PHANTOM

Pricing heuristics against non-human transaction orchestration

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velocitatem.github.io/PHANTOM

Roadmap: one argument in six stages (15 min)

Main research question

How can dynamic pricing preserve margin integrity when transactions are increasingly mediated by non-human agents?

Dynamic pricing has often been treated as a secondary optimization layer; agent-mediated shopping turns it into a primary margin-risk surface.

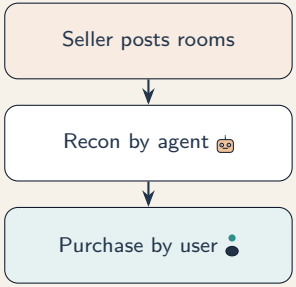
Motivation: one everyday pricing story

Imagine you sell weekend hotel rooms online

A customer asks an assistant to scout many quotes first, then buys in a clean session at the best discovered price.

Why this matters to everyday people

If this behavior is untreated, honest shoppers can face noisier prices and a weaker shopping experience because pricing reacts to manipulated intent signals.



query and purchase split across sessions

Takeaway: protect legitimate shoppers while detecting orchestrated recon before pricing leakage compounds.

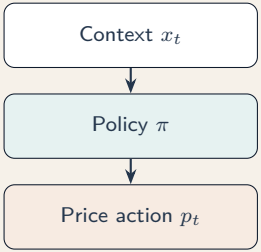
Policy first: one rule maps context into price actions

Policy definition

$$p_t = \pi(x_t)$$

where context x_t includes product state, time, and behavior signals from the session.

- Behavior proxy $\hat{q}$ is tracked for both user-like and agent-like sessions (,).



later extended from contextual bandits to DR-RL

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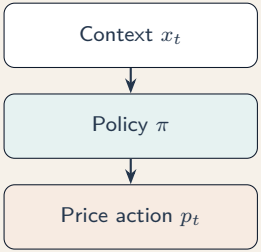
- The score $f(\tau')$ is a soft estimate that a trajectory is agent-mediated 🤖.



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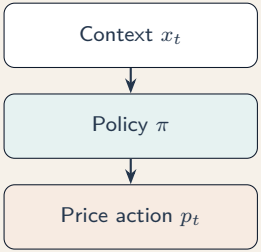
- The score $f(\tau')$ is a soft estimate that a trajectory is agent-mediated 🤖.
- We see reward only for the chosen price action, which motivates a contextual-bandit view first.



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Agentic recon creates direct financial pressure on pricing power

Recon session
samples multiple quotes

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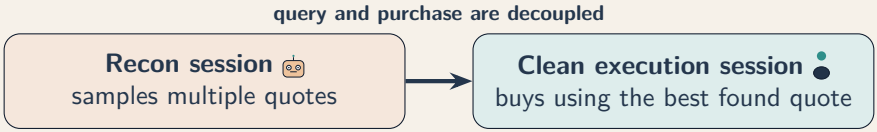

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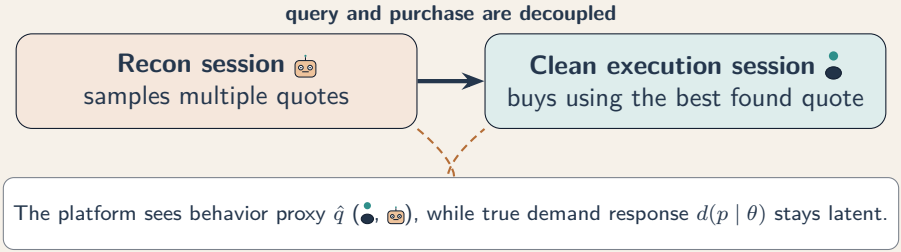

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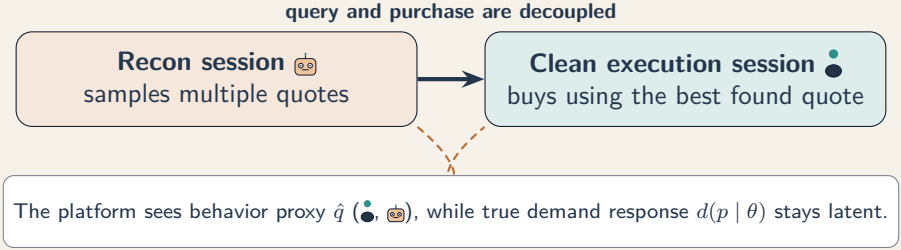

