Online Appendices to: Belief Elicitation and Behavioral Incentive Compatibility

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ONLINE APPENDIX A—ADDITIONAL TABLES AND FIGURES

Table A.1. ϵ-False Reports by Treatment

Treatment	False Reports		
	All Priors	By Prior	
		$\pi_0 = 0.5$	$\pi_0 \neq 0.5$
Information	0.312 (0.036)	0.171 (0.035)	0.406 (0.046)
RCL	**0.227** (0.034)	0.127 (0.034)	**0.294** (0.041)
No Information	**0.162** (0.034)	0.183 (0.040)	**0.147** (0.036)
Feedback $_{(t=1,2)}$	**0.133** (0.032)	0.182 (0.056)	**0.092** (0.046)
Feedback $_{(t=9,10)}$	**0.2** (0.046)	0.117 (0.052)	**0.260** (0.061)
Description	**0.182** (0.034)	0.138 (0.036)	**0.211** (0.039)
N	2,630	2,630	

Note: Standard errors in parentheses clustered by participant (299 clusters) recovered from three separate joint estimates on the false report proportion in the prior elicitations: (i) All priors, dependent variable an indicator for $|q - \pi_0| > 0.05$ with treatment level estimation; and (ii) By Prior column pair, same dependent variable as All priors, but with separate treatment estimates for centered/non-centered prior location.

Table A.2. Posterior Inference (Guesses 2+3): False Reports and Type by Treatment

Treatment	Distant Reports				Distant Report Movement $\pi \in [0.15,0.35] \cup [0.65,0.85]$		
	All	By Posterior Location					
		Center	Non-Centered	Interm.	Center	Near Extreme	Distant Extreme
Information	0.332	0.267	0.348	0.407	0.116	0.025	0.141
	(0.026)	(0.038)	(0.031)	(0.033)	(0.021)	(0.008)	(0.022)
RCL	**0.265**	0.195	0.283	**0.308**	**0.054**	0.043	0.098
	(0.023)	(0.032)	(0.027)	(0.029)	(0.013)	(0.016)	(0.016)
No Information	0.276	0.304	**0.269**	**0.318**	**0.286**	0.068	0.134
	(0.023)	(0.034)	(0.025)	(0.028)	(0.011)	(0.028)	(0.021)
Feedback $_{(t=1,2)}$	**0.246**	0.300	**0.232**	**0.296**	0.065	0.009	**0.056**
	(0.037)	(0.076)	(0.038)	(0.045)	(0.026)	(0.009)	(0.024)
Feedback $_{(t=9,10)}$	0.296	**0.396**	0.271	**0.305**	**0.017**	0.034	0.102
	(0.038)	(0.066)	(0.040)	(0.045)	(0.012)	(0.020)	(0.033)
Description	**0.244**	0.225	**0.249**	**0.267**	**0.039**	0.020	0.118
	(0.024)	(0.032)	(0.032)	(0.030)	(0.011)	(0.013)	(0.019)
N	5,260		5,260			2,458	

Note: Standard errors in parentheses clustered by participant (299 clusters) recovered from three separate joint estimates on the distant-report rate:

(i) Distant Reports, All, proportion of distant reports ($|q - \pi| > 0.15$) over treatment;

(ii) Distant Reports, By Posterior Location, proportion of distant reports over treatment and posterior location (*centered*, $\pi \in (0.35,0.65)$; *non-centered* $\pi \notin (0.35,0.65)$, and intermediate, a subset of non-centered where we additionally exclude posteriors in $\pi \in [0, 0.15) \cup (0.85, 1]$ so distant reports can move in both directions.

(iii) Distant Report Movement proportion of distant reports by location of the movement, conditioning on the intermediate posterior classification. Types in (iii) for $\pi < 0.5$ (with symmetric definition for $\pi > 0.5$) defined as: movements to the exact center ($q = 0.5$); movements to the near extreme ($q = 0$); and to the distant extreme ($q \in (0.5, 1]$).

Bold face coefficients are different from the relevant Information coefficient with $p < 0.1$ (two-sided test).

Figure A.1 Responses to post-experimental questionnaire

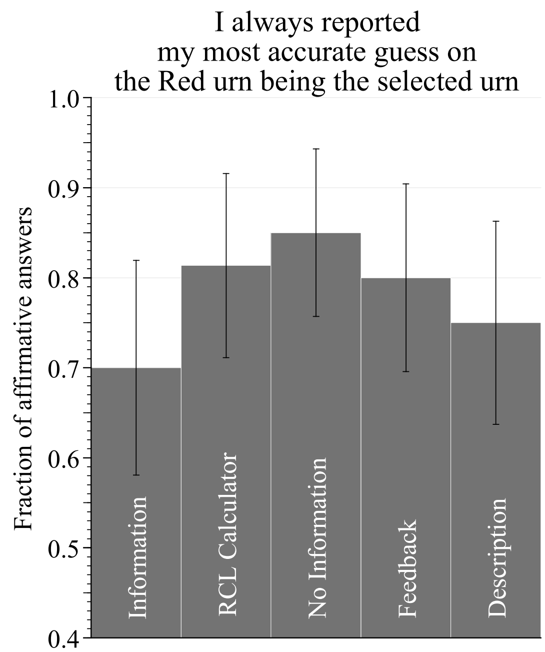


Figure A.2 Proportion of posterior reports by distance from Bayesian posterior

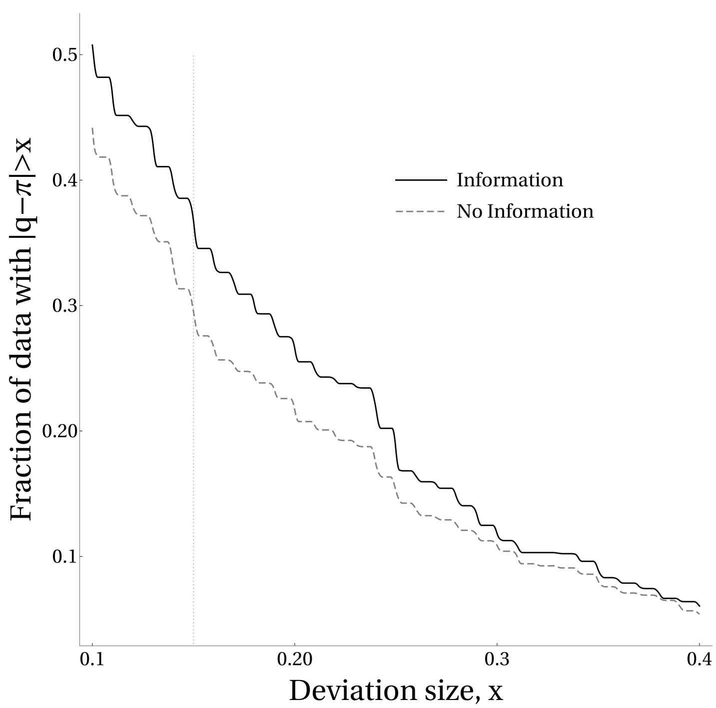


Figure A.3 Interquartile range in reports by elicitation

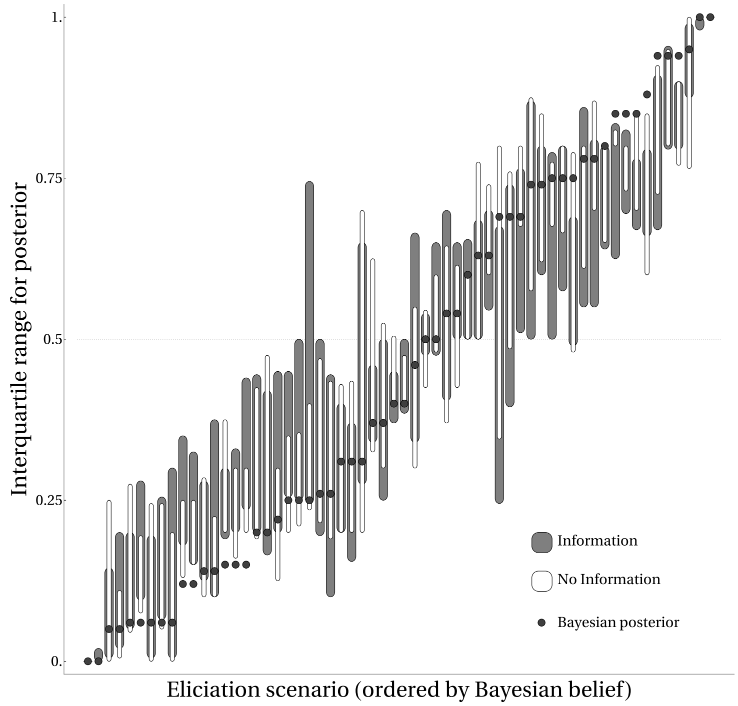


Figure A.4 Share of participants who consistently report the prior

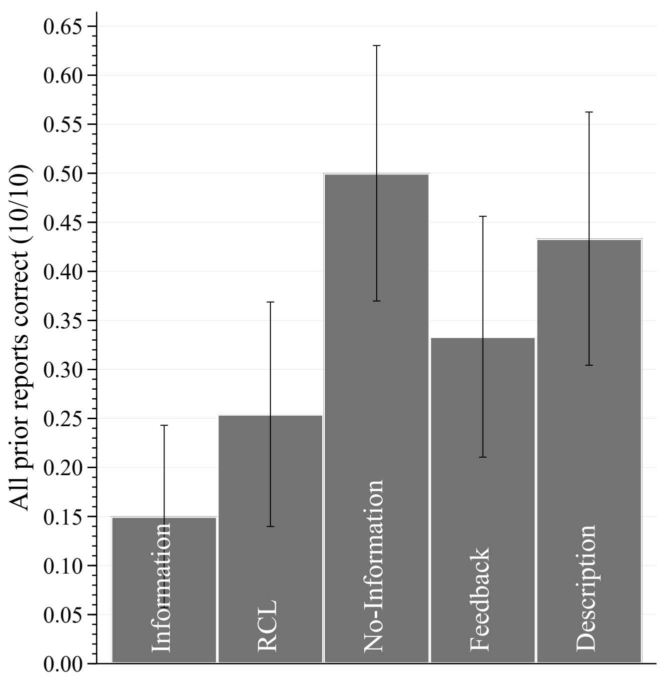


Figure A.5 False reports under QSR with and without information

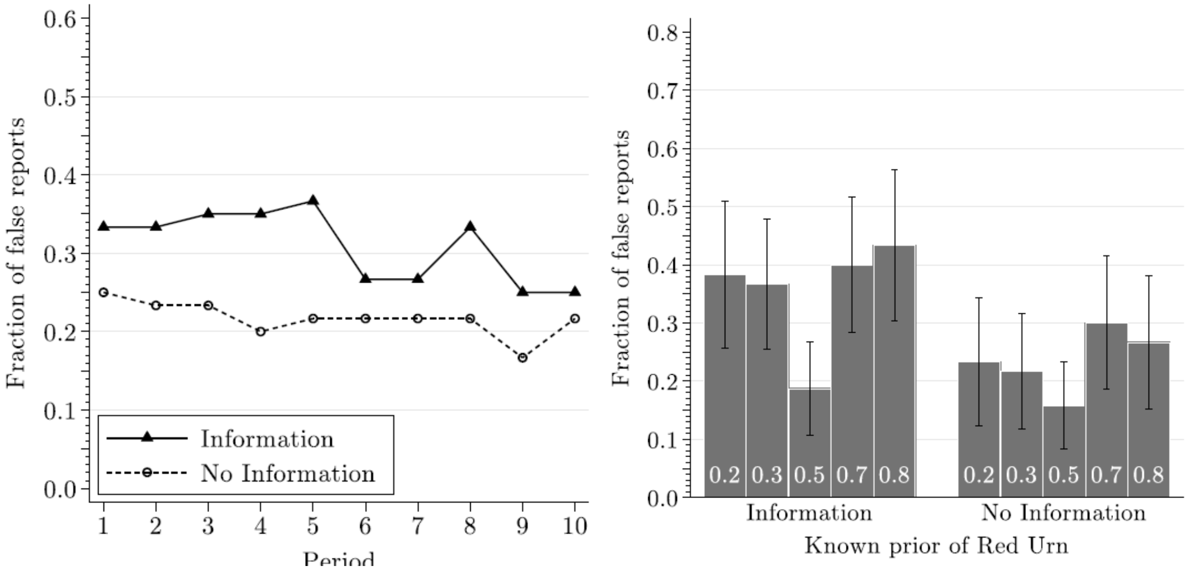
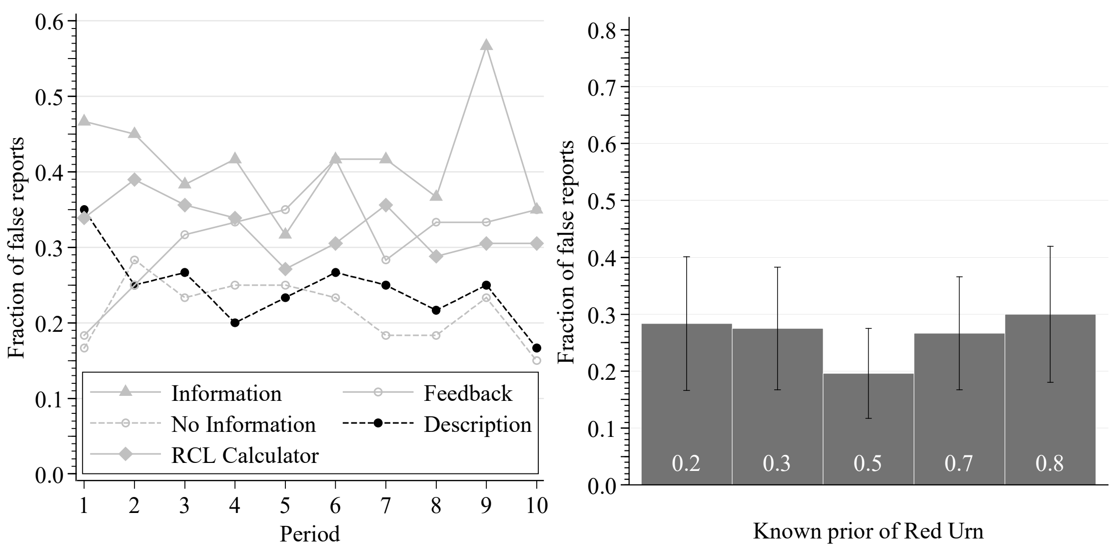


Figure A.5 False reports under the BSR Description Treatment



(A) By Period (B) By Prior

Online Appendix B—Inferential effects

B.1. Model of the Inferential Effects

To outline the potential effects center-biased beliefs can have on inference we consider two simple, representative exercises. Each are built around one of the inferential components of the Niederle and Vesterlund (2007, henceforth NV) gender-competition study, though where we strip out other controls for clarity and concision. We first outline (and sign) the potential effects from center-biased reports. We then outline a complementary with a series of simulations that demonstrate the effects in the specific regressions.

