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

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22th December 2010

Abstract

I study the role and importance of a minimum bid increment (MBI) level in Internet auctions. I estimate the causal effect of MBI on prices and entry using field experiment data. I utilize a rare feature of a Finnish Internet auction site Huuto.net to set up two novel field experiments. I sell two sets of gift cards that are otherwise identical within sets, but are sold using three different minimum bid increment levels. I find that the optimal level for the minimum bid increment seems to be larger that zero and that the eBay-level seems to be close to optimal. Moreover, MBI limits entry as expected. These effects are both statistically significant and economically relevant, and this result is arguably internally and externally valid. Moreover, I propose a structural econometric test that can potentially distinguish between the different theoretical explanations for the main result.

Keywords: Field experiment; Internet auctions; Minimum bid increment.
JEL Classification: C93; D44; L81.

*I thank Brent Hickman, Ari Hyytinen, Klaus Kultti, Laurent Lamy, Emmi Martikainen, Matti Sarvimäki, Otto Toivanen and Hanna Willman-Iivarinen for comments. Conference participants at EARIE and FEAAM, and seminar participants at HECER and LSE provided useful discussions. I am grateful to the Yrjö Jahnsson Foundation for funding this experiment. I also thank the Emil Aaltonen Foundation for funding. I thank STICERD at the LSE for hospitality.
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1 Introduction

Online auctions and electronic procurement account for a large and increasing share of C2C trading, retail trade (B2C) and B2B trading. In this study, I argue that in such online or Internet auctions, a minimum bid increment (MBI), which refers to the minimum amount that a new bid must exceed the current highest bid, is an economically important but currently overlooked feature of the auction design. The received theory predicts that MBI may be an important determinant of Internet auction revenue and that the revenue maximising MBI is larger than zero. The main contribution of this paper is that I use a novel field experiment to show that both of these theoretical predictions are supported by data. I document, in particular, that increasing MBI increases the seller revenue up to a point but limits entry.

MBI is a close relative of a bid increment grid used sometimes in standard auctions, but there are important differences, which result in opposite policy recommendations. In most standard auctions, the optimal increment in zero, but due to the particular features of online auctions, the optimal level of MBI may be larger than zero. In online auctions, the MBI affects not only whether a new bid is accepted, but also how the price is determined. Most importantly, the larger the MBI the larger the likelihood that the pricing rule is based on the first price instead of the second price mechanism. Thus MBI should be an important determinant of bidder behavior, and therefore could have significant impact on the revenue, and that the revenue maximising level may well be larger than zero. In some Internet auction sites, like the Finnish site Huuto.net, it is possible for the seller to choose MBI freely as one parameter of the auction design. However, most Internet auction sites follow eBay and do not allow the seller to choose MBI but rather force an increment schedule that is a step function of the current price. I utilize the properties of Huuto.net to set up a novel field experiment to study the causal effect of MBI on the seller revenue and the buyer participation.

Previously, there has been some work in managenement science and computer science that argue for the importance of MBI in Internet auctions. Bapna et al. (2003) provide theoretical results concerning B2C online auctions. In their model, it turns out that MBI is the most important parameter that the seller can choose. Also Rogers et al. (2007) analyze MBI from a theoretical perspective. According to their model and simulations, the seller can maximise revenue by setting reservation price to zero and MBI to an optimal level that is larger than zero. According to these studies, MBI seems to be even more important mechanism parameter than setting the reservation price optimally, which has been at the center of auction research ever since Myerson's (1981) seminal contribution. However, these results hinge on behavioral assumptions on the bidder behavior. The result in Rogers et al. (2007) for example requires that all bidders submit a single truthful bid. Hickman (2010) provides in a simplified setting the only existing analysis on how MBI affects strategic bidding in Internet auctions. He shows that MBI is a very important and unique feature of electronic auctions and it makes these auctions a hybrid between second and first price auctions. However, his otherwise insighful analysis does not address the relationship between MBI and seller revenue.

Despite the scarcity of theoretical literature, relative to the importance of this question, empirical contributions are even more scarce. Bapna et al. (2003) provide the only other empirical attempt to study the association between MBI and the seller revenue. They use observational data from B2C online auctions. However, Bapna et al. (2003) do not address the potential problems regarding unobserved heterogeneity in any way. Moreover, their sampling procedure introduces a selection bias since they exclude auctions with low participation from the data. Because low participation may be caused by high MBI, this selection may result in overestimating the effect of MBI on the revenue. Therefore, their results should be taken merely as descriptive, but as such these results validate their theoretical argument that MBI is the most important parameter in these auctions. To my knowledge, my study is the first empirical analysis that estimates the causal effects of MBI on auction revenue and entry. Moreover, my experiment allows me to analyze whether eBay uses an optimal increment function. The gap in both the theoretical and empirical literature concerning the analysis of MBI could be due to the seller not being able to set the MBI in the large Internet auction sites like eBay. Another explanation is that MBI may be regarded only as a minor detail of these auctions.

