

# Behavioral Economics

## Lecture 8: Overconfidence and Crowdsourcing

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# What Epping et al. Estimate

$$\text{logit } r_i = \alpha_i \text{logit } p_i + \beta_i$$

## Data engineering move

- ▶ Each annotator reports a probability  $p_i(x)$  that an image is a blast cell
- ▶ A small calibration set has known labels  $y(x)$
- ▶ Fit a logistic regression of truth on the annotator's log odds
- ▶ Use the fitted map to produce recalibrated elicited beliefs  $r_i(x)$

## Parameter interpretation

- ▶  $\alpha_j$ : spread correction
- ▶  $|\alpha_j| < 1$  compresses overconfident reports;  $|\alpha_j| > 1$  amplifies underconfident reports
- ▶  $\beta_j$ : class/response bias correction
- ▶  $\alpha_j < 0$ : flip anti-informative annotators

# The One-Line Connection

The recalibration rule in Epping, Caplin, Duhaime, Holmes, Martin & Trueblood (2026) is the **binary-state version** of the theory paper's **power-weighted distortion** in Chambers, Masatlioglu & Raymond (2023)

**Epping et al. recalibration rule**

$$\text{logit } r_i(x) = \alpha_i \text{logit } p_i(x) + \beta_i$$

**Power-weighted belief distortion**

$$\phi(p)(\omega) = \frac{\psi(\omega)p(\omega)^\gamma}{\sum_{\omega'} \psi(\omega')p(\omega')^\gamma}$$

Epping et al. LLO recalibration equations, CMR Theorem 1

## Binary Algebra: LLO Is Power Weighting

Let  $\Omega = \{1, 0\}$  and write  $p = p(1)$ , looking at state 1:

$$\phi(p)(1) = \frac{\psi_1 p^\gamma}{\psi_1 p^\gamma + \psi_0 (1-p)^\gamma}$$

$$\frac{\phi(p)(1)}{1 - \phi(p)(1)} = \frac{\psi_1}{\psi_0} \left( \frac{p}{1-p} \right)^\gamma$$

$$\text{logit } \phi(p)(1) = \gamma \text{ logit } p + \log \left( \frac{\psi_1}{\psi_0} \right)$$

The LLO rule has the same form, with  $\alpha = \gamma$  and  $\beta = \log(\psi_1/\psi_0)$

# What Coherence Requires

A distorted belief is a map

$$\phi : \Delta(\Omega) \rightarrow \Delta(\Omega)$$

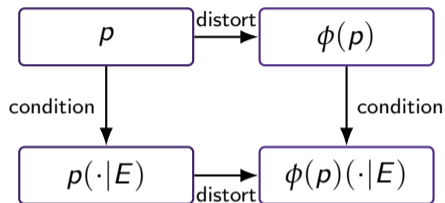
**Coherence:**

$$\phi(p(\cdot | E)) = \phi(p)(\cdot | E)$$

whenever  $p(E) > 0$

The timing of distortion and conditioning should not matter

CMR Definition 1 and Theorem 1



CMR show: positivity + continuity + coherence  $\iff$  power-weighted distortion

## Connection to Grether

- ▶ CMR consider a generalized class of distortions where the DM can distort, independently, both their prior and the Blackwell experiment (belief updating)
- ▶ The coherency conditions imply that two distinct operations must be equivalent: (i) distorting the prior, distorting the signal, and then Bayesian updating; and (ii) Bayesian updating with true probabilities, and then distorting the posterior
- ▶ CMR find that coherence requires:
  1. Distortions to priors must take on the familiar power-weighted form
  2. Distortions to signals take on a non-normalized power weighted form
  3. The powers of the two distortions are the same
- ▶ The Grether model is coherent only when the prior and signal powers are equal!

# References I

Chambers, C. P., Masatlioglu, Y. & Raymond, C. (2023), 'Coherent distorted beliefs', *arXiv preprint arXiv:2310.09879* .

Epping, G. P., Caplin, A., Duhaime, E., Holmes, W. R., Martin, D. & Trueblood, J. S. (2026), 'Improving crowdsourcing for ai through cognitive-inspired data engineering', *Preprint, submitted December 30*.