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Valtion taloudellinen tutkimuskeskus
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Abstract

I study the role of minimum bid increments (MBI) in internet auctions using field experiment data. I sell identical gift cards while varying the MBI. Internet auctions have typically been viewed as second-price, implying truthful bidding. However, due to the presence of the MBI, equilibrium bidding behavior involves bid-shading. I test between truthful bidding and equilibrium bidding. Truthful bidding is rejected. Bidders conduct bid-shading in a pattern consistent with equilibrium bidding. I also report that the revenue maximizing level for the MBI is higher than zero and the eBay level is close to optimal. Moreover, a high MBI inefficiently limits entry.

Key words: Field experiment; internet auctions; minimum bid increment; revenue; strategic bidding

JEL classification numbers: C52, C72, C93, D44, L81

Tiivistelmä

Tarkastelen minimikorotustason vaikutuksia Internet-huutokaupoissa kenttäkokeen avulla. Myyn muuten identtisiä lahjakortteja, mutta vaihtelen minikorotustason suuruutta. Yleensä Internet-huutokauppoja on mallinnettu toiseksi korkeimman hinnan huutokauppoina, missä todellisen arvostuksen tarjoaminen on tasapaino. Kuitenkin minimikorotustaso johtaa sellaiseen tasapainoon, missä tarjoukset mitoitetaan omaa arvostusta pienemmiksi. Testaan vastaako tarjousaineisto todellisen arvostuksen tarjoamista vai minimikorotustason huomioivan tasapainon mukaista tarjoamista. Todellisen arvostuksen tarjoaminen hylätään. Aineiston havainnot ovat linjassa rationaalisen tasapainokäyttäytymisen kanssa. Näytän myös, että myyjän voitot maksimoiva minikorotustason on korkeampi kuin nolla ja että eBayn käyttämä tason on lähellä optimaalista. Kuten odotettua, korkea minikorotustaso kuitenkin rajoittaa tarjoajien lukumäärää.

Asiasanat: kenttäkoe, Internet-huutokauppa, minimikorotustaso, tuotot, strateginen tarjoaminen

JEL-luokittelu: C52, C72, C93, D44, L81

Contents

1 Introduction

Internet auctions (also referred to as online or electronic auctions) and electronic procurement account for a large and increasing share of C2C trading, retail trade (B2C) and B2B trading. The defining feature of internet auctions is what eBay calls proxy-bidding, where bidders reveal to the auction server the maximum bid that the server can submit on their behalf. The server then acts as a proxy and increases the current bid in response to competitive bids up to the submitted maximum, but where possible, to equal the second-highest bid plus a minimum bid increment (MBI). The MBI also defines the minimum amount by which a new bid must exceed the current price for it to be accepted. I argue that in internet auctions, the MBI is an important but empirically overlooked feature of the auction design. The received theory (Hickman (2010), Bapna et al. (2003) and Rogers et al. (2007)) predicts that the MBI may be an important determinant of internet auction bidding strategies and revenue and that the revenue maximizing the MBI may be higher than zero. I use a novel field experiment to show that all of these theoretical predictions are supported by data. I document, in particular, that increasing the MBI increases bid-shading but also seller revenue, but only up to a point limited by the entry effect. To my knowledge, this is the first field experimental or causal evidence on the topic in the literature.

In internet 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 is that the pricing rule is based on the first-price rather than the second-price mechanism. If the highest and the second-highest proxy bids are within one MBI of each other, the first-price rule is used, because the currect price cannot exceed the highest bid. Because the MBI adjusts the probability that the pricing rule in a given auction is either a second-price or a first-price rule, it should have a significant impact on bidder behavior. Accordingly, Hickman (2010) shows that in equilibrium, bid functions converge towards first-price auction bid functions as the MBI increases. The main contribution of my paper is that I show by applying a test to my field experiment data that bidders do indeed account for the MBI in their bidding strategies. The main implication of this test is that internet auctions should not be modeled as second-price auctions as most of the existing literature does (e.g. Bajari and Hortacsu 2003 and Song 2004).

This test contributes to the recent discussion on what is the correct framework for the analysis of internet auctions. Zeithammer and Adams (2010) also provide novel model validation tests and empirical evidence that the second-price sealed bid assumption that is prevalent in the empirical literature is not the correct one in eBay auctions. They show evidence that while some bidders may submit sealed bids, a significant number of bidders conduct a variation of ascending auction behavior called incremental bidding, where the current price is raised by one MBI at a time repeatedly up to a valuation. This is a more fundamental distinction than just whether these are sealed-bid or standard ascending auctions, because with incremental bidding, the top two bids in these auctions no longer reflect the true bidder valuations. Hortacsu and Nielsen (2010) contribute to this discussion by providing a commentary on Zeithammer and Adams (2010). They argue for the importance of incorporating richer models in structural empirical analysis of online auctions, but remain optimistic that it is possible to do so[1]. Although Zeithammer and Adams (2010) utilize information on MBI's in their tests, they overlook the implications of MBI's on entry and strategic behavior. My contribution is to show causal empirical evidence that even if some bidders submit sealed bids, they are not second-price bids because the MBI induces bid-shading behavior similar to first-price auctions. This is an even more fundamental concern than incremental bidders for the empirical analysis of internet auctions, because it is not clear how the bidders formulate first-price bidding strategies in this context. Since the number of potential bidders may be unknown to everyone, and unlike in second-price auctions or incremental bidding, standard first-price auction equilibrium strategies are a function of the number of potential bidders, and it is not clear how to analyze online auction equilibrium bidding.

The other main contribution of this paper is the analysis of the revenue effects of MBI's. The use of online auctions and e-commerce has been growing rapidly over 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 just about any item ranging from cloth diapers to start-up companies. For example, the largest online auction site, eBay, had a gross merchandize volume of $60 billion in 2007 (all of the company's sites). The sheer volume of transactions conducted in online auctions makes it very important to understand all the details of these auction mechanisms that may effect revenue, because even small deviations from an optimal auction mechanism may cause significant

[1] Hickman et al. (2011) indeed provide a structural estimation technique that accounts for MBI in a setting with independent private values and exogenous entry.

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 is also very important from the social planner's perspective to understand how the auctioneer can maximize its profits in internet auctions.

The MBI is a close relative of the bid increment grid sometimes used in standard auctions, but there are important differences which may result in opposite policy recommendations. In most standard auctions, the optimal grid increment is zero (Chwe (1989), Rothkopf and Harstad (1994) and David et. al (2007)). Therefore, if internet auctions were simply standard ascending auctions, the optimal MBI would be zero. However, due to the particular features of online auctions, especially the presence of proxy-bidding, the optimal level of the MBI may be higher than zero. Because the MBI affects the probability that the pricing rule in a given auction is either a second-price or a first-price rule, it could have a significant impact on revenue in situations where the revenue equivalence theorem does not hold (e.g. risk-averse, budget-constrained or asymmetric bidders). In particular, the revenue maximizing MBI may well be higher than zero in cases where first-price auctions generate more revenue than second-price auctions.

On some internet auction sites, like the Finnish site Huuto.net, it is possible for the seller to choose the MBI freely as one parameter of the auction design. However, most internet auction sites mimic eBay and do not allow the seller to choose the 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 the MBI on bidding strategies, seller revenue and bidder participation. 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 cards each 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.

My field experiment data allow me to test for truthful bidding. If bidders behave as if this was a second-price auction, they would submit their true valuations as bids. Assuming truthful bidding, I can calculate valuation functions based on the winning bids and the actual pricing rule that was used in each auction. I then test whether these calculated valuation functions for different MBI levels are the same, as they should be if bidders submit truthful bids. I reject the null of truthful bidding, and find that auctions with a higher MBI have calculated valuation functions that have more weight at lower valuations. Since the MBI cannot affect real valuations, this result is consistent with bid-shading that increases with the MBI. Hickman (2010) proposes the only model so far that correctly allows the MBI to affect bidding strategies in online auctions. My empirical results are consistent with his model predictions. Moreover, I find that for higher MBI's, the calculated value functions attain a higher peak. These results are also consistent with and complementary to the Monte Carlo evidence presented by Hickman et al. (2011). They compare structural estimates that assume truthful bidding to those that correctly account for the MBI. In their analysis, value functions based on misspecified estimates are to the left of and have a higher peak than the true valuation function. They also find that not accounting for the MBI in estimation leads to statistically significantly different structural parameter estimates compared to using a correctly specified model. To summarize, the analysis of my experimental data shows that the MBI should be accounted for in future theoretical and empirical analysis of all electronic auctions that use the MBI. These include online auctions, electronic public procurement and online advertising auctions such as Google runs (e.g. Varian 2009). This is the main result of this paper.