The use of online auctions and e-commerce has been growing rapidly during the last decade and continues to do so. Currently, a massive amount of transactions are conducted via the Internet and a market can be found for most imaginable items ranging from cloth diapers to start-up companies. For example, the largest online auction site eBay (company's all sites) had a gross merchandise volume of \$60 billion in 2007. The sheer volume of transactions conducted in the online auctions makes it very important to understand all the details of these auction mechanisms, because even small deviations from an optimal auction mechanism may cause significant aggregate losses for the seller side of the market.

It is likely that an increasing share of public procurement will also be conducted electronically in the future. For example, the new European public procurement directives (2004/17/EC and 2004/18/EC) make it clear that procuring entities can require suppliers to use electronic means (Arrowsmith 2006) and the majority of the member states have declared their intention to adopt eAuction systems (Renda and Schrefler 2006). In a public procurement setting, the social planner prefers the auctioneer's revenue over the bidders', because a public auctioneer needs to collect costly and distortionary taxes to pay the winning bidder. Therefore, it also very important from the social planner's perspective to understand how the auctioneer can maximise its profits in the Internet auctions.

Despite the lack of studies concerning MBI in particular, Internet auction sites like eBay have proven to be a rich source of both observational and experimental data for auction researchers, for example wanting to test theory. Moreover, they have also been the main objects of numerous studies, both theoretical and empirical. Bajari and Hortacsu (2004) and Ockenfels et al. (2006) survey the literature on Internet auctions. In a typical Internet auction, the auctioneer can make several choices concerning how to sell the object, of which all have been extensively studied with the exception of MBI. These choices all have implications on the expected revenue. First, the seller can set a public reservation price. Reiley (2006) finds in a field experiment that the buyers in his data behave as symmetric risk-neutral bidders with independent private values would in an equilibrium and therefore the seller should set a non-zero reservation price. Second, it is possible to also set a secret reservation price. Katkar and Reiley (2006) compare the use of public and secret reserve prices and find that making the reserve price secret makes the sellers worse off. Third, the seller can allow a buy-now option. There exists many studies concerning the buy-now effects, both theoretical and empirical, including a field experiment by Standifird et al. (2005) but they do not provide a clear answer on when the seller should allow buy-now and at what level. Furthermore, a wide variety of marketing options are available that the site sells to the auctioneer (Canals-Cerda 2006). There are also different ways to disclose information about the object (Andrews and Benzing 2007) and sellers have also the possibility to use an intermediary seller to increase reputation (Resnick et al. 2006). Furthermore, the auction sites differ to some extend in the auction mechanism that they use. For example, the stopping rule can be strict or soft, which has implications on the equilibrium behavior (Ockenfels and Roth 2006). It should ne noted that some studies (e.g. Ockenfels and Roth 2006) do account correctly for MBI in their model, but it is not the object of interest.

In my field experiment, I sell 72 Stockmann gift cards each valued at 15 euro at three different MBI levels and also 72 Stockmann gift each cards valued at 50 euro at three different MBI levels. Stockmann is the largest department store chain in Finland. I use increments of 1 cent, 33 cent and 50 cent for the 15 euro cards and increments of 1 cent, 66 cent, 100 cent for the 50 euro cards. 1 cent is the smallest possible level, and 33 cent and 66 cent correspond to what eBay would have set at that particular price range. I find that using the eBay increments increase the seller revenue compared with using the 1 cent

MBI. This result is statistically significant at 5 % level. The eBay level brings the highest revenue but the difference is not statistically significant from the higher 50 cent or 100 cent MBI levels. The number of participating bidders seems to decrease the higher the MBI level is.

Besides showing that MBI has a statistically significant effetcs, the experiment allows for different ways to quantify the economic importance of the revenue effect. Using the eBay increments increase the seller revenue compared with using the 1 cent MBI on average by 0.68% of the nominal value or by 0.77% of the average selling price. When aggregating over all the transactions conducted in eBay, even this small percentage would have amounted to about 460 million dollars in 2007. This is an estimate of the increase in trade volume that resulted from eBay using their current levels instead of a contrafactual 1 cent MBI for all. A better measure of the revenue gains is the difference the MBI levels make on the costs of running this experiment as measured by the nominal value minus the selling price. Using the eBay level instead of the 1 cent MBI, decreases the costs of this experiment on average by 5,7% per unit of observation. In summary, my experiment reveals that MBI is a relevant determinant of the online auction revenues, both in statistical and economic terms. Its estimated effect on turnover is just below 1% and on profits just below 6%.

