Designing Online Advertising Markets

Susan Athey
Introduction

- Platform markets
  - Media markets, credit cards, dating, video games, operating systems…
  - Two groups of customers, externalities (typically indirect network effects)
    - Platform can help internalize externalities
- Auction-based platforms
  - Online advertising
  - Used cars
    - eBay
- Market design matters
Auction-Based Two-Sided Markets

- Like other two-sided markets, except...
  - Use of auction to match buyers and sellers, determine transaction price
  - It is a method for sorting as well as a method for platform to extract revenue
  - Limits discretion of market-maker
  - Still, rules and fees play an important role in determining the size and distribution of “the pie”
What Matters in Market Design for a Platform Market?

- Focus on efficiency and long-term participation
  - Participation crucial with competing platforms
- Extract rents to minimize distortions, keep more sensitive side of market engaged
- Auction design matters broadly
  - The design determines short term efficiency and distribution of rents
  - Determines participation and first-order issues of competition
    - See Athey, Levin and Seira (QJE, 2011) and Athey, Coey, and Levin (2011) for timber industry examples where impact of auction design on participation is quantitatively important:
      - First price v. open ascending auction format, small business set-asides
Market design v. Mechanism Design

- **Mechanisms**
  - Traditionally specify mapping from messages to actions, allocations and transfers, in a general setting with hidden information and/or actions

- **Market Design includes mechanism design, plus, e.g.**:
  - Defining the object for sale (e.g. impressions, clicks, conversions)
  - How and what information is:
    - Solicited from participants
    - Revealed to participants (accounting in search advertising, information about participants, transparency)
    - Presented (look of the website, search technology)
    - Created (upload technology, portability)
  - Set of standards, language for participants
  - Ex-post mechanisms: feedback, contract specification, remedies for bad outcomes
Influencing Market Design

- Theoretical framework is key
  - Makes arguments coherent and precise
  - Identifies equilibrium effects
  - Advertiser and consumer choices incorporated

- What kinds of theories to focus on?
  - Theories tested and fruitfully applied before
  - Key parameters can be calibrated to resolve tradeoffs
  - Robustness to real-world departures from assumptions
  - Business/gov't focuses on expected outcomes within a range, avoiding disasters, or particular upsides
    - Mitigation could include changing the rules ex post
The Role of Data and Experimentation

- In online marketplaces, data plays a key role
- Data can inform what kinds of designs will work better or worse in range of environments similar to existing one
- Advocacy for design issues is much more effective with theory and data combined
- Experimentation crucial but also has limitations
  - Short-term experiments can’t show long-term outcomes, feedback effects
- One part of empirical economics focuses structure on empirical analysis in order to learn model “primitives” and perform “counterfactuals”
  - Learn bidder values, predict equilibrium responses
  - Map between short-run user experience and long-term willingness to click
Search Advertising Auctions

- Advertiser submit bids for keywords
  - Offer a dollar payment *per click*.
  - Alternatives: price per impression, or per conversion.

- Separate auction for every query
  - Positions awarded in order of bid (more on this later).
  - Advertisers pay bid of the advertiser in the position below.
  - “Generalized second price” auction format.

- Some important features
  - Multiple positions, but advertisers submit only a single bid
    - Choice to sell clicks rather than different positions on the page
      key design choice, results in much thicker market
  - Search is highly targeted, and transaction oriented.
Current Auction Format

- Real-time
- Pay-per-click
- Click weighted
- Generalized second price auction
Generalized Second Price Auction with Click-Weighting

- Price for position $m$ determined using $m + 1^{st}$ revenue per impression
- Bidder 1 pays $s_2 b_2 / s_1$ per click; this is the lowest price that would have put him in the first position.
- If $s$ is the click-through rate and $R$ is a per impression reserve price, these would be prices (but note that $s$ may incorporate other factors):

<table>
<thead>
<tr>
<th>Per-Click Bid</th>
<th>Estimated Revenue Bid</th>
<th>Price Per Click</th>
<th>Estimated Revenue (normalized to first position)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b_1$</td>
<td>$s_1 b_1$</td>
<td>$s_2 b_2 / s_1$</td>
<td>$s_2 b_2$</td>
</tr>
<tr>
<td>$b_2$</td>
<td>$s_2 b_2$</td>
<td>$s_3 b_3 / s_2$</td>
<td>$s_3 b_3$</td>
</tr>
<tr>
<td>$b_3$</td>
<td>$s_3 b_3$</td>
<td>$s_4 b_4 / s_3$</td>
<td>$s_4 b_4$</td>
</tr>
<tr>
<td>$b_4$</td>
<td>$s_4 b_4$</td>
<td>$R / s_4$</td>
<td>$R$</td>
</tr>
</tbody>
</table>
Why a real-time auction?

