May The Most Experienced Man Win: Why Do More Experienced Bidders Shade Less?*

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Abstract

This paper tries to rationalize the empirical finding that more experienced bidders, as measured by the number of auctions in which they have participated or won, tend to lower, or "shade", their bids less than do bidders with little or no previous experience. This is surprising because although we do expect shading to occur in order to correct for the "winner's curse" - winning an auction but at the cost of overpaying - previous experimental evidence suggests that bidders become better at accounting for this effect with experience and should, if anything, shade more. I use the asymmetric ascending auction model of Hong and Shum (2003), together with a unique data set of roughly ten thousand online automobile auctions from Sweden, to show that this can be explained by a difference in the accuracy of bidders' private signals; through experience, bidders become better at estimating the value of automobiles being auctioned and, as a consequence, less reliant on the more inaccurate private information of bidders with little or no experience.

JEL Codes: L62, C51, D44, D82
Key words: Ascending (English) Auctions, Asymmetric Auctions, Experience, Learning, Winner's Curse, Bid Shading, Signal Precision

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1 Introduction

Imagine auctioning off a jar full of coins, the value of which is known to you but unknown to everyone else - an example of a common value auction, one in which the object being auctioned has the same value to all auction participants. Although the value of the jar is the same for every participant, each will have their own unique estimate of what's inside; someone may take the scientific approach, guessing the volume of the jar and the volume of the average coin whereas someone else may pick a number at random. Assuming these estimates are correct on average, if the participants are inexperienced, chances are that the average placed bid will be below and the average winning bid above the true value of the coins in the jar. In other words, the winner will on average end up bidding more for the jar than it is actually worth, overpaying in the process. This example described by Richard H. Thaler (Thaler, 1982) beautifully exemplifies the "winner's curse" whereby bidders do not correctly account for the possibility that their estimates may be overly optimistic. In theory, if bidders were fully rational, they would foresee the possibility of the winner's curse and correctly reduce their bids to reduce the risk of overpaying, a process known as bid "shading".

The winner's curse phenomenon was first discussed in early work by Capen, Clapp and Campbell (1971), pondering why oil companies drilling for oil in the Gulf of Mexico weren't getting the returns they had anticipated from their investments. The authors conclude that the industry as a whole was paying far more for the drilling rights than they were actually worth. Not because of bad luck, however, but because of the complexity of the bidding environment the companies were competing in for the drilling rights. Additional evidence of the winner's curse has also been found for example in studies of auctioned books (Dessauer, 1981), free agents in major league baseball (Cassing and Douglas, 1980) and corporate takeovers (Roll, 1986). Although these earlier studies highlighted the winner's curse problem, more recent work has tried to quantify how bidders account for the effect; Bajari and Hortaçsu (2003) study eBay coin auctions and find that in the average auction, bidders lower their bid by roughly 3% for every additional participating bidder. In a similar manner, Hong and Shum (2002) show that in low-price highway procurement auctions, increasing the number of bidders from 3 to 10 results in an increase of a bidder's median bid from \$0.2m to over \$0.6m.[1]

Experimental evidence also suggests that bidders fail to account for the winner's curse; Bazerman and Samuelson (1983) auctioned off jars of coins, paperclips and other miscellaneous objects with a value of \$8 to M.B.A. students, finding that on average, they overpaid for the contents by roughly \$2. These results are not unique, with other experiments confirming that participants tend to overbid even in a classroom environment (Bazerman and Samuelson, 1985, Kagel and Levin, 1986, Kagel, Levin and Harstad, 1987 and Dyer, Kagel and Levin, 1987). Interestingly, in their classroom experiment involving both students and experts, Dyer et al. (1987) found that industry experts tended to overbid just as much as the college students.