$$\mathrm{COI}(\pi) = \mathbb{E}[P] - \underline{p}$$

pricing power KPI

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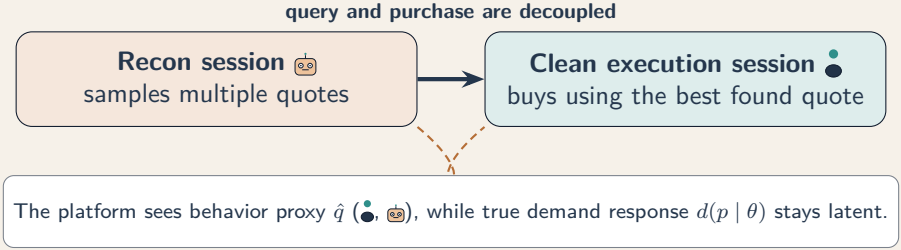

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$$\lim_{N\to\infty} \mathrm{COI} = 0$$
theorem as intuition guide

Agentic recon creates direct financial pressure on pricing power

query and purchase are decoupled

Recon session 🤖
samples multiple quotes

→

Clean execution session 👤
buys using the best found quote

The platform sees behavior proxy $\hat{q}$ (👤, 🤖), while true demand response $d(p \mid \theta)$ stays latent.

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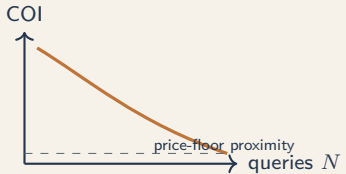

The theorem gives direction, not prophecy: more independent recon pressure pushes realizable prices toward the floor.

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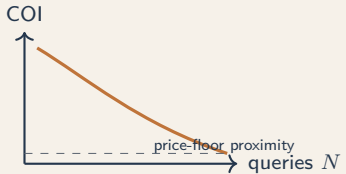

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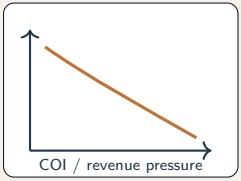
Implication: when quote discovery and purchase split, session-based pricing can overestimate willingness to pay.

The thesis answers one chain: mechanism → signal → control

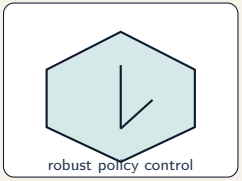
SQ1

Can we distinguish and sessions from interactions alone?



SQ2

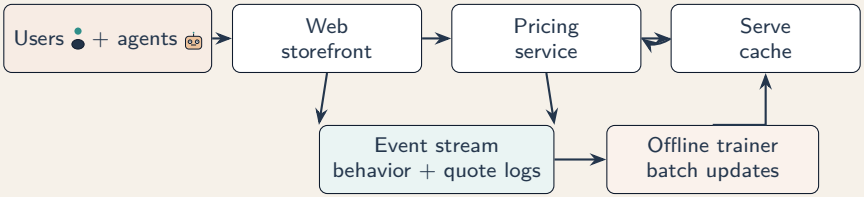
How strong is price and revenue erosion under agentic contamination?



SQ3

Can policy design recover margin while keeping UX stable?

Stage 1: We built a dual-loop platform to observe behavior and price exposure together



- Every quote has a matching behavioral context in the log stream.

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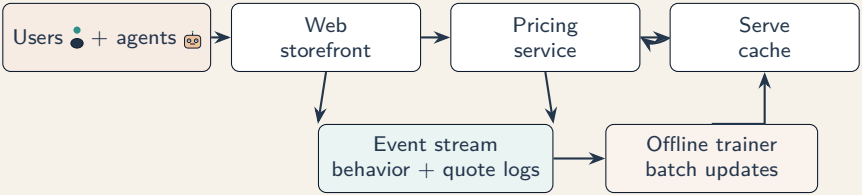

- Every quote has a matching behavioral context in the log stream.
- The same architecture supports reproducible stress tests before any live deployment.

Dataset card: compact, labeled, and experiment-ready

WhoClickedIt dataset card

`huggingface.co/datasets/velocitatem/whoclickedit`

Human rows 798 **Agent rows** 3076

Flat schema and explicit actor labels simplify session-aware train/test splits.

Kafka provenance is retained for reproducibility and downstream analysis.

