

How Do Digital Advertising Auctions Impact Product Prices?

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Paid Placement

BUY IT AGAIN
See all and manage

- 4 Boxes of Kimbo Espresso, Arancio, Velvety Compatible, 18 Count (Pack of 4)
\$13.99 (3.50/Count)
Save with Subscribe & Save
Qualifies FREE One Day
Get 2 deliveries, May 17
- Caffè Kinoko Espresso Neapolitano (Espresso) - 8.5 oz can
\$14.99 (1.75/Count)
Get 2 Thu, May 19, Thu, May 24
FREE Delivery

RESULTS
Price and other details may vary based on product size and color.

- Kimbo Napoli 100% Arabica Ground Coffee - Blended and... 18 Count (Pack of 4)
\$13.99 (3.50/Count)
FREE Delivery (Prime members)
- Caffè Valet Pods of Honor Coffee Capsules, 100% Arabica Coffee, M Count
\$14.99 (3.50/Count)
Qualifies FREE Delivery Thu, May 19
Only 1 left in stock - order soon
- Ry Espresso Single Serve Coffee Compatible Capsules, 100%, 18 Count (Pack of 4)
\$14.99 (3.75/Count)
Save with Subscribe & Save Discount
Qualifies Today 9 PM - 10 PM
FREE Delivery (Prime members only)
- Intelligencia Coffee, Medium Roast Whole Bean Coffee - 18oz., 12 Count (Pack of 3)
\$14.99 (1.25/Count)
Save with Subscribe & Save Discount
Qualifies Today 9 PM - 10 PM
FREE Delivery (Prime members only)

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MIT Executive Certificates Choose 1 of 3 certificate tracks
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https://connect.darden.virginia.edu/ + advanced + leaders
- New Perspectives | C-Suite Programs | Advanced Leaders**
Prepare yourself, or your high-performing senior executives to lead at the highest level.

Native Shoes (Default)

Kicking and Dreaming. Piled on a Bunbury. Swing on a Tree. Free Shipping on orders \$50+

- Big boot child - Sun Yellow/Bone... Shop Now
- Flora Mega... Shop Now
- ot child - olive/Bone... Shop Now
- Flora - Fire Truck Red... Shop Now
- Jefferson - Loli Green/Smol... Shop Now

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{ How Does the
AdWords Auction }
Work?

PRIZED AUCTION ITEMS

"Insurance"

TOTAL GOOGLE EARNINGS

\$32.2 BILLION
in advertising revenue.

Shift in Ad Tech: Automated Bidding

- Advertiser submits budget and defines broad objectives only (e.g., clicks).
- Platform allocates budget (no more manual bidding).
- Over 80% of Google advertisers (60% of ad spend) used this option in 2023.



Advertiser

Set your average daily budget for this campaign

Budget

Select your bid strategy [?] Pav for [?]

Bidding

Target CPA


Start date End date

Start and end dates



Channel


A Ubiquitous Shift

Campaigns  290840859114085 (290...)

Bid strategy

The way you want Meta to bid in the auction, based on your cost goals and your optimization for ad delivery. This will display as either lowest cost, cost cap, bid cap, target cost, highest value or minimum ROAS depending on your cost or ROAS control selection.

[Learn more](#)



The diagram shows a blue box labeled "Portfolio Bidding" with three dollar signs above it. Below the box are three icons: a Search campaign (Google G), a Shopping campaign (Shopping cart), and a Display campaign (Screen). An arrow points from the box to the text below.

Multiple, single-channel campaigns added to a portfolio bidding strategy and using a **shared budget**.

amazon ads Small business Enterprise

Settings

Campaign name ⓘ

Portfolio ⓘ

Start ⓘ **End** ⓘ

Daily budget ⓘ

Targeting

- Automatic targeting
Amazon will target keywords and products that are similar to the product in your ad.
- Manual targeting
Choose keywords or products to target shopper searches and set custom bids.

