Dynamic updating about menus

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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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- But, environment complex:
  - Information arrives sequentially
  - About a menu of individuals
  - With different prior distributions of ability.
- **Goal:** Study dynamic belief formation about individuals who are evaluated with others.

Introduction

- Use lab experiment to study how evaluators update based on incremental information
  - How features of distribution from which evaluatee sampled affect learning.
  - How comparison between individuals affects learning, depending on their respective groups.

Outline

Design

Econometric strategy

Aggregate analysis

Sequence effects

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Overview of design

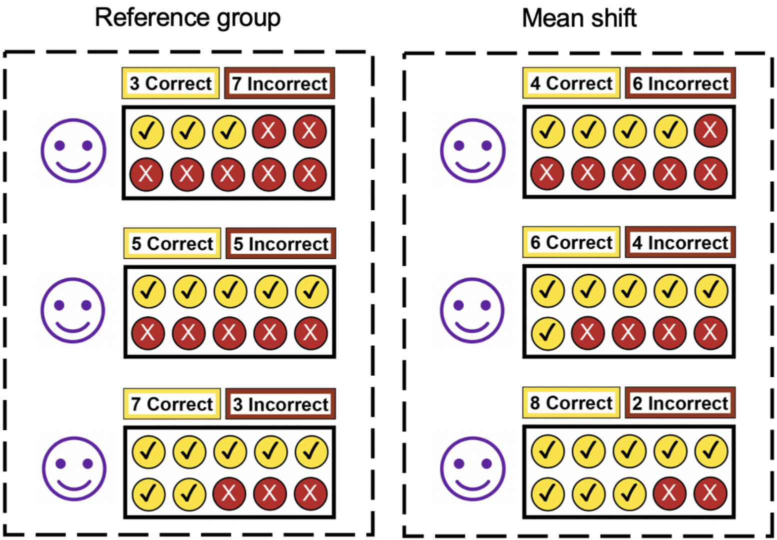
- Experimental “employers” complete a statistical learning task.
  - Create groups of experimental “workers” with varying ability.
  - Worker drawn from a given ability distribution.
  - Employer receives information on worker ability incrementally and reports beliefs.
- Vary environment in which learning task done.
  - Single worker in isolation.
  - Pairs drawn from same distribution evaluated simultaneously.
  - Pairs drawn from different distributions evaluated simultaneously.

Workers and their task

- Hired 160 people ("workers") on Prolific to complete a set of questions from the ASVAB.
  - Test used by US military to assess cognitive skills.
  - Split into three quizzes: science, math, verbal. Examples
- Each worker got score out of 10 on math quiz. This is "ability" parameter employers subsequently make inferences about.

Worker groups for employer treatments

- From pool of workers, construct two groups, each with different distribution of scores.



Employers and their evaluation task

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$$P(y|score) = \begin{cases} score/10 & \text{if } y = correct \\ 1 - score/10 & \text{if } y = incorrect \end{cases}$$

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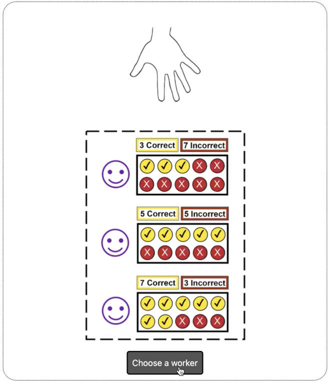
$$P(y|score) = \begin{cases} score/10 & if\, y = correct \\ 1 - score/10 & if\, y = incorrect \end{cases}$$

- **Bayesian benchmark:** Calculate posterior distribution of score according to:

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

Individual treatment (*Individual*)

- Step 1: Employer randomized to one of two groups and views group. Gives accurate prior.
- Step 2: Single worker drawn with replacement from the group.



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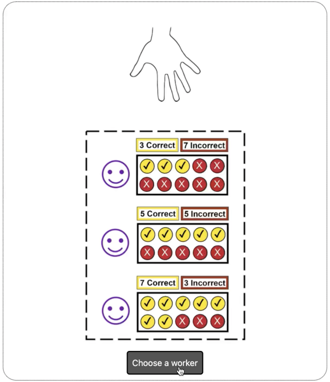
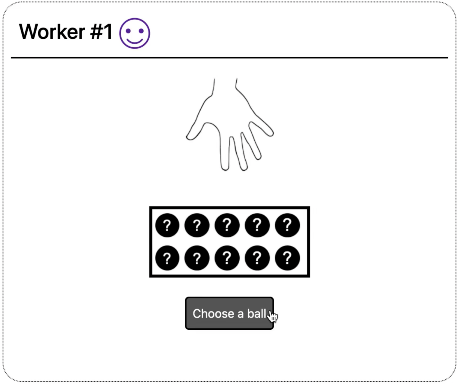


- Step 3: Complete 3 identical rounds about worker.

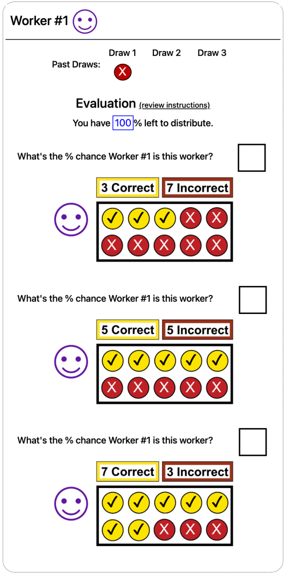
Part 1 of Round: View signal

- View whether question drawn with replacement from quiz answered correctly or incorrectly:



Part 2 of Round: Posterior

- Report full posterior distribution of worker's score:



Sequence and payment

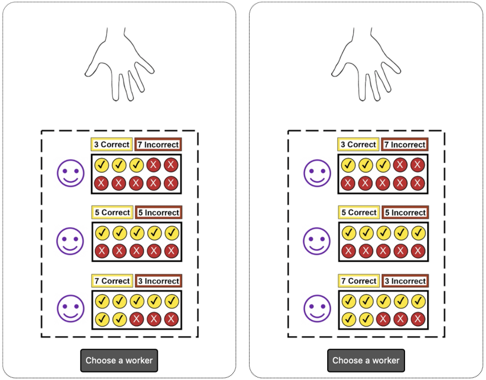
- 24 rounds overall: 3 rounds each for 8 workers.

