Abstract

A great deal of late bidding has been observed on internet auctions such as eBay, which employ a second price auction with a fixed deadline. Much less late bidding has been observed on internet auctions such as those run by Amazon, which employ similar auction rules, but use an ending rule that automatically extends the auction until at least ten minutes have passed without a bid. This paper reports an experiment that allows us to examine the effect of the different ending rules under controlled conditions, without the other differences between internet auction houses that prevent unambiguous interpretation of the field data. We find that the difference in auction ending rules is sufficient by itself to produce the differences observed in the field data. The experimental data also allow us to draw conclusions about the effect of auction design on efficiency, revenue, and the speed with which bidders learn to approximate equilibrium behavior.
I. Introduction

How to end an auction is a subject of active concern in the auction design literature. The concern is that late bidding hampers price discovery and efficiency.¹

Roth and Ockenfels (forthcoming) compare the timing of bids in eBay and Amazon second-price auctions on the internet whose rules were essentially identical at the time of their study except for the rule for ending the auction.² eBay auctions have a fixed deadline (a “hard close”), that is, they end at a scheduled time, most often after seven days. Amazon auctions, in contrast, have a similar scheduled end time, but are automatically extended if necessary, past the scheduled end time, until ten minutes have passed without any bid being submitted. Roth and Ockenfels observed that compared with Amazon auctions, bids in eBay auctions are much more concentrated near the end of the auction. A summary of the distribution of bids over time in their sample (of computers and antiques) auctions is presented in Table 1.

<table>
<thead>
<tr>
<th></th>
<th>share of all bidders’ last bids</th>
<th>share of all auctions’ last bids</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>eBay (%)</td>
<td>Amazon (%)</td>
</tr>
<tr>
<td>in last hour,</td>
<td>20 %</td>
<td>7 %</td>
</tr>
<tr>
<td>last 10 minutes</td>
<td>14 %</td>
<td>3 %</td>
</tr>
<tr>
<td>last 5 minutes</td>
<td>13 %</td>
<td>1 %</td>
</tr>
<tr>
<td>last 1 minute</td>
<td>8 %</td>
<td>0 %</td>
</tr>
<tr>
<td>last 10 seconds</td>
<td>2 %</td>
<td>0 %</td>
</tr>
</tbody>
</table>

Table 1. Frequencies of late bidding in eBay and Amazon (Roth and Ockenfels, forthcoming)³

¹ For example, the FCC auctions of radio spectrum licenses include “activity rules” intended to prevent bidders from concentrating their serious bids only near the end of the auction (see e.g. Milgrom, 2001, Roth, forthcoming).

² After the Roth and Ockenfels (forthcoming) data were collected, eBay changed some rules, which makes a field data comparison more difficult now. For example, since October 2000, eBay’s bid history for each auction includes all bids, but Amazon’s data continue to include only each bidder’s last bid. Also, eBay sellers now have the opportunity to modify the reservation price during the auction under certain circumstances.

³ The timing of bids in Amazon is defined with respect to a ‘hypothetical’ deadline that differs from the actual closing time if a bid comes in later than ten minutes before the initial end time. This hypothetical deadline is defined as the current actual deadline at the time of bidding under the assumption that the bid in hand and all subsequent bids were not submitted. Suppose, for example, one bid comes in one minute before the initial closing time and another bidder bids 8 minutes later. Then, the auction is extended by 17 minutes. The first bid therefore is submitted 18 minutes and the second bid 10 minutes before the actual
The left columns tabulate the last bids submitted by each bidder in an auction, while the right columns record the very last bid submitted in each auction. The table shows that more than two-thirds of the eBay auctions are still active an hour before the scheduled end time, as more bids have yet to come in. In contrast, an hour before the scheduled end of an Amazon auction, less than one quarter of the auctions in the sample are still active. In the last 10 minutes, only 11 percent of the Amazon auctions received bids (i.e. only 11 percent of the Amazon auctions were extended past the scheduled deadline), while more than half of the eBay auctions received bids in the last ten minutes.

Bids on eBay antique auctions are even more concentrated near the end than those on eBay computer auctions. Bid distributions on both kinds of eBay auctions are much later than those on either kind of Amazon auctions, and there was no significant difference between Amazon computer and antique auctions. Furthermore, more experienced bidders (as measured by their “feedback ratings”)\(^4\) are more likely to bid late on eBay, and less likely to bid late on Amazon.

Ockenfels and Roth (2001) demonstrate that there are multiple reasons why the difference in ending rules between eBay and Amazon might produce this difference in bidding behavior. They model a second price auction conducted over time in which early bids give other bidders time to respond, but can be submitted with certainty, while very late bids do not give other bidders time to respond, but have a chance that they will not be successfully transmitted.\(^5\) They show that in such an environment late bidding can arise as a rational response to many different causes. In both private value and common value auctions, and both in equilibrium and as best response to incremental bidders, the ending auction close. The bids show up in our data, however, as one and two minutes before the (hypothetical) deadline, respectively. See Ockenfels and Roth (2001) for a detailed description and statistical analysis of the data.

\(^4\) Ockenfels (forthcoming) describes eBay’s feedback mechanism along with some of its problems and merits.

\(^5\) Surveys of late bidders by Roth and Ockenfels (forthcoming) identified at least two sources of risk involved in late bidding. One was that bidders who plan to bid late sometimes find that they are unavailable at the end of the auction. The other involves bidders who are attempting to bid at the last moment but who do not succeed due to, e.g., erratic Internet traffic or connection times. In particular, more than 80 percent of the bidders who successfully bid at least once in the last minute of an eBay auction replied that it happened at least once to them that they started to make a bid, but the auction was closed before the bid was received. This risk is not restricted to bids placed by hand. The artificial bidding agent offered by esnipe.com, that automatically submits a predetermined bid a few seconds before the end of the eBay auction, cannot guarantee that the bids are actually placed. In fact, esnipe.com reports on the basis of
rules create incentives to bid late on eBay, in contrast to Amazon. The observation that the bidding behavior between the two auctions differs in the predicted way lends support to the hypothesis that these strategic incentives induced by the rule for ending the auction are the cause of the difference.

However, interpretation of the field data is complicated by the fact that there are other differences between eBay and Amazon than their ending rules. eBay has many more items for sale than Amazon, and many more bidders. Furthermore, buyers and sellers themselves decide in which auctions to participate, so there may be differences between the seller and buyer characteristics and the objects for sale on eBay and Amazon. Some combination of these uncontrolled differences between eBay and Amazon might in fact be the cause of the observed difference in bidding behavior, instead of the differences in rules.6

Moreover, the “feedback ratings” used by Ockenfels and Roth (2001) as proxies for experience are imperfect. They only reflect the number of completed transactions, but not auctions in which the bidder was not the high bidder. Also, more experienced buyers on eBay may not only have more experience with the strategic aspects of the auction, they may have other differences from new bidders, e.g. they may also have more expertise concerning the goods for sale.

While the field data suggest that strategic incentives cause late bidding on eBay, the data do not easily allow us to focus on how each of the multiple reasons for late bidding contribute to the differences in bidding behavior on eBay and Amazon. For instance, the fact that bids on eBay antique auctions are even more skewed towards the deadline than those in auctions of computers suggests that the information conveyed by bids may play a role in promoting late bids on eBay auctions for goods with common values.7 In auctions with common values, late bidding could result because bidders might change their own evaluation as a reaction to the information in others’ bids. Similarly, bidders might want

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6 In Roth and Ockenfels (forthcoming) we briefly discuss possible self selection effects and their potential impact on bidding behaviors in eBay and Amazon. Another uncontrolled reason for late bidding in the field is that a bidder who is interested in an item available simultaneously in multiple auctions may want to delay his decision in which auction to bid.

