The Impact of Privacy Policy on the Auction Market for Online Display Advertising

Garrett Johnson

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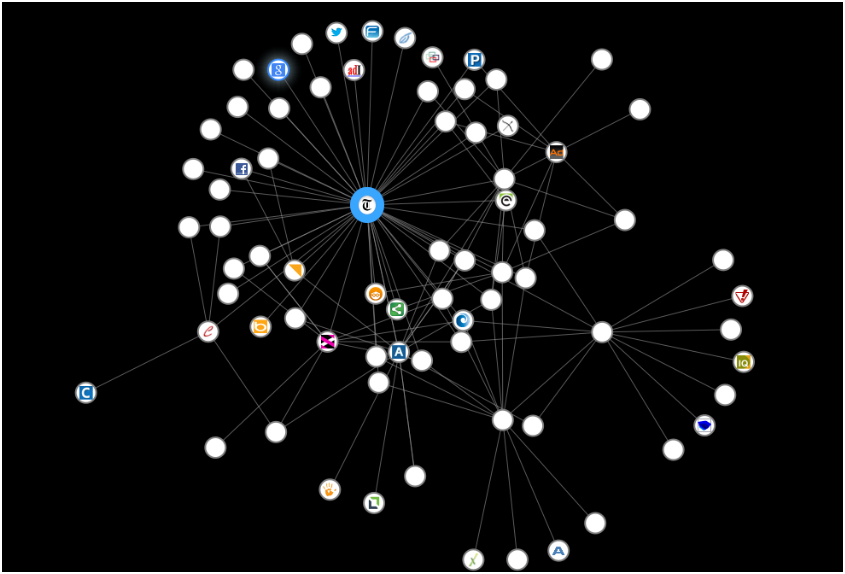
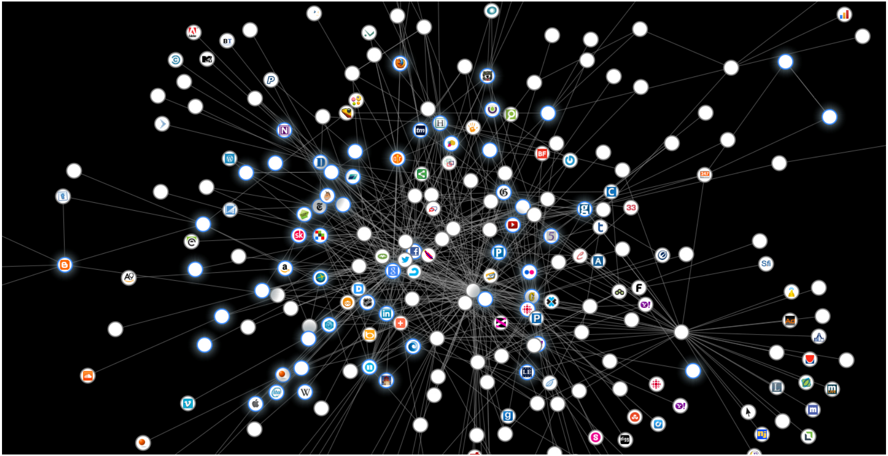
[1]Note: Impact estimates are preliminary and should not be cited for policy purposes.

Advertisers track you online (Disconnect Chome Add-On)

From a single visit to chicagotribune.com: dozens of tracking cookies



Users are profiled by their browsing histories



Purpose: Market impact of privacy policy

- *Motivation*: US regulators seek privacy policy that balances
  - Privacy concerns: enable privacy choice
  - Industry surplus: revenues grew $1.7 billion (2002) to $7.9 billion (2013)
- *Goal*: Measure effect on advertiser and publisher profits
- *Method*: Empirical auction analysis using proprietary ad auction data
- *Complication*: User tracking profiles are unobserved
- *Solution*: Extend unobserved heterogeneity models in auctions
- *Results*: Ban on tracking causes industry surplus to fall 43.5%

