Bounding Causal Effects in Survey Experiments with Noncompliance or Inattention

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La Carta de Tapas

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  - New computational approach to partial identification + confidence intervals

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- Key: the screener S is observed, but actual attention A is not!

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- Good intentions: avoids post-treatment conditioning problems
- However: ignores the potential for differential attention
- Also ignores what we care most about: attention to the stimulus
- Thus, we need a method for post-treatment attention checks/screeners.

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

$$P[S(d) = 1 \mid A(d) = 1] = 1$$
$$P[S(d) = 1 \mid A(d) = 0] = \alpha_d$$

Sensitivity analysis: explore different values of α_d

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- A4: False positive rate does not depend on Y.

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- A6: Fixed attention/screener.

$$A(1) = A(0), \quad S(1) = S(0)$$

(Only guaranteed for pre-treatment screeners.)

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- If $S = A$ always, then ATAC is boundable (Lee 2009)
- No method for bounding ATAC when $S \neq A$

New computational approach

- Parameterize joint distribution of all potential outcomes

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  - CIs much smaller than `autobounds` (Duarte et al. 2024).

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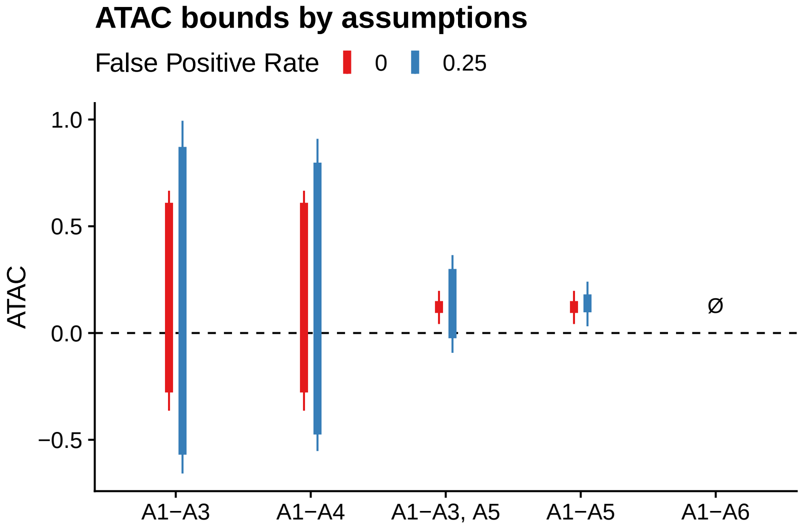
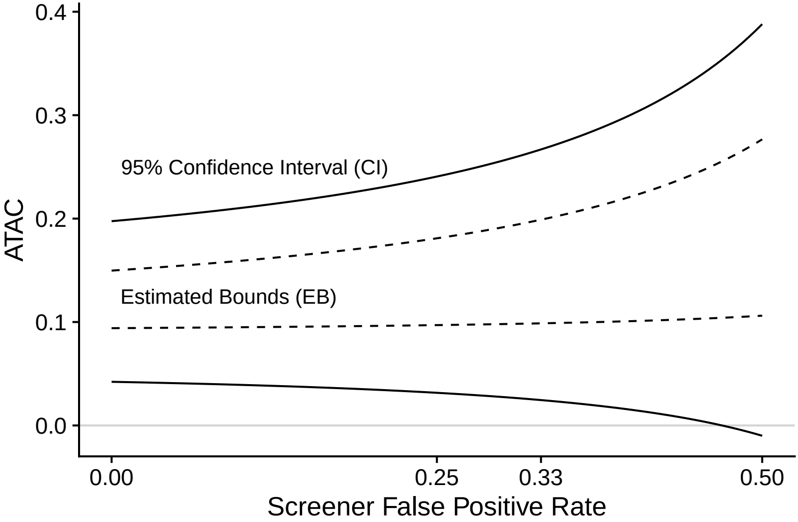
- What's the effect among always-attentive respondents?

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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