7 See Bajari and Hortaçsu (2000) and Ockenfels and Roth (2001) who have explored the incentives that bidders have to bid late in common value auctions.

more than 4200 bids per day, that on average 4.5 percent of esnipe's bids failed to be successfully transmitted in September 2000 (http://www.esnipe.com/stats.asp, 2000).
to bid late in order not to convey their information to others. However, the fact that the
difference between eBay and Amazon auctions is clear even for auctions of computers
seems to suggest that the different ending rules elicit different strategic incentives also in
private value auctions (although even computers might possess some common value
properties). Laboratory experiments will allow us to look at the difference in auction
closing rules while controlling away all other differences.

Here we report laboratory experiments on second-price auctions that differ only in
the rule for how the auctions ended. Subjects were randomly assigned to each auction
type, so there were no differences in bidder characteristics across auctions, and the
number of bidders per auction was kept constant. Each bidder in the experiment
participated in a sequence of auctions, allowing us to observe in detail how bidding
changes as bidders gain experience with the auction environment. The goods offered in
our auctions were artificial, purely private-value commodities (each bidder was given a
redemption value he would be paid in cash if he won the auction, and these values were
drawn independently from the values of other bidders).

We experimentally compare several kinds of auctions, to allow us to separate
different explanations of late bidding put forward by Ockenfels and Roth (2001). Finally,
since we control individual valuations, we can also compare the revenues resulting from
the different types of auctions (which could not be compared in field data involving
different commodities and different numbers of bidders), and the relative efficiency of
the different auctions (since in the lab we will know in each auction which bidder has the
highest value for the item auctioned).^8

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^8 This study is part of a broader effort to understand the role of timing in transactions. Others have noted
deadline effects in internet auctions (cf. Bajari and Hortacsu, 2000, Wilcox, 2000), and similar deadline
effects have been noted in studies of bargaining (cf. Roth, Murnighan, and Schoumaker, 1988, and
subsequent studies). Nonhuman animals have also been observed to change their behavior as a function of
temporal distance from the end of the experience. Rats and pigeons respond more vigorously as the
expected end of a fixed interval reinforcement schedule approaches (a pattern known as scalloping), even
when the increased behavior does not increase payoffs (Ferster and Skinner, 1957; Dews, 1969). Similarly,
people who monitor the time of a task become increasingly impatient toward its end (Ceci and
Bronfenbrenner, 1985), people use different strategies when games are framed as getting close to the end
(even when these are arbitrary break points; Coroson, 1996). Experiments have also been conducted to
better understand why transactions in some markets are forced earlier, rather than later (see Kagel and
Roth, 2000, and Haruvy, Roth, and Ünver, 2001, which are motivated by studies of timing in entry level
II. Experimental environment, a model and hypotheses

II.1 The auction games

The treatments include four auction types: sealed bid, Amazon, eBay.8, and eBay1 (the latter two treatments differ only in the probability that a “last minute” bid will be transmitted). There were exactly two competing bidders in each auction. Each bidder in each auction was assigned a private value independently drawn from a uniform distribution between $6 and $10. The winner of an auction received his private value minus the final price, and a loser received nothing for that auction. The final price was determined by the second price rule, that is, the bidder who submitted the highest bid won and paid (at most) a small increment ($0.25) above the highest bid of the opponent, or, if the opponent did not bid, the price was the minimum bid of $1. All auctions were run in discrete time, so that we can precisely define ‘bidding late’ without running into problems of continuous time decision making such as typing and server speed.

It will be easiest to describe the different auction conditions by first describing the eBay.8 treatment. It consists of two kinds of bidding stages, stage 1 (early) and stage 2 (late).

\textit{eBay.8}

Stage 1 is divided into discrete periods. In each period, each trader has an opportunity to make a bid (simultaneously). At the end of each period, the high bidder and current price (minimum increment over second highest bid) are displayed to all. Stage 1 ends (only) after a period at which no player makes a bid.

Stage 2 of the eBay.8 auctions consists of a single period. The bidders have the opportunity to submit one (last) bid; it has probability \( p = 0.8 \) of being successfully transmitted.

\textit{eBay1}

\footnote{The price never exceeds the highest submitted bid: If the difference between the highest and the second highest submitted bid is smaller than the minimum increment, the price paid is equal to the highest bid. If both bidders submitted the highest bid, the bidder who submitted his bid first is the high bidder at a price equal to the reservation price. If identical bids are submitted simultaneously, one bidder is randomly chosen to be the high bidder. Also, a bidder can bid against himself without penalty if he is the current high bidder, because it raises his proxy bid without raising his bid.}
In the eBay condition, the probability that a bid made in stage 2 will be transmitted successfully is $p = 1$, i.e. stage 2 bids are transmitted with certainty. So in this condition, stage 2 is a conventional sealed bid second price auction.

Amazon

In the Amazon condition, stage 1 is followed by stage 2, as in the eBay conditions, but after a successfully submitted stage 2 bid, stage 1 starts again (and is followed by stage 2 again, etc.). The probability that a stage 2 bid will be successfully transmitted is $p = 0.8$. Thus in the Amazon condition, the risk of bidding late is the same as in the eBay condition, but a successful stage 2 bid causes the auction to be extended.

Sealed bid

In the sealed bid condition, the auction begins with stage 2 (with $p = 1$), and ends immediately after, so that each bidder has the opportunity to submit only a single bid, and must do so without knowing the bids of the other bidder. While the sealed bid auction obviously cannot yield any data on the timing of bids, it provides a benchmark against which the revenues in different auctions can be measured.

As in the internet counterparts, bidders in the eBay and Amazon conditions were always informed about current prices as the auction progressed, but the magnitude of the high bidder’s current bid was never revealed to the low bidder. Also, each bid had to meet or exceed the current minimum acceptable bid, either $1$ if no bid was submitted yet or the smallest increment ($0.25$) over the current price and one’s own previously submitted bids (if any). As a consequence, players could make only a finite number of potentially profitable bids.

Our experimental games reproduce the pricing and feedback policies employed by Amazon and eBay on the internet, and capture the essential differences in ending rules. First, there is sufficient time to submit bids and respond to others’ bids early in the experimental conditions (that is, in stage 1). Second, there is a hard close in the eBay

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10 In a situation in which the difference between the (current) price and the low bidder’s (current) bid is smaller than the minimum increment, however, the low bidder can infer that the price equals the high bidder’s (current) bid.
treatments that does not allow bidders to respond to very late (that is, stage 2) bids. The risk involved in submitting late bids in the eBay.8 condition reflects the fact that late bids run the risk of being lost in internet auctions (see Section I). eBay1, on the other hand, allows us to study the impact of this risk and therefore to separate different contributory causes of late bidding (see below). Third, successfully submitted late bids in the experimental Amazon condition automatically extend the auction (that is, move the auction back to stage 1), giving other bidders sufficient time to respond to all bids, while at the same time late bidding on Amazon faces the same risk as late bidding in eBay.8. Finally, as in eBay and Amazon auctions on the internet, the second price rule allowed a bidder in the experiments to have his bid used to bid for him by proxy. That is, a bidder could submit a bid early in the auction and have the resulting price register as the minimum increment above the second highest bid. As the other bidder submits subsequent bids, the price rises to the minimum increment over the other player’s bid until the bid is exceeded. Hence, as in the internet auction houses, an early bid that is higher than any other submitted during the auction will win the auction and pay only the minimum increment above the second highest submitted bid. Table 2 summarizes our experimental auctions.