In Section 2, I describe how a typical Internet auction works and discuss some Internet auction specific theory to frame the experiment. I also discuss what questions the theoretical literature should target in my opinion. In Section 3, I present and discuss how I set up the field experiment and in Section 4 I analyze the results of the experiment. I also propose a structural test to distinguish between different theoretical explanations for my results in Section 5, but that test is not yet conducted. Section 6 concludes.

2 The institutional set up and some theory

In this section, I discuss the properties of eBay, the largest Internet auction site and Huuto.net, the site where I conduct the experiment. Most Internet auction sites work in exactly the same way as eBay. eBay auction is a variation of an ascending auction with a minimum bid increment, fixed closing time and a proxy bidding system. In eBay, the bidders are forced to use the proxy system, but they can of course circumvent this by submitting only bids equal to the current price plus MBI. This is called incremental bidding. Both eBay and Huuto.net sites advice the buyers to submit only their true valuation once and let the proxy do the rest. This is called proxy bidding. Although from the surface these auctions look like ascending auctions, it is generally accepted that the equilibrium in Internet auctions is equivalent to the equilibrium in sealed bid second price auctions, and not that in ascending auctions (e.g. Bajari and Hortacsu 2003). However, due to the MBI, which's effects on equilibrium behavior the previous literature, with exception of Hickman (2010), has overlooked, this is not entirely true.

The main difference between the auction mechanisms used by Huuto.net and eBay, is that the former applies a soft stopping rule and the latter a strict stopping rule. The soft closing rule in Huuto.net means that if a bid is submitted when the auction is about to close in less than 5 minutes, 5 minutes are added to the time that auction is open. In eBay the closing time is strict. Also for example the Amazon auctions use a soft closing rule. Stopping rule has implications on the equilibrium bidding. In particular, the strategic advantages of the so called late bidding or sniping, that is often observed in eBay, are severely attenuated in auctions that apply an automatic extension rule (Ockenfels and Roth 2006). In Yahoo! auctions, the seller can set the closing rule. Brown and Morgan (2009) use this feature to construct a field experiment on the effects of the closing rule. They find that prices and bidder counts are unaffected by the auction ending rule. Therefore, it is fair to assume that the results obtained from a field experiment set up in Huuto.net apply also to eBay and other platforms that use the strict closing rule.

The seller has to set some starting price, which is equivalent to setting a public reservation price. There is also a possibility to set a secret reservation price. In addition to these parameters, the sites sells the sellers a wide variety of marketing options. In Huuto.net, it is also possible to set MBI level. This is not possible in eBay. Table 1 shows the MBI schedule that is used in eBay. As explained below, I use the eBay level as one of the treatments in my field experiment.

Table 1: MBI schedule in eBay.

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

There is some theoretical work that analyze bid increments in traditional auctions. Chwe (1989) shows that in a first-price sealed-bid auction with no entry and bidding costs, the auctioneer should set the increments as small as possible. Rothkopf and Harstad (1994) show, althought with restriction on the number of bidders or the number of possible increment levels and on the distribution of valuations, that English auctions with discrete bid levels generate less expected revenue than auctions with continuous increments. This implies that the auctioneer should always set the increment level to zero to maximise revenue. The main idea of their proof is that although there are special cases where a high increment could result in a higher revenue, the probability of these events is lower than that of those cases where high increment decreases revenue. David et. al (2007) generalize these results for Eglish auctions and come to same the conclusions. However, they make a point that if submitting a bid or time spent in auction is costly, the revenue gains from small increments should be weigted against these costs. Despite the results that support the use of low MBI, eBay uses quite large MBI's and in Huuto.net, the sellers typically set them higher than the smallest possible level. One reason for this behavior is that if the bidding process in Internet auctions is the same as in a sealed-bid second-price auction, instead that of an English auction, and since the winner pays the second highest bid plus MBI, then the expected revenue is equal to the second highest bidder's valuation plus MBI (e.g. Bapna 2003). However, this holds only if there is no endogenous entry and bidders submit true valuations. Next, I present another potential explanation for this behavior that is related to how the Internet auction protocol differs from a traditional auction.

