Dynamic updating about menus

Kim Sarnoff

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Introduction

- Inference about ability is a key input into many economic decisions, e.g. hiring.
- Typically assume evaluators (e.g. employers) act as sophisticated statisticians.
- But, environment complex:
  - Information arrives sequentially
  - About a menu of individuals
  - With different prior distributions of ability.

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- Typically assume evaluators (e.g. employers) act as sophisticated statisticians.
- But, environment complex:
  - Information arrives sequentially
  - About a menu of individuals
  - With different prior distributions of ability.
- This project: Study dynamic belief formation about individuals evaluated with others.

Outline

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Design

Econometric strategy

Aggregate analysis

Sequence effects

Overview of design

- Experimental "employers" complete a statistical learning task.
  - Create groups of experimental "workers" with varying ability.
  - Worker drawn from a given ability distribution.
  - Employer receives information on worker ability incrementally and reports beliefs.

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- Vary environment in which learning task done.
  - Single worker in isolation.
  - Pairs drawn from same distribution evaluated simultaneously.
  - Pairs drawn from different distributions evaluated simultaneously.

Workers

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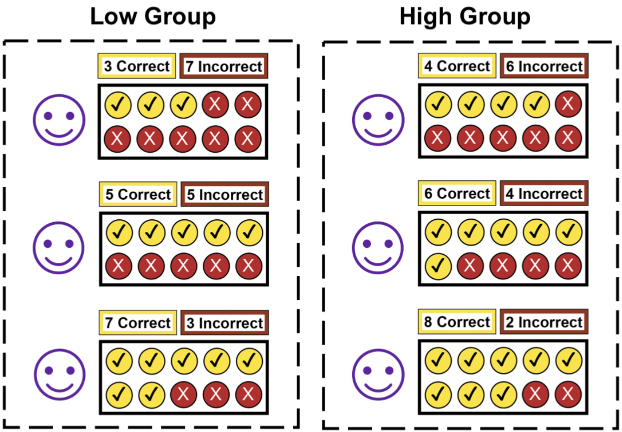
- Create two groups of workers, with different distribution of scores.



Baseline treatment (*Individual*)

- Employer randomly assigned to low group or high group.

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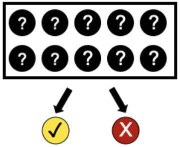

Step 2: Report full posterior distribution

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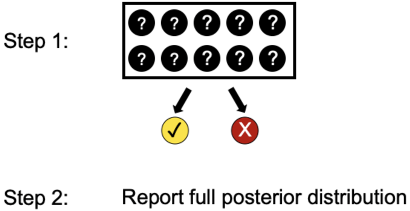

- Complete 8 inference tasks, where worker drawn with replacement.

Two workers from same group (*Same*)

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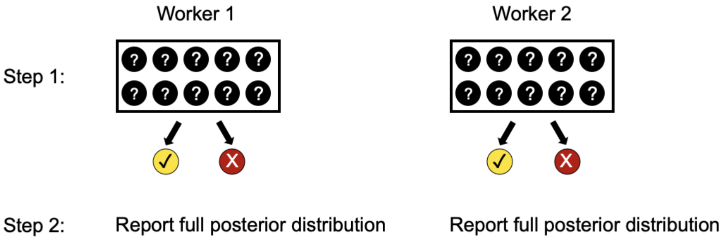

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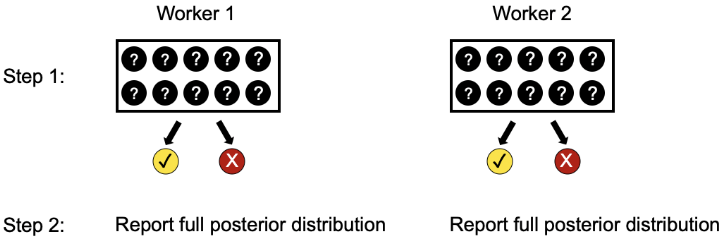

- Complete **4** inference tasks, where **two workers** drawn with replacement.

Two workers from different groups (*Diff*)

- Employer observes **low group and high group**.

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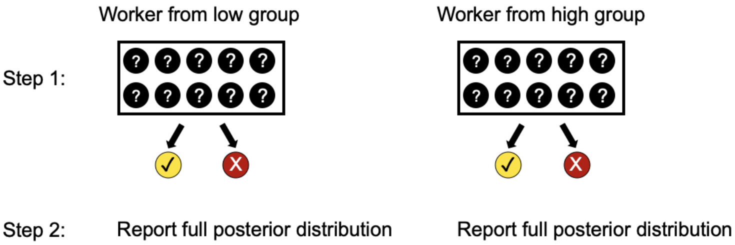

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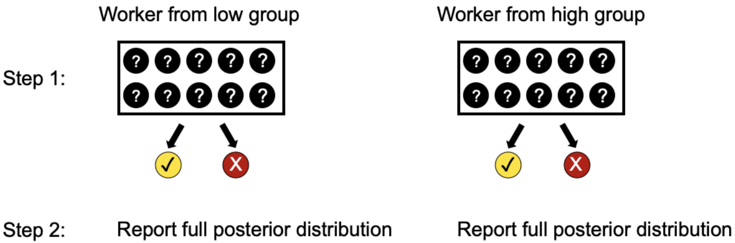

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Predictions

- Bayesian benchmark: Calculate posterior distribution of score according to

$$P(score|y) = \frac{P(y|score)P(score)}{\sum_{score} P(y|score)P(score)}$$

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$$P(score|y) = \frac{P(y|score)P(score)}{\sum_{score} P(y|score)P(score)}$$

- $P(score|y)$ only depends on prior and signal, not treatment

Signals

Individual

	Group G
Worker 1	0,0,1
Worker 2	0,1,1
Worker 3	0,0,0
Worker 4	1,1,0
Worker 5	0,1,1
Worker 6	1,0,0
Worker 7	1,1,1
Worker 8	0,0,1

Same Group

	Group G	Group G
Pair 1	0,0,1	0,1,1
Pair 2	0,1,1	1,0,0
Pair 3	0,0,0	1,1,1
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Different Groups

	Group G	Group G'
Pair 1	0,0,1	0,1,1
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- *Individual*
  - 24 rounds overall: 3 rounds each for 8 workers.
  - Pay for half of the rounds, chosen randomly, with BSR.

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- *Individual*
  - 24 rounds overall: 3 rounds each for 8 workers.
  - Pay for half of the rounds, chosen randomly, with BSR.
- Pair treatments
  - 12 rounds overall: 3 rounds each for 4 worker pairs.
  - Pay for one worker, chosen randomly, each round.

