Learning to bid, but not to quit – Experience and Internet auctions

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Abstract

A classic argument in economics is that experience in the market place will eliminate mistakes and cognitive biases. Internet auctions are a popular market were some bidders gather extensive experience. In a unique data set from a Scandinavian auction site I question if and what bidders learn. At face value experienced bidders do adapt better bidding strategies. However, the so-called pseudo-endowment effect does not disappear. Regardless of their experience, bidders will be inclined to increase their willingness to pay as a response to having had "ownership" (the leading bid) before being outbid. Thus, this data can confirm that feedback, and especially negative feedback, seems to be a critical component in learning.

Keywords: Experience, Learning, Internet auctions, Reference-Dependent Preferences, Endowment Effect, Bidding behavior, eBay.

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1 Introduction

A long standing debate between Neoclassical and Behavioral Economists is whether experience eliminates cognitive biases in decision making. The neoclassical argument is that irrationality will be exploited in the market. Thus, participants need to become rational if they are to continue trading.

Underlying this learning argument is basically three conditions. First of all, past experiences need to be both relevant and applicable for the specific decision problem. Most people would have extensive experience in buying clothes, but only little experience in buying a house. Generally, we would therefore expect participants to learn more about buying clothes than buying houses.

Second, learning by your mistakes requires that you *realize* these mistakes. For instance, some buyers of 4x4 SUVs might actually be better off with a more economical MPV, but if they do not realize that, they will continue to buy SUVs. Generally the outcome must provide positive or negative feedback about the decision, and the decision maker will need to reflect and be able to act upon this feedback.

Finally, if rationality is taught by the market, the market must be characterized by rational behavior. If stock markets, for instance, are characterized by irrational exuberance, it may not be optimal to base decision on rational models (at least in the short run), and it may certainly be difficult to learn to be rational. Behavior taught by the market is therefore not always rational as such.

Internet auctions have made auctions available for everyone. In this market we find both the amateurs who are bidding for the first time, the bidders with extensive experience and the professionals who are buying with the purpose of re-sale. In this standardized environment there is no doubt that experiences from one auction are relevant to other auctions. Internet auctions are therefore a market setting where we can zoom in on the second and third condition and test if and what bidders learn.

This is not the first study to consider the effect of experience in internet auctions. In the early paper by Wilcox (2000) experience is found to change the bidding behavior and make late bidding more pronounced. As this observation is found in eBay data, where this could be the dominating strategy[1], he concludes that bidders learn to be more rational. Similar observations have

[1]Due to e.g. hard endings and common value. For an overview on this, see Bajari and Hortacsu (2004)

been performed by e.g. Ockenfels and Roth (2002) and Borle et al. (2006). Although these observations surely reveal that experience does play a role, the unique data behind the present study allows me to explore this deeper.

Lauritz.com is a Scandinavian auction site with a proxy bidding system much like eBay's. Yet, there are important differences in the setup such that late bidding is no longer the strategically dominating strategy. In fact, the analysis in Bramsen (2008a) concludes that an early bid is the optimal strategy. From that point of view this article can confirm that experience does improve bidding by making bidders bid earlier and fewer times.

That experienced bidders are able to change their bidding towards more optimal strategies is *not* necessarily the same as saying that they are able to decrease their cognitive biases and become rational. In fact this article presents evidence that this is not the case.

When bidders at some point start expecting to win, the prospect of losing can make bidders increase their willingness to pay. This pseudo-endowment effect is found in both the laboratory by Ariely et al. (2004) and empirically from inexperienced bidders by Bramsen (2008b). This article continues down this path and demonstrates that even with extensive experience, the average bidder will still be affected by having had the leading bid.

Generally, this article demonstrates that if the feedback is teaching us to become more rational, we can learn. But if feedback is either missing, weak or delayed, mistakes and biases can be difficult to eliminate.

The paper is organized as follows. Section 2 presents the auction and the data used. Section 3 explores the development in bidding as bidders get more experienced and section 4 is concerned with the pseudo-endowment effect. Section 5 draws parallels to the literature and concludes.

2 The data

Lauritz.com is an auction house based primarily in Denmark, but with activities in Germany, Norway and Sweden. All their auctions are internet auctions much like eBay.com, but there are some important differences. Lauritz.com is not only an internet site, but also a physical auction house with 18 locations (2008) where the goods are located and available for inspection during business hours. Potential bidders therefore have the opportunity to examine the goods thoroughly before bidding. Lauritz.com was a traditional auction house before 2000 and has kept the tradition of making an expert estimate of the value of the items. Most, if not all, the necessary information for evaluating the item's common and private value is therefore accessible from the start.

The particular data I have access to are from all the modern furniture auctions in 2005, which amount to about 37,000 auctions[2]. More specifically, I have access to the complete bidding histories, i.e. exact time of bids, the bidders' ID numbers etc., much like the available information on any eBay auction just after expiry[3]. From these histories I can backtrack the bidders' actual bids (both incremental- and max-bids), and when they were submitted.

Furniture is one of the traditional goods for auction houses, and especially Lauritz.com has branded itself as reselling classic Scandinavian furniture designs. Although it is classic designs, the vast majority of the furniture for sale is different and normally there are no competing auctions with similar furniture at the same time.

While Laurtiz.com was well established on the Danish market in 2005, this was a period of expansion in Germany and Sweden. I have therefore limited my analysis to the 27,000 Danish auctions. Since this is an analysis of bidding behavior, I have limited the data to auctions with at least two bidders[4]. Excluding some extreme auctions brings the number of auctions down to 16,864[5].

The typical auction procedure is that the seller brings the item to the nearest auction house where an expert makes a valuation. If the seller is interested in selling, Lauritz.com puts it on the internet site with auction expiration exactly one week later[6]. By policy none of the auctions have a reserve price, but the first available bid is $50 (2005) since this will cover the minimum fee

[2]Modern furniture consists of two categories: 1) miscellaneous (29%) and 2) tables and chairs (71%).

[3]The data used for this article is therefore in principle publicly available. I did, however, receive the data directly from Lauritz.com with a few extras which are not used here.

