Online Appendix

Expectations-Based Loss Aversion May Help Explain Seemingly Dominated Choices in Strategy-Proof Mechanisms.

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A Correlated Admission Probabilities

In the main text, we consider a setting in which a rejection from school i is completely uninformative about the probability of admission to school j. This is done mainly in order to simplify notation and to make the presentation of our predictions clear. We now focus on the other extreme case, where school priorities are perfectly correlated, which we view as the most empirically relevant alternative. We show that our main results hold. We apply this extension to the two-school flipping example (section 2.3) and (in appendix D) to the general n-school extension (section 2.5). The application to omissions is straightforward but less insightful.

As in the main text, we assume that a latent variable $\epsilon_{\theta s}$ reflects the θ-indexed applicant's priority at school s; she gets admitted (conditional on proposing) if $\epsilon_{\theta s} > \kappa_s$ for some known cutoff κ_s. Dropping the subscript θ for ease of presentation, the probability of admission to a school conditional on proposing to it is therefore given by

$$Pr(\epsilon_{\theta s} \geq \kappa_s | \text{Rejections from schools ranked above } s).$$

Departing from the main text, we do not assume $\epsilon_s \perp \epsilon_{s'}$ $\forall s \neq s'$. Instead, we assume the other extreme, i.e., $\epsilon_s = \epsilon$ for all $s \in S$, that is, priorities are perfectly correlated. Assume that ϵ is distributed according to a continuous, strictly increasing CDF F. Then we can assume WLOG that ϵ is uniformly distributed over $[0, 1]$ and that each school's threshold κ_s is in $[0, 1]$.[1] Conditional on a rejection from a school with a threshold κ_s, ϵ is uniformly distributed on $[0, \kappa_s]$. Redefine $q_i \equiv 1 - \kappa_{s_i}$ to be the probability of admission to school s_i *when it is ranked first*. Then conditional on a rejection from school s_j, the updated probability of admission to school s_i is not q_i (as in the zero-correlation case in the main text) but $\max\left\{\frac{q_i - q_j}{1 - q_j}, 0\right\}$.

As before, we denote the list $s_1 \widehat{\succ} s_2$ by r^*. In addition, we denote the flipped list $s_2 \widehat{\succ} s_1$ by r'. The unconditional probabilities given each list are therefore $p_1(r^*) = q_1$, $p_2(r^*) = q_2 - q_1$ and $p_1(r') = 0$, $p_2(r') = q_2$. Inequality (3) from the main text now takes the form

$$[2q_1 - (\lambda - 1)\, q_1\,(1 - q_1)]\, m < 2q_1 - (\lambda - 1)\,[q_2\,(1 - q_2) - (q_2 - q_1)\,(1 - (q_2 - q_1))]\,, \qquad (1)$$

where $m \equiv \frac{m_1}{m_2}$.

To get a sense of how correlation quantitatively affects our predictions, we can go back

[1] To see why, notice that since F is strictly monotonic, $\epsilon \geq \kappa_s$ is equivalent to $F(\epsilon) \geq F(\kappa_s)$ and that since F is continuous, $F(\epsilon)$ is uniformly distributed over the unit interval.

to the example from section (2.3), where $q_1 = \frac{1}{2}$, $q_2 = 1$, and $\lambda = 3$. With these parameters, the condition for flipping reduces to $m < 3$, the same cutoff as in the uncorrelated case from the main text. However, with $q_1 = \frac{1}{4}$, $q_2 = \frac{1}{2}$ and $\lambda = 3$, the condition for flipping becomes $m < 3$ in the correlated case but $m < 2\frac{1}{3}$ in the uncorrelated case. It can be shown that given λ and the same baseline probabilities q_1 and q_2, the range of m such that flipping is preferred is weakly wider in the perfect- than in the zero-correlation case, as is clearly visible in figure 1.

B Prior Expectations

B.1 Two Schools

In this section we relax the assumption that Lori's inherited beliefs are 0 in all dimensions, and examine other possible prior expectations. We consider three possible beliefs entering submission period: (a) Lori expected to attend s_1 (with probability 1); (b) Lori expected to attend s_2 (with probability 1); and (c) Lori expected the lottery generated by ranking truthfully (that is, attending s_1 with probability q_1 and s_2 with probability $(1 - q_1)q_2$).

Table B.1: Utility with Prior Expectations

Submission Utility	Prior Expectations			
	$(s_1, 0; s_2, 0)$ (Baseline)	$(s_1, 1)$ (s_1 for sure)	$(s_2, 1)$ (s_2 for sure)	$L\left(s_1 \widehat{\succ} s_2\right)$ (Truthful)
$u_1\left(L\left(s_1 \widehat{\succ} s_2\right)\right)$	$q_1 m_1 + (1 - q_1) q_2 m_2$	$-\lambda(1 - q_1) m_1 + (1 - q_1) q_2 m_2$	$q_1 m_1 - \lambda(1 - (1 - q_1) q_2) m_2$	0
$u_1\left(L\left(s_2 \widehat{\succ} s_1\right)\right)$	$(1 - q_2) q_1 m_1 + q_2 m_2$	$-\lambda(1 - (1 - q_2) q_1) m_1 + q_2 m_2$	$(1 - q_2) q_1 m_1 - \lambda(1 - q_2) m_2$	$-\lambda q_1 q_2 m_1 + q_2 q_1 m_2$
$u_1\left(L\left(s_1\right)\right)$	$q_1 m_1$	$-\lambda(1 - q_1) m_1$	$q_1 m_1 - \lambda m_2$	$-\lambda(1 - q_1) q_2 m_2$
$u_1\left(L\left(s_2\right)\right)$	$q_2 m_2$	$-\lambda m_1 + q_2 m_2$	$-\lambda(1 - q_2) m_2$	$-\lambda q_1 + q_1 q_2 m_2$
$u_1\left(L\left(\emptyset\right)\right)$	0	$-\lambda m_1$	$-\lambda m_2$	$-\lambda q_1 m_1 - \lambda(1 - q_1) q_2 m_2$

Notes: Period-1 news utility from submitting different ROLs, given different prior expectations.

Table B.1 shows period-1 news utility from all possible ROLs, given different prior expectations, assuming independent priorities. In general, period-1 utility in each dimension i in this case is given by

$$u_1^i\left(p|\hat{p}\right) = \begin{cases} (p_i - \hat{p}_i) m_i & p_i \geq \hat{p}_i \\ -\lambda(\hat{p}_i - p) m_i & \hat{p}_i > p_i \end{cases},$$

where p_i denotes as usual the ROL-determined probability of attending s_i, and $\hat{p}_i$ denotes the probability Lori assigned to attending s_i entering period 1. Since Lori updates her beliefs according to her submitted ROL, period-2 utility is not affected by prior expectations. Of course, period-3 consumption utility is not affected by prior beliefs either.