Sample

- Total sample is 180
  - 30 participants for each group in individual treatment.
  - 30 participants for each group in same group treatment.
  - 60 participants for different groups treatment.
- Estimation sample is 150
  - Drop participants who make mistakes in more than half the rounds.

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Econometric strategy

- Evaluator i reports belief about worker w in time t
- For given worker, t goes from 1 to 3

$$\overbrace{log\left(\frac{P(score_j|signal)_{i,w,t}}{P(score_k|signal)_{i,w,t}}\right)}^{\text{log posterior odds}} =$$

$$\beta_C * 1[s_t = correct] * \overbrace{log\left(\frac{P(correct|score_j)_{i,w,t}}{P(correct|score_k)_{i,w,t}}\right)}^{\text{LLR if signal in } t \text{ correct}}$$

$$+ \beta_I * 1[s_t = incorrect] * \overbrace{log\left(\frac{P(incorrect|score_j)_{i,w,t}}{P(incorrect|score_k)_{i,w,t}}\right)}^{\text{LLR if signal in } t \text{ incorrect}}$$

$$+ \delta * \overbrace{log\left(\frac{P(score_j)_{i,w,t-1}}{P(score_k)_{i,w,t-1}}\right)}^{\text{log prior odds}} + \epsilon_{i,w,t}$$

Econometric strategy

- Suppose true model is each i has fixed weights on prior & data:

$$
\begin{aligned}
log\left(\frac{P(score_j|signal)_{i,w,t}}{P(score_k|signal)_{i,w,t}}\right) = \\
\beta_{Ci} * 1[s_t = correct] * log\left(\frac{P(correct|score_j)_{i,w,t}}{P(correct|score_k)_{i,w,t}}\right) \\
+ \beta_{Ii} * 1[s_t = incorrect] * log\left(\frac{P(incorrect|score_j)_{i,w,t}}{P(incorrect|score_k)_{i,w,t}}\right) \\
+ \delta_i * log\left(\frac{P(score_j)_{i,w,t-1}}{P(score_k)_{i,w,t-1}}\right) + \epsilon_{i,w,t}
\end{aligned}
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\end{aligned}
$$

- If run population regression, $\epsilon_{i,w,t}$ contains δ_i, β_{Ci}, β_{Ii} $\implies$ $E[\epsilon_{i,w,t}|\boldsymbol{X}] \neq 0$
- Instrumenting with Bayesian prior not a solution Detail

Simulated maximum likelihood

$$y_{it} = \begin{cases} \beta_{Ci} 1[s_t = correct] s_{it} + \beta_{Ii} 1[s_t = incorrect] s_{it} + \epsilon_{it} & \text{if } t = 1 \\ \beta_{Ci} 1[s_t = correct] s_{it} + \beta_{Ii} 1[s_t = incorrect] s_{it} + \delta_i y_{i,t-1} + \epsilon_{it} & \text{if } t > 1 \end{cases}$$

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$$\begin{pmatrix} \beta_{Ci} \\ \beta_{Ii} \\ \delta_i \end{pmatrix} \sim \text{MVN} \left(\begin{pmatrix} \mu_{\beta_{Ci}} \\ \mu_{\beta_{Ii}} \\ \mu_{\delta_i} \end{pmatrix}, \begin{pmatrix} \sigma^2_{\beta_{Ci}} & \sigma_{\beta_{Ci}\beta_{Ii}} & \sigma_{\beta_{Ci}\delta_i} \\ \sigma_{\beta_{Ii}} & \sigma^2_{\beta_{Ii}} & \sigma_{\beta_{Ii}\delta_i} \\ \sigma_{\delta_i\beta_{Ci}} & \sigma_{\delta_i\beta_{Ii}} & \sigma^2_{\delta_i} \end{pmatrix} \right)$$

$$\epsilon_{it} \sim_{iid} N(0, \sigma^2)$$

Estimation

- Log likelihood of an observation is:

$$\mathcal{L}_{it} = \ln(\phi\left[y_{it} - \theta_i x_{it}\right])$$

where $\theta_i = [\beta_{Ci}, \beta_{Ii}, \delta_i]$, $x_{it} = [s_{it}, y_{i,t-1}(\theta_i)]'$

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- Don't observe $\theta_i \implies$ can't do maximum likelihood directly. Need to integrate it out:

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$$\mathcal{L}_{it}^{sim} = \ln\left[\frac{1}{S}\sum_{s} \phi\left[y_{it} - \theta_{is} x_{it}\right]\right]$$

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- Maximize the simulated likelihood: $\sum_i \sum_t \mathcal{L}_{it}^{sim}$

Outline

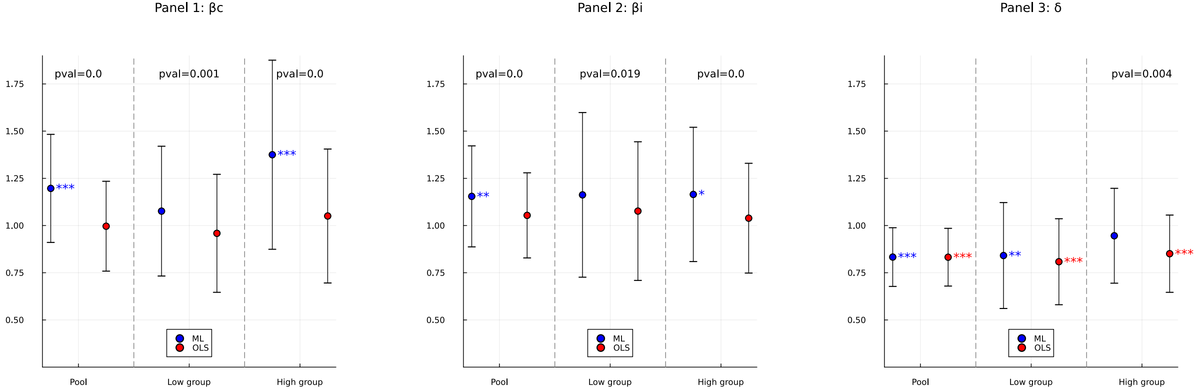
Baseline model

$$y_{it} = \begin{cases} \beta_{Ci} 1[s_t = correct] s_{it} + \beta_{Ii} 1[s_t = incorrect] s_{it} + \epsilon_{it} & \text{if } t = 1 \\ \beta_{Ci} 1[s_t = correct] s_{it} + \beta_{Ii} 1[s_t = incorrect] s_{it} + \delta_i y_{i,t-1} + \epsilon_{it} & \text{if } t > 1 \end{cases}$$