2.1 MBI and the proxy bidding system

Rogers et al. (2007) study the joint effect of proxy bidding system and minimum bid increments on revenue. They motivate their work by stating that they try to solve the contradiction between the usual assumptions that eBay behaves as a second price auction whereby the expected revenue is equal to the second highest bidder's valuation plus MBI (e.g. Bapna 2003 and Ockenfels and Roth 2006[1]) and the

[1] Unlike Rogers et al. (2007) imply, these papers do not make claims about the expected revenue, they merely describe that price is determined in this manner, which is a different matter, unless truthful bidding and no endogenous entry is assumed.

results by David et al. (2007) and Rothkopf and Harstad (1994) who both argue that these auctions generate less revenue than the second highest valuation because of the discrete bid grid. Rogers et al. (2007) provide a model of eBay auction protocol with two bidders that have private values. This model allows a detailed analysis of how the proxy bidding system and minimum bid increment interact and affect the properties of these auctions. They simulate the results for more than two bidders.

The main finding in Rogers et al. (2007) is that the expected revenue depends on the MBI and this effect is dependent on how the bidders play the game. If all bidders submit their true valuations to the proxy, the expected revenue is higher than the second highest valuation but by an amount less than the MBI. In this case, there is an optimal value for the MBI that is larger than zero. The selling price is increasing in the MBI but this effect is limited from above by the effect of MBI on entry. If all the bidders use incremental bidding, the expected revenue is less than the second highest valuation. To understand how the MBI affect the revenue, we need to understand how the proxy bidding system works. According to the description in the sites, this proxy protocol is exactly the same in both eBay and Huuto.net, which I confirmed by some experimenting in the Huuto.net.

For the bid to be accepted, it must exceed the current bid (or the reservation price for the first bidder) plus the MBI. This is the minimum amount that the proxy accepts. It is also possible to set any value that is higher than this to the proxy. The value entered does not need to follow the grid imposed by the MBI. According to Rogers et al. (2007), the common belief is that proxy then engages in incremental bidding each time it is overbid up to the amount given to the proxy. However, this is not the case as Rogers et al. (2007) show by providing a pseudo-code for the eBay protocol. What rather happens is that, whenever a new bidder informs his proxy of his valuation, the current bid immediately advances to the minimum of the highest price entered so far and the second highest price plus the MBI. As argued by Rogers et al. (2007), this system gives rise to the optimal value of MBI. This formula (1) for the current price reveals immediately how the expected current price and therefore the expected selling price is strictly increasing in MBI. However, higher the MBI, the higher is the chance that a new arrival is not willing to submit any bid, even if he has the highest valuation, because the current price plus MBI is more likely to be larger than his valuation when MBI is larger. The current price formula (1) also implies that the current price and therefore the selling price need not be restricted to the integer multiples of the MBI.

$$\text{(1)} \qquad \text{Current Price} = \min(\text{Highest bid submitted, Second highest bid submitted} + \text{MBI})$$

Besides deterring entry, a higher MBI level implies that the current price would more often be determined as the highest bid submitted to the proxy. If MBI is zero, abstracting from endogenous entry, the price is determined as in a second-price-sealed bid auction. If MBI is infinite, then the price is determined as in a first-price sealed-bid auction. With intermediate levels of MBI, Internet auction is a hybrid between these two auctions formats. Hickman (2010) shows that this imposes behavior similar to the first-price sealed-bid auctions, where the bidders shade their proxy bids away from the true valuation in equilibrium. Indeed, he shows that in a Bayes-Nash equilibrium of this game, bidders submit bids that are below their valuations by an amount that is increasing in MBI. Therefore, the optimal MBI is lower than what would be implied in Rogers et al. (2007) setting of truthful bidding.

Hickman (2010) simplifies the model by assuming exogenous entry, symmetric risk-neutral bidders and independent private valuations. Each bidder submits only a single bid to the proxy. Highest bidder wins and the winner pays according to equation (1). Hickman (2010) does not analyze the effect on MBI on revenue, but it is clear that in his model the revenue equivalence theorem (Riley and Samuelsson 1981, Myersson 1981) holds. Therefore, increasing the MBI has two opposite effects on expected revenue that exactly cancel out each other. Increasing MBI increases revenue based purely on the expected revenue being an increasing function (1) of MBI, but simultaneously it increases bid shading by the same amount.

