

# Discussant for Llobet and Gauthier et al.

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EPSA (2025)

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  - Leads to a puzzle about the ‘continuous’ strategy

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- If the coefficient's magnitude is of interest  $\rightarrow$  rescale!

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- “extremely heavy-tailed distributions like the Pareto, all methods exhibit limitations”
  - How likely are we to be in this world?
  - Is income Pareto or log-normal?

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- Simulations do multiple modalities → applications are separate?

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- More explicit dialogue with existing methods (e.g., Ratkovic!)

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    - “Native elder watches bulldozers destroy burial sites.” → conservative?
    - Depictions of police brutality → very moderate?