Some evidence on late bidding in eBay auctions

by Ladislav Wintr

January 2008 No 126

NationalBank
OF BELGIUM
Eurosystem

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ISSN: 1375-680X (print)
ISSN: 1784-2476 (online)

Abstract

Bidding in the last seconds or minutes of an auction is a common strategy in Internet auctions with fixed end-times. This paper examines the three explanations of late bidding in eBay auctions that survived the first scrutiny in Roth and Ockenfels (2002). There is no indication that late bidding could lead to collusive gains for bidders. Late bidding is a strategic response to the presence of bidders placing multiple bids. Experts protecting their private information are typically the last to bid while collectors are often the first. As bidders gain familiarity with eBay rules, they tend to bid slightly earlier.

JEL-code: D44 (Auctions).
Key-words: Online Auctions, Internet, Late Bidding, eBay.

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I am grateful to Wayne Gray, Axel Ockenfels, Gregory de Walque, Christophe Van Nieuwenhuyze, an anonymous referee, and the participants of the Spring Meeting of Young Economists 2005 in Geneva, Switzerland, and the International Conference on Business, Management and Economics 2007 in Izmir, Turkey, for very helpful comments and discussion on earlier drafts of this article.

TABLE OF CONTENTS

1 Introduction

Bidding in the last minutes or seconds of an auction is a common strategy pursued in online auctions with fixed end-times. For instance, Roth and Ockenfels (2002, 2006) observed bids in the last minute and last 10 seconds in 37 and 12 percent of eBay auctions, respectively. Bajari and Hortacsu (2003) documented a similar pattern.

Roth and Ockenfels (2002) put forth several explanations of late bidding. In their study of eBay auctions with fixed end-times and Amazon auctions with flexible end-times,[1] they find evidence consistent with the following three explanations of late bidding.

(1) Last-minute bidding constitutes an optimal response to the presence of a bidder or bidders who submit multiple bids in one auction.[2] Bidding late is an efficient strategy that deprives the incremental bidder of sufficient time to respond.
(2) Late bidding might be an optimal strategy for well-informed bidders (experts) who want to protect their private information concerning the value of a particular item. Assume that only experts can recognize the true resale value of the auctioned item (e.g. antique furniture). When the expert bids early in the auction, her bid might be a signal for other bidders that the object is unusually valuable. Bidding just before the end of a fixed end-time auction allows the expert (who can be recognized by her frequent participation or high feedback number) to profit from her information without leaving other bidders enough time to closely examine the item and bid.
(3) Last-minute bidding could result from implicit collusion among bidders

[1] Whenever a bid is cast on Amazon in the last 10 minutes of an auction, the auction is automatically extended for an additional 10 minutes from the time of the latest bid. The auction can close only when there is no bid for 10 minutes.
[2] There are many reasons why a bidder might decide to bid incrementally. First, the standard auction theory explains multiple bidding as an endowment effect (i.e. increase in the willingness to pay in the course of auction). Roth and Ockenfels (2002) suggest that incremental bidding is due to naïve bidders who make a wrong analogy with English auctions and continuously raise their bids to maintain the status of the currently winning bidder. In a similar fashion, bidders might be afraid of "shill bidders"—dishonest sellers who attempt to raise the price by using another identity. Ku, Malhotra, and Murninghan (2004) argue that multiple bidding may be driven by emotional factors (e.g. "competitive arousal"). In the model of Rasmusen (2001), the assumption that the bidder discovers his private value only at some cost can lead to multiple bidding.

against the seller giving higher payoff to the successful bidder. For instance, assume you want a new computer. It is worth $1,000 to you, and you believe one other bidder is willing to pay $1,000. If both of you use the proxy bidding system,[3] the price quickly rises to $1,000. Even if the tie is resolved in your favor, this is no bargain. But suppose you bid $300 early on and your competitor bids $500 in the last minute. You then bid $600 but take a chance that your bid might not be transmitted before the auction closes. Even if you get the computer for $600 only half the time (assuming there are many auctions for the same computer running approximately at the same time), it is better than paying $1,000.

The aim of this paper is to test the explanations of late bidding proposed by Roth and Ockenfels (2002). After describing and exploring the primary data set in sections two and three, respectively, section four tests whether late bidding creates collusive gains. We examine whether the prices in auctions with late bids are systematically lower than prices in the remaining auctions. Section five proposes a duration model to analyze the effects of multiple bidding (hypothesis one) and expertise (hypothesis two) on the timing of the last or winning bid (the number of seconds the last or winning bid arrived before the end of the auction).[4] Section six concludes.