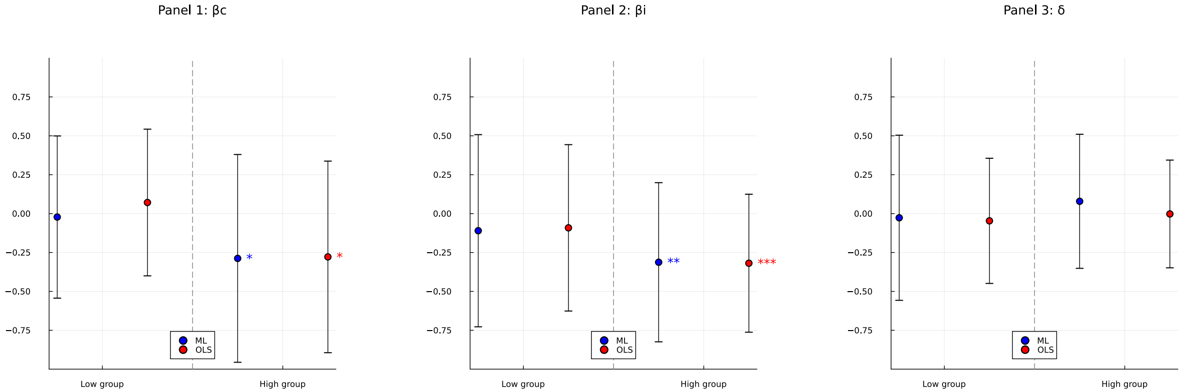
- Will show estimate of $\mu_{\beta_{Ci}}, \mu_{\beta_{Ii}}, \mu_{\delta_i}$

$$\begin{pmatrix} \beta_{Ci} \\ \beta_{Ii} \\ \delta_i \end{pmatrix} \sim \text{MVN} \left(\begin{pmatrix} \mu_{\beta_{Ci}} \\ \mu_{\beta_{Ii}} \\ \mu_{\delta_i} \end{pmatrix}, \begin{pmatrix} \sigma^2_{\beta_{Ci}} & \sigma_{\beta_{Ci}\beta_{Ii}} & \sigma_{\beta_{Ci}\delta_i} \\ \sigma_{\beta_{Ii}} & \sigma^2_{\beta_{Ii}} & \sigma_{\beta_{Ii}\delta_i} \\ \sigma_{\delta_i\beta_{Ci}} & \sigma_{\delta_i\beta_{Ii}} & \sigma^2_{\delta_i} \end{pmatrix} \right)$$

Individual treatment



Comparing pair treatments



Within pair distance in final belief

- Calculate within pair distance in final belief in *Diff*
- Compare to within pair distance in simulated pairs from *Same*

Same Group

	Group G	Group G
Pair 1	0,0,1	0,1,1
Pair 2	0,1,1	1,0,0
Pair 3	0,0,0	1,1,1
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Different Groups

	Group G	Group G'
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	Group G'	Group G'
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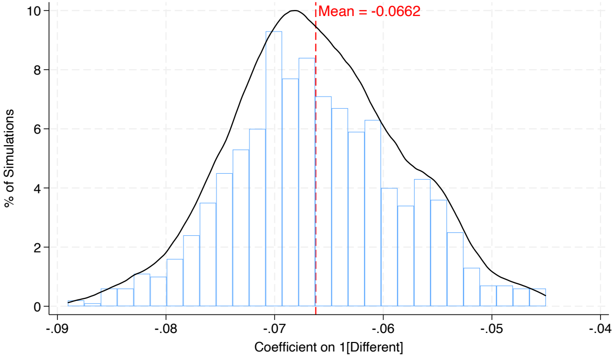
Pair 4	1,1,0	0,0,1

Partner from different group leads to compression within pair.

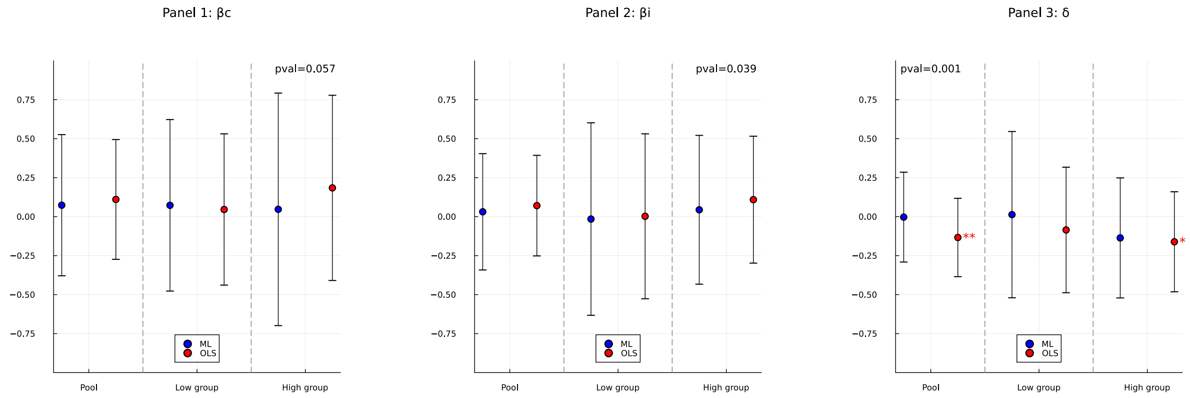
- Perform 1000 simulations, estimating

$$\text{Distance within pair} = \beta_0 + \beta_1 1[\textit{Different}] + \epsilon$$

SE clustered at individual level, where this is simulated individual in *Same*.



Simultaneous evaluation alone has no effect.



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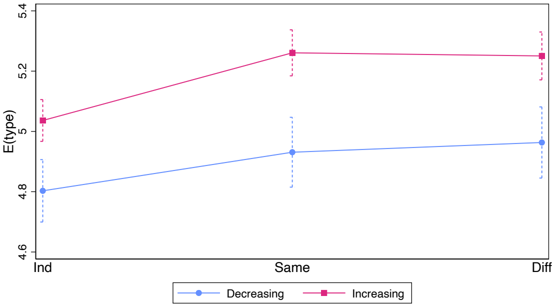
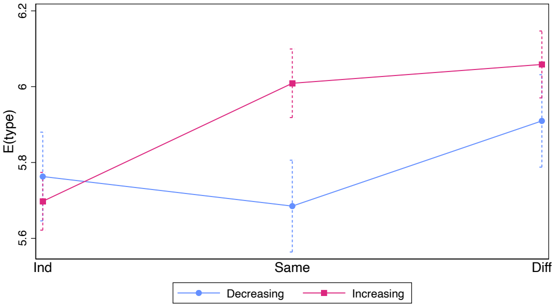
Beliefs generally higher after increasing sequences.

