DISCUSSION

The Bidder Exclusion Effect

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Auction Design: Theory versus Practice

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- identify important model properties.
- evaluate counter-factual auctions.

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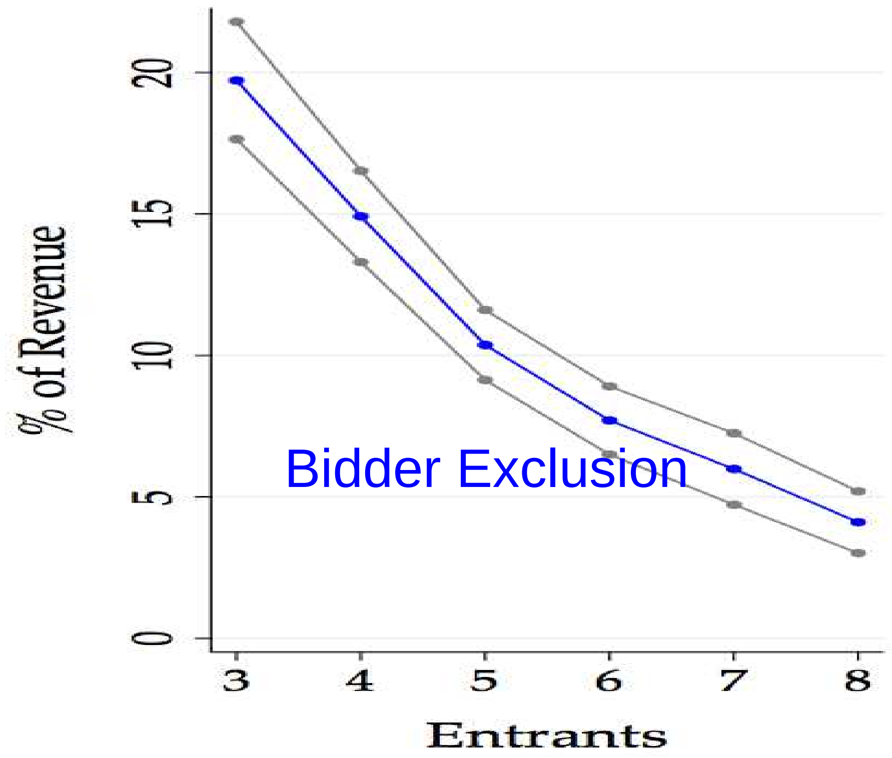
Worst Case Bounds
vs
Empirical Bounds

Empirical vs Worst-case Bounds



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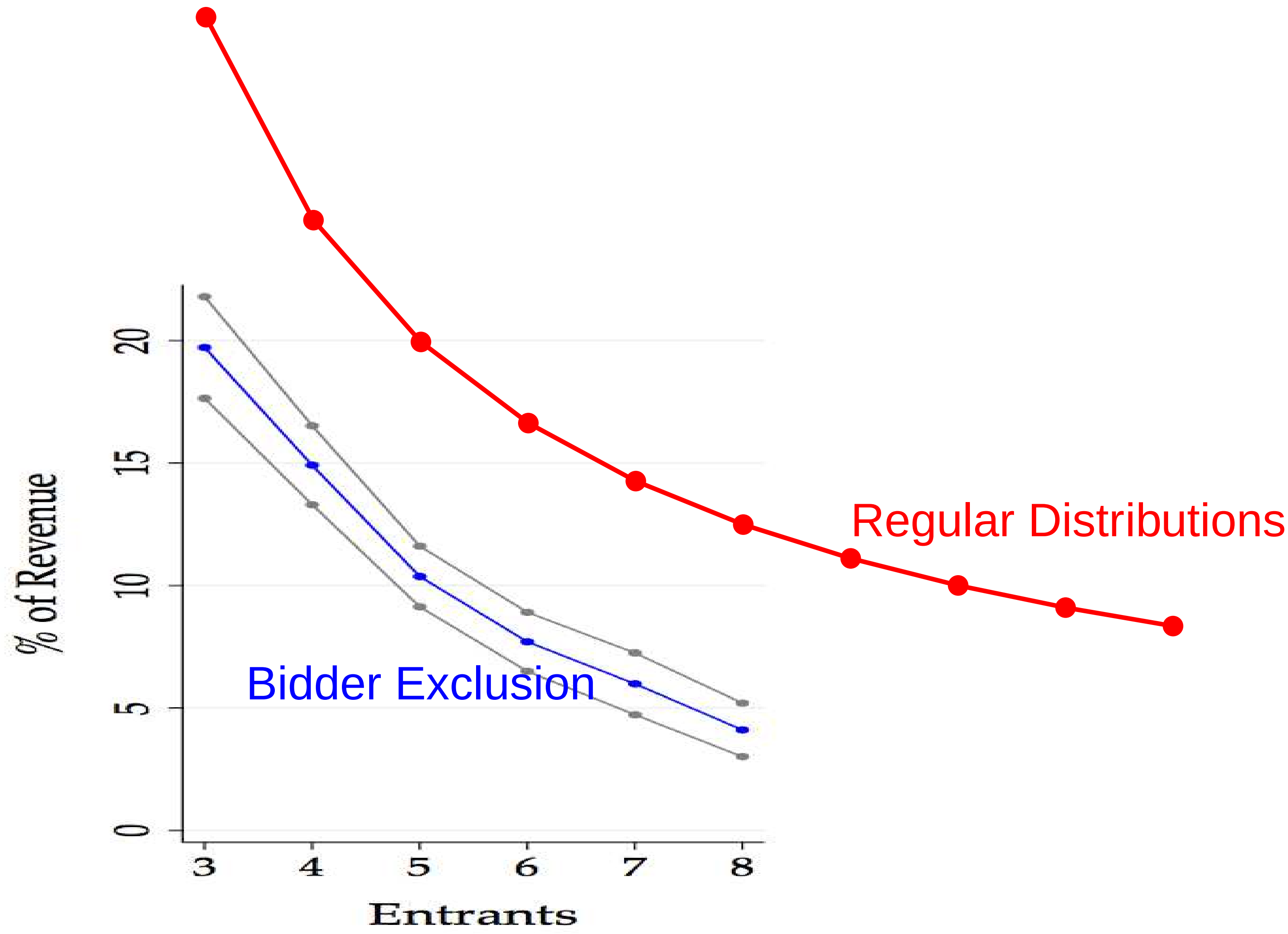

