Data, Competition, and Digital Platforms

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Introduction

Digital platforms: **information** gatekeepers and **competition** managers.

- **Surplus creation** from matching consumers and products thanks to data from past and concurrent transactions.

- Concerns over surplus **extraction** from inducing seller market power.

Dual gatekeeper position under recent regulatory scrutiny:

*One cannot exclude the possibility that a dominant platform could have incentives to sell “monopoly positions” to sellers by showing buyers alternatives which do not meet their needs.*  

Crémer et al. (2019)

Research Questions

- Do platforms transfer their market power “downstream” to sellers?
- Can we quantify the effect of a digital platform’s (a) superior information and (b) market power on equilibrium prices both on and off the platform?
- This paper: how do different data-governance mechanisms affect the creation and distribution of surplus, both on and off digital platforms?
- Next paper: how do different advertising-auction mechanisms affect the creation and distribution of surplus, both on and off digital platforms?
Today

A model of digital platforms where:
- Platforms monetize data through *managed advertising campaigns*.
- Different information structures can be compared.
- Sellers have multiple sales channels.

Superior information on the platform improves *match quality*:
- Consumers find their favorite sellers.
- Sellers offer consumers efficiently “tailored” products.

Information also introduces the potential for *surplus extraction*:
- Endogenously local monopolies.
- No price discrimination, but *product steering*. 
Managed Campaigns

About automated bidding

Automated bidding takes the heavy lifting and guesswork out of setting bids to meet your performance goals. Unlike Manual CPC bidding, there’s no need to manually update bids for specific ad groups or keywords. Google Ads automatically sets bids for your ads based on that ad’s likelihood to result in a click or conversion that helps you achieve a specific goal for your business.

Different types of automated bidding strategies can help you increase clicks, visibility and conversions. Automated bid strategies learn as they go, using information about a bid’s performance to inform future bids. Learn how to determine a bid strategy based on your goals.

This article describes different business goals and the automated bid strategy that best achieves each goal.

Note: If you’d like to automate your bidding specifically for a Shopping campaign, read About automated bidding for Shopping campaigns.

About automated bidding for Shopping campaigns

Automated bid strategies for Shopping help you optimize your advertising spend. Using advanced machine learning, they monitor your campaign’s performance and set a bid in every auction to help you achieve your goals.

This article explains the different automated bid strategies that are available for Shopping campaigns and how to choose the right one for you.

Benefits

• You can focus on high level goals and allow Smart Bidding to set the right bid for you. Whether you’re trying to drive more visitors to your site or more revenue to your business, automated bidding allows you to start concentrating on overall performance of the campaign and less on how to set the perfect bid for each product group.

• Your campaign’s historical performance and future goals are always taken into account when determining how much to bid.
Managed Campaigns

Example - Search Term Report

Google’s search terms move will make millions in ad spend invisible to advertisers

The change removes visibility into more than 20% of search terms, one agency finds.

Unsurprisingly, the move has angered advertisers.

Example (1/5) - Drivers of optimizations are more automated

Before
- Structure granular
- Targeting Selection
- Manual Bid
- Query mining
- Ad Testing

Current
- Structure aggregated
- Broad targeting Selection
- Automated Bid
- Query mining limited visibility
- Ad Testing on autopilot
Related Literature


  → Our model: multiple gates, heterogeneous products.


  → Our model: sponsored content, auction-like mechanism, no merchant fees.

- Data externalities on digital platforms: Choi et al. (2019), Acemoglu et al. (2021), Kirpalani and Philippon (2021), Bergemann et al. (2022).

  → Our model: participation externalities.
Single-Seller Example
Single Seller

Single seller (Mussa and Rosen, 1978) and a unit mass of consumers.

Binary consumer type $\theta \in \{\theta_L, \theta_H\}$ with distribution $f(\theta)$.

Consumer type $\theta$ has valuation

$$\theta \cdot q$$

for a product of quality level $q$.

Seller produces goods of quality $q$ at cost $c(q) = q^2/2$.

$1 - \lambda$ consumers single home (buy directly from the seller).