Sequence and payment

- 24 rounds overall: 3 rounds each for 8 workers.
- Pay for half of the rounds, chosen randomly.
- Beliefs incentivized with binarized scoring rule.

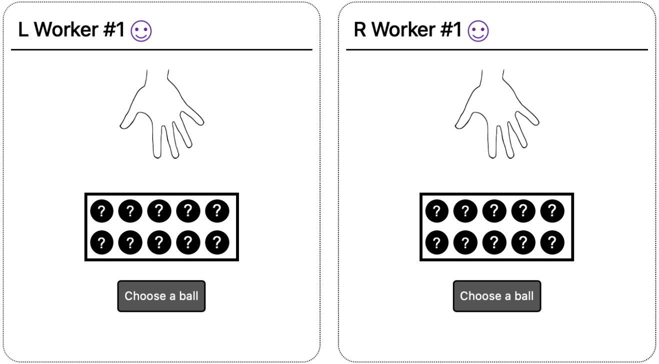
Two workers from same group (*Same*)

- Step 1: Randomized to a group and view group.
- Step 2: Draw two workers, each with replacement.



Two workers from same group (*Same*)

- Step 3: Complete rounds simultaneously for both workers in pair via split interface.



- 12 rounds overall: 3 rounds for 4 worker pairs.
- Pay for one worker each round, chosen randomly.

Two workers from different groups (*Different*)

- Step 1: View both groups.
- Step 2: Draw one worker with replacement from each group.
- Step 3: Complete rounds simultaneously for both workers in pair via split interface.
- 12 rounds overall: 3 rounds for 4 worker pairs.
- Pay for one worker each round, chosen randomly.

Signals

- Signal sequences are (using 1 to indicate signal = correct question, 0 for signal = incorrect question):

	Individual		Same Group			Different Groups	
	Group G		Group G	Group G		Group G	Group G'
Worker 1	0,0,1	Pair 1	0,0,1	0,1,1	Pair 1	0,0,1	0,1,1
Worker 2	0,1,1	Pair 2	0,1,1	1,0,0	Pair 2	0,1,1	1,0,0
Worker 3	0,0,0	Pair 3	0,0,0	1,1,1	Pair 3	0,0,0	1,1,1
Worker 4	1,1,0	Pair 4	1,1,0	0,0,1	Pair 4	1,1,0	0,0,1
						Group G	Group G'
Worker 5	0,1,1				Pair 1	0,1,1	0,0,1
Worker 6	1,0,0				Pair 2	1,0,0	0,1,1
Worker 7	1,1,1				Pair 3	1,1,1	0,0,0
Worker 8	0,0,1				Pair 4	0,0,1	1,1,0

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.

Outline

Design

Econometric strategy

Aggregate analysis

Sequence effects

Econometric strategy

- Evaluator i reports belief about worker w in time t
- For a given worker, t goes from 1 to 3
- Normally, estimate log-linear form of Bayes rule

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

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

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

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

Econometric strategy

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

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

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

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

$$+ \delta_i * log\left(\frac{P(score_j)_{i,w,t-1}}{P(score_k)_{i,w,t-1}}\right) + \epsilon_{i,w,t}$$

- 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:

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

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:

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

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

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

Outline

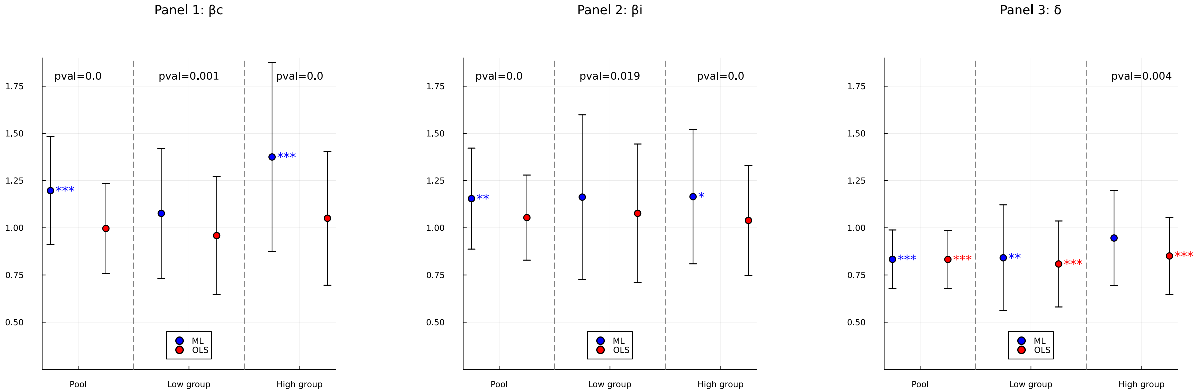
Baseline model

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

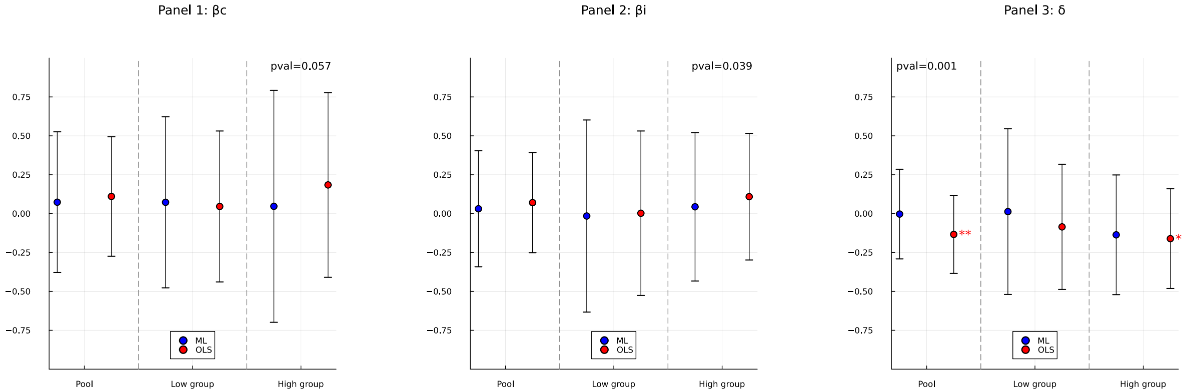
- Will show estimate of $\mu_{\beta_{Ci}}, \mu_{\beta_{Ii}}, \mu_{\delta_i}$