When Lori enters period 1 expecting to attend a school s_i with probability 1 (that is, when $\hat{p}_i = 1$), the incentive to omit s_i from the ROL completely vanishes. To see why, observe that for any p_i, $\lambda m_i > \lambda(1-p_i)m_i + (\lambda-1)p_i(1-p_i)m_i$. The LHS of this inequality is the cost of omitting s_i, and the RHS is the cost of including it, both assuming $\hat{p}_i = 1$. Using similar arguments, we can show that the same is true for *both* schools when prior expectations are the lottery generated by the submission of a truthful list.

Figures B.1-B.3 show the model's predicted submission for various values of q_1, q_2, m and λ, assuming independent priorities (panel a) and perfectly correlated priorities (panel b).

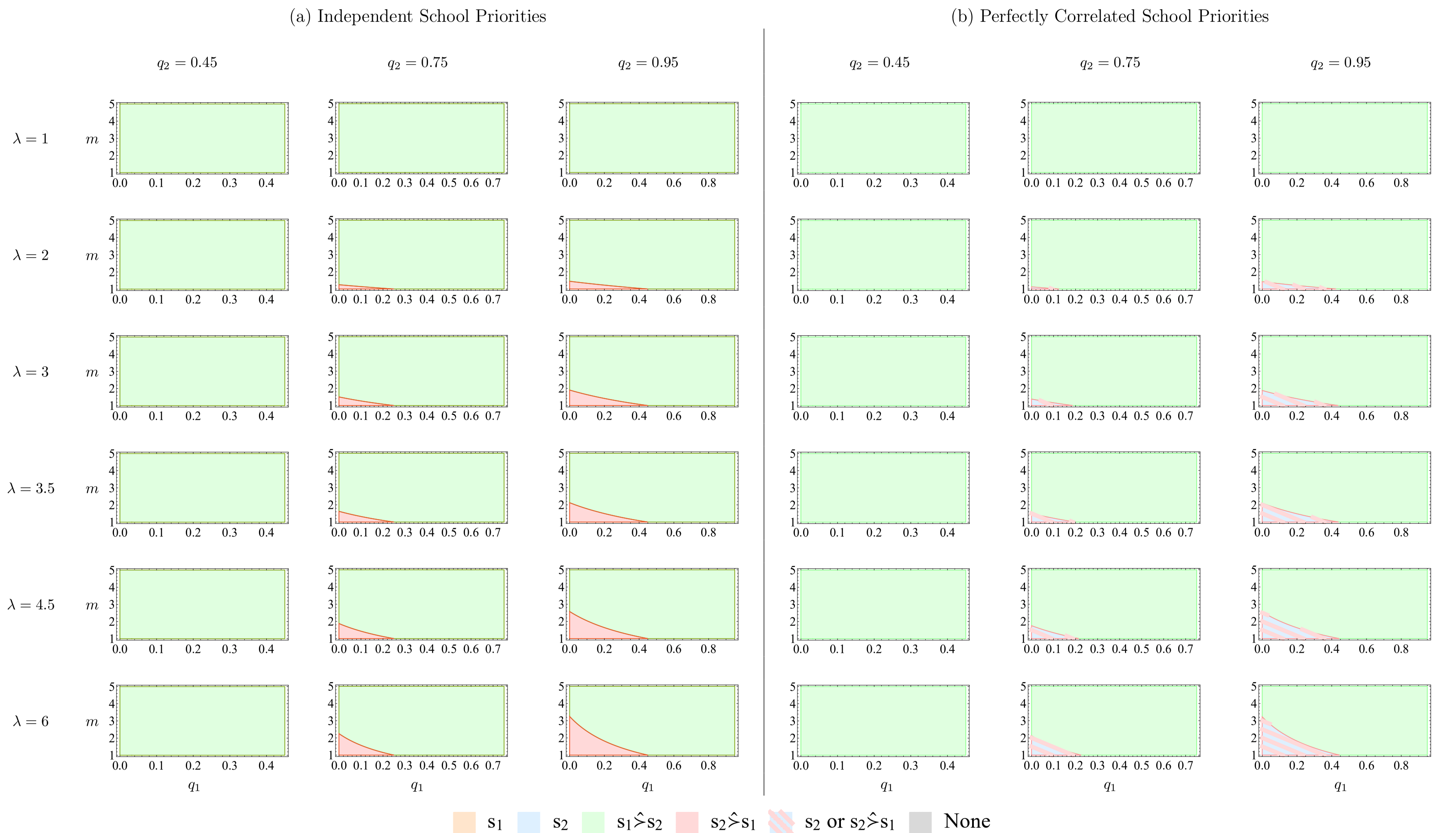
Figure B.1: Theoretical Predictions (Prior $(s_1, 1)$)

Notes: Model-predicted submitted list as a function of the model's parameters: each subplot shows the model's predictions for combinations of q_1 and m, fixing q_2 and λ. "s_1" and "s_2" denote lists containing only one school, with the other school omitted (s_1 is the preferred school). "None" denotes an empty list. Prior expectations: s_1 with certainty.

Figure B.2: Theoretical Predictions (Prior $(s_2, 1)$)

Notes: Model-predicted submitted list as a function of the model's parameters: each subplot shows the model's predictions for combinations of q_1 and m, fixing q_2 and λ. "s_1" and "s_2" denote lists containing only one school, with the other school omitted (s_1 is the preferred school). "None" denotes an empty list. Prior expectations: s_2 with certainty.

Figure B.3: Theoretical Predictions (Prior $L\left(s_1 \widehat{\succ} s_2\right)$)



Notes: Model-predicted submitted list as a function of the model's parameters: each subplot shows the model's predictions for combinations of q_1 and m, fixing q_2 and λ. "s_1" and "s_2" denote lists containing only one school, with the other school omitted (s_1 is the preferred school). "None" denotes an empty list. Prior expectations: the lottery generated by the submission of a truthful list.

B.2 Funded Positions

We now examine the effect of prior expectations on observed violations of FOSD (obvious misrepresentations). Let $\hat{p}$ be the probability that Lori assigns to getting a funded position entering period 1. The amount of funding is given by $\$x$. In period 1 Lori learns that if she ranks the funded position truthfully, she will get it with probability p. For simplicity, we focus on the omission versus ranking truthfully only. First, if Lori is overoptimistic, that is, if $\hat{p} > p$, omission is preferred to ranking truthfully iff

$$-\lambda\hat{p}m^{\text{money}}(x) > -\lambda(\hat{p} - p)m^{\text{money}} - (\lambda - 1)p(1 - p)m^{\text{money}} + pm^{\text{money}}.$$

It is straightforward to see that this inequality never holds, so Lori is never predicted to omit funding in this case.

