Platfrom design when sellers use pricing algorithms

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Context – Platform rules

Amazon:

- **Buy Box**: Decides the default seller based on various factors like price, shipping.
- **A9 Algorithm**: Ranks products in searches using relevance, performance, seller history.
- **Fulfillment**: Sellers using FBA service have more visibility.

Booking.com:

- **Visibility Boost**: Enhanced visibility for higher commission.
- **Preferred Partner**: Greater visibility for high-performing hotels.

eBay:

- **Best Match**: Ranks items based on relevance and seller history.
- **Top Rated Sellers**: Enhanced visibility for high-performing sellers.

Buy Box

Add to Basket

Buy Now

Dispatches from	Amazon
Sold by	Amazon
Returns	Returnable within 30 days of receipt
Payment	Secure transaction

Gift-wrap available.

Buy Used: Very Good
£5.19

Add to List

Other sellers on Amazon

Compare New & Used (22) from

£5.19

+ £2.80 delivery

May be available at a lower price from other sellers, potentially without free Prime shipping.

14 other options Filter (1) ›
sorted by price + delivery: low to high

New
-17% £9.99
RRP: ~~£11.99~~

Add to Basket

FREE delivery **30 - 31 October**. Details

Dispatches from	Burash Ltd
Sold by	Burash Ltd
Seller rating	4.5
	826 lifetime rating count
	92% positive over last 12 months

See less

New
-30% £8.39
RRP: ~~£11.99~~

Add to Basket

£2.80 delivery **7 - 9 November**. Details

Dispatches from	swestbooks
Sold by	swestbooks
Seller rating	4.5

The Evolving Dynamics of Online Marketplaces

- **Platform's Regulatory Power**:
  Online platforms exert influence through their design and rules, shaping the nature of competition and determining which products or sellers get more visibility.

- **Shift in Competition**:
  Sellers are increasingly using pricing algorithms to set prices, changing the landscape of competition, making it more dynamic and unpredictable. Potentially collusive strategies and higher prices.

- **Gap in Knowledge**:
  There's limited insight into how these algorithms respond to platform-design rules, raising questions about long-term impacts of these rules on competition and consumer welfare.

This paper

- **Focus**: Explored the ability of online platforms to design marketplaces that enhance competition, consumer surplus, and platform profits.
- **Methodology**: Combined theoretical models with AI pricing algorithm simulations, particularly Q-learning algorithms.
- **Key Insights**:
  - Demand-steering rules, which reward firms for price reductions with more consumer exposure, can foster beneficial effects.
  - These policies remain effective even when sellers are patient and inclined towards collusion.
- **Simulation Outcomes**:
  - Platform design can favor both consumers and the platform.
  - Policies need to consider past behavior and treat sellers non-neutrally, disrupting algorithm-driven demand rotation and profit splitting.

Theoretical model

Sellers:

- $n \geq 2$ firms with differentiated products.
- Same constant production cost $\tilde{c} > 0$ and unit fee f.
- Effective marginal cost $c = \tilde{c} + f$.
- Infinite horizon with a common discount factor $\delta \in (0, 1)$.
- Compete over a monopoly platform.
- Observe all history and simultaneously set prices $p_i^t \geq 0$ in period t.

Platform:
Displays a subset N^t of the products to consumers in period t.

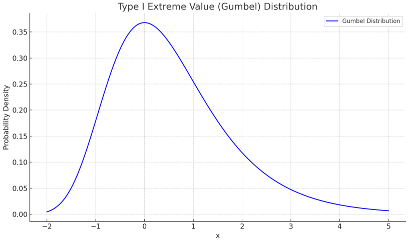
Theoretical model

Consumers:

- A unit mass of consumers in each period t.
- Each buys at most one product.
- Spend one period then exit and replaced by a new cohort.
- Utility of a representative consumer buying product i in period t:

$$u_i^t = a - p_i^t + \zeta_i$$

- Outside option utility: $u_0^t = \zeta_0$.
  ζ_i and ζ_0 follow Gumbel distribution with scale parameter $\mu > 0$.