29 Interviews
labeled trajectories in observed samples

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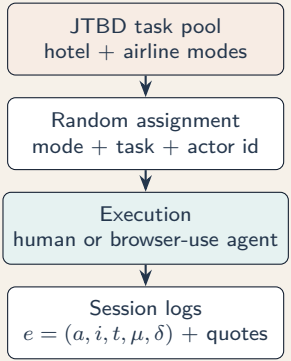
2 streams
interaction + price-log records

Experimental design controls goals, not instructions



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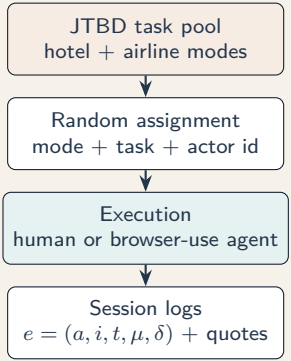

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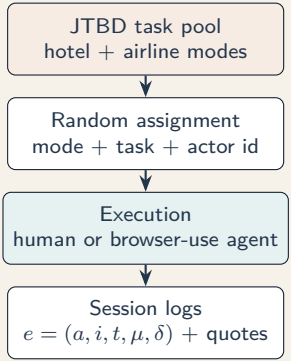


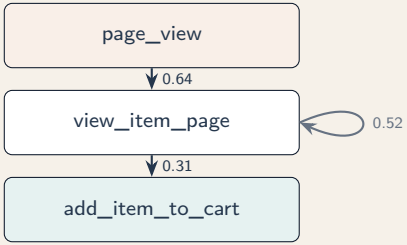
- Agents run with **browser-use** and a model-swappable LLM router (default `gpt-5-mini`).
- Tasks are defined by outcomes, not scripted clicks, to preserve behavioral variety.
- Current release is stronger on hotel flows than airline flows.

Stage 2: A behavior kernel is a compact signature of navigation dynamics

Definition

$$\hat{P}(s' \mid s) = \frac{N(s, s')}{\sum_k N(s, k)}$$

- Build one kernel per session, then prototypes for human and agent cohorts.



Kernel rows encode "what usually comes next."

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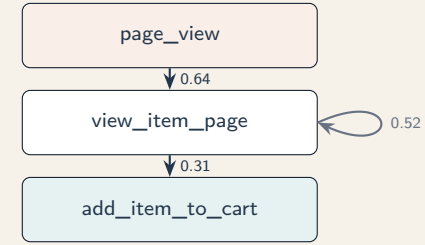
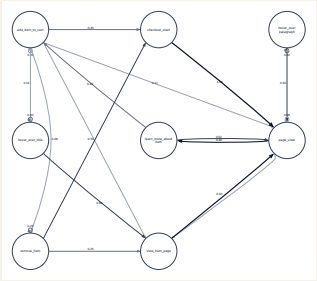
- Compare each incoming session to both prototypes with KL divergence.



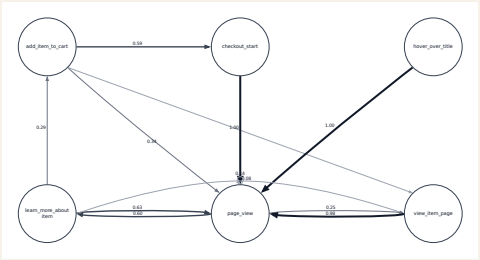
Kernel rows encode "what usually comes next."

Human and agent kernels are separable in the controlled cohort

Human transition structure



Agent transition structure



-3.35
mean gap (human)

+1.65
mean gap (agent)

$p < 0.001$
Mann-Whitney rank test

Two divergence scores become one continuous control signal

$$\Delta_H = D_{KL}(\hat{T}' \,||\, \bar{T}_H), \quad \Delta_A = D_{KL}(\hat{T}' \,||\, \bar{T}_A)$$

Two divergence scores become one continuous control signal

$$g(\tau') = \Delta_H - \Delta_A$$

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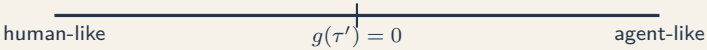
$$f(\tau') = P(A \mid \tau') = \sigma\left(\frac{g(\tau')}{T}\right)$$



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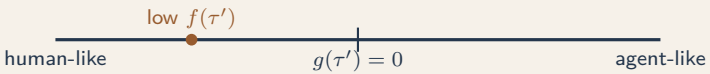

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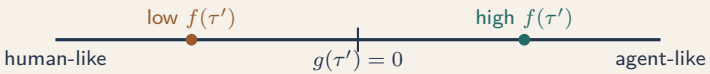

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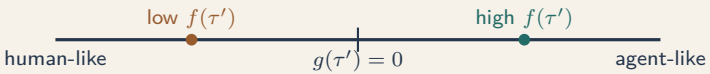

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- Continuous scoring is used to steer contamination-aware pricing.

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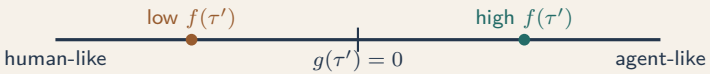

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- Temperature T calibrates how sharply the score moves away from uncertainty.
- Continuous scoring is used to steer contamination-aware pricing.
- The design target is guidance, not a hard user-level ban decision.