<table>
<thead>
<tr>
<th>Auction type</th>
<th>Number of stage 1 periods</th>
<th>Number of stage 2 periods</th>
<th>Probability of stage 2 period to register</th>
</tr>
</thead>
<tbody>
<tr>
<td>sealed bid</td>
<td>0</td>
<td>1</td>
<td>100%</td>
</tr>
<tr>
<td>eBay1</td>
<td>endogenous</td>
<td>1</td>
<td>100%</td>
</tr>
<tr>
<td>eBay.8</td>
<td>endogenous</td>
<td>1</td>
<td>80%</td>
</tr>
<tr>
<td>Amazon</td>
<td>endogenous</td>
<td>endogenous</td>
<td>80%</td>
</tr>
</tbody>
</table>

**Table 2.** Experimental treatments

**II. 2 Experimental procedure**

The study was conducted with 30 groups of six participants each (8 groups each in Amazon, eBay.8, and eBay1, and 6 in sealed bid). Within each group we randomly rematched pairs of two bidders for a total of 20 auctions per bidder. A matching error in
trial 19 rendered the data in all eBay auctions numbers 19 and 20 incomparable.\textsuperscript{11} Consequently, we report here only the results for trials 1-18 of all conditions in order to simplify the comparisons. We note, however, that there was no sign of an end game effect in any session, and that the conclusions we draw are invariant to whether we include auctions 19 and 20 in the sessions in which no problems occurred.

In each treatment, all rules were publicly explained with the help of example auctions (all written instructions can be found in Appendix B). Auctions were run on networked computers,\textsuperscript{12} and each participant could see on his screen both private and public information, updated after each period. The private information included the bidder’s own private value, his own highest submitted bid so far, and a list of the auctions won earlier along with corresponding profits. The public information, known to both bidders, included the auction number (between 1 and 20), the period number within the current auction, the period type (stage 1 or stage 2), the current price (at most an increment above second highest submitted bid), and the high bidder’s identification number. Participants were paid their cumulative earnings in the auctions plus a show-up fee of $5 plus an additional $5 if they were at least 5 minutes early.

\textbf{II.3 The theory of a simplified experimental environment}

A theoretical treatment of our experimental environment is feasible if one abstracts away from the fact that the price exceeds the second highest submitted proxy bid by (at most) one minimum increment. Including this price increment would considerably complicate the theoretical analysis because it may create incentives for the bidders to try to save (up to) one increment (25 cents in our experiments) by bidding just above the opponent’s highest bid.\textsuperscript{13} In particular, the price increment destroys the advantageous properties of second price auctions such as the existence of dominant truth revealing strategies and efficiency even in the simplest second price auction format, the Vickrey auction, and even if the price increment is arbitrarily small (say, not larger than the smallest money unit). Even worse, if money is modeled continuously, equilibria

\textsuperscript{11} Some of those auctions had 3 bidders, while others had only 1.
\textsuperscript{12} We used the z-Tree software toolbox by Fischbacher (1998).
typically do not exist in the presence of price increments (see Ockenfels and Roth, 2001). Since we believe that it is implausible that the small price increment drives the bidding behavior in important ways in our lab study or in the field, and to make the auction formats theoretically tractable, we abstract away from the price increment requirement in the following analyses. (Nevertheless, we will partly discuss how the price increment may affect our results as we go along.) All other details of the auction formats, including the minimum bid increment requirement,\textsuperscript{14} are taken into account.

It is well known that the sealed bid second price auction has a unique equilibrium in (weakly) dominant strategies in which all bidders bid their private values (Vickrey, 1961). Neglecting the price increment, this is also the case in our experimental sealed bid treatment.\textsuperscript{15} The situation on eBay and Amazon is, however, more complicated, because in these open auction formats a bidder does not have any dominant strategy,\textsuperscript{16} which opens the door to multiple equilibria. However, it is straightforward to see that simple truth-revealing equilibria also exist on Amazon and eBay. In particular, it is an equilibrium on Amazon, eBay.8 and eBay1 for bidders to bid their values in period 1 of stage 1 and then not to bid anymore until the auction is over. This is the kind of equilibrium behavior eBay promotes when it explains why it recommends “bidding the absolute maximum that one is willing to pay for an item early in the auction” on its

\textsuperscript{13} Recall that if the difference between the winning and the losing bid is smaller than the minimum increment, the price paid is equal to the highest bid. So the winner can save up to the increment by bidding slightly above the losing bid.

\textsuperscript{14} That is, analogous to eBay and Amazon each new bid must be a minimum increment above the current price, but unlike the internet auction counterparts we assume here that the current price always exactly equals the second highest submitted bid.

\textsuperscript{15} Neglecting the price increments in the sealed bid case is not overly restrictive in the following sense: Since a winner can never advantageously affect the price in case of winning by bidding higher than his value, and since a winner can never push the price down by more than one increment by underbidding, bidding one’s true value may be called an “s-dominant strategy”, where s is the (maximal) price increment. That is, bidding one’s true value is a strategy that always yields a payoff not more than the price increment below the supremum achievable by any other strategy, regardless of the distribution of values, there may be equilibria (if they exist) in which bidders bid their values, even in the presence of price increments, though not in dominant strategies (see Ockenfels and Roth, 2001).

\textsuperscript{16} That is, a bidder i has no strategy that is a best reply to every strategy that could be chosen by the other bidder. Briefly, if the other bidder j plans to bid $100 if and only if bidder i bids in stage 1, then i’s best reply is to bid only in stage 2. But if e.g. bidder j’s strategy is not to bid at all, then every best reply of bidder i will involve bidding in stage 1, since a bid only in stage 2 has a positive probability of being lost. So no best reply to j’s second strategy is also a best reply to the first strategy (cf. Ockenfels and Roth, 2001). As we will explain later, however, there are subgames in our eBay auctions in which bidding true values are (weakly) dominant strategies.
auction sites (http://pages.ebay.com/aw/notabuse.html, 1999). But the field data raises the question, whether there are also robust equilibria in which bidders want to bid in stage 2 on eBay and Amazon, in particular when there is a positive probability that the bid is lost.

The propositions in this section show how this question must be answered differently for the eBay and Amazon conditions, because of the differences in their auction ending rules. Because the field data also indicate a great deal of persistent non-equilibrium play, in particular incremental bidding (Ockenfels and Roth, 2001), and because the subjects in the early rounds of the experiment will be inexperienced, we also consider how the different auction rules change the best response to incremental bidding behavior.

**Proposition 1 [eBay1]:** In the eBay1 environment, both bidding private values in stage 1 and bidding private values in stage 2 may occur in subgame perfect equilibria in undominated strategies.

Applying standard second price auction arguments, it is easy to see that mutually bidding true values in the first period constitutes an equilibrium, and that mutually bidding true values in stage 2 and not bidding in stage 1 constitutes an equilibrium (though recall that unlike in the sealed bid condition there are no weakly dominated strategies). Furthermore, it is also an equilibrium if one of the bidders bids his value early and the other bids his value late and does not bid early. That is, in those equilibria in which each bidder submits only one bid, bidders are indifferent with respect to the timing of bids, and so the predicted outcome will look very much like the outcome in the sealed bid condition.