A Policy Concern

UK Competition & Markets Authority's 2020 report:

*Where an advertising platform has market power [...] advertiser bids in its auctions are higher, resulting in higher prices. In addition, the **platforms may be able to use levers** including the use of reserve prices or mechanisms **such as automated bidding to extract more rent from advertisers.** [...]*

*Higher advertising prices matter because they represent increased costs to the firms producing goods and services which are purchased by consumers. **We would expect these costs to be passed through to consumers** in terms of higher prices for goods and services, even if the downstream market is highly competitive.*

This paper: what is the effect of autobidding on equilibrium product prices?

Key Features

“Discrete pass-through” exercise: bidding vs. submitting a **budget**.

- Budget → bidder’s payment is independent of the consumer type.

Advertiser doesn’t have private information; the **platform** does.

- > 60% of digital ad revenue generated on platforms’ own websites.
- For Google, even larger share, 206/237 billion USD in 2023.

Sellers have **parallel sales channels**:

- Impact of ad sales mechanism spills over to off-platform markets.

Model

Consumers and Sellers

- Sellers (advertisers) $\{1, 2, \dots, J\}$ with unique, indivisible products.
- Sellers post an off-platform price \bar{p}_j .
- Sellers can also join a monopolist platform.
- Consumers with unit demand and heterogeneous tastes.
- Consumer utility for purchasing at price p_j is $v_j - p_j$.
- Willingness to pay for a seller's product $v_j \in [\underline{v}, \bar{v}]$ is drawn independently across sellers and consumers from distribution F with monopoly price p_M .

On and Off the Platform

The platform:

- Knows every consumer's willingness to pay for every product.
- Shows a single “personalized offer” to each consumer that visits it.

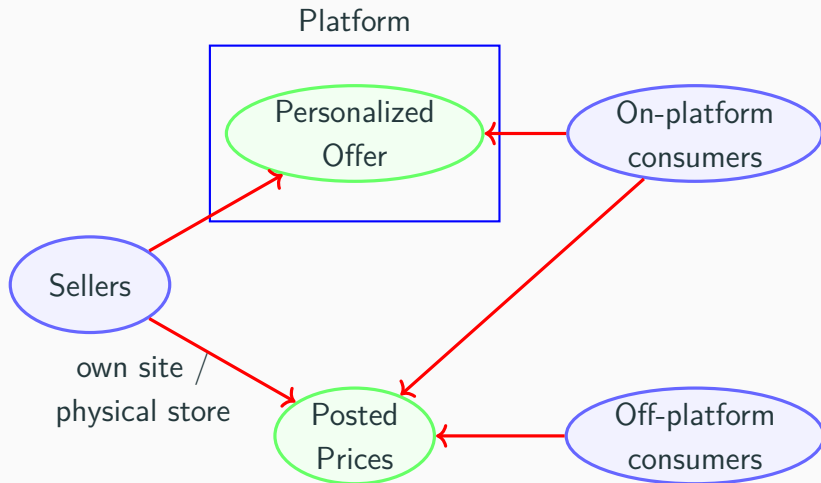
A fraction λ of consumers are on-platform shoppers:

- they see their personalized offer *and* all sellers' off-platform prices.

The remaining $1 - \lambda$ shop off-platform only.

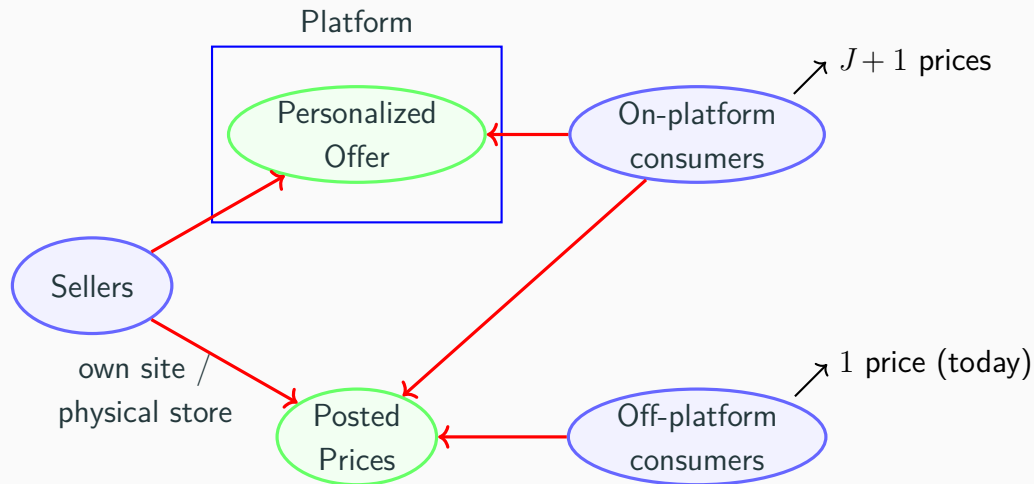
- Today: evenly split captive consumers who each see one price.
- Paper: they see (some or) all posted prices.