2 Data

This paper uses two data sets collected from eBay by a "spider" program. The primary data set contains all eBay auctions in categories reported in Table A.2 that were listed on eBay on particular days. Out of the 140,000 auctions downloaded, we exclude those that did not receive any bid (46.8 percent), auctions with the "Buy it Now" option[5] (17.4 percent), auctions in currencies other than US dollars (7.9 percent), Dutch auctions (5.9 percent),

[3] Whenever you bid on eBay, you enter the maximum amount you are willing to pay for the item (the value is kept confidential). The system places bids on your behalf, using only as much of your bid as is necessary to maintain your "winning" status.

[4] The value of the highest bid is not disclosed in eBay auctions and hence the last bid can be lower than the highest previous bid as long as it is higher than the reported (second highest) bid.

[5] In a "Buy it Now" auction, a bidder can immediately win the item by exercising this option (for a price specified by the seller).

auctions in which the reserve price was not met [6] (3.5 percent), and those where identities of bidders were not disclosed (1.2 percent). The number of remaining auctions for each category is given in Table A.2. This paper employs the following variables:

- `TPRICE`, the total price in dollars paid by the winner (i.e. the winning price in the auction plus shipping and handling cost); [7]
- `BIDCOUNT`, the number of bids per auction;
- `BIDDERS`, the number of bidders that placed their bids in the auction;
- `DMULTBID`, dummy variable that identifies the occurrence of multiple bidding;
- `SELLERRAT`, seller's rating (feedback score), in thousands; [8]
- `AUCTIONLEN`, auction's duration in days (with the precision of seconds);
- `LASTBTEND`, the number of seconds the last bid was received before the auction closed (also referred to as the duration of the last bid);
- `LASTFEEDB`, the rating (feedback score) of the last bidder, in thousands.

The second data set mimics the structure of the primary data set and the additional information it carries will be described in detail in section 5.3.

3 Descriptive Statistics

The basic descriptive statistics of the variables defined above for the primary data set are presented in Table A.1 in Appendix A. Table A.2 breaks down the data set into eBay's categories and reveals the differences of the key variables across the product categories.

Approximately half of the primary data set comes from the computer category. Another one-quarter is formed by decorative arts and antiquities that belong to the antiques category, and the remaining auctions were taken from two other main categories on eBay—stamps and coins.

[6] Reserve price is a minimum price the seller is willing to accept for the item. The buyer does not see the reserve price, and there is only a note saying whether the reserve has been met or not.

[7] Shipping and handling costs were extrapolated for auctions that did not explicitly state the amount. It was calculated as an average S&H cost in the particular category (the most narrow classification of categories on eBay was used for this purpose).

[8] Every eBay member has a feedback profile that includes a rating number (also called feedback score). Every trading partner can leave positive (+1), neutral (0) or negative (-1) feedback to the counterpart after a transaction. Finally, the numbers are added to a rating number, also called feedback score.

Table 1
Timing of Auction's Last Bid, auctions with two and more bids only

	% of auctions with their last bid in the last				Last bid's
Category	10 seconds	1 minute	5 minutes	1 hour	median time†
PC Components	17.6	37.5	48.3	66.6	394
Drives	19.2	40.4	51.8	71.4	223
Laptops	24.6	50.5	63.6	79.2	57
Monitors	21.7	45.1	56.9	73.5	109
Stamps, European	19.1	35.6	43.6	59.2	1052
Decorative Arts	21.3	39.1	47.7	62.0	481
Coins, Ancient	22.2	40.6	49.1	64.1	358
Antiquities	16.6	36.4	47.6	62.7	503
Roth & Ockenfels	12	37	50	68	

Note: † Median number of seconds the last bid was received before the end of the auction.

The average total price in the complete data set is $90.76, which is considerably more than the median price and indicates that the distribution of price is skewed to the right. The items selling for the lowest prices were, according to expectation, stamps. This was also the reason for the extremely low minimum value of `TPRICE` in the whole data set.
The median number of bids per auction was five, which exceeds the median number of bidders by two. This is a result of multiple bidding-bidders submitting more than one bid were present in nearly 60 percent of the auctions.

Table A.2 documents relatively big differences among the individual categories. In general, computer auctions attract more bidding activity, measured by the number of bidders, bids, or multiple bids. Table A.2 also reveals that sellers of European stamps, ancient coins, and decorative arts are, on average, more active eBay members (measured by their rating). This might be due to the fact that occasional sellers are much more common in computer categories and/or the above-named categories are dominated by collectors and Internet stores.
Although auctions lasted on average 6 days and 16 hours, 50 percent of the last bids were received less than 26 minutes before the auction's end.