Utilities

Firm $i \in N^t$ (standard logit) demand:

$$D_i(p^t) = \frac{exp\left(\frac{a-p_i^t}{\mu}\right)}{\sum_{j\in N^t} exp\left(\frac{a-p_j^t}{\mu}\right)+1} \tag{1}$$

$Q(p_t) = \sum_{j\in N^t} D_j(p^t)$: total industry output. Consumer surplus:

$$U(p^t) = \mu \log\left[\sum_{j\in N^t} exp\left(\frac{a-p_j^t}{\mu}\right)+1\right] = -\mu \log(1-Q(p^t)) \tag{2}$$

Given $\omega \in [0,1]$, the platform's payoff:

$$\Omega(p^t) = \omega f Q(p^t) + (1-\omega)U(p^t) \tag{3}$$

Note: last term captures benefits of growing consumer base and competition with other platforms.

Price-directed Prominence (PDP)

Definition:
In any given period t, each consumer only observes k firms with the lowest prices, for some fixed integer $k \in 1, 2, \ldots, n-1$.

Competitive market: In each period, suppose n firms play a one-shot Bertrand-Nash pricing game in the absence of PDP, there is a unique equilibrium where each firm charges strictly mark-up over effective marginal cost.

Lemma 1: Under PDP, in a competitive market the k lowest prices equal effective marginal cost $c = \tilde{c} + f$.

Price-directed Prominence (PDP)

Proposition 1: In a competitive market, compared to when all n firms are displayed, PDP increases consumer surplus and the platform's payoff iff $k/n \geq \lambda$, where $e^{-\frac{n}{n-1}} < \lambda < e^{-1} \approx 0.368$.

When at least 37% products are displayed, gains from reduced price outweigh variety loss (thus total output loss).

Proposition 2: Platform's payoff under PDP (when $k = n - 1$) satisfies:

$$\frac{\Omega^{PDP}}{\Omega^{MAX}} \geq 1 - \frac{1}{n}, \ \frac{\Omega^{PDP} - \Omega^{BN}}{\Omega^{MAX} - \Omega^{BN}} \geq 1 - \frac{e}{n(e-1)}. \qquad (4)$$

The bounds also apply to consumer surplus U.

Price-directed Prominence (PDP)

Cartelized market: In each period, n firms set prices to maximaze their joint profits, leading to fully collusive prices.

Lemma 2: Under PDP, an n-product monopolist would charge the same price $p^m(k)$ on k of the products, and charge weakly more than $p^m(k)$ on the remaining $n - k$ products.

Full collusion is sustainable for the broadest range of discount factors when:

1. All firms charge $p^m(k)$ in each period.
2. After a deviation firms play the one-shot Bertrand-Nash equilibrium in Lemma 1 forevermore.

Price-directed Prominence (PDP)

The critical discount factor $\hat{\delta}_k$ for full collusion to hold varies with k.
Intuition:

- As k decreases,the monopoly profit is lower.
- As k decreases, the value of deviating by undercutting $p^m(k)$ increases as a result of higher demand.

Proposition 3: Under PDP, showing fewer products to consumers makes it harder to fully collude, in the sense that the critical discount factor $\hat{\delta}_k$ increases as k becomes smaller:

$$\hat{\delta}_1 \equiv 1 - 1/n > \hat{\delta}_2 > \ldots > \hat{\delta}_{n-1}.$$

Proposition 4: Suppose δ is large enough for full collusion. Fully collusive prices are lower when fewer firms are displayed to consumers:

$$p^m(1) < p^m(2) < \ldots < p^m(n).$$

However, consumer surplus and the platform's payoff are also lower.

Dynamic PDP

Definition:
In period 0, firms set prices and the firm with the lowest price is the only one shown to customers, and is given an "advantage" in period 1. In any period $t > 0$ in which firm i has the advantage, firm i is the only firm shown to consumers, and also receives the advantage in period $t + 1$, so long as:

1. firm i has not raised its price in period t,
2. no rival in period t undercuts firm i by strictly more than a fixed value ADV > 0.

If either of the conditions is violated, then in period t a firm with the lowest price is the only firm shown to consumers, and that firm also receives the advantage in period $t + 1$.

Dynamic PDP

Proposition 5: Consider dynamic PDP with an advantage $0 < \text{ADV} \leq p^m(1)$.

1. There exists a $\hat{\delta} \geq \hat{\delta}_1$ such that if $\delta < \hat{\delta}$, then in any pure-strategy subgame-perfect Nash equilibrium the transaction price equals effective marginal cost in all periods.
2. Moreover, if ADV is sufficiently large, then $\hat{\delta} = 1$ so that the transaction price is effective marginal cost for all value of δ.

How about consumer surplus and platform payoff?