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

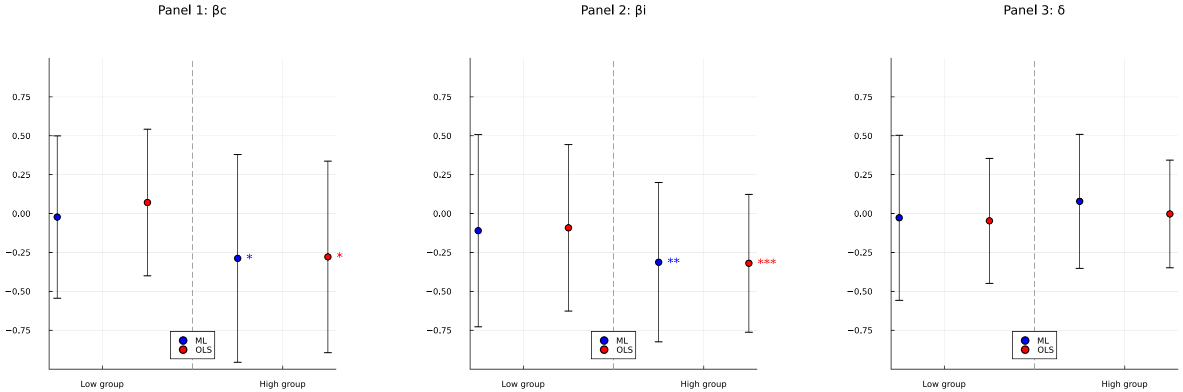
Individual treatment



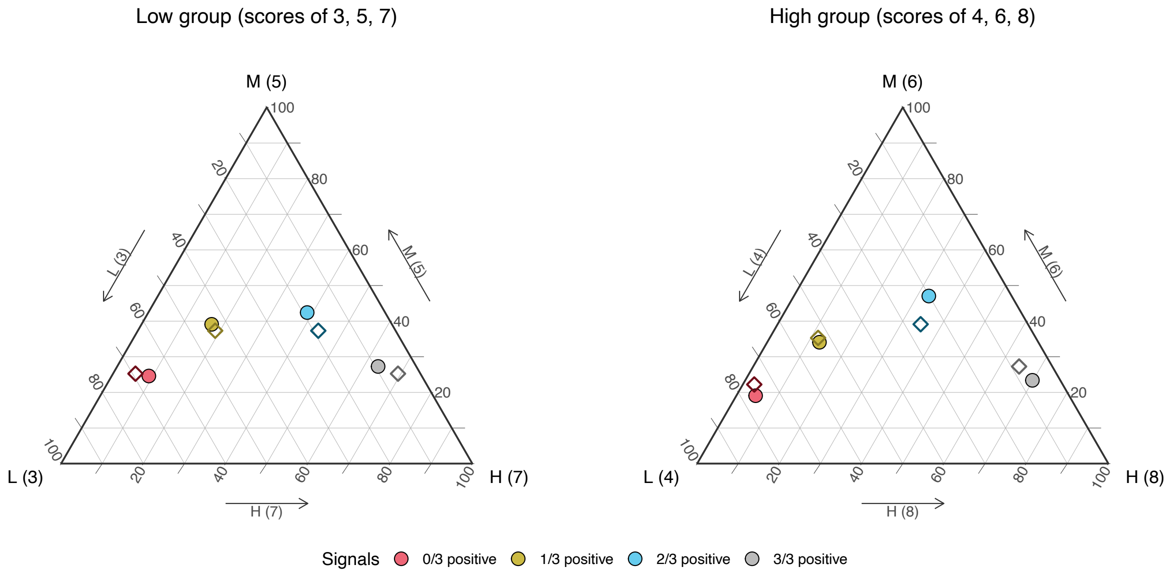
Effect of simultaneous evaluation



Effect of partner from different group



Final belief in *Individual* treatment



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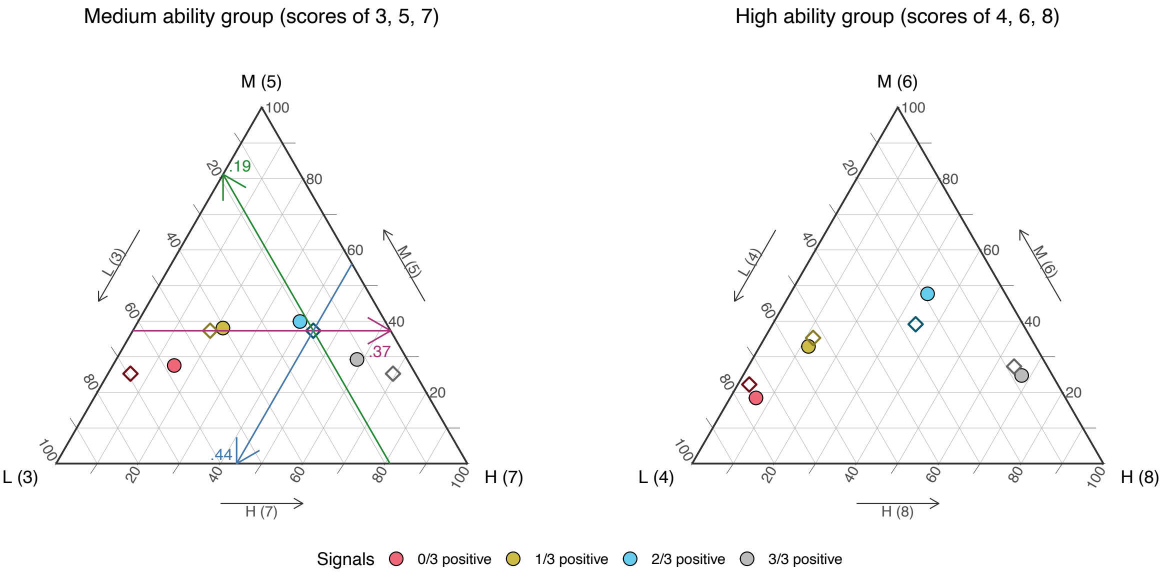