The two exercises we consider are: (i) The elicited belief q_i used as a dependent (left-hand-side) variable to be explained, where we are looking for a difference in means across a binary group comparison (in the specifics of the NV study, a difference in confidence between men and women). (ii) The elicited belief q_i used as a control (right-hand-side) variable, where we are trying to make inference on a difference in the variable y over the group comparison but controlling for the beliefs (in NV a gender difference in tournament entry, after taking confidence into account). Each exercise therefore seeks to uncover a discrete difference in effect over the binary group/treatment.[2] Our focus will be on how center bias in the reports alters inference on the estimated group difference.

To make the exercise concrete, and dovetail with our subsequent test of the mechanic, we consider the two main results in NV, where the group variable is the gender of the respondent. We set-up the regression model to measure the difference δ between women and men. The first inferential exercise examines whether men and women differ in their confidence, and is given by:

$$(1) \qquad q_i = \mu_q + \delta_q \cdot \text{Female}_i + \epsilon_q,$$

where the estimated effect $\hat{\delta}_q$ tells us how women differ from men in their confidence level.

The second inferential regression instead examines the tournament entry decision y_i, where the inferential regression is

$$(2) \qquad y_i = \mu_y + \delta_y \cdot \text{Female}_i + \beta_q \cdot q_i + \epsilon_y.$$

The point of the exercise here is to ask whether women and men have distinct preferences for competition after controlling for the confidence effect estimated by $\hat{\beta}_y \cdot q_i$.

To understand the potential inferential distortions when beliefs are center-biased we make use of a very simple model. When information is provided the measured belief q_i is modeled as random variable: with probability α the constant c is observed, and with

[2] Having inference be over a continuous variable is similar in intuition but introduces additional parameters.

probability $1-\alpha$ the true belief $q_i^\star$ is observed. Using this model of distortion in the measured beliefs we can examine how inference will be distorted in the two inferential regressions for $\hat{\delta}_q$ (women's average confidence, relative to men) and $\hat{\delta}_y$ (women's average tournament-entry relative to men, holding constant confidence).

We make the following simplifying assumptions to reduce the number of parameters:

- The sample is balanced with N men and N women.
- The econometric errors ϵ_q and ϵ_y are independent mean zero errors, each drawn from a distribution with finite variance (given by σ_q^2 and σ_y^2).
- The distributions for men and women's beliefs have true means given by μ_q and $\mu_q+\delta_q$, which is essentially the content of equation (1), but this is maintained for equation (2).

Given these assumptions, what then is the effect on inference for center-biased distortions in the beliefs? When $\alpha=0$ and no beliefs are mismeasured, the OLS coefficients are unbiased and consistent estimators of the true gender effects δ_q and δ_y. However for $\alpha>0$ both estimators are biased where the distorted belief $\tilde{q}_i$ is used in place of the true beliefs.

Beliefs as a dependent variable

When the belief is the dependent variable, as in (1) the expected values (and probability limit) of the OLS coefficients are attenuated so that:

$$\mathbb{E}\left(\hat{\delta}_q(\alpha)\right)=\operatorname{plim}\left(\hat{\delta}_q(\alpha)\right)=(1-\alpha)\cdot\delta_q.$$

Relative to the true effect δ_q the asymptotic bias in the estimator is:

$$\text{Asym. Bias}\left(\hat{\delta}_q(\alpha)\right)=-\alpha\cdot\delta_q.$$

The intuition when the beliefs are the dependent variable is simple. Measured beliefs for both men and women move to the same center point c, and this movement to the center creates a distortion over the means for both men and women, $\hat{\mu}_q$ and $\hat{\mu}_q+\hat{\delta}_q$ moving both to the center. The *difference* between the two populations is therefore directly attenuated.

The estimated effect-size is therefore attenuated in direct proportion to $(1-\alpha)$. However, inference is potentially more complicated, as standard errors could potentially decline here. The inflation/deflation of the variance ratio of the biased/unbiased estimator is given by

$$(3)\qquad \frac{\operatorname{Var}\left(\hat{\delta}_q(\alpha)\right)}{\operatorname{Var}\left(\hat{\delta}(0)\right)}=(1-\alpha)\cdot[1+\alpha\cdot\Delta_c],$$

where Δ_c is a measure of the distance between the center point c and the two group means:

$$\Delta_c:=\frac{1}{2}\cdot\left(\frac{\mu_q+\delta_q-c}{\sigma_q}\right)^2+\frac{1}{2}\cdot\left(\frac{\mu_q-c}{\sigma_q}\right)^2.$$

The effective T-statistic on the $\hat{\delta}_q(\alpha)$ coefficient is given by

$$T\big(\hat{\delta}_q(\alpha)\big) = \frac{\hat{\delta}_q(\alpha)}{\sqrt{\widehat{\mathrm{Var}}\big(\hat{\delta}_q(\alpha)\big)}}.$$

However, because $\Delta_c > 0$ we can bound the variance ratio in (3) from below by $1-\alpha$. As such the probability limit for the ratio of the T-statistics is:

$$\frac{T\big(\hat{\delta}_q(\alpha)\big)}{T\big(\hat{\delta}_q(0)\big)} = \frac{\hat{\delta}_q(\alpha)}{\hat{\delta}_q(0)} \cdot \sqrt{\frac{\mathrm{Var}\big(\hat{\delta}_q(0)\big)}{\mathrm{Var}\big(\hat{\delta}_q(\alpha)\big)}} \leq (1-\alpha) \cdot \frac{1}{\sqrt{1-\alpha}} = \sqrt{1-\alpha}$$

The conclusion then is that center bias attenuates both the size of the coefficient, but also the qualitative inference over whether an effect exists, towards zeros.[3]

Proposition 1 (*LHS effect*) When observed beliefs are center-biased at rate α, the estimated treatment effect $\hat{\delta}_q$ from econometric equation (1) is attenuated towards zero at rate (1-α).

Beliefs as a control variable

The right-hand side variables from equation (2) can be arranged into a column vector of $2N$ ones (the constant), a column vector of N zeros followed by N ones (the indicator for women), and a column vector of the beliefs (N observations from men, N observations from women.) The OLS estimator for (2) is therefore given by,

$$\begin{pmatrix} \widehat{\mu_y} \\ \widehat{\delta_y} \\ \widehat{\beta_q} \end{pmatrix} = \begin{bmatrix} 2N & N & \sum_{\mathrm{M}} q_i + \sum_{\mathrm{F}} q_i \\ N & N & \sum_{\mathrm{F}} q_i \\ \sum_{\mathrm{M}} q_i + \sum_{\mathrm{F}} q_i & \sum_{\mathrm{F}} q_i & \sum_{\mathrm{M}} q_i^2 + \sum_{\mathrm{F}} q_i^2 \end{bmatrix}^{-1} \begin{pmatrix} \sum_M y_i + \sum_F y_i \\ \sum_F y_i \\ \sum_M q_i\, y_i + \sum_F q_i\, y_i \end{pmatrix}.$$

Letting $\boldsymbol{\iota}_N$ be a column vector of N ones, $\mathbf{0}_N$ a column vector of N zeros, and $\mathbf{q}_0^M$ and $\mathbf{q}_0^F$ the true belief vectors for the male and female sample, respectively, the undistorted data is given by the $2N \times 3$ matrix:

[3] False inference is possible with the belief as a dependent variable if the null assumes a non-zero effect. So for example, if the belief is the dependent variable, and the independent variable were the Bayesian beliefs π with $q_i = \beta_0 + \beta_1 \pi_i + \epsilon_q$, an obvious null would be that the agent was Bayesian with ($\beta_\pi = 1$). The same model of center bias would lead to an attenuated estimator $\hat{\beta}_\pi$, where if α is large enough the econometric inference could be to falsely reject the null even if the agent were Bayesian.

$$\mathbf{X}_0 = \begin{bmatrix} \boldsymbol{\iota}_N & \mathbf{0}_N & \mathbf{q}_0^M \\ \boldsymbol{\iota}_N & \boldsymbol{\iota}_N & \mathbf{q}_0^F \end{bmatrix},$$

while fully center-biased data would be given by:

$$\mathbf{X}_c = \begin{bmatrix} \boldsymbol{\iota}_N & \mathbf{0}_N & c \cdot \boldsymbol{\iota}_N \\ \boldsymbol{\iota}_N & \boldsymbol{\iota}_N & c \cdot \boldsymbol{\iota}_N \end{bmatrix}.$$

The dependent variable (a $2N$ column vector) is given by

$$\mathbf{y} = \mathbf{X}_0 \begin{pmatrix} \mu_y \\ \delta_y \\ \beta_q \end{pmatrix} + \boldsymbol{\epsilon}_y$$

The probability limit for the OLS estimator (using the assumption that each entry in $\boldsymbol{\epsilon}_y$ is a mean-zero independent error and that $\alpha < 1$ so that the inverse is well defined) is:

$$\begin{aligned} \operatorname{plim} \begin{pmatrix} \widehat{\mu_y} \\ \widehat{\delta_y} \\ \widehat{\beta_q} \end{pmatrix} &= \operatorname{plim} \left(\frac{\alpha}{N} \mathbf{X}_c^T \mathbf{X}_c + \frac{1-\alpha}{N} \mathbf{X}_0^T \mathbf{X}_0 \right)^{-1} \left(\frac{\alpha}{N} \mathbf{X}_c^T \mathbf{X}_0 + \frac{1-\alpha}{N} \mathbf{X}_0^T \mathbf{X}_0 \right) \begin{pmatrix} \mu_y \\ \delta_y \\ \beta_q \end{pmatrix} \\ &= \begin{pmatrix} \mu_y \\ \delta_y \\ \beta_q \end{pmatrix} + \operatorname{plim} \left(\frac{\alpha}{N} \mathbf{X}_c^T \mathbf{X}_c + \frac{1-\alpha}{N} \mathbf{X}_0^T \mathbf{X}_0 \right)^{-1} \frac{\alpha}{N} \mathbf{X}_c^T (\mathbf{X}_0 - \mathbf{X}_c) \begin{pmatrix} \mu_y \\ \delta_y \\ \beta_q \end{pmatrix} \end{aligned}$$

The asymptotic bias is therefore:

$$\operatorname{plim} \begin{pmatrix} \widehat{\mu_y} - \mu_y \\ \widehat{\delta_y} - \delta_y \\ \widehat{\beta_q} - \beta_q \end{pmatrix} = \left(\alpha \begin{bmatrix} 2 & 1 & 2c \\ 1 & 1 & c \\ 2c & c & 2c^2 \end{bmatrix} + (1-\alpha) \begin{bmatrix} 2 & 1 & 2\mu_q + \delta_q \\ 1 & 1 & \mu_q + \delta_q \\ 2\mu_q + \delta_q & \mu_q + \delta_q & 2\sigma_q^2 + \mu_q^2 + (\mu_q + \delta_q)^2 \end{bmatrix} \right)^{-1}$$
$$\alpha \begin{bmatrix} 0 & 0 & (\mu_q - c) + (\mu_q + \delta_q - c) \\ 0 & 0 & (\mu_q + \delta_q - c) \\ 0 & 0 & c((\mu_q - c) + (\mu_q + \delta_q - c)) \end{bmatrix} \begin{pmatrix} \mu_y \\ \delta_y \\ \beta_q \end{pmatrix}.$$

The determinant of the inverse in the above is given by $2 \cdot (1-\alpha) \cdot \sigma^2 (1 + \alpha \cdot \Delta_c)$, and the bias can be reduced to:

$$\begin{aligned} \operatorname{plim} \begin{pmatrix} \widehat{\mu_y} - \mu_y \\ \widehat{\delta_y} - \delta_y \\ \widehat{\beta_q} - \beta_q \end{pmatrix} &= \frac{\alpha \beta_q}{2(1-\alpha)\sigma_q^2 (1 + \alpha \cdot \Delta_c)} \begin{pmatrix} 2(1-\alpha)\sigma_q^2 (\mu_q - c + \mu_q \Delta_c) \\ 2(1-\alpha)\sigma_q^2 \delta_q (1 + \Delta_c) \\ -2(1-\alpha)\sigma_q^2 \Delta_c \end{pmatrix}, \\ &= \frac{\alpha \beta_q}{1 + \alpha \Delta_c} \begin{pmatrix} \mu_q (1 + \Delta_c) - c \\ \delta (1 + \Delta_c) \\ -\Delta_c \end{pmatrix}. \end{aligned}$$

The asymptotic bias in the group variable estimator $\hat{\delta}_y$ is therefore given by:

$$\text{Asym. Bias}\big(\hat{\delta}_y(\alpha)\big) = \alpha \cdot \beta_q \cdot \delta_q \cdot \frac{1 + \Delta_c}{1 + \alpha \cdot \Delta_c},$$

where Δ_c is the expected square-difference between the true populations means for men and women and the center point c.

