

The Effect of Minimum Bid Increment on Revenue in Internet Auctions: Evidence from a Field Experiment

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1 Motivation

Internet auctions form a very large marketplace (Ebay's (company's all sites) gross merchandise volume was \$60 billion in 2007). E-commerce is growing rapidly.

-> important to understand all the details.

In Europe and elsewhere, public sector moving to E-procurement.

-> maximising auctioneer's revenue maximises welfare (since taxes are distortionary).

-> what elements of online auctions should be used and how in E-procurement.

My focus is on a particular feature of these auctions called the minimum bid increment (MBI).

MBI determines the minimum amount that a new bid must exceed the current price for it to be accepted.

MBI is also present in how the current price is set. (This fact is often overlooked).

Q1: How auctioneer maximises revenue with respect to the MBI level, i.e. what is the optimal MBI? (Efficient MBI is zero.)

Q2: How MBI affects entry?

Q3: What sort of bidder behavior may explain my experiment's results.

Usually Internet auctions are modeled either as an ascending or a sealed bid second price auction. MBI seen as too small to have an impact on bidder behavior or auction outcomes.

Yet MBI may well be an important question in designing an optimal Internet auction.

Some evidence that more important than the much studied reservation price (Bapna et al. 2003, Rogers et al. 2007). But these are behavioral models with unsatisfactory empirics.

Very little theoretical or empirical research thus far on MBI. Only economics study is (Hickman 2010, IJIO). Bidding strategies in a simplified model that incorporates MBI. Shows that MBI is very important for strategic behavior, but his model is revenue equivalent wrt MBI.

I provide field experimental evidence on the effects of MBI on the seller revenue and entry, and on the optimal level of MBI.

I also propose a test between some explanations for my experimental result that mid-range MBI is optimal using structural auction econometrics.

2 This talk

Motivation

Main features of internet auctions like eBay and some theory

The experiment

Results

3 Seller's choices in internet auctions

1. The level of reservation price.
2. Public or secret reservation price (or both).
3. The level of bid increment (in most sites fixed, in some sites allowed to be set).
4. Buy-it-now, marketing options, information disclosure, reputation (professional sellers), multi- vs. single-unit format, closing rule...

4 Important features of internet auctions

Proxy bidding system jumps the current price (CP) immediately to a new current price after each accepted new bid.

First bid accepted if it is higher than public reserve price + MBI and following bids accepted if higher than $CP + MBI$. Need NOT to follow the grid imposed by MBI.

The function that determines the current price includes MBI.

After first bid: $CP = RP + MBI$

For subsequent bids: $CP = \min(shb + MBI, hb)$

$$CP = \min(shb + MBI, hb)$$

CP=current price

shb=second highest proxy bid

hb=highest proxy bid

-> Expected CP is an increasing fct of MBI.

-> Revenue is increasing in MBI (up to a point) if bidders are not strategic. eBay and Huuto.net explicitly encourages to submit single truthful bid to the proxy.

Rogers et al. (2007, ACM...) solve and simulate models with truthful bidding and pedestrian bidding and include entry. Mid-range MBI optimal for truthful, zero for pedestrian. Proxy bidding system joint with MBI gives rise to optimal level.

$$CP = \min(shb + MBI, hb)$$

with $MBI=0$ -> second price auction

with $MBI=\text{large}$ -> first price auction

with $MBI=\text{mid-range}$ -> a hybrid between FP and SP. This hybrid is modeled in (Hickmann 2010, IJIO). Shows that bid shading increases in MBI. MBI is a parameter that can be used to switch between FP and SP auctions. In Hickmann's eBay data, about 22 % auctions ended with FP rule.

If no element that would break revenue equivalence, the higher the MBI the higher is bid shading so that it exactly counters the expected revenue gains from the function of CP.

If endogenous entry, lower MBI preferred, because MBI may cause highest value bidder not to enter.

High MBI good if FP revenue $>$ SP revenue.

Theory when revenue in $FP > SP$.

Yes: Risk aversion (Maskin&Riley, 1984 Etrica); Budget constraints (Che&Gale, 1998 ReStud).

Maybe: Bidder asymmetry (Maskin and Riley, 2000 ReStud).

No: Affiliation (Milgrom&Weber, 1982 Etrica).