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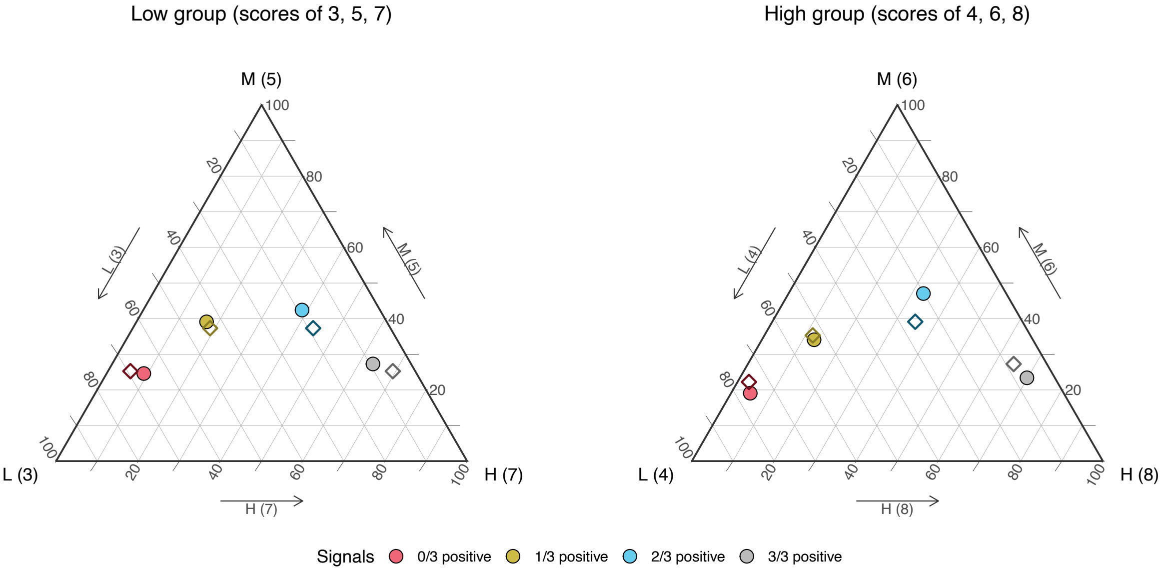
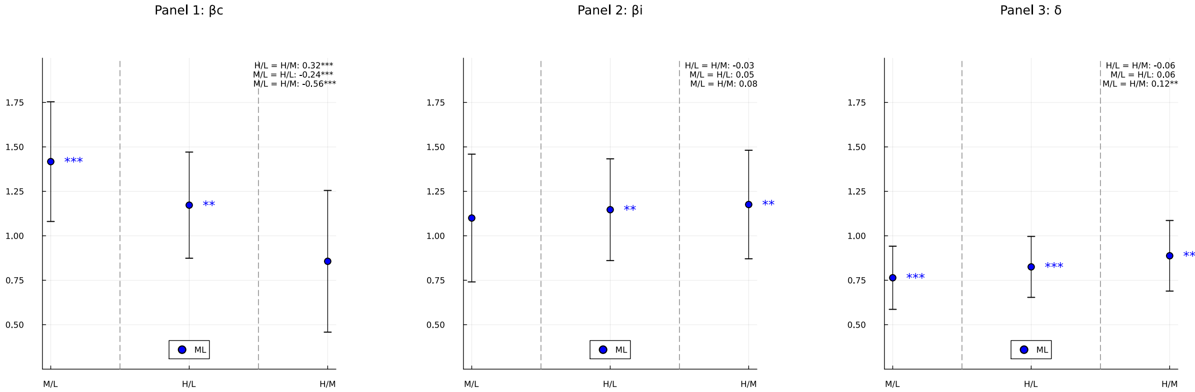


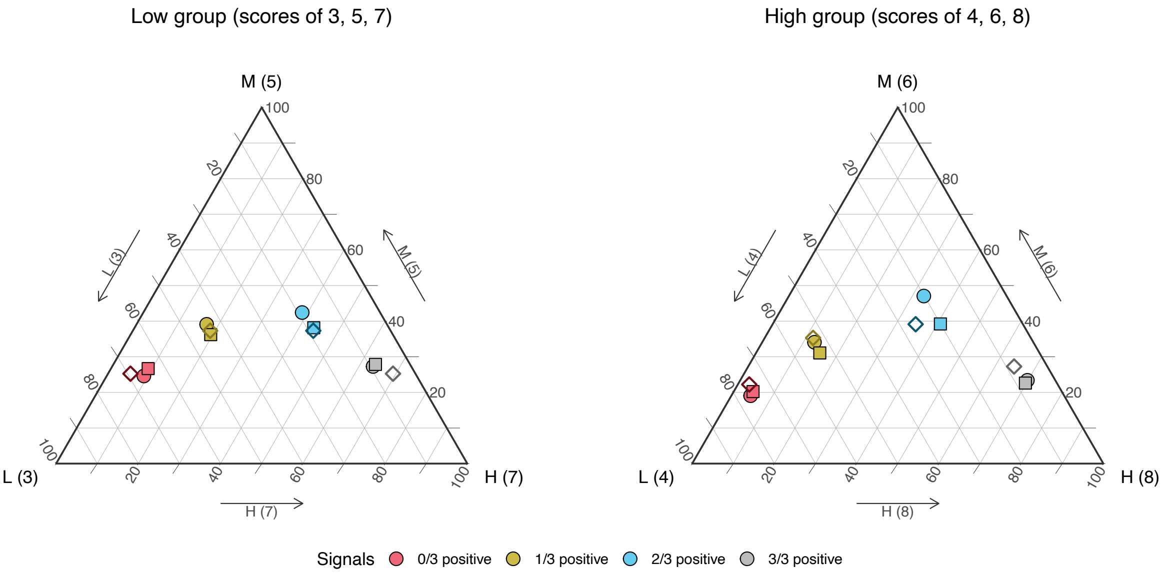
Model with state effects

$$y_{it} = \begin{cases} [\beta_{Ci} + \beta_{C,state}]1[s_t = cor]s_{it} + [\beta_{Ii} + +\beta_{I,state}]1[s_t = inc]s_{it} + \epsilon_{it} & \text{if } t = 1 \\ [\beta_{Ci} + \beta_{C,state}]1[s_t = cor]s_{it} + [\beta_{Ii} + \beta_{I,state}]1[s_t = inc]s_{it} + [\delta_i + \delta_{state}]y_{i,t-1} + \epsilon_{it} & \text{if } t > 1 \end{cases}$$