Stage 3: DR-RL trains against plausible contamination shifts, not one fixed world

Ideal robust object

$$\mathcal{U}_\epsilon(\hat{P}_N) = \{Q : W_p(Q, \hat{P}_N) \leq \epsilon\}$$

robust against distribution shift around the empirical demand law

Engine approximation used in experiments

$$\mathcal{A}_{\epsilon_\alpha}(\alpha_0) = \{\alpha : |\alpha - \alpha_0| \leq \epsilon_\alpha\}$$

small grid over α $\rightarrow$ inner worst-case candidate

Practical boundary

In code we solve a local robust loop around α_0, not the full continuous Wasserstein adversary.

Reward composition penalizes leakage while guarding user experience

$$r_t = \underline{R(p_t, \hat{Q}_t)}$$

Revenue term
keeps market objective explicit

Reward composition penalizes leakage while guarding user experience

$$r_t = \underline{R(p_t, \hat{Q}_t)} - \underline{\lambda\, f(\tau'_t)\, c_{\text{info}}}$$

Revenue term
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scales with agent-likelihood score

- Baseline experiments use a query-tax leakage surrogate where higher $f(\tau')$ 🤖 increases leakage penalty.

Reward composition penalizes leakage while guarding user experience

$$r_t = R(p_t, \hat{Q}_t) - \lambda\, f(\tau'_t)\, c_{\text{info}} - \eta_{\text{ux}}\, UX(\tau'_t, p_t)$$

Revenue term
keeps market objective explicit

Leakage term
scales with agent-likelihood score

UX term
discourages unstable pricing behavior

- Baseline experiments use a query-tax leakage surrogate where higher $f(\tau')$ 🤖 increases leakage penalty.
- Supra-competitive anchor penalties are tracked as an additional safety rail.

Computationally, wide sweeps are feasible only with aggressive optimization

$$4 \times 4 \times 3 \times 2 \times 2 = \mathbf{192}$$

algorithms × contamination × robustness × COI penalty × action grid

160 PFLOPS
peak aggregate TPU budget

~180 days
net compute logged in full study

Hot-path rewrite impact

Mode	Before	After
Baseline step/s	26.0	220.0
Robust step/s	7.2	136.0

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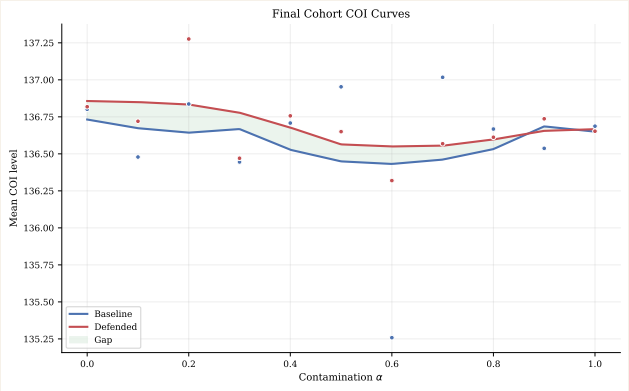
- Throughput gains (8.5×, 19×) made broad sweeps practical.

Results: contamination hurts revenue; defended policies recover COI



-90,140
baseline contamination slope

~3%
short-run revenue cost of defense

Regime-dependent
COI gains strongest at harder settings

Yes, with boundaries: we can defend margin integrity under agentic orchestration

SQ1 Distinguishability	SQ2 Theoretical impact	SQ3 Mitigation
kernels are separable $p < 0.001$	COI erosion mechanism proved in baseline limit	robust control shifts COI/revenue/UX trade-off

Boundary conditions

Evidence is from a controlled platform and a small labeled cohort; this is mechanism validation, not full production external validity.

What this implies for real pricing systems

- **Financially:** untreated reconnaissance behaves like an information leak and can compress sustainable margins.

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- **Strategically:** robust pricing should be calibrated by regime; there is no single penalty that wins everywhere.
- **Before deployment:** larger human baselines, governance review, and legal safeguards are mandatory.

Thank you

Questions and discussion

Appendix follows: COI theorem derivation, reward composition, and sample-size notes.

