Behavioral Attenuation

Ben Enke, Thomas Graeber, Ryan Oprea, and Jeffrey Yang; *Working Paper.*

Shivani Pandey and Dylan Baker

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Variation in Parameters and Pre-Registered Simple Points

- The authors varied the central decision-relevant parameter over a wide range, which they argue moves problem complexity, to explore the "demand side" of information-processing.

- In most experiments, they included "potential simple points" at natural boundaries at which optimizing was expected to be easy.

Cognitive Uncertainty Elicitation

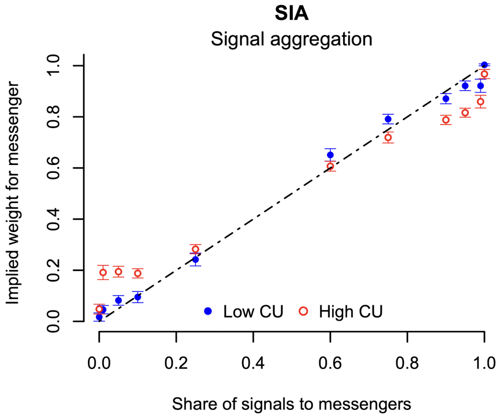
- The authors elicited cognitive uncertainty essentially by asking participants how certain they were that they optimized.

- Example:
    - Continuous decisions in subjective tasks, illustrated by Effort supply: "How certain are you that completing somewhere between [Y-1] and [Y+1] tasks is actually your best decision, given your preferences?"

Results

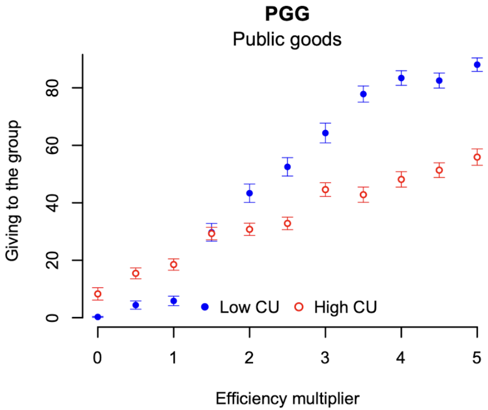
Example Experimental Results - Objective Task

- To the right is an example of the results from an objective task.
- Note that attenuation is present across most of the parameter space, i.e., the elasticity is smaller than expected for an optimizing agent.
- This is especially true once off the boundary and is stronger for high CU participants.



Example Experimental Results - Subjective Task

- To the right is an example of the results from a subjective task.
- Although there's no objective benchmark, we can see a similar pattern emerge.



Econometric Strategy

- For each experiment, e, the authors estimate

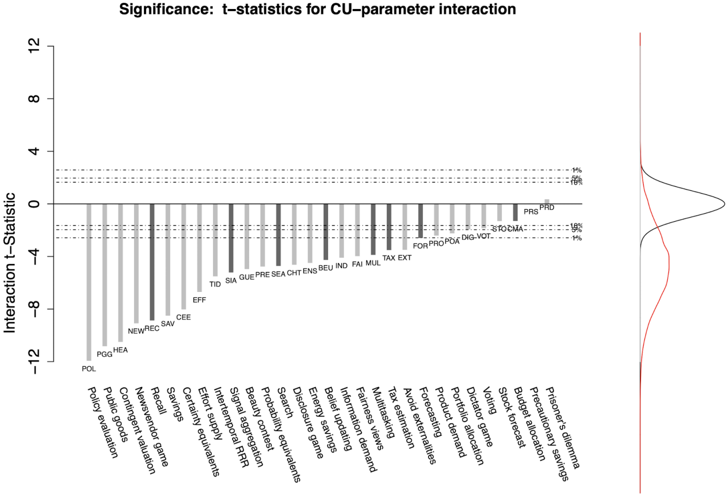
$$a^e_{i,j} = \alpha^e + \gamma^e \theta^e_j + \beta^e \theta^e_j CU^e_{i,j} + \delta^e CU^e_{i,j} + \sum_x \chi^e d^e_x + \epsilon^e_{i,j}$$

where

- i: Individual
- j: Parameter order, i.e., $\theta_j > \theta_{j-1}$
- $a^e_{i,j}$: Decision
- d^e_x: Controls
- $CU^e_{i,j}$: Elicited cognitive uncertainty
- θ^e_j: Parameter value
- γ^e: Coefficient on the parameter normalized to be positive
- β^e: Coefficient of interest on the interaction between CU and parameter

T-Stat Results

- The attenuation hypothesis is that β^e is negative.
- The authors report the t-statistic for each experiment.
- The black-curve presents a $\mathcal{N}(0,1)$ distribution for reference.
- 28/30 are negative; 24/30 are significant at the 5% level.