Similarly, the asymptotic bias on the beliefs control variable is given by:

$$\text{Asym. Bias}\big(\hat{\beta}_q(\alpha)\big) = \frac{-\alpha\beta_q\Delta_c}{1 + \alpha \cdot \Delta_c},$$

which always moves in the opposite direction from the true effect of the belief (an attenuating effect).

The above leads to the following conclusion

Proposition 2 *(RHS effects)* When observed beliefs are center-biased at rate α, the bias in the estimated treatment effect $\hat{\delta}_y$ in the econometric equation (2) has a bias signed by the product $\delta_q\beta_q$, and the estimated belief effect $\hat{\beta}_q$ is attenuated towards zero.

B.2. Simulations of the effects of center bias in the NV-study

We now use the model of center-bias to simulate the impact of center bias on inference within the NV-setting. To this end, we first estimate the degree of center bias from participants' beliefs about objective priors in our BSR-study. We then use this estimate to simulate center bias for the NV-study, which shows that most of the inferential distortions observed in the actual data can be forecasted by with the help of the center-bias model. We next illustrate that the reverse exercise is not successful—that is, attempting to recover the unbiased estimates using the bias-model and the distorted data in the NV-Information treatment.

B.2.1 Estimation of center bias from objective prior reports (BSR study)

We restate the center-bias model for participant i's report q_i as:

$$q_i = (1 - \alpha) \cdot q_i^\star + \alpha \cdot c, \tag{4}$$

which is an α-weighted average of the uniform (or "center") belief c and her true belief $q_i^\star$. With $\alpha = 0$, the participant reports truthfully, and with $\alpha = 1$ all participants are fully center-biased. Intermediate values of α express the degree of the participant's center bias. Finally, since in the BSR study participants' report on a binary prior, the uniform belief is c=1/2.

Since equation (4) is linear in our parameter of interest α, we can estimate it via OLS.[4] Table B.1 shows the regression results for the BSR-No-Information data (column 1) and the BSR-Information data (column 5).

Table B.1. Estimated center bias from beliefs about objective priors.

	BSR-No-Information				BSR-Information			
	(1) All priors	(2) Close to center (p=0.3,0.7)	(3) Further from center (p=0.2,0.8)	(4) Divergence dependent	(5) All priors	(6) Close to center (p=0.3,0.7)	(7) Further from center (p=0.2,0.8)	(8) Divergence dependent
α/α_0	0.034	0.001	0.063	-0.045	0.223***	0.149**	0.289***	0.045
	(0.044)	(0.047)	(0.047)	(0.061)	(0.054)	(0.060)	(0.061)	(0.085)
α_1				0.388*				0.877**
				(0.218)				(0.334)
N	600	240	120	600	600	240	120	600
R^2	0.959	0.967	0.954	0.959	0.939	0.945	0.907	0.940

Note: OLS estimates; standard errors corrected for clusters on the individual level.

In the No-Information (column 1), the estimated center bias is $\alpha = 0.034$, which is not statistically different from zero (p=0.437). This result corroborates our previous findings of undistorted prior reports in No-Information. In contrast, in the Information treatment

[4] The results of tobit regressions are very similar with estimated α (cluster-corrected s.e.) of 0.028 (0.047) in the No-Information treatment and 0.219 (0.055) in the Information treatment.

(column 5) the estimated center bias is $\alpha = 0.223$ and significantly different both from zero ($p<0.001$) and the estimate in the No-Information treatment ($p=0.007$).

In addition to the baseline model, Table B.1 also reports on a simple extension of the model capturing a regularity of center-bias that will be important for our out-of-sample predictions. The extension is motivated by the relative strengths of the hedging motives, per Table 1 in the paper's introduction (echoed in the post-experimental questionnaire for the Information treatment), which suggest that deviations from truth-telling could be increasing in the distance of true belief from the center. Columns (6) and (7) present evidence supporting this hypothesis.[5] Here, we estimate the center-bias model separately for "less extreme" priors of 0.3 and 0.7 and for "more extreme" priors of 0.2 and 0.8, respectively. The estimated α is significantly different from zero in both groups but about twice as large for more extreme priors than for less extreme priors ($p=0.011$). That is, participants in the BSR-Information treatment show robust center bias but the degree of center bias is larger for priors further away from uniform.

To capture this dependency in a parsimonious and portable way our simulations will also allow for α to depend on the distance between the participant's true belief and the uniform belief. Specifically,

$$(5) \qquad \alpha = \alpha_0 + \alpha_1 \Delta_{\mathrm{KL}}(\mathrm{b}, \mathrm{u}),$$

where $\Delta_{\mathrm{KL}}(\boldsymbol{b}, \boldsymbol{u})$ is a normalized Kullback–Leibler divergence between the participant's true belief $\boldsymbol{b}$ and the uniform belief $\boldsymbol{u}$ given by

$$(6) \qquad \Delta_{\mathrm{KL}}(\boldsymbol{b}, \boldsymbol{u}) = \sum_{k=1}^{K} b_k ln(b_k/u_k) \,/ ln(K),$$

where K is the number of states measured in the elicitation.[6]

The extended center-bias model nests the constant center-bias model as a special case with $\alpha_1 = 0$, which provides us with a simple way to test whether a belief's divergence from uniform affects the degree of center-bias.

Column (4) and (8) in Table B.1 show the estimated α_0 and α_1 using the BSR-No-Information and BSR-Information treatment, respectively. We first confirm that there is no significant center bias in the No-Information treatment also with this more flexible specification. In the BSR-Information treatment, the estimate of $\alpha_1 = 0.877$ is large and significantly different from zero, reflecting a rejection of the constant center-bias model in favor of the divergence-dependent center-bias.

[5] In the BSR-No-Information treatment (columns 2 and 3), the estimated center bias is not significant different from zero for any prior group and there is no significant difference between the estimated parameters of center bias (p=0.080), which further corroborates the finding of no significant distortions in this setting.

[6] The normalization by ln(K) ensures that the measure is in [0,1] for any K, where $1 - \Delta_{\mathrm{KL}}(\mathrm{b}, \mathrm{u}) = -\sum_{k=1}^{K} b_k ln(b_k) \,/ ln(K)$ is therefore the normalized Shannon entropy.

B.2.2 Simulating center bias effects from on unbiased data (NV-No-Information)

We now simulate center-bias in the NV-study using our center-bias estimates from the BSR-study. Mirroring the original NV-study, we conduct simulations where the elicited belief is used as a left-hand side variable and when it is used as a right-hand-side variable. In both cases, the simulations are based on the actual data of the NV-No-Information treatment—in which no center bias is found—and it is the data of the NV-information treatment that is being simulated. Following the paper, we focus our simulations on the belief attached to winning the tournament.

Beliefs as an independent variable

In each of 10,000 iterations, we draw a bootstrap sample of stated beliefs (participants' guessed chance of ranking first) from the NV-No-Information sample (fixing the gender strata). For each bootstrapped belief, there is an α_i chance that the belief is replaced with a centered belief of c = ¼. In case of the extended center-bias model, this chance α depends on the divergence of the original bootstrapped belief (considering all four states, see equation (6)) and the estimated parameters α_0 and α_1 from the BSR-Information data (see column 8 in Table B.1). We next run an OLS regression of the center-biased bootstrap beliefs on a constant, a gender dummy, the participant's tournament performance (round 2), and the difference between the participant's tournament performance (round 2) and their piece-rate performance (round 1). This is the same specification as in Table V of the original NV-study except for running OLS instead of ordered probit regressions (subjects guessed their tournament rank in the original study).[7] We then record the value of the estimated coefficient for each independent variable. After completion of the 10,000th iteration, we look at the bootstrap distribution of each independent variable and determine the bootstrapped mean and standard error of each coefficient.

Table B.2 shows the results of this simulation for the constant center-bias model with $\alpha = 0.22$, $\alpha = 0.5$, and the divergence-dependent model (columns 3-5, respectively). Columns 3 and 4 show that the constant-center-bias model can predict the change in the qualitative conclusion from NV-Information study but only if the degree of center bias is large (here $\alpha = 0.5$). Here, the coefficient on the gender dummy is: (*i*) significant in the NV-No-Information treatment but not in the simulated NV-Information data, and (*ii*) much smaller in the simulated NV-Information data than in the NV-No-Information treatment. This pattern mirrors the findings from the actual NV-replication data (columns 1 and 6).[8]

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[7] Where our theory section used a simple specification, here we use the full specification per the NV parameter estimates in the paper.

[8] Column (1) and (6) show the results of OLS regressions using the actual data in the NV-No-Information and NV-Information treatment, respectively. The table also shows the results of the bootstrap exercise as described above except that we do not simulate center bias (i.e., we do not replace any bootstrapped belief with c = ¼; see column 2) as well as simple OLS regressions based on the actual data of the No-Information

TABLE B.2. SIMULATION OF CENTER BIAS: BELIEFS AS A LHS VARIABLE

	Reported probability of ranking 1st					
	NV-No-Information		NV-Information			
	(1) Actual data (OLS)	(2) Actual data (bootstrap)	(3) Simulated (bootstrap) $\alpha = 0.223$	(4) Simulated (bootstrap) $\alpha = 0.5$	(5) Simulated (bootstrap) α=.05+ .88$\Delta_{KL}(\mathbf{b},\mathbf{u})$	(6) Actual data (OLS)
Female	−0.148***	−0.148***	−0.115**	−0.074	−0.076*	−0.038
	(0.051)	(0.057)	(0.055)	(0.048)	(0.043)	(0.059)
Tournament	0.008*	0.008	0.006	0.004	0.004	0.018***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.003)	(0.005)
Tournament− piece rate	0.017**	0.017**	0.013*	0.008	0.005	−0.021**
	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.010)
Constant	0.305***	0.307***	0.295***	0.279***	0.277***	0.059
	(0.097)	(0.110)	(0.105)	(0.092)	(0.079)	(0.101)
R^2	0.273	—	—	—	—	0.187
N	74	74	74	74	74	68

Note: Asterisks represent *p*−values: **p*<0.1, ***p* <0.05, ****p*<0.01. Columns 2-4 are based on 10,000 bootstrap samples. In each bootstrap iteration of column 3-5, an observation is replaced by the uniform belief of 1/4 with probability α.

As noted above, the value of $\alpha = 0.5$ needed to explain the actual NV-data is much larger than the estimate of $\alpha = 0.223$ obtained from the BSR data. The larger α is needed because the constant-center-bias model does not account for the larger intensity of center-bias near the extremes. In contrast, the divergence-dependent center-bias model in column (5) can explain the change in the qualitative conclusion with the parameters estimated from the BSR data. This highlights the importance of accounting for the observed center-bias regularity when assessing the sensitivity of qualitative results to center bias out of sample.

Beliefs as a control variable

We repeat the exercise for the case where elicited beliefs are used as a right-hand-side variable. Our simulation approach is the same except that inferential here acts through a probit regression of the tournament-entry decision, mirroring the paper's specification that includes the confidence variable as a control.

treatment (column 1) and the Information treatment (column 6). A comparison of columns 1 and 2 shows that for the actual No-Information data, the results are virtually the same whether we use simple OLS or bootstrap estimates.

Table B.3 shows the simulation results together with the regressions from the actual data. The actual NV-No-results are provided in (column 1),[9] while the results from the simulated model are given in columns (3) to (5). Per the LHS variable, with constant center bias, for an effect of $\alpha = 0.5$, the gender coefficient using the distorted beliefs becomes larger and gains marginal statistical significance (column 4). Directionally, but much smaller, this reflects what is observed in the actual NV-information treatment, where the gender coefficient remains highly significant (column 6). Again, using the estimates of the divergence-dependent center-bias model (column 5) yields very similar results as the inflated constant center-bias model. To summarize, for the case of a control variable, the center bias model can partially explain the actual changes in the estimated gender coefficients (see columns 1 and 6).

B.2.3 Attempted recovery of subjective beliefs from biased data

The previous section showed that simple models of center bias can predict inferential mistakes, out-of-sample, in applied settings. Using the same model, the following section illustrates that the reverse exercise—attempts to recollect truthful reports from center-biased data—is more challenging and not successful for the NV-setting.

The first major challenge of the reverse approach is the identification of "likely biased" observations. While it is straightforward to transform unbiased data for a given center-bias model, the reverse approach requires identification of "likely biased" observations. In other words, given biased data we cannot be sure which observations are distorted and which are true beliefs. Even if we solve the first issue, the second issue is in trying to recover where the biased observation came from. Even if biased observations could be perfectly identified, it is often not feasible to fully recover the original data point.

[9] Column 2 shows again that the results are very similar for simple OLS and bootstrap estimates (without simulating center bias).