Second, if Lori is pessimistic (or otherwise is less aware of funding prior to the submission period), or $\hat{p} < p$, then she prefers to omit over ranking truthfully iff

$$-\lambda\hat{p}m^{\text{money}}(x) > (p - \hat{p})m^{\text{money}} - (\lambda - 1)p(1 - p)m^{\text{money}} + pm^{\text{money}},$$

which reduces to

$$\hat{p} < p(1 - p - \frac{2}{\lambda - 1}),$$

which means that if Lori enters period 1 with enough pessimism about her chances of receiving funding, and if she is sufficiently loss averse, she is predicted to obviously misrepresent.

C Omissions

We can analyze Lori's decision when allowing for omissions and assuming $\lambda > 3$ in a few simple steps. First, we check if $U(L(s_2)) \geq 0$, or $q_2 \geq$ þ. Since $q_1 < q_2$, if this inequality does not hold, Lori will not submit a ROL at all: even though she wants to attend a school, she does not apply to any school in order to avoid disappointment. Second, we check if $U(L(s_1)) > 0$, or $q_1 \geq$ þ. It is straightforward to see that if $q_1 <$ þ $\leq q_2$, Lori ranks only s_2. If both q_1 and q_2 are greater than þ, we check whether Lori will want to add s_1 to her list below s_2. Since $q_1(1 - q_2) < q_2(1 - q_1)$ by assumption, if $q_1(1 - q_2) >$ þ holds, then Lori will list both schools, and the analysis continues as in 2.3. If adding s_2 under s_1 is utility *decreasing* ($q_2(1 - q_1) <$ þ), then Lori ranks only one school and compares between s_1 and s_2.[2] She submits s_2 if $U(L(s_2)) > U(L(s_1))$, and s_1 otherwise. Note that this

[2]Note that the omission of s_2 is possible even when s_2 is a "safe school," that is, even when $q_2 = 1$. Since $q_1 < 1$, there is a chance that Lori will not get matched with any school, and yet, she chooses not to rank

inequality depends both on λ and the probabilities, which determine the degree of expected loss, and on m, which captures by how much Lori prefers s_1 over s_2. In words, Lori trades off her future expected loss and future consumption utility. Last, if $q_2(1-q_1) > þ$ but $q_1(1-q_2) < þ$ then Lori compares $s_1 \widehat{\succ} s_2$ and s_2, which also trades off between future loss and future consumption.

D Proof of Section 2.5's Proposition

Proof. Denote the truthful ROL by r^*. Assume by contradiction that there exists such a pair s_i, s_{i+1}, and that for every m_i, m_{i+1}, r^* is optimal.

Denote $p_j(r^*)$ by p_j:

$$p_j \equiv (1-q_1)\cdot(1-q_2)\cdot\ldots\cdot(1-q_{j-1})\cdot q_j = q_j \cdot \prod_{k=1}^{j-1}(1-q_k).$$

Denote $\widetilde{q_1} \equiv p_i$ and $\widetilde{q_2} \equiv q_{i+1}\cdot \prod_{k=1}^{i-1}(1-q_k)$. Hence, $\widetilde{q_1}$ and $\widetilde{q_2}$ are the (unconditional) probabilities of getting matched with schools s_i and s_{i+1}, respectively, if they are ranked at the ith place (with the remainder of the list according to r^*). Notice that if we restrict our attention to dimensions i and $i+1$, $\widetilde{q_1}$ and $\widetilde{q_2}$ are the same as q_1 and q_2 from section 2.3. Since $q_{i+1} > q_i$ by assumption, we have $\widetilde{q_2} > \widetilde{q_1}$. We can now proceed with the analysis as in section 2.3 from the main text, focusing on schools s_i and s_{i+1}: If Lori flips s_i and s_{i+1} keeping the rest of her ranking unchanged, then p_j, and thus u^j, will remain constant for $j \neq i, i+1$. If m_i, m_{i+1} satisfy (3) (it is straightforward to see that if $\widetilde{q_1} > \widetilde{q_2}$, we can find such m_i, m_{i+1}), flipping s_i and s_{i+1} will strictly increase $u^i + u^{i+1}$, without changing the utility in all other dimensions, and therefore ranking truthfully is not optimal.

We can extend the proof to the perfectly correlated case in a straightforward way using the same general definition of q_i as the probability of acceptance to a school when it is ranked first. That is, we let $S = \{s_1, s_2, ..., s_n\}$ again be a set of schools, ordered from the most to least preferred, and $\boldsymbol{\kappa} = (\kappa_1, ..., \kappa_n)$ be the corresponding cutoffs with $\kappa_j \in (0,1)\ \forall j = 1, ..., n$, such that there exists at least one pair of schools s_i, s_{i+1} with $\kappa_i > \kappa_{i+1}$. As above, we consider two ROLs r^* and r', which are identical except that r' flips schools i and $i+1$. We therefore know that $p_j(r^*) = p_j(r')$ for all $j < i$ (because in both ROLs the order is identical up to i) and for all $j > i+1$ (because they are both conditioning on rejections from the same set of schools). Denote the variable $\epsilon |$rejections from schools $1, ...i-1$ by $\widetilde{\epsilon}$. We can then redefine the cutoffs κ_i, κ_{i+1} as $\widetilde{\kappa}_1, \widetilde{\kappa}_{i+1}$ so that $\widetilde{\epsilon}$ is uniformly distributed over the unit interval as in A,

school s_2 at all.

and $\widetilde{\kappa}_{i+1} < \widetilde{\kappa}_i$, so using the same notation as above we have $\widetilde{q}_2 > \widetilde{q}_1$. We can find $m \equiv \frac{m_i}{m_{i+1}}$ satisfying (1), and therefore flipping strictly improves Lori's utility in dimensions i and $i+1$ as above, and we are done. Below we show that for any $0 < q_1 < q_2 \leq 1$ there exists m that satisfies inequality (1), provided that $\lambda > 1$. $\square$

Showing that for any $\lambda > 1$ there exists m satisfying inequality (1). Notice that (1) can be written as

$$2q_1 (m-1) < (\lambda - 1) \left[q_1 (1-q_1) m - q_1^2 - q_1 + 2q_1 q_2\right].$$

Since $\lambda > 1$ and $q_1 < q_2$, at $m = 1$, we have

$$\text{LHS} = 0 < \text{RHS} = (\lambda - 1) \left(2q_1 q_2 - 2q_1^2\right).$$

Since both the RHS and the LHS are linear (and in particular continuous) in m, there exists $m > 1$ that satisfies the inequality.

E Instructions (Reproduced From Li, 2017)

<u>GAME 3</u>

You will play this game for 10 rounds. In each round of this game, there are four prizes, labeled A, B, C, and D. Prizes will be worth between $0.00 and $1.25. For each prize, its value will be **the same for all the players** in your group.