As a remark, observe that there may be also equilibrium strategies that call for multiple bidding. Here, the minimum bid increment constraint may prevent a bidder from submitting his value and the bidder with the higher value from winning. However, even in these cases the outcome will not differ much from what we expect to see in sealed bid auctions, because each bidder will submit a bid ‘close’ to his value. To see why, note that in any equilibrium in undominated strategies, none of the bidders will bid more than his true value at any time. Furthermore, any strategy in which a bidder fails to
bid his value in stage 2, whenever possible, is a weakly dominated strategy. There are two scenarios in which bidding one’s value in stage 2 is not possible. First, if the bidder has already bid his value before stage 2, and second if the current price in stage 2 is less than a minimum bid increment below the value and the opponent is the high bidder. Only in the latter case will the final bid deviate from the value. But the deviation is bounded, because due to the second price rule the bidder must have submitted a bid earlier in the auction that was not more than 25 cents (50 cents if one considers the price increment) below his private value. In this sense, all final bids are predicted to be ‘close’ to values, regardless of the stage 1 history.

**Proposition 2** [eBay.8]: In the eBay.8 experimental environment, there are multiple subgame perfect equilibria in undominated strategies, including one in which no bids are placed until stage 2, at which time bidders bid their private values.

Proof: Similarly to eBay1, mutually bidding true values in the first period is also an equilibrium on eBay.8. But given the analysis above it may come as a surprise that there are also equilibria on eBay.8 in which both bidders submit values in stage 2 and do not bid in stage 1, even though stage 2 bidding involves a risk that the bid is lost.

Extending the simple example of Ockenfels and Roth (2001)\(^{17}\) to our experimental environment, consider the following late bidding strategies, which we will show constitute an equilibrium for risk neutral bidders on eBay.8. On the equilibrium path, each bidder \(i\)’s ‘sniping strategy’ is not to bid until stage 2 and then to bid his value, unless the other bidder deviates from this strategy by bidding in stage 1. Off the equilibrium path, if player \(j\) places a bid in period 1 of stage 1, then player \(i\) bids his true value in period 2 of stage 1. That is, each player’s strategy is to do nothing until stage 2, unless the other bidder makes a stage 1-bid, that would start a price war at which the equilibrium calls for a player to respond by bidding his true value in the subsequent period.

\(^{17}\) In their example, all bidders had the same private value and this was common knowledge among all players.
Suppose for the moment that bidder 1’s value is $10, the highest possible value in our experiment, and bidder 2’s value is $6, the smallest possible value in our experiment. Let \( p = 0.8 \) be the probability of a successfully transmitted bid at stage 2, as on eBay. If bidders follow the strategy described above, bidder 1 earns $9 (= value – minimum bid) if his bid at stage 2 is successfully transmitted and the other bidder’s bid is lost, which happens with probability 0.16 (= \( p(1 - p) \)), and he earns $4 (= value – opponent’s value) if both stage 2-bids are successfully transmitted, which happens with probability 0.64 (= \( pp \)). If bidder 1’s bid is lost at stage 2, which happens with probability 0.2 (= 1 – \( p \)), his payoff is zero yielding a total expected payoff of $4 for bidder 1. Similarly, bidder 2 earns $5 (= value – minimum bid) if his stage 2-bid is successfully transmitted and the opponent’s stage 2-bid is lost, which happens with probability 0.16, and zero else, yielding a total expected payoff of $0.8 for bidder 2.

Unilateral deviation from the sniping strategy is not profitable for either bidder. First, in the subgame starting in stage 2, any other bid than the true value is weakly dominated. (Recall that stage 2 is a second price sealed bid auction.) Second, in stage 1, any bid triggers an ‘early’ price war in which each player bids his true value in stage 1 (which constitutes a Nash equilibrium in our model). The price war yields a payoff of $4 ($10 – $6) for bidder 1 and zero payoffs for bidder 2, which is equal to the corresponding sniping payoffs for bidder 1, and which is smaller than the corresponding sniping payoff for bidder 2. This proves that the sniping strategy is a best reply for bidders with values $10 and $6.

In fact, the sniping strategies constitute an equilibrium for any realizations of the values. To see why, observe that for a bidder 1 with value \( v_1 > v_2 \) the expected profit from mutual sniping is \( 0.16*(v_1 - $1) + 0.64*(v_1 - v_2) \), while the expected payoff after an early bidding war (that is, after mutually bidding true values in stage 1) is \( v_1 - v_2 \). Inspection shows that the difference of these payoffs \( (= - 0.2v_1 + 0.36v_2 - 0.16) \), is decreasing in \( v_1 \) and increasing in \( v_2 \). In the last paragraph, we have shown that if \( v_1 \) takes the maximal value ($10) and \( v_2 \) takes the minimal value ($6), the sniping strategies constitute an equilibrium. Hence, all other combinations of private values make sniping

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\(^{18}\) The payoff comparisons yield even stronger conclusions in favor of the sniping strategy if we took the price increment requirement into account.
even more profitable for a bidder 1 with $v_1 > v_2$. Since the sniping strategies always yield a higher payoff for the bidder with the lower value compared to an early bidding war, the sniping strategies constitute an equilibrium for all combinations of private values.

The intuition behind last-minute bidding at equilibrium on eBay is that there is an incentive to avoid a bidding war that raises the expected final price when there is still time for other bidders to react. Mutual delay until stage 2 can keep the final price down and therefore raise the expected profit of both bidders, because of the positive probability that another bidder’s stage 2 bid will not be successfully transmitted on eBay. On Amazon, on the other hand, there is no way to delay one’s bid until the opponent cannot react, because there is always time to respond to a successfully submitted bid. That is, the Amazon ending rule removes the advantage but not the risk of sniping, so that subgame perfect equilibrium bidding on Amazon does not involve stage 2 bids. The proof assumes, however, a ‘willingness to bid’ assumption that implies that a bidder who earns 0 prefers to do this by winning the auction. One can think of this assumption as a tie breaker in situations when bidders are indifferent between bidding or not.

*Proposition 3 [Amazon]:* Assuming a willingness to bid, there are no stage 2-bids in Amazon at a subgame perfect equilibrium in undominated strategies.

**Proof.** We extend the simple example of Ockenfels and Roth (2001) to our experimental environment. At a subgame perfect equilibrium in undominated strategies:

1. No bidder ever bids above his value: Any strategy that calls for bidder $j$ to bid above $v_j$ in any period $t$ is dominated by the otherwise identical strategy in which $j$ bids at most $v_j$ at period $t$.

2. There is a finite number $t^*$ such that the auction receives its last bids in period $t^*$, because proxy bids must rise by at least 25 cents with each new submission and

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19 The ‘willingness to bid’ assumption would not alter our eBay proposition, but it would break the tie in favor of bidding early on eBay, because analogously to the internet counterparts, earlier bids in our experiments take precedence.

20 As in the eBay case, their example is characterized by identical private values.
because no bidder will ever submit a reservation price greater than $v_{\text{max}} = 10$. If the auction gets to this period, there is only room for the price to rise by no more than 25 cents (50 cents if one considers the price increment).

3. In principle, the last period $t^*$ with bidding activity may either be a stage 1- or a stage 2-period. However, the bidder who at $t^*$ is not the current high bidder and who has a value greater by 25 cents than the current price will – and by our experimental design can – make sure that $t^*$ is a stage 1-period so that his last bid is transmitted with certainty (recall that a stage 2-period can only be reached if no bid is submitted in the previous period). Here, the willingness to bid comes into play, because it rules out possible indifference between bidding and not. Since no bidder is indifferent between casting the winning bid and not, any strategy profile that caused a player to bid at a stage 2-period would have a lower expected payoff (because $p < 1$) than a strategy at which he bid at stage 1, when bids are submitted with certainty. And, because this will be the last period with bids in the auction, the standard Vickrey second-price private value argument implies that a bid of less than the true value would constitute part of a dominated strategy: it could only cause some profitable opportunities to be missed.