Table B.3. Simulation of center bias: Beliefs as a RHS Control

	Tournament entry					
	NV-No-Information		NV-Information			
	(1)	(2)	(3)	(4)	(5)	(6)
	Actual data (probit)	Actual data (bootstrap)	Simulated (bootstrap) α=0.223	Simulated (bootstrap) α=0.5	Simulated (bootstrap) α=.05+.88 Δ_{KL}(b,u)	Actual data (probit)
Female	−0.146	−0.121	−0.159	−0.190*	−0.189*	−0.382***
	(0.115)	(0.125)	(0.105)	(0.093)	(0.097)	(0.124)
Tournament	0.017	0.018	0.019	0.020*	0.019*	−0.011
	(0.014)	(0.015)	(0.013)	(0.012)	(0.012)	(0.014)
Tournament− piece rate	−0.015	−0.016	−0.009	−0.004	−0.003	−0.004
	(0.021)	(0.025)	(0.022)	(0.019)	(0.020)	(0.022)
Belief weight on rank 1	1.275***	1.295***	1.117***	1.021***	1.125***	0.994***
	(0.432)	(0.494)	(0.459)	(0.516)	(0.505)	(0.329)
Pseudo R^2	0.303	—	—	—	—	0.208
N	74	74	74	74	74	68

Note: The table reports marginal effects for a man with average performances and belief. Asterisks represent *p*-values: **p*<0.1, ***p* <0.05, ****p*<0.01. Columns 2-4 are based on 10,000 bootstrap samples. In each bootstrap iteration of column 3-5, an observation is replaced by the uniform belief of 1/4 with probability α. $\Delta_{KL}(b,u) \in [0,1]$ is the normalized Kullback–Leibler divergence of the NV-No-Information belief reports from uniform.

Throughout the following sections, we adopt a very simple and straightforward method for solving these two issues, where we briefly discuss the use of more sophisticated approaches at the end of this section.

Beliefs as an independent variable

Starting with beliefs as the left-hand-side variable we first detail our approach. In each simulation, we first split the bootstrap sample into two groups: those with centered beliefs, and those with and non-centered beliefs. We do this by calculating the distance of each bootstrapped belief from the centered belief of 0.25, and then figuring out the α-sized sample that is closest to the centered belief.[10] We then replace the centered-data beliefs with a linear prediction based the non-centered sample (but therefore accounting for the observations covariates). As before, we then conduct OLS regressions to estimate parameters for each simulated sample.

[10] To assure that α is the same across simulations (given that beliefs are discrete), the assignment to the centered and non-centered group is random for beliefs that are at the distance threshold for α, where beliefs with a smaller distance are all centered and beliefs with a larger distance are all non-centered.

TABLE B.4. REVERSE SIMULATION: BELIEF ON LHS

	Reported probability of ranking 1st			
	Information	No-Information		
	(1)	(2)	(3)	(4)
	Actual data (OLS)	Simulated (bootstrap) α = 0.223	Simulated (bootstrap) α = 0.5	Actual data (OLS)
Female	−0.038	−0.060	−0.044	−0.148***
	(0.059)	(0.071)	(0.104)	(0.051)
Tournament	0.018***	0.019***	0.023**	0.008*
	(0.005)	(0.006)	(0.008)	(0.004)
Tournament−piece rate	−0.021**	−0.022**	−0.032**	0.017**
	(0.010)	(0.010)	(0.015)	(0.008)
Constant	0.059	0.073	0.045	0.305***
	(0.101)	(0.122)	(0.172)	(0.097)
R^2	0.187	—	—	0.273
N	68	68	68	74

Note: Asterisks represent *p*−values: *p<0.1, **p <0.05, ***p<0.01. Columns 2-3 are based on 10,000 bootstrap samples. In each bootstrap iteration, the share α of the most centered beliefs (closest to uniform 0.25) is replaced by predictions based on regressions from the non-centered observations of the same bootstrap sample. Specifically, in each iteration, we first estimate the specification in this table for the non-centered observations to then predict the values of each centered observation based on their gender and performances.

Table B.4 shows the results of this simple exercise for the two values of the constant center-bias model α = 0.223 (column 2) and α = 0.5 (column 3). It is apparent that the reverse simulations are not successful in recovering estimates close to the observed NV-No-Information results (column 4), nor those from the original NV study. In fact, the bootstrap estimates and standard errors of the gender coefficients are virtually the same as in the original NV-Information data (column 1) they are based off. As such, the simulation results provide little hope for an effective strategy to recover true beliefs once they are affected by center bias.

Beliefs as a control variable

For completeness, we now repeat the reverse simulations of the previous section, except where beliefs are used as a RHS control (per Table B.3). Analogue to the previous section, Table B.5 provides the results of the reverse simulations, in which centered beliefs are replaced by predicted values based on individual characteristics, but where the specification has beliefs on the RHS (as in Table B.2).

Table B.5. reverse Simulation: Belief on RHS

	Tournament entry			
	Information	No- Information		
	(1)	(2)	(3)	(4)
	Actual data (probit)	Simulated (bootstrap) α=0.223	Simulated (bootstrap) α=0.5	Actual data (probit)
Female	−0.382***	−0.363***	−0.346**	−0.146
	(0.124)	(0.133)	(0.138)	(0.115)
Tournament	−0.011	−0.013	−0.011	0.017
	(0.014)	(0.015)	(0.017)	(0.014)
Tournament− piece rate	−0.004	−0.001	0.000	−0.015
	(0.022)	(0.026)	(0.030)	(0.021)
Belief weight on rank 1	0.994***	1.020***	0.760*	1.275***
	(0.329)	(0.353)	(0.442)	(0.432)
Pseudo R^2	0.208	—	—	0.303
N	68	68	68	74

Note: The table reports marginal effects for a man with average performances and belief. Asterisks represent *p*-values: **p*<0.1, ** *p* <0.05, *** *p*<0.01. Columns 2-3 are based on 10,000 bootstrap samples. In each bootstrap iteration, the share α of the most centered beliefs (closest to uniform 0.25) is replaced by predictions based on regressions from the non-centered observations of the same bootstrap sample. Specifically, in each iteration, we first estimate the specification in Table B.1 for the non-centered observations to then predict the values of each centered observation based on their gender and performances.

The reverse simulation exercise again shows that we are not successful in generating data or qualitative findings that reflect the actual NV-No-Information treatment. Again, the qualitative results of the reverse simulations are not substantially different from the actual NV-Information data.

B.2.4 Simulation Conclusions

The simulations in this appendix illustrate that while predicting the effects of the center bias is straightforward and can yield relatively accurate results out-of-sample (here using the objective BSR-date to predict the effects of center-bias in the NV-study), the reconstruction of unbiased estimates from center-biased data is much more challenging and not successful for the NV-study.

While our simulation techniques are intentionally simple to maximize comparability between the two tasks, more sophisticated approaches could clearly improve on the reconstructive approach, e.g., when identifying and separating “likely center-biased” from “likely unbiased” observations. However, we believe that such improvements would not address the two main challenges of the reconstructive approach. If the researcher has only data that is possibly affected by center-bias, then it is difficult to learn the true model and degree of center-bias, more sophisticated classification strategies might introduce additional uncertainty when identifying center bias, and the central problem of how to replace "censored" observations that are likely affected by center bias remains.

Online Appendix C—Experiment Instructions

In the below instructions, treatment differences are indicated in `[square brackets]`. In addition, the RCL treatment uses the term "*Your Submitted Guess*" instead of "*Your Guess*" throughout, and the term "submit" instead of "provide" whenever the instructions referred to the participant reporting.

C.1 Main Experiment Instructions (Handout + read aloud)

Instructions

`[All except QSR-Inf and QSR-No-Information`

Thank you for participating in our study. This is an experiment on decision making. The other people in this room are also participating in the experiment, and you may not talk to them. If you have a question, please raise your hand and an experimenter will come and answer you in private.

You will receive $8 for participating in this experiment, but the decisions you make can further increase these earnings. Any money you make will be paid privately and in cash at the end of the experiment.

`][QSR only as conducted online:`

Thank you for participating in our study. This is an experiment on decision making. The other people in this zoom meeting are also participating in the experiment, and you may not communicate with them. If you have a question, please send the experimenter a private chat message and they will answer you in private.

You will receive $8 for participating in this experiment, but the decisions you make can further increase these earnings. Any money you make will be paid privately via Venmo at the end of the experiment. An additional $0.25 will be added to your payment to cover Venmo's instant transfer fee, so that you can transfer your money to your bank account immediately.

`][All:`

Explanation of your task

The experiment will consist of **ten scenarios**. In each scenario the computer will fill two urns with five balls, either red or blue. We call the urn with more red balls the **Red** urn, and the one with more blue balls the **Blue** urn. One of these two urns is selected to be used in the scenario. Your task is to guess how likely it is that the selected urn is the **Red** urn. Within each scenario you will make a total of three guesses.

Each scenario proceeds as follows:

Computer Fills the Urns: The two urns are filled with five balls each, some blue, some red. You will always see the exact number of blue and red balls in the two urns.

Computer Selects an Urn: The computer selects the Red or the Blue urn by rolling a fair 10-sided die and comparing it to a number **X** between 1 and 10. The selected urn is determined as follows:

- If the die roll is less than or equal to **X** then the Red urn is selected.
- If the die roll is greater than **X** then the Blue urn is selected.

Once the computer selects an urn it is fixed and stays the same for the entire scenario. The die-roll selection rule **X** means that the chance the computer selects the Red urn is **X**-in-10. For example, suppose **X**=6, then there is a six-in-ten chance (60 percent) that the computer selects the Red urn, and a four-in-ten chance (40 percent) that the computer selects the Blue urn.

The number **X** will vary across the 10 scenarios. After the computer has filled the two urns and rolled the 10-sided die to determine which urn is selected, you will be asked to make your guesses. At the beginning of each scenario you will learn how many red and blue balls there are in each urn, and the rule the computer used to select an urn (the number **X**). However, you will not learn which of the two urns has been selected until after you have made your guesses.

You are asked to provide your best guess that the computer has selected the Red urn for the scenario. The three questions are ordered as follows:

Guess 1 Knowing only the rule **X** that the computer used to select an urn, you provide your first guess that the selected urn is the Red one.

Guess 2 The computer fairly draws one of the five balls from the selected urn. After seeing the color of this ball you provide your second guess that the selected urn is the Red one.

Guess 3 After replacing the first-drawn ball back into the selected urn and mixing it, the computer fairly draws a second ball from the five. After seeing the color of the second ball you provide your third guess that the selected urn is the Red one.

Note that the draws from the selected urn in questions 2 and 3 are independent from one another: After the first draw is made, it is as if the ball is returned to the selected urn before the next draw is made. The contents of the selected urn are therefore always the same when a draw is made, and each of the five balls has the same chance of being drawn in each question.

Feedback After you have answered the scenario's three questions you learn which urn the computer selected and drew balls from. Your three guesses will be used to determine your chances of winning an \$8 prize. Your chance of winning the prize is set so that more-accurate guesses lead to a higher chance of winning.

Your Guess

For each question you have to guess the chance that the selected urn is the Red one. Your guess is a percentage probability from 0 to 100—with 0 indicating a 0-out-of-100 chance that the selected urn is the Red urn, and 100 indicating a 100-out-of-100 chance. The number you provide is called *Your Guess*.

You choose *Your Guess* by clicking the response bar on your screen. The width of the

red part of the bar indicates your guess that the Red urn was selected.

- Larger values of *Your Guess* represent a greater chance that the Red urn was selected and a smaller chance that the Blue urn was selected
- Smaller values of *Your Guess* represent a smaller chance that the Red urn was selected and a greater chance that the Blue urn was selected

The width of the blue part of the bar is 100−*Your Guess*, and represents your guess that the Blue urn was selected.

Payment Rule

`[Information, RCL, Description treatments:`

We now explain how *Your Guess* is used to determine whether you win the \$8 prize.

- The computer chooses two numbers between 1 and 100, where each number is equally likely, as if rolling two 100-sided dice. These numbers are called *Computer Number A* and *Computer Number B*.
- The computer determines whether you win the \$8 prize according to which urn was selected:

The selected urn is the Red urn: You will win the \$8 prize if *Your Guess* is **greater than or equal** to **either** of the two *Computer Numbers*.

The selected urn is the Blue urn: You will win the \$8 prize if *Your Guess* is **less than either** of the two *Computer Numbers*.

`][QSR Information:`

We now explain how *Your Guess* is used to determine how much you earn.

The selected urn is the Red urn: You will earn $8*(1 − (1 − *Your Guess*/100)^2)

The selected urn is the Blue urn: You will earn $8*(1 − (*Your Guess*/100)^2)

To help you understand the payment rule, as you move *Your Guess* the computer will inform you of:

- Your earnings if the Red urn was selected
- Your earnings if the Blue urn was selected

][Information, RCL treatments:

To help you understand the payment rule, as you move *Your Guess* the computer will inform you of:

- The probability of winning the $8 if the Red urn was selected
- The probability of winning the $8 if the Blue urn was selected

][RCL treatment:

As mentioned above, we designed the payment rule to make sure that your greatest total chance of winning is secured by letting *Your Submitted Guess* equal to your most-accurate guess that the urn is Red (what we will call *Your True Guess* on Red). We provide a calculator to help you determine your total chance of winning the prize given any *True* and *Submitted Guesses*.

The calculator will appear in a gray box on the bottom of your screen. When you have

entered *Your True Guess* that the urn is Red the calculator will use *Your Submitted Guess* to compute your total chance of winning. The formula used to calculate your total chance of winning is given by:

(True Guess on Red) × (Prob. of Winning if Red given Submitted Guess)

+

(True Guess on Blue) × (Prob. of Winning if Blue given Submitted Guess).

][All except QSR-Information and QSR-No-Information

Final Payment

The payment rule is designed so that you can secure the largest chance of winning the prize by reporting your most-accurate guess. [No-Information treatment: The precise payment rule details are available by request at the end of the experiment.]

At the end of the experiment, the computer will randomly choose two of the ten scenarios for payment. From each of these two scenarios, one of the three guesses will be randomly chosen for payment. Every guess has the same chance of being selected for payment.

