Reserves Prices in Internet Advertising Auctions
Michael Ostrovsky and Michael Schwarz (2009)

Chutima Tontarawongsaa

Department of Economics
Duke University

Market Design I: Auction Theory, Fall 2010
Overview

- Test if setting optimal reserve prices increase seller’s revenues
- Importance of optimal reserve prices - show table 1
- Context: Sponsored search auctions by Yahoo!
- Contributions: using a large dataset in a properly designed experimental setting (theoretically optimal reserve prices are implemented)
Auction format: Generalized second-price auction (GSP)

They first consider the following incentive-compatible direct revelation mechanism. This is similar to the case of single-object optimal auction; but here, the probability of receiving the object is replaced by the expected number of clicks.

Expected payment of each bidder:

\[ t_k(s_k) = t_k(0) + x_k(s_k)s_k - \int_0^{s_k} x_k(u_k)du_k \]
This implies that the expected revenue is

$$\sum_{1 \leq k \leq K} t_k(0) + \int_{S} \left( \sum_{1 \leq k \leq K} \psi_k(s_k) x_k(s) f(s) \right) ds$$

Assuming: increasing virtual value function and $v_i \sim F(\cdot) \forall i$

Maximizing this pointwise for every $s$. The solution is then to assign positive probabilities to bidders with positive virtual values where bidders with higher values receive higher probabilities.

This mechanism is equivalent to the relevant mechanism: GSP with $r^*$ such that $VV(r^*) = 0$.

To find an optimal reserve price, we need to find the lowest type with $VV = 0$. Since we have no entry fee, this is equivalent to the optimal reserve price, so the same reserve price from the above maximizes the revenue in this case as well.
Experiment Design

STEP 1: Estimating the Distributions of Bidder Values

- For several combinations of true values of the number of potential bidders, the mean and std deviation of the lognormal distribution of values, simulate the following:
  1. observed number of bidders
  2. average bid in positions 2
  3. standard deviation of the bids in positions 2 and below

- Match the observed and simulated parameters to estimate the parameters of the distribution of bidder values and the number of potential bidders (including those below reserve prices)
Experiment Design

STEP 2: Setting Reserve Prices

- Use the estimated distribution of bidders’ values to calculate optimal reserve prices from the model we derive earlier.
- Need to adjust for company-specific ads quality to be consistent with the actual pricing system. Ads with higher quality scores faces lower reserve prices.
- Optimal reserve price = \((r^*) \times (\text{Adj factor}) + (10) \times (1-\text{Adj factor})\)
- Adjustment factor: 0.4, 0.5, 0.6 for most keywords
The number of advertisements shown on the page reduces by a factor of 0.91.

Revenues increase by almost 13% but the estimate is only marginally statistically significant. This may be because number of searches for each keyword changes during the time of data.

To control for this, they compute the revenue difference between pre- and post-intervention revenues for each keyword, then multiply the difference by the number of searches for this keyword before the intervention (this is similar to calculating the Laspeyres index).

The estimate drops to 2.7% but it is now highly statistically. Given the size of the market, this is very big.
Results

Subsamples

Divide the sample into groups using 3 dimensions along which keywords differ substantially.

- Rarely-searched keywords and frequently-searched keywords
  Revenues decrease in the rarely-searched subsample. They suggest that this is because advertisers do not bid optimally.

- High optimal reserve price and low optimal reserve prices
  negative effect on the low-r group. They admit that their model might not be good enough to find an optimal reserve price due to several simplications

- Many advertisers and few advertisers (referred to as ”depth”)
  positive and highly significant for both subsamples
Divide the sample into groups using 3 dimensions along which keywords differ substantially.

- Rarely-searched keywords and frequently-searched keywords
  Revenues decrease in the rarely-searched subsample. They suggest that this is because advertisers do not bid optimally.

- High optimal reserve price and low optimal reserve prices
  negative effect on the low-r group. They admit that their model might not be good enough to find an optimal reserve price due to several simplications

- Many advertisers and few advertisers (referred to as ”depth”) positive and highly significant for both subsamples
Divide the sample into groups using 3 dimensions along which keywords differ substantially.

- Rarely-searched keywords and frequently-searched keywords. Revenues decrease in the rarely-searched subsample. They suggest that this is because advertisers do not bid optimally.

- High optimal reserve price and low optimal reserve prices have a negative effect on the low-r group. They admit that their model might not be good enough to find an optimal reserve price due to several simplications.

- Many advertisers and few advertisers (referred to as "depth") have a positive and highly significant for both subsamples.
Divide the sample into groups using 3 dimensions along which keywords differ substantially.

- Rarely-searched keywords and frequently-searched keywords. Revenues decrease in the rarely-searched subsample. They suggest that this is because advertisers do not bid optimally.

- High optimal reserve price and low optimal reserve prices have a negative effect on the low-r group. They admit that their model might not be good enough to find an optimal reserve price due to several simplifications.

- Many advertisers and few advertisers (referred to as “depth”) have a positive and highly significant effect for both subsamples.