Revenue equivalence between different levels of MBI is broken if endogenous entry is introduced. However, since high MBI limits the potential gains by prohibiting the expected entry of even the highest value bidder, it is likely that endogenous entry would only imply that the optimal MBI is zero. The behavioral explanation of truthful bidding, as analyzed by Rogers et al. (2007) may explain observed seller behavior of setting nonzero MBI and the results of my experiment that optimal MBI is not zero. However, due to not taking bid shading into account, Rogers et al. (2007) overstate the potential revenue gains from MBI. Nonetheless, the presence of bid shading does not mean that there may not be an optimal level above zero even in the presence of endogenous entry. Increasing MBI may increase expected seller revenue in such cases where the first price auction revenue is known to dominate the second price auction revenue, because by increasing MBI the seller increases the probability that an Internet auction behaves as a first price auction instead of a second price auction. Maskin and Riley (1984) show that with risk averse bidders, the revenue from first price auctions dominates the revenue from second price auctions, because risk averse bidders try to avoid the risk of not winning the auction by bid shading less than risk-neutral bidders. In this case, higher MBI means higher expected revenue. By the same logic and the results by Milgrom and Weber (1982), we know that with affiliation the optimal MBI is zero, because then second price revenue dominates first prive revenue. Also with binding reservation price, second price auction and therefore zero MBI is preferred (Myersson 1981). The effect of bidder asymmetry may go either way (e.g. Krishna 2002). Therefore, the main candidates for revenue gains from higher than zero MBI are risk aversion and truthful bidding.

First, the simulation approach that Rogers et al. (2007) use for the n-bidder case is not a perfect substitute for an explicit solution nor is it satisfactory to abstract away from strategic considerations. Fully characterising the strategic behavior of bidders in online auctions in relation to the MBI in setting that incorporates endogenous entry and other realistic features of these auctions would be an important contribution to the literature, but is clearly beyound the scope of this paper. Such a model would allow for a structural empirical analysis of these bidding markets. On the contrary, one purpose of this study is to provide field experimental evidence to show that MBI is indeed an important subject of further research. However, using data generated by an experiment it is possible to construct a structural test at least for the truthful bidding assumption.

3 The experiment

I conduct a field experiment to study how MBI affects selling prices. As a secondary objective, I also look at how it affects the number of observed bids and observed bidder identities. In this experiment, I sell Stockmann gift cards. Stockmann is the largest department store chain in Finland. The gift cards are valid in all of Stockmann's seven large department stores in Finland. These seven stores are located in the six largest cities in Finland that together have 1.6 million inhabitants or about 30 % of the entire population. These stores sell millions of different commodities and services. They are also valid in company's subsidiary stores like Seppälä, that sells clothes in 90 different Finnish cities and tows. Seppälä is thus easily accessible by most of the population in Finland. These gift cards were chosen for this experiment mainly because there is a large demand for these products. It is almost like selling money. It is very likely that the potential demand for the last card sold is about the same as for the first card sold. However, this assumption is not necessary for the internal validity of the experiment. It is enough that demand is fairly stable within each card batch that I sell.

Another property that the gift cards in general have, is that bidders have very likely private valuations for them, since there is no significant common uncertainty about the value of these objects. Relevant uncertainty is essentially private. For example, the bidders may have different transaction costs, may discount future at different rates, have different use for these cards and may have different perceptions on the trustworthiness of the seller. All this uncertainty is private. This assumption of private values is not necessary for this experiment either. With independent private values, it is just more likely that the experiment would result in revenue gains from increasing MBI than under other information assumptions.

In the first experiment, I sell a total of 72 identical 15 euro Stockmann gift cards. 24 are sold at 1 cent MBI. This constitutes the control group. There are two treatment groups, the 33 cent MBI (eBay level) and the 50 cent MBI. The second experiment is run in exactly the same way, with the exception that the the cards have now a nominal value of 50 euro, and the MBI levels are now 1 cent, 66 cent (eBay level) and 100 cent. It would be interesting to set one treatment in the experiment to optimal MBI, but unfortunately it is not possible.To be able to calculate the optimal MBI for the objects sold in the experiment, I would need to know many unobservable factors, such as the number of potential bidders and their value distributions, the nature of the entry process and bidder strategies. Therefore, the most interesting possible set up is to look how the eBay level performs compared with the minimum level and a higher level.

The experiment is conducted with objects that have both the reservation price (starting price plus MBI) and the maximum selling price (the nominal value of the card) within the range where eBay would have kept the MBI the same throughout the auction. For the the 15 euro cards, the reservation price was 8 euro (about $12) in the experiment and the maximum value of the object for the buyers was 15 euro (about $22.5). Therefore, the current price was always between $5 and $24.99, also allowing for reasonable changes in the currency exchange rates between the euro and the US dollar. In practice, the 1 cent MBI cards have a 7.99 euro starting price level, 33 cent MBI cards have 7.67 euro and 50 cent MBI cards have 7.5 euro. Since the first accepted bid is the starting price level plus the MBI, all the cards have a de facto reservation price of 8 euro. In the 50 euro card experiment, I followed the same logic and set the de facto reservation price to 30 euro. The MBI level for the 15 euro cards would have been $0.50 (about 33 cents around the experiment date) and $1 (about 66 cents) for the 50 euro cards in these price ranges.