[Information, RCL, Feedback treatments: At the end of each scenario you find out which urn was actually selected, and learn your chance of winning the $8 if the guess is selected for payment.]

For the selected questions we will use *Your Guess* and whether the selected urn was the Red urn to determine your chance of winning $8. After determining your chance of winning, the computer will conduct the lottery for the prize to see if you won the $8.

Your payment for this experiment will therefore be:

- $8 if you do not win the $8 on either guess.
- $16 if you win the $8 prize on one of the two selected guesses.
- $24 if you win the $8 prize on both selected guesses

][Both QSR treatments:

Final Payment:

The payment rule is designed so that you can secure the largest expected earnings by reporting your most-accurate guess. [QSR-No-Information treatment: The precise payment rule details are available by request at the end of the experiment.]

At the end of the experiment, the computer will randomly choose two of the ten scenarios for payment. From each of these two scenarios, one of the three guesses will be randomly chosen for payment. Every guess has the same chance of being selected for payment. [QSR-Information: At the end of each scenario, you find out which urn was actually selected, and learn your earnings if the guess is selected for payment.

[QSR-Information:

For the selected questions we will use *Your Guess* and whether the selected urn was the Red urn to determine your earnings. You may earn between $0 and $8 for each selected guess.

Including your $8 for participating in the experiment, your payment for this experiment will therefore be between $8 and $24 depending on your earnings from the two guesses selected for payment.

]

Summary

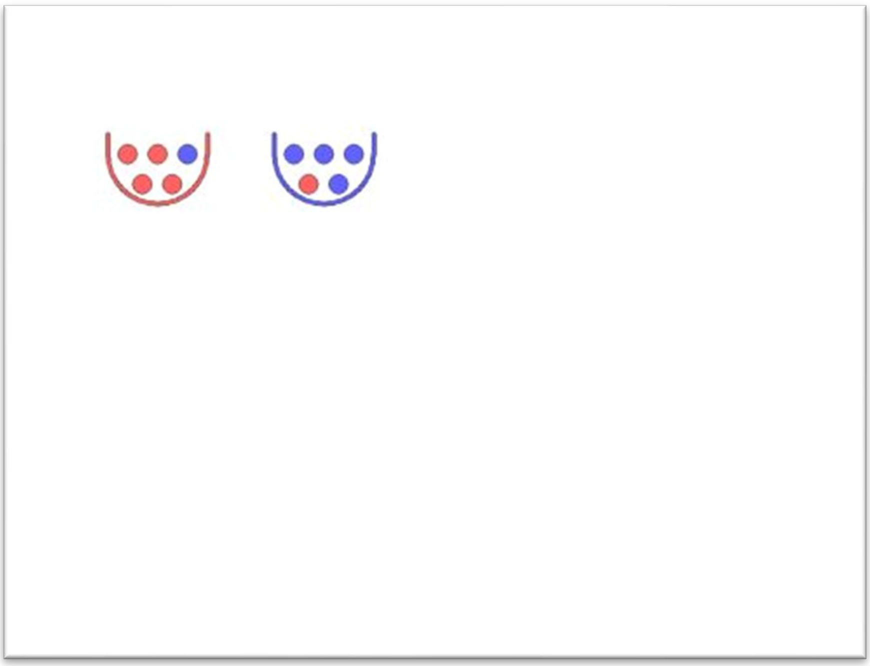
[All except QSR:

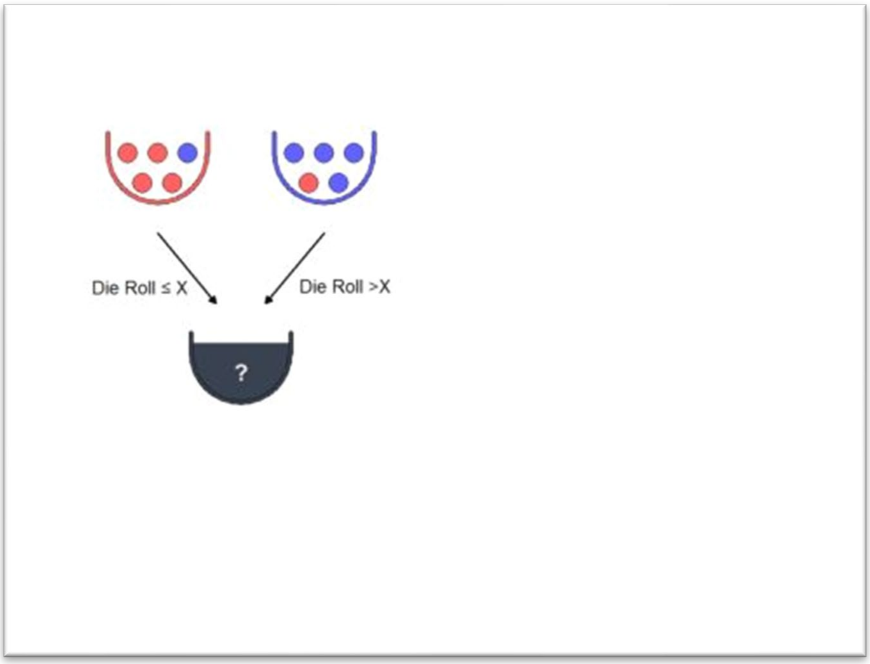
For a brief summary please take a look at the presentation at the front of the lab.

][QSR as online:

For a brief summary please follow the presentation on the next slides.]

C.2. Slides (shown) and Script (read aloud) as summary

Slides	Script (read out loud by experimenter)
	We now summarize the task in each scenario. To begin with the computer fills the two urns. Each urn is filled with five balls, which are either blue or red. The red urn is the urn with more red balls in it.



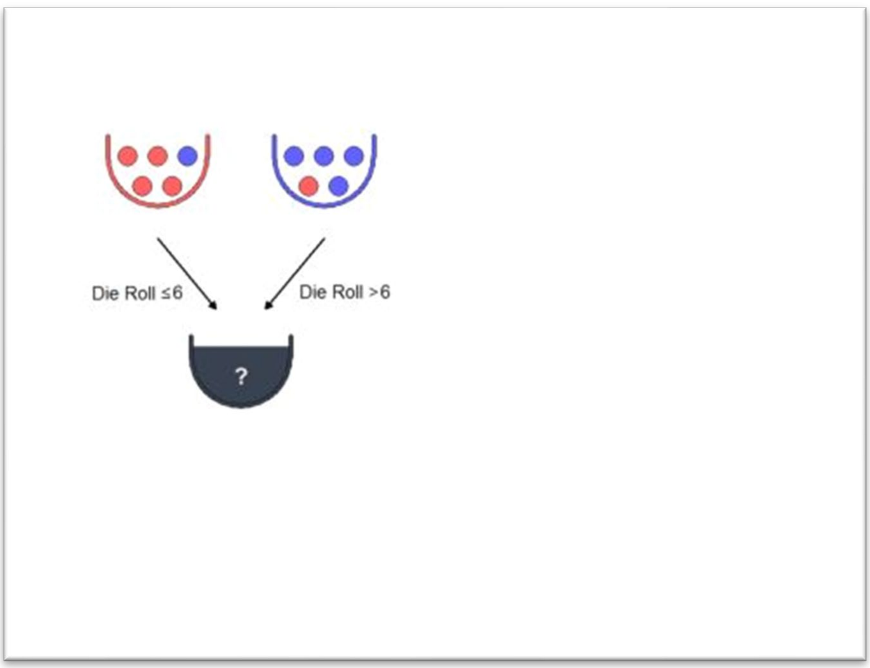
Next the computer selects one of the two urns for the scenario.

It does this using the rule X and a 10-sided die roll.

If the die roll is equal to less than X the red urn is selected.

If it's greater than X, the blue urn is selected.

Because of this rule, the chance of selecting the red urn is X-in-10.

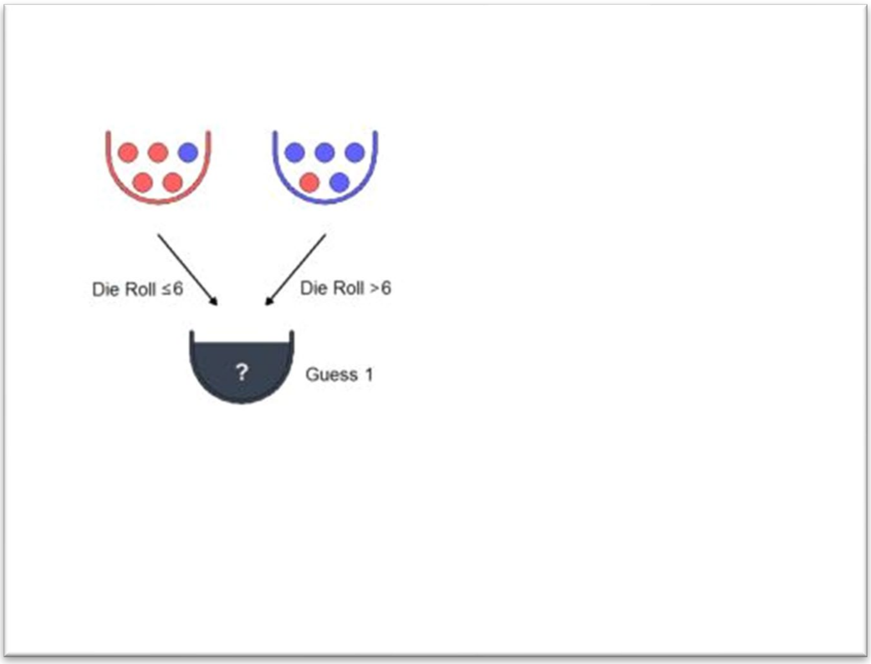


Suppose that X is equal to 6. So for die rolls of 1 to 6 the Red urn is selected.

And for die rolls from 7 to 10 the Blue urn is selected.

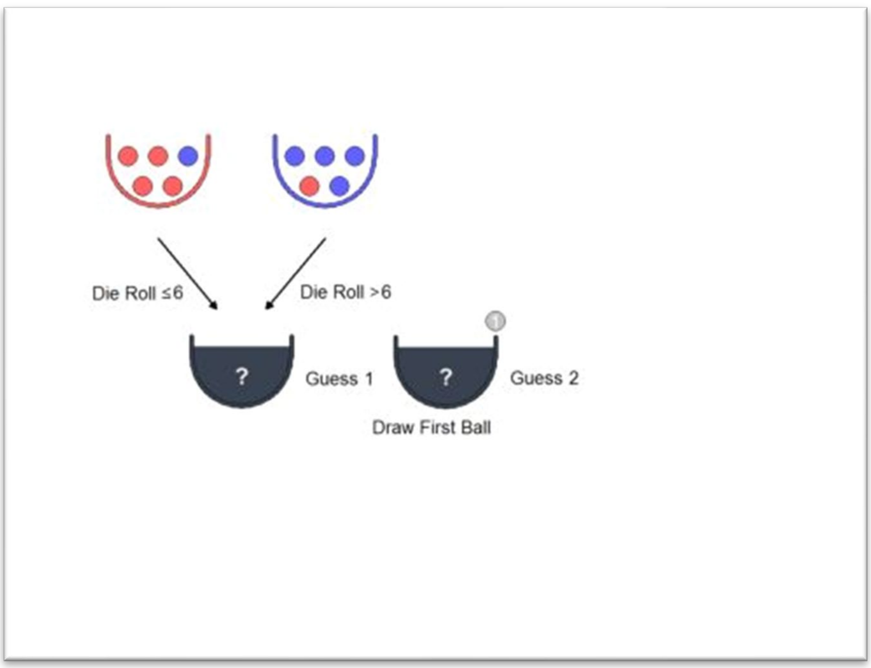
So the chance the red urn is selected is 6-in-10, or 60 percent.

The selected urn remains the same for the entire scenario.



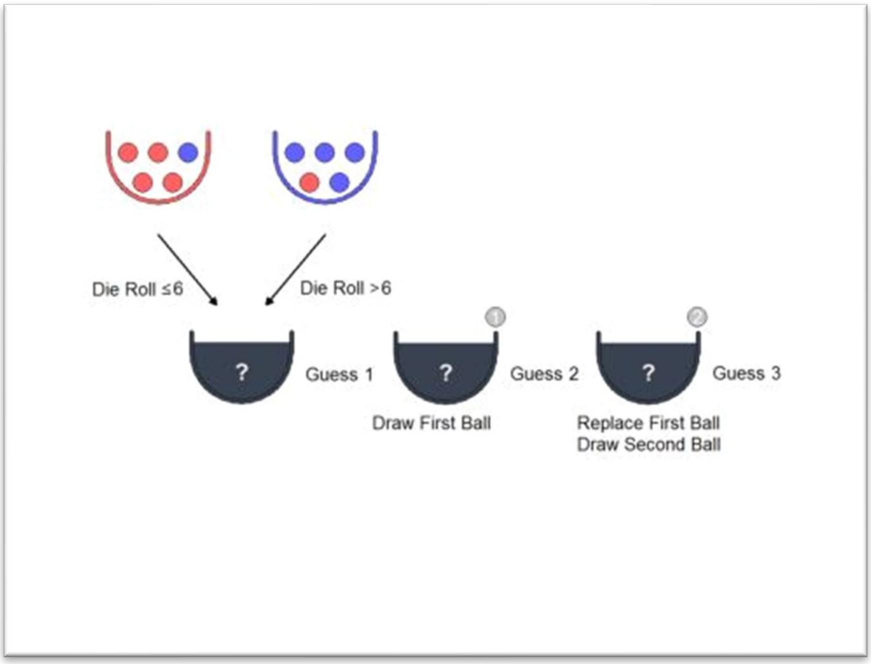
After the computer has selected one of the two urn you make your first guess.