Besides showing that the MBI has statistically significant effects on bidding strategies, it is straightforward to study its revenue and entry effects given the design of the experiment. I find that using the eBay level increments increases seller revenue compared to using the 1 cent MBI. This result is statistically significant at the 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, which is consistent with a high MBI deterring the entry of late-arriving bidders. These results imply that eBay has been able to set its MBI schedule close to the optimum. On the other hand, my experiment does not allow an analysis of the dynamic features of the eBay MBI rule.

The experiment allows for different ways to quantify the economic importance of the revenue effect. Using the eBay increments increases seller revenue compared with using the 1 cent MBI by an average of 0.84% of the nominal value or by 1% of the average selling price. When aggregating over all the transactions conducted on eBay, even this small percentage would have amounted to about 600 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 counterfactual 1 cent MBI for all. An alternative 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 by an average of 6% per unit of observation. In summary, my experiment reveals that the MBI is a relevant determinant of online auction revenues and entry. These effects are statistically significant and economically small but non-negligible.

Different internet auction sites differ to some extent in the auction mechanism that they use. For example, the stopping rule can be strict, as on eBay or soft as on Amazon or Huuto.net. The stopping rule has implications for equilibrium behaviour, for example on the incentives to snipe (Ockenfels and Roth 2006). Moreover, on many sites, bidders always have to use the proxy, but on some sites bidders may also opt to circulate the proxy and submit jump bids. Sites also differ in how they charge sellers and bidders. Huuto.net differs in some potentially important ways from eBay, for example. It is important to point out that these differences will not hurt the external validity of my results concerning strategic bidding as opposed to naive truthful bidding. If bidders who are normal people are strategic and rational on one site, there is no reason to suspect that similar bidders would not be rational on other sites, even if the equilibrium bidding strategies may differ due to the different mechanisms. On the other hand, these differences may question the external validity of my revenue results. Therefore, I discuss the differences between Huuto.net and eBay extensively after presenting the revenue results, and analyze external validity, for example by using different subsample analyses.

In Section 2, I describe how a typical internet auction works. I discuss the existing literature and define naive and strategic bidders in Section 3. In Section 4, I present and discuss how I set up the field experiment and in Section 5 I analyze the revenue and entry results of the experiment. I conduct a test to distinguish between different bidding strategies in Section 7. Section 8 concludes.

2 Institutional setting

In this section, I discuss some of 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 almost exactly the same way as eBay. eBay auctions are a variant of an ascending auction with a minimum bid increment and a proxy-bidding system. Proxy refers to the algorithm that will conduct the bidding in the place of the real person. Submitting only one bid to the proxy is called proxy-bidding. On eBay, bidders are forced to use the proxy system, but they can circumvent this by submitting only bids equal to the current price plus the MBI. This is called incremental bidding. Both the eBay and Huuto.net sites advise buyers to submit only their true valuation once and let the proxy do the rest.

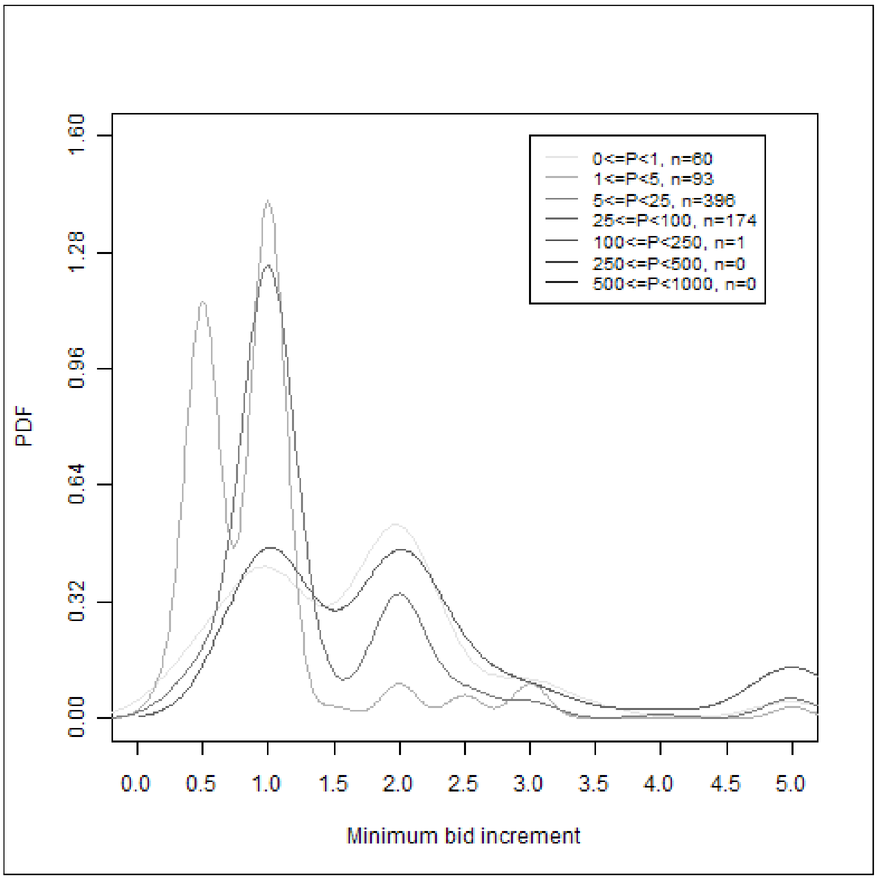
In these auctions, the seller has some control over the auction menchanism. The seller has to set some starting price, which is equivalent to setting a public reservation price. It is also possible to set a secret reservation price. In addition to these parameters, the sites offer sellers a wide variety of marketing options. On Huuto.net, it is also possible to set the MBI level. This is not possible on eBay. I discuss the other differences between eBay and Huuto.net in the results Section, where I analyze the external validity of my revenue results. Table 1 shows the MBI schedule that is used on eBay.

Table 1: MBI schedule in eBay.

Current Price	Bid Increment
\$ 0.01 - \$ 0.99	\$ 0.05
\$ 1 - \$ 4.99	\$ 0.25
\$ 5 - \$ 24.99	**\$ 0.50**
\$ 25 - \$ 99.99	**\$ 1.00**
\$ 100 - \$ 249.99	\$ 2.50
\$ 250 - \$ 499.99	\$ 5.00
\$ 500 - \$ 999.99	\$ 10.00
\$ 1000 - \$ 2499.99	\$ 25.00
\$ 2500 - \$ 4999.99	\$ 50.00
\$ 5000 and up	\$ 100.00

As explained in detail later, I use the eBay level as one of the treatments in my field experiments. The price ranges that I use in my experiment are given in bold in Table 1. eBay uses relatively large MBI's, especially for low-value objects, and on Huuto.net sellers typically set the MBI higher than the smallest possible level. In Figure 1, I show the empirical density of the MBI's used in some Huuto.net auctions. MBI's of 0.5, 1 and 2 euro are the most common and very small MBI's are rare. In the next Section, I speculate on the potential reasons for choosing these relatively high MBI levels.

Figure 1. Density functions of MBI's by starting value groups in Huuto.net for packages of used children's clothing in auctions that started between 28.12.2010 and 3.1.2011.



To understand how the MBI may affect strategies and revenue, we need to understand how the proxy-bidding system works. According to the description given on the sites, this proxy protocol is very similar on both eBay and Huuto.net, which I confirmed by some experimenting on Huuto.net. For a 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 higher than this to the proxy. The value entered does not need to follow the grid imposed by the MBI. This implies that even if sellers for some reason prefer even numbers, the MBI cannot be used to achieve them. According to Rogers et al. (2007), the common belief is that the 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. This 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.

$$(1) \qquad CP_t = min(HB_t, SHB_t + MBI),$$

where CP_t denotes the current price at time t and therefore also the revenue for the auctioneer at time $t = T$, where T denotes the closing time. HB_t is the highest bid submitted in the auction and SHB_t the second-highest bid at time t. A higher MBI level implies that the current price will more often be determined as the highest bid submitted to the proxy. If the MBI is zero, the price is determined as in a second-price sealed-bid auction. If the MBI is very high, then the price is determined as in a first-price sealed-bid auction. With intermediate levels of MBI, an internet auction is a hybrid between these two auction formats.