More

Outline

Literature review

- Tracking policy: Goldfarb & Tucker (2011); Budak et al. (2015); Beales & Eisenach (2014); Aziz & Telang (2015)
- Privacy policy: Tucker (2011; 2012)
- Online display ad market:
  - Overview: Evans (2009)
  - Theory: Abraham, Athey, Babaioff & Grubb (2011); Levin & Milgrom (2010); Mahdian, Ghosh, McAfee & Vassilvitskii (2012)
  - Empirical: Celis, Lewis, Mobius & Nazerzadeh (2012)
- Unobserved auction heterogeneity: Krasnokutskaya (2011); Hu, McAdams & Shum (2009)

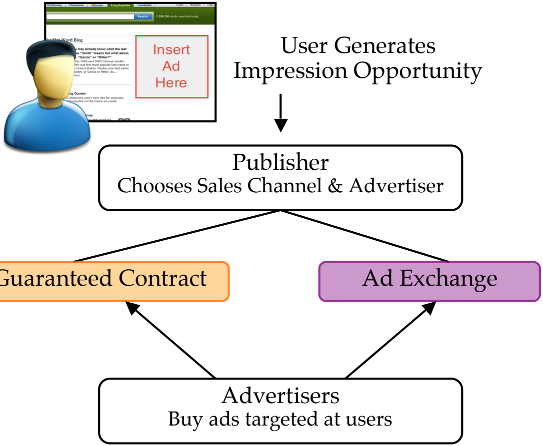


Figure : Online display ad market agents & operation ▸ More

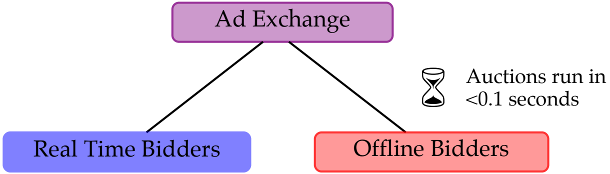


Figure : Online display ad auction operation & bidding methods

Real-Time bidders

- Evaluate & bid on *individual* ads
- Employ computer algorithms

Offline bidders

- Like *proxy* bidders, specify rules:
  1. Target audience attributes
  2. Fixed bid
  3. Randomly submit bid (budget-smoothing)

BOTH bidders employ user tracking information

Outline: Auction Model with Tracking

Model tracking as unobserved auction heterogeneity

- *Unobserved Auction Heterogeneity*: Bidders know more about attributes of item for sale than the modeler
- Here, we have
  - Observed heterogeneity: modeler & bidder observe some attributes of publisher site and ad slot
  - Unobserved auction heterogeneity: only bidders see user tracking attributes
- Problem: Existing models of unobserved auction heterogeneity require no reserve price & observe all bids
- Solution: Develop new models leveraging repeat user auctions (panel)
  1. Offline bidders
  2. Real time bidders

Target audience size key to offline bidder model

- Offline bidders choose target audience, fixed bid, and bid probability
- Want to measure size of target audience

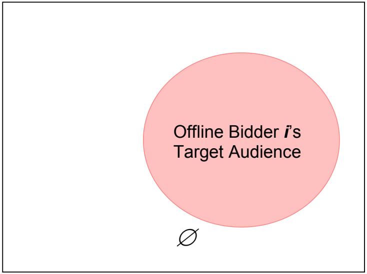


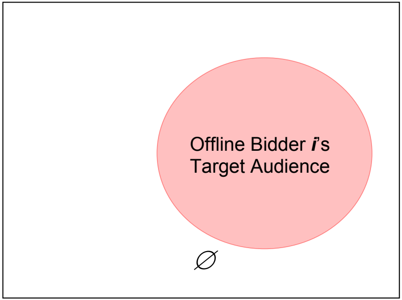
Figure : Ad targeting within the space of users

Offline bidder counterfactual bid example Suppose $B_i = \$1$ on Men and $\Pr[Men] = \frac{1}{2}$.