$\lambda \in [0, 1]$ consumers dual home (visit the seller and a platform that runs ads).
Managed Campaign and Posted Prices

Platform knows each consumer’s type and offers seller a **managed campaign**.

Platform charges a fixed upfront fee $t$ (e.g., campaign budget).

Seller “uploads” personalized offers $(q(\theta), p(\theta))$ for on-platform consumers.

Platform shows each consumer $\theta$ the relevant offer.
(Consumer type is a *targeting category*: ads condition on $\theta$.)

Seller posts menu of quality, price pairs $(\hat{q}(\theta), \hat{p}(\theta))$ for off-platform consumers.

The on-platform offers may differ from the posted products and prices.
Summary

Platform: auto-bidding

Custom offers

Platform

Online consumer

Seller

Platform

Own store

Menu of products

Search

Offline consumer
Seller’s Problem

Off-platform, seller screens consumer types as in Mussa and Rosen (1978).

- Low type $\theta_L$ obtains zero rent, high type $\theta_H$ obtains efficient quality.

On-platform consumers see one product only.

“Showrooming” constraint (buy directly) limits rent extraction:

$$U(\theta) := \theta q(\theta) - p(\theta) \geq \theta \hat{q}(\theta) - \hat{p}(\theta) =: \hat{U}(\theta) \quad \forall \theta.$$  

Total cost of serving $(1 - \lambda)f(\theta_L)$ type-$\theta_L$ consumers off-platform:

$$(1 - \lambda)\hat{U}(\theta_H)f(\theta_H) + \lambda U(\theta_H)f(\theta_H),$$

where

$$\hat{U}(\theta_H) = (\theta_H - \theta_L)\hat{q}_L.$$
Optimal Menus

Proposition (Single Seller, Binary Types)

The seller offers the efficient quality levels to each on-platform buyer type, \( q(\theta) = \theta \) for all \( \theta \). Showrooming binds, \( U(\theta) = \hat{U}(\theta) \) for all \( \theta \).

The optimal off-platform menu of products is given by

\[
\hat{q}(\theta_L) = \max \left\{ 0, \theta_L - \frac{f(\theta_H)}{f(\theta_L)} (\theta_H - \theta_L) \left( 1 + \frac{\lambda}{1 - \lambda} \right) \right\},
\]

\[
\hat{q}(\theta_H) = \theta_H.
\]

Trade under symmetric information; limited ability to price discriminate.

Additional opportunity cost of serving the low type off-platform: rents to high types off platform \( \Rightarrow \) rents to high types on the platform.
Optimal Menus

Type $\theta_H$ buys the efficient quality $q_H = \hat{q}_H = \theta_H$ at the same price $p_H = \hat{p}_H$ on and off the platform. Type $\theta_L$ buys $q_L = \theta_L$ on the platform and $\hat{q}_L < \theta_L$ off platform. Each type obtains the same information rent on both channels, $U_H > U_L = 0$. 

$q_H = \hat{q}_H = \theta_H$

$q_L = \theta_L$

$\hat{q}_L(\lambda)$

$p_H(\lambda) = \hat{p}_H(\lambda) \leq \theta_H^2$

$\hat{p}_L(\lambda) = \theta_L \hat{q}_L(\lambda)$

$p_L(\lambda) = \theta_L^2$
Taking Stock

Off platform: lower quality $\hat{q}(\theta_L)$ and higher prices $\hat{p}(\theta_H)$ as $\lambda \uparrow$.

On platform: efficient qualities; no rent for low type; positive rent for high type.

What about the platform’s fee $t^*$?

- Seller can guarantee the Mussa and Rosen (1978) profits off-platform.
- Fee $t^* =$ on-platform profits minus losses from distortions off-platform menu.
- This means on-platform profits $> t^*$. Campaign “delivers” ROI $> 0$. 
Too Easy or Too Hard?

The example is “too easy:”

- Single seller vs. competing sellers.
- Two types vs. arbitrary type distributions.
- Symmetric information (consumers and platform).

Full model:

- How can the platform create “local monopolies” by managing the advertising campaigns of competing multiproduct sellers?