You make your first guess only knowing the die roll rule (here 6) and how many red and blue balls are in each urn.



After you make your first guess, you then get to see a drawn ball from the selected urn. The drawn ball can be either red or blue, where the chance of this depends on which urn was selected for the scenario.

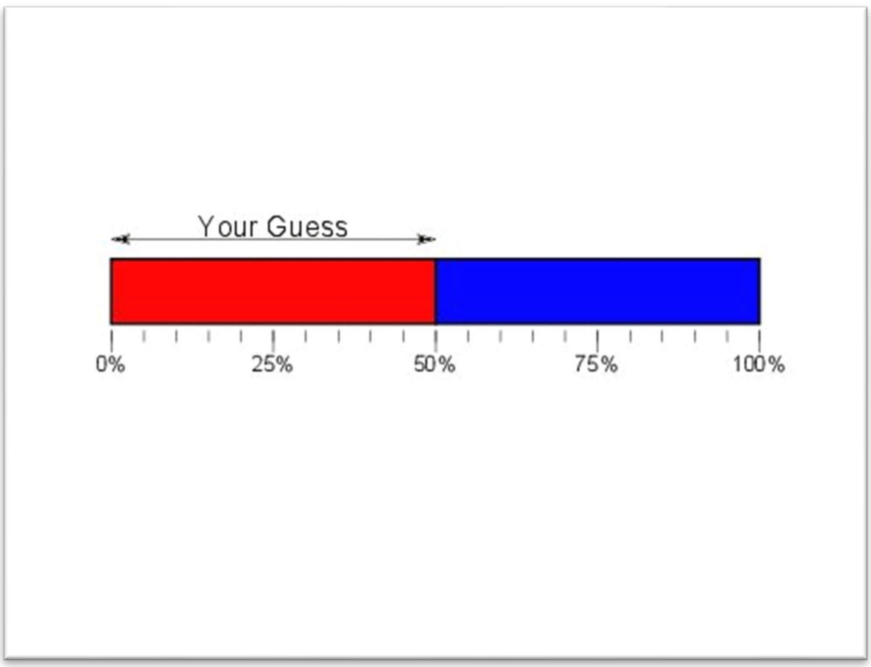
After seeing the color of the drawn ball, you make your second guess.



The first ball is put back into the selected urn, and the balls mixed.

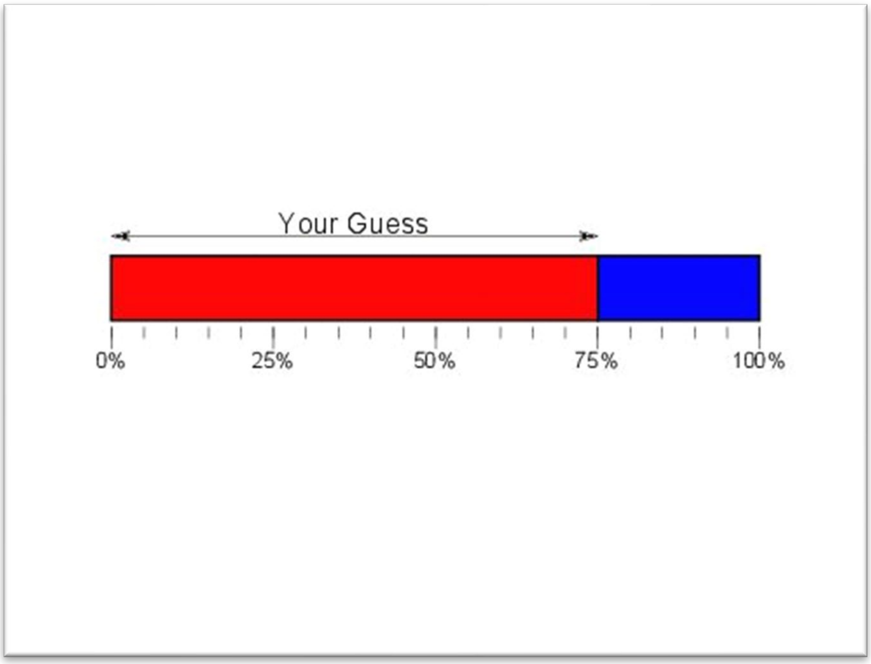
You then draw a second ball from the urn and see what color it is.

After seeing the color, you make your third and final guess.

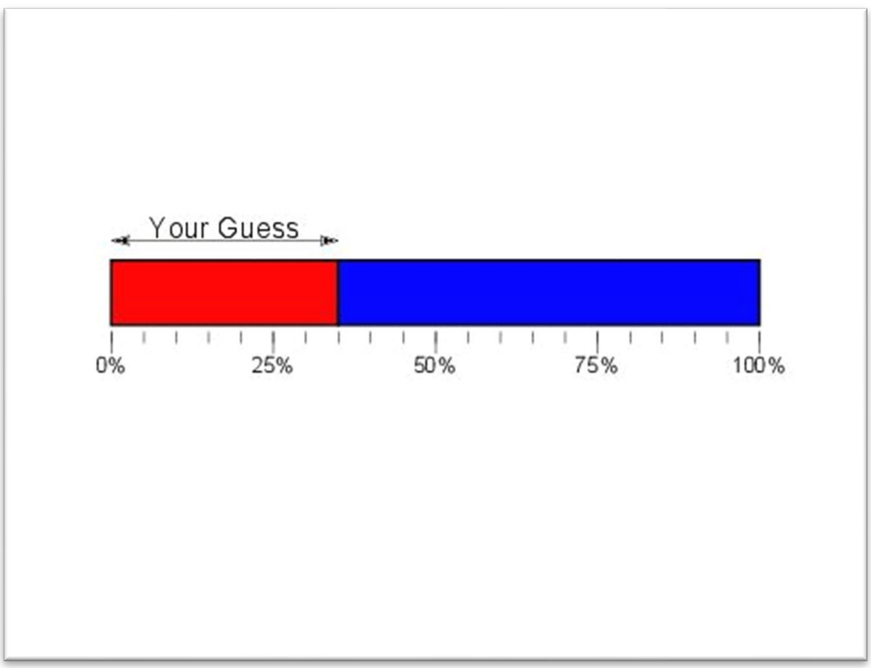


You enter Your Guesses by clicking the response bar on your screen.

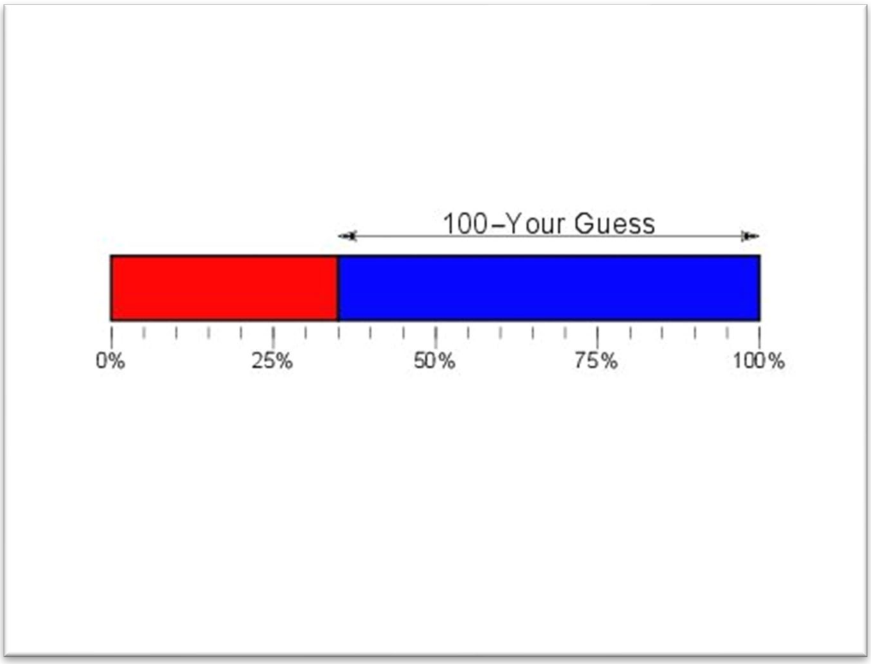
The width of the red part of the bar indicates your percentage chance that the red urn was selected.



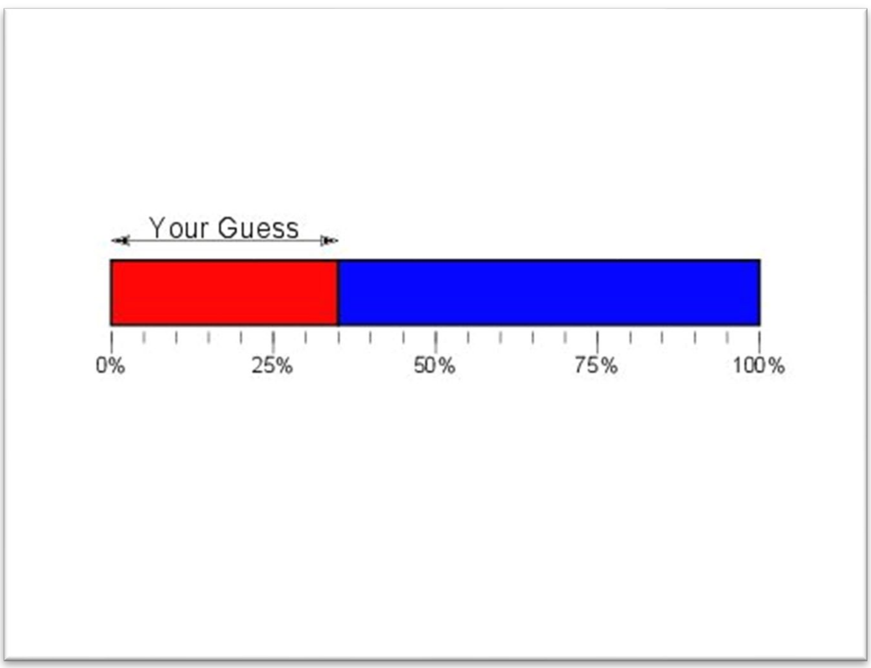
Your Guess is the width of the red part of the bar, and so wider selection represents a greater chance that the Red urn was selected.



A thinner red selection represents a smaller chance that the red urn was selected.

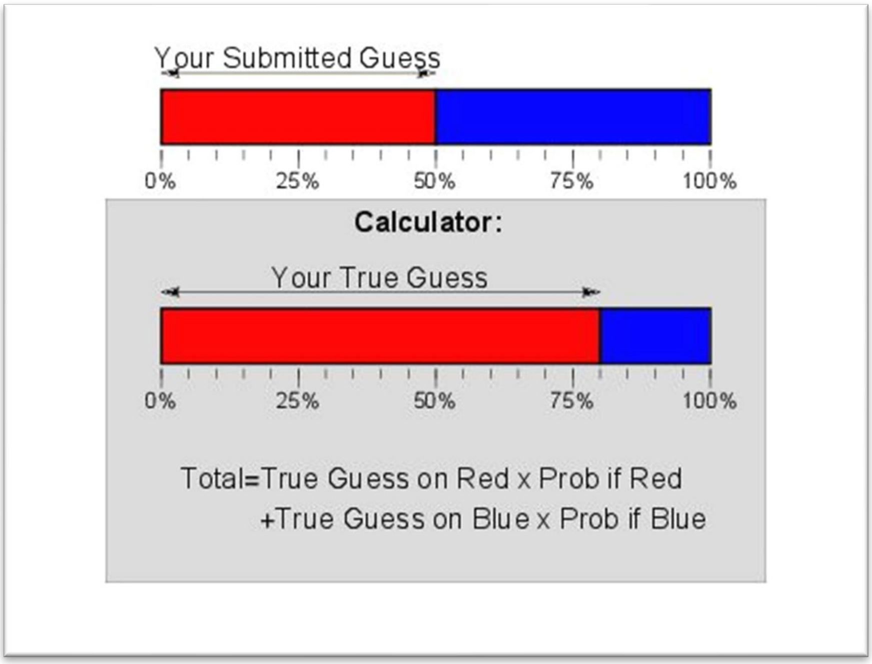


The width of the blue part represents 100-Your Guess and is the percentage chance that the blue urn was selected.



Remember, in every question we ask you for a guess that the Red urn is the selected urn.

[RCL treatment only]



In addition to the bar where you enter Your Submitted Guess, we also provide you with a calculator.

To use the calculator, you enter *Your True Best* guess.

For any selection of Your Submitted Guess and Your True best Guess the calculator will provide you with your total chance of winning.