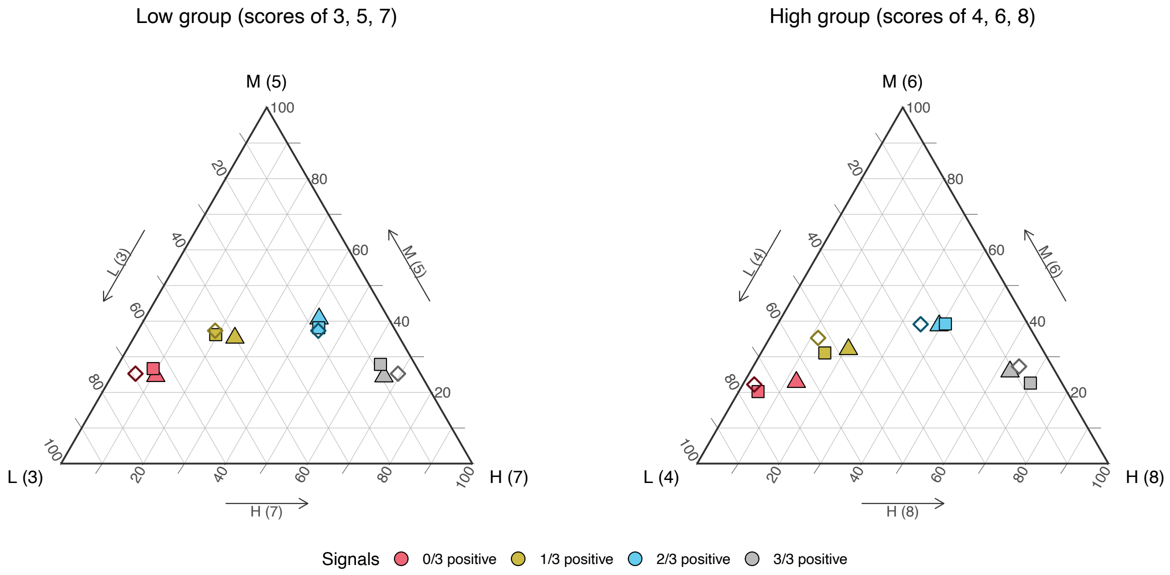
State specific effects in *Individual* treatment



Effect of simultaneous evaluation

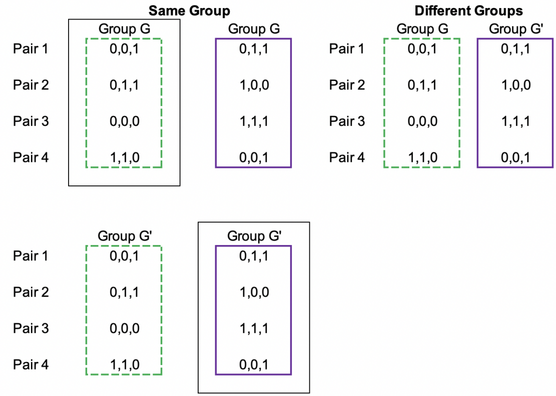


Effect of partner from different group



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*

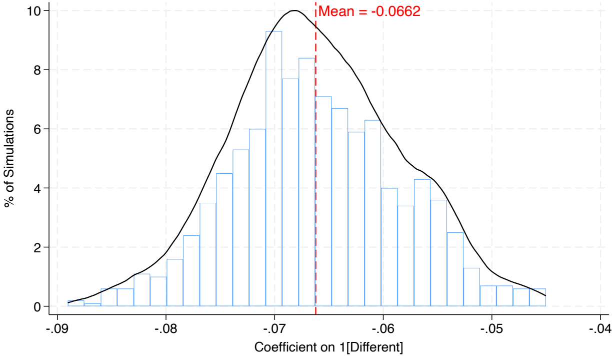


Partner from different group leads to compression within pair.

- 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*.



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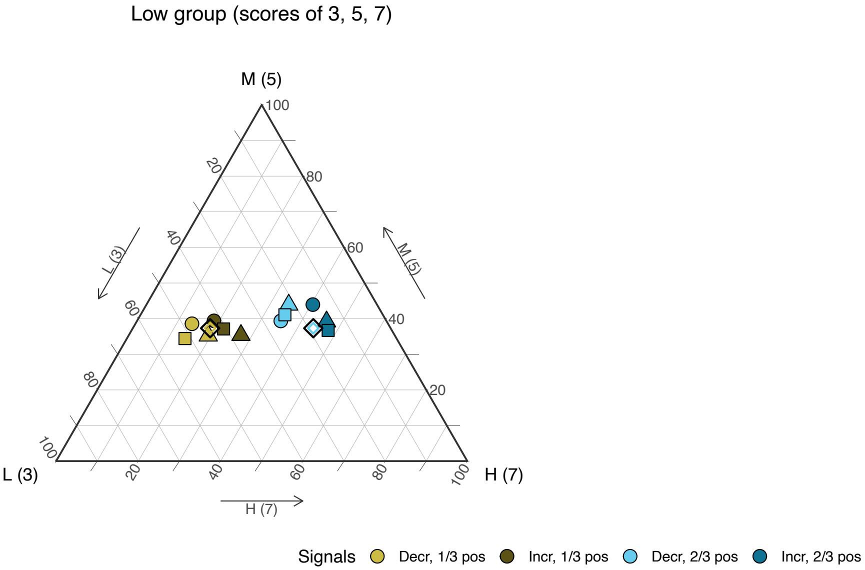
Generally, beliefs higher after increasing sequence.