[4]Excluding auctions with only one bidder will bias the observed bidding bidding behavior. However, the behavior in auctions with one bidder seems less interesting and may also be adversely biased for this purpose. I have therefore chosen not to include these. This will also allow a more direct comparison to second part of the analysis, since competition is needed to activate the pseudo-endowment effect.

[5]Only auctions with a valuation between $200 and $6,000 are included. Also, there are a few auctions with an error in the time of start that subsequently have been altered by mistake and have therefore been removed. The remaining auctions are the same as used in Bramsen (2008a) and Bramsen (2008b)

[6]To even out the load some are put for sale or set for expiration during the evening, but almost all the auctions have close to one week of duration, and the selected auctions all have a duration of 7 days +/- 6 hours.

to Lauritz.com for the seller. Generally, the seller pays 10% of the reached auction price (if above $500), and the buyer must pay additionally 20% plus a fixed fee of $5[7].

During the auction bidders can either make the next available bid (the current price plus some predetermined increment of e.g. $10) or use the max-bid service (proxy bidder) and let the auction site bid for them. In economic terms bidders can therefore bid as if it was a normal first price ascending auction, or as if it was a sort of second price auction by putting in their maximum bid. This bidding procedure is very close to the proxy bidding system used on eBay, only the max-bids are also restricted to the increments. However, if a bid arrives within the last 3 minutes, the auction is extended with 3 minutes. This is a so-called soft ending with always at least 3 minutes of time to react.

Once the auction is over the winner can pick up the item at the physical auction house. Due to the Danish Sale of Goods Act there is, however, the rather peculiar feature that buyers can regret and return the item within two weeks. Although this feature could potentially affect the bidding, it does not present a problem to this analysis[8].

Although some bidders without doubt think a lot about how and when to bid, theoretically there should be no effect of bidding behavior. The objective valuation and the possibility to see the item physically minimizes the information about value from other people's bidding. The common value argument for bidding late is therefore in theory absent. Furthermore, the soft ending minimizes the possibility to surprise incremental bidders with a late bid. Hence, this argument for bidding late as mentioned in the literature is also missing[9]. Finally, as there are no auctions directly competing with each other at the same time, bidders do not need to wait and see which one to bid for. From a neoclassical point of view bidders should therefore simply minimize their transaction costs and put in their maximum willingness to pay as a max-bid at the point where they discover the auction.

[7]Since these are Danish auctions all prices are originally in DKK. The conversion rate used throughout is 1 USD = 5 DKK (2008).

[8]If there is uncertainty about WTP it can potentially make it less costly to bid. However, bidders will still have incentive to bid what they believe is their WTP. It must therefore be the same underlying mechanisms that affect bidding with or without this option. Furthermore, there are transaction costs and only a very limited number does actually use the option (in this data, 6.5%). In comparison to eBay, where a bidder can ignore the purchase (perhaps with a black-listing as consequence) bidding on Lauritz.com seems to be more committing.

[9]See e.g. Ockenfels and Roth (2006) for a theoretical and empirical analysis on this.

3 Bidding strategies

Most literature on experience in internet auctions have so far focused on the actual bidding behavior. Wilcox (2000), for instance, finds that experience leads to fewer bids and more late bidding. Similar results have been found by Ockenfels and Roth (2002) and Borle et al. (2006). This analysis therefore start by simply comparing the timing and amount of bidding by different groups of bidders characterized by their experience.

In furniture auctions on Lauritz.com you can find several kinds of bidders. At present (2008) the number of new sign-ups is 8000 pr month, indicating a high amount of newcomers and amateurs. On the other side of the spectrum there are bidders who participate in several hundred furniture auctions per year and win auctions by the dozen[10]. It would be quite exceptional for private consumers to buy more than a handful expensive furniture during only one year. Hence, I also expect that there are professional bidders with a motive of re-sale.

Optimally, there would be data on the single bidder's total participation since sign-up. Moreover, it could be useful to know if, for instance, the user is private or professional. However, the only available information is the bidding for modern furniture per buyer id during 2005. I will therefore use the number of auctions which the single bidder has participated in as a proxy for classifying the bidder.

In Table 1 I have defined five groups of bidders depending on their level of participation during 2005[11]. The table also shows the number of bidders in each group (Bidders) and the total combination of bidder and auction (N), i.e. the unit of observation. Similarly, you can also find the total number of bidders (Bidders_{sub}) and the number of observations they represent (N_{sub}) from the subset used in Section 4.

An alternative way of defining these groups could be to include the number of wins. Due to transaction costs you could, for instance, expect professional bidders to have at least a certain percentage of wins. Yet, using winning as part of the definition would create an endogeneity problem. I suspect that a high proportion of wins will at least partly be a result of the bidding behavior. Thus, the simple definition in Table 1 will be used throughout the paper.

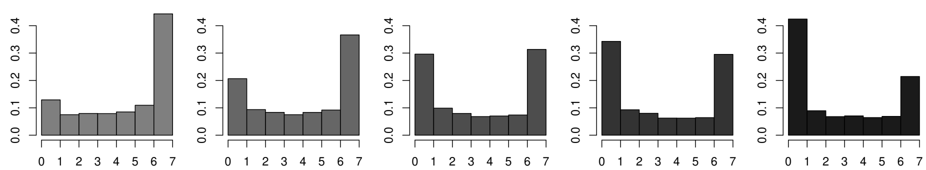
[10] In this data up to 1554 auctions and 212 wins during 2005.

[11] Whereas all other measure are calculated on the selected subset with more than one bidder, the participation is a measure of total participation of all modern furniture auctions in 2005

Group name	Participation	Bidders	N	Bidders_{sub}	N_{sub}
Novice	$[0, 5]$	18,024	28,863	3,022	3,403
Amateur	$[6, 20]$	3,800	24,167	1,636	2,796
Experienced	$[21, 50]$	739	14,356	486	1,611
Semi-Prof.	$[51, 200]$	322	17,868	257	1,789
Professional	$[201, \infty]$	56	15,467	48	1,912
Total	-	22,941	100,721	5,449	11,511

Table 1: Definition of groups

Perhaps the most important part of a bidding strategy is *when* to bid. Especially the time of entry has been discussed widely in the literature. Figure 1 shows the empirical distributions of the first bid during the week of the auctions for the 5 groups. More specifically, the proportions of first bids for each day is plotted in a histogram for each group, where the total area of each histogram is 1.