Proposition 6: Suppose δ is sufficiently high that, absent platform design, firms would fully collude. Compared to the case where all n firms are shown to customers, Dynamic PDP with sufficiently large ADV increases consumer surplus and platform payoff iff

$$n < \tilde{n} = exp\left(1 + exp\left(\frac{a-c}{\mu}\right)\right)$$

Dynamic PDP

Potential downside: compressing sellers' revenues can reduce seller entry, both consumers and platform may be harmed.

Extensions in online Appendix:

- Allow for revenue sharing or endogenous platform fees (REMARKS 1-6).
- Allow for a sufficiently low probability that the advantage is taken away and reassigned to the firm with the lowest price in the period (REMARK 7).
- Allow more firms ($1 < k < n$) to be shown (REMARK 8).

Pricing algorithm

Q-learning algorithm with a single agent:

1. finite sets of states $s \in \mathcal{S}$ and actions $x \in \mathcal{X}$ give a Q-table of size (s, x) often initialized with zeros.
2. Learning rate (α) determines the weight of new info.
   Discout factor (δ) decides importance of future rewards.
3. ε-greedy policy: With probability $1 - \varepsilon$, choose the action with the highest Q-value for the current state (**exploitation**).
   With probability ε, choose a random action (**exploration**).
4. After action x, observe the reward r and new state s.
5. Update Q-value for (s, x) using the bellman equation:

$$Q(s, x) = (1 - \alpha)Q(s, x) + \alpha[r + \delta \text{max}_{x'} Q(s', x')]$$

6. Repeat 3-5 for a predetermined number of iterations or until convergence. Obtain the optimal action $x^*(s)$.

Pricing algorithm

Multi-Agent Reinforcement Learning (MARL):
Multiple agents interact both with the environment and with each other and receive feedback in the form of rewards or penalties.

Setting:

- $n = 2,\ \delta = 0.95,\ c = 1,\ a = 2,\ ,\mu = 1/4,\ ADV = 0.3$
- Action space: a set contains fifteen equally spaced prices in [1,2.1].
- State space: the set of possible prices charged by all agents in the previous period, with 15^n elements.
- A proportion of $\gamma \in [0, 1]$ consumers is shown only one product, the remaining is shown n products.
- learning parameters $(\alpha, \beta) = (0.15, 10^{-5})$, where $\varepsilon_t = e^{-\beta t}$.
- Run until the strategies of agents don't change for 100,000 periods.

Simulation results: PDP

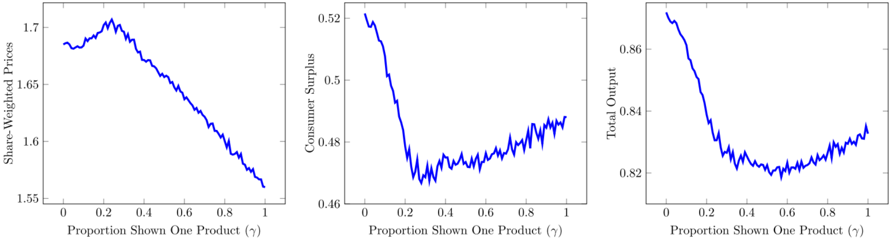
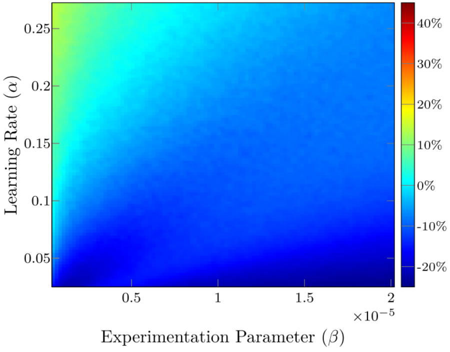


FIGURE 1.—The effect of PDP on prices (left panel), consumer surplus (middle panel), and total output (right panel).

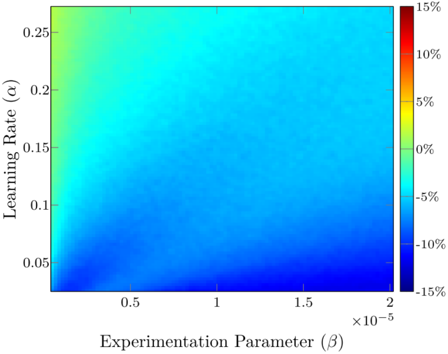
When $\gamma = 0$, Bertrand-Nash price is 1.47, collusive price is 1.94.