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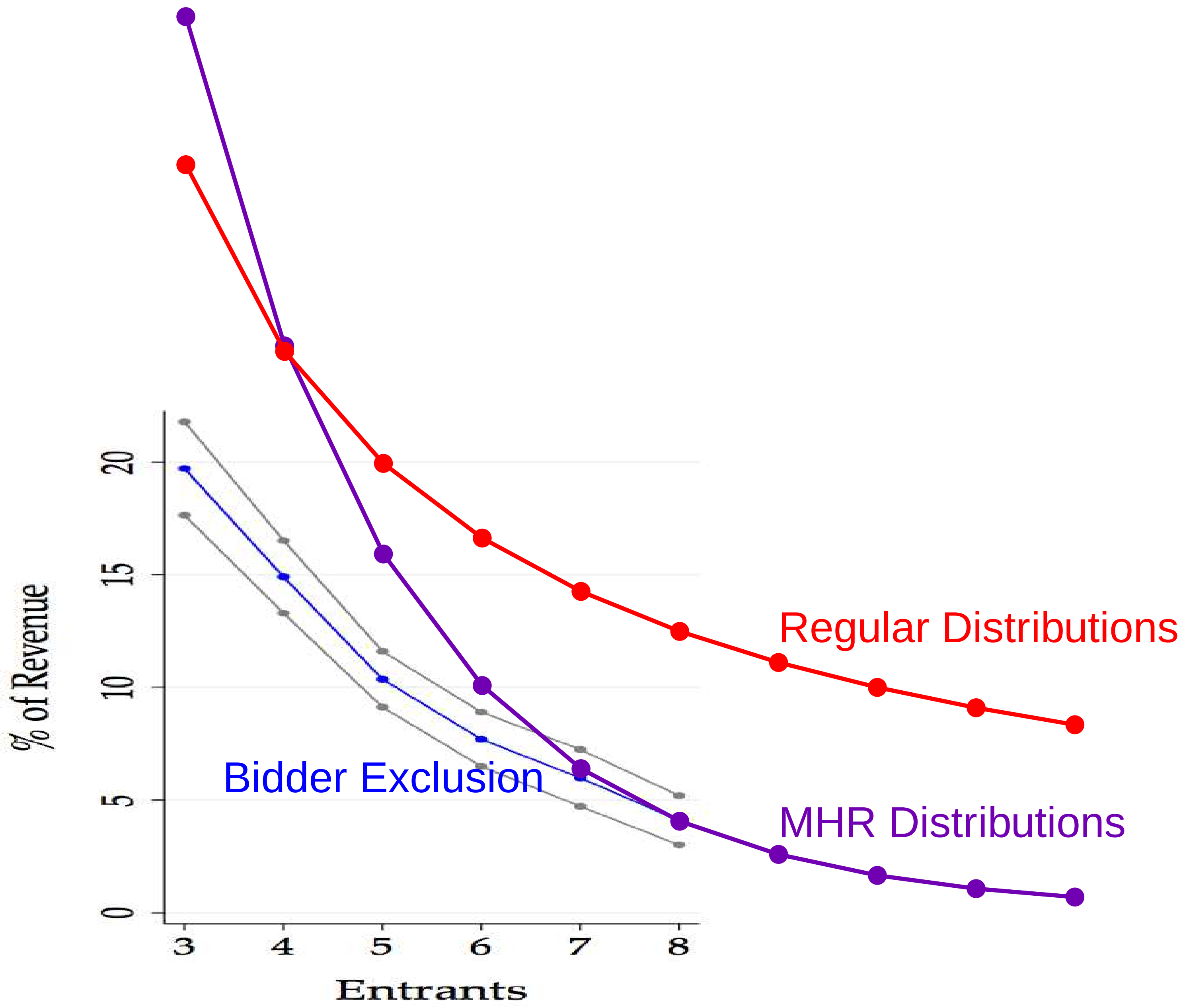

