Discussion: Algorithmic Fairness and Partisan Agenda Control

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  - "EI": endogeneity in data-generating process

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  - "TM": Game-theoretic model of Gatekeeper and Floor
  - "EI": $\beta > 0$ as ATE > 0

Questions and Food for Thought

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- Penn & Patty
  - How does the model account for **probabilistic predictions**?
    - Algorithm says $\widehat{\theta} = p(Y_{sucess} = 1|\text{signal}) = 0.65$
    - Human says $\tilde{Y}_{sucess} = \mathbf{1}(\widehat{\theta} > 0.5) = 1$
  - The goal is perfect calibration?
    - Page 9 notes: the algorithm wants $\Pr(d_i = s_s|\delta) = \delta_{s_i}$
    - This differs from accuracy and compliance
  - Maybe helpful to clarify what s_i and ϕ are in the four examples

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- Kistner & Boris
  - Why not modeling with more **natural quantities**?
    - $S_M \Rightarrow$ the prop. of legislators in the majority party supporting the bill
    - $S_F \Rightarrow$ the prop. of legislators across parties supporting the bill
    - $S_{IG} \Rightarrow$ the prop. of legislators IGs can "turn"?
  - The model can make predictions directly?
    - E.g., $p(Y_{gate} = 1) = \Phi_{\mu=0.5,\sigma=0.5}(S_M + S_{IG})$
    - Compare the prediction with relative frequency in the data
  - Maybe helpful to formalize estimands, state assumptions, draw DAGs, model other theories