THE FUTURE OF AUCTIONS WITH AI AGENTS: THE WINNER'S CURSE WITH A DATABASE-BACKED PIPELINE

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Reproducible LLM-agent experiments for common-value first-price auctions with auditable databases.

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GITHUB: HTTPS://GITHUB.COM/GILD229/COURNOT-AN-INTERDISCIPLINARY-STUDY

INTRODUCTION

- Common-value first-price auctions (CV-FPSB) often suffer from the winner's curse: the highest bidder tends to overestimate value and incur losses.
- As LLM/AI agents enter bidding environments (ads, compute/data exchanges), we need auditable and reproducible experiments to evaluate mechanism interventions.
- We propose a database-backed pipeline that links theory → agent experiments → mechanism improvements in one loop.

PIPELINE

Signal Gen → Prompting → Bidding → Auction Outcome→ Structured Logging → Validation → Metrics & Plots →Reproduction Map

METHODOLOGY

Environment: Common-value first-price auction; V U[1000,1500]V\simU[1000,1500]V U[1000,1500]; 3 bidders; each observes a private signal sis_isi.
Treatments: Control / Winner's-Curse Reminder / Public Signal (noisy common signal).
Logging: run_id, agent_id, seed, sigma, treatment, signal, bid, V, profit, time.
Reproducibility: README Reproduction Map: script → artifact → figure/page (all plots regenerated from logs).

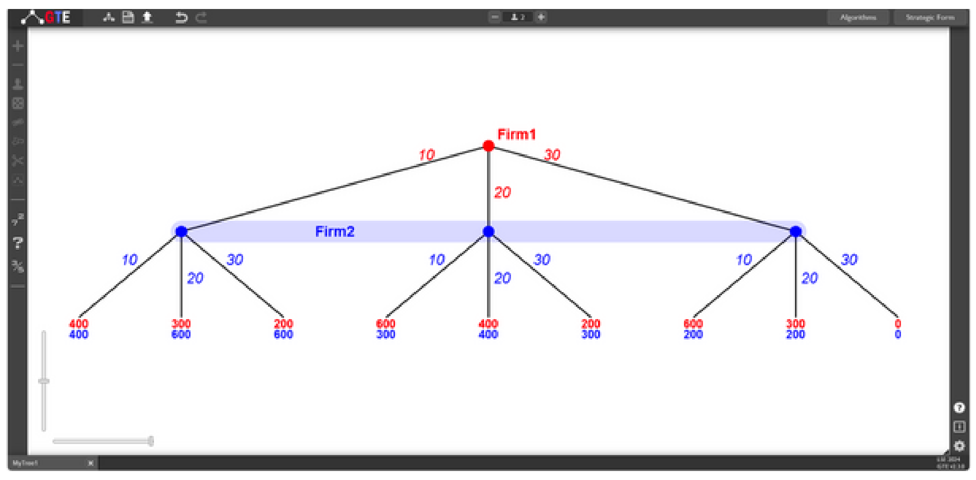
NOBEL/TURING INSPIRATION

- Kahneman (Nobel 2002) — Systematic judgment biases (over-optimism) explain winner's-curse behavior; motivates behavior-aware design.
- Stonebraker (Turing 2014) — Database systems and data governance enable scalable, trustworthy scientific workflows.
- Behavioral insights motivate the treatments; database engineering ensures auditability and one-click reproduction of all figures.

THEORETICAL INNOVATION

- Interdisciplinary Workflow
- Economist → CV-FPSB model & equilibrium benchmarks (rational shading).
- Computational Scientist → Verified solutions & simulation tools
- Behavioral Scientist → LLM-agent bidding with promptable priors and reminders.
- Mechanism Designer → Treatments that alter information sets or cognition (public signal, winner's-curse reminder, reserve/disclosure variants).

Model: 3-bidder common-value first-price auction with V U[1000,1500]V\sim U[1000,1500]V U[1000,1500] and private noisy signals sis_isi; treatments = Control / Winner's-Curse Reminder

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- Discrete Cournot duopoly with strategies q_i ∈ {0,⋯,30}, price p = max(0, 60 - (q1 + q2)), and profits π_i = p·q_i.
- The solver finds pure-strategy Nash equilibria: [(19, 21), (20, 20), (21, 19)].
  • At (q1=19, q2=21): total Q=40, price p=20: payoffs (π1=380, π2=420): CS=800, W=1600, DWL=200.
  • At (q1=20, q2=20): total Q=40, price p=20: payoffs (π1=400, π2=400): CS=800, W=1600, DWL=200.
  • At (q1=21, q2=19): total Q=40, price p=20: payoffs (π1=420, π2=380): CS=800, W=1600, DWL=200.
- Continuous Cournot benchmark: q1=q2=20.0 (total Q=40.0): discrete equilibria cluster around this point.
- Utilitarian first best (zero cost) is Q_FB=60 (p=0): equilibrium has Q below Q_FB, implying underproduction and deadweight loss.
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CONNECTION TO SDGS

- SDG 8 — Decent Work & Economic Growth. Reproducible mechanisms reduce mispricing and waste, supporting efficient AI-enabled markets.
- SDG 9 — Industry, Innovation & Infrastructure. Open, database-backed workflows strengthen scientific and industrial infrastructure for trustworthy AI.

KEY RESULTS

Treatments operationalize the theoretical prediction that increased information/caution should raise rational shading and curb loss events; results below test these claims.

- LLMs (Control): Over-optimistic bidding with a noticeable winner's-curse loss rate.
- LLMs (Reminder / Public Signal): Shading increases and negative-profit rate drops; bids align more closely with the theoretical benchmark.

AI Auctions: Seller revenue and round-to-round stability improve; effects are robust across seeds, temperatures, noise σ\sigmaσ, and bidder counts.

Related literature

- Capen, E. C., R. V. Clapp, & W. M. Campbell (1971). Competitive Bidding in High-Risk Situations. Journal of Petroleum Technology.
- Wilson, R. (1969). Competitive Bidding with Asymmetric Information. Management Science.
- Milgrom, P., & R. Weber (1982). A Theory of Auctions and Competitive Bidding. Econometrica.
- Kagel, J. H., & D. Levin (2002). Common Value Auctions and the Winner's Curse. Princeton University Press.
- Klemperer, P. (2004). Auctions: Theory and Practice. Princeton University Press.
- Kahneman, D., & A. Tversky (1979). Prospect Theory: An Analysis of Decision under Risk. Econometrica.
- Stonebraker, M. (2018). The 2014 ACM Turing Award: A Retrospective. Communications of the ACM.
- Chen, D. L., M. Schonger, & C. Wickens (2016). oTree—An Open-Source Platform for Laboratory, Online, and Field Experiments. Journal of Behavioral and Experimental Finance.

Ethics & Transparency: prompt templates, model/version, temperature, and seeds disclosed in the repo; logs anonymized; scripts and data regenerate all figures.