3 Competing models

I do not present any new results in this theory Section. The purpose of this discussion is to frame and give background to the field experiment, and to explain the theoretical models that are put to the test in the empirical analysis. Previous literature on MBI's has analyzed two cases. First, Hickman (2010) presents a model where the MBI affects equilibrium bidding strategies. I call this the strategic bidding model. Second, Bapna et al. (2003) and Rogers et al. (2007) analyze the effects of MBI's, but assume that it will not affect bidding strategies. In addition, with the exception of Hickman (2010) and Hickman et al. (2011), all of the existing literature (see for example a survey by Ockenfels et al. 2006) on online auctions in general has overlooked the possible effects of MBI's on equilibrium bidding strategies. I call these the naive bidding models.

3.1 Strategic bidding model

Although on the surface internet auctions resemple ascending auctions, it is generally thought that the equilibrium in internet auctions is equivalent to the equilibrium in sealed bid second-price auctions, and not that in ascending auctions (Bajari and Hortacsu 2003). From the empirical perspective, there is not much difference between sealed bid second-price auctions and ascending auctions, because in both of these situations the transaction price is the second-highest valuation in equilibrium.[2] However, due to the interplay between the MBI and the pricing rule, the second-price scenario does not exactly apply in these auctions.

I will first briefly discuss Hickman's (2010) model and results. He assumes that there are N potential symmetric risk-neutral bidders with independent private valuations. $F_V(v)$ and $f_V(v)$ denote respectively the cumulative distribution function and probability density function of the valuations. $f_V(v)$ is positive on the compact support $[\underline{v}, \overline{v}]$, where $\underline{v}$ weakly exceeds zero. N, $F_V(v)$ and $[\underline{v}, \overline{v}]$ are common knowledge to all bidders. The object is awarded to the highest bidder. The winner pays according to the equation (1). All bidders submit a single sealed bid to the proxy simultaneously and submitting a bid incurs no costs. Hickman (2010) shows that in this setting, a unique symmetric monotone pure-strategy Bayes-Nash equilibrium exists.

The above notation is not needed here, but rather in Section 7 where I test the theory. I refrain from presenting the details and formalities of the fairly complex model here. Intuitively, bidders maximize a sum of two things: expected profits under the first-price rule and expected profits under the second-price rule. The MBI adjusts the probability that a particular pricing rule is used and therefore each expectation is formed over the joint probability of winning and the pricing rule realization. The resulting equilibrium bid function can be characterized as a complex differential equation. The main implications are that bidding truthfully is not an equilibrium, whereas equilibrium involves bid-shading that is increasing in MBI.

Hickman (2010) does not analyze the effect of the MBI on revenue. Because he maintains all the assumptions

[2] From a theoretical perspective, there are larger differences, because in ascending auctions bidders can update their valuations.

required by the revenue equivalence theorem (Riley and Samuelsson 1981, Myersson 1981), it is clear that in his model the MBI cannot affect revenue. Therefore, an increasing the MBI has two opposite effects on the expected revenue that exactly cancel each other out. An increasing MBI increases revenue based purely on the fact that the realized selling price, conditional on the highest bid, is an increasing function (1) of the MBI, but, simultaneously, the MBI increases bid-shading by the same amount in expectation.

In the strategic bidding model, an increasing the MBI may increase expected seller revenue in cases where the first-price auction revenue is known to dominate the second-price auction revenue, because by increasing the 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, a higher MBI means higher expected revenue. Che and Gale (1998) show that budget constraints impose a similar bid function as risk-aversion, therefore providing another case where increasing the MBI may increase revenue. By the same revenue comparison logic and the results of Milgrom and Weber (1982), we know that with affiliation the optimal the MBI is zero, because then second-price revenue dominates first-price revenue. The effect of bidder asymmetry may go either way (e.g. Krishna 2002). Because risk-aversion is plausibly a common real-world phenomenon and it clearly predicts revenue increases from higher MBI's, it is the main (but not the only) candidate for rationalizing the common use of fairly high MBI's both on eBay and Huuto.net.

3.2 Naive bidding models

I call naive those bidders who either submit their true valuations to the proxy as their maximum bid or use the incremental bidding strategy. Most of the existing literature assumes that bidders behave in this truthful manner, just as they would in a second-price auction (whether ascending or sealed-bid). The reason for this assumption is easy to understand. If the MBI was zero, the price that the winning bidder pays would always equal the second-highest bid. And since at first glance the MBI may seem small compared to the selling price, the assumption of a second-price auction format has been seen as innocuous. In the case of naive bidders, discussion of the bidding strategy is not possible because bidding behavior is assumed in the definion of naivety. However, it is interesting to discuss the revenue implications of these assumptions in relation to the MBI.

Bapna et al. (2003) provide theoretical results concerning B2C online auctions. In their model, it turns out that the MBI is the most important parameter that the seller can choose. Rogers et al. (2007) also analyze the MBI's from a theoretical perspective. According to their model and simulations, the seller can maximize revenue by setting the reservation price to zero and the MBI to an optimal level that is higher than zero. According to these studies, the MBI seems to be an 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 regarding bidder behavior. In other words, they are not equilibrium results. The results in Rogers et al. (2007), for example, require that all bidders submit a single truthful bid.

Rogers et al. (2007) study the joint effect of the proxy-bidding system and minimum bid increments on revenue under the assumption that bidders are naive. They motivate their work by stating that they are trying 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 the MBI (e.g. Bapna 2003 and Ockenfels and Roth 2006[3]) and the 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 the eBay auction protocol with two bidders with independent 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 behave. Formula for the current price (Eq. 1) reveals immediately how the expected current price and therefore the expected selling price is strictly increasing in MBI. With a sufficiently high MBI, the pricing rule is always first-price, and with truthful proxy-bidding, the auctioneer can collect all the rents. Therefore the analysis of proxy-bidding is interesting only with an additional feature, namely entry.

[3] Unlike Rogers et al. (2007) imply, to my understanding these two papers do not make claims about the expected revenue, but rather merely describe that the price is determined in this manner.

Rogers et al. (2007) introduce sequential entry to the model. In their model, bidders come to the auction site randomly and sequantially. The higher the MBI, the higher the chance is that a new arrival is not willing to submit any bid, even if he has the highest valuation, because the current price plus the MBI is more likely to be higher than his valuation when the MBI is higher. In this case, the highest-value bidder is deterred and revenue (as well as efficiency) is lost. My experiment will reveal that this is a relevant concern for the auctioneer.

With truthful proxy-bidding and sequeantial enty, 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 higher than zero. The selling price is increasing in MBI but this effect is limited from above by entry. Under the alternative assumption of incremental bidding, Rogers et al. (2007) show that the expected revenue is less than the second-highest valuation. Therefore, the incremental model advocated by Zeithammer and Adams (2010) cannot explain why sellers on Huuto.net often choose a high MBI. Moreover, I will show in my experiment that a low level MBI does worse in terms of revenue than higher levels, which is not consistent with incremental bidding. Neither does the bid history that I observe support incremental bidding as the typical behavior. Ruling out incremental bidding is relevant later on when I construct a test for bid-shading. Zeithammer and Adams (2010) show that the MBI together with incremental bidding imply that the first and second bids may be downward-biased from true first and second valuations. Therefore, telling bid-shading apart from incremental bidding is challenging empirically.

Also in Hickman's (2010) model, revenue equivalence between different levels of the MBI is broken, if sequential entry is introduced to the model. However, since a high MBI limits the potential gains by potentially prohibiting the expected entry of even the highest-value bidder, it is likely that 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 the observed seller behavior of setting a non-zero MBI and the results of my experiment that the optimal MBI is not zero. However, due to not taking bid-shading into account, Rogers et al. (2007) overstate the potential revenue gains from the 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.