The example is also “too hard:”

- Single product & personalized pricing vs. product steering & quality pricing.
Full Model
Setup

$J$ sellers and a unit mass of consumers with continuous types.

Consumer $\theta = (\theta_1, \ldots, \theta_j, \ldots, \theta_J) \in \mathbb{R}_+^J$ has value

$$\theta_j \cdot q_j$$

for a product of quality levels $q_j$ produced by firm $j$.

Sellers offer vertically differentiated products with cost $c(q_j) = q_j^2/2$.

$1 - \lambda$ consumers buy directly from sellers.

$\lambda \in [0, 1]$ consumers visit a monopolist platform that runs ads.
Information Structure

Consumers’ valuations $\theta_i$ with distribution $F$, i.i.d. across $j$.

The platform observes $\theta \in \mathbb{R}^J$ perfectly.

Every consumer observes a noisy signal $s$ about $\theta$.

Posterior mean $m_j = \mathbb{E}[\theta_j | s]$ with distribution $G$.

$F$ is a mean-preserving spread of $G$. Assume same support.
On Platform: Managed Campaigns

Platform allocates a single advertising slot through a managed campaign:

- Charges a fixed fee $t$ to participating sellers (e.g., campaign budget).
- Solicits personalized ads—functions $q_j(\theta)$ and $p_j(\theta)$—from each seller $j$.
- *Selection rule* $\sigma$ specifies which $j$ gets the slot for each consumer $\theta$:

  $$\sigma : \Theta \times \mathbb{R}^J_+ \times \mathbb{R}^J_+ \rightarrow [J],$$

  and advertises the selected $j$’s $q_j(\theta)$ and $p_j(\theta)$.

- Reveals to the consumer her value $\theta_j$ for the selected product $q_j$.

(For now) platform chooses seller $j$ and the ad $(q_j, p_j)$ that maximize the total value of the match $\theta_j q_j - c(q_j)$ among sellers that participate in the mechanism.
Off Platform: Search and Information Frictions

- Off-platform consumer with expectations $m$ faces search costs $\gamma > 0$.

- First search is free (as in Diamond, 1971) $\Rightarrow$ all types search.

- Seller $j$ elicits consumer wtp $m_j$ through menu $(\hat{q}_j(m_j), \hat{p}_j(m_j))$.

- Not an inspection good: learning $\theta_j$ requires the platform’s data.
Timing and Equilibrium

1. Platform announces managed campaign mechanism $\mathcal{M} = (\sigma, t)$.

2. Sellers simultaneously choose whether to participate in $\mathcal{M}$, their on-platform products and prices $(q_j, p_j)$, and their off-platform menus $(\hat{q}_j, \hat{p}_j)$.

3. Type $\theta$ is realized, and a (seller, ad) pair is selected to be shown.

4. Consumer learns $\theta_j$, buys on platform, or searches off-platform.

**Solution concept:** Perfect Bayesian equilibrium with symmetric consumer beliefs on and off the path of play.
Equilibrium Search Patterns
Symmetric Equilibrium

Off the platform:

- $1 - \lambda$ consumers with beliefs $m$ face search costs $\gamma > 0$;
- they expect symmetric menus and visit $\hat{j} = \arg\max_j m_j$ only.

On the platform:

- $\lambda$ consumers infer $\theta_j^* = \max_j \theta_j$ (cannot detect deviations);
- they expect symmetric menus off-platform, both on and off path.

Proposition (Consideration Sets)

Every on-platform consumer $\theta$ compares the advertised seller’s offer $(p_j^*(\theta), q_j^*(\theta))$ only with the corresponding off-platform offer $(\hat{p}_j^*(\theta^*_j), \hat{q}_j^*(\theta^*_j))$. 
Equilibrium Search Patterns: Example

Consumer: expected values $m$

$\theta_2 = \max_j \theta_j$

Firm 2’s offer $(q_2(\theta), p_2(\theta))$

Firm 2’s menu $(\hat{q}_2, \hat{p}_2)$

$m_1 = \max_j m_j$

Firm 1’s menu $(\hat{q}_1, \hat{p}_1)$

on platform

off platform
...or in fewer words...
Interpretations

With a better-informed platform, equivalent interpretation:

- each brand has \((1 - \lambda)/J\) loyal (imperfectly informed) customers already shopping off-platform;

- the remaining \(\lambda\) consumers are not currently shoppers—they do not recognize any brands without the platform’s data;

- these consumers can be turned into shoppers by informative advertising;

- in that case, they only consider the advertised brand (online and offline).