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Corollary: I.i.d. regular: $\mathrm{SPA}(n) \geq (1-1/n)\,\mathrm{OPT}(n)$. (tight!)
[e.g., Dughmi et al. ’12]

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Theorem: I.i.d. MHR: $\mathrm{SPA}(n) \geq (1 - \rho^{n-1})\,\mathrm{OPT}(n)$. (tight!)

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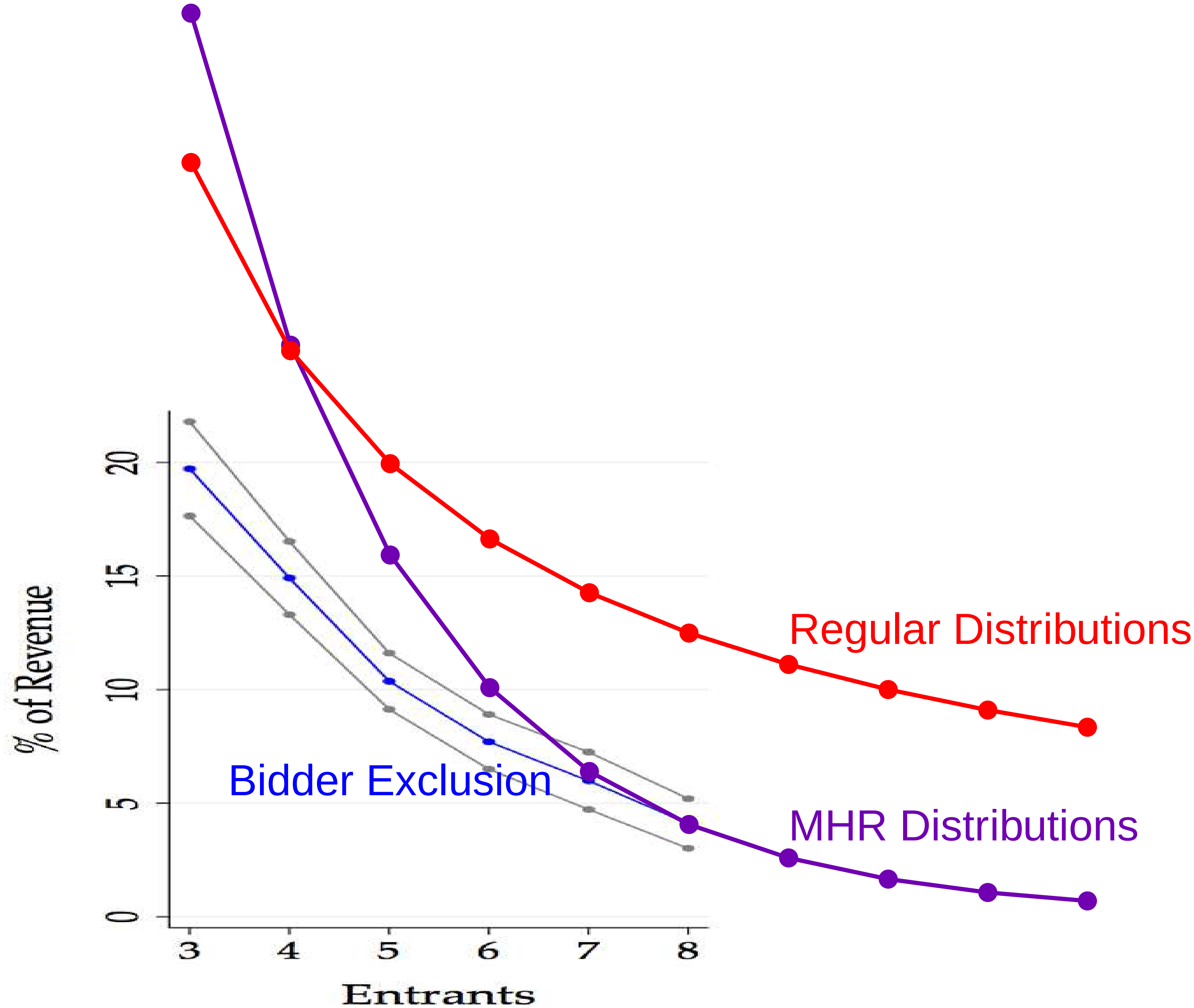

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- n agents, $n/2$ unit auction: worst-case loss $= 50\%$.
- $n = 6$, position auction: log-normal loss $= 20\%$.

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Question: Can "bidder exclusion like methods" give much better bounds (than worst-case) for these settings?