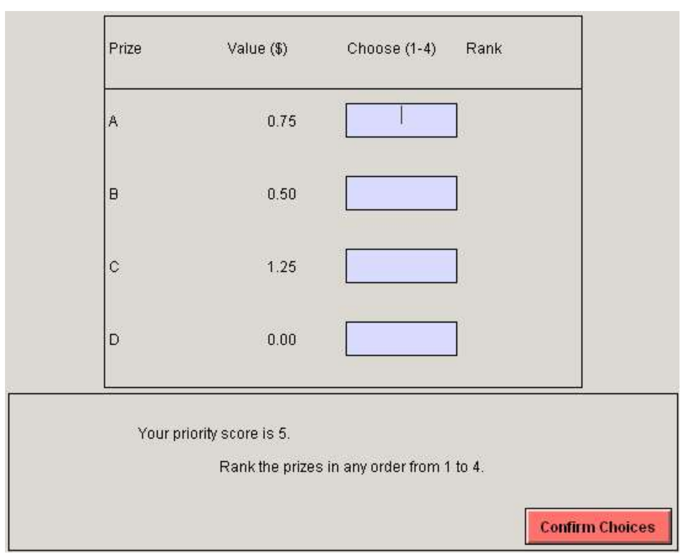
At the start of each round, you will learn the value of each prize. You will also learn your priority score, which is a random number between 1 and 10. Every whole number between 1 and 10 is equally likely to be chosen.

The game proceeds as follows: We will ask you to list the prizes, **in any order of your choice**. All players will submit their lists privately and at the same time.

After all the lists have been submitted, we will assign prizes using the following rule:
1. The player with the highest priority score will be assigned the top prize on his list.
2. The player with the second-highest priority score will be assigned the top prize on his list, among the prizes that remain.
3. The player with the third-highest priority score will be assigned the top prize on his list, among the prizes that remain.
4. The player with the lowest priority score will be assigned whatever prize remains.

If two players have the same priority score, we will break the tie randomly.

You will have 90 seconds to form your list. You do this by typing a number, from 1 to 4, next to each prize, and then clicking the button that says “Confirm Choices”. Each prize must be assigned a different number, from 1 (top) to 4 (bottom). Your choices will not count unless you click the button that says “Confirm Choices”.



5 of 6 BB

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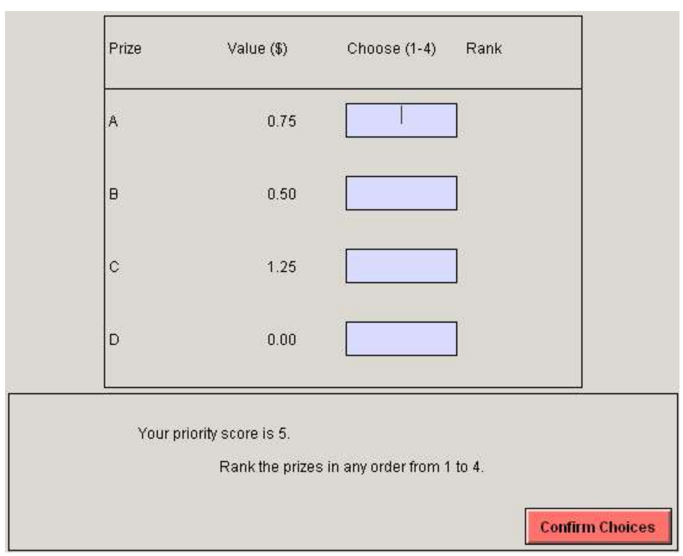


F Derivation of Equation (5)

Recall that there are 4 prizes $x_1, ..., x_4$ ordered from highest to lowest. The player wins each x_i with probability p_i, where p_i is a function of the submitted ROL and the player's beliefs about others' behavior. Under the assumptions we make in section 3, the timing is the following: in period 1, the player submits the ROL and gets a positive surprise (relative to expecting zero), in period 2, uncertainty is resolved and the player gets positive and/or negative news utility. Consumption occurs in period 3. Periods 1 and 3 are simple to analyze: in both of these periods the player enjoys the expected value of the lottery (in period 1 in the form of a positive surprise relative to zero, and in period 3 in the form of expected consumption). Therefore, the combined utility in these two periods is just:

$$2 \cdot \sum_{i=1}^{4} p_i x_i.$$

We now focus on period 2. It is convenient to construct expected news utility from the resolution of the lottery by looking at all possible prize comparisons. For example, comparing x_1 and x_4 occurs in two possible states: First, in the event the player wins x_1, the player experiences a gain (positive surprise)

$$p_4(x_1 - x_4).$$

This is the difference between the prizes, weighted by p_4, the player's expectation to get x_4. This event occurs with probability p_1. Second, in the event that the player wins x_4, the player experiences a loss (disappointment)

$$p_1\lambda(x_4 - x_1) = -\lambda p_1(x_1 - x_4).$$

This is the difference between the prizes, weighted by p_1, the player's expectation to get x_1, and the coefficient of loss aversion λ. This event occurs with probability p_4.

Summing up both terms, the x_1-to-x_4 comparison yields in expectation

$$-(\lambda - 1)p_1 p_4(x_1 - x_4).$$

In order to get the overall expected news utility in period 2, we need to apply the same procedure to all pairs in the prize pool x_i,x_j $j \neq i$.[3] Summing up over all terms yields

[3]In our case, the pairs (represented by their indices) are $\{1,4\}$,$\{1,3\}$,$\{1,2\}$,$\{2,4\}$,$\{2,3\}$ and $\{3,4\}$.

$$-(\lambda-1)\sum_{i=1}^{4} p_i \sum_{j>i} p_j(x_i-x_j).$$

Overall, the expected utility over the three periods is given by

$$u\left(\boldsymbol{x},\boldsymbol{p}\right)=2\cdot\sum_{i=1}^{4} p_i x_i-(\lambda-1)\sum_{i=1}^{4} p_i \sum_{j>i} p_j(x_i-x_j).$$