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 characterizing the strategic behavior of bidders in online auctions in relation to the MBI in a setting that incorporates sequential or endogenous entry and other realistic features of these auctions would be an important contribution to the literature, but is clearly beyond the scope of this paper. Such a model could allow for a structural empirical analysis of these bidding markets. Hickman et al. (2011) take a first step in this direction by discussing how to incorporate the MBI into a structural analysis of independent private values online auctions with exogenous simultaneous entry. However, one limitation of structural empirical analysis of internet auctions is that the number of potential bidders is not known and could be hard to estimate because it may be very high. Moreover, it is not unobservable only to the econometrician but also to all the bidders. The auction model should also incorporate this uncertainty. Unlike in structural modeling, the main purpose of this study is to provide reduced form field experimental evidence to show that the MBI is indeed an important subject of further research. Moreover, using data generated by an experiment it is possible to construct a test for the truthful bidding assumption.

3.3 Empirical literature

Despite the scarcity of theoretical literature, especially 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 the MBI and 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 may introduce a selection bias since they exclude auctions with low participation from their data. Because low participation may be caused by a high MBI, this selection may result in overestimating the effect of the MBI on revenue. Therefore, their results should be taken merely as descriptive, but as such these results do not contradict their theoretical argument that the MBI is the most important parameter in such auctions. To my knowledge, my study is the first empirical analysis that estimates the causal effects of the MBI on bidding behavior, 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's could be due to the seller not being able to set the MBI on large internet auction sites like eBay. Another explanation is that the MBI has been regarded only as a minor detail of these auctions.

Despite the lack of studies concerning MBI's 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 earlier literature on internet auctions. In a typical internet auction, the auctioneer has many choices concerning how to sell the object. For example, the auctioneer can set either a secret or public reservation price, or both. Another option is to allow the buy-now option. Auctioneers also have different ways to disclose information, to market the product or to use an intermediary seller to increase their reputation. Most of these and other possible choices have been extensively studied with the exception of the MBI. Since there are many elements to adjust and running experiments in internet auctions is relatively easy and cheap, many experimental papers have emerged on fairly irrelevant details. Thus it is important to stress that the MBI is not an irrelevant detail. The pricing rule is arguably a very important feature of the auction mechanism design and the MBI determines the pricing rule.

4 The experiment

I conduct a field experiment to study how the MBI affects bidding behavior and the selling price. As a secondary objective, I also look at how it affects the number of 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. These cards can also be spent in the company's subsidiary stores like Seppälä, which sells clothes in 90 Finnish cities and towns. Seppälä is thus easily accessible to most of the Finnish population. These gift cards were chosen for this experiment mainly because there is a large demand for them. 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; the object was chosen simply to guarantee that each auction generates bid data.

Another property that the gift cards have in general is that bidders are likely to have private valuations for them, since there is probably no significant common uncertainty about the value of the objects. What this means is that bidders would not update their valuations if they learned their competitors' valuations or signals. At least most of the relevant uncertainty regarding valuations is essentially private. For example, bidders may have different transaction costs, may discount the future at different rates and have different uses for the cards. They would not update their valuations if they learned their competitors' transaction costs, for example. On the other hand, the perceived trustworthiness of the seller, for example, may be a potential common value component. Moreover, reselling the cards is possible, which would also imply common values. However, the difference between selling prices and nominal values will turn out to be quite small, and therefore the potential gains from reselling are likely to be lower than the costs. It is important to note that the information regime is not relevant for the the internal validity of the experiment, although it may play a role in interpreting the results and evaluating the external validity. For example, with independent private values, it could be that a higher MBI would lead to higher revenue gains than under some other information assumptions such as the affiliated values framework.

In the first experiment, I sell a total of 72 identical 15 euro Stockmann gift cards. 24 are sold at a1 cent MBI. This constitutes the control group in the regressions. There are two treatment groups, the 33 cent MBI (corresponding to the eBay level) and the 50 cent MBI. The second experiment is run in exactly the same way, with the exception that the cards now have a nominal value of 50 euro, and the MBI levels are now 1 cent, 66 cent (corresponding to the eBay level) and 100 cent. It would have been interesting to have one treatment in the experiment at the optimal MBI, but unfortunately this was 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, quite apart from the fact that the relevant theory for this calculus does not exist yet either. Therefore, the most interesting possible set-up is to look at how the eBay level performs compared with the minimum level and a higher level.

The experiment is conducted with objects that have both a reservation price (the starting price plus the MBI) and a maximum selling price (the nominal value of the card) within range where eBay would have kept the MBI the same throughout the auction. For the 15 euro cards, the reservation price was 8 euro (about $12 at the time of the experiment) in the experiment and the maximum value of the object to buyers was 15 euro (about $22.5). Therefore, the current price was always between $5 and $24.99, also allowing for reasonable changes in 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, the 33 cent MBI cards 7.67 euro and the 50 cent MBI cards 7.5 euro. Since the first accepted bid is the starting price level plus the MBI, all the cards have a limit of 8 euro for the first bid to be accepted. In the 50 euro card experiment, I followed the same logic and set the level of acceptance of the first bid at 30 euro. Within these price ranges, 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.

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 last 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 creates 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 achieves good power with relatively few observations, when compared to randomization at the cluster level only. Typical issues impairing experiments with within-cluster variation include risks of contamination, and ethical, political, administrative or financial reasons (e.g Moerbeek 2005). None of these problems are present in my experiment. Moreover, my reputation as a seller increased during the experiment, but with within-cluster variation in the 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.

This experiment is what List (2011), for example, calls a natural field experiment. In these experiments, real economic agents operate in the real and same environment where they would usually operate, without knowing that they are participating in an experiment. Therefore the observed treatment effect cannot be a result of subjects reacting to simply the fact that they are in an experiment and being observed by researchers.

Typically, natural field experiments are very reliable both in the sense of estimating internally valid causal effect and being broadly generalizable (Al-Ubaydi and List 2012).

One limitation of my experiment compared to an ideal natural field experiment is that I cannot randomize over the participating bidders. I will later analyze bidder participation in more detail, but it turned out that only 13 different bidders participated and a single bidder won about half of the auctions. This is potentially problematic both for the internal and external validity of the results. I will deal with this issue when analyzing revenue and entry effects. Firstly, I add the winning-bidder fixed effects in addition to the week fixed effects. Secondly, I repeat the analysis using a leave-one-out strategy, where I drop all the auctions won by a given bidder from the data, one bidder at the time. Since the week fixed and winning bidder fixed effects may not remove all correlation between the error terms, for example if different bidders select into different weeks and different MBI levels, I also report the results clustered either at the week level or the winning-bidder level or both simultaneously using two-way clustering.

5 Results

5.1 Revenue and entry

The main questions of interest in this Section are the effects of the 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 true 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. However, there is no reason to assume that the bias in this variable is correlated with the MBI. Therefore, even if the levels may be biased, regressing the number of bidder identities on the MBI treatments should identify the treatment effect of the MBI on entry.

In table 2, I describe the variables of interest in the first experiment. The mean price is 13.24 euros. The average price is lowest for the 1 cent MBI and highest for the 33 cent MBI. All the auctions receive bids from at least two different bidders. The average number of bids is 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

Notes: "price" denotes the transaction price at which the object is sold. "bidders" means the number of different bidder identities that are observed to submit bids.

In table 3, I describe the variables of interest in the second experiment. The mean price is 44.46 euros. The 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. All the auctions receive bids from at least two different bidders and the average number of bidders is 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

Notes: "price" denotes the transaction price at which the object is sold. "bidders" means the number of different bidder identities that are observed to submit bids.

The objects sold 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 entered in the auction and the MBI differ systematically. Therefore I regress the variables of interest on the week fixed effects and the treatment dummies. To control for not being able to randomize over the potential and actual bidders, I also report results with winning bidder identity fixed effects.[4] When I analyze the 15 and 50 euro experiment data separately, I include either week or winning-bidder level clustering. When I pool the data, I also report two-way clustering on both levels simultaneously. However, the number of clusters may be a bit too small for the clustering to work properly.

The results for the 15 euro experiment are presented in Table 4. The auctions with the 1 cent MBI receive more bids than the auctions with a higher MBI, but the difference is not statistically significant in most cases. Both the eBay level and the highest MBI give the seller more revenue than the 1 cent MBI and the difference is statistically significant at the 5% level in three of the five specifications. There is no statistically significant difference between the two higher-level treatments. The revenue result is very stable to adding controls, which suggests that the randomization works as intended.