(a) Novice (b) Amateur (c) Experienced (d) Semi-Prof (e) Professional

Figure 1: Timing of first bid

Generally, bidders enter either the first or last day perhaps due to two subcategories at the site: “New items” and “Last chance”. Still, there is a significant development in the timing of entry as bidders get more experienced. Beginners have a tendency to bid on the last day while this shifts towards the first day for the “Professionals”. Thus, experience leads to earlier entry.

The timing of bids has typically been coupled to late bids and sniping. With this in mind, I have measured the bidding according to the three following definitions;

Late bids If a bidder bids within the *last hour*, I measure this as a “Late bid”.

Sniping bids If the bidder bids within the *last 10 minutes*, I phrase this as a “Sniping bid”

Bidding wars If a bidder bids *two times within the last 10 minutes*, i.e.

she bids and rebids as a response to another bidder's bid, I interpret this as willingness to engage in a "Bidding war".

I do not have data for possible extensions due to the 3 minutes rule (soft ending). The exact time of finish in the data is therefore including possible extensions. As a consequence, some "late bids" may have been intended to be sniping bids. This is the reasoning behind the rather wide limit of 10 minutes for "sniping bids".

For each bidder I calculate the share of the auctions in the subset where she is represented with such bids. In Appendix A there is three plots with every bidder's percentage. Naturally, there is quite a variation, especially if the bidder only participated a few times. There is, however, a clear picture if you consider the average for the 5 bidding groups. They are shown in Figure 2. Novice bidders, for instance, use sniping bids in 15% on average of the auctions they participate in, while Experienced use sniping in 7% on average. Unambiguously, these averages indicate that as bidders get more experienced they less often make late bids, sniping bids and engage in bidding wars.

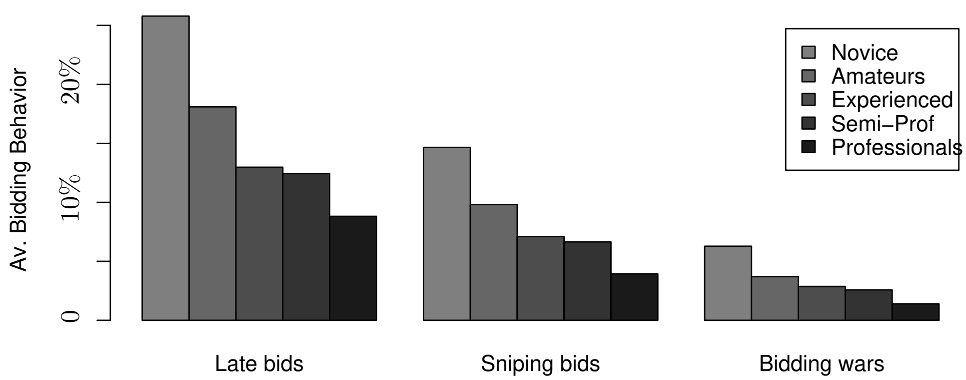


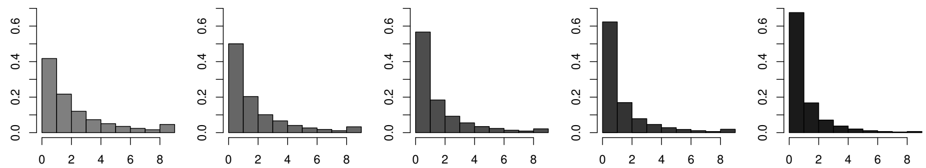
Figure 2: Group averages for late bidding

Although this is a very clear picture it could, in principle, be due to the group limits. To reject any doubt, two smoothing regressions are therefore added to each of the plots in Appendix A – the difference being a different level of smoothing. Basically, these regressions all confirm that late bidding in any form is less frequent when bidders become more experienced[12].

Another typical subject is the number of bids per auction. Figure 3 shows

[12]There is a shifts within the group of professionals, but this is due to the low number of observations and should therefore not be of any concern.

the distribution of actual bids per auction for the 5 groups [13]. Again, there is a clear effect of experience. As bidders learn, they use fewer bids per auction and in more than 67% of the auctions which the "Professionals" participate in, they only bid once. This downtrend is also confirmed by the plot and smoothing regressions in Appendix A.



(a) Novice (b) Amateur (c) Experienced (d) Semi-Prof (e) Professional

Figure 3: Number of bids per auction

Generally, by looking at the data we can therefore observe a clear development in the bidding behavior with experience. As further confirmation Table shows the result of simple regressions with $\ln(Participation)$ as the explanatory variable. Comparing with the standard deviations in brackets it is evident that in all the cases the negative estimate for $\ln(Participation)$ is three-star significant.

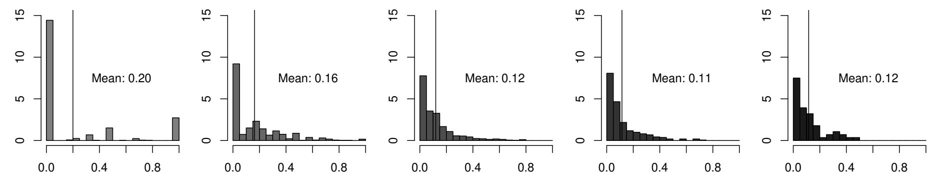
	No. of bids	Late bids	Sniping	Wars
Intercept	3.05	0.282	0.162	0.071
	(0.02)	(0.003)	(0.003)	(0.002)
$\ln(Participation)$	-0.25	-0.043	-0.027	-0.014
	(0.02)	(0.002)	(0.002)	(0.001)

Table 2: Effect of experience - simple regressions

The overall conclusion must be that bidders do learn something. Yet, it is still not totally obvious what it is they learn. Before addressing this question, it could be useful to explore the winning ratio, i.e. the number of auctions the bidder is winning as a fraction of the total number of auctions she participates in.

Figure 4 shows the distribution of winning ratios for the five groups. Although the mean is diminishing with participation, the picture is a bit more ambiguous. To further illustrate, Figure 5 shows a plot of all the bidders winning ratio compared to their participation level. Moreover, the predictions of two different smoothing regressions are also shown – the dark grey being more smoothing. Group limits are indicated with thin broken lines.