5 Some literature

Survey: Bajari&Hortacsu (2004, JEL), Ockenfels et al. (2006, HBeis)

Sniping, entry: Ockefels&Roth (200,2 AER; 2006, GEB), Bajari&Hortacsu (2003, RAND)

Winner's curse, fraud: Jin&Kato (2002, wp), Bajari&Hortacsu (2003, RAND)

Reputation: Rescnick et al. (2006, Exp. Econ.), Cabral&Hortacsu (forthcoming JIE)

Mechanism/market comparisons: Lucking-Reiley (1999, AER), List&Lucking-Reiley (2000, AER), Brown&Morgan (2010, JPE)

Reservation price: Reiley (2006, RAND), Barrymore&Raviv (2009 wp), Choi et al. (2010 wp)

BIT: Sandifird et al. (2004, IJEC), Hidvegi et al. (2004, JET)

-> Ebay has been widely used as a source of observational data and as a place to conduct field experiments. A subject of research as well as data for study of auctions more generally.

But no experimental and only one observational (Bapna et al. 2003) empirical work concerning the effects of MBI level on prices and entry.

Why not?: Ebay, Amazon and Yahoo! force the bid increment schedule on the seller.

BUT the MBI level can be set in a Finnish site Huuto.net!

This allows for a field experiment.

What is the effect of MBI on selling price (& nro of bidders and bids).

6 The experiment

I sell 72 Stockmann 15 euro giftcards and 72 50 euro cards at "Huuto.net" auction site.

Stockmann is the largest department store chain in Finland. Close to selling money. Demand unlikely to change from first to last card.

Buyers do not know that they are participating in an experiment.

When they asked why I sell these cards, I told politely that "none of your business".

Identical auctions except for the MBI and date.

The eBay MBI function:

Current Price	Bid Increment
\$ 0.01 - \$ 0.99	\$ 0.05
\$ 1.00 - \$ 4.99	\$ 0.25
\$ 5.00 - \$ 24.99	\$ 0.50
\$ 25.00 - \$ 99.99	\$ 1.00
\$ 100.00 - \$ 249.99	\$ 2.50
\$ 250.00 - \$ 499.99	\$ 5.00
\$ 500.00 - \$ 999.99	\$ 10.00
\$ 1000.00 - \$ 2499.99	\$ 25.00
\$ 2500.00 - \$ 4999.99	\$ 50.00
\$ 5000.00 and up	\$ 100.00

15 euro: 24 at 0.01 e MBI, 24 at 0.33 e MBI (eBay level, 1.5 exchange rate) and 24 at 0.5 e MBI.

50 euro: 24 at 0.01 e MBI, 24 at 0.66 e MBI (eBay level) and 24 at 1 e MBI.

Use of increments this high is common in these auctions (according to some descriptive data we scraped).

Reservation prices (7.99, 7.67 and 7.5 de facto 8 for all 15 e cards, similarly 30 e for 50 euro cards) set because to keep in the eBay window.

For both experiments: 6 batches of 12 cards, with 4 of each MBI type in each single batch.

Ordering randomized within batch. About 1 minute lag between each object.

Auction runs from tuesday afternoon to sunday afternoon each week (5 days).

15 e: First week 45:2009, last week 50:2009; 50 e: First week 13:2010, last week 18:2010.

7 Results

OLS

Batch dummies to control for trust, reputation, possible demand changes (e.g. Christmas gets closer, more bidders may find these) etc. Also should deal with clustering type problems if error terms correlated within batches.

$N=72$, 2 treatment dummies and 5 time dummies for both experiments.

Observe the selling price and two proxies for the number of actual entrants.

Descriptive statistics for the 15 euro experiment.

Sample	Variable	Obs	Mean	Std. Dev.	Min	Max
All	price	72	13.24	0.20	13	13.65
MBI=1	price	24	13.18	0.20	13	13.51
MBI=33	price	24	13.27	0.18	13	13.65
MBI=50	price	24	13.26	0.22	13	13.52
All	bidders	72	3.06	0.98	2	5
MBI=1	bidders	24	3.25	0.99	2	5
MBI=33	bidders	24	3.04	1.08	2	5
MBI=50	bidders	24	2.88	0.85	2	5
All	bids	72	4.25	2.03	2	10
MBI=1	bids	24	5.38	2.36	2	10
MBI=33	bids	24	3.83	1.88	2	8
MBI=50	bids	24	3.54	1.28	2	6

Descriptive statistics for the 50 euro experiment.