Table 4. Results of the 15 euro experiment

			Price		
	(1)	(2)	(3)	(4)	(5)
MBI33	0.090	0.090**	0.073**	0.073	0.073**
s.e.	0.057	0.043	0.035	0.054	0.016
MBI50	0.081	0.081*	0.085**	0.085	0.085***
s.e.	0.057	0.043	0.034	0.082	0.008
R^2	0.04	0.50	0.77	0.77	0.77
			Nro of Bidders		
	(6)	(7)	(8)	(9)	(10)
MBI33	-0.208	-0.208	-0.115	-0.115	-0.115
s.e.	0.299	0.209	0.196	0.179	0.189
MBI50	-0.375	-0.375*	-0.250	-0.250	-0.250
s.e.	0.266	0.218	0.218	0.309	0.220
R^2	0.03	0.55	0.68	0.68	0.68
Week FE	no	yes	yes	yes	yes
Winner FE	no	no	yes	yes	yes
Clustering	no	no	no	week	winner

[4]Using random effects instead of fixed effects does not change the results substantially.

Notes: N=72. The reference (control) group for the treatment groups is the 1 cent MBI. "MBI33" and "MBI50" denote dummies for the 33 cent and 50 cent MBI treatments. All standard errors are robust to heteroskedasticity. In the last two columns, the standard errors are clustered either at the week level or at the winning-bidder identity level. The clustered significance levels are corrected for the small number of clusters. * denotes 10% significance level, ** denotes 5% level and *** 1% level. The null hypothesis for mbi33=mbi50 is not rejected in any of the specifications.

The results for the 50 euro experiment are presented in Table 4. The auctions with a 1 cent MBI receive more bids than the auctions with a higher MBI. The difference is typically statistically significant, especially for the highest MBI. The eBay level gives the seller more revenue than the 1 cent MBI, but the difference is statistically significant only at the 10% level and only in two out of the five specifications. There is a statistically significant difference between the two higher-level treatments in one specification. The revenue result is again very stable to adding controls.

Table 5. Results of the 50 euro experiment

			Price		
	(1)	(2)	(3)	(4)	(5)
MBI66	0.380	0.380	0.323*	0.323	0.323*
s.e	0.390	0.239	0.163	0.231	0.134
MBI100	0.092	0.092	-0.071	-0.071	-0.071
s.e	0.371	0.243	0.133	0.220	0.198
R^2	0.02	0.61	0.88	0.88	0.88
			Nro of Bidders		
	(6)	(7)	(8)	(9)	(10)
MBI66	-0.542*	-0.542**	-0.548**	-0.548	-0.548*
s.e	0.300	0.223	0.229	0.315	0.245
MBI100	-0.583**	-0.583***	-0.639***	-0.639**	-0.639*
s.e	0.257	0.196	0.198	0.228	0.305
R^2	0.07	0.55	0.57	0.57	0.57
Week FE	no	yes	yes	yes	yes
Winner FE	no	no	yes	yes	yes
Clustering	no	no	no	week	winner

Notes: N=72. The reference (control) group for the treatment groups is the 1 cent MBI. "MBI33" and "MBI50" denote dummies for the 33 cent and 50 cent MBI treatments. All the standard errors are robust to heteroskedasticity. In the last two columns, the standard errors are clustered either at the week level or at the winning-bidder identity level. The clustered significance levels are corrected for the small number of clusters. * denotes 10% significance level, ** denotes 5% level and *** 1% level. The null hypothesis for mbi33=mbi50 is rejected only in specification (3) at the 5% level.

To get more power out of the experiments, I pool the data. To run the pooled regressions on price, I construct a new variable called "discount". This is calculated by dividing the selling price by the nominal value of the card. It is very interesting to note that this discount is very much the same in both the experiments. The average value of the "discount" is 0.88 in the 15 euro and 0.89 in the 50 euro experiment. One interpretation of this evidence is that transaction costs are not very important, since a fixed transaction cost should make the average of the "discount" variable higher for the low-value than for the high-value cards. It also makes sense now to run a series of pooled regressions, since especially the mean but to a lesser extent the variance (0.013 for 15 euro and 0.026 for 50 euro data) of the explanatory variable are about the same in both the experiments.

According to the pooled results in Table 6, higher MBI levels decrease entry. Moreover, we find a stable revenue effect both in terms of statistical significance and the level, suggesting valid randomization. Using the eBay increments increases seller revenue compared to using the 1 cent MBI by an average of 0.84% of the nominal value (or by 1% of the average selling price) in the richest specification. This result is statistically significant at least at the 5% level, except in specification (1), where I do not yet control for anything. Although the percentage of the revenue increase is small compared to the nominal value of the object for sale, it represents quite a large share of the costs of the experiment, namely 6%. Moreover, if that is aggregated over all the transactions conducted for example on eBay, even this small percentage of 1% would amount to a difference of 600 million dollars based on total transaction in 2007. In summary, my experiment reveals that the MBI is a relevant determinant of online auction revenues, both in statistical and economic terms.

Table 6. Pooled results of both experiments

	Discount					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0068	0.0068**	0.0084***	0.0084**	0.0084***	0.0084**
s.e	0.0043	0.0028	0.0023	0.0032	0.0020	0.0026
Treatment 2	0.0036	0.0036	0.0043*	0.0043	0.0043	0.0043
s.e	0.0042	0.0028	0.0023	0.0037	0.0026	0.0026
R^2	0.02	0.59	0.77	0.77	0.77	0.77
	Nro of Bidders					
	(7)	(8)	(9)	(10)	(11)	(12)
Treatment 1	-0.375	-0.375**	-0.404***	-0.404**	-0.404*	-0.404*
s.e	0.236	0.153	0.146	0.177	0.198	0.194
Treatment 2	-0.479**	-0.479***	-0.505***	-0.505**	-0.505	-0.505
s.e	0.216	0.146	0.144	0.210	0.298	0.296
R^2	0.03	0.64	0.69	0.69	0.69	0.69
Week FE	no	yes	yes	yes	yes	yes
Winner FE	no	no	yes	yes	yes	yes
Clustering	no	no	no	week	winner	two-way

Notes: N=144. The reference (control) group for the treatment groups is the 1 cent MBI. "Treatment 1" and "Treatment 2" denote dummies for the mid-level and high-level MBI treatments. All the standard errors are robust to heteroskedasticity. In the last three columns, the standard errors are clustered either at the week level, at the winning bidder identity level or at both levels using two-way clustering (The method of Cameron, Gelbach and Miller (2006) is implemented with ivreg2 in STATA). The clustered significance levels are corrected for the small number of clusters. * denotes 10% significance level, ** denotes 5% level and *** 1% level. The null hypothesis for mbi33=mbi50 is rejected only in specifications (5) and (6) at the 5% level.

The optimal level of the MBI can be studied further by running the price regressions while treating the MBI as a continuous variable instead of a treatment dummy. I also include a quadratic term of continuous MBI. This allows for calculation of the optimal value of the MBI for both the experiments. The standard errors for the effect of the MBI on prices are quite large in these regressions (not reported). Nonetheless, this approach 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 (in a specification with week but not winner fixed effects). The eBay levels are very close to these levels.

5.2 External validity

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 three reasons. The results may not generalize in respect of the characteristics of the bidders, the objects sold and the auction site.

The first reason is related to whether the bidders represent a typical set of bidders in internet auctions. In Table 7, I describe how many auctions each of the observed bidders won. Altogether 13 different bidder identities are observed in the data. 8 different identities won auctions in the first experiment and 8 in the second, of which 3 were also winners 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. Besides winning most of the objects, this bidder pays on average the lowest prices. The issue 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 in both the first and the second experiment. Moreover, the price is not determined by the winning bidder alone, as in standard 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 in respect of bidders should be fairly strong.

Table 7. How many auctions each bidder won.

bidder	w1	w2	w3	w4	w5	w6	w7	w8	w9	w10	w11	w12	total	price 15	price 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

Notes: "w1-w6" denotes weeks 1 to 6 , which constitute the first experiment. "w7-w12" are the weeks of the second experiment. "price 15" denotes the average winning bid of each bidder in the first experiment and "price 50" in the second experiment.