[13]Note: Above 8 bids per auction is accumulated in the last bar.



(a) Novice (b) Amateur (c) Experienced (d) Semi-Prof (e) Professional

Figure 4: Distribution in winning ratios

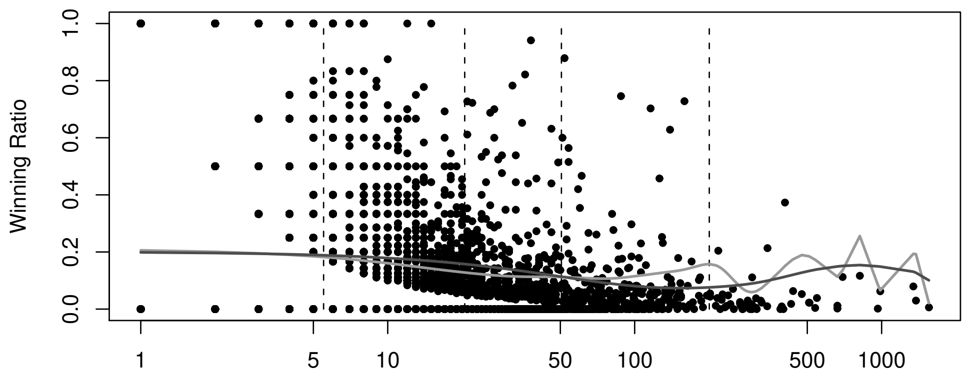


Figure 5: Average winning ratio (bidder)

A little caution must be exercised evaluating the winning ratio for Novice bidders. These will naturally have a tendency either to win or not to win as many of them only participate once or twice, but this division could also be a result of underlying preferences. On one side, there might be bidders that simply use the auction as entertainment. On the other side, there could be bidders that find exactly what they have been looking for, and price will be of less importance. However, this does not seem to be a major problem here as the smoothing regressions are, in fact, smooth.

Overall, the conclusion must be that bidders who participates more is winning less often. Yet, this is not necessarily the same as saying that experience makes the bidder less successful. Indeed, I will argue that the opposite is true. Perhaps it is exactly due to learning that bidders win less often. If the main objective is to get a good deal it may not be optimal to win all the auctions you participate in.

The literature on eBay argues that sniping is the optimal behavior (see e.g. the review of Bajari and Hortacsu (2004)). This auction is, as described in Section 2, very different on key points and sniping is not necessarily the optimal bidding strategy on Lauritz.com. The analysis in Bramsen (2008a) does, in fact, suggest the opposite for this auction. The reason is that early bids will scare of potential bidders, who otherwise would have been willing to run up the bid if they had entered.

In that case bidders do seem to adapt a more optimal bidding strategy. Fewer bids and earlier entry indicate that bidders learn to use max-bids. This will save transaction costs, but perhaps more importantly, it can scare off bidders and depress the winning bid.

Some of the bidders in the group “Professionals” do seem to win more often. and the smoothing regression does make an upward shift for the bidders with the most experience in Figure 5. However, this nicely corresponds to the argument that real professionals might have higher transactions costs for bidding and must therefore win more often compared to amateur bidders, who also bid for fun.

In sum, these data can basically support the underlying conclusions from previous studies on eBay data. Experience will make bidders more comfortable with the proxy bidding procedure and make them bid fewer times. Moreover, as argued, experience will also make the timing of bids more optimal.

4 Pseudo-endowment

Auctions have traditionally been blamed for causing “auction fever”, and internet auctions seem not to be the exception. For instance, there are studies which show that bidders on eBay end up paying much more than from other relevant alternatives because they “get caught by the game” (Lee and Malmendier, 2006; Ariely and Simonsen, 2003). Although these are extreme examples, they are part of the evidence suggesting that bidders change their willingness to pay (WTP) during the auction (see also Bajari and Hortacsu (2003) and Bramsen (2008a)). The bidding as such is therefore just part of the test for rationality through market experience.

One explanation behind increasing bids is that bidders start to see the auction as a competition where winning is the aim (Lee and Malmendier, 2006; Wolf et al., 2006). In such a case you would expect bidders to make more late bidding where the “battle” to win is the most intense. If so, the development in late bidding as observed in Section 3 does suggest that experience diminishes “auction fever”.

Competition is not the only possible reason behind increasing bids. Bidders might actually change their underlying WTP during the auction if they get attached to the item. More specifically, as bidders start to expect to win they might be affected by a sort of endowment effect – even though they do not has the actual ownership yet. Such a pseudo-endowment[14] effect have been found in a laboratory experiment by Ariely et al. (2004) and empirically by Bramsen (2008b). The effect of experience on the pseudo-endowment effect is therefore another test for the hypothesis that market experience will lead to rationality.

The critical and problematic element in asking what changes WTP is that I, in fact, have no way of knowing what a bidder's actual WTP is. Yet, by critically disregarding any bid that simply cannot be a credible representation of a bidder's WTP, chances are that at least a significant proportion of the remaining bids are representing WTP. This is the approach of Bramsen (2008b) and will also be the approach here.

Following the argumentation in Bramsen (2008b) the exact selection criteria of the bids in the 100,721 auction·bidder sample from section 3 are:

Only bids that are outbid There is no reason for a bidder to revise WTP and rebid if her bid is not outbid.

First bids only Although all bids might represent WTP I chose to focus only on the first bid and the probability to rebid a second time. One observation is therefore again the combination auction·bidders.

Only reasonably high bids Only first bids above 60% of the actual final price are considered.

Only max-bids In the auction bidders can chose to bid the next increment (as a first price auction) or a higher max-bid (a proxy bid). Only bids above the next increment are considered.

Only low second bids If the bid increases from the first bid to the second bid is higher than 20%, the first bid is unlikely to be a representation of WTP and is therefore disregarded.

Not too many bids Bidding more than 5 times in total in the auction indicates that the first bid is unlikely to represent WTP and is therefore disregarded.

Not fast rebidding Rebidding within minutes indicates that this is not a pseudo-endowment effect but perhaps in stead auction fever. Only bids that have not be increased within 4 hours are included.

[14]Although Ariely et al. (2004) call it quasi-endowment effect, Prelec (1990) was the first to name it pseudo-endowment in another context.