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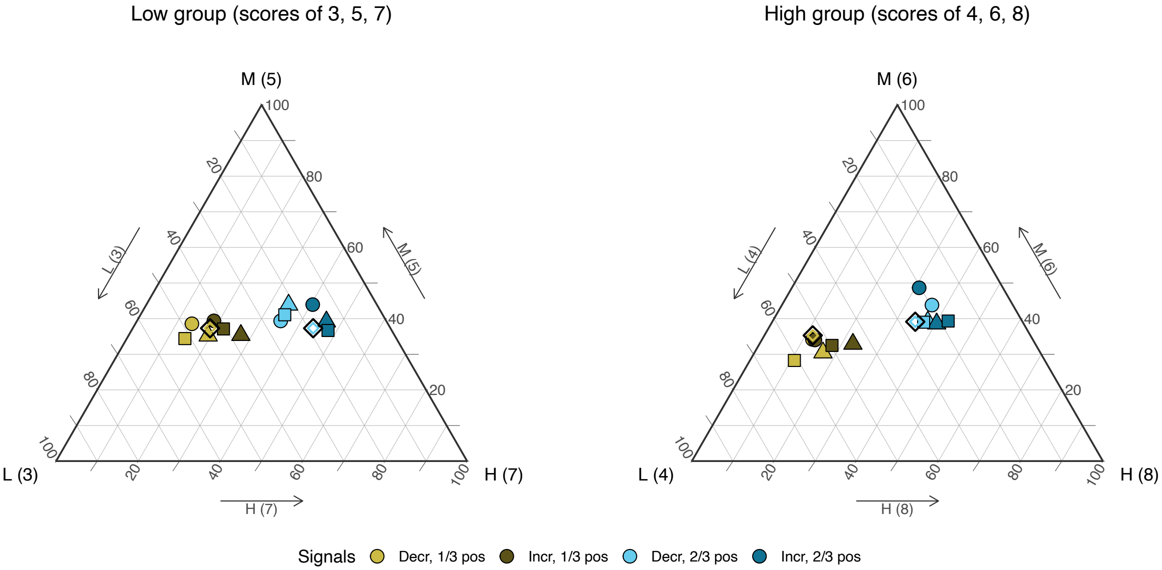
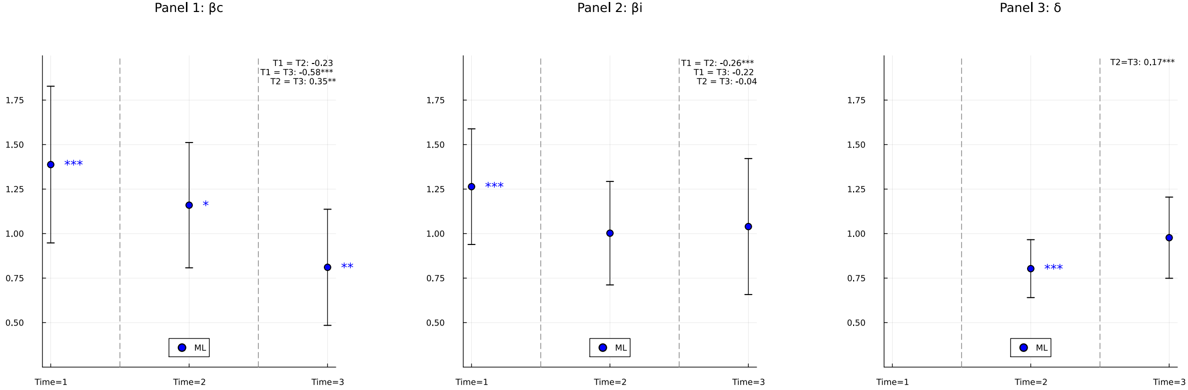