To evaluate the previous arguments concerning the robustness of the results in respect of the set of bidders, I report two separate pieces of evidence in Tables 8 and 9. In Table 8, I show the number of auctions that each bidder wins in each MBI category. There is no systematic evidence in Table 8 implying that some bidders prefer some MBI levels over others. In Table 9, I show the results of the leave-one-out type regressions. To be more specific, in Table 9, I report results where I omit all auctions won by a single bidder from the data, one winner at a time. The six smallest winners are dropped out together. I include the week fixed effect, but not the winner fixed effect, because here the winner effects are analyzed by dropping out data. All the results are qualitatively similar to the full sample results. None of the Treatment 1 effects are statistically significantly different from the comparable full sample effect (0.068) and all of them are significantly different from zero, at least at the 10% level, which is acceptable given the smaller number of observations.

Table 8. Distribution of wins over treatments for each bidder

bidder	statistics	MBI=1	treatment 1	treatment 2
1	obs	27	26	25
	mean	0.870	0.877	0.873
6	obs	5	1	3
	mean	0.901	0.900	0.901
9	obs	1	3	3
	mean	0.900	0.909	0.897
11	obs	6	5	6
	mean	0.896	0.896	0.900
13	obs	5	5	4
	mean	0.910	0.911	0.900
rest	obs	4	8	7
	mean	0.885	0.902	0.901

Notes: "obs" denotes the number of auctions that a given bidder wins in each treatment group. "mean" denotes the mean of price/(nominal value). "rest" denotes bidders 2,3,4,5,7,8,10 and 12 together.

Table 9. Results when data won by a given bidder is omitted.

Omitted auctions won by bidder:	1	2,4,5,7,8,10	3	6
Treatment 1	0.0042*	0.0061*	0.0057*	0.0081**
s.e.	0.0019	0.0026	0.0026	0.0025
Treatment 2	-0.0009	0.0032	0.0031	0.0032
s.e.	0.0038	0.0018	0.0017	0.0027
N	66	133	140	135
Omitted auctions won by bidder:	**9**	**11**	**12**	**13**
Treatment 1	0.0065*	0.0072*	0.0064*	0.0075*
s.e.	0.0030	0.0031	0.0030	0.0031
Treatment 2	0.0039*	0.0035	0.0037*	0.0053***
s.e.	0.0019	0.0021	0.0019	0.0004
N	137	127	140	130

Notes: The response variable is "discount". All the specifications include week fixed effects but exclude winner fixed effects. The standard errors are clustered both at the week and winning bidder identity levels using two-way clustering (The method by Cameron, Gelbach and Miller (2006) is implemented with ivreg2 in STATA). The clustered significance levels are corrected for the small number of clusters. * denotes 10% significance level, ** denotes 5% level and *** 1% level.

The second potential concern for the external validity of the results is related to whether the objects sold are a good representation of typical objects sold in internet auctions. Although there were many other types of gift cards for sale at the same time, only a few other Stockmann gift cards were on sale. Thus the object that I sell is not a typical object. On the other hand, there is large heterogeneity in the objects sold in internet auctions. Because all imaginable objects are sold there, there is no such thing as a representative object of sale. Thus it is more relevant to concentrate on selling objects that guarantee that the experiment generates reliable data that is easy to analyze. Therefore, high demand for and the simplicity of the sold objects are more important than how common the object is. Moreover, the presence of identical or similar objects sold by other sellers may potentially add unnecessary noise to the experiment since they may affect bidder behavior in the experiment's auctions. Furthermore, it is not clear why the results should be related to object characteristics as such. The effect of the MBI depends more on the bidder characteristics and their strategies, their risk attitudes and the nature of the entry process. To the extent that these factors vary systematically between different products, the external validity is questionable. Even if some peculiar product or market characteristic would make all bidders use incremental bidding in one market, truthful proxy-bidding in some other other market 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 to make these results of external interest. For these reasons, the external validity of these results also in respect of the objects sold should be fairly strong.

The main concern for external validity is caused by the differences between Huuto.net and the other internet auction sites, most importantly eBay. One 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 on 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 the auction is open. On eBay the closing time is strict. Amazon auctions, for example, also use a soft closing rule. The stopping rule has implications for equilibrium bidding. In particular, the strategic advantages of so-called late bidding or sniping, which is often observed on 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 on Huuto.net also apply to eBay and other platforms that use a strict closing rule.

There are two other differences between the two auction sites that are more problematic. Firstly, Huuto.net gives preferential treatment to winners who submit their bid to the proxy earlier than the second-highest bid. In that case, the winner pays only the second-highest bid. Therefore, in the case of early-placed winning bids, Huuto.net auctions are really just second-price auctions instead of hybrid auctions that use the pricing rule (1). In my experiment, 28% of the auctions were won by an early proxy bidder. This set-up creates further incentives for early bidding beyond the soft closing rule. In my experiment, no last-minute bidding was observed. Due to this rule, I probably estimate the lower bound for the effects of the MBI compared to conducting this experiment on eBay, because equation (1) is only relevant for auctions where a later proxy bidder wins. Therefore, qualitatively speaking my findings should be robust for this difference in the pricing rule. Secondly, bidders are allowed to jump bid. If a jump bidder wins, she pays her bid. Unlike on eBay, bidders are not forced to use the proxy machine, which is more of an option. 23% of the auctions in my experiments were won by a jump bid. This is a non-negligible share. Unfortunately, jump bidding creates many complexities for an analysis of bidding strategies which are clearly beyond the scope of this paper. In this respect, the external validity is limited. However, jump bidding wins was equally common in all the three different MBI treatment groups, which may imply that the results concerning the MBI should not be much affected by the possibility of jump bidding. Moreover, I repeat the analysis by excluding observations that result in a jump bid winning in Table 10.[5] The effects of the MBI on revenue are slightly smaller in the richest specification and the effect on entry is smaller for this sample than for the full sample. Therefore it seems that on average jump bidders may be able to deter entry with a high MBI. However, the differences with the full sample and the sample excluding jump bids are not statistically significant. On the other hand, it is worrying that the revenue result is less stable for this subset than for the full sample. I also account for these different rules and strategies in the bidding

[5]The sample in Table 9 also excludes 14 auctions for which I do not observe the pricing rule. This is due to a human error. Originally, I did not record the information from my experiments on the pricing rule that was used. I added that information later. Between these two recording events I lost the back-up paper copies of 14 of my auctions while moving office. This lost information is not easily recoverable because Huuto.net keeps information on its auctions for 3 months only. However, I have verified that omitting these 14 observations only changes nothing of practical importance relative to Table 6.

strategy test by analyzing a subsample of data.

Table 10. Pooled estimation results when auctions won by jump bids are omitted

	Discount					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0136**	0.0082*	0.0049	0.0049	0.0049*	0.0049*
s.e	0.0056	0.0043	0.0031	0.0041	0.0024	0.0025
Treatment 2	0.0115**	0.0081*	0.0024	0.0024	0.0024	0.0024
s.e	0.0051	0.0044	0.0034	0.0062	0.0038	0.0040
	Nro of Bidders					
	(7)	(8)	(9)	(10)	(11)	(12)
Treatment 1	-0.067	-0.064	-0.195	-0.195	-0.195	-0.195
s.e	0.262	0.196	0.199	0.287	0.337	0.341
Treatment 2	-0.325	-0.283	-0.367*	-0.367	-0.367	-0.367
s.e	0.246	0.194	0.187	0.272	0.345	0.331
Week FE	no	yes	yes	yes	yes	yes
Winner FE	no	no	yes	yes	yes	yes
Clustering	no	no	no	week	winner	two-way

Notes: N=99. The reference (control) group for the treatment groups is the 1 cent MBI. "Treatment 1" and "Treatment 2" denote dummies for the mid-level and high-level MBI treatments. All the standard errors are robust to heteroskedasticity. In the last three columns, the standard errors are clustered either at the week level, at the winning bidder identity level or at both levels using two-way clustering (The method by Cameron, Gelbach and Miller (2006) is implemented with ivreg2 in STATA). The clustered significance levels are corrected for the small number of clusters. * denotes 10% significance level, ** denotes 5% level and *** 1% level.