3.1 Timing of Last Bids

Table 1 documents the extent of late bidding in auctions with two and more bids in the primary data set.[9] At first sight, there seems to be more late bidding in auctions for monitors and laptops. This contrasts with the findings of Roth and Ockenfels (2002, 2006) who report more late bidding in their antiques category than in computer auctions. More specifically, they find that 40 percent of their computer auctions (consisting only of laptops and monitors) and 59 percent of antiques auctions received last bids in the last five minutes. These numbers fall far out of the corresponding intervals established in Table 1.

Roth and Ockenfels (2002, 2006) argue that there are more incentives to protect private information concerning the value of the items in antique auctions than in auctions for standardized computer components and laptops where pricing information is readily available. As a result there should be *ceteris paribus* more late bidding in auctions for antiques. Table A.2 documents the difference in auction characteristics between computer and antique auctions. For instance, multiple bidding is more common in computer auctions and might by itself generate more late bidding in computer auctions according to hypothesis one. The left-hand side graph in Figure 1 presents the same information as Table 1 in continuous time covering all computer and antique auctions. Since there are no censored observations in our data set, the survival function can be interpreted as the cumulative distribution function of T_i (duration of the last bid), or more precisely its mirror image.[10] The survival function of antique auctions lies completely above the function for computer auctions, confirming that there is more late bidding in computer auctions no matter how it is defined. We want to see to what extent the differences in the survival functions can be ascribed to differences in the characteristics of auctions and bidders between the computer and antique groups. The right-hand side graph in Figure 1 reveals that the difference nearly disappears after controlling the effects of auction's length, seller's rating, total price, number

[9] To ensure comparability with Roth and Ockenfels, Table 1 excludes auctions that received only one bid. Nevertheless, the rest of the paper exploits the whole data set because as we deal with *implicit* collusion, it is important only that bidders *believe* that there is at least one additional bidder ready to place his or her bid and not whether he or she finally does so.

[10] Time zero on the horizontal axis represents the end of each auction. For any number of seconds before the end of an auction on the horizontal axis, the survival function gives the percentage of auctions that received their last bid in more than the particular number of seconds (days) before the end of the auction.

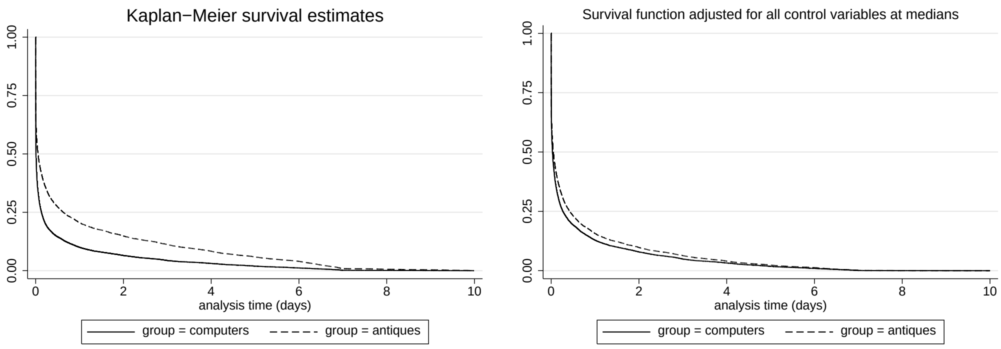

Fig. 1. Survival functions of last bid's duration T_i

of bidders and naive bids, and the feedback of the last bidder.[11] Although the difference between the two survival functions greatly diminishes, it remains statistically significant.[12]

The reason we observe larger extent of late bidding in computer auctions as compared to Roth and Ockenfels (2002, 2006) might be related to the difference in sampling periods between the papers. Roth and Ockenfels randomly selected 240 auctions on eBay between October 1999 and January 2000. The primary data set used in this paper is based on the set of all auctions that were listed on eBay in the selected categories on several days in February and March 2004 (see Table A.2). EBay evolved into a global marketplace during the four years that separate the two data sets. The number of registered users on eBay increased more than eight times to 105 million between the first quarter 2000 and the first quarter 2004 and the number of auctions hosted on its servers multiplied more than six times (eBay 2002, 2004). As discussed below, this more liquid market allowed bidders in computer auctions to follow new strategies incorporating late bidding that would not have been feasible before or that might still not be viable in auctions for more unique or rare items such as antiques or collectibles.