Your total chance of winning is calculated as

Your True Best Guess on Red times the Likelihood that you Win if Red is Selected, given Your Submitted Guess

+ Your True Best Guess on Blue times the Likelihood that you Win if Blue is Selected, given Your Submitted Guess

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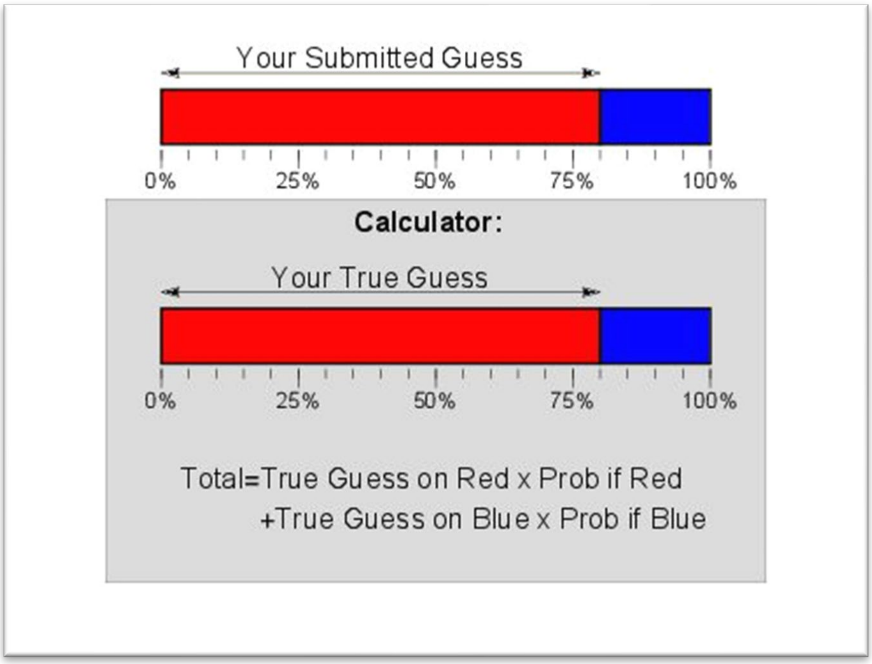
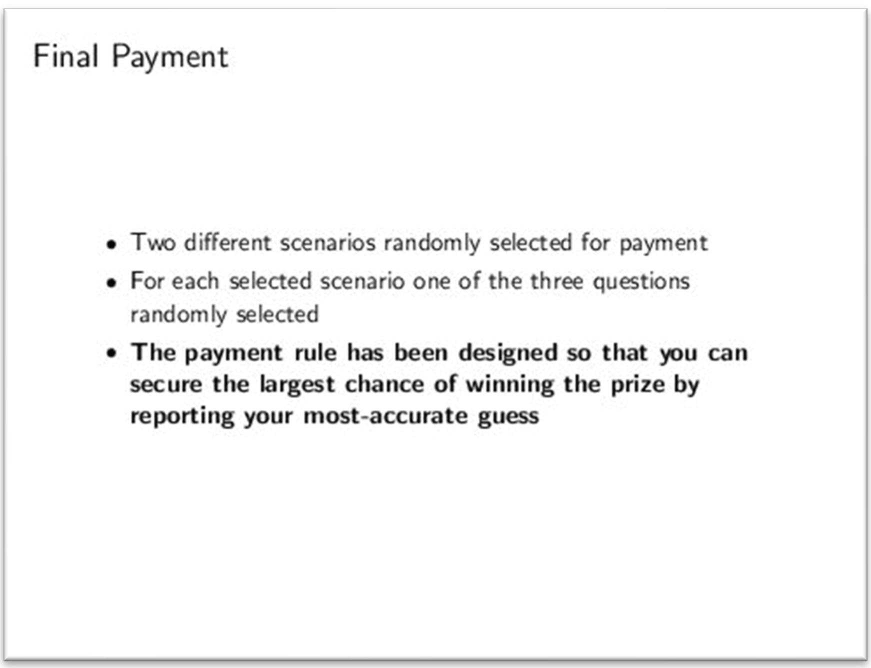
[RCL treatment only]



The calculator allows you to verify that whatever your True Best Guess might be, the payment rule ensures that you will maximize your total chance of winning by setting your submitted guess equal to your True Guess.



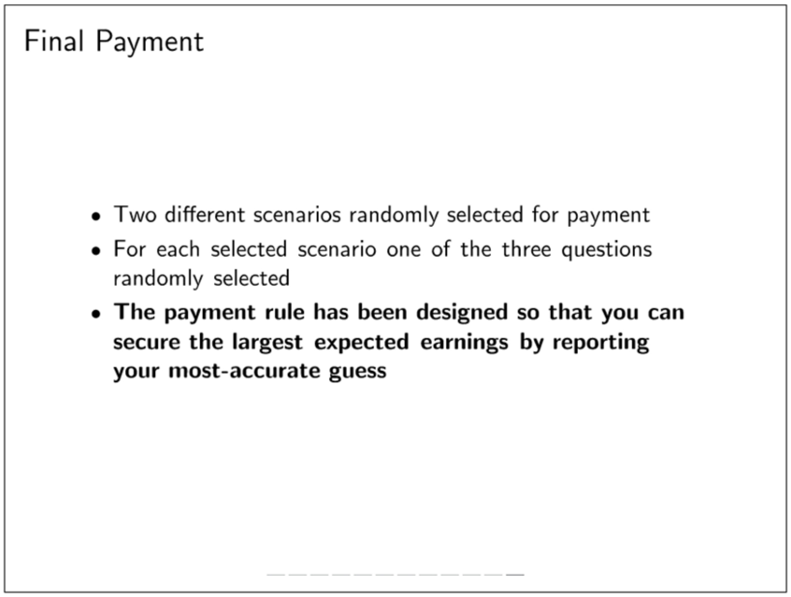
Final Payment for the experiment will be $8 plus payment for two different scenarios.

For each selected scenario one of the three guesses is selected for payment.

The payment rule we use is designed so that you can secure the largest chance of winning the prize by reporting your most-accurate guess [RCL treatment: (Your True Guess)].

We will now start the experiment.

[QSR Treatments only]



Final Payment for the experiment will be $8 plus payment for two different scenarios.

For each selected scenario one of the three guesses is selected for payment.

The payment rule we use is designed so that you can secure the largest expected earnings by reporting your most-accurate guess.

We will now start the experiment.

C.3 NV-replication Elicitation

Core Niederle-Vesterlund Task

[Common to both Information and No-Information]

Welcome

This is an experiment about decision making. The other people in this Zoom session are also participating in the experiment. You must not talk to them or communicate with them in any way. If you have a question, please send the researcher a private chat message over Zoom and we will answer you in private.

The study involves decision tasks. We will give you the details of those decision tasks immediately before proceeding to them. Your decisions in each task are anonymous; no one will be able to determine which decisions were made by you. At the end of the experiment, we will pay you your earnings over Venmo. Your earnings in today's experiment may be affected by your individual decisions, decisions of others, and chance. Your total earnings will equal the sum of your earnings from the tasks plus $6 for showing up to the experiment, plus a payment of $4 for completing the experiment.

We ask that you give us your full attention throughout the experiment. You must remain on Zoom and keep your video on. Please refrain from all other activities, including using your phone and browsing the internet. If we find that you are not paying attention or are violating any rules you will be dismissed with only your show-up payment.

Your current and future status with the University of California, Santa Barbara, and any other benefits for which you qualify will be the same whether you participate in this study or not.

This study is being conducted by researchers at the University of Pittsburgh. The researchers can be reached at [email address].

[Piece-Rate Instructions (Onscreen+ Read aloud)]]

Instructions: Round 1 - Piece Rate

You will first complete four rounds. At the end of the experiment we will randomly select one of the rounds to count for payment. We do this by drawing a number between 1 and 4; with all numbers equally likely to be drawn.

The method we use to determine your earnings varies across rounds. Before each round we will describe in detail how your payment is determined.

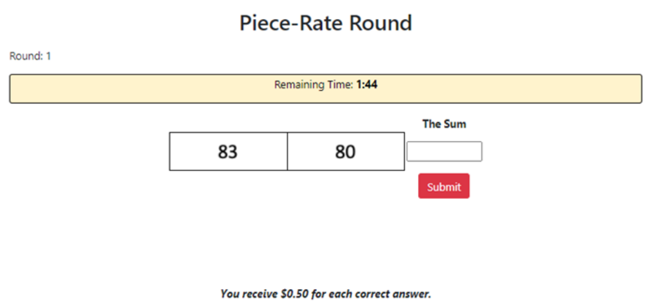
Round 1 - Piece Rate

In Round 1 you will be asked to calculate the sums of two randomly chosen two-digit numbers. You will be given 2 minutes to calculate the correct sums of a series of these problems. The use of a calculator is not permitted. You submit an answer by clicking the submit button with your mouse. When you enter an answer, the computer will immediately tell you whether your answer is correct or not.

If Round 1 is the one randomly selected for payment, then you get $0.50 per problem you solve correctly in the 2 minutes. Your payment does not decrease if you provide an incorrect answer to a problem. We refer to this payment as the piece rate payment.

Please send Researcher 1 a private chat message if you have any questions before we begin.
Please click OK when you have your questions answered and are ready to proceed.

[Piece Rate Real Effort Entry Screen:]



[Tournament Instructions (Onscreen+ Read aloud)]

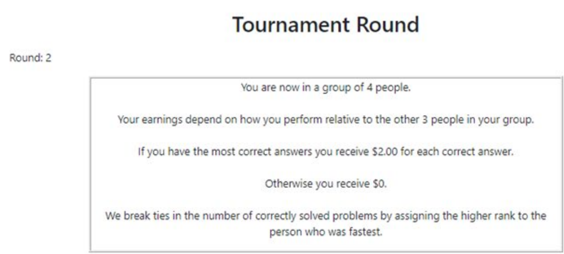
Instructions: Tournament Round

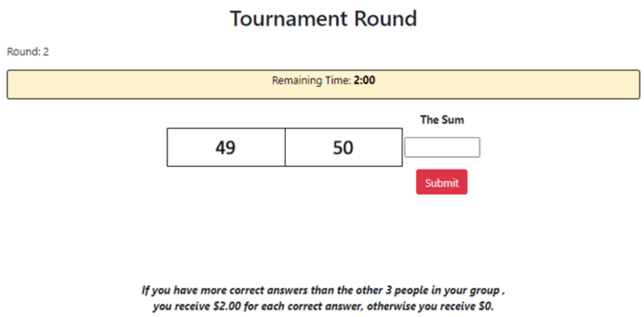
As in Round 1, you will be given 2 minutes to calculate the correct sums of a series of two randomly chosen two-digit numbers. However, in this round your payment depends on your performance relative to that of a group of other participants. Each group consists of four randomly selected people. The three other members of your group are also participants in this Zoom session. If Round 2 is the one randomly selected for payment, then your earnings depend on the number of problems you solve compared to the three other people in your group. The individual who correctly solves the most problems will receive $2.00 per correct problem, while the other participants receive no payment. We refer to this as the tournament payment. You will not be informed of how you did in the tournament until all four rounds have been completed. We break ties in the number of correctly solved problems by assigning the higher rank to the person who was fastest.

Please send Researcher 1 a private chat message if you have any questions before we begin.

Please click OK when you have your questions answered and are ready to proceed.

[Tournament Round Real Effort Screens]





[Incentive Choice (Onscreen+ Read aloud)]

Instructions: Choice Round

As in the previous rounds, you will be given 2 minutes to calculate the correct sums of a series of two randomly chosen two-digit numbers. However, you will now get to choose which of the two previous payment schemes you prefer to apply to your performance in this round.

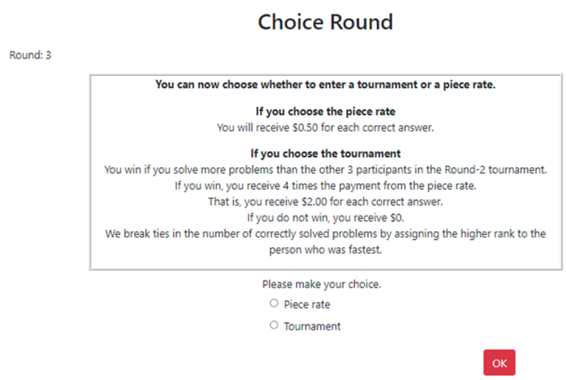
If Round 3 is the one randomly selected for payment, then your earnings for this round are determined as follows. If you choose the *piece rate* you receive $0.50 per problem you solve correctly. If you choose the *tournament* your performance will be evaluated relative to the performance of the other three participants of your group in the Round-2 tournament. The Round-2 tournament is the one you just completed. If you correctly solve more problems than they did in Round 2, then you receive four times the payment from the piece rate, which is $2.00 per correct problem. You will receive no earnings for this round if you choose the tournament and do not solve more problems correctly in this round, than the others in your group did in the Round-2 tournament. You will not be informed of how you did in the tournament until all four rounds have been completed. We break ties in the number of correctly solved problems by assigning the higher rank to the person who was fastest.

The next computer screen will ask you to choose whether you want the piece rate or the tournament applied to your performance in this round. You will then be given 2 minutes to calculate the correct sums of a series of two randomly chosen two-digit numbers.

Please send Researcher 1 a private chat message if you have any questions before we begin.

Please click OK when you have your questions answered and are ready to proceed.

[Choice Round Selection Screen]



Round 4 – Submit Piece Rate

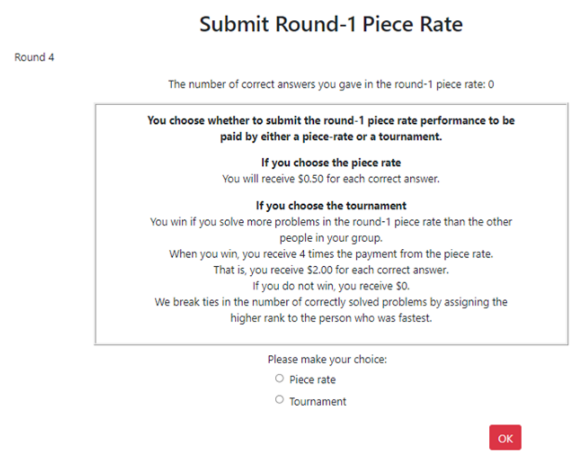
You do not have to add any numbers for the fourth and final round. Instead you may be paid one more time for the number of problems you solved in the Round-1 piece rate. However, you now have to choose which payment scheme you want applied to the number of problems you solved. You can either choose to be paid according to the piece rate, or according to the tournament.