G Empirically Correct Beliefs

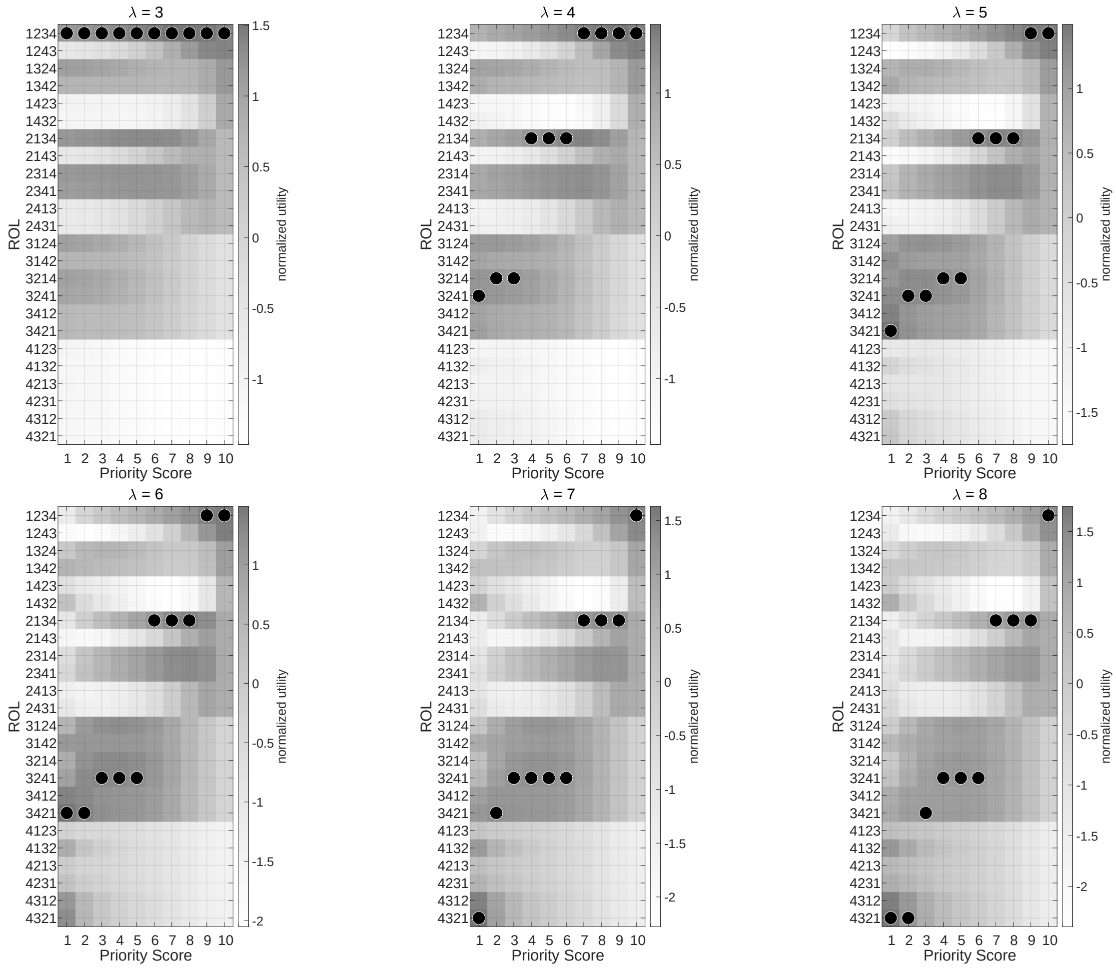
This appendix analyzes the model's predictions under the assumption that subjects' beliefs are empirically correct. We start by estimating empirically correct probabilistic beliefs. For each score-list combination, we estimate the probability of winning each of the four prizes through simulation with the following data generating process (DGP). In each round, three priority scores (one for each of the three other players in the group) and four additional tie-breaking numbers are drawn uniformly. Conditional on the priority score drawn for each player, the probability of the player submitting each of the 24 possible lists is taken to be the same as its empirical density (across all player-rounds) for that priority score. We estimate the probability of winning each prize by simulating the outcome of each list-priority score combination 100,000 times. For example, we fix a priority score 5 and a list 1234 for one player, simulate the DGP described above, and use the proportion of rounds that player won the highest prize as the estimated probability of winning the highest prize when submitting 1234 with a priority score 5. We repeat this process for all other score-list combinations to get a $4\times 24\times 10$ matrix that has the probability of winning each of the four prizes, for each 24 possible ROLs, for each of the 10 priority scores. This distribution is empirically correct in the sense that a player's belief about other players' behavior (and therefore about her chances of winning each of the prizes given her priority score and submitted list) is correct.

Figure G.1a presents the theoretical predictions under the assumption that subjects' beliefs are empirically correct. This assumption implies that each list results in a different lottery, because when other players may misrepresent, there is a positive probability of winning each of the prizes, for all score-list combinations. The figure therefore presents predictions for each of the 24 possible lists.

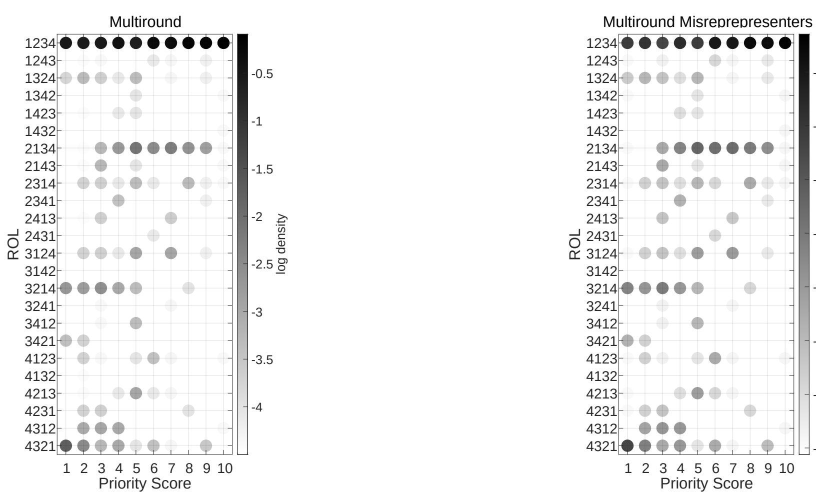
The predictions in this case are qualitatively similar to the predictions in section 3.2 in the main text: subjects with a high-enough λ submit lists with lower prizes on top, the higher is their λ and the lower is their priority score. However, under this assumption, for a given λ, the model predicts less misrepresentation; we therefore expand the range of λ's for which we

Figure G.1: Preferences over Lists and Empirical Distribution of Lists (Empirically Correct Beliefs)

(a) Theoretical Predictions



(b) Empirical Distribution (Multiround)



Notes: Panel (a): Utility is normalized for each priority score. Distance between prizes is equal. Panel (b): $N = 720$ (Multiround), $N = 440$ (Misrepresenters). Log density as a share of observations per priority score.

make predictions. Intuitively, when other subjects submit non-1234 lists, the expected loss in payoff from misrepresentation is greater. In addition, while in the previous case ranking a prize lower than its relative value completely eliminates the probability of winning it, in this case the probability of winning the downranked prize remains always positive, so flipping is less effective in reducing the dispersion of the distribution and hence in avoiding loss. For this reason, complete reversal (4321) is predicted only for subjects with rather high λ's.