Figure 1 controls for several key auction characteristics and even the feedback number of the last bidder. However, there is still at least one additional factor that remains out of our control, namely the extent to which close sub-

[11] The adjustment for the control variables is accomplished by fitting Cox proportional hazard regression models separately for computer and antique auctions. The individually calculated baseline survivor functions are then retrieved and evaluated at median values of the control variables. For more details, see Hosmer and Lemeshow (1999).
[12] The employed non-parametric tests for equality of the two survivor functions tests were Log-rank, Wilcoxon and Peto-Peto.

stitutes are offered in other simultaneously running auctions. The items sold in computer auctions are typically standardized products that are in most cases listed in multiple auctions ending within few hours. One might argue that there are potentially many bidders who might "explore" the price over the course of several auctions by submitting "lowball" bids in the last seconds of the auction hoping that all competing higher bids will not be transmitted successfully. The risk that they take is relatively small—if they lose the auction, they will follow the same strategy with a slightly higher bid in the next auction for the same item and so on until they win the item or reach their willingness to pay. Bidding seems to be fun for many bidders who might in fact pursue this strategy in the computer category. However, it fails in most cases in auctions for collectibles and antiques because of heterogeneity of items offered in these categories. If a bidder decides to extend his collection of Roman dinars coined under Julius Caesar, there might not be many auctions for the coins of interest. And when one of the desired items becomes available, the cost of following the dynamic late bidding strategy described above can be high—when losing, one would have to wait a relatively long time for another auction.

4 Collusive Gains

In this section we turn back to hypothesis three (as outlined in the introduction) and address the issue whether or not late bidding can lead to collusive gains for bidders.

First, let us express a theoretical reservation to the existence of arbitrage profits on eBay. If there are arbitrage gains and no barrier to entry, we would expect entry to occur. If items consistently sell for less than bidders' valuations, entry would eliminate this gain and pose problems for sustainability of the collusive equilibria. It is hard to assume the existence of large arbitrage profits in auction house like eBay which hosts millions of potential bidders, some of whom make their living by searching the market for under-priced items.

If there were collusive gains, then the conditional median (or mean) price in auctions that received late bids would be *ceteris paribus* lower than the median (mean) price in the remaining auctions and the difference would be statistically significant.[13] This implication can be tested by the two-sample Mann-Whitney test for equality of two population medians (corresponding to the two random samples, i.e. the sample of prices in auctions where late bidding occurred and the sample of remaining prices). The Mann-Whitney test is used to test the null hypothesis that the population distribution functions are identical against the alternative that they have different medians.[14] In simple terms, under the null hypothesis there are no collusive gains.

The results of the Mann-Whitney test in the primary data set are summarized in Table 2 which lists the largest subcategories of each computer category in the data set. All auctions in the selected groups were checked by hand for misplaced items.[15] Table 2 shows that there are 288 items in the category 256 MB SDRAM memories, out of which 111 auctions received a bid in the last 60 seconds of the auction. The conditional median price in auctions with late bid was \$42, nearly \$1 less than the median price in the remaining auctions. However, this cannot be interpreted as an indication of collusive gains in auctions with late bidding since the Mann-Whitney test cannot reject the null hypothesis that the two sample medians are statistically identical.

The next category—128 MB SDRAM memory chips—leads to the opposite conclusion (using 5 percent significance level). However, since the 128 MB SDRAM memories were produced at three different speeds, it is possible that the null hypothesis was rejected because the mix of the three types was different in the late bidding and early bidding sample. After sorting out the 128MB memories at 133MHz (PC133), the P value of the Mann-Whitney test increases nearly five times and the difference between prices in the two samples turns out to be insignificant. A similar pattern repeats in the IDE hard drives category after selecting 40 GB hard drives out of the eBay category 20–40 GB

[13] The *ceteris paribus* condition would ideally mean identical product and auction characteristics (e.g. seller's rating). To obtain relatively homogenous groups of items, this section focuses on computer auctions.

[14] Notice that if we cannot reject the null hypothesis, we obtain stronger rejection of the collusive gain hypothesis than is in fact needed (the two sample medians are not only statistically indistinguishable but they also come from the same distribution).

[15] Items are placed into categories by sellers without eBay's control. Hence, incorrectly filed items can occur due to seller's mistake (e.g. DDR RAM memory included in the SDRAM category), due to unclear definition of a category (e.g. auctions for a lot of two 256 MB SDRAM chips were found in both 256 MB and 512 MB categories), and finally it can be the intention of the seller (e.g. there were several auctions for the latest Dell laptop that closed with a price of few dollars; however, the item description declared that this is not an auction. It only provides information how to obtain the laptop by entering some dubious game). Similarly, auctions for malfunctioning items were excluded.