Appendix roadmap

A. Objects

Notation, COI, proxies

B. Mechanism

Order stats, kernels, KL

C. Control

Simulator, robust loop, factorial grid

Figures

Full charts, MDPs, extra revenue view

Appendix: core notation (quick reference, I)

$$\tau_s = (e_{s,1}, \ldots, e_{s,L_s})$$ session

$$\hat{q}_{t,i} = \sum_{s \in S_t} \sum_{k} \omega(a_{s,k})\, \mathbf{1}[i_{s,k} = i]$$ proxy (👤, 🤖)

$$Q(p) = (1-\alpha)\, \mathbb{E}_{\theta \sim D_H}[d(p;\theta)] + \alpha\, \mathbb{E}_{\theta \sim D_A}[d(p;\theta)] + \epsilon_t$$ mixture of 👤/🤖

$$\mathrm{COI}(\pi) = \mathbb{E}[P] - \underline{p}$$ COI

Appendix: core notation (quick reference, II)

- $\underline{p}$: minimum viable price anchor (thesis simplification).
- α: contamination with agent traffic in the mixture.
- $\omega(a)$: hand-engineered action weights for the proxy (baseline).

Reading guide

Objects on the left are **observable**; $d(\cdot)$ and many θ remain hidden.

Appendix: COI as a reporting functional

$$\mathrm{COI}(\pi) = \mathbb{E}_{P \sim F_\pi}[P] - \underline{p}$$

Interpretation

Premium above the floor induced by policy π; used as a KPI and as the object Theorem 1 attacks under query saturation.

Appendix: demand proxy vs. latent demand

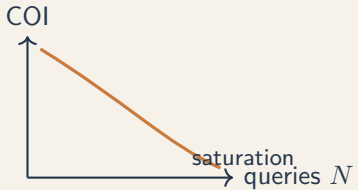
$$\hat{q}_{t,i} = \sum_{s \in S_t} \sum_{k=1}^{L_s} \omega(a_{s,k})\, \mathbf{1}[i_{s,k} = i]$$

Key distinction

$\hat{q}$ is an operational sensor from logs ( , ); true demand $d(p;\theta)$ stays latent. Pricing reacts to $\hat{q}$, so agent-shaped behavior can poison the signal.

Appendix: independent draws and order statistics (intuition)

- Independent price draws $\{P_i\}_{i=1}^{N}$ from fixed offer law.
- Purchase-side minimum behaves like $P_{(1)}$: mass shifts left as N grows.
- Expected premium vs. $\underline{p}$ compresses: COI pressure.



Appendix: Theorem 1 scope (what is and is not claimed)

Inside the baseline proof

Non-collusive sessions, independent draws, fixed offer distribution across queries.

Outside (handled elsewhere)

Collusion, pooled recon, sequential repricing that breaks iid structure: evidence moves to the simulator.

Appendix: empirical transition kernel (MLE)

$$\hat{P}(s' \mid s) = \frac{N(s, s')}{\sum_k N(s, k)}$$

Use

Human and agent centroids $\bar{T}_H, \bar{T}_A$ for divergence-to-prototype scores.

Appendix: KL to prototypes (shared support)

$$\Delta_H = D_{\mathrm{KL}}(\hat{T}' \,\|\, \bar{T}_H), \qquad \Delta_A = D_{\mathrm{KL}}(\hat{T}' \,\|\, \bar{T}_A)$$

Asymmetric choice

KL measures deviation from the **human** reference; symmetric JS/Wasserstein on behavior was not the design target.

Appendix: softmax to sigmoid (algebra)

Let $z_A = -\Delta_A/T$, $z_H = -\Delta_H/T$. Then

$$P(A \mid \tau) = \frac{e^{z_A}}{e^{z_A} + e^{z_H}} = \frac{1}{1 + e^{z_H - z_A}} = \sigma\big(z_A - z_H\big)$$
$$= \sigma\left(\frac{\Delta_H - \Delta_A}{T}\right).$$

Takeaway

Two-class softmax over (z_A, z_H) is exactly one sigmoid on the gap $(\Delta_H - \Delta_A)$.

Appendix: contamination generator $\mathcal{G}(\alpha)$

$\mathcal{G}(\alpha)$: inject synthetic agent trajectories until mixture reaches target α

Role in the lab

Supplies controlled stress tests for the pricing learner; not a claim of production-faithful agents.

Appendix: Wasserstein ambiguity (ideal object)

$$\mathcal{U}_\epsilon(\hat{P}_N) = \left\{ Q : \; W_p(Q, \hat{P}_N) \leq \epsilon \right\}$$

What the code implements instead

A **local** grid over α near α_0 with radius ϵ_α: tractable inner worst case, not a full ball solver.