This result requires an (arbitrarily small) informational advantage:

- without advantage vs. buyers, platform does not control outside options—consumers’ beliefs determine where they search off platform.
Equilibrium Product Lines
Matching and Product Steering

On platform, sellers can extract surplus through product steering.

“Showrooming constraint” for seller $j$ shown to consumer $\theta$:

$$ U_j(\theta) \triangleq \theta_j q_j(\theta) - p_j(\theta) \geq \max_m [\theta_j \hat{q}_j(m) - \hat{p}_j(m)] \triangleq \hat{U}_j(\theta). $$

Incentive-compatible menus off platform $\Rightarrow$ on-platform consumer compares

$$(q_j(\theta), p_j(\theta)) \text{ and } (\hat{q}_j(\theta), \hat{p}_j(\theta)).$$

On platform, optimal to offer efficient quality $q_j(\theta) = q^*_j(\theta) = \theta_j$.

On platform, surplus extraction limited by $\hat{U}_j(\theta)$. 
Seller $j$’s Problem

Consider offline menu $(\hat{q}_j, \hat{U}_j)$. Seller $j$’s profits on online type $\theta$:

$$
\pi_j(\theta, \hat{U}_j) = \frac{\theta_j^2}{2} - \hat{U}_j(\theta).
$$

Seller’s choice of menu off-platform (wlog a function of $\theta_j$):

$$
\max_{\hat{q}, \hat{U}} (1 - \lambda) \int_0^1 \left( \theta_j \hat{q}(\theta_j) - \hat{q}(\theta_j)^2/2 - \hat{U}(\theta_j) \right) G^{J-1}(\theta_j) dG(\theta_j)
$$

$$
+ \lambda \int_0^1 \left( \frac{\theta_j^2}{2} - \hat{U}(\theta_j) \right) F^{J-1}(\theta_j) dF(\theta_j),
$$

s.t.

$$
\hat{U}'(\theta_j) = \hat{q}(\theta_j) \quad (IC),
$$

$$
\hat{U}(\theta_j) \geq 0 \quad (IR).
$$
Equilibrium Menus

Proposition (Symmetric Equilibrium Menus)

There exists a unique symmetric equilibrium.

The equilibrium quality levels are given by

\[ q(\theta_j) = \theta_j, \]
\[ \hat{q}(\theta_j) = \max \left\{ 0, \theta_j - \frac{1 - G^J(\theta_j)}{JG^J - 1(\theta_j)g(\theta_j)} - \frac{\lambda}{1 - \lambda} \frac{1 - F^J(\theta_j)}{JG^J - 1(\theta_j)g(\theta_j)} \right\}. \]

Furthermore,

\[ U(\theta_j) = \hat{U}(\theta_j) = \int_0^{\theta_j} \hat{q}(m_j)dm_j. \]
Equilibrium Properties

On platform: data matches consumer to favorite brand.

Sellers invest in efficient quality (product customization).

Off platform: inefficient matching based on insufficient information, and inefficient quality under asymmetric information.

Opportunity cost of off-platform sales: positive rents on platform.

Quality $\hat{q}$ further distorted downward, more so the larger the platform size $\lambda$.

Seller equilibrium profits = Mussa and Rosen (1978) profits off platform (i.e., under type distribution $(1 - \lambda)G'^J$).
Quality Provision

\[ \lambda = \frac{1}{2}, J = 5, G(m) = m, F(\theta) = \text{Beta}(\theta, 1/4, 1/4) \]
Payments

\[ \lambda = 1/2, \ J = 5, \ G(m) = m, \ F(\theta) = Beta(\theta, 1/4, 1/4) \]
Nonlinear Tariffs

Every offline product is sold at a lower price online.

\[
U > 0 \quad U = 0
\]
Equilibrium Consumer Surplus

\[ \hat{U}_j(\theta) = U_j(\theta) \] for all \( \theta \) and all \( j \).