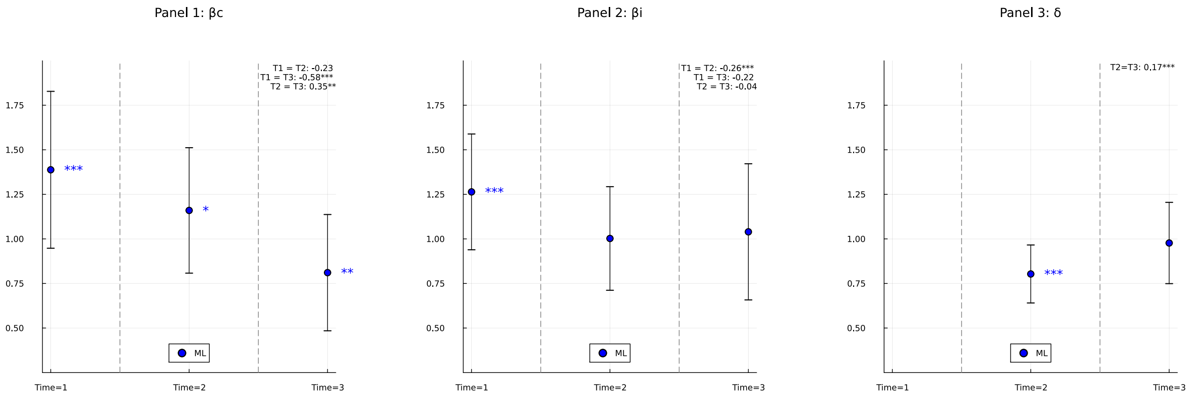




Model with time effects

$$y_{it} = \begin{cases} [\beta_{Ci} + \beta_{Ct}]1[s_t = correct]s_{it} + [\beta_{Ii} + +\beta_{It}]1[s_t = incorrect]s_{it} + \epsilon_{it} & \text{if } t = 1 \\ [\beta_{Ci} + \beta_{Ct}]1[s_t = correct]s_{it} + [\beta_{Ii} + \beta_{It}]1[s_t = incorrect]s_{it} + [\delta_i + \delta_t]y_{i,t-1} + \epsilon_{it} & \text{if } t > 1 \end{cases}$$

Time specific effects in *Individual*

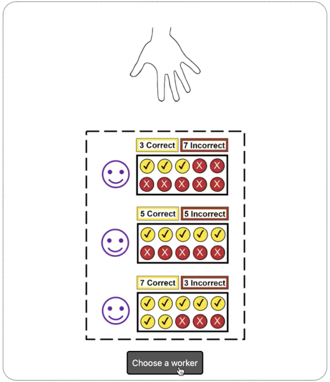


Conclusion

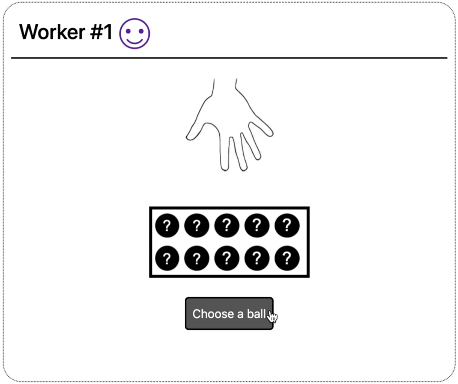
- Study sequential updating, varying whether workers viewed in tandem or alone.
- Updating is time dependent.
- When pair comes from different groups, there is compression.
- Increasing sequences, for the most part, increase beliefs.