I sell all the cards in separate auctions that each last 5 days, from Tuesday afternoon to Sunday afternoon. 12 cards are auctioned at the same time. Both the experiments lasts six weeks and constitute each of six 12 card batches (clusters) with each batch including 4 cards of each of the different MBI's. Note that this set up allows for balanced variation in the treatment within each cluster. Therefore, even if the auctions within each cluster are not independent, for example due to the presence of decreasing average transaction costs per card bought, the experiment achivies good power with relatively few observations when compared to randomization at only the cluster level. Typical issues that prevent experiments with within cluster variation include risks of contamination, and ethical, political, administrative or financial reasons (Moerbeek 2005). None of these problems are present in my experiment. Moreover, my reputation as seller increased during the experiment, but with within cluster variation in treatment this causes no problems, since this potential effect is easily controlled by adding weekly (cluster) fixed effects to the regressions. These fixed effects also control for any other unobserved weekly changes.

4 Results

The main questions of interest in this analysis are the effects of MBI on the selling price and the number of actual bidders. I observe the selling price and bidding history in the data. The bidding history includes the current price and the current highest bidder after each accepted new bid. Therefore, it does not reveal the bids submitted to the proxy bidding system. Nor does it reveal the number of actual bidders, since a new bidder may place an accepted bid, but I would only observe that particular bidder if her bid was the highest. Thus, the variable for the number of observed bidder identities, which I call the number of bidders, is a lower bound or a downwards biased proxy for the number of actual bidders. Another proxy for the number of actual bidders is the number of observed bids. One bidder can be observed bidding many times either because they submit many bids (incremental bidding) or because they are the highest bidder while new entrants submit new second highest bids. Thus the number of bids variable is an upper bound or an upwards biased proxy for the number of actual bidders. I analyse both of these proxies. If the effect of MBI on both of these variables is to the same directions, we can be fairly confident that the effect on actual bidders is also to the same direction. I also observe how many times the object is viewed but this is a very noisy signal of the number of potential bidders, since this variable counts all the views of each bidder and the seller. In order not to allow the monitoring of the experiment to influence its results, I viewed each auction within a branch the same number of times. Therefore, I analyze only selling price, the number of bidders and the number of bids.

In table 2, I describe the variables of interest in the first expriment. The mean price is 13.24 euros. The average price is lowest for the 1 cent MBI and highest for the 33 cent MBI but differences are not statistically significant. All the auctions receive bids from atleast two different bidders. Both the average number of bids and bidders are lower, the higher the MBI is. There is enough variation in all the response variables to warrant meaningful regression analysis.

Table 2. 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

"price" denotes the winning bid for which the object is also sold. "nbidders" means the number of different bidder identities that are observed to submit bids. "nbids" is the number of different bids that are observed.

In table 3, I describe the variables of interest in the second expriment. The mean price is 44.46 euros. Conditional descriptive statistics look exactly as in the first experiment. The average price is lowest for the 1 cent MBI and highest for the 66 cent MBI but these differences are smaller than respective standard deviations. All the auctions receive bids from atleast two different bidders and both the average number of bids and bidders are lower, the higher the MBI is. Again there is much variation in all the variables.

Table 3. 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

"price" denotes the winning bid for which the object is also sold. "nbidders" means the number of different bidder identities that are observed to submit bids. "nbids" is the number of different bids that are observed.

In table 4, I describe how many auctions each of the observed bidders won. Alltogether 13 different bidder identities are observed in the data. 7 different identities won auctions in the first experiment and 8 in the second, of which 3 were winners also in the first experiment. A large share of the auctions are won by bidder 1. She dominates especially the first experiment, which may be a concern for the external validity of these results. Being a randomized trial with identical objects, the internal validity of these results is very strong. However, the external validity may be less strong for two reasons. The first reason is related to whether the bidders represent a typical set of bidders in Internet auctions. The problem in the first experiment is that, although there are many different bidders that participate in these auctions, one bidder wins most of the auctions. It is tempting to argue that the results could have been different if that particular bidder was not present. On the other hand, this particular bidder does not dominate the second experiment and yet the results are very similar. Moreover, the price is not determined by the winning bidder alone, as in the first price auctions, but rather as a joint function of both the highest and the second highest bid, as can be seen from equation (1). In these experiments, there is much more variation in the sets of participants than there is in the winner identities. For these reasons, the external validity of these results with respect to bidders should be strong.