Appendix: per-step reward sketch

$$r = R(p, d) - \lambda\, \mathrm{COI}_{\mathrm{leak}}(p, \tau') - \eta\, \mathrm{UX}(\tau', p) - \text{(supra-competitive excess)}$$

- Query-tax style $\mathrm{COI}_{\mathrm{leak}}$: minimal nonzero surrogate to expose the control channel.
- UX and anchor penalties prevent trivial solutions (flat but exploitative prices).

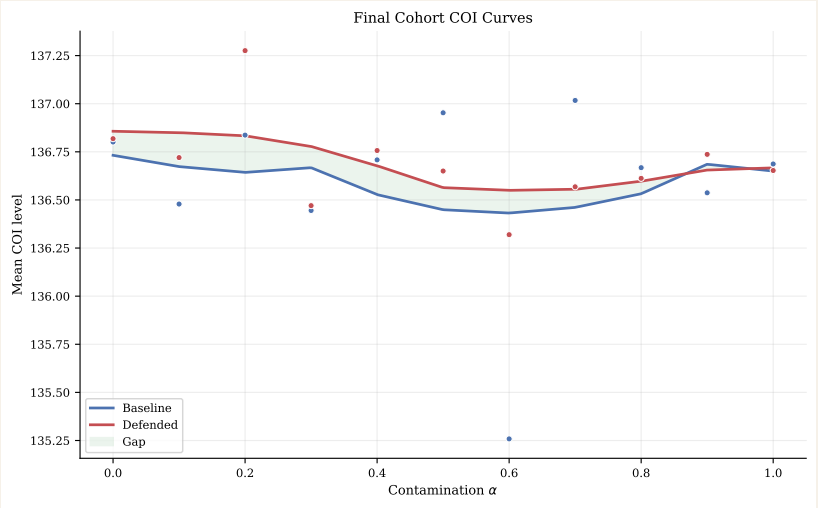
Appendix: factorial design (192 cells)

Axis	Levels	Count
RL algorithm	PPO, A2C, DQN, Q-table	4
Contamination α	4 representative values in $[0.1, 0.6]$	4
Robustness radius ϵ_α	3	3
COI penalty λ_{coi}	2	2
Action granularity	2	2
Total		$4 \times 4 \times 3 \times 2 \times 2 = \mathbf{192}$

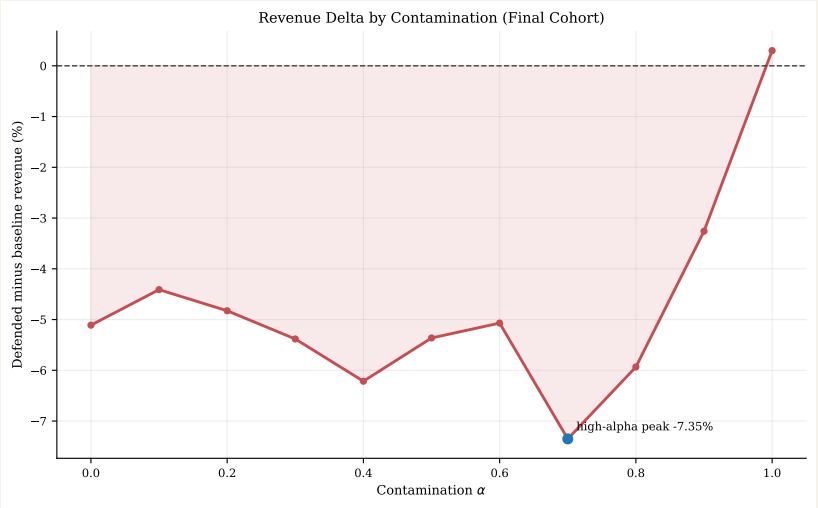
Appendix: engineering note (pandas $\rightarrow$ JAX)

- Hot path was label-indexed transition lookups; profiling showed pandas overhead dominated.
- Integer-indexed arrays + JAX inner loop: large step/s throughput (thesis numbers; environment dependent).
- Kronecker expansion of product-conditioned kernels: research simulator cost, scales with catalog.