4. Inductive step. Suppose at some period $t$, it is known that at the next period the bidders who is not the current high bidder and who has a value greater by 25 cents than the current price will place bids in the amount of their values with certainty. Then all bidders will bid their true values in a stage 1-period. Since a price war will result if the auction is extended by a successful bid at a stage 2-period, any strategy profile that calls for a bidder who is not already the high bidder to bid at stage 2 is not part of an equilibrium, since that bidder gets a higher expected return by bidding his true value at a stage 1-period. As a result, there are no stage 2-bids in any subgame perfect equilibrium.

There are more factors that may affect the timing of bids. Ockenfels and Roth (2001) observe that many bidders on eBay bid incrementally. An incremental bidder

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21 See also the examples of incremental bidding on eBay by Ockenfels and Roth (forthcoming).
does not use eBay’s proxy bidding agent but starts with a rather low bid and is then prepared to raise his bid whenever he is outbid. Bidding late may be a best reply to incremental bidding, because bidding very near the deadline of the auction would not give the incremental bidder sufficient time to respond to being outbid. In particular, by bidding in stage 2 in our eBay treatments, bidder 1 might win the auction against bidder 2, the incremental bidder, even though the incremental bidder's private value exceeds bidder 1’s private value. In the field, there are a couple of reasons for why bidders may want to submit multiple bids, including that bidders sometimes can get information from others’ bids that causes them to revise their willingness to pay in auctions with interdependent values, and the endowment effect implying that a bidder’s maximum willingness to pay is increasing over time. None of these explanations is valid in our experimental environment, because values are exogenously induced and independent.

However, incremental bidding might also be caused by naïve, inexperienced bidders, who may be present both in the field and in our lab, and who mistakenly treat the eBay auctions like English first price auctions in which the high bidder pays his maximum bid. (In fact, the field evidence in Ockenfels and Roth (2001) suggests that multiple bidding is negatively correlated with experience as measured by the feedback rating.) Therefore, we will in the following restrict ourselves to the simplest, naïve form of incremental bidding defined as a strategy that calls for bidding in minimum increments until the high bidder status is reached, but not more than the private value.

**Proposition 4** [Incremental bidding]: The gain from bidding in stage 2 against an incremental bidder is high in eBay1, smaller in eBay.8, and zero in Amazon.

Proof: Let us start with eBay1 and suppose bidder $j$ knows that he is matched with an incremental bidder $i$. If $j$ refrains from bidding early and bids his value in stage 2, he will win the auction for sure at a price of $1 (\$1.25 if we consider the price increment requirement), because $i$ bids $1$ in the first period (which is the smallest bid sufficient to reach the high bidder status) and then never again, since he only realizes that he was outbid in stage 2 when the auction is over. On the other hand, each bid by bidder $j$ in
stage 1 increases the final price to at least $1.25. Consequently, bidding late is always a best response against an incremental bidder in eBay1.

The eBay.8 case is more complicated since late bids get lost with positive probability which creates a cost of sniping. Suppose bidder \( j \) with value \( v_j \) knows that he is facing an incremental bidder \( i \). If \( j \) bids his value in stage 1, his profits are positive if and only if \( v_j \geq v_i \), where \( v_i \) denotes the incremental bidder’s value. The expected payoff from this strategy is $1. If, on the other hand, bidder \( j \) bids late, he wins with probability 0.8 at a price of $1. Inspection shows that it is always (that is, for all values \( v_j \)) advantageous not to get involved in an early price war with an incremental bidder.\(^{22}\) However, the incentive to refrain from bidding early is smaller than on eBay1 since the risk of late bidding reduces the expected benefit from waiting until stage 2.\(^{23}\)

The Amazon case is trivial. Any late bid either extends the auction so that an incremental bidder can respond with probability one, or it is lost. An early bid also extends the auction so that an incremental bidder can respond with probability one, but it is transmitted with certainty.

**II.4 Hypotheses**

The experimental data will allow us to address the following hypotheses, partly derived from our simplified model above and partly derived from our field observations (Roth and Ockenfels, forthcoming).

**Hypothesis 1 [Late bidding on eBay.8 and Amazon]**

Comparing the eBay.8 condition with the Amazon condition (which has the same stage 2 probability of transmission, \( p = 0.8 \)) will allow us to test the hypothesis that the fixed-deadline auction closing rule elicits more late bidding (stage 2-bidding) than the automatic-extension closing rule.

\(^{22}\) This holds also if we consider the price increment requirement.

\(^{23}\) A more complete model would incorporate the difficulty to identify incremental bidders. Suppose bidder \( i \) submitted a bid in the first period, while bidder \( j \) did not bid. Then bidder \( j \) does not know whether \( i \) is an incremental bidder and bid $1, or whether he is a rational bidder who bid his true value (which is part of an equilibrium strategy). But the higher the (unobservable) bid amount of bidder \( i \), the smaller the benefits from bidding in stage 2 for bidder \( j \). For our analysis of the behavior in the lab, it is however sufficient to know that if incremental bidders exist the incentive to bid late is higher on eBay1 than on eBay.8. Therefore we refrain from devising a more complicated model here.
Hypothesis 2 [Late bidding on eBay.8 and eBay1]
Comparing the eBay.8 and the eBay1 conditions will further allow us to assess the contributions to late bidding we observe in these fixed-deadline auctions from (a) implicit collusion by all bidders to avoid price wars, or (b) a best response by sophisticated bidders to incremental bidding by others. As elaborated above, if sniping is primarily occurring because of implicit collusion to keep prices down, we expect to see more stage 2 bids on eBay.8 than on eBay1, because the effect of late bidding on prices comes from the positive probability that the bid is lost. If, on the other hand, sniping is a reaction against incremental bidders, we expect to see the opposite, because a positive probability of a bid loss in this case reduces the expected benefit from sniping.

Hypothesis 3 [All final bids are bounded by values]
All bids that exceed the private value are (weakly) dominated, regardless of the auction format and regardless of whether we consider the price increment or not. So we expect bids to be bounded by values. Taking the price increment into account, also bids between value and value minus price increment (25 cents) are weakly dominated, because if the opponent j bids more than $v_i - 25$ cents, the price will be at least $v_i$ so that bidder i’s payoff cannot exceed zero. But by bidding $v_i - 25$ cents bidder i can save up to 25 cents if j’s bid is between $v_i - 50$ cents and $v_i - 25$ cents.

Hypothesis 4 [Amount of final bids]
In all treatments with a definitely final period in stage 2 (sealed bid, eBay.8 and eBay1), there is an equilibrium in (weakly) dominant strategies of the subgame starting in stage 2, in which all bidders bid their private values if possible. As a result, final bids of experienced bidders should be ‘close’ to private values (that is, each final bid is at most 25 cents, or 50 cents if one considers the price increment, below the respective private value) in these three conditions. On Amazon, on the other hand, there is no subgame in which bidding (close to) true value is a weakly dominant strategy. Thus, there could be more bids on Amazon that are substantially below true value than in the other treatments.
We can say more if we hypothesize that bidders bid incrementally in the sense that a bidder with a private value greater than an increment above the current price increases his bid with probability $1$. Incremental bidders will raise the price until the lower value (or, due to the minimum bid increment constraint, an amount ‘close’ to the lower value) is reached. At this point, even when the price is below the high bidder’s value, the high bidder has no reason to increase his bid. So, there are two consequences of incremental bidding. First, final prices will be ‘close’ to lower values, similar to the other treatments (see Hypothesis 5). Second, since incremental bidding can easily be exploited in our eBay formats (see Proposition 4) but not on Amazon, we expect bidders on Amazon to learn more slowly to bid close to values compared to the eBay auction formats (Hypothesis 6).