6 Testing theory

I showed in the previous Sections that the optimal MBI is higher than zero. The main candidates that could explain the revenue gains from an MBI higher than zero are strategic equilibrium bidding together with either risk-aversion or budget constraints, or alternatively naive truthful bidding. In this section, I test for truthful bidding. The tests cannot distinguish between the different strategic explanations but they can potentially reject truthful bidding. If that is the case, we can conclude that the second-price auction framework is not the proper model for the analysis of internet auctions.

The test hypothesis is formulated as:

H_0: Truthful bidding

H_1: MBI influences bidding

First, I use the bid history data to infer which auctions used which of the four the possible price rules. In Table 11, I show these pricing rules, how a given pricing rule is identified based on the bid history and what we know about the valuations under each pricing rule when we assume H_0. I denote the winning or selling price by WP, the highest bid by HB and the second-highest bid by SHB. t_{HB} and t_{SHB} denote the time when these bids are submitted. V denotes valuation and $N:N$ is the highest order statistic among N realizations of a random variable and $(N-1):N$ is the second-highest order statistic.

Table 11. Pricing rules and value function estimation.

Pricing rule	Timing	Bid history	Valuation calculus	Share
$WP = SHB + MBI$ (eq. (1))	$t_{HB} > t_{SHB}$	$WP - SHB = MBI$	$WP - MBI = V_{(N-1):N}$	48%
$WP = HB$ (eq. (1))	$t_{HB} > t_{SHB}$	$WP - SHB < MBI$	$WP = V_{N:N}$	2%
$WP = HB$ (jump bid)	not relevant	$WP - SHB > MBI$	Not conducted	23%
$WP = SHB$ (early winner)	$t_{HB} < t_{SHB}$	$WP - SHB = 0$	$WP = V_{(N-1):N}$	28%

It is possible to detect all the different pricing rules that are used based on the bid history. Firstly,.the second-price rule with an MBI was used if the last observed price increase is exactly the MBI. Secondly, the first-price rule was used if the last price increase is smaller than the MBI. In Hickman's (2010) eBay data, about 22% of the auctions used the first-price rule. This may seem to be surprising, because on eBay, the MBI's are quite small compared to the current prices. However, this is not the correct comparison. The ex-ante probability of the first-price rule is determined by the difference between the highest valuation and the second-highest valuation relative to the MBI. This probability may be high even if the MBI is low relative to the current price. In my data, only 2% of all the auctions and 5% of the auctions that ended with the pricing rule determined by equation (1) use this pricing rule. Compared to Hickman's (2010) data, this is a low number even when accounting for the fact that in a third of my auctions (those with the 1 cent MBI), the first-price rule is not possible. Moreover, 2% is a very low number compared to the emphasis I put on the pricing equation

(1). However, its low representation in my data set does not mean that the MBI is not accounted for in the bidding strategies. Thirdly, the last price increase can be higher than the MBI only if a jump bid wins the auction. Fourthly, the last price increase can be zero only if an early proxy bidder wins the auction. Due to the use of this preferential treatment of early bidders, it is harder to reject the null hypothesis than it would be if the same experiment was run without this preferential treatment.

I estimate the value functions for both the experiments separately under different MBI's by utilizing order statistics as in Table 11. Only the winning price data can be used. This estimation strategy assumes H_0. I should emphasise that this assumption does not need to be correct for the purposes of testing. On the contrary, the test will reveal whether this assumption is correct. Auctions with a jump bid winner are omitted because it is not realistic to assume H_0 for them. To simplify testing, I only include auctions where the winning price equals the second-order statistic. Order statistic calculus requires information on the number of potential bidders, N. N is unknown, but it can be assumed to be the same within each batch or within each experiment and it can be estimated. I use the total number of bidder identities observed in all the auctions in the entire experiment. This is 8 for both the experiments. Given balanced batches in respect of different MBI levels, the assumption regarding N should not influence the results to a large extent.

Given N and the pricing rule, I can use the order statistic formula and estimate the distribution of the valuations F_V either with non-parametric or parametric techniques. I use parametric approach due to the small number of observations. Experimental data is very useful in this exercise because there are no observable or unobservable characteristics that need to be controlled for, with the possbile exception of the week and winner fixed effects. However, these were shown not to affect the revenue results. Moreover, the data set is too small to condition the function estimation on these observables. I divide the calculated valuations by the nominal value $NP = 15$ or 50, and then estimate the parameters of a Weibull distribution that is upper-truncated at 1. The Weibull specification is chosen because it is fairly flexible. The test hypotheses for the two experiments are:

H_0: $F_V(.|MBI = 1, NP = 15) = F_V(.|MBI = 33, NP = 15) = F_V(.|MBI = 50, NP = 15)$

H_1:$F_V(.|MBI = 1, NP = 15) \neq F_V(.|MBI = 33, NP = 15)$ or $F_V(.|MBI = 1, NP = 15) \neq F_V(.|MBI = 50, NP = 15)$ or $F_V(.|MBI = 33, NP = 15) \neq F_V(.|MBI = 50, NP = 15)$, and

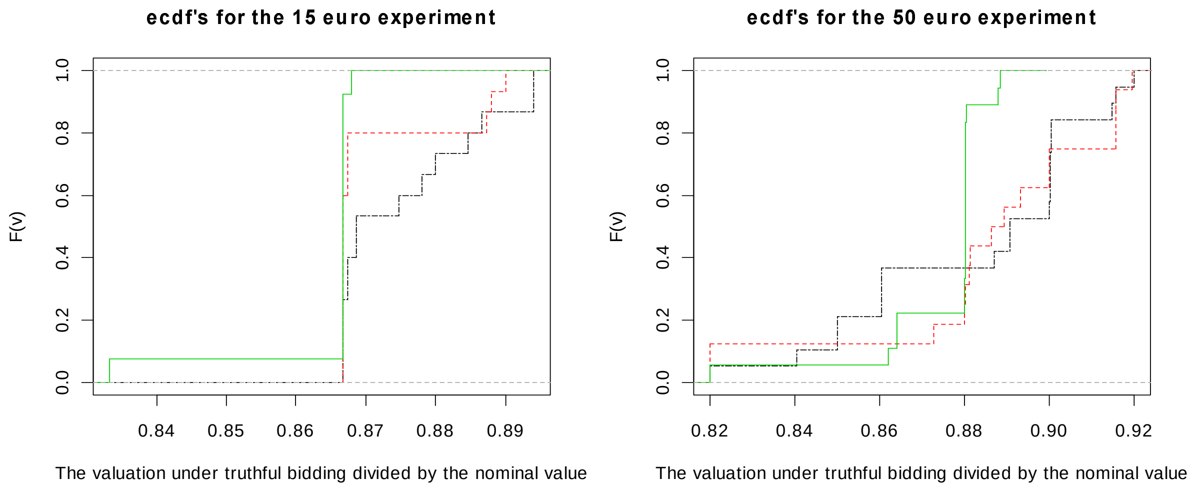
H_0: $F_V(.|MBI = 1, NP = 50) = F_V(.|MBI = 66, NP = 50) = F_V(.|MBI = 100, NP = 50)$

H_1: $F_V(.|MBI = 1, NP = 50) \neq F_V(.|MBI = 66, NP = 50)$ or $F_V(.|MBI = 1, NP = 50) \neq F_V(.|MBI = 100, NP = 50)$ or$F_V(.|MBI = 66, NP = 50) \neq F_V(.|MBI = 100, NP = 50)$.

In Table 12, I present the testing results. I test both for the differences in the empirical cumulative distributions of $V_{(N-1):N}$ (Figure 2) and the differences between the estimated parameters of the Weibull distributions (Figures 3 and 4). I reject the H_0 of truthful bidding. Therefore, bidders seem to shade their bids strategically. Reacting strategically to risk-aversion or budget constraints are possible candidate explanations but not the only possible ones. One out-of-sample piece of evidence supporting these results as following from Hickman (2010)-type bid-shading as a reaction to the MBI is that the observed pattern is similar to what Hickman et al. (2011) find in their Monte Carlo analysis. They compare estimations based on truthful bidding in the presence of an MBI to the true value distributions (and estimates that account for the MBI). They find that truthful estimates are located to the left and have a higher peak than the true distribution. This pattern is replicated in my experiment because a higher MBI leads to a higher peak and a location to the left of the distributions with a lower MBI. Overall, this Section implies that most of the previous literature that assumes that internet auctions are second-price auctions is overly simplistic. In my opinion, this is the most interesting result of this study.

