What Factors Affect Targeting and Bids in Online Advertising? A Field Measurement Study

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Targeted advertising is very opaque



Little public data on how ads are targeted is available



Makes informed decision making on privacy difficult

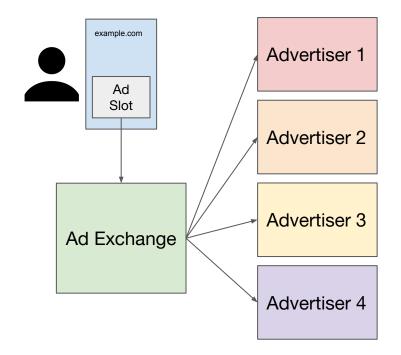
Images: Vectors Market and Freepik via flaticon.com

Our study: basic measurements of targeted advertising on the web

- How prevalent are behavioral targeting and contextual targeting on the web?
 - Behavioral targeting: targeting of individual users based on interests inferred from browsing behavior
 - Contextual targeting: targeting based on the website the ad appears on
- How do ads differ across demographic groups due to behavioral targeting?

Measuring bid values in header bidding ad auctions

- Ad auction: advertisers bid to place an their ad on a web page/app, conducted in real time for each ad each individual user loads
- Header bidding: meta-auction between multiple ad networks, often in the browser



Measurements of bid values in header bidding ad auctions

- Bid values can help reveal which signals advertisers find valuable for targeting
- How much do advertisers bid to place ads on the web?
- How do individual, demographic, and contextual factors affect bid values?

Introduction

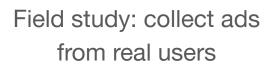
Study Design and Methodology

Results – Ad Targeting
Results – Winning Bid Values
Discussion

Measurement Goals

Measure individual, demographic, and contextual factors in targeted advertising







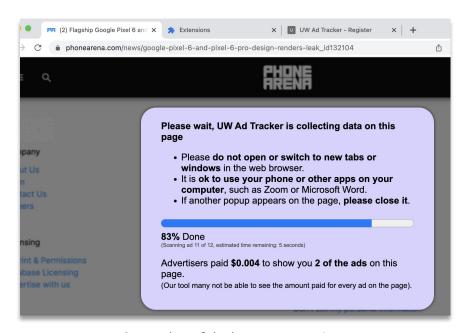
Demographically representative sample (in the U.S)



Control for website effects

Chrome extension for data collection

- Detects ads on page using EasyList
- 2. Takes a screenshot of each ad
- 3. Extracts winning bid values for each ad from header bidding scripts (prebid.js)
- 4. Auto refreshes page



Screenshot of the browser extension used by participants

Field Study Protocol

- IRB approved study
- Recruited participants via Prolific
- Part 1: Pre-Screening Survey (n=1460)
 - Participants provided demographic information
 - We screened out ad blocker users, stratified by age/gender/ethnicity
- Part 2: Extension Study (n=286)
 - Install browser extension
 - Visit list of 10 websites
 - Survey + data exclusion

Data analysis



Winning bid value (some of the time)



Screenshot of ad



Extract ad category from screenshot

- OCR
- Topic modeling
- Manual auditing of clusters



Demographic characteristics



Website ad appeared on

Analysis techniques

- Targeting: analyze distribution of ad categories
- Bid values: model using linear mixed regressions

Dataset overview

- 41,032 ads
 (143.5 ads / participant)
- 10 websites
 - All used prebid.js
 - Spans a variety of topics and popularity (in Tranco top 10k)
- 52 categories of ads
 - e.g. apparel, healthcare, electronics, travel

- businessinsider.com
- weather.com
- speedtest.net
- usnews.com
- foodnetwork.com
- detroitnews.com
- ktla.com
- phonearena.com
- fashionista.com
- oxfordlearnersdictionary .com

Limitations

- Small sample size
 - Data collected from only 10 websites
 - Some demographic segments are small
- Header bidding data is incomplete
 - Websites often ignored winner only 7,117 ads were "rendered"
- Targeting analysis is limited to correlations
 - No ground truth on targeting parameters

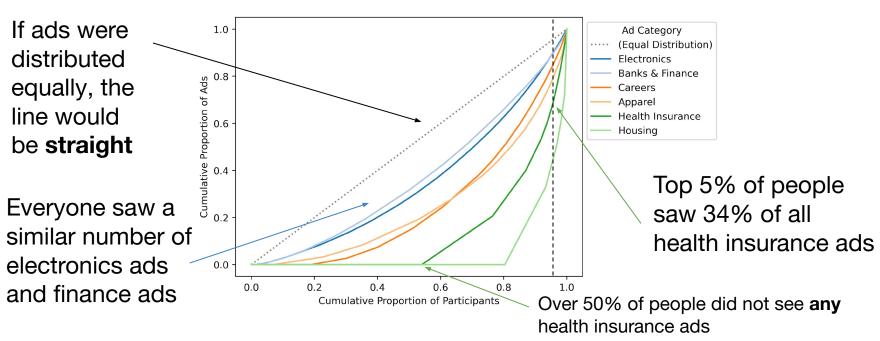
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Clear contextual targeting on some sites