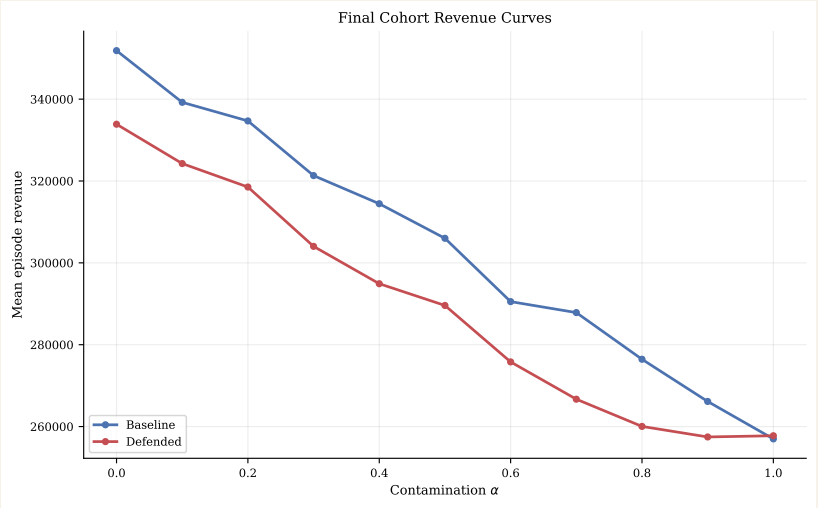
Appendix figure: COI by α (full)



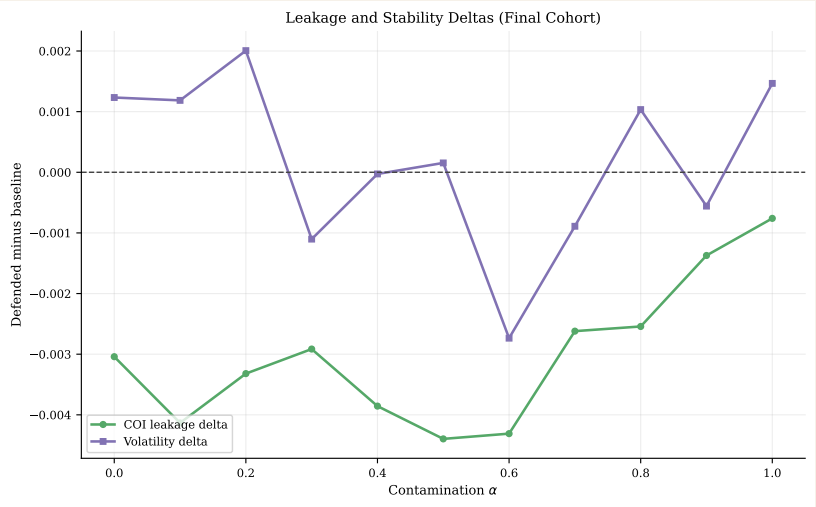
Appendix figure: revenue deltas (full)



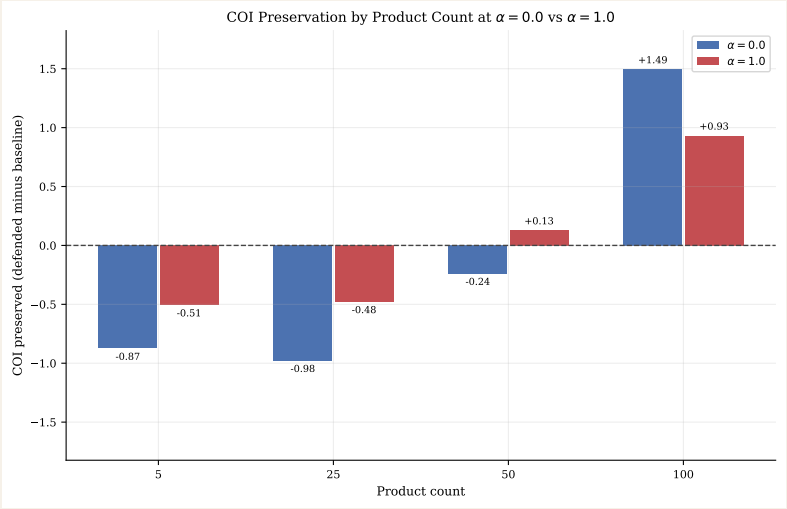
Appendix figure: revenue by α (full)



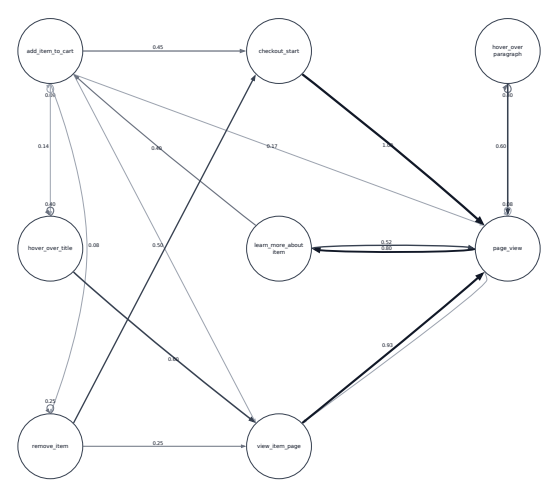
Appendix figure: risk / stability deltas (full)