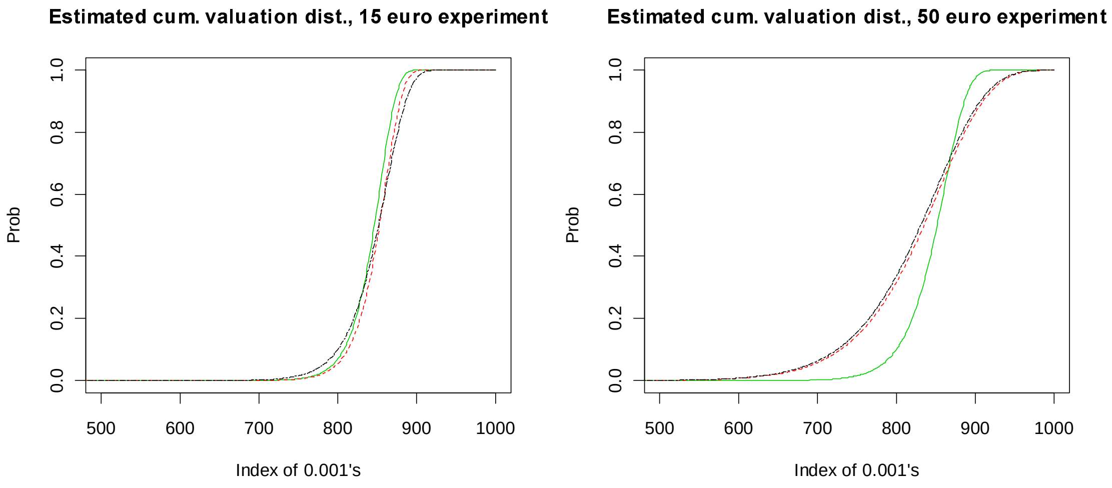
There is a potential risk of over-interpretation of the data involved in this testing approach, because I have treated each auction as an iid observation. Unfortunately, I cannot conduct a direct test of this assumption. There are various realistic reasons for the observations not to be iid. First, it is possible that a new draw of a given bidder is closer to her own old draw than the draw of some other bidder. This is the case of asymmetric bidders, where a separate value function should be estimated for each bidder. On the one hand, the symmetry assumption is standard in empirical auction literature. On the other hand, it is not likely that bidder 1, in particular, is identical to the other bidders. However, this unrealistic assumption is not likely to bias the comparison of the treatments, because each bidder wins about the same amount of auctions in each treatment (see Table 8). An even worse possible case is that bidders draw valuations only once. In that case, I have been replicating data. However, if that is really the case, there should have been less variation in prices under truhtful bidding than I observe in the data. Furthermore, the distribution from which valuations are drawn may change over time, for example as a function of items won in the past. However, if this was likely to confound the test here, it should also have affected the revenue results earlier, which it did not.

Figure 2. Empirical cumulative distributions for the valuations calculated under H0.



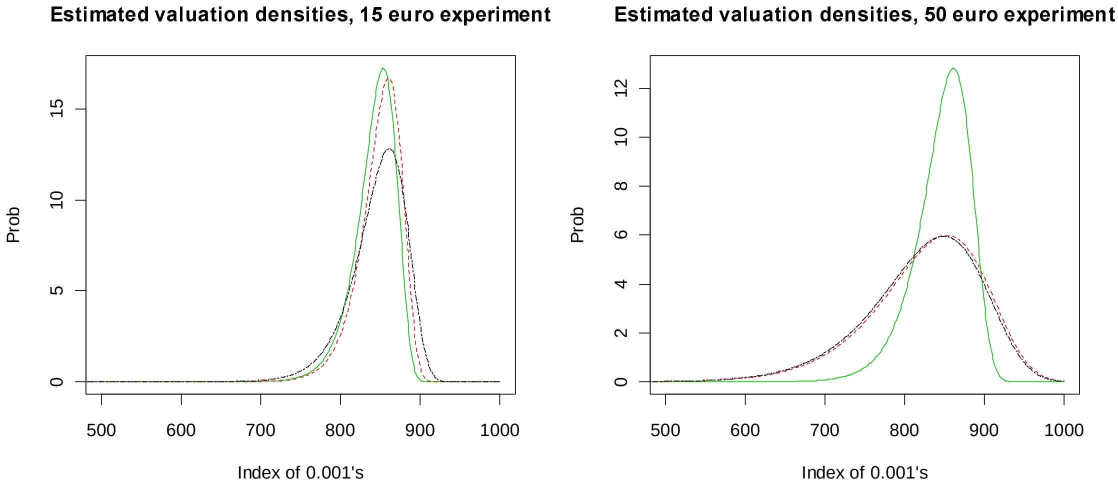
Notes: The green connected line represents the high MBI auction, the red dotted line the mid-range MBI auctions and the black semi-dotted line the low MBI auction.

Figure 3. Estimated cumulative Weibull distributions for the valuations calculated under H0.



Notes: The green connected line represents the high MBI auction, the red dotted line the mid-range MBI auctions and the black semi-dotted line the low MBI auction.

Figure 4. Estimated Weibull density distributions for the valuations calculated under H0.



Notes: The green connected line represents the high MBI auction, the red dotted line the mid-range MBI auctions and the black semi-dotted line the low MBI auction.

Table 12. Testing for truthful bidding.

	15 euro experiment			50 euro experiment		
	Location and shape parameters of the Weibull distribution					
MBI	**1**	**33**	**50**	**1**	**66**	**100**
Location	0.862***	0.861***	0.854***	0.85***	0.86***	0.86***
se	0.0042	0.0032	0.0038	0.0084	0.0092	0.0042
Shape	30.0***	39.1***	40.0***	13.8***	13.9***	30.0***
se	5.70	9.94	9.67	2.35	2.66	5.70
	Testing for differences in the Weibull parametes					
MBI	**1 - 33**	**1 -50**	**33 - 50**	**1 - 66**	**1 - 100**	**66 - 100**
Location	0.0013	0.0080	0.0067	-0.0087	-0.0039	-0.0048
se	0.0053	0.0056	0.0049	0.0094	0.0125	0.0101
Shape	-9.08	-9.97	-0.90	-0.16	-16.27*	-16.1*
se	8.99	11.22	11.90	3.55	6.17	6.29
	Testing for differences in the ecdf's					
MBI	**1 - 33**	**1 -50**	**33 - 50**	**1 - 66**	**1 - 100**	**66 - 100**
t-test		**		**		
Wilcox-test		***	*			*
KS-test		**			**	**

Notes: *** denotes statistical significance at <0.1%, ** denotes significance at <1%, and * at <5%.

7 Conclusions

In this study, I argue that the MBI is an important yet often overlooked feature of internet auctions. I conduct a field experiment to study the effects of the MBI on bidding strategies, seller revenue and entry in internet auctions. The institutional set up of the Finnish internet auction site Huuto.net 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 lowest possible level. The level corresponding to the eBay schedule seems to be a good choice. I also find that the number of actual bidders is decreasing in the MBI. Since my experiment reveals that the MBI is a relevant determinant of both of these outcomes, the effects of the MBI on bidder behavior and auction outcomes should be incorporated into further analyses of internet auctions.

I also discuss some potential theoretical explanations for the results of my experiment. This discussion is based on existing literature. The main candidates that can explain the positive effect of a non-zero MBI on seller revenue are truthful bidding and strategic reaction to the MBI under risk-aversion or budget constraints. I use a novel econometric test to distinguish between these theoretical explanations. I reject the truthful bidding hypothesis. This implies that these auctions cannot be modeled as second-price auctions. This observation challenges the validity of many of the previous studies on internet auctions.

In summary, I present a novel field experiment that is both internally and externally fairly valid and provides statistically significant and economically non-negligible results on the effects of the MBI on auction outcomes. Furthermore, I propose and use a test to distinguish between a naive 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 is not appropriate. However, this study does not allow an analysis of whether there should be more steps in the eBay schedule nor do we know if the schedule is appropriate when selling objects of different values than those analyzed here.

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