Simulation results: PDP

Fix $\gamma = 0.7$, $\alpha = [0.025, 0.2725]$, $\beta = [4 \times 10^{-7}, 2.02 \times 10^{-5}]$



(a) Consumer Surplus



(b) Total Output

FIGURE 2.—Heatmaps of the effects of PDP on consumer surplus and total output, for $\gamma = 0.7$. Consumer surplus increases in 13.8% of the cases, while total output increases in 1.7% of cases.

Simulation results: PDP

Reduce μ from $1/4$ to $1/20$: steeper curve, lower product differentiation.

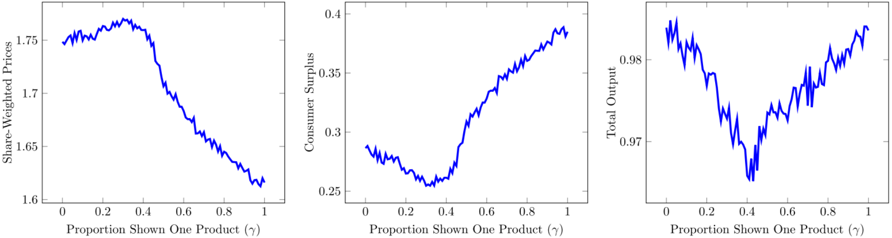


FIGURE 3.—The effect of PDP on prices (left panel), consumer surplus (middle panel), and total output (right panel), with lower differentiation ($\mu = 1/20$).

Intuition: Less loss in product variety.

Simulation results: PDP

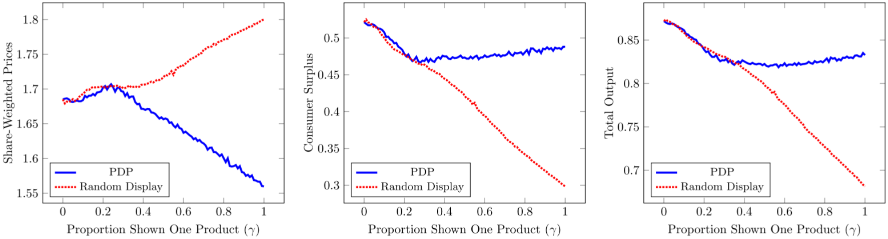


FIGURE 4.—A comparison of the effects of a benchmark of randomly displaying a firm on prices (left panel), consumer surplus (middle panel), and total output (right panel), compared to PDP.

Simulation results: Dynamic PDP

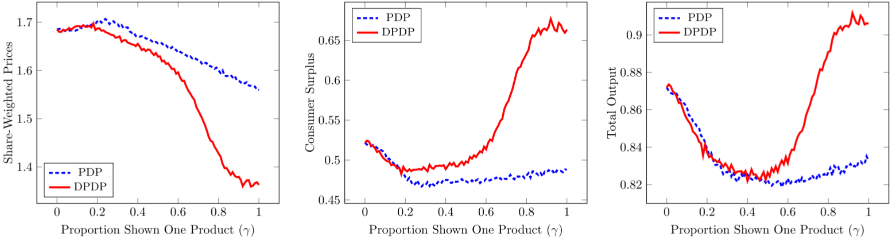


FIGURE 5.—The effect of Dynamic PDP on prices (left panel), consumer surplus (middle panel), and total output (right panel), with ADV $= 0.3$.

Simulation results: Dynamic PDP

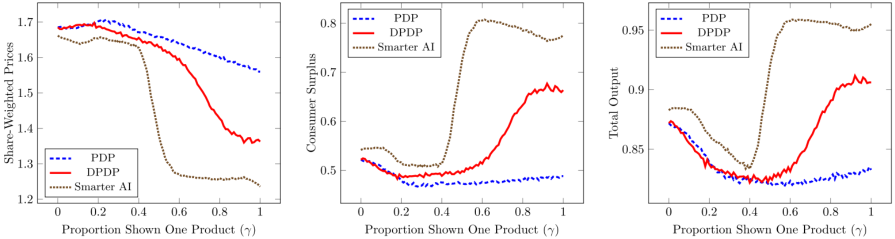


FIGURE 7.—The effect of a Smarter AI that includes in its state space the identity of the firm with the pricing advantage, on prices (left panel), consumer surplus (middle panel), and total output (right panel), with ADV $= 0.3$.

Smarter AI: Sellers track the identity of the firm with the advantage.

Thank you!

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References I