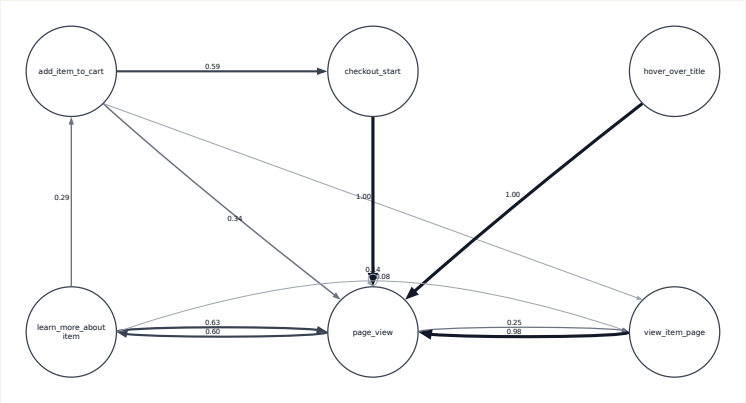
Appendix figure: COI preservation grid (full)



Appendix figure: human MDP (full)



Appendix figure: agent MDP (full)



Appendix: threat model map

Claim boundary

Residual contamination after security controls is the motivating scenario.

Appendix: evaluation checklist (robustness culture)

1. Session-aware labels: avoid splitting rows inside a trajectory if that inflates scores.
2. Document how prototypes $\bar{T}_H, \bar{T}_A$ were fit (full cohort vs. held-out); state explicitly in writing.
3. Report temperature T as calibration, not as a tuned hyperparameter unless a sweep is shown.
4. Separate **architecture** claims from **coverage** claims (hotel vs. airline balance at release).

Appendix: sim-to-real gap (explicit)

- Kernels and generators reflect a **small labeled cohort** and a **browser-use style** agent class.
- RL policies are trained in a **surrogate** market with engineered rewards and discretized prices.
- Deployment would require legal review, fairness testing, and refreshed baselines at scale.

Appendix: leakage surrogate (query-tax form)

$$\mathrm{COI}_{\mathrm{leak}}(p, \tau') \approx f(\tau') \cdot c_{\mathrm{info}}$$

Reading

$f(\tau')$ is the weak agent score; c_{info} is a minimal constant leakage proxy to expose the control channel. Revelation-style $-\log \pi(p \mid \tau')$ is the natural upgrade.

Appendix: robust pricing template (symbolic)

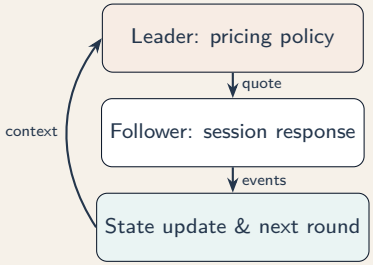
$$\max_{\pi} \min_{Q \in \mathcal{U}_\epsilon(\hat{P}_N)} \mathbb{E}_{d \sim Q}\left[R(p,d) - \lambda\,\mathrm{COI}_{\mathrm{leak}} - \eta\,\mathrm{UX}\right]$$

Code-level substitute

Inner min over a **finite grid** of $\alpha_k \in [\alpha_0 \pm \epsilon_\alpha]$ around the nominal generator mix, not a continuous adversary over all Q in the ball.

Appendix: why a Stackelberg game is a useful abstraction

- **Leader move**: the platform commits a quote via policy $p_t = \pi(x_t)$.
- **Follower move**: session behavior then reacts (click, continue, abandon, purchase).
- This ordering matches real serving APIs: price is emitted before response is observed.
- Repeating this local sequence gives a tractable leader-follower control model.



Boundary

We do **not** claim a full market equilibrium. We claim a useful timing model for explainable policy updates under contamination.

Appendix: why Theorem 1 helps (without over-claiming)

What the theorem gives us

- A directional mechanism: independent recon pressure compresses COI.
- A sanity check for reward design: leakage penalties should grow with recon likelihood.
- A clean explanatory anchor for stakeholders and governance review.

What the theorem does not claim

- It is not a finite-sample forecast for every market.
- It does not cover collusion or all adaptive adversaries.
- It does not replace simulator evidence or offline policy validation.

Three evidence layers used in this thesis

Theorem 1 (mechanism direction) $\rightarrow$ **simulator** (finite-regime quantification) $\rightarrow$ **implementation** (local robust policy training).

Appendix: composite strip (five plots, small multiples)

Same PDFs as the main talk, shrunk to scan the full panel at once.