Hypothesis 5 [Revenue and efficiency]
Revenue and efficiency depend on both the timing and the amount of bids. In particular, assuming that the Hypotheses 1 and 4 are confirmed, the second highest submitted bids do not differ across Amazon and eBay, so that revenue and efficiency will be correspondingly lower on eBay than on Amazon, because stage 2-bids are lost with positive probability.

Hypothesis 6 [Experience and bid amounts]
Comparing final bids to private values in early and late auctions will also allow us to investigate the general hypothesis observed in many experiments that bidders will adapt to the strategic features of the game slowly over time (see e.g. Erev and Roth, 1995, Feltovich, 2000). The general learning hypothesis is that bidders will submit final bids that are closer to their private values in the later auctions than in the earlier auctions, though we expect that on average even experienced bidders’ final bids in Amazon stay below the corresponding eBay bids (because incremental bidders in eBay will learn that they are sometimes outbid in stage 2 at prices below their values, while incremental bidders in Amazon are never outbid at prices below their values; see Hypothesis 4 and 5).

24 Incremental bidding is a special case of what has been sometimes called ‘straightforward bidding’ (Milgrom, 2001).
Also, since learning is possible even within an auction on eBay and Amazon (a bidder who is outbid early has enough time to reconsider and adjust his bidding strategy in the course of the same auction), this should speed up the learning process in the dynamic auctions relative to the sealed bid auctions.

*Hypothesis 7 [Experience, bid timing and multiple bidding]*
Comparing the early and late auctions in the eBay and Amazon conditions will allow us to investigate the hypothesis, formulated from the field data, that more experience will cause more late bidding in the eBay conditions, and less late bidding in the Amazon condition (we will look both at the frequency of early and late bidding, and the magnitude of early and late bids), as well as more multiple bidding early in the auction both on eBay and on Amazon.

### III. Experimental Results

#### III.1 Frequencies of late and early bidding

As in the field data from the internet, there is more late bidding in the fixed-deadline (eBay) conditions than in the automatic extension (Amazon) condition. Furthermore, as bidders gain experience, they are more likely to bid late in the eBay conditions, and less likely to bid late in the Amazon condition. This can be seen by looking at Figure 1, which shows the number of bids per bidder in each stage of the eBay and Amazon conditions, over time (in absolute numbers for stage 1 bids and relative numbers in stage 2 bids).

Figure 1a graphs the amount of sniping by recording the percentage of bidders who place a bid in stage 2. Since at most one stage 2 bid is recorded per bidder in each auction, these numbers can also be interpreted as the probability that a bidder will make a stage 2 bid. Each of the three multi-period auction conditions starts with about 40% of bidders submitting stage 2 bids, but by trial 18 Amazon has only about 10 percent, eBay.8 has 50 percent, and eBay1 has 80 percent late bidders. We can reject the null-hypothesis that the overall numbers of stage 2 bids within each of the three auction types are from the same population (a Kruskal Wallis \(H\)-test based on the 8 independent
sessions for each auction type yields $p = 0.000$). Overall, there are weakly significantly more stage 2 bids in eBay1 than in eBay.8 (two-sided Mann Whitney $U$-test, $p = 0.058$), and there are significantly more stage 2 bids in each of the eBay auction types, than in Amazon ($p = 0.000$, for each comparison separately). A probit analysis in Appendix A.1 confirms the time trends are highly significant: in both eBay conditions the trend is towards more late bidding as bidders gain experience, while in Amazon experienced bidders submit fewer late bids.

Figure 1b graphs the number of stage 1 bids per bidder over time. Comparison of Figures 1a and Figure 1b shows that the rise in stage 2 bidding in the two eBay conditions is not part of a general increase in bidding activity, but just the opposite: the number of stage 1 bids is strongly decreasing in all three multi-period auctions.

Overall, the average number of submitted bids in stage 1 and stage 2 (including lost stage 2 bids) per bidder and auction in Amazon, eBay.8 and eBay1 is 3.2, decreasing from 4.5 in trial 1 to 2.5 in trial 18. There are no statistically detectable differences in the bid numbers between these auction games (Kruskal Wallis $H$-test, $p = 0.125$).

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25 Restricting the analysis to experienced bidders (trials 10-18), the difference becomes significant at the 1 percent level.

26 The OLS-regression in Appendix A.2 confirm that the number of stage 1-bids is significantly decreasing with experience – particularly for the two eBay conditions. The statistical analysis also reveals that the number of subject’s stage 1-bids is increasing in the number of the opponent’s stage 1-bids, implying that we see bidding wars in stage 1. These observations correspond to Ockenfels and Roth’s (2001) field findings that the number of bids submitted by a bidder to an eBay auction is decreasing in experience as measured by his feedback number, and increasing in the number of bids submitted by other bidders.
(a) Percentage of bidders who place stage 2-bids (in Amazon: first stage 2), over time (by auction #)

(b) Number of stage 1 bids per bidder, over time (by auction #)

Figure 1. Number of bids per bidder and auction over time

\textsuperscript{27} In Amazon, there may be more than one stage 2. In Figure 1 we included only the first stage 2 that determines whether the auction is extended at all. We included also stage 2 bids that are lost, which
Figure 2. Share of bids submitted by current high bidder

Figure 2 shows that stage 1-bids are rarely placed by the current high bidder; early bids are mostly made in incremental bidding wars, when the low bidder raises his bid in an apparent attempt to gain the high bidder status. On the other hand, stage 2-bids in the eBay conditions are made almost equally often by the current high bidder and the current low bidder. That is, late bids on eBay appear to be planned by bidders regardless of their status at the end of stage 1. While there is no difference across auction types with respect to stage 1 (Kruskal Wallis $H$ test, $p = 0.977$), there are significant differences with respect to stage 2 ($p = 0.000$). In particular, there are more high bidders submitting stage 2 bids in both eBay types, respectively, than in Amazon (two-sided Mann-Whitney $U$ test, $p = 0.001$ for each comparison separately), and there are more snipes by high bidders in eBay1 than in eBay.8 ($p = 0.045$). We turn next to examine the magnitude of early and late bids.

III.2 The size of late and early bids, and price discovery

 happened with probability 0.8 in eBay.8 and Amazon. Figure 1a includes lines that show the results of simple OLS-regressions.
Figures 3a-c summarize by how much bids exceed the current minimum bid required, which is either the current price plus the minimum increment of $0.25, or, before the first bid, the reservation price of $1. (For the Amazon auctions, we graph all stage 2 bids, not only from the first stage 2). The graphs show the average increase of bids, conditional on bids being placed, so we have to interpret them together with the information in Figure 1, which shows the numbers of bids over time.
Figure 3. Average increase of bids (conditioned on bidding) over current minimum bid

Figure 3a shows that the average size of the bid increments placed in stage 1 on Amazon clearly grows over time, while the size of bid increments in stage 2 does not reveal a strong time trend. This is consistent with our earlier observation that the numbers of both stage 1- and stage 2-bids in Amazon auctions decline over time. As bidders place fewer bids in stage 1, and hardly any bids in stage 2 (reflected by the large variances in Figure 3a), they bid in bigger increments in stage 1.