Table 4. 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

"w1-6" denote the weeks from 1 to 6 that consist the first experiment. "w7-12" are the weeks of the second experiment. "bid 15" denotes the average winning bid of each bidder in the first experiment and "bid 50" in the second experiment.

The second potential concern for the external validity of the results is related to whether the sold objects represent well a typical object sold in the Internet auctions. Although there were many other types of gift cards for sale at the same time, only few other Stockmann gift cards vere present. Thus the object that I sell is not typical object. Moreover, there is large heterogeneity of objects sold in Internet auctions. Because most imaginable object are sold there, such a thing as representative object of sale does not exist. Thus it is more relevant to concentrate on selling objects that quarantee the internal validity of the results. Therefore, large demand and small characteristics space of the sold objects is more important than how common the object is. Furthermore, it is not clear why the results should be related to object characteristics as such. The effect of MBI depends more on the bidder characteristics and their strategies, and their risk attitudes and the nature of entry process. To the extend that these factors vary systematically between different products, the external validity is questionable. Even if some peculiar product or market characteristic would make all the bidders use incremental bidding in one market, truthful proxy bidding some other other marker and strategic bidding in yet another market, there should be a huge number of markets where the entry behavior and bidder characteristics are similar enough to the Stockmann gift card markets that these results are of external interest. For these reason, the external validity of these results also with respect to the sold objects should be fairly strong.

The sold objects are identical in all but two dimensions. Since I randomize the order in which the cards are placed on the auction within each patch, only the week that they are put to auction and the MBI differ systematically. Therefore, I regress the variables of interest on week dummies and the treatment dummies. The results are presented in tables 5 and 6. Auctions with 1 cent MBI receive more bids and bidders than auctions with higher MBI. Both the eBay levels and the highest MBI brings more revenue to the seller than the 1 cent MBI and the difference is statistically significant in the 15 euro experiment. There is no statistically significant difference between the two treatments but the eBay level brought in a little more money than the highest MBI. These results imply that the eBay level is close to optimal for these auctions, since we would expect that the entry effect would start dominating if MBI was increased further.

In the 15 euro experiment, when the eBay level is compared to the 1 cent MBI, it increased the revenue on average by 0,78% relative to the nominal level. In the 50 euro experiment, this revenue gain was was 0,78%. Relative to the difference between the nominal price and the average selling price, which is an upper bound of the potential buyer's gains and an exact value for the average cost of this experiment per observational unit, the revenue gain for setting the eBay level was considerable. Setting the eBay level instead of the 1 cent level would have reduced the unit costs of this experiment by 5,1% on average. For the 50 euro expetiment, this measure of the revenue is 6,9%.

Table 5. Results of the first experiment.

	price			bidders			bids		
Variable	**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

"w2 - w6" denote the dummies for the experiment weeks 2 - 6. The reference group is the first week. "mbi33" and "mbi50" denote dummies for the 33 cent and 50 cent MBI treatments. The reference (control) group is the 1 cent MBI. The number of observations is 72. For the effects of MBI on the number of bids regression, the $R^2 = 0.52$ and the null hyphothesis for mbi33=mbi50 is not rejected (p-value 0.50). In the number of participating bidders regression, $R^2 = 0.55$ and the null hyphothesis for mbi33=mbi50 is not rejected (p-value 0.41). In the number of submitted bids regression, $R^2 = 0.50$ and the null hyphothesis for mbi33=mbi50 is not rejected (p-value 0.83).

Table 6. Results of the second experiment.

	price			bidders			bids		
Variable	**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

"w8 - w12" denote the dummies for the experiment weeks 8 - 12. The reference group is the first week of the second experiment (week 7). "mbi66" and "mbi100" denote dummies for the 66 cent and 100 cent MBI treatments. The reference (control) group is the 1 cent MBI. The number of observations is

72. For the effects of MBI on the number of bids regression, the $R^2 = 0.61$ and the null hyphothesis for mbi66=mbi100 is not rejected (p-value 0.25). In the number of participating bidders regression, $R^2 = 0.55$ and the null hyphothesis for mbi66=mbi100 is not rejected (p-value 0.83). In the number of submitted bids regression, $R^2 = 0.71$ and the null hyphothesis for mbi66=mbi100 is rejected (p-value 0.01).

To run the pooled regressions on price, I construct a new variable called "discount". It is calculated by dividing the selling price with the nominal value of the card. It is very interesting to note from Table 7, that this discount is very much the same in both the experiments. One interpretation of this result is that transaction costs are not very important, since a fixed transaction cost should make the average of my discount variable larger for the low value than for the high value cards. It also makes sense now to run a pooled regression, since especially the mean and to some extent the variance of the explanatory variable are about the same in both the experiments.