Naturally, the limit of each criteria is arbitrary, but all the limits have no significant effect on the resulting endowment effect, in a sensitivity analysis as reported in Appendix D. The exception is the last criteria as fast rebidding can reverse the effect. However, fast rebidding could be a sign of auction fever. As argued in Bramsen (2008b) high intensity rebidding is in that case expected to dominate a slower underlying pseudo-endowment effect. I therefore see this as a confirmation rather than a problem.

With this selection the remaining number of observations (first bids) is 11,511 (N_{sub}). The distribution between the five groups can be found in Table 1. The selection of max-bids means that the average ratio of bidders rebidding after the first bid decreases from 50.18% to 24.51%.

The idea is basically to ask if pseudo-ownership (in some form) affects the probability for bidders to rebid a second time if their first bid is outbid. The answer goes through a logit regression. More precisely, if y_i is a binary variable being 1 if bidder i rebids and 0 if bidder i does not rebid if outbid, then y_i can be represented by a binomial distribution where $y_i \sim B(1, p_i)$ for $i = 1, .., N$. I assume that p_i can be described using a logit model where pseudo-ownership is an explanatory variable[15].

As the main objective in Bramsen (2008b) is to establish the pseudo-endowment effect, experienced bidders are disregarded based on the assumption that experience could make the effect less clear. The idea with this section is basically to follow the same approach, but for all bidders, and to focus explicitly on the effect of experience. The general specification of the logit model here is therefore:

$$\ln\left(\frac{p_i}{1-p_i}\right) = f(\text{experience}_i \cdot \text{pseudo-endowment}_i) + g(\text{controls}_i) + \epsilon_i$$

where ϵ_i is a random stochastic variable. I will use a simple linear specification of $f()$ and $g()$. The controlling variables of $g()$ can be found in Appendix B.

In Bramsen (2008b) two measures of pseudo-endowment are found to have effect on the probability to rebid when outbid. One measure is the amount of time that a bidder has the leading bid before being outbid. This corresponds nicely to the observation by Strahilevitz and Loewenstein (1998) who observed that the endowment effect is enhanced with duration of ownership.

The other measure is "Depth" of ownership. Depth is defined as the amount between the current auction price and the max-bid of the bidder. If for

[15] Actually, i represent the combination of bidder and auction in the first model, but only the bidder in the second model as explained below.

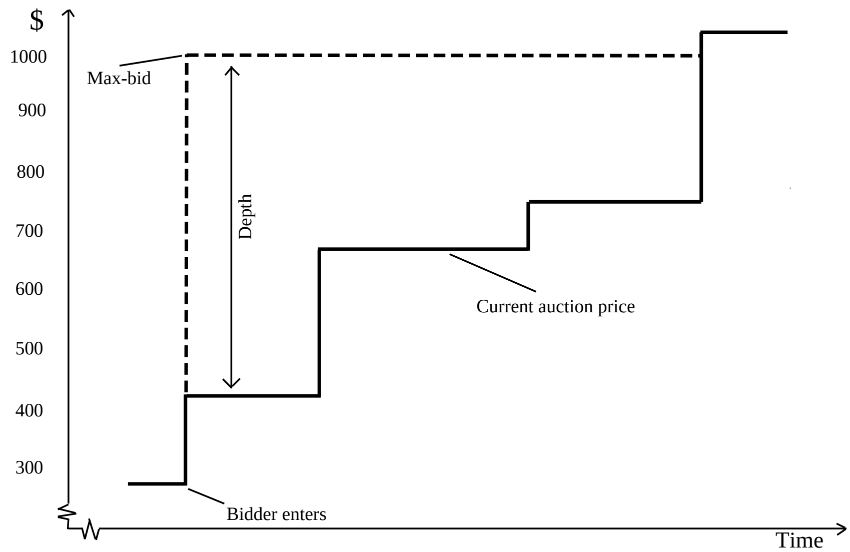


Figure 6: The “Area of pseudo-endowment”

instance the bidder puts in a max-bid of \$1000 and the previous leading bidder’s max is \$400, the current price will increase to \$420 (\$400 plus an increment) and the Depth will be \$1000-\$420 = \$580. A bidder must generally be more optimistic about the probability to win the lower the current price and the higher the depth. Depth must therefore be a proxy of the expectation to win.

These two measure can be combined in what can be characterized as an “Area of pseudo-endowment”. An example of such an Area is shown in Figure 6 where our bidder from before is outbid after periods with prices of \$420, \$680 and \$740. The main result of Bramsen (2008b) is that the logarithm to this area is the best determination of the pseudo-endowment effect. Thus, a larger area predicts a higher probability to rebid if outbid[16]. The question I ask here is therefore if the “Area of pseudo-endowment” is equally important for the probability to rebid as bidders get more experienced.

I use the 5 groups as described in Table 1 as specification of experience. Thus, the logit regression is an estimation of group specific pseudo-endowment effects: $group_i \cdot \ln(Area)$. The full result can be found in Appendix C, but Figure 7 shows the pseudo-endowment effects for the 5 groups with 95% confidence bands.

[16]It is somewhat ambiguous when the area is zero. This could either be because the bidder was outbid right away or because the current price equals the bidder’s max bid. If the latter is the case the bidder will still feel some sort of ownership. In this case I have added a dummy to absorb the pseudo-endowment effect.