- **Real-time auction**
  - Prices vary widely: $.05 to $30, $50 or even higher
  - Millions of search phrases
  - Hundreds of thousands of advertisers
  - Small advertisers join system all the time
  - Time sensitive items
  - Changing products and profits

- **Costs of real-time auction**
  - Firms need to monitor and fine-tune
  - Commitment to auction limits ability to price discriminate (but granular reserve prices available…)

Why a pay-per click (PPC) auction? (1)

- Alternatives
  - Pay per “impression” – this is what is being sold
  - Pay per action – pay for conversions

- Pay per impression
  - Advertiser bears risk for traffic quality
  - Search engine has private information about bot traffic, etc.
  - Traffic quality on partner network especially uncertain
  - In long term, advertisers monitor performance and adjust bids, but short term risk from fluctuations
Why a pay-per click (PPC) auction? (2)

- Pay per action
  - Use cookies to track conversions
  - Allows firms to enter profit on each item to advertising platform and let platform optimize for you
  - Events are rare, difficult to estimate probabilities
  - Advertiser controls (and can manipulate) probabilities
    - Agarwal, Athey and Yang (AER, 2009) show how multi-dimensional actions lead to manipulation in equilibrium
    - Successful pay per action models often have a close relationship with retailer, can monitor conversions

- Pay per click
  - Thicker market than pay per impression
  - Minimizes risk for advertisers relative to pay per impression, generalizes to broad match
  - Simpler for search engine, easy technology
Click-weighted auctions

- All three search engines use click-weighted auctions
  - Original design: rank firms by their bids
  - Yahoo! last to introduce in 2008 (now Bing provides Y! results)
- Unweighted per-click auctions can lead to lower revenue
- Example: search for Paris
  - Paris, France travel
    - Profit $0.50/click, click-through rate 5% = $0.025
  - Paris Hilton sex videos
    - Profit $5/click, click-through rate 0.25% = $0.0125
  - Paris Hilton sex videos outbids Paris, France travel, revenue lower
- Advantages of unweighted or partially weighted auctions
  - Price discrimination (Lahaie and Pennock)
  - Do not require search engine to estimate click-through rates
  - Advertisers don’t want unnecessary clicks, write accurate ad text (see Athey and Ellison; note that in click-weighted auctions, more clicks leads to proportionally lower PPC so advertiser “does not pay” for the clicks in steady state)
Auction Format

- **Pay-your-bid**
  - Early auction designs used a pay-your-bid format
  - Outcome was cycling
  - Firms incrementally outbid one another prices so high that it is unprofitable to win; then drop bid dramatically
  - Leads to inefficient outcomes (Edelman & Ostrovsky)

- **Generalized second price**
  - Bing and Google now use a variant of a second-price auction, where advertisers pay minimum required to maintain position
  - Nice stability properties
  - The search engines continue to update their rules

- **Vickrey**
  - In simplified model, outcome-equivalent to the lowest-revenue envy-free Nash equilibrium of GSP
  - Athey-Nekipelov show that GSP is inefficient in more realistic environments
Choices in Auction Design in Baseline Model

- Baseline equilibrium analysis: Varian, Edelman/Ostrovsky/Schwarz
  - Model can be used to analyze market design
- How many slots to sell?
  - Revenue vs. Efficiency
- Setting a reserve price?
  - Optimal reserve prices raise more revenue than restricting slots
  - Myerson’s approach can be adapted and optimal reserve price is independent of the number of slots or competitors (Ostrovsky & Schwarz) assuming a priori symmetric bidders
- Clickability, “squashing”, and quality scores for price discrimination
  - Downweighting clickability in rankings can increase revenue at the expense of efficiency (Lahaie and Pennock)
  - A form of price discrimination
Market Design Matters in Practice