If Round 4 is the one selected for payment, then your earnings for this round are determined as follows. If you choose the piece rate you receive $0.50 per problem you solved in the Round-1 piece rate.

If you choose the tournament your performance will be evaluated relative to the performance of the other three participants in your Round 2 - tournament group. If your number of correctly solved problems on Round 1 is greater than the Round-1 performance of your Tournament group members then you receive four times the earnings of the piece rate, which is equivalent to $2.00 per correct problem. You will receive no earnings for this round if you choose the tournament and did not solve more problems correctly in Round 1 than the other members of your group. The next computer screen will tell you how many problems you correctly solved in Round 1, and will ask you to choose whether you want the piece rate or the tournament applied to your performance.

If you have any questions, please send Researcher 1 a private chat message.
Please click OK when you have your questions answered and are ready to proceed.

[Round 4 Submit Screen]



Elicitation Tasks within NV-Replication

Guess Your Rank

For this question you are asked to guess how your number of correct answers ranked in your group of four. We ask you to guess how likely it is that you were ranked first, second, third or fourth. You do this by entering a percent chance between 0 and 100 for each possible rank, with the four percentages summing up to 100.

Earnings:

We will reward the accuracy of your guess by using a payment rule that secures the highest chance of winning $4 when you provide your most-accurate guess. [Information only: Using your guess, the payment rule provides four chances-to-win—one for each possible rank. The chance-to-win that counts for payment is the one that corresponds to your actual rank.

You will learn your chance-to-win for each of the four possible ranks as soon as you have entered your guess that sums to 100 percent across the four ranks. Suppose you submit a guess of $\{P_1, P_2, P_3, P_4\}$ that each of the four ranks occurred, and that we denote the percent chance you attached to your actual rank by p_A.

Then, your chance-to-win is given by the equation:

$$\text{Chance} - \text{to} - \text{win} = 50(1 + 2\frac{\text{p}_\text{A}}{100} - \text{w})$$

Where w is the sum-of-squares across all four probabilities, $w = \left(\frac{P_1}{100}\right)^2 + \left(\frac{P_2}{100}\right)^2 + \left(\frac{P_3}{100}\right)^2 + \left(\frac{P_4}{100}\right)^2$.

---]

Below you see the form for entering your guess with two valid examples [Information only:-- and the corresponding chance-to-win conditional on each rank being the actual rank---].

Example 1

Suppose you entered the guess shown below:

Possible Rank	Percent Chance
You ranked 1st	0 %
You ranked 2nd	100 %
You ranked 3rd	0 %
You ranked 4th	0 %
Sum total	100%

[No Information Example 1 Image]

Possible Rank	Percent Chance	Chance-to-win $4 Prize (if your actual rank)
You ranked 1st	0 %	0.0%
You ranked 2nd	100 %	100.0%
You ranked 3rd	0 %	0.0%
You ranked 4th	0 %	0.0%
Sum total	100%	

[Information Example 1 Image]

This guess puts a 100 percent chance on your actual rank being second, and a zero percent chance on every other rank. This is a valid guess as the four percentages sum to 100 (100+0+0+0). [Information only:--- The chance-to-win the $4 if each rank was your actual rank is shown in the rightmost column. Your chance-to-win would be 100 percent if your actual rank was second, and you would have 0 percent chance-to-win if your actual rank was first, third or fourth.

To see why, note that the sum-of-squares is 1 ($w = 0^2 + 1^2 + 0^2 + 0^2$). So, if your actual rank was second, then $P_A = P_2 = 1$ and Chance-to-win $= 50 \cdot$

$\left(1+2\frac{P_A}{100}-w\right)=50\cdot(1+2\cdot 1-1)=100$ percent. If instead the rank was fourth, then $P_A=P_4=0$ and the Chance-to-win=$50\left(1+2\frac{P_A}{100}-w\right)=50\cdot(1+2\cdot 0-1)=0$ percent. ---]

Example 2

Suppose instead that you entered the guess shown below:

Possible Rank	Percent Chance
You ranked 1st	25 %
You ranked 2nd	25 %
You ranked 3rd	25 %
You ranked 4th	25 %
Sum total	100%

[No Information Example 2 Image]

Possible Rank	Percent Chance	Chance-to-win $4 Prize (if your actual rank)
You ranked 1st	25 %	62.5%
You ranked 2nd	25 %	62.5%
You ranked 3rd	25 %	62.5%
You ranked 4th	25 %	62.5%
Sum total	100%	

[Information Example 2 Image]

This guess puts an equal chance on your rank being first, second, third or fourth. This is a valid guess as the four percentages sum to 100 (25+25+25+25).

[Information only:--- Suppose your actual rank was second then your chance-to-win $4 is 62.5 percent. This is because the sum-of-squares is $w=0.25^2+0.25^2+0.25^2+0.25^2=0.25$. Attaching a 25 percent chance to your actual rank, $P_A=P_2=0.25$, your Chance-to-win= $50\left(1+2\frac{P_A}{100}-w\right)=50\cdot(1+2\cdot 0.25-0.25)=62.5$ percent. If instead you were ranked fourth, then $P_A=P_4=0.25$, with the same w, and so the chance-to-win is again 62.5 percent.

---]

You can revise your guess [Information only: and review your corresponding chance-to-win for each of the four ranks] until you are ready to finalize your report.

Remember the payment rule is set so that you will have the highest chance of winning $4 when you provide your most-accurate guess of how likely it is that you were ranked first, second, third or fourth.

If you have any questions, please send Researcher 1 a private chat message before we begin. Please click OK when you have your questions answered and are ready to proceed.

Decision Screen: Tournament Belief

Guess Round 2 – Tournament Rank

Think back to your performance on the Round 2 – Tournament. What do you think your rank was relative to the other participants in your group? Please indicate below how likely you believe it is that you held each of the following ranks.

You must enter integers that add up to 100. You receive $4 if you win and $0 if you lose.

Click "Finalize Decision" to finalize your decision.

[Example input screen: initialized]

Guess Round 2 - Tournament Rank

Think back to your performance on the Round 2 - Tournament. What do you think your rank was relative to the other participants in your group? Please indicate below how likely you believe it is that you held each of the following ranks.

You must enter integers that add up to 100. You receive $4 if you win and $0 if you lose.
Click "Finalize Decision" to finalize your decision.

Possible Rank	Percent Chance	Chance-to-win $4 Prize (if your actual rank)
You ranked 1st	0 %	
You ranked 2nd	0 %	
You ranked 3rd	0 %	
You ranked 4th	0 %	
Sum total		

(The "Finalize Decision" button will appear after the instructions are finished being read aloud.)

Decision Screen: Piece Rate Belief

Guess Round 1 – Piece Rate

Think back to your performance on the Round 1 – Piece Rate. What do you think your rank was relative to the other participants in your group? Please indicate below how likely you believe it is that you held each of the following ranks.

You must enter integers that add up to 100. You receive $4 if you win and $0 if you lose.

Click "Finalize Decision" to finalize your decision.

Guess Round 2 - Tournament Rank

Think back to your performance on the Round 2 - Tournament. What do you think your rank was relative to the other participants in your group? Please indicate below how likely you believe it is that you held each of the following ranks.

You must enter integers that add up to 100. You receive $4 if you win and $0 if you lose.
Click "Finalize Decision" to finalize your decision.

Possible Rank	Percent Chance	Chance-to-win $4 Prize (if your actual rank)
You ranked 1st	0 %	
You ranked 2nd	0 %	
You ranked 3rd	0 %	
You ranked 4th	0 %	
Sum total		

(The "Finalize Decision" button will appear after the instructions are finished being read aloud.)

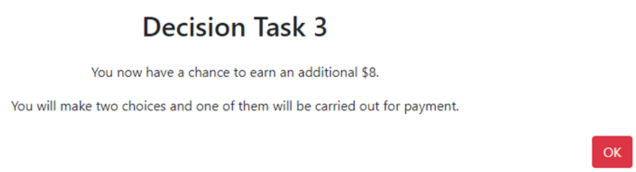
C.4 Incentives-only Treatment

These instructions were attached as module following a strategic study of public-good provision with two previous tasks.

[Intro to task screen:]

> **Decision Task 3:**
>
> You now have a chance to earn an additional $8.
>
> You will make two choices and one of them will be carried out for payment.

[Screenshot:]



[Decision Screen, Choice 1:]

Decision Task 3: Choice 1

You will choose a pair of lottery tickets, one red and one blue. Only one of the lottery tickets will count for payment. **There is a 30% chance that the red lottery ticket is the one that counts and therefore a 70% chance that the blue lottery ticket is the one that counts.** Each lottery ticket gives you a chance of winning $8, and the chance of winning varies. You get to decide which pair of lottery tickets will count for you (A through K). Please select the pair of lottery tickets that you want by clicking your preferred row.

[There then follows a table of eleven lotteries:]

	Chance of winning $8	
Lottery pair	**Red lottery ticket**	**Blue lottery ticket**
A	100%	0%
B	99%	19%
C	96%	36%
D	91%	51%
E	84%	64%
F	75%	75%
G	64%	84%
H	51%	91%
I	36%	96%
J	19%	99%
K	0%	100%

[Screenshot:]

Decision Task 3: Choice 1

You will choose a pair of lottery tickets, one red and one blue. Only one of the lottery tickets will count for payment. **There is a 30% chance that the red lottery ticket is the one that counts and therefore a 70% chance that the blue lottery ticket is the one that counts.** Each lottery ticket gives you a chance of winning $8, and the chance of winning varies. You get to decide which pair of lottery tickets will count for you (A through K). Please select the pair of lottery tickets that you want by clicking your preferred row.

		Chance of winning $8	
	Lottery pair	Red lottery ticket	Blue lottery ticket
○	A	100%	0%
○	B	99%	19%
○	C	96%	36%
○	D	91%	51%
○	E	84%	64%
○	F	75%	75%
○	G	64%	84%
○	H	51%	91%
○	I	36%	96%
○	J	19%	99%
○	K	0%	100%

Next

[Decision Screen, Choice 1:]

Decision Task 3: Choice 2

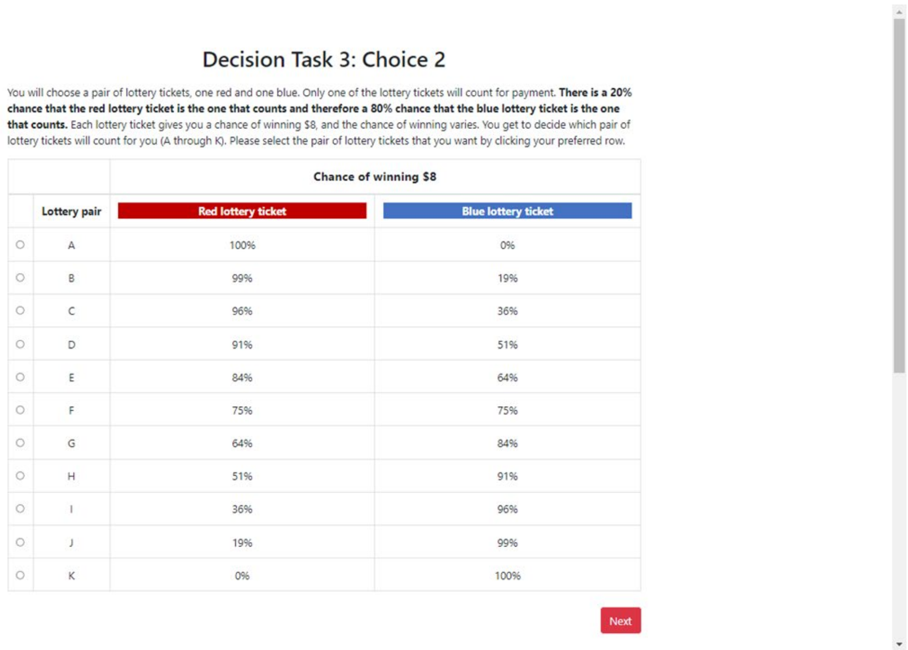
You will choose a pair of lottery tickets, one red and one blue. Only one of the lottery tickets will count for payment. **There is a 20% chance that the red lottery ticket is the one that counts and therefore a 80% chance that the blue lottery ticket is the one that counts.** Each lottery ticket gives you a chance of winning $8, and the chance of winning varies. You get to decide which pair of lottery tickets will count for you (A through K). Please select the pair of lottery tickets that you want by clicking your preferred row.

[There then follows a table of eleven lotteries:]

	Chance of winning $8	
Lottery pair	**Red lottery ticket**	**Blue lottery ticket**
A	100%	0%
B	99%	19%
C	96%	36%
D	91%	51%
E	84%	64%
F	75%	75%
G	64%	84%
H	51%	91%
I	36%	96%
J	19%	99%

K	0%	100%

[Screenshot:]



Decision Task 3: Choice 2

You will choose a pair of lottery tickets, one red and one blue. Only one of the lottery tickets will count for payment. **There is a 20% chance that the red lottery ticket is the one that counts and therefore a 80% chance that the blue lottery ticket is the one that counts.** Each lottery ticket gives you a chance of winning $8, and the chance of winning varies. You get to decide which pair of lottery tickets will count for you (A through K). Please select the pair of lottery tickets that you want by clicking your preferred row.

		Chance of winning $8	
	Lottery pair	Red lottery ticket	Blue lottery ticket
○	A	100%	0%
○	B	99%	19%
○	C	96%	36%
○	D	91%	51%
○	E	84%	64%
○	F	75%	75%
○	G	64%	84%
○	H	51%	91%
○	I	36%	96%
○	J	19%	99%
○	K	0%	100%

Next