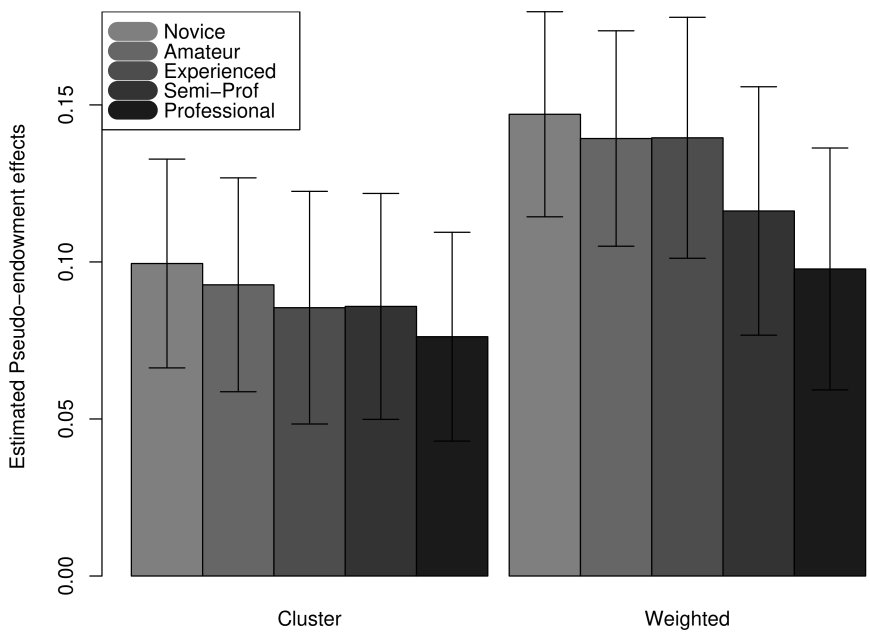


Figure 7: Estimated effects from logit regressions

The logit regression needs to be slightly more complicated than that of Bramsen (2008b). First of all, as some bidders are represented with a large number of bids the possible correlation between these bids must be taken into account."Cluster" is estimated using a robust variance estimator making the standard deviations slightly larger than in a simple logit regression.

Another possible modification is that bidders should count equally in the regression regardless of the number of auctions they participate in. "Weighted" is therefore a logit model were the bids are down-weighted such that all bidders only count as one in the subset. Effectively the data set therefore consists of 5449 bidders in stead 11,511 first bids.

In my opinion the right result is intuitively somewhere in between the two models, as you can also argue that more important bidders should have more influence on the result. Either way, both models show that the pseudo-endowment effect *does not* disappear with experience. In both models the group effect of "Professionals", that participated in more than 200 furniture auctions in 2005, is highly significant.

As expected there is some tendency of the pseudo-endowment effect to diminish through experience, but especially in the Cluster model this tendency is weak. It also seems that the effects are stronger if the bids are Weighted, but as other parameters also change from one model to the other, these parameters cannot be directly compared.

Statistically, the relevant question is if the groups are necessary when describing the pseudo-endowment effect of a bidder. I test this hypothesis in a Wald-test. For the Cluster model the result is a P-value of 0.1723 and for the Weighted model the P-value is 0.00369. Thus, the Cluster model cannot reject this hypothesis while the Weighted model can. In other words, one model suggests that there is no statistically significant effect of experience, while the other suggests that there is some.

To conclude, the observation from this part of the analysis is that bidders may learn a little, but generally they will still be affected by the pseudo-endowment effect regardless of their experience. From this perspective experience will therefore not lead to rationality.

5 Discussion and conclusions

The results in this paper are at face value ambiguous. By only looking at the bidding it appears that bidders do learn to bid more optimal. They bid fewer times, engage in fewer bidding wars and bid early in the auction perhaps to scare off other bidders as suggested by Bramsen (2008a). However, even experienced bidders are still affected by the pseudo-endowment effect. Yet, these seemingly conflicting findings do correspond to other findings in the literature.

There are a number of studies with evidence of learning by market experience. As mentioned in Section 3 there are several surveys on eBay data showing that experience optimizes the bidding. Livingston (2008) also finds that experienced bidders learn to take the reputation of sellers into account when they decide to bid on eBay. On the endowment effect List (2003) finds that experience in the trading of sports cards does, to some extent, eliminate the endowment effects of these cards. Moreover, this learning effect appears to transfer over to the trading of other items like mugs and candy bars (List, 2004).

Although bidders and traders do seem to learn, the evidence does not necessarily suggest that they become rational. In laboratory experiments of second-price auctions people learn to bid more consistently and like each other, but they do not learn to use their dominant strategy (see e.g. Kagel and Levin (1993), Garratt and Wooders (2004) and Noy and Rafaeli (2005)). In stock markets traders value stocks higher once they own them and, although this endowment effect is more pronounced for private traders, the effect does not disappear for institutional brokers. An even stronger observation is done by Haigh and List (2005) who find that professional stock brokers exhibit more loss aversion than a control group of students. Thus, it may not always be rationality that we learn in the market.

The underlying explanation may be found in the feedback as suggested by Loomes et al. (2003). The classical argument is that market participants will learn through experience. Yet, learning is not derived from experience *per se*, but from the feedback you can get through experience. Some feedback may push you towards rationality while other feedback may push you further away. Although Loomes et al. (2003) focus on separating the two cases[17] the main point here is that you can only learn what the feedback directly or indirectly is teaching you. In light of this the conflicting evidence reported here appears reasonable.

Of all feedback, negative feedback appears to be the most influential. In Braga et al. (2006) it is actual losses in lotteries that reverse participants' preferences for lotteries over sure outcomes. Even more relevant is the analysis of newly registered eBay bidders by Wang and Hu (2007). They conclude that above all it is the loosing experiences that develop these new bidders' bidding behavior.

Learning by losing also seems to be the case for bidding on both eBay and Lauritz.com. Beginners being outbid in the last second on eBay will learn to use the dominating strategy of sniping. With the soft ending on Lauritz.com the likely loss for a beginner is the intension of bidding late, but to forget. The lesson here will be to save transaction costs and bid earlier with a max-bid. Though, it can also be the case that feedback is limited to observing the bidding of others. In that case learning is more a question of copying behavior (herding).

When it comes to the pseudo-endowment effect there is, however, no feedback. You cannot learn by observing others, and the negative feedback from paying "to much" is hidden. Once the bidders actually get to own the items they will feel the endowment effect even stronger and not be able to recognize their inflated WTP[18]. Even professional bidders may not realize their own pseudo-endowment effect as the negative feedback is likely to be absent or delayed. This is the case if the item is resold with a profit after all or if the resale happens several month later. Yet, this reasoning is speculation

[17]When participants are corrected towards underlying rational preferences Loomes et al. (2003) label this as the *market discipline* hypothesis. The contrary is when markets are shaping behavior decoupled from rationality. This is labeled as the *shaping* hypothesis.

[18]Or at least they will have a hard time recognizing their mistake due to cognitive dissonance.

and the coupling between the auction and resale market is an obvious object for further investigation.