The situation is almost the opposite in each of the two eBay conditions. Figures 3b and 3c show that, while the average stage 1-bid increment stays relatively constant over time – slightly increasing in eBay.8 and slightly decreasing in eBay1 – the average stage 2-bid increment strongly grows in each eBay condition.28 Moreover, these records tend to understate the difference between stage 1- and stage 2-bids over time because as Figure 1 showed, in both eBay conditions the stage 2-bid increments are getting larger at the same time as stage 2-bids are becoming more frequent, and stage 1-bids becoming less frequent.

As a result of these dynamics, the average stage 2-increment is about twice the size of stage 1-increments on eBay.8, and four times the size on eBay1, while it is only about

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28 Straightforward OLS regressions confirm all statements with respect to the time trends seen in Figure 3 at very high significance levels.
half the size of stage 1-increments on Amazon. Mann-Whitney U tests based on the 8 independent sessions per auction type confirm these observations. There are no statistical differences between average bid increases across auction types with respect to stage 1, but the stage 2-increase is significantly larger in each of the eBay conditions than on Amazon ($p = 0.001$ for each comparison separately), and significantly larger on eBay1 than on eBay.8 ($p = 0.021$). Also, while in Amazon stage 1 increases are significantly larger than stage 2 increases ($p = 0.012$), the opposite is true in each of the eBay conditions ($p = 0.059$ and 0.002 for eBay.8 and eBay1, respectively). That is, on eBay most of the ‘serious’ bidding is done in stage 2 while on Amazon most of the serious bidding is done in stage 1.

![Figure 4](image)

**Figure 4.** Final stage 1-price (in Amazon: first stage 1) as percentage of final price

Figure 4 displays price discovery, that is, how well the price in the early part of the auction (at the end of stage 1 in both eBay conditions and at the end of the first stage 1 in Amazon) predicts the final price. Figure 4 shows that stage 1 prices are an increasingly good predictor for final prices on Amazon (after bidders gained experience, the stage 1-price reached more than 90 percent of the final price), whereas the opposite is true on
eBay.8 (about 70 percent) and eBay1 (less than 50 percent). This reflects the differential bid magnitude in stage 1 and stage 2 across the different auction conditions as shown in Figure 3.

III.3 Adaptative behavior

![Figure 5. Median of final bids (including lost stage 2-bids) over value](image)

Figure 5 shows that in all treatments the median of relative bids is increasing over time. But learning is not the same across the different conditions. For inexperienced bidding, final bids in the sealed bid condition are substantially lower than final bids in the other conditions (up to trial 7). It appears that in line with Hypothesis 7 learning in the sealed bid auctions takes place across auctions, while learning in the dynamic auctions also takes place within auctions. For example, a bidder who imagines that he can win with a low bid is not corrected as quickly as in the auctions conducted over time, in which he can revise his bid as soon as he is outbid.

29 The Spearman rank correlation coefficient between final (first) stage 1 price and final price is highest in Amazon (0.947), lower in eBay.8 (0.570), and lowest in eBay1 (0.270). All correlations are significant at $p = 0.000$.

30 We used medians because there are a few outliers in one of the eight Amazon sessions between round 6 and 10 yielding very high average bids in these rounds.
On the other hand, for experienced bidding, Figure 5 shows that while the median of final bids in the Amazon condition never reaches 100 percent, the median final bid in all other auction treatments converges to 100 percent. This is in line with our Hypotheses 4 and 5 that suggest that in the final round of sealed bid, eBay.8 and eBay1 the dominance criterion demands a bid close to the private value, whereas the dominance criterion in Amazon only excludes bids above private values but allows bids below private values. In no treatment does the median ever exceed 100 percent (so that our Hypothesis 3 is confirmed) of bidders’ personal values, though, as we will see in the next paragraph, individual bidding may substantially deviate from these predictions.
Figure 6. Median, second quartile, and third quartile of the difference between private value and final bid (including lost stage-2 bids). Positive numbers mean bids below personal value.
As can be seen from Figure 6, players in the sealed bid auction (Figure 6d) started by setting their bids much below their private value but learned by the end of the experiment to set their final bids close to their private values. In the three multiple period auctions the initial difference was not as large (note that the range of the scale in the three multiple bid methods is narrower), and hence overall learning was lower. Most interesting for our purpose is the comparison between Amazon and the two eBay conditions: in the two eBay conditions the median approached a difference of 0 while in Amazon the different reached a number that was clearly above 0, indicating players strategically under bid. Note that despite these differences final bids rose with experience to near 100 percent of bidders’ personal values, however they remain significantly below 100 percent. And while the difference is a small one in the aggregate, we will see next when we examine individual behavior that this does not imply that the majority of bidders are in fact bidding precisely their personal values, and that the different auction formats affect the bidders differently in this regard.

![Graph](image)

**Figure 7.** Frequency of bidders setting their final bid (including lost bids) to their private value, above and below their private value for the first and last set of trials, respectively.
The proportion of bidders who set the highest bid to equal their private value was relatively low. This proportion was lowest in Amazon (0.125), a big higher in sealed bid (0.151) and much higher in eBay1 (0.234) and eBay8 (0.251). [The proportion of bidders whose final bid is the value or at most 50 cents below value is lowest in Amazon (56 percent), slightly higher eBay8 (56 percent) and substantially higher in eBay8 (66 percent). As can be derived from Figure 5, most bidders stay below their private values, yet, as can be seen in Figure 7 the proportion of those bidding exactly their private values grows over time in all auctions, but remains well under 40%. So, the fact that final bids approach values in aggregate (Figure 5) does not imply that bidders bid values. Conversely, of course, the observation that many bidders are not bidding values does not imply that behavior is far from equilibrium (see Hypotheses 4 and 5).

**III. 4 Revenue and efficiency**
Revenue and efficiency are not entirely determined by final bids in the two auction conditions in which there is only $p = 0.8$ that stage 2 bids will be successfully transmitted. Figure 8 shows the average revenues relative to a situation in which all bidders will bid their private values. (We record revenue as a percentage rather than simple revenue in dollars, because the randomly generated private values mean that slightly different revenues are predicted in the different conditions.) The Amazon condition has slightly higher revenues (even though bids are lower) and is slightly more efficient, i.e. the auction is more often won by the bidder with the high value, than the others (see Figure 9). In particular, confirming Hypothesis 6, Amazon dominates eBay.
with respect to both, revenues and efficiency (one-sided Mann-Whitney U test, \( p = 0.037 \), for both dimensions separately). On the other hand, average revenues are slightly lower and average efficiency is substantially lower in sealed bid than in all other conditions. This is because bidders in the sealed bid condition needed a particularly long time to learn truthful bidding, and thus created a lot of noise hampering price discovery and efficiency.

IV. Conclusions (This section is even more a work in progress than the rest of the paper)

The experiment presented here was designed to investigate the effects of auction closing rules on bidding behavior. It was motivated by comparisons of bidder behavior on eBay and Amazon. The experiment confirms, under controlled conditions, that the difference in ending rules between eBay and Amazon is sufficient to cause the pattern of behavior observed in the field data. The experiment also allowed us to observe aspects of behavior that are not readily available in the field data (expertise, learning, bidding relative to personal value, etc.), which allows us to gather evidence about revenues and efficiency.