Table 2
Collusive gains in selected categories

	Late bidding in the last 1 minute					
	Obs.		Median price‡		M-W test†	
Category	early	late	early	late	U stat.	P val.
SDRAM memory						
512 MB	87	60	65.66	66.00	0.029	0.864
256 MB	177	111	42.98	42.00	0.458	0.499
128 MB	204	118	23.60	22.48	4.601	0.032
128 MB PC133	88	54	20.83	19.65	2.066	0.151
Hard drives IDE						
5–10 GB	107	56	21.52	23.50	0.457	0.499
10–20 GB	111	81	30.29	31.21	0.045	0.831
20–40 GB	154	104	48.47	46.98	0.290	0.590
40 GB	92	68	50.99	51.48	0.001	0.979
Dell laptops						
2–2.4 GHz	80	45	853.50	890.00	0.648	0.421
1–1.4 GHz	39	28	769.57	812.68	0.089	0.765
700–750 MHz	60	55	487.37	465.00	1.517	0.218
400–466 MHz	29	40	280.00	273.29	0.072	0.789
Monitors						
LCD 17”	246	215	380.00	375.85	2.375	0.123
LCD ≤15”	248	226	237.50	235.51	0.084	0.772
CRT 17”	281	201	76.44	76.94	1.315	0.251

Note: † The population medians are equal under the null hypothesis of the Mann-Whitney (M-W) test.
‡ Calculated from `TPRICE`, i.e. includes extrapolated shipping cost.

HDDs. The P value of the Mann-Whitney test in this narrow category reaches nearly 98 percent which strongly suggests that prices are statistically identical in auctions for homogeneous items no matter whether they received late bids. This general conclusion is in line with the findings of Hasker et al. (2004).

5 Duration Model

This section proposes tests of hypotheses one and two as stated in the introduction. The test is based on models of the duration of the last or winning bid (i.e. the number of seconds the last or winning bid was received before the end of the auction). The goal is to assess the effect of the main determinants of late bidding, including multiple bidding and expertise on the duration of the last and winning bid.

5.1 Modeling Strategy

The duration model is a simple generalization of the classical linear regression model $T_i = \mathbf{x}_i'\beta + \epsilon_i$, where the dependent variable T_i is now duration time (duration of the last or winning bid). The assumption that residuals are normally distributed is not tenable in this context as it would lead to normally distributed duration times. An easy remedy is offered by the exponential regression model

$$T_i = \exp(\mathbf{x}_i'\beta)\ \varepsilon_i, \tag{1}$$

where the residuals ε_i follow the exponential distribution with its parameter equal to one. The regression coefficients can be estimated by the maximum likelihood technique from the linearized version of equation (1), $\ln T_i = \mathbf{x}_i'\beta + \ln\varepsilon$ (this is the so called accelerated failure-time model). Here, the error term, $\ln\varepsilon$, follows extreme minimum value distribution. Once we know the distribution of the dependent variable, we can derive the survival function $S(t, \mathbf{x}, \beta) = 1 - F(t, \mathbf{x}, \beta)$ and the hazard rate $h(t, \mathbf{x}, \beta) = f(t, \mathbf{x}, \beta)/S(t, \mathbf{x}, \beta)$, where $F(\cdot)$ is the cumulative distribution function and $f(\cdot)$ the probability density function of T_i.[16]

The exponentiated β-coefficients from the accelerated failure-time model can be interpreted as a ratio of duration times in response to a one-unit change in the independent variable corresponding to the β-coefficient. The survival function corresponding to the exponential distribution can be expressed as $S(t, \mathbf{X}, \beta) = \exp\{-t/\exp[\mathbf{X}\beta]\}$. To obtain the median duration time (denoted t_{50}), we set $S(\cdot) = 0.5$ and solve for t_{50}. Finally, we can express the ratio of median duration times (TR) for two arbitrary realizations of the independent

[16] The survival function gives the probability that the event of interest (failure) has not occurred by duration t. Hazard function describes the instantaneous rate of failure given duration time t.

