Bounding Causal Effects in Survey Experiments with Noncompliance or Inattention

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  - New computational method for partial identification + confidence intervals; generalizes broadly

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- Crucially, S_i is observed but A_i is not!

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- A2: D_i randomly assigned.
- A3: Known false positive/negative rate.

$$P[S_i(d) = 1 \mid A_i(d) = 1] = 1$$
$$P[S_i(d) = 1 \mid A_i(d) = 0] = \alpha_d$$

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- A6: Fixed compliance/screener.

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- Not point identifiable: observe either $A_i(0)$ or $A_i(1)$, not both
- If $S_i = A_i$ always, then ATAC is boundable (Lee 2009)
- No method for bounding ATAC when $S_i \neq A_i$

Computational method

- Parameterize joint distribution of all potential outcomes

$$\pi^*(a_0, a_1, s_0, s_1, j, k) = P[A_i(0) = a_0, A_i(1) = a_1, S_i(0) = s_0, S_i(1) = s_1, Y_i(0) = y_j, Y_i(1) = y_k]$$

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- R calculation: about 1 second; Newton-like convergence guarantees (c.f. Duarte et al. 2024)

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- Theorem 3: CI = solution to two second-order cone programs
- Similar speed and convergence guarantees as EB/linear program (use similar convex optimization algorithms)

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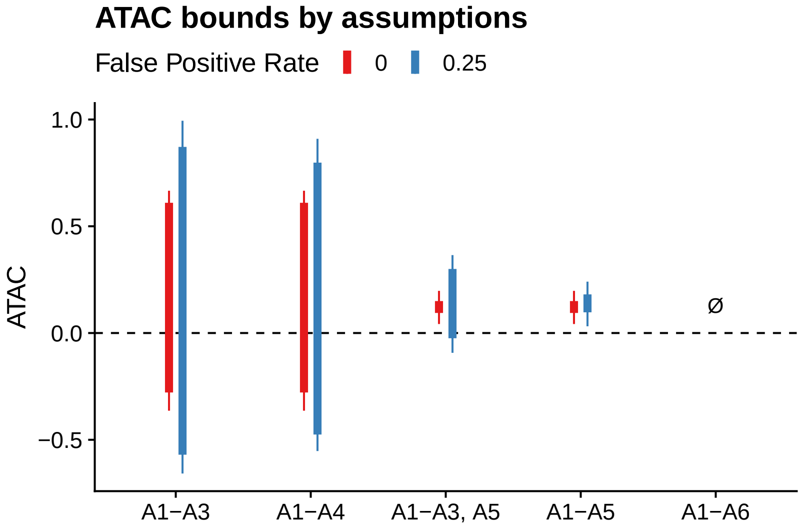
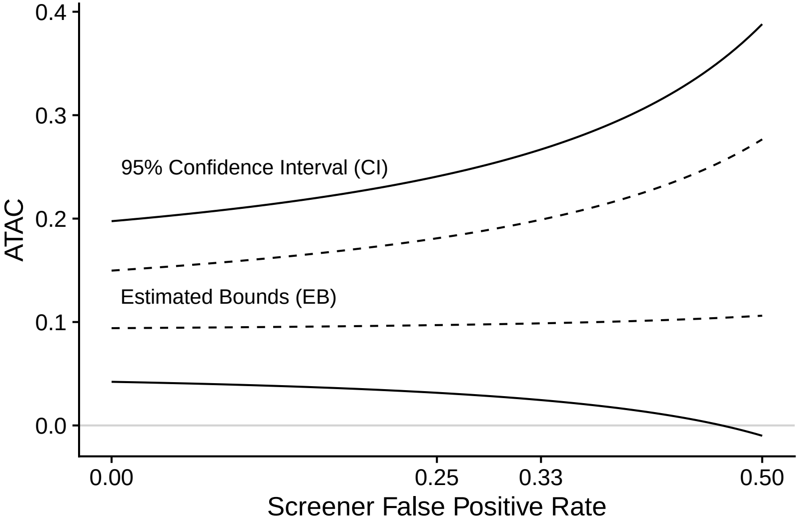
- What's the effect among always-compliant respondents?

Assumption sensitivity



False positive rate sensitivity (A1-A5)



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- Future work: Apply the computational method to other causal inference settings.

Thank You

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