Table 7. Discount comparisons.

Experiment	Variable	Obs	Mean	Std. Dev.	Min	Max
Value 15	discount	72	0.88	0.01	0.87	0.91
Value 50	discount	72	0.89	0.03	0.82	0.93

According to the pooled results, using the eBay increments increase the seller revenue compared with using the 1 cent MBI on average by 0.68% of the nominal value or by 0.77% of the average selling price.. This result is statistically significant at 5 % level. Although the percentage of the revenue increase is small compared to the nominal value of the object for sale, it is again a quite large share of the costs of the experiment, namely 5,7%. Moreover, if you aggregate over all the transactions conducted for example in the eBay, even this small percentage of 0.77% would have amounted to 460 million dollars of difference in total trades in 2007.

Table 8. Pooled results.

	discount			bidders			bids		
Variable	**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" includes both the 33 cent and 66 cent MBI's. Treatment 2 includes both the 50 cent and the 100 cent MBI's.

In Table 9, I present the results for running the regressions while treating MBI as a continuous variable instead of a treatment dummy. I also include a quadratic term of MBI. This allows for calculation of the optimal value of the MBI for both the experiments. Although the standard errors for the effect of MBI on prices are quite large here, this provides a best guess for the optimal values. For the 15 euro cards it would have been 38 cents and for the 50 euro cards it would have been 54 cents. eBay level is very close to this.

Table 9. Results for calculating the optimal value of MBI.

	Value 15			Value 50		
Variable	**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

5 Testing theory

I found in these experiment that the optimal MBI is larger than zero. I discussed previously that the main candidates for revenue gains from higher than zero MBI are risk aversion and truthful bidding. In this section, I discuss how one could potentially test for truthful bidding using the data generated from these auctions. These test are not yet fully thought through nor have they been concucted yet. Therefore, I only briefly present the idea here. This section will obviously be finished later.

H_0: Truthful bidding

H_1: Strategic bidding

First, I use bid history data to infer which auctions used the first price rule and which the second price rule. First price rule is used if the last price increase was smaller than the MBI. In Hickman's (2010) eBay data, about 22% of the auctions used this rule. I have yet to calculate these numbers for my data.Then, I estimate the value functions under different MBI's assuming H_0 by utilizing order statistics. The winning price WP when first price rule was used is $V_{N:N}$, where V denotes valuation and $N:N$ is the highest order statistic among N realizations of a random variable. In the case of second price rule,

$WP - MBI = V_{(N-1):N}$. The number of potential bidders N is unknown, but it can be assumed to be the same within each batch and can be proxied. And with balanced batches with respect to MBI, assumptions on N should not influence the results. Then I can use order statistic formulas and estimate $F(V)$ either with nonparametric or parametric techniques. The test would be conducted by testing whether (NP is nominal price)

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

$F(V|MBI = 1, NP = 50) = F(V|MBI = 66, NP = 50) = F(V|MBI = 100, NP = 50)$ as they would be under H_0. If I reject H_0, the strategic bid shading may be the only other explanation, but I am not yet sure about this. If strategic bidding is the case, risk aversion is our main candidate explanation but perhaps not the only possible.

6 Conclusions

In this study, I argue that MBI is an important yet overlooked feature of Internet auctions. My experiment reveals that MBI is an important determinant of both entry and selling price in internet auctions, thus showing that so far this question has been negletted for no good reason. To test the few existing theoretical predictions about the effects of MBI on revenue and entry, I conduct a field experiment to study these effects. The institutional set up of the Finnish Internet auction site allows for a novel field experiment. I sell otherwise identical objects with different MBI's. To my knowledge, this is the first experimental study on this subject. I find that it is optimal for the seller to set the minimum bid increment level higher than the smallest possible level. The level corresponding to the eBay schedule seems to be a good guess. I also find that the number of actual bidders is decreasing in the MBI. These results verify the theoretical possibility theorems that the seller revenue may be increasing in MBI, put only up to a point limited by entry.

In summary, this paper discusses some theory on the role of MBI in Internet auctions, and especially presents a novel field experiment that is both internally and externally valid and provides statistically significant and economically important results on the effects of MBI. Furthermore, I propose a test to distinguish between a behavioral and a strategic explanation of the results. This study can also be seen as an evaluation of the eBay bid increment schedule. I find no evidence that the eBay schedule would not be well chosen. However, this study does not allow analyzing whether there should be more steps in the eBay schedule nor do we know if the schedule is well chosen when selling object of different values than analyzed here.

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