Attenuation Ratio

- Under the authors' specification, we have:

$$\frac{\partial \mathbb{E}\left[a_{i,j}^e\right]}{\partial \theta_j^e} = \gamma^e + \beta^e \mathrm{CU}$$

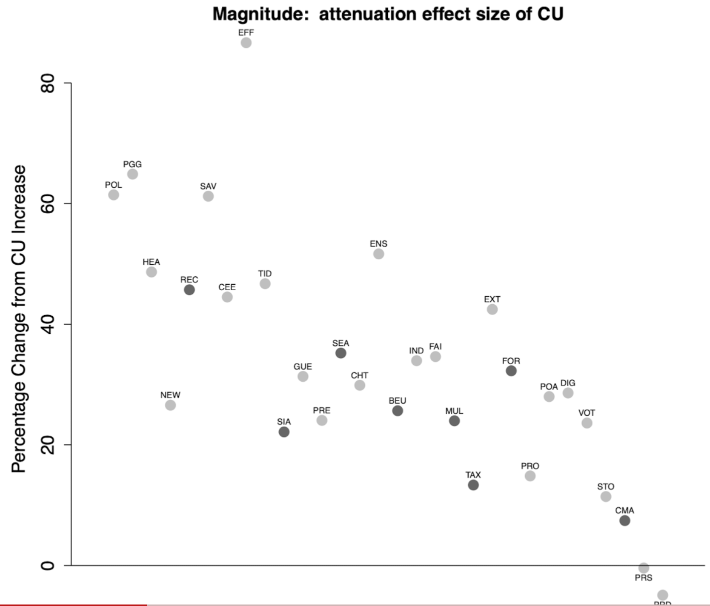
- From which, we can define another measure for cross-experiment comparison:

$$\begin{aligned} CU \text{ attenuation ratio } &\equiv \frac{(\text{ Sensitivity at } CU = 0) - (\text{ Sensitivity at } CU = 0.5)}{(\text{ Sensitivity at } CU = 0)} \\ &= -\frac{0.5\hat{\beta}^e}{\hat{\gamma}^e} \end{aligned}$$

- Interpretation: How much the sensitivity decreases as CU increases from 0 to 0.5.

Attenuation Ratio Figure

- The reduction in sensitivity is 33% on average and up to 87%.



Attenuation to Objective Benchmarks

- We then consider the subset of experiments with objective benchmarks.
- The authors estimate:

$$a^e_{i,j} = v^e + \omega^e \theta^e_j + \sum_x \chi^e d^e_x + u^e_{i,j}$$

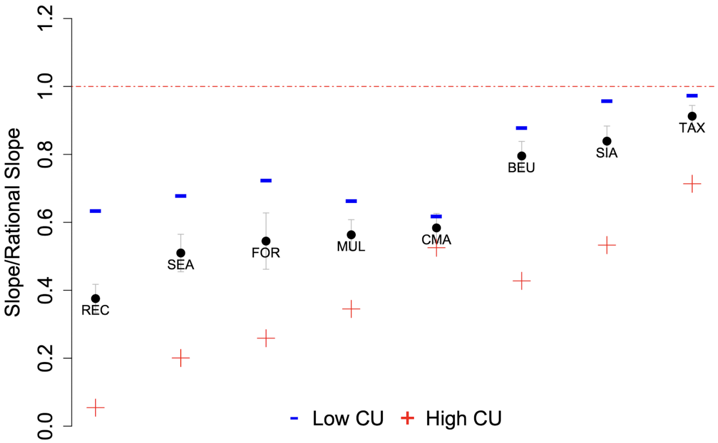
where the term of interest is ω^e.

- Specifically, we consider the ratio between the estimated ω^e and the rational benchmark:

$$\frac{\hat{\omega}^e}{\omega^e_R}$$

Attenuation to Objective Benchmark

- The black dots reflect $\frac{\hat{\omega}^e}{\omega_R^e}$
- The red and blue symbols plot the fitted values at 100% CU and 0% CU, respectively.
- The main takeaway is to notice that all dots are below one and the high and low CU split as expected.



Within- and Across-Subject Variation

- Subject FE explain 44% of the variation in CU, suggesting that subject-level differences in cognitive ability – the so-called “supply side” of information processing – may be important for attenuation
- The authors then estimate an adjusted version of the earlier specification

$$a^e_{i,j} = \alpha^e + \gamma^e \theta^e_j + \beta^e \theta^e_j \overline{CU}^e_i + \delta^e \overline{CU}^e_i + \sum_x \chi^e d^e_x + \epsilon^e_{i,j}$$

with $\overline{CU}^e_i$ rather than $CU^e_{i,j}$ reflecting the use of the subject-level average, rather than the individual decision's CU.

- This results in a large drop in the average attenuation effect size (33.0 to 8.8) and t-statistic (-4.8 to -1.39), suggesting a meaningful role for within-subject variation.