But \( F \succ_{mps} G \) and \( U \) convex \( \Rightarrow \mathbb{E}_{F,j} U > \mathbb{E}_{G,j} U \).

This has several implications:

1. Ex ante, an individual consumer prefers to be on the platform.

2. Ex ante (holding prices fixed), an individual consumer wants the platform to disclose their information to sellers.

3. In equilibrium, all consumers are worse off.
Equilibrium Advertising Fees

Proposition (Optimal Mechanism)

The managed campaign mechanism showing the seller \( j \) and the product \((q_j, p_j)\) that maximize total surplus among all participating sellers also maximizes the platform’s revenue.

- Platform can extract sellers’ revenue up to a fixed outside option.
- Managed campaign maximizes social surplus and eliminates competition.

Equilibrium fee \( t^* \) under managed campaign implies \( ROI > 0 \):

\[
t^* = \lambda \mathbb{E}_F[\pi^*(\theta, \hat{U}^*)] + (1 - \lambda)\mathbb{E}_G[\pi(\theta, \hat{q}^*, \hat{U}^*]) - (1 - \lambda)\mathbb{E}_G[\pi(\theta, \hat{q}^{MR}, \hat{U}^{MR})].
\]
Comparative Statics

Proposition (Platform Size)

- The equilibrium quality $\hat{q}^*(\theta_j)$ is decreasing in $\lambda$ for all $\theta_j < 1$, and the information rent $\hat{U}^*(\theta_j)$ is decreasing in $\lambda$ for all $\theta_j$.

- For every $\theta_j < 1$, there exists $\hat{\lambda} < 1$ such that $\hat{q}^*(\theta_j) = 0$ for all $\lambda \geq \hat{\lambda}$.

- The platform’s fee $t^*$ is strictly increasing in $\lambda$. 
Informed Consumers: Types

Suppose $F = G$: consumers know their types $\theta$.

In a symmetric equilibrium, each consumer shops at their favorite firm.

Firm $j$ can avoid paying the fee and serve $1/J$ consumers by solving

$$\max_{\hat{q}, \hat{U}} \int_0^1 \left( \theta_j \hat{q}(\theta_j) - \hat{q}(\theta_j)^2 / 2 - \hat{U}(\theta_j) \right) \left( (1 - \lambda) dG^{J-1}(\theta_j) + \lambda dF^{J-1}(\theta_j) \right)$$

s.t. $\hat{U}(\theta_j) \geq \hat{U}^*(\theta_j)$.

Solution: Mussa and Rosen (1978) quality for mixture $(1 - \lambda)G^J + \lambda F^J$.

Strictly higher deviation profits than baseline $\Rightarrow$ strictly lower platform fees.
Informed Consumers: Types

Proposition (Symmetric Information)

With complete information about $\theta$ for all on-platform consumers, the equilibrium qualities on and off platform are unchanged, but the advertising budget $t^*$ is strictly lower than if the platform had exclusive information about $\theta$.

⇒ Positive value of small informational asymmetry.

Corollary (Value of Additional Information)

For all $J > 1$, the platform benefits strictly from any information advantage,

$$\lim_{G \to F} t^*(G) > t^*(F).$$
Conclusions

Digital platforms monetize superior information about consumer preferences by auctioning access to the consumers’ attention.

Consumer surplus on- and off-platform is driven by information rents off platform and by the availability of organic information.

The growth of a platform’s database reduces each consumer’s outside option and therefore leads to higher prices.

Mitigating factors: fully informed consumers; free organic content (i.e., public off-platform prices); and privacy protection (e.g., cohort-based ads).

Product design and price decisions interact with modes of data governance (e.g., with the rules by which a platform shares its data).
Looking Ahead

Seller heterogeneity:

- In some cases, very little happens off-platform; sponsored listings only.
- In other cases, organic links and own websites.
- Heterogeneous $\lambda \Rightarrow$ inefficient matching in optimal managed campaign.