Visual Representation



Showrooming constraint: personalized price \leq posted price.

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Digital Advertising and Personalized Pricing

Literal interpretation: coupons, *personalized discounts* (Rhodes and Zhou, 2024).

→ Value creation (more trade) and value extraction (price discrimination).

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Broader interpretation: *product steering* (Bergemann and Bonatti, 2024).

Each firm offers a range of products varying in quality and price.

Platform shows each consumer a different (quality, price) pair.

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For small differences in product quality, product steering \approx personalized pricing.

Related Literature

- Online ad auctions: Varian (2007), Edelman et al. (2007), Levin and Milgrom (2010), Athey and Ellison (2011), Hummel and McAfee (2016).
- Autobidders in online auctions: Deng et al. (2022), Liaw et al. (2022), Mehta (2022), Golrezaei et al. (2021), Li and Lei (2023).
- Pass-through of online ad costs: Bar-Isaac and Shelegia (2023), Motta and Penta (2023), Varian (2022).
- Showrooming, steering, multiple channels: de Cornière and de Nijs (2016), Wang and Wright (2020), Miklos-Thal and Shaffer (2021), Anderson and Bedre-Defolie (2022), Bar-Isaac and Shelegia (2022), Ronayne and Taylor (2022), Teh and Wright (2022), Bergemann and Bonatti (2024).
- “Partial” mechanism design: Philippon and Skreta (2012), Tirole (2012), Calzolari and Denicolò (2015), and Fuchs and Skrzypacz (2015).

Managed Campaigns

Managed Campaign: Mechanism

- Platform requests a fixed fee t from each firm.
- $A = \{0, 1\}^J$ denotes firms' accept / reject decisions; $(\bar{p}_j)_{j=1}^J$ posted prices.
- Platform commits to a *steering* (selection) and (personalized) *pricing* policy

$$(s, p) : V^J \times A \times \mathbb{R}_+^J \rightarrow \{1, \dots, J\} \times \mathbb{R}_+.$$

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\implies price-match guarantee by efficient firm $k \implies$ discourages deviations in \bar{p}_j .

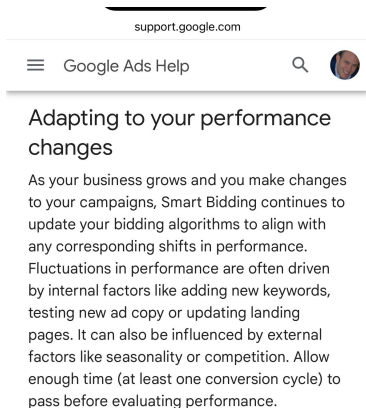
Managed Campaigns: Practice

	Narrow	Broad
Product Lines	Single product	Multiple products
Pricing	Personalized pricing	Product steering
Operations	Advertised price reacts to all posted prices	“Catalog ads” select most profitable ad
Timing	One-time pricing	Learning over time

Real-world managed campaigns implement our mechanism based on adaptive behavior


Setting Smarter Search Bids

How our bidding algorithms learn



The screenshot shows the top portion of a web page from support.google.com. The browser address bar displays 'support.google.com'. Below the address bar is a navigation bar with a hamburger menu icon, the text 'Google Ads Help', a search icon, and a profile picture. The main content area features the article title 'Adapting to your performance changes' in a large, bold font. Below the title is a paragraph of text explaining how Smart Bidding algorithms adapt to performance changes.

support.google.com

☰ Google Ads Help 🔍 

Adapting to your performance changes

As your business grows and you make changes to your campaigns, Smart Bidding continues to update your bidding algorithms to align with any corresponding shifts in performance. Fluctuations in performance are often driven by internal factors like adding new keywords, testing new ad copy or updating landing pages. It can also be influenced by external factors like seasonality or competition. Allow enough time (at least one conversion cycle) to pass before evaluating performance.