Appendix

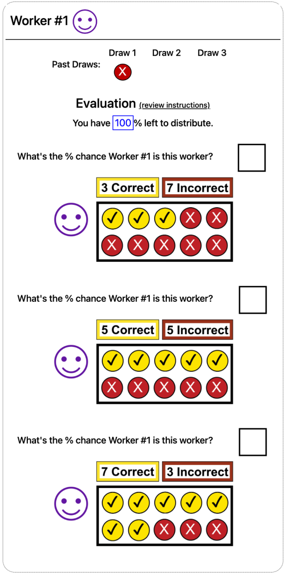
Individual: Worker draw



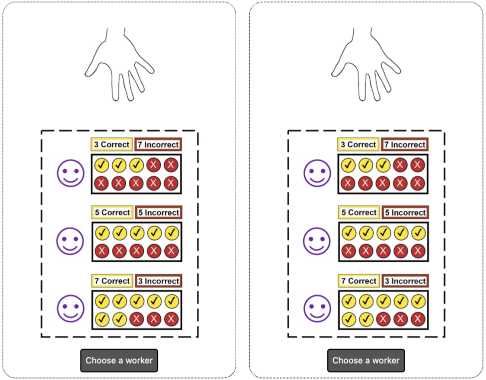
Observe signal



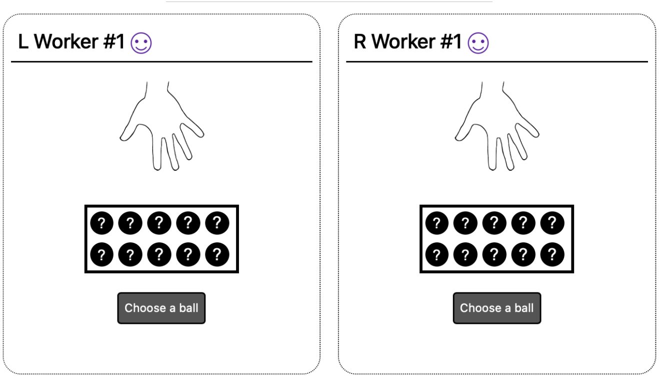
Individual: Posterior



Signal draw for pairs

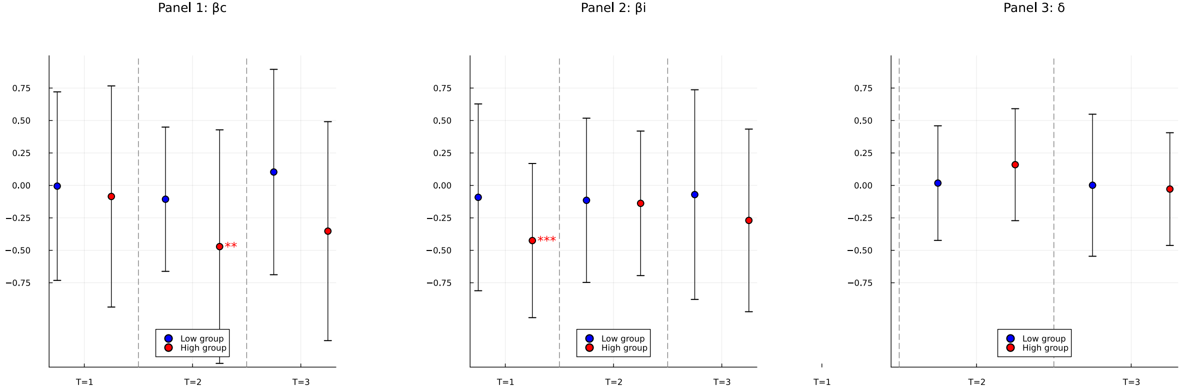


Posterior report for pairs

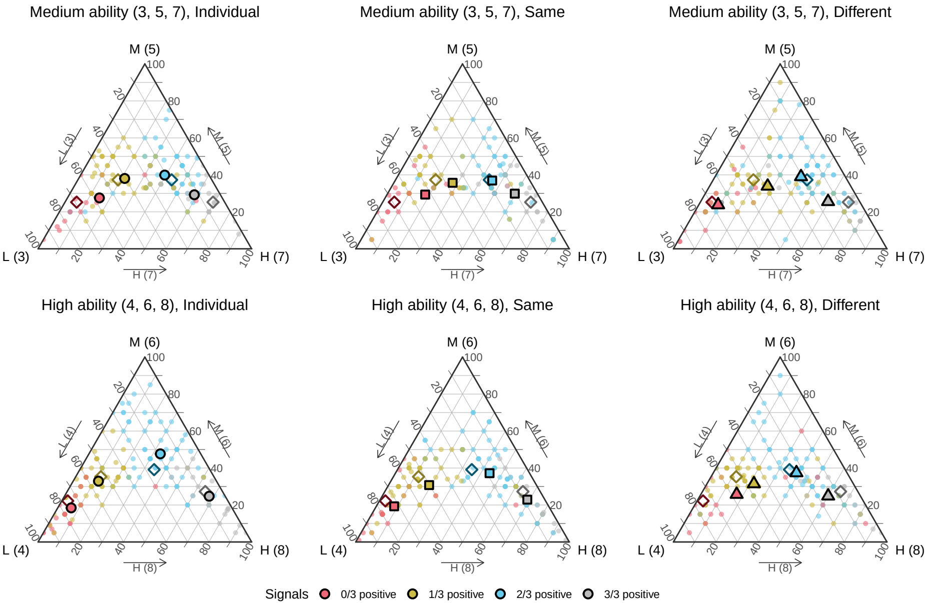


Appendix

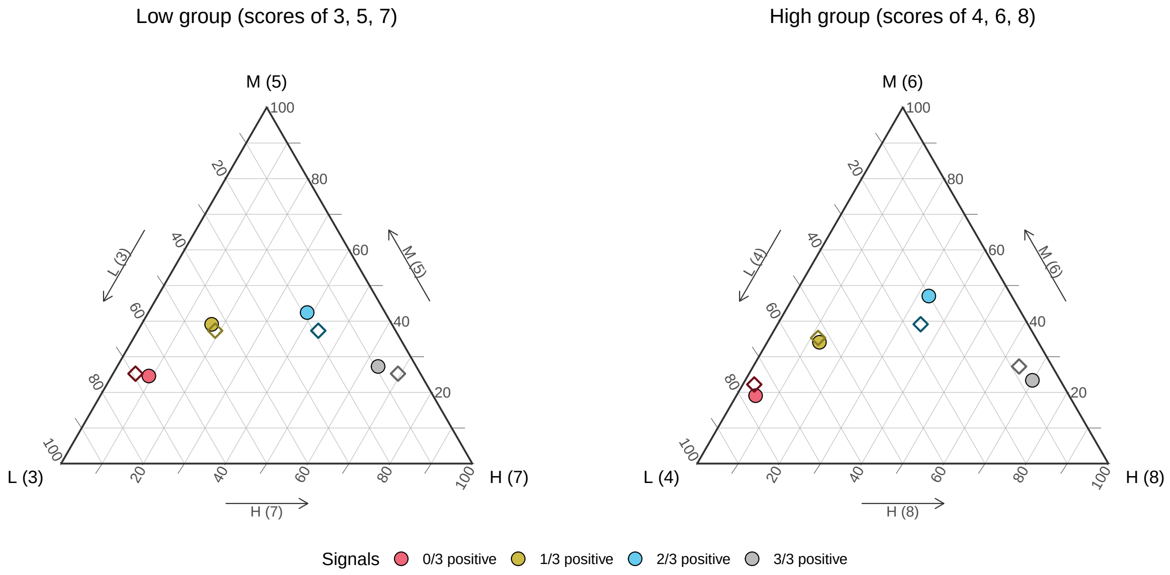
Effect of partner from different group, by time