Sample	Variable	Obs	Mean	Std. Dev.	Min	Max
All	price	72	44.46	1.30	41	46.64
MBI=1	price	24	44.31	1.33	41	46
MBI=66	price	24	44.69	1.36	41	46.64
MBI=100	price	24	44.40	1.23	41	45.4
All	bidders	72	4.08	0.99	2	7
MBI=1	bidders	24	4.46	0.98	3	7
MBI=66	bidders	24	3.92	1.10	2	6
MBI=100	bidders	24	3.88	0.80	2	5
All	bids	72	6.25	3.16	2	16
MBI=1	bids	24	7.50	3.12	3	13
MBI=66	bids	24	6.29	3.69	2	16
MBI=100	bids	24	4.96	2.01	2	11

Results of the 15 euro experiment.

Variable	price			bidders			bids		
	Coef.	Std. Err.	p-value	Coef.	Std. Err.	p-value	Coef.	Std. Err.	p-value
w2	-0.155	0.061	0.01	-0.83	0.28	0.00	-1.58	0.60	0.01
w3	0.065	0.061	0.29	1.25	0.28	0.00	1.67	0.60	0.01
w4	0.140	0.061	0.03	-0.75	0.28	0.01	-2.17	0.60	0.00
w5	0.285	0.061	0.00	-0.17	0.28	0.56	-0.75	0.60	0.22
w6	0.103	0.061	0.10	0.33	0.28	0.24	-0.67	0.60	0.27
mbi33	0.090	0.043	0.04	-0.21	0.20	0.30	-1.54	0.43	0.00
mbi50	0.081	0.043	0.06	-0.38	0.20	0.07	-1.83	0.43	0.00
Constant	13.107	0.050	0.00	3.28	0.23	0.00	5.96	0.49	0.00

Results of the 50 euro experiment.

Variable	price			bidders			bids		
	Coef.	Std. Err.	p-value	Coef.	Std. Err.	p-value	Coef.	Std. Err.	p-value
w8	-1.577	0.352	0.00	-1.17	0.29	0.00	-4.25	0.73	0.00
w9	-2.247	0.352	0.00	0.00	0.29	1.00	0.08	0.73	0.91
w10	0.219	0.352	0.54	1.00	0.29	0.00	2.83	0.73	0.00
w11	0.450	0.352	0.21	-0.75	0.29	0.01	-3.75	0.73	0.00
w12	-0.243	0.352	0.49	-0.08	0.29	0.77	-1.92	0.73	0.01
mbi66	0.380	0.249	0.13	-0.54	0.20	0.01	-1.21	0.51	0.02
mbi100	0.092	0.249	0.71	-0.58	0.20	0.01	-2.54	0.51	0.00
Constant	44.872	0.287	0.00	4.63	0.23	0.00	8.67	0.59	0.00

Pooled results. Average "discount" = SP/NP for 15e is 0.88 and for 50e is 0.89.

Variable	discount			bidders			bids		
	Coef.	Std. Err.	p-value	Coef.	Std. Err.	p-value	Coef.	Std. Err.	p-value
w2	-0.0103	0.0057	0.07	-0.83	0.28	0.00	-1.58	0.67	0.02
w3	0.0043	0.0057	0.45	1.25	0.28	0.00	1.67	0.67	0.01
w4	0.0093	0.0057	0.11	-0.75	0.28	0.01	-2.17	0.67	0.00
w5	0.0190	0.0057	0.00	-0.17	0.28	0.56	-0.75	0.67	0.26
w6	0.0069	0.0057	0.23	0.33	0.28	0.24	-0.67	0.67	0.32
w7	0.0230	0.0057	0.00	1.17	0.28	0.00	-1.67	0.67	0.01
w8	-0.0086	0.0057	0.14	0.00	0.28	1.00	2.58	0.67	0.00
w9	-0.0220	0.0057	0.00	1.17	0.28	0.00	2.67	0.67	0.00
w10	0.0274	0.0057	0.00	2.17	0.28	0.00	5.42	0.67	0.00
w11	0.0320	0.0057	0.00	0.42	0.28	0.14	-1.17	0.67	0.08
w12	0.0181	0.0057	0.00	1.08	0.28	0.00	0.67	0.67	0.32
Treatment 1	0.0068	0.0029	0.02	-0.38	0.14	0.01	-1.38	0.33	0.00
Treatment 2	0.0036	0.0029	0.21	-0.48	0.14	0.00	-2.19	0.33	0.00
Constant	0.8741	0.0044	0.00	3.37	0.22	0.00	6.02	0.51	0.00

"Treatment 1": 33c and 66c MBI's. "Treatment 2": 50c and 100c MBI's.