Equilibrium with Best-Value Pricing

Theorem (Best-Value Pricing Equilibrium)

In any full-participation, symmetric equilibrium:

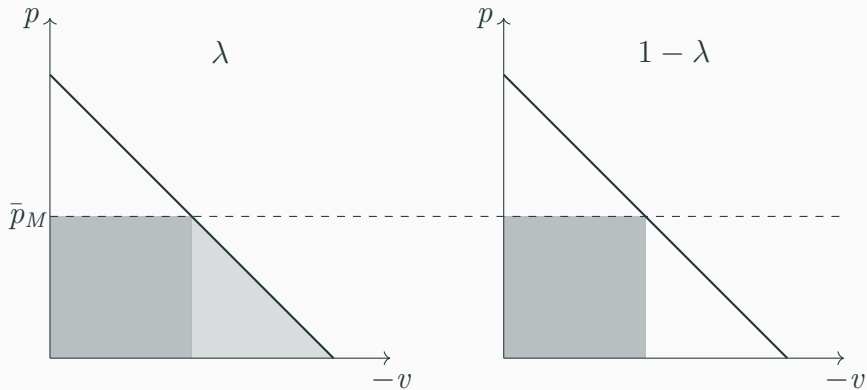
- ① *On-platform consumers v with $v_j = \max_k v_k$ buy from firm j at*

$$p_j(v) = \min\{v_j, p_V\}.$$

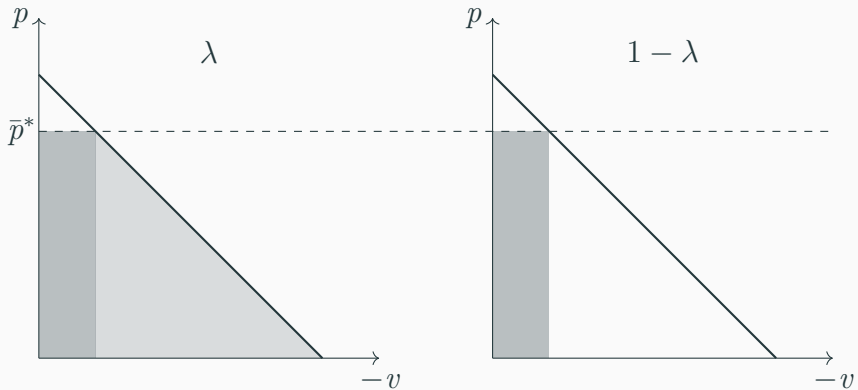
- ② *The posted price $p_V > p_M$ satisfies the following equation:*

$$\underbrace{(1 - \lambda)(1 - F(p_V) - p_V f(p_V))}_{\text{off-platform consumers}} + \lambda J \underbrace{\int_{p_V}^{\bar{v}} F^{J-1}(v) dF(v)}_{\text{on-platform consumers}} = 0.$$

Intuition: Dual Channels



Intuition: Incentives to Raise Posted Price



More Formally...

Suppose $J = 1$. Optimal posted price solves:

$$\max_p \left[(1 - F(p))p + \frac{\lambda}{1 - \lambda} \int_{\underline{v}}^{\bar{v}} \min\{v, p\} dF(v) \right].$$

Optimal posted price balances monopoly profits + on-platform benefits.

Profit is supermodular in $(p, \lambda) \implies p_V > p_M$ by monotone comparative statics.