Model with time effects

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

Time specific effects in *Individual*



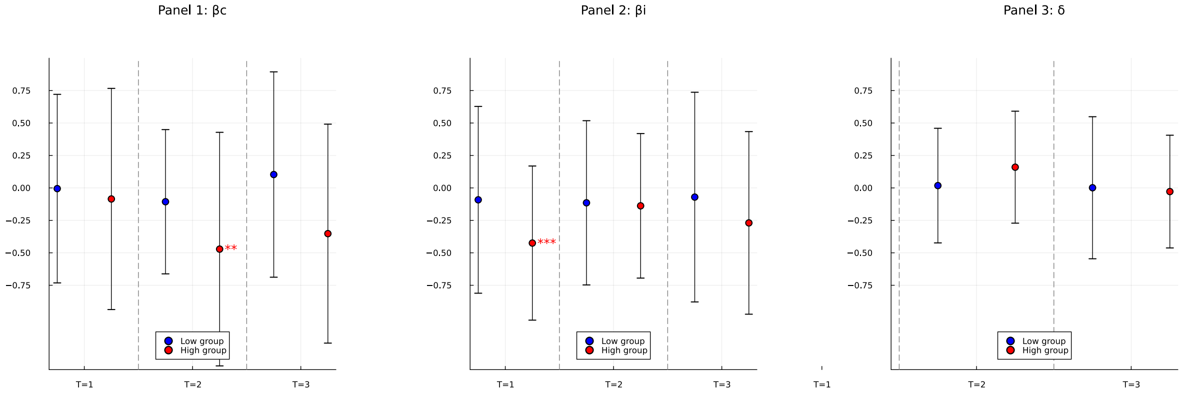
Conclusion

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

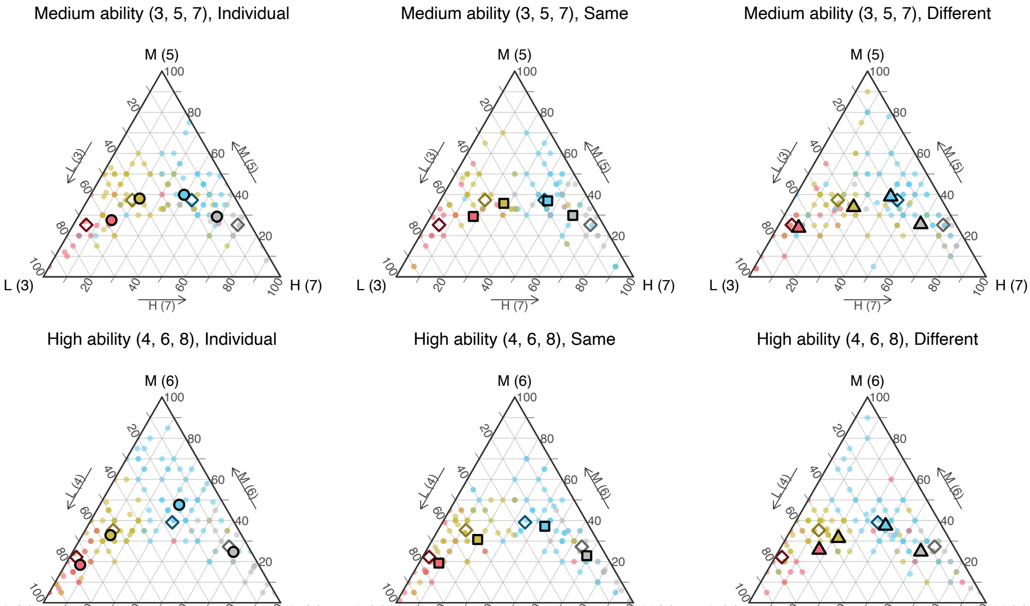
Appendix

Appendix

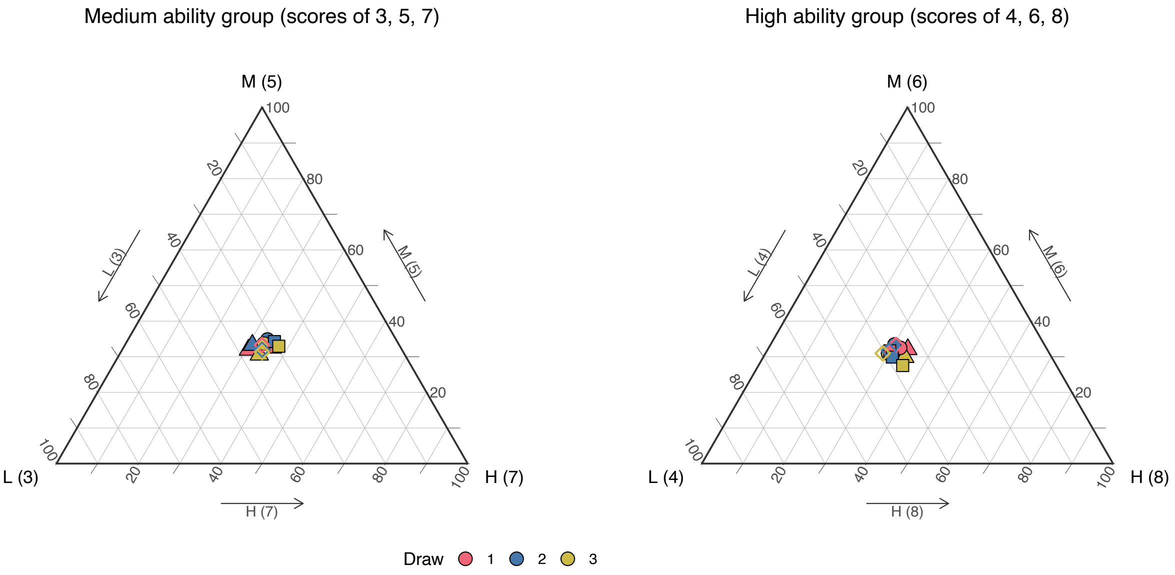
Effect of partner from different group, by time



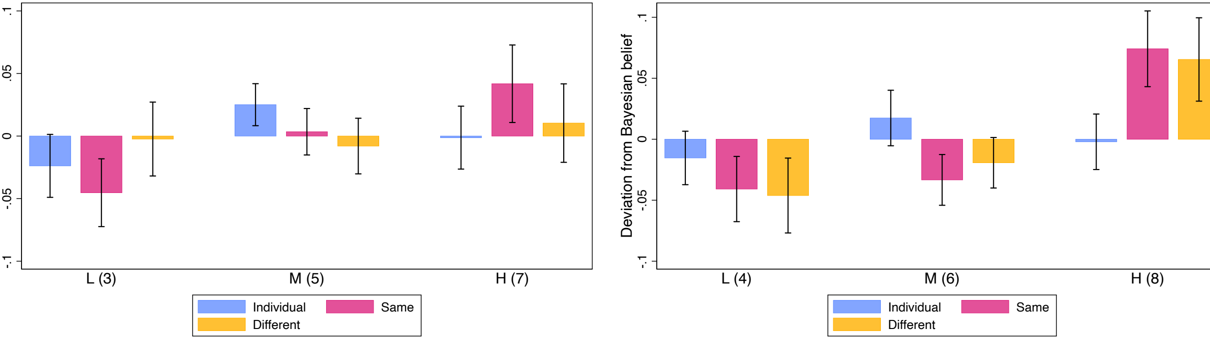
Scatter plot of final beliefs by treatment



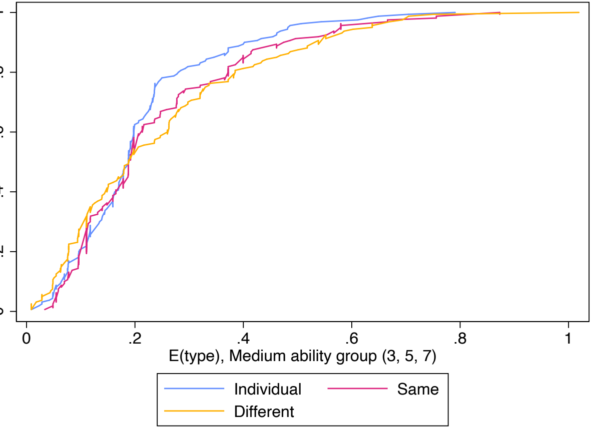
Belief by signal draw

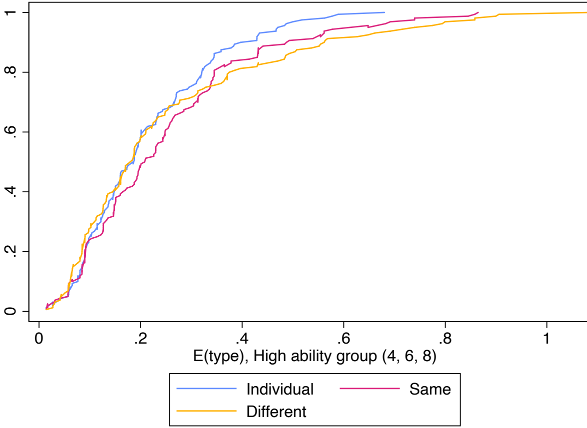


Distance from Bayesian belief in final round



CDF, Distance from Bayesian belief in final round





Appendix

Effect of *Same* by group.

	(1) P(L)	(2) P(M)	(3) P(H)
Same	-0.021	-0.022	0.043
	(0.018)	(0.024)	(0.029)
High ability group (4, 6, 8)	0.015	-0.007	-0.013
	(0.016)	(0.019)	(0.021)
Same × High ability group	-0.004	-0.029	0.033
	(0.026)	(0.034)	(0.040)
Constant	0.008	-0.010	0.054**
	(0.019)	(0.043)	(0.025)
Effect of *Same* in high ability group (*Same* + *Same* × High)	-0.026	-0.051**	0.076***
Control for Bayesian belief	✓	✓	✓
Observations	640	640	640

▸ Back

Effect of *Same* by worker signals.