Generally, the observations on experience and auction behavior is likely to be a consequence of the feedback. When bidders learn to change their bidding strategy they are likely to respond to negative feedback. And when bidders have more difficulties learning their pseudo-endowment effect it is due to the lack in feedback.

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APPENDIX

A Robustness of bidding behavior

In Section 3 the bidding behavior of five groups of bidders were analyzed. However, group averages could potentially conceal substantial variation within the groups. In order to check for such effects the data for each bidder is plotted in Figure 8 to 11 with the level of participation on the x-axis with a logistic scale. Group limits are indicated with thin broken lines. Moreover, I have also added two smoothing-regressions such that the local average can be observed. The difference in the two smoothing regressions is the degree of smoothing where the dark grey line is more smoothing than the brighter grey. In all four figures there do not seem to be major movements within the groups. "Professional" (above 200) does seem to have some variation, but this is mainly due to the small amount of bidders in this group.

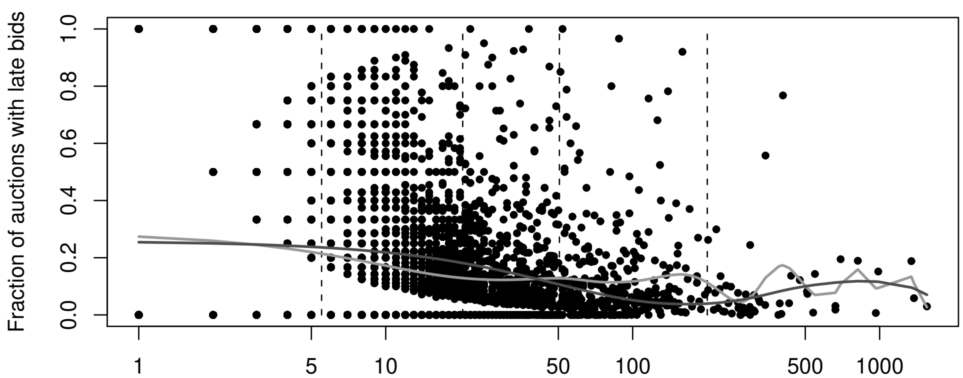

Figure 8: Auctions with late bids (last hour)

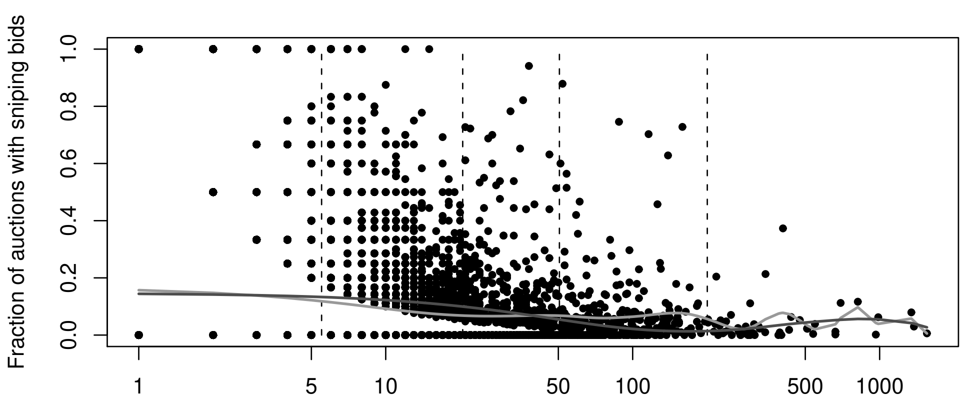

Figure 9: Auctions with sniping bids (a bid within last 10 min)

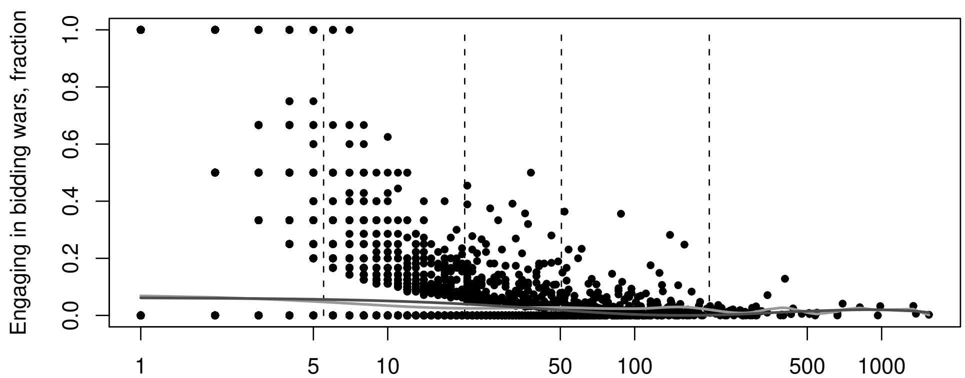

Figure 10: Auction with two bids within last 10 min (bidding war)

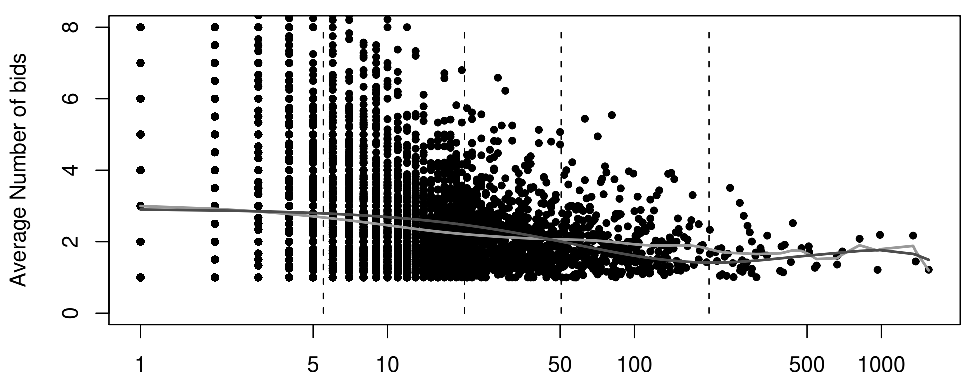

Figure 11: Average number of bids (bidder)

B Controlling variables

The controlling variables are basically the same as in Bramsen (2008b). Although the selection of first bids is supposed to be strict, other factor could still affect the stated WTP (bid) resulting in a variation in the rebidding. The factors I use in the logit regressions are:

Group More experienced bidders may in general be less likely to rebid. To separate this effect from the pseudo-endowment effect, I use groups as controls.