Website	Top categories	% of ads on site	
businessinsider.com	B2B Products Careers Credit Cards	26% 21% 13%	Top categories make up large % of ads + match site topic
phonearena.com	Electronics Phone Service Software	35% 14% 14%	
weather.com	Medications Food and Drink	8% 7%	Top categories are smaller, not
oxfordlearners dictionary.com	B2B products Apparel	15% 10%	relevant to site

Behavioral targeting is evident in individuals

Lorenz curve – distribution of ads across individuals



Behavioral targeting by demographics is less clear

Gender (women vs. men)

- **↑** Apparel +2.1%
- **1** Beauty +1.5%
- **↓** Gaming -0.9%

Ethnicity (vs. even distribution)

- White: Movies and TV -0.4%
- ↑ Asian: Education +1.5%
- ♠ Black: Jewelry +1.3%

Age (vs. even distribution)

- **1** 45-54: Jewelry +1.4%
- **1** 25-34: Food and Drink +0.9%
- **↓** 18-24: Careers -0.9%

9-16% of ad categories were over- or under-represented across demographic groups

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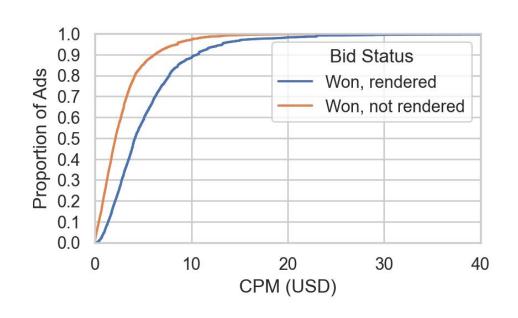
Bid value summary

Average winning bid value:

o Mean: \$5.47 CPM

o Median: \$4.16 CPM

 Winners ignored by website had lower bids



Winning bid values differ across

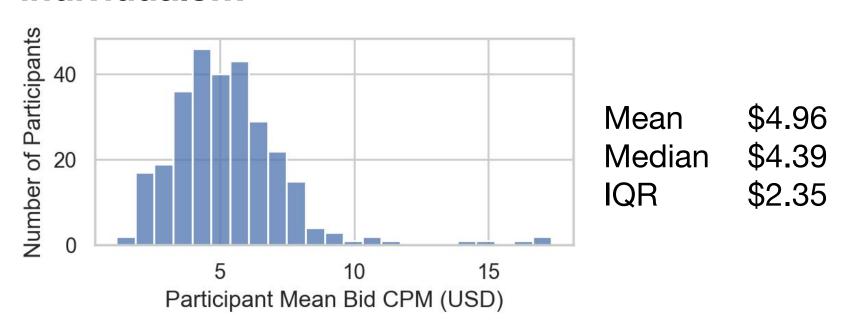
across ad categories

Ad Category	Avg. Bid	Estimated Intercept
Medications	\$6.95	+\$1.14
Beauty	\$7.27	+\$1.12
Credit Cards	\$4.92	-\$0.37
Healthcare	\$3.86	-\$0.78
Charity	\$2.99	-\$1.89

and between websites

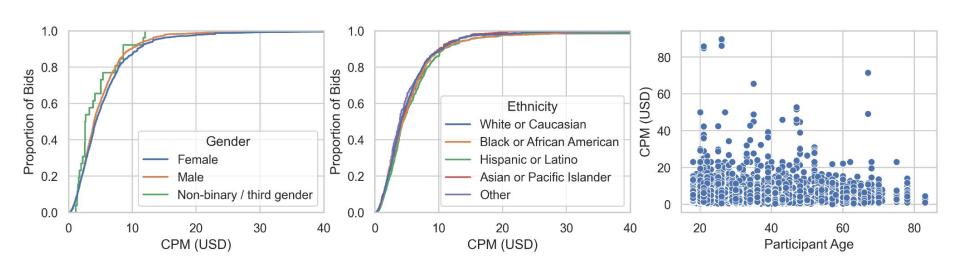
Website	Avg. Bid	Estimated Intercept
speedtest.net	\$9.95	+\$3.66
businessinsider.com	\$7.95	+\$2.34
foodnetwork.com	\$6.03	+\$0.57
weather.com	\$5.39	-\$0.17
ktla.com	\$2.44	-\$2.62

Winning bid values vary between individuals...



(Bid values are denoted in CPM – cost per 1000 impressions)

...but do not appear to differ across demographic groups



High bid values indicate retargeting

Retargeted ads: when you visit a site, and get ads from that site later

- 18% of ads may have been retargeted (participant self-report)
- Bids for (likely) retargeted ads were
 \$1.07 more than others
- Outlier values: \$52.80-\$89.75 CPM





Ads with the highest bids in our dataset.

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Discussion

- Alternatives to behavioral targeting on the web are prevalent, and valued by advertisers
 - What would a web with only contextual targeting and retargeting look like? Do we need Google's FLoC/Topics?
- Demographic disparities in targeting are hard to detect
- Need more transparency from ad tech

Thanks for listening!

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