Optimal posted price satisfies:

$$(1 - \lambda)(1 - F(p_V) - p_V f(p_V)) + \lambda \int_{p_V}^{\bar{v}} \mathbf{1} dF(v) = 0.$$

When $J > 1$, selection effects appear, but qualitative results remain:

$$\int_{p_V}^{\bar{v}} F^{J-1}(v) dF(v) \quad \text{replaces} \quad \int_{p_V}^{\bar{v}} \mathbf{1} dF(v).$$

Theorem (Optimal Managed Campaign)

The highest-price, full-participation equilibrium:

- ① *maximizes revenue for the platform among all steering and pricing policies;*
- ② *attains the integrated (collusive) gross profit for the firms.*

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Intuition:

- Efficient outcome & worst outside option for sellers \implies maximal fee t^* .
- Why worst outside option? If j does not participate, the BVP policy tries to sell the next-best product k and competes in price until it sets $p_k = 0$.

On-platform consumers buy from the high-value firm at $p_j(v) = \min(v_j, p_V)$.

\implies First-best total surplus; consumer surplus > 0 thanks to posted prices.

Welfare Implications

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Off-platform consumer v buys from a random firm j iff $v_j \geq p_V$.

⇒ Consumer and total surplus decrease with p_V .

⇒ Incentive to raise price above p_M unambiguously bad for CS and TS .

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Proposition (Posted Prices and Welfare Effects)

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As $\lambda \rightarrow 1$, posted price $p_V \rightarrow \bar{v}$ and therefore zero consumer surplus.

Data-Augmented Auctions

Data-Augmented Bidding: Mechanism

The platform runs an auction to sell the sponsored slot.

- Each seller j submits bid *function* $b_j(v)$ and advertised price *function* $p_j(v)$.
- High bidder j^* wins the slot: platform offers their product at price $p_{j^*}(v)$.
- Winner pays second-highest bid $b_k(v)$. (FPA is equivalent.)

The consumer's type v is a targeting category.

- *Data-augmented* bids: sellers leverage the platform's data (which they never see) to condition bids and prices on each shopper's characteristics.

Sequential game: posted prices \bar{p}_j followed by bids and advertised prices.

Advertiser's Problem

Personalized advertised prices. Seller j sets $p_j(v)$ as if they won the auction.

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Seller j 's advertises price $p_j(v) = (v_j - \underline{u}(v, \bar{p}))_+$ to consumer v .

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Proposition (Efficient Steering)

For any off-platform prices $(\bar{p}_1, \dots, \bar{p}_J)$, the socially efficient seller, $j = \arg \max_k v_k$, submits the highest bid.

Data-Augmented Bidding: Equilibrium

Theorem (Symmetric Equilibrium)

In the (generically unique) symmetric equilibrium in undominated strategies:

- ① *Consumer v receives and buys a sponsored offer from $j = \arg \max_k v_k$.*
- ② *Each firm k posts price $\bar{p}_k = p_B$ satisfying*

$$(1 - \lambda)(1 - F(p_B) - p_B f(p_B)) + \lambda J \int_{p_B}^{\bar{v}} F^{J-1}(v - p_B) dF(v) = 0.$$

- ③ *Firm $j = \arg \max_k v_k$ bids $b_j(v) = p_j(v) = \min(v_j, p_B)$.*

Comparing Mechanisms

Comparing Advertising Mechanisms

Theorem (Welfare and Posted Price Comparison)

The posted price p_V in the optimal managed campaign is higher than the posted price p_B under data-augmented bidding:

$$p_V \geq p_B \geq p_M.$$

Total consumer surplus and total welfare are lower in the optimal managed campaign than under data-augmented bidding.

Proof idea: turn both auction and managed campaign equilibria into maximization problems; parametrize; show mcs moving from one to the other.

In the paper: ranking of prices is robust to off-platform competition.

Comparing Advertising Mechanisms

Efficient matching under both mechanisms: on-platform consumers buy from seller $j = \arg \max v_k$ at $p_j(v) = \min\{v_j, \bar{p}_j\}$.

Common benefit of raising posted price \bar{p}_j : increase revenue on all $v_j > \bar{p}_j$.

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\implies “Advertising cost pass-through” due to different competitive responses.