Scatter plot of final beliefs by treatment



Final belief in *Individual* treatment



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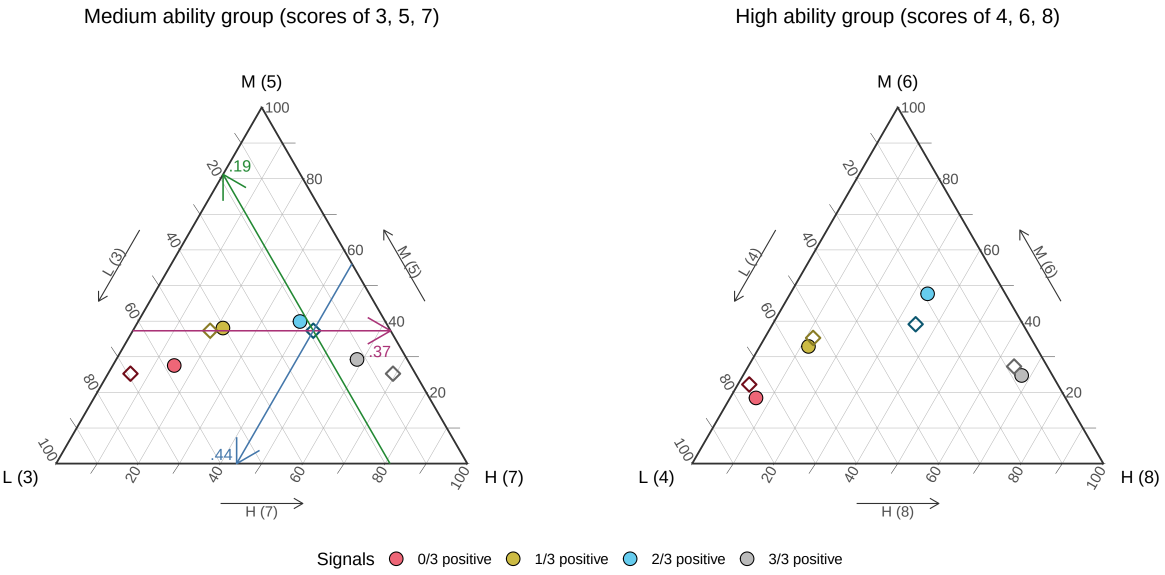
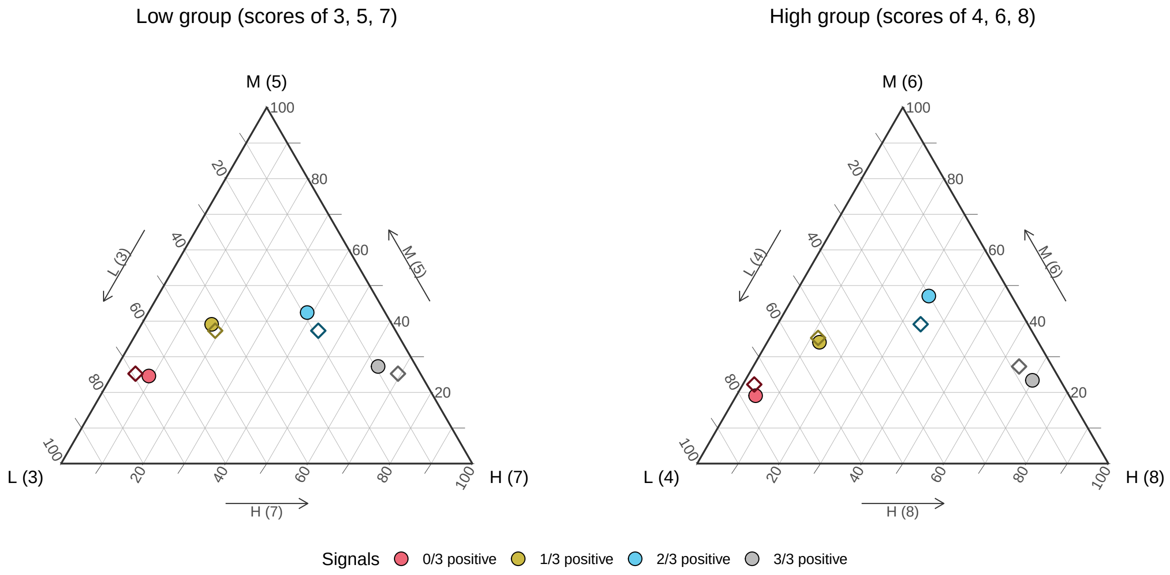
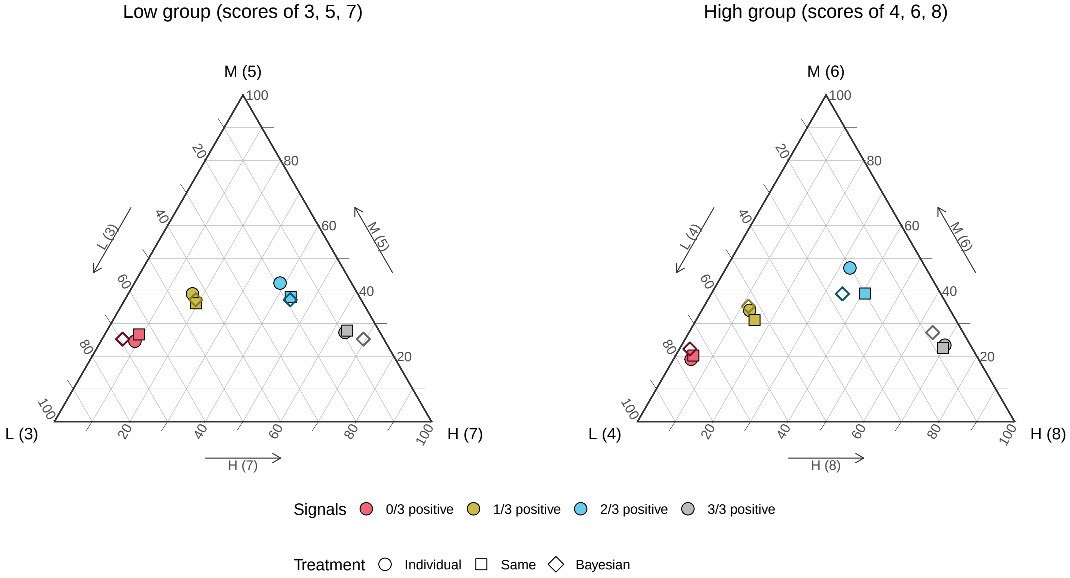