In figure G.1b, we show for each priority score the empirical distribution of each of the 24 possible lists separately. Comparing G.1b to the predictions in G.1a, the empirical patterns seem to be consistent with the theoretical predictions (for higher λ's) also with empirically correct beliefs. 2134 is most common among subjects with medium-to-high priority scores, while 3214 and 4321 are most common among low-to-medium-score subjects. The model sometimes predicts lists that are not empirically common (e.g., 3241), but the difference in utility between them and other, empirically common lists (e.g., 3214) is small and is therefore consistent with a small, unexplained error term. Similarly, the list 4312, which is never predicted by the model, seems to be somewhat common at low priority scores, but again, the difference in utility between this list and 4321 is negligible.

H Raw Distribution of Lists

Table H.1: Empirical Distribution of Eight List Sets (Multiround, Misrepresenters Only)

ROLs	#ROLs	Priority Score									
		1	2	3	4	5	6	7	8	9	10
1234	1	34.0%	37.9%	29.8%	44.4%	33.3%	59.4%	60.0%	75.0%	73.8%	86.3%
1243	1	1.9%	1.7%	2.1%	0.0%	0.0%	3.1%	2.0%	0.0%	2.4%	0.0%
13XX	2	5.7%	5.2%	4.3%	2.8%	7.7%	0.0%	2.0%	0.0%	2.4%	2.0%
14XX	2	0.0%	1.7%	0.0%	2.8%	2.6%	0.0%	0.0%	0.0%	0.0%	2.0%
2*3*4*	3	3.8%	5.2%	10.6%	19.4%	23.1%	18.8%	16.0%	18.8%	14.3%	3.9%
2*4*3*	3	0.0%	3.4%	10.6%	0.0%	2.6%	3.1%	4.0%	0.0%	0.0%	2.0%
3XXX	6	18.9%	15.5%	21.3%	11.1%	17.9%	0.0%	10.0%	3.1%	2.4%	0.0%
4XXX	6	35.8%	29.3%	21.3%	19.4%	12.8%	15.6%	6.0%	3.1%	4.8%	3.9%
Total	24	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
N		53	58	47	36	39	32	50	32	42	51

Notes: Share of decisions as a percentage of choice situations with the same priority score. ROLs are grouped into sets as explained in figure 4a.

Table H.2: Empirical Distribution of Eight List Sets (One Shot)

ROLs	#ROLs	Priority Score									
		1	2	3	4	5	6	7	8	9	10
1234	1	92.3%	26.7%	69.6%	47.8%	71.4%	47.1%	55.0%	87.5%	81.8%	81.0%
1243	1	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.0%	0.0%	0.0%	0.0%
13XX	2	0.0%	0.0%	0.0%	0.0%	0.0%	5.9%	0.0%	0.0%	0.0%	9.5%
14XX	2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2*3*4*	3	7.7%	33.3%	8.7%	21.7%	21.4%	23.5%	25.0%	4.2%	4.5%	0.0%
2*4*3*	3	0.0%	0.0%	0.0%	4.3%	0.0%	0.0%	5.0%	0.0%	4.5%	0.0%
3XXX	6	0.0%	13.3%	21.7%	13.0%	0.0%	17.6%	0.0%	0.0%	0.0%	9.5%
4XXX	6	0.0%	26.7%	0.0%	13.0%	7.1%	5.9%	10.0%	8.3%	9.1%	0.0%
Total	24	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
N		13	15	23	23	14	17	20	24	22	21

Notes: Share of decisions as a percentage of choice situations with the same priority score. ROLs are grouped into sets as explained in figure 4a.

Table H.3: Empirical Distribution of Lists (Multiround)

ROL	Priority Score									
	1	2	3	4	5	6	7	8	9	10
1234	61.1%	57.1%	58.8%	67.7%	55.2%	79.0%	74.4%	85.7%	84.3%	91.3%
1243	1.1%	1.2%	1.3%	0.0%	0.0%	1.6%	1.3%	0.0%	1.4%	0.0%
1324	2.2%	3.6%	2.5%	1.6%	3.4%	0.0%	1.3%	0.0%	1.4%	0.0%
1342	1.1%	0.0%	0.0%	0.0%	1.7%	0.0%	0.0%	0.0%	0.0%	1.3%
1423	0.0%	1.2%	0.0%	1.6%	1.7%	0.0%	0.0%	0.0%	0.0%	0.0%
1432	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.3%
2134	1.1%	1.2%	3.8%	6.5%	12.1%	8.1%	10.3%	7.1%	5.7%	1.3%
2143	0.0%	1.2%	3.8%	0.0%	1.7%	0.0%	0.0%	0.0%	0.0%	1.3%
2314	1.1%	2.4%	2.5%	1.6%	3.4%	1.6%	0.0%	3.6%	1.4%	1.3%
2341	0.0%	0.0%	0.0%	3.2%	0.0%	0.0%	0.0%	0.0%	1.4%	0.0%
2413	0.0%	1.2%	2.5%	0.0%	0.0%	0.0%	2.6%	0.0%	0.0%	0.0%
2431	0.0%	0.0%	0.0%	0.0%	0.0%	1.6%	0.0%	0.0%	0.0%	0.0%
3124	1.1%	2.4%	2.5%	1.6%	5.2%	0.0%	5.1%	0.0%	1.4%	0.0%
3142	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3214	6.7%	6.0%	7.5%	4.8%	3.4%	0.0%	0.0%	1.8%	0.0%	0.0%
3241	0.0%	0.0%	1.3%	0.0%	0.0%	0.0%	1.3%	0.0%	0.0%	0.0%
3412	0.0%	0.0%	1.3%	0.0%	3.4%	0.0%	0.0%	0.0%	0.0%	0.0%
3421	3.3%	2.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4123	1.1%	2.4%	1.3%	0.0%	1.7%	3.2%	1.3%	0.0%	0.0%	1.3%
4132	0.0%	1.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4213	1.1%	1.2%	0.0%	1.6%	5.2%	1.6%	1.3%	0.0%	0.0%	0.0%
4231	1.1%	2.4%	2.5%	0.0%	0.0%	0.0%	0.0%	1.8%	0.0%	0.0%
4312	0.0%	4.8%	5.0%	4.8%	0.0%	0.0%	0.0%	0.0%	0.0%	1.3%
4321	17.8%	8.3%	3.8%	4.8%	1.7%	3.2%	1.3%	0.0%	2.9%	0.0%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
N	90	84	80	62	58	62	78	56	70	80

Note: Share of decisions as a percentage of choice situations with the same priority score.