Table 3
Exponential models of the duration of last bids

	Interval estimates of duration time ratios ($e^{\hat{\beta}}$)	
Category	Multiple bidding	Feedback of the last bidder (1000s)
PC components	0.469–0.526	0.620–0.708
Drives	0.444–0.499	0.647–0.734
Laptops	0.286–0.335	0.483–0.560
Monitors	0.244–0.298	0.661–0.844
European stamps	0.341–0.376	0.912–0.994
Decorative arts	0.443–0.498	0.710–0.773
Ancient coins	0.398–0.446	0.857–0.948
Antiquities	0.490–0.610	0.419–0.552
Complete data set	0.362–0.378	0.791–0.823

Note: The table reports 95% confidence intervals (Wald-statistic-based intervals) of the exponentiated coefficients. Estimates are based on exponential models (for each product category) with the duration of the last bid as the dependent variable and multiple bidding dummy, feedback of the last bidder, number of bidders and weekend dummy as explanatory variables. For complete results, see Table A.3

variables $\mathbf{x}^a = \mathbf{a}$ and $\mathbf{x}^b = \mathbf{b}$

$$TR = \frac{t_{50}(\mathbf{x}^a = \mathbf{a}, \beta)}{t_{50}(\mathbf{x}^b = \mathbf{b}, \beta)} = \frac{-\ln(0.5) \times \exp(\mathbf{a}'\beta)}{-\ln(0.5) \times \exp(\mathbf{b}'\beta)} = e^{(\mathbf{a}-\mathbf{b})'\beta}. \qquad (2)$$

More details on the derivation and interpretation of coefficients in the accelerated failure-time models can be found for instance in Hosmer and Lemeshow (1999).

5.2 Hypothesis One—Multiple Bidding

According to hypothesis one, we expect shorter durations of last bids in auctions with a bidder (or bidders) who submitted multiple bids. This can be easily tested in model (1) containing a set of control variables and a dummy variable indicating multiple bidding in the auction (`DMULTBID`). The dummy variable in the exponential model is highly significant and predicts that the duration of the last bid in auctions with incremental bidder or bidders is shorter by about 64 percent in the complete data set, all else equal. [17]

[17] The observed pattern can be also the result of a bidding war between incremental bidders who consequently outbid each other as the auctions approaches its end which shortens the duration of the last bid. The distinction between the two hypotheses

Table 3 presents interval estimates of the exponentiated `DMULTBID` coefficient for each product category. Multiple bidding has the largest impact on duration times of laptops and monitors. The presence of an incremental bidder shortens *ceteris paribus* the duration of the last bid in the above-named categories by 67 to 77 percent. On the other hand, multiple bidding has the smallest effect in the category of PC components and antiquities. Nevertheless, even here it cuts the duration of the last bid by at least 40 percent.

Given the widespread practice of multiple bidding, the fear of incremental bidding can be a reason for late bidding even in auctions where each bidder placed just one bid. Someone placing her first bid in such an auction might fear that the previous bidders could respond to her bid if they had enough time to do so. The argument suggests that multiple bidding can be an even more important explanation of late bidding than is suggested by the duration analysis in Table 3.

5.3 Hypothesis Two—Expert Bidding

If experts can be recognized by their frequent participation, then the large number of transactions they carry out will be typically reflected in their high feedback numbers. As experts have more incentives to protect their private information and bid late, durations of last bids submitted by bidders with high feedback numbers should be *ceteris paribus* shorter.

This seems to be confirmed in the exponential model discussed in the previous section (see the last column in Table 3). The coefficient corresponding to the feedback number of the last bidder is significant and implies that its increase by one thousand shortens *ceteris paribus* the duration of the last bid by 19 percent. However, the feedback number is not a reliable proxy for expertise. First, bidders with high feedback are not necessarily experts and vice versa. More importantly, it is possible that high feedback *per se* is capturing other effects as well, e.g. “learning by doing.” If bidders who engage in many transactions learn that late bidding is a superior strategy, it would also lead to a negative relation between the last bid’s duration and feedback numbers. Ariely, Ock-

can be based on the following observation. If the bidder is trying to “outsmart” the incremental bidder, he submits only one bid in the auction right before its end. On the other hand, if the last bid is a result of bidding war, the last bid will be executed by a bidder who did already bid in the auction. The data show that nearly 70% of last bids were executed by bidders submitting only one bid in the auction.

enfels and Roth (2003) show in an experiment that this might well be true and, hence, the results in the last column of Table 3 must be interpreted with caution as they mingle two effects.