- Historical benchmarking and various industry studies assert:
  - Ads per page, ads in top positions above algorithmic results
    - Google < Microsoft < Yahoo!
  - Google’s ads more “relevant”
    - Better advertiser base, more exact match bidding, more data to predict user response to ads
    - More selective policies (filtering, matching, reserve prices)
  - Google has much higher RPS, higher cost per acquisition
Extending Theory to Incorporate Platform Economics

- Market design incorporating consumers:
  - Endogenize clicking behavior
  - Incorporate search costs and welfare

- Athey-Ellison (2008, forthcoming QJE) setup
  - Ads vary in quality, this is unknown to consumers
  - Distribution of consumer search costs in population
  - Consumer propensity to search depends on anticipated quality
  - Analyze the impact of market design choices on welfare
Athey-Ellison Results

- Eqm bidding \( \rightarrow \) ads ranked by quality
- Propensity to click depends on perceived quality
  - Implies platform must consider impact of policies on quality
- Market design considerations altered to economize on consumer search and convey information to consumers
- Total welfare and consumer welfare are proportional
  - Consumer welfare is producer welfare LESS search costs--divergence
  - Consumers search in proportion to perceived quality of ads, which is proportional to value created for advertisers before fees
  - “Tuning dials” for consumer welfare also maximizes social welfare
- Platform profits in conflict with advertiser profits
- Optimal reserve prices derived
- Reduced use of click-through weighting incentives more accurate ad text, economizes on consumer search
- Asymmetries lead to non-existence of efficient equilibria
Consumer, Advertiser Participation Exogenous (Monopoly Platform)

- Reserve prices
  - Reduce supply of advertisements (size of “pie”)
  - Redistribute surplus between search ad platform and advertisers

- Consumers are helped by low to moderate reserve prices (conserving search costs), but harmed by high reserve prices because fewer ads are displayed

- Monopoly search ad platforms raise reserve prices beyond the social optimum
  - At social optimum, further increase in reserve raises search ad platform profits faster than it hurts total surplus
  - Search ad platform sets reserve prices inefficiently high
Competition Reduces Reserve Prices

• Competition pressures search ad platform to lower reserve price
  – Consumers and advertisers more responsive to reserve price in presence of a competing search ad platform

• Lower reserve prices attract more consumers and more advertising spend

• Advertiser profit is more sensitive to reserve prices than consumer welfare

• Consumer optimum is close to social optimum
A Structural Model for Counterfactual Analysis

- Many auction design issues involve tradeoffs
  - Bidder-facing experiments expensive
  - With a calibrated model, you can quantify the magnitudes and make predictions about long-term bidder responses
- Athey-Nekipelov (2010)
  - The same bid applies to many user queries
  - Model the uncertainty faced by advertisers
  - Establish existence & uniqueness of equilibrium
  - Develop structural model, show identification, statistical properties
  - Estimate bidder values using historical data from Microsoft
  - Develop computational algorithm to compute equilibrium bids using homotopy method, apply to do counterfactual simulations
  - Shows that under uncertainty, GSP is inefficient, but revenue comparison with Vickrey is ambiguous
Bid for “mortgage calculator”: $X/click

Ad 1: Mortgage Offers - www.LendingTree.com
$400,000 for Only $1,910/Month or $200,000 for Only $955/Month!

Ad 2: Mortgage - LendingTree® - www.LendingTree.com
$200,000 for Only $955/Month. When Banks Compete, You Win.

1. User enters query
2. Delivery engine queries database to identify applicable bids
3. Scoring algorithm produces scores
4. Ads are selected, ranked and scored; no more than one ad per account on a page
5. User clicks on ads

Process repeats for new user
Reformulate Problem

\[
\max_b v \cdot Q(b) - TE(b)
\]

\[
TC(q) = TE(Q^{-1}(q))
\]

\[
\max_q v \cdot q - TC(q) = q \cdot (v - AC(q))
\]

\[
\text{FOC: } v = MC(q) = AC(q) + q \cdot AC'(q)
\]

• This is just classic monopsonist problem
• Can also relate it to more standard uniform-price auction objective function
• Can estimate these quantities from search engine data by simulating impact of hypothetical bid changes
Estimates of AC(q), MC(q), and implied value for a high-value search phrase
Model Predictions Out of Sample
Bid Shading, Profits Per Click Vary by Position (implies inefficient allocation…)

