$G^2 = -2 \sum_{i=1}^N \ln[f_i(y|\theta)] \quad \text{Eq. A6}$$

where N refers to the total number of choices, and $f_i(y|\theta)$ refers to the probability that a particular set of parameters θ predicts an observed choice y correctly.

Because we assumed a linear value function with no loss aversion, there were only two free parameters to estimate: the curvature r and elevation s of the probability-weighting function. We let r and s vary between 0 and 2 to allow for both over- and underweighting of rare events. To fit r and s , we performed a grid search that varied each parameter from 0 to 2 in .01 increments, attempting to minimize G^2 .

Fitting procedure for Experiment 2. To estimate the probability-weighting functions in Experiment 2, we first calculated the probability that a participant would choose option A as the proportion of A-cards in their selected deck. In this manner, we obtained an “observed” probabilistic choice that we compared with the “predicted” probabilistic choice derived from the model’s choice rule. Instead of using G^2 , we used the mean squared deviation (MSD) between observed and predicted choices for each individual and problem as a measure of discrepancy. We then varied r and s , attempting to minimize the MSD. Other than that, the procedure was the same as in Experiment 1.

Table A.1a

Experiment 1a: Coefficient estimates and their standard errors in several regression models

Independent variable	Model							
	1		2		3		4	
Des. chose risky option	4.5	(1.0)	4.7	(1.0)	4.3	(1.0)	4.5	(1.1)
Exp. chose risky option	4.0	(1.0)	3.1	(1.2)	4.3	(1.1)	3.4	(1.2)
Sample size			-.04	(.02)			-.04	(.02)
Sample size * Exp. chose risky			.05	(.03)			.04	(.03)
Intercept	-4.2	(1.0)	-3.3	(1.0)	-4.2	(1.0)	-3.3	(1.0)
Random effects	No		No		Yes		Yes	

Note. $N = 144$. The dependent variable in all models is whether a dyad chose the risky option. Models 1 and 2 are basic logistic regression models; Models 3 and 4 are mixed-effects models with participant- and problem-level random intercepts. Standard errors (*SEs*) are in parentheses. Coefficients in bold are significant at $p < .05$.

Table A.1b

Experiment 1b: Coefficient estimates and their standard errors in several regression models

Independent variable	Model			
	1	2	3	4
Des. chose risky option	3.1 (.23)	3.1 (.24)	2.9 (.24)	3.0 (.25)
Exp. chose risky option	1.9 (.23)	1.2 (.34)	1.8 (.24)	1.3 (.35)
Sample size (Exp.)		-.02 (.01)		-.02 (.01)
Sample size * Exp. chose risky		.02 (.01)		.02 (.01)
Intercept	-2.4 (.22)	-1.9 (.29)	-2.3 (.27)	-1.8 (.33)
Random effects	No	No	Yes	Yes

Note. $N = 648$. The dependent variable in all models is whether a dyad chose the risky option. Models 1 and 2 are basic logistic regression models; Models 3 and 4 are mixed-effects models with participant- and problem-level random intercepts. Standard errors (*SEs*) are in parentheses. Coefficients in bold are significant at $p < .05$.

Table A.2

Experiment 2: Coefficient estimates and their standard errors in several regression models

Independent variable	Model									
	1		1.p		2		2.c		2.a	
Sample size	.002	(.002)	.02	(.01)	.002	(.002)	.004	(.001)	.003	(.003)
Intercept	.35	(.06)	-.26	(.36)	.35	(.06)	.41	(.05)	.29	(.11)
Random effects	No		No		Yes		Yes		Yes	

Note. $N_1 = N_2 = 274$; $N_{1,p} = 21$; $N_{2,c} = 104$; $N_{2,t} = 149$. The dependent variable in all models is the implied weight on experience, $1-w_d$. Models 1 and 1.p are basic linear regression models; Models 2, 2.c, and 2.a are mixed-effects models with participant- and problem-level random intercepts and participant-level random slopes. Standard errors (*SEs*) are in parentheses. Coefficients in bold are significant at $p < .05$.