Platform revenue models:

- “How Do Digital Advertising Auctions Impact Product Prices?” (Bergemann, Bonatti, and Wu).
- Managed campaigns vs. data-augmented auctions for sponsored links.
- To restrict competition with organic links, platform can control both selection rule and pricing rule (“sophisticated campaign”).
- “Best-value pricing” achieves vertical-integration producer surplus.
Informed Consumers: Prices

1. Platform announces managed campaign $\mathcal{M}$ and fee $t$.

2. Sellers simultaneously choose whether to participate in $\mathcal{M}$, their on-platform products and prices $(q_j, p_j)$, and their off-platform menus $(\hat{q}_j, \hat{p}_j)$.

3. Type $\theta$ is realized, and a (seller, ad) pair is selected to be shown.

4. Consumer learns full type $\theta$ and all off-platform menus.

5. Consumer can buy on-platform from $j^*$ or off-platform from any seller.
Search and Shopping with Organic Links

Consumer: beliefs $m$

$\theta_2 = \max_j \theta_j$

Firm 2’s offer $(q_2(\theta), p_2(\theta))$

Any firm’s menu $(\hat{q}_j, \hat{p}_j)$

$m_1 = \max_j m_j$

Firm 1’s menu $(\hat{q}_1, \hat{p}_1)$
Proposition (Equilibrium with Organic Links)

1. The equilibrium quality and utility \( \hat{q}^*(\theta_j) \) and \( \hat{U}^*(\theta_j) \) are weakly higher for all \( \theta_j \) with organic links than without.

2. Firms’ profits are lower and their outside options are higher with organic links than without.

Intuition:

- Platform shows efficient seller, which posts efficient quality.
- No search costs: other sellers can poach consumers with off-platform menus.
- On path, efficient matching but lower prices.
- Off path, non-participating sellers can win a fraction of their best consumers.
- The platform’s fee is lower than without organic links.
Cohort-Based Ads

Suppose information $\theta$ is shared with consumer but not with sellers.

Platform only announces ranking of consumer valuations $\theta_j$.

Sellers condition ads on each cohort (i.e., ranking), as in Google’s Topics.

Consumers have private information on the platform too: each seller $j$ must offer a menu s.t. $U_j(\theta_j) \geq \hat{U}_j(\theta_j)$.

Result 1: efficient matching, but downward distorted qualities online.

Result 2: offline quality, consumer surplus increase.
Cohort-Based Ads

Proposition (Cohort-Based Quality)

Assume $F^J \succ_{lr} G^J$ over all $\theta_j$ for which both virtual values are positive.

In the unique symmetric equilibrium, each firm offers quality levels

$$\hat{q}(\theta_j) = q(\theta_j) = \max \left\{ 0, \theta_j - \frac{1 - \lambda F^J(\theta_j) - (1 - \lambda)G^J(\theta_j)}{\lambda JF^J-1(\theta_j)f(\theta_j) + (1 - \lambda)JG^J-1(\theta_j)g(\theta_j)} \right\}.$$ 

→ Mussa-Rosen menu for the mixture of the highest order statistics.

Corollary (Information Structures Comparison)

Quality provision and information rents under cohort-based ads satisfy

$$\theta_j \geq \hat{q}_{\text{cohort}}(\theta_j) \geq \hat{q}_{\text{full}}(\theta_j) \quad \text{and} \quad \hat{U}_{\text{cohort}}(\theta_j) \geq \hat{U}_{\text{full}}(\theta_j).$$
Information Design

Managing information: what to reveal to consumers and sellers?
Managing competition: how to select which seller to advertise?

Proposition (Managing Information and Competition)

- Symmetric information structures are optimal—platform does not gain by revealing more information to sellers than to consumers.
- As $\lambda \to 1$, efficient matching and full information revelation are optimal.

Suppose consumers are initially uninformed. ($m_j \equiv \mathbb{E}_F[\theta_j]$)

- Efficient matching is always optimal.
- Optimal information design: pool at the prior mean, reveal everything else.
Optimal Information Design

On-platform profits and optimal pooling region