<table>
<thead>
<tr>
<th>Avg. Ranking</th>
<th>(VPC-Bid)/VPC</th>
<th>(VPC-Bid)/CPC</th>
<th>(Bid-CPC)/CPC</th>
<th>(VPC-CPC)/CPC</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Search Phrase #1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[1,1.5)</td>
<td>0.61</td>
<td>3.61</td>
<td>1.18</td>
<td>4.79</td>
</tr>
<tr>
<td>[1.5,2.5)</td>
<td>0.22</td>
<td>0.54</td>
<td>0.86</td>
<td>1.39</td>
</tr>
<tr>
<td>[2.5,4)</td>
<td>0.21</td>
<td>0.36</td>
<td>0.31</td>
<td>0.68</td>
</tr>
<tr>
<td>[4,5.5)</td>
<td>0.20</td>
<td>0.34</td>
<td>0.31</td>
<td>0.65</td>
</tr>
<tr>
<td>[5.5,8)</td>
<td>0.20</td>
<td>0.34</td>
<td>0.28</td>
<td>0.62</td>
</tr>
<tr>
<td><strong>Search Phrase #2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[1,1.5)</td>
<td>0.32</td>
<td>0.75</td>
<td>0.44</td>
<td>1.19</td>
</tr>
<tr>
<td>[1.5,2.5)</td>
<td>0.36</td>
<td>0.81</td>
<td>0.40</td>
<td>1.21</td>
</tr>
<tr>
<td>[2.5,4)</td>
<td>0.43</td>
<td>1.12</td>
<td>0.43</td>
<td>1.55</td>
</tr>
<tr>
<td>[4,5.5)</td>
<td>0.35</td>
<td>0.79</td>
<td>0.34</td>
<td>1.13</td>
</tr>
<tr>
<td>[5.5,8)</td>
<td>0.28</td>
<td>0.52</td>
<td>0.30</td>
<td>0.82</td>
</tr>
</tbody>
</table>
GSP is inefficient; Revenue Comparison Ambiguous

<table>
<thead>
<tr>
<th>Model</th>
<th>All</th>
<th>Pos. 1</th>
<th>Pos. 2-5</th>
<th>Pos. 6-8</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Search Phrase #1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Revenue GSP</td>
<td>2.35</td>
<td>1.51</td>
<td>0.80</td>
<td>0.03</td>
</tr>
<tr>
<td>Revenue Vickrey</td>
<td>1.94</td>
<td>1.05</td>
<td>0.87</td>
<td>0.03</td>
</tr>
<tr>
<td>Welfare GSP</td>
<td>10.80</td>
<td>8.85</td>
<td>1.89</td>
<td>0.05</td>
</tr>
<tr>
<td>Welfare Vickrey</td>
<td>10.92</td>
<td>8.92</td>
<td>1.95</td>
<td>0.05</td>
</tr>
<tr>
<td><strong>Search Phrase #2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Revenue GSP</td>
<td>3.18</td>
<td>1.84</td>
<td>1.23</td>
<td>0.10</td>
</tr>
<tr>
<td>Revenue Vickrey</td>
<td>3.25</td>
<td>1.90</td>
<td>1.24</td>
<td>0.11</td>
</tr>
<tr>
<td>Welfare GSP</td>
<td>6.92</td>
<td>3.58</td>
<td>3.16</td>
<td>0.18</td>
</tr>
<tr>
<td>Welfare Vickrey</td>
<td>6.97</td>
<td>3.70</td>
<td>3.10</td>
<td>0.17</td>
</tr>
</tbody>
</table>
“Squashing” Raises Revenue Substantially at Modest Efficiency Cost