	(1) P(L)	(2) P(M)	(3) P(H)
2-3 positive signals	-0.060* (0.033)	0.052*** (0.017)	-0.000 (0.031)
Same	-0.036 (0.033)	-0.016 (0.018)	0.052* (0.031)
Same × 2-3 pos	0.026 (0.046)	-0.040** (0.019)	0.014 (0.040)
Constant	0.081*** (0.030)	-0.023 (0.042)	0.053** (0.022)
Effect of *Same* for 2-3 pos signals (*Same* + *Same* × 2-3 pos)	-0.010	-0.056***	0.067***
Control for Bayesian belief	✓	✓	✓
Observations	640	640	640

Back

Appendix

Effect of *Different* by group and worker signals.

- Worker in g with sequence s, partner is worker in g' with s'
- Worker in g with sequence s, partner is worker in g with s'

	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)
Different	0.052	-0.028	-0.024	-0.065	0.021	0.043
	(0.042)	(0.028)	(0.046)	(0.041)	(0.021)	(0.040)
2-3 positive signals	0.008	0.010	-0.036	-0.157***	0.222**	0.079
	(0.049)	(0.009)	(0.043)	(0.055)	(0.101)	(0.051)
2-3 pos × *Different*	-0.018	0.032	-0.014	0.119**	-0.015	-0.104**
	(0.061)	(0.028)	(0.057)	(0.051)	(0.027)	(0.050)
Constant	0.062	0.108*	0.104**	0.194***	1.101**	0.082**
	(0.049)	(0.056)	(0.043)	(0.066)	(0.542)	(0.037)
Control for Bayesian belief	✓	✓	✓	✓	✓	✓

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 × 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 × 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)	(2)	(3)	(4)	(5)	(6)
	P(L)	P(M)	P(H)	P(L)	P(M)	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:

$$
\begin{aligned}
log\left(\frac{P(score_j|signal)_{i,w,t}}{P(score_k|signal)_{i,w,t}}\right) = \\
\beta_{Ci} * 1[s_t = correct] * log\left(\frac{P(correct|score_j)_{i,w,t}}{P(correct|score_k)_{i,w,t}}\right) \\
+ \beta_{Ii} * 1[s_t = incorrect] * \overbrace{log\left(\frac{P(incorrect|score_j)_{i,w,t}}{P(incorrect|score_k)_{i,w,t}}\right)}^{\text{LLR if signal in } t \text{ incorrect}} \\
+ \delta_i * \overbrace{log\left(\frac{P(score_j)_{i,w,t-1}}{P(score_k)_{i,w,t-1}}\right)}^{\text{log prior odds}} + \eta_{i,w,t}
\end{aligned}
$$

- 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:

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

- 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

Figures

Effect of *Same* treatment

Effect of *Different* treatment

Effect of signal order

Endogeneity

OLS estimates of log-linear updating rule

Other

Individual vs same treatment.

	(1) log P(L)/P(M)	(2) log P(M)/P(H)	(3) log P(L)/P(H)
log prior	0.855***	0.785***	0.869***
	(0.052)	(0.051)	(0.046)
LLR correct	1.052	0.447***	0.834**
	(0.088)	(0.095)	(0.071)
LLR incorrect	0.941	1.149	1.034
	(0.127)	(0.100)	(0.094)
log prior odds × Same	-0.164**	-0.042	-0.153*
	(0.072)	(0.073)	(0.082)
LLR correct × Same	0.056	0.433*	0.176
	(0.117)	(0.230)	(0.123)
LLR incorrect × Same	0.130	-0.168	-0.015
	(0.238)	(0.166)	(0.163)
Prior + prior × Same = 1	0.692***	0.742***	0.716***
Correct + correct × Same = 1	1.108	0.880	1.010
Incorrect + incorrect × Same = 1	1.071	0.981	1.019
Observations	1910	1893	1883

Same vs different: partner from high ability.

	(1) log P(L)/P(M)	(2) log P(M)/P(H)	(3) log P(L)/P(H)
log prior	0.689***	0.832***	0.706**
	(0.057)	(0.062)	(0.115)
LLR correct	1.108	0.771	0.962
	(0.130)	(0.258)	(0.163)
LLR incorrect	0.494*	0.745	0.655*
	(0.286)	(0.197)	(0.191)
log prior odds × Diff: partner from high	-0.011	-0.264**	-0.013
	(0.081)	(0.101)	(0.133)
LLR correct × Diff: partner from high	-0.047	-0.043	0.011
	(0.171)	(0.299)	(0.186)
LLR incorrect × Diff: partner from high	0.527	0.231	0.323
	(0.331)	(0.227)	(0.220)
Prior + prior × Diff = 1	0.678***	0.568***	0.693***
Correct + correct × Diff = 1	1.062	0.728*	0.973
Incorrect + incorrect × Diff = 1	1.021	0.976	0.977
Observations	952	944	939

Same vs different: partner from medium ability

	(1) log P(L)/P(M)	(2) log P(M)/P(H)	(3) log P(L)/P(H)
log prior	0.657***	0.661***	0.698***
	(0.078)	(0.068)	(0.084)
LLR correct	1.106	0.944	1.054
	(0.082)	(0.321)	(0.129)
LLR incorrect	1.653***	1.241*	1.389**
	(0.224)	(0.142)	(0.148)
log prior odds × Diff: partner from med	-0.181*	-0.120	-0.084
	(0.097)	(0.144)	(0.108)
LLR correct × Diff: partner from med	-0.273**	-0.422	-0.350**
	(0.120)	(0.429)	(0.173)
LLR incorrect × Diff: partner from med	-0.585**	-0.251	-0.403**
	(0.281)	(0.197)	(0.195)
Prior + prior × Diff = 1	0.477***	0.541***	0.614***
Correct + correct × Diff = 1	0.833*	0.521*	0.704**
Incorrect + incorrect × Diff = 1	1.068	0.989	0.986
Observations	955	940	940

Appendix

Figures

Effect of *Same* treatment

Effect of *Different* treatment

Effect of signal order

Endogeneity

OLS estimates of log-linear updating rule

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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Related literature

- Large literature on inferential biases (Benjamin, 2019)
- Most relevant are lab experiments on learning about others' ability:
  - Are prior beliefs correct? (Bohren et. al, 2022; Bordalo et al., 2019)
  - Do people learn about groups over time? (Le Page, 2022)
  - Do people make errors in combining individual-level and group info? (Esponda et al., 2022; Mengel and Campos Mercade, 2022)

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

<u>Banal</u> 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