Problem Complexity and Diminishing Sensitivity

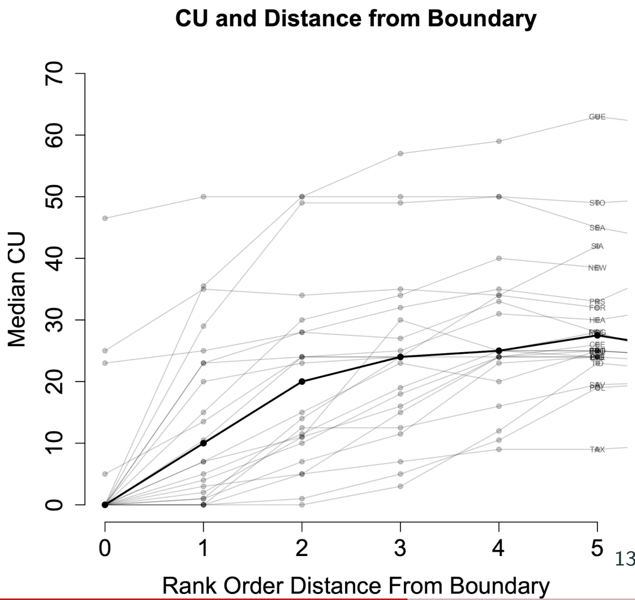
Problem Complexity and Diminishing Sensitivity

- The authors now leverage the fact that, within a given task type, some configurations of the task will demand more information-processing than others.

- Motivated by this, we first return to the "simple points" referenced earlier.

CU and Distance from Boundary

- The figure to the right shows median CU by distance from the boundary.
- Notice that at the boundary, median CU tends to be 0.
- The solid line displays the overall median across experiments.



Diminishing Sensitivity

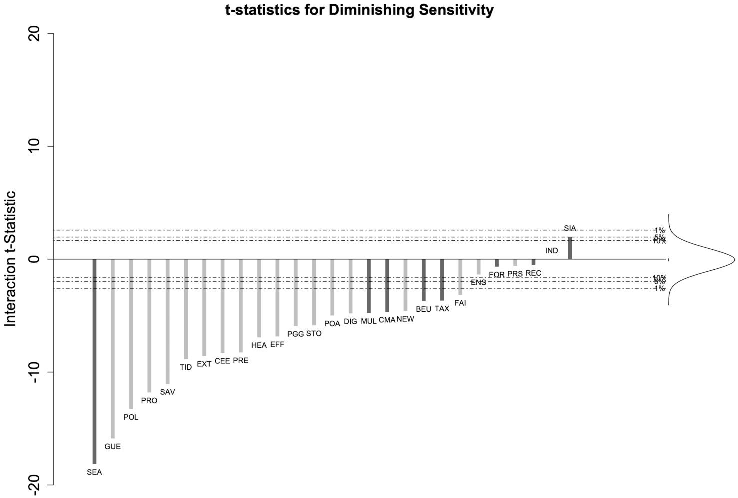
- The presented model predicts that there should be diminished sensitivity to the parameter value as the distance from the boundary increases due to the heightened CU.
- To assess for diminished sensitivity, the authors estimate

$$a_{i,j}^e = \alpha_d^e + \gamma_d^e \theta_j^e + \beta_d^e \theta_j^e \Delta_j^e + \delta^e \Delta_j^e + \sum_x \chi^e d_x^e + v_{i,j}^e$$

  where Δ_j^e is the distance from the nearest boundary
- Diminished sensitivity is captured by: $\hat{\beta}_d^e < 0$.

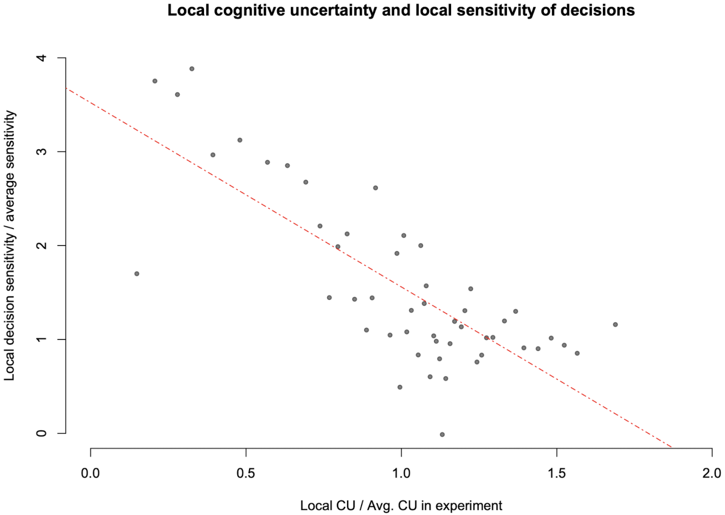
Diminished Sensitivity T Statistics

- The figure to the right displays the t-statistics for $\hat{\beta}_d^e$.
- Almost are all negative and statistically significant, as expected.



Across-Problem Variation in Complexity and Elasticity

- We now link variation in task complexity and diminished sensitivity by comparing sensitivity and CU not across individuals, but across task parameters.
- The authors construct comparable measures of CU and sensitivity across experiments by computing the local average and normalizing by the experiment average. (See figure to the right.)



Discussion

- Behavioral attenuation can (at least partially) explain many previously studied anomalies, including many explored in the paper.
- Additionally, the authors argue that behavioral attenuation offers a more parsimonious explanation than the oft-offered alternative of domain-specific preferences.
- Finally, the authors conclude with a note of optimism for the power of the cognitive lens to speak to a wide variety of economic phenomena with only a limited set of principles.