Note that, despite the superior control that we achieve in the laboratory, if we presented only experimental data we could not be confident that the same effect would be observed on the internet. It might be that, in the laboratory, people bid late because it gives a slight advantage and has little cost: they are already committed to staying until the end of the experiment. In real life, it might be supposed, people have better things to do. The fact that we see the same pattern of behavior both in the lab and in the field gives us an indication of its robustness.

Note also that, while the results of the experiment replicate the basic observations in the field data, we do not claim that the field data are fully explained by the experimental data. By design, the experimental setting eliminated many of the factors present in the field data (number of bidders, multiple items offered simultaneously, heterogeneity of sellers, bidders, and products, etc). By eliminating these sources of variation, the experiment showed that they are not necessary to produce the observed differences: the
difference in auction rules is sufficient. However, that is not to say that none of the factors that we eliminated from the experiment could not nevertheless contribute to the effects observed in the field data. For example, while the experimental results show that we get the predicted effect even when we control for number of bidders, that isn’t to say that the number of bidders doesn’t have an effect on bidding in eBay vs. Amazon. The experimental results also don’t tell us whether these different auction formats would attract different numbers of buyers and sellers if they were free to self select, as in the field data. That is, the higher Amazon revenues we observe in the experiment, holding the number of bidders constant might attract sellers to choose automatic extensions, but maybe the prospect of higher bidder profits on eBay would attract additional bidders, which would change sellers’ choices, etc. The experimental data demonstrated some sufficient conditions for late bidding but not necessarily the full set of factors that take place on the internet.

Thus the experimental and field data, together with the theory developed to explain them, are complements, not substitutes. Together they help us to understand how, in auctions as well as in other markets, the rules of the market influence the timing of transactions, which can have important implications for prices and efficiency.

References
Ceci and Bronfenbrenner 1985
Coroson 1996
Dews 1969

Ferster and Skinner 1957


### Random Effects Probit Model

Maximum Likelihood estimates (and T-statistics)

Dependent variable = “1” for stage 2-bid (in Amazon: first stage 2) per bidder and per auction, and “0” else

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Coefficients</th>
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<tr>
<td>Constant a</td>
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<tr>
<td>Trial number (between 1 and 18) if Amazon and 0 else</td>
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<tr>
<td>Trial number if eBay.8 and 0 else</td>
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<tr>
<td>Trial number if eBay1 and 0 else</td>
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<tr>
<td>Log-likelihood</td>
<td>- 1184.896</td>
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* denotes significance at the 5 percent level (two-sided), ** significance at the 1 percent level (two-sided).

a There is no statistically significant level effect across treatments, so we do not include treatment dummies here.

b Individual subject differences in the basic tendency to give are clearly present as indicated by the highly significant RHO, the Hausman test statistic for the presence of random effects.

c Each bidder in each auction is one observation, making a total of 2592 observations (= 3 treatments*48 bidders per treatment*18 trials).

**Table A1.** Probit regression: Stage 2-bids

The regression shows that over time the frequencies of sniping decrease on Amazon, increase on eBay.8 and even stronger increase on eBay1. The differences of the experience effects are significant.
### A2. Number of Stage 1-bids

**OLS estimates (and T-statistics)**

Dependent variable = number of stage 1-bids per bidder and auction

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<th>Independent variables</th>
<th>Coefficients</th>
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<tr>
<td>Constant&lt;sup&gt;a&lt;/sup&gt;</td>
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<td></td>
<td>(22.348)</td>
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<td>Trial number (between 1 and 18)&lt;sup&gt;a&lt;/sup&gt;</td>
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</tr>
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<td></td>
<td>(- 8.480)</td>
</tr>
<tr>
<td>Number of stage 1-bids by the opponent&lt;sup&gt;a&lt;/sup&gt;</td>
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<td>(17.586)</td>
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<tr>
<td>Number of own stage 2-bids if Amazon, zero else</td>
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</tr>
<tr>
<td></td>
<td>(2.827)</td>
</tr>
<tr>
<td>Number of own stage 2-bids if eBay.8 (0 or 1), zero else</td>
<td>- 0.354**</td>
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<tr>
<td></td>
<td>(- 2.907)</td>
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<td>Number of own stage 2-bids if eBay1 (0 or 1), zero else</td>
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<tr>
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* denotes significance at the 5 percent level (two-sided), ** significance at the 1 percent level (two-sided).

<sup>a</sup> There is no statistically significant level effect across treatments, so we do not include treatment-specific variables here.

<sup>b</sup> Each bidder in each auction is one observation, making a total of 2592 observations (= 3 treatments*48 bidders per treatment*18 trials).

**Table A2. OLS regression: Stage 1-bids**

The regression shows that the number of stage 1-bids decreases over time, that the opponent’s bidding activity seems to trigger ‘reciprocal’ stage 1-bidding, and that if bidders in the eBay conditions decide to bid in stage 2 they bid less in stage 1, while on Amazon stage 2-bids lead to even more stage 1-bids during the extension of the auction.
A3. Final price

OLS estimates (and $T$-statistics)
Dependent variable = final price per auction

<table>
<thead>
<tr>
<th>Independent variables</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>- 0.736</td>
</tr>
<tr>
<td></td>
<td>(-1.136)</td>
</tr>
<tr>
<td>Trial number (between 1 and 18)</td>
<td>0.051**</td>
</tr>
<tr>
<td></td>
<td>(3.108)</td>
</tr>
<tr>
<td>The smaller of the two private values in the auction</td>
<td>0.853**</td>
</tr>
<tr>
<td></td>
<td>(9.967)</td>
</tr>
<tr>
<td>Number of stage 1-bids in Amazon</td>
<td>0.249**</td>
</tr>
<tr>
<td></td>
<td>(8.735)</td>
</tr>
<tr>
<td>Number of stage 1-bids in eBay.8</td>
<td>0.148**</td>
</tr>
<tr>
<td></td>
<td>(5.140)</td>
</tr>
<tr>
<td>Number of stage 1-bids in eBay.1</td>
<td>0.092**</td>
</tr>
<tr>
<td></td>
<td>(2.964)</td>
</tr>
<tr>
<td>Number of stage 2-bids in Amazon</td>
<td>- 0.242</td>
</tr>
<tr>
<td></td>
<td>(-1.554)</td>
</tr>
<tr>
<td>Number of stage 2-bids in eBay.8</td>
<td>- 0.438**</td>
</tr>
<tr>
<td></td>
<td>(-2.941)</td>
</tr>
<tr>
<td>Number of stage 2-bids in eBay.1</td>
<td>0.143</td>
</tr>
<tr>
<td></td>
<td>(1.119)</td>
</tr>
<tr>
<td>Number of observations</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1296</td>
</tr>
<tr>
<td>$R^2$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.164</td>
</tr>
</tbody>
</table>

* denotes significance at the 5 percent level (two-sided), ** significance at the 1 percent level (two-sided).

There is no statistically significant level effect across treatments, so we do not include treatment dummies here.

Each auction is one observation, making a total of 1296 observations (= 3 treatments*24 auctions per trial*18 trials).

Table A3. OLS regression: Final price

The regression shows that the final price in the dynamic auctions is slightly increasing over time, highly correlated with the smaller one of the two private values (that corresponds with the equilibrium prediction for the final price), increases in the number of stage 1 bids in all auction conditions, and significantly decreases with the number of stage 2-bids oneBay.8 (reflecting that sniping on Bay.8 keeps the price down) while sniping on Amazon has a non-significant negative and sniping on eBay.1 a non-significant positive effect.

Appendix B: Instructions