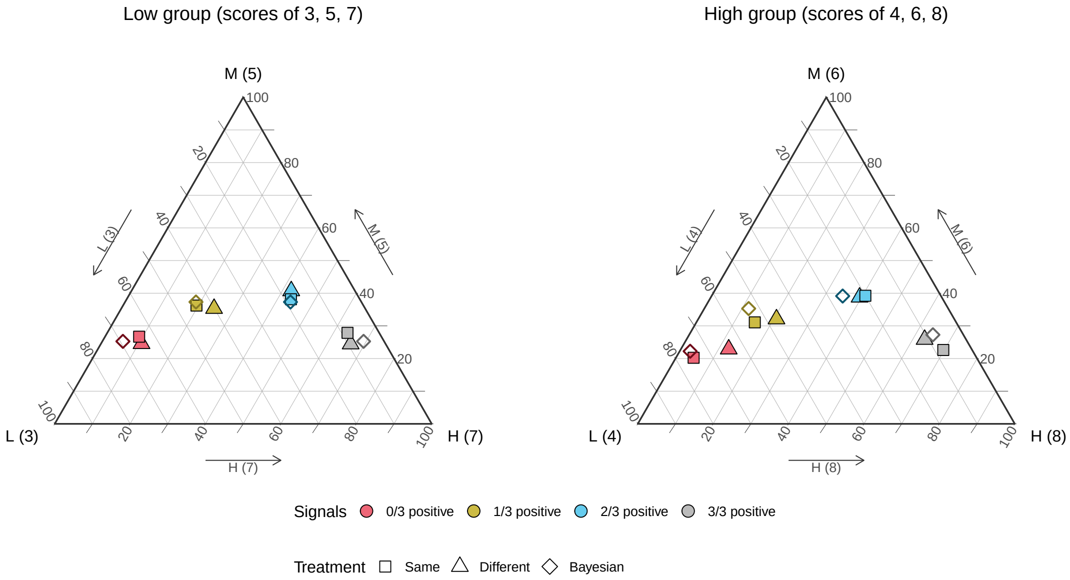
Final belief in *Individual* treatment



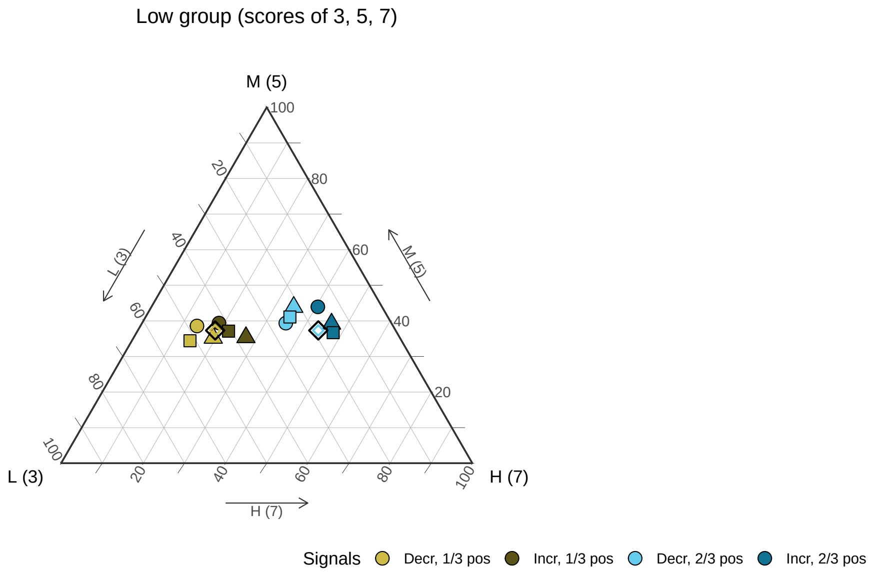
Effect of simultaneous evaluation on final belief



Effect of partner from different group on final belief



Generally, beliefs higher after increasing sequence.



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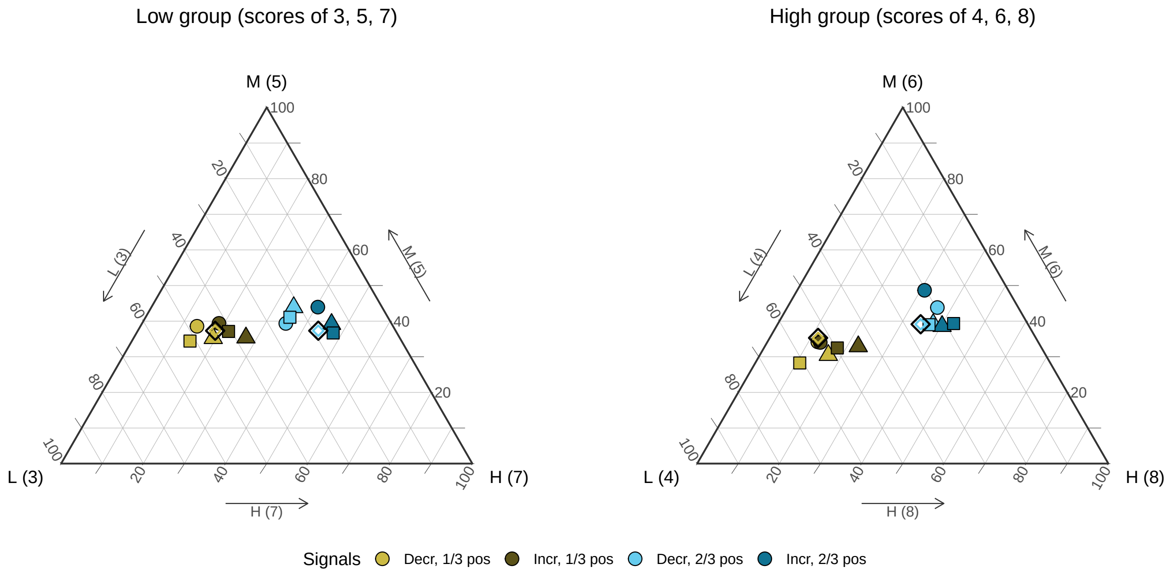

Appendix

Order effect in *Individual* treatment by group.

	(1) P(L)	(2) P(M)	(3) P(H)
High ability (4, 6, 8)	-0.083**	0.027	0.036
	(0.032)	(0.027)	(0.034)
Increasing signals	-0.094***	0.038***	0.056**
	(0.030)	(0.012)	(0.025)
High ability $\times$ increasing	0.120***	-0.020	-0.100**
	(0.038)	(0.025)	(0.039)
Constant	0.016	-1.143***	0.028
	(0.049)	(0.346)	(0.038)
Effect of incr signals in high ability group (Incr + High $\times$ incr)	0.026	0.018	-0.044
Control for Bayesian belief	✓	✓	✓
Observations	240	240	240

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Order effect in individual vs pair treatments by group.