Table H.4: Empirical Distribution of Lists (Multiround, Misrepresenters Only)

ROL	Priority Score									
	1	2	3	4	5	6	7	8	9	10
1234	34.0%	37.9%	29.8%	44.4%	33.3%	59.4%	60.0%	75.0%	73.8%	86.3%
1243	1.9%	1.7%	2.1%	0.0%	0.0%	3.1%	2.0%	0.0%	2.4%	0.0%
1324	3.8%	5.2%	4.3%	2.8%	5.1%	0.0%	2.0%	0.0%	2.4%	0.0%
1342	1.9%	0.0%	0.0%	0.0%	2.6%	0.0%	0.0%	0.0%	0.0%	2.0%
1423	0.0%	1.7%	0.0%	2.8%	2.6%	0.0%	0.0%	0.0%	0.0%	0.0%
1432	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	2.0%
2134	1.9%	1.7%	6.4%	11.1%	17.9%	15.6%	16.0%	12.5%	9.5%	2.0%
2143	0.0%	1.7%	6.4%	0.0%	2.6%	0.0%	0.0%	0.0%	0.0%	2.0%
2314	1.9%	3.4%	4.3%	2.8%	5.1%	3.1%	0.0%	6.3%	2.4%	2.0%
2341	0.0%	0.0%	0.0%	5.6%	0.0%	0.0%	0.0%	0.0%	2.4%	0.0%
2413	0.0%	1.7%	4.3%	0.0%	0.0%	0.0%	4.0%	0.0%	0.0%	0.0%
2431	0.0%	0.0%	0.0%	0.0%	0.0%	3.1%	0.0%	0.0%	0.0%	0.0%
3124	1.9%	3.4%	4.3%	2.8%	7.7%	0.0%	8.0%	0.0%	2.4%	0.0%
3142	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3214	11.3%	8.6%	12.8%	8.3%	5.1%	0.0%	0.0%	3.1%	0.0%	0.0%
3241	0.0%	0.0%	2.1%	0.0%	0.0%	0.0%	2.0%	0.0%	0.0%	0.0%
3412	0.0%	0.0%	2.1%	0.0%	5.1%	0.0%	0.0%	0.0%	0.0%	0.0%
3421	5.7%	3.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4123	1.9%	3.4%	2.1%	0.0%	2.6%	6.3%	2.0%	0.0%	0.0%	2.0%
4132	0.0%	1.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4213	1.9%	1.7%	0.0%	2.8%	7.7%	3.1%	2.0%	0.0%	0.0%	0.0%
4231	1.9%	3.4%	4.3%	0.0%	0.0%	0.0%	0.0%	3.1%	0.0%	0.0%
4312	0.0%	6.9%	8.5%	8.3%	0.0%	0.0%	0.0%	0.0%	0.0%	2.0%
4321	30.2%	12.1%	6.4%	8.3%	2.6%	6.3%	2.0%	0.0%	4.8%	0.0%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
N	53	58	47	36	39	32	50	32	42	51

Note: Share of decisions as a percentage of choice situations with the same priority score.

Table H.5: Empirical Distribution of Lists (One Shot)

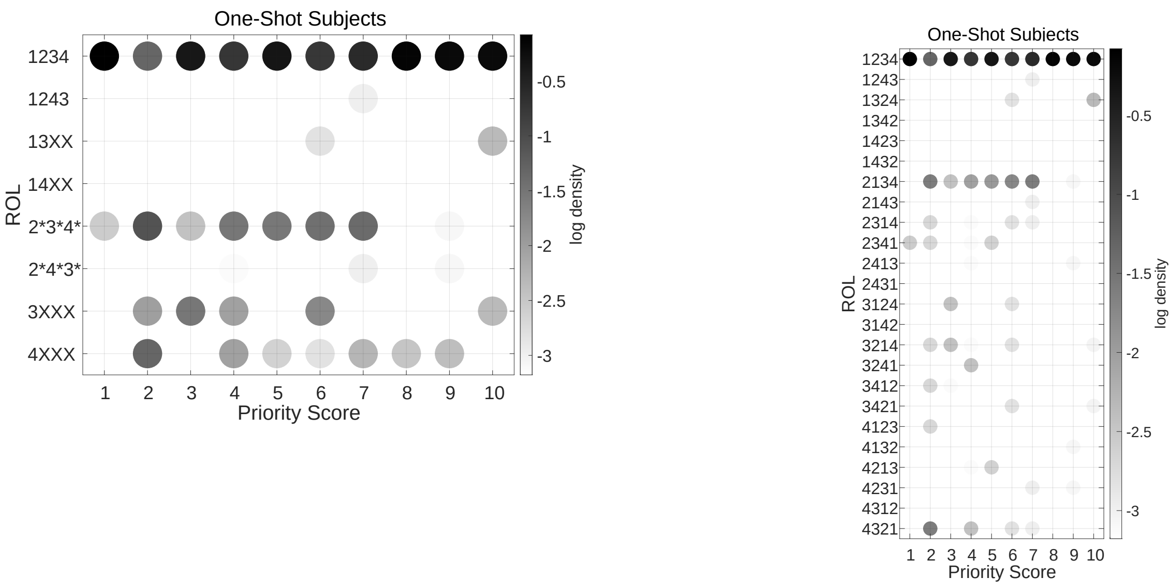
ROL	Priority Score									
	1	2	3	4	5	6	7	8	9	10
1234	92.3%	26.7%	69.6%	47.8%	71.4%	47.1%	55.0%	87.5%	81.8%	81.0%
1243	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.0%	0.0%	0.0%	0.0%
1324	0.0%	0.0%	0.0%	0.0%	0.0%	5.9%	0.0%	0.0%	0.0%	9.5%
1342	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
1423	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
1432	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2134	0.0%	20.0%	8.7%	13.0%	14.3%	17.6%	20.0%	4.2%	4.5%	0.0%
2143	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.0%	0.0%	0.0%	0.0%
2314	0.0%	6.7%	0.0%	4.3%	0.0%	5.9%	5.0%	0.0%	0.0%	0.0%
2341	7.7%	6.7%	0.0%	4.3%	7.1%	0.0%	0.0%	0.0%	0.0%	0.0%
2413	0.0%	0.0%	0.0%	4.3%	0.0%	0.0%	0.0%	0.0%	4.5%	0.0%
2431	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3124	0.0%	0.0%	8.7%	0.0%	0.0%	5.9%	0.0%	0.0%	0.0%	0.0%
3142	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3214	0.0%	6.7%	8.7%	4.3%	0.0%	5.9%	0.0%	0.0%	0.0%	4.8%
3241	0.0%	0.0%	0.0%	8.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3412	0.0%	6.7%	4.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3421	0.0%	0.0%	0.0%	0.0%	0.0%	5.9%	0.0%	0.0%	0.0%	4.8%
4123	0.0%	6.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4132	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	4.2%	4.5%	0.0%
4213	0.0%	0.0%	0.0%	4.3%	7.1%	0.0%	0.0%	0.0%	0.0%	0.0%
4231	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.0%	4.2%	4.5%	0.0%
4312	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4321	0.0%	20.0%	0.0%	8.7%	0.0%	5.9%	5.0%	0.0%	0.0%	0.0%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
N	13	15	23	23	14	17	20	24	22	21

Note: Share of decisions as a percentage of choice situations with the same priority score.