$\Longrightarrow$ In counterfactual, bid $B_i^{cf} = \$0.50$ on untargeted ads.

Offline unobs. hetero. model identified as mixture model

- Want to identify bidder i's targeting prob. & random bidding prob.
- *Challenge*:
  1. Random bidding means not all targeted users are observed
  2. Observe winning bid W_{ut}, so competition censors i's bids



- *Solution*: View as mixture model over users' true targeting type
- Estimate mixture model using maximum likelihood ▸ Offline MLE

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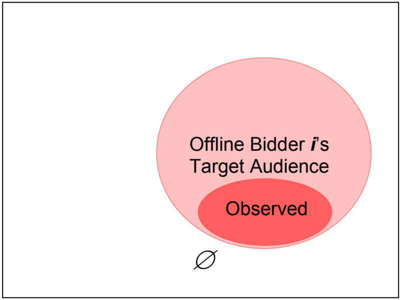

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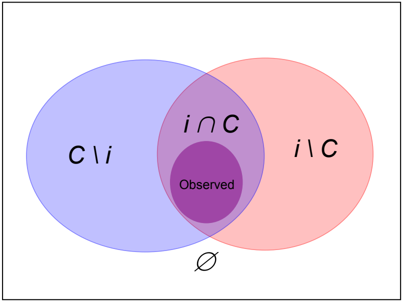

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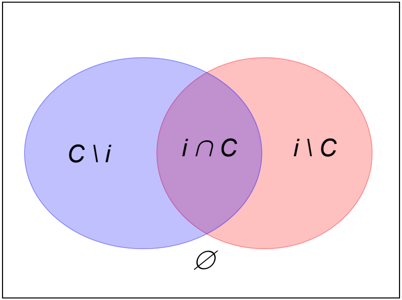

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Real-Time bidder unobserved heterogeneity model

- M symmetric bidders with valuation (conditional on observables)

$$v_{iut}^{RT} = x_{it} y_u$$

  - Recall notation: bidder i, user u, auction t
  - x_{it}: idiosyncratic taste term (bidder-auction level)
  - y_u: unobserved heterogeneity term (common, user-level)

- Assume: a) $y_u \perp x_{it}$ b) y_u, x_{it} are i.i.d.
- *Counterfactual*: Shut down tracking by fixing $y_u = \overline{y_u}$ at mean

$$v_{it}^{cf} = x_{it} \overline{y_u}$$

Real-Time model identified by support variation

- *Challenge*: Past approaches rule out censoring, ordered bids, or non-separable unobserved heterogeneity
- *Solution*: Identify component distribution by support variation
  - Within-user bid variation: idiosyncratic taste component F_x
  - Between-user bid variation: user-level unobserved heterogeneity component F_y

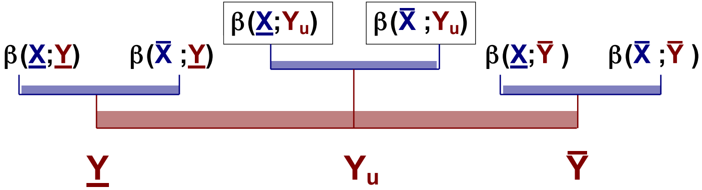


Figure : Identification by support variation

- ML estimation exploits long panel: Observe >500 auctions for some users

Outline

Two classes of bidders play by different rules

Hybrid auction mechanism

- Offline bidders play by Second Price rules
  - Offline winner pays second highest bid (regardless of bidder type) or the binding reserve price
- Real-Time bidders play by First Price Rules
  - Real-Time winner pays its bid