	Medium ability (3, 5, 7)			High ability (4, 6, 8)		
	(1) P(L)	(2) P(M)	(3) P(H)	(4) P(L)	(5) P(M)	(6) P(H)
Increasing signals	-0.094***	0.038***	0.056**	0.026	0.018	-0.044
	(0.030)	(0.012)	(0.025)	(0.023)	(0.022)	(0.030)
Pair	-0.021	0.006	0.014	0.045*	-0.063***	0.018
	(0.033)	(0.026)	(0.031)	(0.024)	(0.023)	(0.027)
Increasing × *Pair*	0.023	-0.057***	0.034	-0.108***	-0.001	0.110**
	(0.040)	(0.018)	(0.037)	(0.036)	(0.025)	(0.043)
Effect of incr in *Pair* (Incr + Incr × *Pair*)	-0.071***	-0.020	0.090***	-0.082***	0.017	0.066**
Control for Bayesian belief	✓	✓	✓	✓	✓	✓
Observations	360	360	360	360	360	360

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Appendix

Endogeneity

- Evaluator i reports belief about worker w in time t.
- For a given worker, t goes from 1 to 3.
- Suppose true model is each i has fixed weights on prior & data:

$$log\left(\frac{P(score_j|signal)_{i,w,t}}{P(score_k|signal)_{i,w,t}}\right) =$$

$$\beta_{Ci} * 1[s_t = correct] * log\left(\frac{P(correct|score_j)_{i,w,t}}{P(correct|score_k)_{i,w,t}}\right)$$

$$+ \beta_{Ii} * 1[s_t = incorrect] * \overbrace{log\left(\frac{P(incorrect|score_j)_{i,w,t}}{P(incorrect|score_k)_{i,w,t}}\right)}^{\text{LLR if signal in } t \text{ incorrect}}$$

$$+ \delta_i * \overbrace{log\left(\frac{P(score_j)_{i,w,t-1}}{P(score_k)_{i,w,t-1}}\right)}^{\text{log prior odds}} + \eta_{i,w,t}$$

- In round 1, log prior odds exogenously set to 0. In round 2 and 3, use lagged reported posterior.
- ϵ is i.i.d mean zero noise.

Endogeneity

$$\overbrace{log\left(\frac{P(score_j|signal)_{i,w,t}}{P(score_k|signal)_{i,w,t}}\right)}^{\text{log posterior odds}} =$$

$$\beta_{Ci} * 1[s_t = correct] * \overbrace{log\left(\frac{P(correct|score_j)_{i,w,t}}{P(correct|score_k)_{i,w,t}}\right)}^{\text{LLR if signal in } t \text{ correct}}$$

$$+ \beta_{Ii} * 1[s_t = incorrect] * \overbrace{log\left(\frac{P(incorrect|score_j)_{i,w,t}}{P(incorrect|score_k)_{i,w,t}}\right)}^{\text{LLR if signal in } t \text{ incorrect}}$$

$$+ \delta_i * \overbrace{log\left(\frac{P(score_j)_{i,w,t-1}}{P(score_k)_{i,w,t-1}}\right)}^{\text{log prior odds}} + \eta_{i,w,t}$$

- In round 1, log prior odds exogenously set to 0.
- In round 2 and 3, use lagged reported posterior.

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Endogeneity

- Say that we just run the population regression:

$$
\begin{aligned}
log\left(\frac{P(score_j|signal)_{i,w,t}}{P(score_k|signal)_{i,w,t}}\right) = \\
\beta_C * 1[s_t = correct] * log\left(\frac{P(correct|score_j)_{i,w,t}}{P(correct|score_k)_{i,w,t}}\right) \\
+ \beta_I * 1[s_t = incorrect] * log\left(\frac{P(incorrect|score_j)_{i,w,t}}{P(incorrect|score_k)_{i,w,t}}\right) \\
+ \delta * log\left(\frac{P(score_j)_{i,w,t-1}}{P(score_k)_{i,w,t-1}}\right) + \epsilon_{i,w,t}
\end{aligned}
$$

- In this case, $\epsilon_{i,w,t}$ contains δ_i, β_{Ci}, β_{Ii}.
- In rounds 2 and 3 about a worker, δ_i, β_{Ci}, β_{Ii} will not be randomly assigned with respect to the prior: this is because use lagged posterior, which itself contains δ_i, β_{Ci}, β_{Ii}.
- Means $E[\epsilon_{i,w,t}|\boldsymbol{X}] \neq 0$.

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Appendix

Interface

Figures

Final belief: simplexes

Effect of signal order

Endogeneity

Other

$$\left(\frac{1}{NT}\sum_i\sum_t\begin{bmatrix} s_{it}^2 & s_{it}p_{it} \\ s_{it}p_{it} & p_{it}^2 \end{bmatrix}\right)^{-1} \times \frac{1}{NT}\sum_i\sum_t\begin{bmatrix} s_{it} & p_{it} \end{bmatrix} y_{it} =$$

$$\left(\frac{1}{NT}\sum_i\sum_t\begin{bmatrix} s_{it}^2 & s_{it}p_{it} \\ s_{it}p_{it} & p_{it}^2 \end{bmatrix}\right)^{-1} \times \frac{1}{NT}\sum_i\sum_t\begin{bmatrix} s_{it} \\ p_{it} \end{bmatrix}\left[\begin{bmatrix} s_{it} & p_{it} \end{bmatrix}\begin{bmatrix} \beta_i + \beta_t \\ \delta_i + \delta_t \end{bmatrix}\right] \neq$$

$$\left(\frac{1}{NT}\sum_i\sum_t\begin{bmatrix} s_{it}^2 & s_{it}p_{it} \\ s_{it}p_{it} & p_{it}^2 \end{bmatrix}\right)^{-1} \times \frac{1}{NT}\sum_i\sum_t\begin{bmatrix} s_{it} \\ p_{it} \end{bmatrix}\begin{bmatrix} s_{it} & p_{it} \end{bmatrix}\frac{1}{NT}\sum_i\sum_t\begin{bmatrix} \beta_i + \beta_t \\ \delta_i + \delta_t \end{bmatrix}$$

- If $X'X$ only contains signals, this will factor.

IV doesn't fix it

$$\left(\frac{1}{NT}\sum_i \sum_t \begin{bmatrix} s_{it}^2 & s_{it}\, piv_{it} \\ s_{it}\, piv_{it} & piv_{it}^2 \end{bmatrix}\right)^{-1} \times \frac{1}{NT}\sum_i \sum_t \begin{bmatrix} s_{it} \\ piv_{it} \end{bmatrix} \left[\begin{bmatrix} s_{it} & p_{it} \end{bmatrix} \begin{bmatrix} \beta_i + \beta_t \\ \delta_i + \delta_t \end{bmatrix}\right]$$

- This is true whether piv_{it} comes from instrumenting with Bayesian belief, or instrumenting i's prior today with i's belief in $t-1$.

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Example ASVAB questions

Math

How many 15 passenger vans will it take to drive all 52 members of the football team to the stadium?

- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5

Verbal

Banal most nearly means

- ☐ commonplace
- ☐ forceful
- ☐ tranquil
- ☐ indifferent

Science

When water is taken apart by electricity, what two substances are formed?

- ☐ Carbon and oxygen
- ☐ Hydrogen and oxygen
- ☐ Oxygen and nitrogen
- ☐ Hydrogen and nitrogen

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