<table>
<thead>
<tr>
<th>Per-Click Bid</th>
<th>Estimated Revenue Bid</th>
<th>Price Per Click</th>
<th>Price Per Click with Squashing</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b_1$</td>
<td>$s_1 b_1$</td>
<td>$b_2 (s_2/s_1)$</td>
<td>$b_2 (s_2/s_1)^a$</td>
</tr>
<tr>
<td>$b_2$</td>
<td>$s_2 b_2$</td>
<td>$R/s_2$</td>
<td>$R/(s_2)^a$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Outcomes</th>
<th>All</th>
<th>Pos. 1</th>
<th>Pos. 2-5</th>
<th>Pos. 6-8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advertiser Profit After Squashing</td>
<td>3.3</td>
<td>1.6</td>
<td>1.6</td>
<td>0.1</td>
</tr>
<tr>
<td>Advertiser Profit Before Squashing</td>
<td>4.0</td>
<td>2.1</td>
<td>1.7</td>
<td>0.1</td>
</tr>
<tr>
<td>Revenue After Squashing</td>
<td>3.6</td>
<td>1.8</td>
<td>1.7</td>
<td>0.1</td>
</tr>
<tr>
<td>Revenue Before Squashing</td>
<td>3.3</td>
<td>1.8</td>
<td>1.4</td>
<td>0.1</td>
</tr>
<tr>
<td>Welfare After Squashing</td>
<td>6.9</td>
<td>3.4</td>
<td>3.3</td>
<td>0.2</td>
</tr>
<tr>
<td>Welfare Before Squashing</td>
<td>7.3</td>
<td>3.9</td>
<td>3.2</td>
<td>0.2</td>
</tr>
</tbody>
</table>
# Short-Term Effects Smaller than Long-Term Limitation to Short-Term Experiments

<table>
<thead>
<tr>
<th>Search Phrase #1</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Revenue After Squashing</td>
<td>3.29</td>
</tr>
<tr>
<td>Revenue After Squashing, Fixed Bids</td>
<td>3.15</td>
</tr>
<tr>
<td>Revenue Before Squashing</td>
<td>3.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Search Phrase #2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Revenue After Squashing</td>
<td>3.58</td>
</tr>
<tr>
<td>Revenue After Squashing, Fixed Bids</td>
<td>3.41</td>
</tr>
<tr>
<td>Revenue Before Squashing</td>
<td>3.32</td>
</tr>
</tbody>
</table>

This only incorporates advertiser long-term model. Athey-Ellison model suggests additional user feedback: users click less, moderating effects.
Improving Click Prediction Accuracy Has Competing Effects: Reduced Welfare, Increased Revenue

<table>
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<th>Outcomes</th>
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<tr>
<td><strong>Search Phrase #1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Profit Coarsened Scores</td>
<td>5.27</td>
<td>3.82</td>
<td>1.43</td>
<td>0.01</td>
</tr>
<tr>
<td>Profit Original</td>
<td>7.64</td>
<td>5.53</td>
<td>2.09</td>
<td>0.02</td>
</tr>
<tr>
<td>Revenue Coarsened Scores</td>
<td>5.05</td>
<td>3.34</td>
<td>1.68</td>
<td>0.04</td>
</tr>
<tr>
<td>Revenue Original</td>
<td>3.00</td>
<td>1.82</td>
<td>1.15</td>
<td>0.03</td>
</tr>
<tr>
<td>Welfare Coarsened Scores</td>
<td>10.32</td>
<td>7.16</td>
<td>3.11</td>
<td>0.06</td>
</tr>
<tr>
<td>Welfare Original</td>
<td>10.64</td>
<td>7.35</td>
<td>3.24</td>
<td>0.05</td>
</tr>
<tr>
<td><strong>Search Phrase #2</strong></td>
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<td></td>
<td></td>
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<tr>
<td>Profit Coarsened Scores</td>
<td>1.74</td>
<td>0.86</td>
<td>0.80</td>
<td>0.08</td>
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<tr>
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<td>2.15</td>
<td>1.73</td>
<td>0.11</td>
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<tr>
<td>Revenue Coarsened Scores</td>
<td>4.57</td>
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<td>2.35</td>
<td>0.17</td>
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<tr>
<td>Revenue Original</td>
<td>3.32</td>
<td>1.79</td>
<td>1.44</td>
<td>0.09</td>
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<tr>
<td>Welfare Coarsened Scores</td>
<td>6.31</td>
<td>2.90</td>
<td>3.15</td>
<td>0.26</td>
</tr>
<tr>
<td>Welfare Original</td>
<td>7.31</td>
<td>3.94</td>
<td>3.17</td>
<td>0.20</td>
</tr>
</tbody>
</table>

Revenue effects rely heavily on advertiser bidding response. With fixed bids, revenue increases are smaller and sometimes negative.
Conclusions

- Economic models can help guide design
- Platform considers welfare of all participants
  - Platform market considerations about sensitivity of various participants to decisions
  - Competition affects how participants are weighted
- Consumer search costs matter, and this affects decisions about reserve pricing and click weighting
- GSP creates incentives for “demand reduction” that are asymmetric across bidders
  - Inefficiency results, but relatively small