To disentangle the effect of experience with eBay auctions and expertise concerning the value of auctioned items, we need additional information on individual bidders. EBay members typically do not disclose any personal data. One exception are so called eBay Groups that connect eBay members with common interests. One of the largest groups dealing with antiques (called "! Antiques and Collectibles Worldwide") includes a discussion thread in which the group leader asks the members (about 800 as of July 2006) to introduce themselves. Exactly 100 members posted sufficient information to classify them as expert, collector, or neither. In what follows, we define an expert as someone who buys on eBay primarily for resale (mostly users with eBay or brick-and-mortar antique stores). Collector is someone who identifies himself or herself directly as a collector. The complementary data set used in this section contains information on auctions won by those 100 "eBayers" between April and July 2006 (as long as the seller left feedback). Since the additional information on experts or collectors is available only for the winner of the auction, we focus on the duration of the winning bid in contrast to the duration of the last bid considered up to now. The data set covers 30 experts, 20 collectors, and 541 auctions. Its structure mimics that of the main data set except that it does not count feedback from selling on eBay. This way the feedback number relates more directly to the learning effect from participating in auctions.

Table 4 assesses the role of the crucial determinants of late bidding in eBay auctions that were discussed in this paper by estimating two exponential duration models using the complementary data set.

It concludes that experts, who have the highest incentives to protect their private information, are the last to submit their winning bids in both Model A and B. The duration of their winning bids is *ceteris paribus* approximately 20 percent shorter than the duration of winning bids executed neither by experts nor by collectors.

Section 3.1 suggests that collectors run a high risk by bidding late because if they lose, they might need to wait a relatively long time for another auction for the same item. The results confirm this argument as collectors are the first to submit their bids. In Model A, duration of winning bids executed by

Table 4
Exponential model of the duration of winning bids, Time Ratios ($e^{\hat{\beta}}$)

Variable	Model A	Model B
Expert	0.809*	0.780**
Collector	1.456***	1.160
Feedback from buying	1.001***	1.001***
Multiple bidding	0.373***	0.127***
Number of bidders†		0.430***
Auction ends on weekend	0.716***	0.747***
Cat: Comp. & Electronics	0.751	0.672*
Cat: Collectibles	0.765*	0.908
Cat: Art	1.115	1.192
Cat: Antiques	0.564***	0.608***

Note: † Number of bidders set to zero in auctions with incremental bid(s); */**/*** indicate significance at the 10/5/1 percent level, respectively. Model B extends model A by including the number of bidders as explanatory variable.

collectors is 45 percent longer as compared to the base group, all else equal. The coefficient loses its statistical significance in Model B.

As previously mentioned, Ariely et al. (2003) found in an experiment that the probability of late bidding in eBay-type auctions with 80 percent successfully transmitted late bids is slightly increasing in consequent repeated auctions (from about 40 percent in the first auction to 50 percent in the 18^{th}). In contrast, our results suggest that bidders who bought more items on eBay tend to bid earlier in the auction, although the effect is relatively small. In other words, after winning 100 additional auctions (more precisely after receiving 100 new feedback messages from sellers), the duration of the winning bid increases by about 10 percent. One could argue that the learning effect is limited to the first 20, 50 or 100 auctions. However, there is no apparent structural break in the effect of "experience" on the duration time. Ariely et al. (2003) also show that the probability of late bidding significantly depends on the probability that the last bid is lost. Hence, the two results could be reconciled if the probability of transmitting late bids was lower than 80 percent. One also must bear in mind that the feedback number does not record auctions in which the bidder did not win or did not receive feedback from the seller.

Bidders are more likely to follow live the end of the auction during weekends, and hence we would expect more late bidding in auctions that end on Saturdays or Sundays. The results in Table 4 suggest that duration of winning bids in auctions ending on weekends is shorter by 25 to 28 percent, all else equal.

The presence of multi-bid bidders postpones not only last bids (as demonstrated in the previous section) but also the winning bids. According to Model A, the duration of winning bids in auctions with incremental bidder or bidders reaches *ceteris paribus* less than 40 percent of its duration in auctions without multi-bid bidder(s). In addition, Model B investigates whether the fear of multiple bidding itself can cause late bidding. The variable "number of bidders" was set to zero in auctions with incremental bids, and hence it implies that one additional bidder in an auction without a multi-bid bidder shortens *ceteris paribus* the duration of the winning bid by 57 percent.

Lastly, Models A and B include a set of product category dummies (the base group being all other categories). Even after controlling for all the factors discussed above, there remain some unexplained differences in the extent of late bidding across the product categories. More specifically, there is significantly more late bidding in auctions for antiques than in any other product category, all else equal.

6 Conclusion

This paper examines the three hypotheses of late bidding in eBay auctions that survived the first scrutiny in Roth and Ockenfels (2002). We found no indication that late bidding could lead to collusive gains for bidders. The result holds for all considered product categories, as long as they form a homogenous group. Nevertheless, one cannot rule out that bidders submit late bids because they mistakenly believe that late bidding can lead to more favorable prices.