Equilibrium bid function: valuations to bids

Theorem

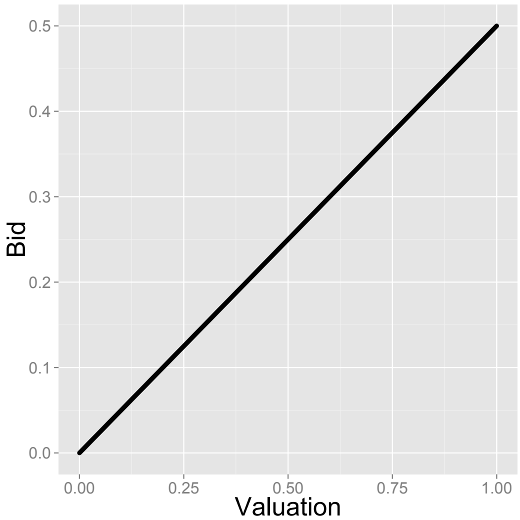
Assume bidder valuations are conditionally independent & private. In equilibrium, the following bid functions $\beta^{type}(v)$ maps valuations v into bids b.

1. *Second price bidder bids its valuation,* $\beta^{SP}(v) = v$
2. *First price bidder shades its bid below its valuation,* $\beta^{FP}(v) \leq v$
3. *When the distribution of competitor bids has a mass point (competitor bids B with $\Pr[B] > 0$), $\beta^{FP}(v)$ is discontinuous. That is, the first price bidder avoids bidding in some interval,* $\beta^{FP}(v) \notin (b_L, B]$

▸ 1;2 Proof

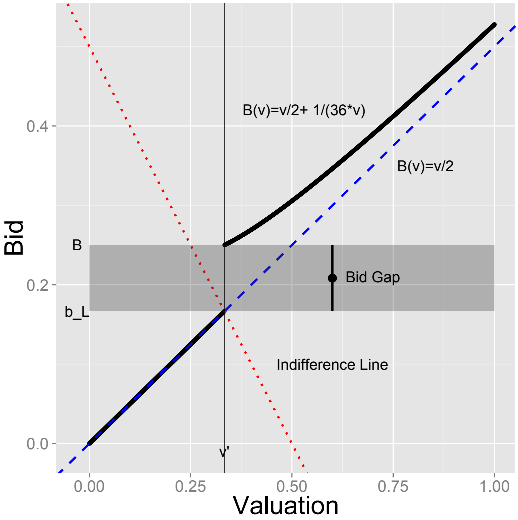
Simple first price bidder example

- 2 Symmetric $U[0,1]$ bidders
- Bid function: $\beta(v) = \frac{v}{2}$



Example (cont.): Introducing 'Offline bid' creates bid gap

- Two $U[0,1]$ bidders facing bid $B = 0.25, \Pr[B] = \frac{1}{2}$ U[0,1] Ex.



Outline

Privacy Counterfactual Results (Preliminary)

Policy	Total	Publisher	Advertisers
Ban	-43.5%	-38.5%	-45.5%

- Scope of results: U.S. users on top 3 website (50% of revenues)
- Back of the envelope: Ban: -$523 Million loss
    - $6.8B Ad Revenues * 20% Auction Share * Publisher Impact

Privacy Choice in Internet Advertising: Who Opts Out and at What Cost to Industry?

- Digital Advertising Alliance AdChoices program
  - Industry self regulation program enables user opt-out of 'personalized' advertising
  - 'Revealed preference' study of user privacy
  - Proprietary ad exchange dataset
- Research questions:
  - How many opt out?
  - Who opts out?
  - How do marketplace outcomes differ for opt-out users?
  - Who in industry is impacted and how much?

Conclusion

- Policy: Add impact estimate to discussion
- Privacy: Novel structural auction approach
- Marketing: Growing trend towards programmatic bidding requires auction toolkit
- Empirical Auction: New opportunities with large-scale ad exchange panel data
  - Extend unobserved heterogeneity in auctions with 2 models
    - Highly censored bid distribution
    - Ordered bid data

Thank you!

Possible Extensions

1. Supply-side adjustment
   - Adjust reserve price to maintain auction sell-through rate
   - Mitigate revenue collapse
2. Demand-side adjustment
   - Advertisers reallocate budgets towards publishers that host more target users

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