How many auctions each bidder won?

bidder	w1	w2	w3	w4	w5	w6	w7	w8	w9	w10	w11	w12	total	bid 15	bid 50
1	11	12	6	12	5	9	4	11	8				78	13.16	43.1
2	1											1	2	13.35	45
3			4										4	13.45	NA
4			1			1							2	13.49	NA
5			1										1	13.5	NA
6					5				4				9	13.51	45.02
7					2								2	13.5	NA
8						2							2	13.42	NA
9							7						7	NA	45.13
10							1	1					2	NA	43.52
11										8		9	17	NA	44.87
12										4			4	NA	45.72
13											12	2	14	NA	45.39

Regression for the optimal MBI.

Variable	Value 15			Value 50		
	Coef.	Std. Err.	p-value	Coef.	Std. Err.	p-value
w2 / w8	-0.155	0.061	0.01	-1.577	0.352	0.000
w3 / w9	0.065	0.061	0.29	-2.247	0.352	0.000
w4 / w10	0.140	0.061	0.03	0.219	0.352	0.536
w5 / w11	0.285	0.061	0.00	0.450	0.352	0.206
w6 / w12	0.103	0.061	0.10	-0.243	0.352	0.492
mbi	0.516	0.352	0.15	1.553	0.988	0.121
mbisq	-0.687	0.698	0.33	-1.446	0.991	0.150
Constant	13.102	0.051	0.00	44.856	0.290	0.000
optimal mbi	0.376	NA	NA	0.537	NA	NA

8 Summary of results

eBay level treatments increase the revenue most.

eBay level increases revenue compared to 1c MBI by

1. on average by 0.68 % of the nominal value.
2. by 0.77% of the average selling price. This difference would have been 460m dollars in 2007.
3. decreased the costs of this experiment on average by 5,7% per unit of observation.

Both low and high proxy for actual bidders decrease in MBI.

9 Potential Problems

Problem 1: Internal validity is strong but external validity is suspectible for two reasons: 1.1 Is the set of bidders representative? 1.2 Is the market representative?

1.1 One buyer wins about half of the auctions. Only 13 different winners. But: Price depends on not only the winner's strategy but on others' strategies as well and there is much variation in the sets of observed entrants.

1.2 Huuto.net is a small market. I was almost the only one selling Stockmann cards. Few hundred giftcards in general at the same time. But: The main causes of MBI's effects are probably about the same for many other products.

Problem 2: Auctions are not necessarily independent (e.g. transaction cost is the same for one or many). But: Time dummies deal with clustering because variance in treatment within clusters. Moreover, discount analysis reveals that transaction costs are not important.

-> Empirical analysis is fairly solid both internally and externally. However, theoretical analysis and structural tests needs more work.

10 Conclusions

I find in a field experiment that MBI has a causal effect on revenue and entry.

The effect on revenue is not very large, but large enough not to be overlooked.

-> Auctioneers or sites should be careful in setting MBI.

-> MBI should be incorporated in future analyses of Internet auctions. Standard second price auction models (sealed nor open) not correct.

11 Tests for theory

Behavioral:

H_0 : Truthful bidding

H_1 : Something else

Estimate value functions under different MBI's assuming H_0 .

$WP = V_{N:N}$ if pricing rule hb.

$WP - MBI = V_{(N-1):N}$ if pricing rule is shb+MBI.

Then use order statistics formulas and estimate $F(V)$ either with nonparametric or parametric technique.

Number of potential bidders N unknown, but can be proxied and should be the same within branch.

$$H_0: F(V|MBI = 1, NP = 15) = F(V|MBI = 33, NP = 15) = F(V|MBI = 50, NP = 15)$$

$$\text{and } F(V|MBI = 1, NP = 50) = F(V|MBI = 66, NP = 50) = F(V|MBI = 100, NP = 50).$$

If reject H_0 , bid shading happens and some strategic explanation more plausible.