Figure H.1: Empirical Distribution of Lists (One Shot)

(a) Eight List Sets

(b) All ROLs



Notes: $N = 192$. Log density as a share of observations with the same priority score. Panel (a): ROLs are grouped as explained in figure 4a.

I Face-Value Beliefs

Table I.1: Mixed and Standard Logit Specifications

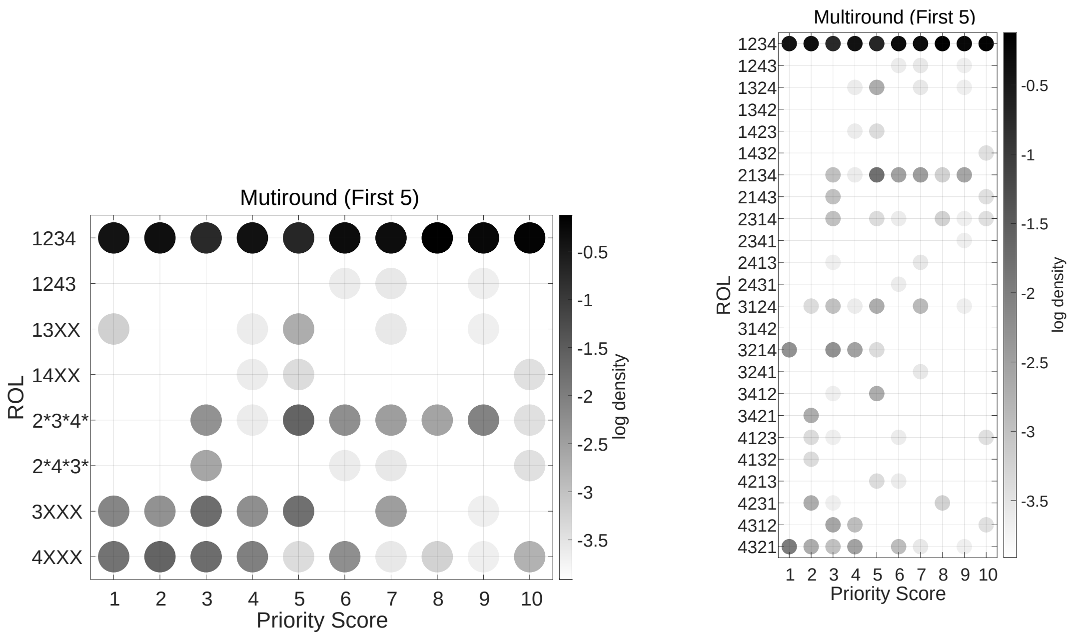
	(1) Multiround All (Logit)	(2) One Shot All (Logit)	(3) Multiround Misrepresenters (Logit)	(4) Multiround Late Misrep. (Logit)	(5) Multiround Misrepresenters (Mixed Logit)
α_1(normalized)	2	2	2	2	2
	(0.1)	(0.2)	(0.15)	(0.18)	(0.14)
λ	1.77	1.63	2.54	2.90	
	(0.18)	(0.37)	(0.31)	(0.38)	
μ_λ					2.42
					(0.45)
σ_λ					2.31
					(0.37)
Log-likelihood	−1717.43	−466.57	−1183.43	−999.17	−1154.51
Likelihood ratio test	20.02	3.16	29.14	29.25	
p-value	0.000	0.076	0.000	0.000	
N	720	192	440	360	440

Notes: The parameters were estimated through Maximum Likelihood (columns 1–4) and Maximum Simulated Likelihood with 1,000 draws (column 5). The probability of winning each prize is based on correct beliefs about priorities, assuming other players play truthfully. Likelihood ratio test: df = 1, $H_0 : \lambda = 1$.

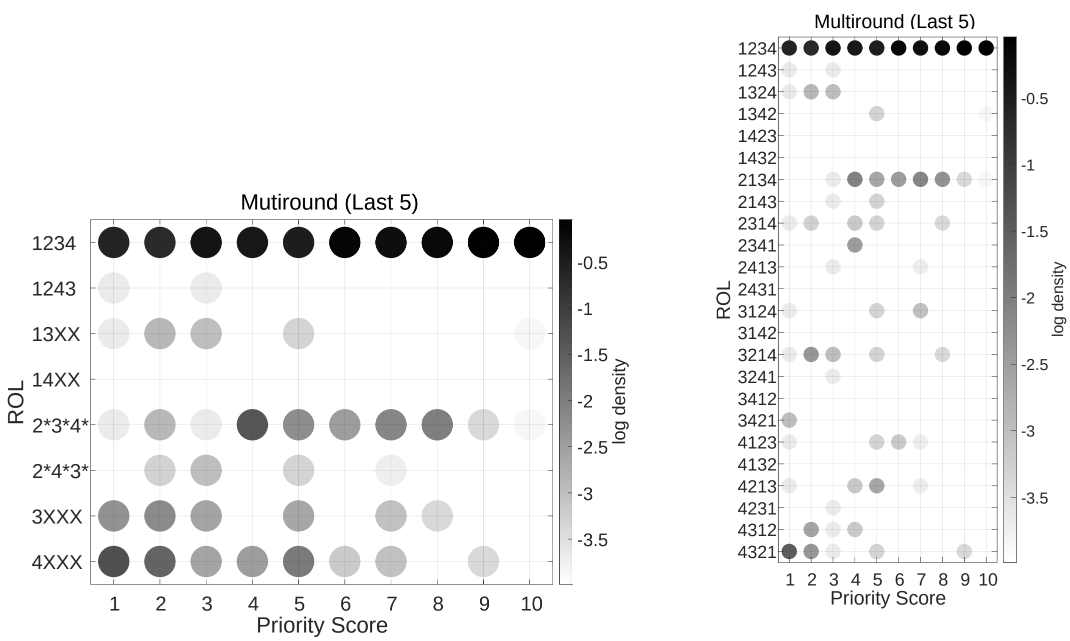
J Early vs Later Rounds

Figure J.1: Empirical Distribution of Lists (by Five Rounds)

(a) First Five Rounds



(b) Last Five Rounds



Notes: $N = 360$. Log density as a share of observations with the same priority score. Panel (a): ROLs are grouped as explained in figure 4a.

Table J.1: Standard Logit (Earlier vs Later Rounds)

	(1) Multiround First 5 Rounds (Logit)	(2) Multiround Last 5 Rounds (Logit)
α_1(normalized)	2	2
	(0.14)	(0.12)
λ	1.86	2.10
	(0.28)	(0.24)
Log-likelihood	-877.67	-766.17
Likelihood ratio test	10.37	24.64
p-value	0.001	0.000
N	360	360

Notes: The parameters were estimated through Maximum Likelihood. The probability of winning each prize is the simulated probability as described in 3.2. Likelihood ratio test: df = 1, $H_0 : \lambda = 1$.