Experience Does basically the same as the individual group effect, but the combination opens up for flexibility.

Time of entry If a bidder is looking for some special item she is more likely to find it earlier in the auction period than bidders who are just randomly searching. Hence, early bidders might have higher WTP.

This is in itself not a problem if the bidder really bids her maximum WTP. However, as the price is likely to be lower early in the auction this can act as an anchor depressing the first bid. The probability to rebid could for this reason be higher.

Valuation As mentioned in Section 2 Lauritz.com lists an estimate of the final price to guide both the sellers and the buyers. For expensive items (e.g. with a valuation of $4000) bidders might hesitate to put in their true WTP. As a consequence they might be more inclined to increase their bid later in the auction.

Price at entry A *relative* low price at entry compared to the actual value (the final price) might depress the bidders entry bid – just as a high valuation or early bids could do.

Basically, these last three controls are therefore taking an "anchoring effect" into account.

C Result of logit regressions

The specific results of the logit regressions as reported in Section 4 can be found in Table 3. I will briefly comment on the result for the controlling parameters.

The independent group effect is decreasing as expected. Although the effect, to a small extend, is counteracted with the "experience" control, the overall conclusion is that more experienced bidders rebid less often in general.

The anchoring effects of "Time of entry" and "Price at entry" are also as expected. Later entry and a higher price at entry will decrease the probability of rebidding. The effect of "Valuation" is the opposite as expected for anchoring, but the effect is not significant.

The "Dummy" is part of the pseudo-endowment effect, and the result is basically that even when Depth=0, but still with a leading bid, it will create a pseudo-endowment effect. Not to complicate the analysis and the interpretation needlessly, I did not combine this caveat of the pseudo-endowment effect with experience.

Further comments on the models and the results can be found in Section 4

Parameters:	**Cluster**	**Weighted**
Intercept (Amateur)	-1.06*** (0.15)	-1.52*** (0.14)
Independent group effects:		
Novice	0.16* (0.06)	0.05 (0.07)
Experienced	-0.15 (0.09)	-0.12 (0.10)
Semi-Prof	-0.18 (0.11)	-0.23* (0.11)
Professional	-0.25 (0.28)	-0.15 (0.27)
Controls:		
Experience (1/100)	0.025 (0.046)	0.039 (0.048)
Time of Entry	-0.053** (0.017)	0.007 (0.017)
Valuation (1/1000)	-0.017 (0.053)	0.013 (0.061)
Price/Valuation	-0.58*** (0.12)	-0.39** (0.13)
Pseudo-endowment effects:		
Dummy	1.31*** (0.29)	2.09*** (0.29)
Novice*ln(Pseudo-endowment)	0.100*** (0.017)	0.147*** (0.017)
Amateur*ln(Pseudo-endowment)	0.093*** (0.017)	0.139*** (0.017)
Experienced*ln(Pseudo-endowment)	0.085*** (0.019)	0.140*** (0.020)
Semi-Prof*ln(Pseudo-endowment)	0.086*** (0.018)	0.116*** (0.020)
Professional*ln(Pseudo-endowment)	0.076*** (0.017)	0.098*** (0.020)

Table 3: Development in the pseudo-endowment effect - Logit regressions

D Sensitivity analysis

The criteria to select the max-bids are based on my best estimates of the bidding behavior, but they are of course arbitrary. To test for dependence on the exact limits, Table 4 shows a sensitivity analysis where I vary one restriction at the time. For every variation I have stated the group specific pseudo-endowment effect for the “Cluster” model and the number of observations in the sample (N_{sub}). Note that for most criteria the actual limit (in bold) is not the one maximizing the pseudo-endowment effect. Furthermore, the resulting pseudo-endowment effects in and between groups are quite robust. This is also true for the significant levels where all (except the two last limits for time) are three star significant.

As mentioned, the exception is the criteria of time between first and second bid. If I allow for a shorter period between bid and rebid, the sample will at a point be dominated by another behavior, perhaps auction fever, and the sign is changed. The same pattern was found in Bramsen (2008b) and I think it basically confirms that this is not auction fever, but something else.

	Novice	**Amateur**	**Experienced**	**Semi-Prof**	**Professional**	$\mathbf{N}_{sub}$
$\geq$ *% of final price*						
80%	0.162	0.184	0.154	0.153	0.151	5492
70%	0.107	0.113	0.098	0.095	0.085	8385
60%	**0.100**	**0.093**	**0.085**	**0.086**	**0.076**	**11511**
50%	0.090	0.084	0.081	0.083	0.071	14658
40%	0.095	0.090	0.086	0.081	0.071	18392
Only max-bids:						
Yes	**0.100**	**0.093**	**0.085**	**0.086**	**0.076**	**11511**
No restriction	0.080	0.074	0.073	0.071	0.069	17272
Bid increase:						
$\leq$**20%**	**0.100**	**0.093**	**0.085**	**0.086**	**0.076**	**11511**
No restriction	0.123	0.118	0.110	0.110	0.102	12093
Number of rebids:						
$\leq$ 6 rebids	0.103	0.094	0.090	0.091	0.080	11574
$\leq$ **4 rebids**	**0.100**	**0.093**	**0.085**	**0.086**	**0.076**	**11511**
$\leq$ 3 rebids	0.096	0.088	0.079	0.079	0.072	11409
$\leq$ 2 rebids	0.098	0.096	0.084	0.082	0.081	11115
Rebid within:						
$\geq$ 8 hours	0.114	0.106	0.094	0.099	0.087	11305
$\geq$ **4 hours**	**0.100**	**0.093**	**0.085**	**0.086**	**0.076**	**11511**
$\geq$ 1 hour	0.045	0.048	0.045	0.044	0.038	12019
$\geq$ 30 minutes	0.015	0.019	0.017	0.017	0.009	12227
No restriction	-0.071	-0.068	-0.071	-0.078	-0.066	15695

Table 4: Sensitivity analysis on Cluster model