Conclusion

The *mechanisms* for allocating sponsored content and the availability of consumer data jointly determine match formation and surplus extraction both on and off large platforms.

The platform's auction mechanisms have significant impact on product prices:

- On-platform, the data made available to the advertisers allows for efficient matching, yet most of the surplus accrues to the platform.
- Off-platform, advertisers raise prices to gain a competitive edge.

Cross-channel distortions become more pronounced the more tools the platform has at its disposal.

Pass-Through

Extend the auction model to allow for entry fees.

Define the “pass-through” of the change in mechanisms as

$$\eta = \frac{p_V - p_B}{T_V - T_B}.$$

Proposition (Advertising Mechanism Pass Through)

The pass-through rate satisfies $\eta > J$: higher advertising costs under a managed campaign (vs. bidding) result in an amplified increase in off-platform prices.

Prices tend to rise more dramatically with more competitors precisely because the sophisticated managed campaign softens competition.

Policy Interventions

Competition Management

UK Competition & Markets Authority (2020, §6.15) concerns:

Although both Google's and Facebook's core services can be accessed by consumers at no direct cost, consumers therefore nevertheless suffer financially from the exercise of market power." The alleged concern is that the platform's market power raises the cost of advertising, which is then passed on to consumers.

Idea: restrict managed campaigns to *rule-based (auto) bidding*.

- Amazon: "take the guesswork out of adjusting bids."
- Google Demand Gen: "offer more control over where and how ads appear."

Independent Managed Campaign

Platform commits to a *steering* policy $s : V^J \times A \rightarrow \{1, \dots, J\}$, and to a *pricing* policy $p : V^J \times A \rightarrow \mathbb{R}_+$ for the selected firm.

Independent pricing: $p_j(v, a)$ can't condition on any \bar{p}_k .

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Intuition: posted-price deviations can now sway consumers from sponsored offers (i.e., not ensuring efficient matching off path induces fiercer competition).

Privacy Sandbox for the Web

Privacy Sandbox for the Web will phase out [third-party cookies](#) by using the latest privacy techniques, like [differential privacy](#), [k-anonymity](#), and [on-device processing](#).

Privacy Sandbox also helps to limit other forms of tracking, like [fingerprinting](#), by restricting the amount of information sites can access so that your information stays private, safe, and secure.



First implementation: “consumer cohorts,” now “Google Topics.”

Privacy Protection: Mechanisms

Restrict the platform's pricing policy space to

$$p : J \times \{0, 1\}^J \times \mathbb{R}_+^J \rightarrow \mathbb{R}_+.$$

“Cohort privacy:” allows ads to condition on rank information only.

Proposition (Cohort Privacy)

In the platform-optimal campaign with cohort privacy, the posted price is

$$p_P = \frac{1 - (1 - \lambda)F(p_P) - \lambda F^J(p_P)}{(1 - \lambda)f(p_P) + \lambda JF^{J-1}(p_P)f(p_P)}. \quad (1)$$

This managed campaign can be implemented by the platform pricing each segment at the lowest off-platform price: $p(i, a, \bar{p}) = \min_i \bar{p}_i$.

On path, the on-platform price is also p_P , and the equilibrium posted price p_P satisfies $p_M \leq p_P \leq p_V$.

Privacy Protection: Welfare

- ① Intuitively, firms face a distributional mixture of consumers.
- ② Efficient steering implies showrooming constraint binds.
- ③ Suboptimal level of trade on platform (not everyone buys).
- ④ But low-value consumers made zero surplus without privacy protection.
- ⑤ Loss in total welfare comes entirely from reduced producer surplus.
- ⑥ Consumer surplus grows.

Conclusion

The *mechanisms* for allocating sponsored content and the availability of consumer data jointly determine match formation and surplus extraction both on and off large platforms.

The platform's auction mechanisms have significant impact on product prices:

- On-platform, the data made available to the advertisers allows for efficient matching, yet most of the surplus accrues to the platform.
- Off-platform, advertisers raise prices to gain a competitive edge.

Cross-channel distortions become more pronounced the more tools the platform has at its disposal.