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

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1Note: Impact estimates are preliminary and should not be cited for policy purposes.
Advertisers track you online (Disconnect Chrome 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

1 Background

2 Identification: Auction Model with Tracking

3 Theory

4 Results

5 Follow-up Work

6 Conclusion
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)
- Unobserved auction heterogeneity: Krasnokutskaya (2011); Hu, McAdams & Shum (2009)
User Generates Impression Opportunity

Publisher Chooses Sales Channel & Advertiser

Guaranteed Contract

Ad Exchange

Advertisers
Buy ads targeted at users

Figure: Online display ad market agents & operation
Auctions run in <0.1 seconds.

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.

Figure: Online display ad auction operation & bidding methods
Outline: Auction Model with Tracking

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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

![Diagram of offline bidder's target audience](image)

**Figure**: Ad targeting within the space of users

Offline bidder counterfactual bid example

Suppose $B_i = $1 on Men and $Pr[Men] = \frac{1}{2}$.

$\implies$ In counterfactual, bid $B_i^{cf} = $0.50 on untargeted ads.
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
Offline unobs. hetero. model identified as mixture model

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![Diagram showing Offline Bidder $i$'s Target Audience and Observed data](image)
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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 \( F_y \)

\[
\begin{align*}
\beta(X; Y) & \quad \beta(X; Y_u) \\
\beta(X; Y) & \quad \beta(\bar{X}; Y_u) \\
\beta(X; \bar{Y}) & \quad \beta(X; \bar{Y}) \\
Y & \quad Y_u & \quad \bar{Y}
\end{align*}
\]

**Figure**: Identification by support variation

- ML estimation exploits long panel: Observe \( >500 \) auctions for some users
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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
Theorem

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

1. **Second price bidder** bids its valuation, $\beta^{\text{SP}}(v) = v$
2. **First price bidder** shades its bid below its valuation, $\beta^{\text{FP}}(v) \leq v$
3. When the distribution of competitor bids has a mass point (competitor bids $B$ with $\Pr[B] > 0$), $\beta^{\text{FP}}(v)$ is discontinuous. That is, the first price bidder avoids bidding in some interval, $\beta^{\text{FP}}(v) \notin (b_L, B)$
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 $B = 0.25, \Pr[B] = \frac{1}{2}$

\[
\begin{align*}
B(v) &= \frac{v}{2} \\
B(v) &= \frac{v}{2} + \frac{1}{36v}
\end{align*}
\]

Indifference Line

Bid Gap

Valuation vs. Bid

0.0 0.2 0.4

0.00 0.25 0.50 0.75 1.00

Valuation vs. Valuation

0.0 0.2 0.4

0.00 0.25 0.50 0.75 1.00

Bid

b_L

Bid

0.0

0.0

0.00 0.25 0.50 0.75 1.00

Valuation
Privacy Counterfactual Results (Preliminary)

<table>
<thead>
<tr>
<th>Policy</th>
<th>Total</th>
<th>Publisher</th>
<th>Advertisers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ban</td>
<td>-43.5%</td>
<td>-38.5%</td>
<td>-45.5%</td>
</tr>
</tbody>
</table>

- 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 Opt 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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