Another hypothesis claims that last-minute bidding is a strategic response to multiple bidding. Indeed, we found that the presence of a bidder or bidders submitting multiple bids in one auction shortens *ceteris paribus* the duration of the last or winning bid by more than 60 percent. In addition, the results suggest that the fear of multiple bidding can be as important cause of late bidding as incremental bidding itself.

We attempted to disentangle the effects of experience with eBay auction rules and expertise concerning the value of the product. The results show that as bidders become more familiar with eBay rules, they tend to bid slightly earlier. We have concluded that experts are the last to bid, while collectors are the first to submit their bids, all else equal. This is in line with the claim that experts bid late in order to protect their private information concerning the value of the auctioned item. On the other hand, late bidding might be too risky for collectors because if their bid is not transmitted on time, they must wait a relatively long time for another auction for the same item. Lastly, auctions ending on weekends receive their winning bids later than auctions ending during workdays, all else equal.

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A Appendix

Table A.1
Descriptive Statistics

Variable	Obs.	Median	Mean	Std. Dev.	Min	Max
TPRICE	51490	30.11	90.76	196.87	0.51	5238.77
BIDCOUNT	51490	5	7.13	7.57	1	79
BIDDERS	51490	3	4.10	3.43	1	35
DMULTBID	51490	1	0.59	0.49	0	1
SELLERRAT	51402	0.406	1.98	5.83	−0.004	78.943
AUCTIONLEN	51490	7	6.67	1.68	0.62	10
LASTBTEND	51490	1507.5	51167.37	124693.70	0	863276
LASTFEEDB	51247	0.054	0.17	0.37	−0.004	12.347

Note: Sellers and bidders can choose not to disclose their rating (feedback score). Variable names are defined in section 2.

Table A.2
Descriptive Statistics by eBay's Categories

		Average number of		Median	
Category	Observations	bids	bidders	TPRICE	SELLERRAT
PC components$^{\circledast}$	8405	7.2	4.2	29.81	0.118
Drives*	7521	8.1	4.6	39.60	0.123
Laptops$^{\circledast}$	5571	14.8	7.3	217.50	0.271
Monitors*	2965	11.8	6.1	135.99	0.176
European stamps*	10344	3.6	2.5	9.09	0.851
Decorative arts$^{\flat}$	6778	5.4	3.1	36.39	0.465
Ancient coins$^{*,\flat}$	7558	5.8	3.9	19.50	0.852
Antiquities*	2348	4.4	2.6	39.82	0.135
Total	51490	7.1	4.1	30.11	0.406

Note: Auctions that were listed on eBay on March 1, March 19 and February 7, 2004 denoted by ($*$), ($\flat$), and ($\circledast$) respectively.

Table A.3. Exponential models of the duration of last bids, complete results

	Components	Drives	Laptops	Monitors	Stamps	Art	Coins	Antiquities	ALL
Number of	0.76	0.74	0.81	0.86	0.73	0.74	0.77	0.64	0.79
bidders	(68.22)	(79.01)	(74.45)	(33.76)	(69.75)	(60.20)	(62.64)	(38.46)	(166.22)
Auction ends	0.75	1.22	1.04	1.45	0.94	1.22	0.92	0.96	1.01
on weekend	(12.66)	(7.26)	(1.46)	(7.96)	(3.15)	(7.96)	(3.68)	(0.98)	(1.40)
Multiple	0.50	0.47	0.31	0.27	0.36	0.47	0.42	0.55	0.37
bidding	(23.81)	(25.36)	(29.11)	(25.92)	(41.01)	(25.08)	(29.86)	(10.80)	(89.84)
Feedback of	0.66	0.69	0.52	0.75	0.95	0.74	0.90	0.48	0.81
last bidder	(12.14)	(11.57)	(17.24)	(4.69)	(2.24)	(13.78)	(4.06)	(10.42)	(21.58)
ln(constant)	11.832	11.636	11.787	11.408	12.067	12.030	11.769	12.417	12.034
	(541.4)	(505.2)	(359.4)	(304.2)	(693.6)	(554.4)	(492.7)	(360.5)	(564.2)
N	8391	7487	5538	2955	10272	6749	7531	2324	51247

Note: Table reports the duration time ratios, i.e. exponentiated coefficients. Model for the complete data set (denoted as 'ALL') is stratified by category. Absolute value of t-statistics in parentheses.

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