It may be unsurprising that inexperienced bidders are not perfectly rational, perhaps never before having participated in auctions. The majority of us do not participate in auctions very frequently, much less auctions in which we stand to incur significant losses by overpaying. Frequent auction winners, although having started out inexperienced, are likely to learn to avoid making costly mistakes or run out of money and stop participating. Experimental evidence suggests this is

[1] In low-price procurement auctions, the winner is the bidder that places the smallest bid. Hence, the winner's curse effect takes the opposite effect to a first or second-price auction; the bidder suffers the winner's curse if he bids an amount which is too small in comparison to the estimated costs of completing the project. This is why to avoid the effect, bidders should increase, rather than decreasing their bids, in procurement auctions.

at least partly the case with more experienced bidders learning to account for the winner's curse by lowering, or shading, their bids after having participated in a number of auctions beforehand (e.g. Kagin and Levin, 1986, Weiner, Bazerman and Carroll, 1987, Garvin and Kagel, 1994). Similarly, frequent participation, which although not as costly as winning and overpaying, is also likely to exhibit effects on behavior similar to winning auctions, albeit at a slower rate.

In this paper, I start by presenting reduced form evidence from a unique data set of roughly ten thousand online automobile auctions carried out in Sweden that, surprisingly, as bidders gain experience their average bid increases and they seem to lower, or shade, their bids less than less experienced bidders. Although counter-intuitive at first, given the previous findings, this behavior has previously been observed in the experiments of Weiner et al. (1987) who saw the average bid drift upward towards the end of their experiment, after bidders had already participated in a number of auctions.

An increase in average bids is the opposite of what we may expect if inexperienced bidders shade too little to account for the winner's curse but start shading more with experience. By using the asymmetric ascending auction model of Hong and Shum (2003), I try to explain why more experienced bidders shade less than do less experienced bidders and find that through experience, bidder's signals become more accurate. In other words, more experienced bidders are better able to estimate the value of the auctioned automobiles and become less reliant on the estimates of others. Because of this, the more experienced bidders do not need to adjust their beliefs as much during the course of the auctions and as a consequence lower their bids less as new information becomes available. I also show that as a consequence of asymmetries in signal precision, when a bidder with an accurate signal drops out, the remaining bidders adjust their beliefs more than when a bidder with an inaccurate signal drops out. In other words, bidders do not treat all information equally, with more accurate public information being more important than less accurate information.

This paper is organized as follows; In Section 2, I present the data used in this study, descriptive statistics together with reduced form evidence of experienced bidders shading their bids less than bidders with little or no past experience. In Section 3, I present the structural asymmetric ascending auction model of Hong and Shum (2003). In Section 4, I discuss the identification of the model and its parameters, and in Section 5, I discuss the simulation procedure used to estimate the parameters from the data. In Section 6, I present and discuss the results and in Section 7 I present the results of various robustness tests. In Section 8 I discuss the revenue consequences of signal precision with Section 9 concluding.

2 A First Look at Bidder Experience

In this section, I begin by presenting a detailed summary of the data used in this study, brief descriptive statistics of the variables used throughout and thereafter present somewhat surprising reduced form evidence that bidders tend to shade their bids less and less, as they gain additional experience.

2.1 Data

The automobile auction data used in this study is collected from Kvarndammen AB (KVD), a large Swedish auction site, using an automated collection algorithm. The site conducts auctions of, among other things, automobiles, boats, motorcycles and commercial real estate property. This study focuses solely on KVD automobile auctions.

Automobile auctions on KVD are conducted on a weekly basis, with new vehicles being listed throughout the day every Friday and ending on either Tuesday, Wednesday or Thursday the following week. Auctions are conducted sequentially, with a single new auction starting every five minutes from 9 a.m. and often proceeding until 9 p.m.[2] Depending on the supply of vehicles a given week, there may be periods when no auctions take place, often lasting no more than a few hours.

Once a car has been listed for auction, anyone is free to follow the bidding process and view the detailed vehicle information without having to register an account. Persons interested in placing a bid have to register an account and are able to place bids, with a minimum incremental bid of 500 SEK,[3] at no cost.[4] If a bidder wants to withdraw a bid, it is possible to do so, although cannot be done by bidders themselves,[5] up until six hours before the final countdown (described below) is officially initiated. Should a bidder place the winning bid, the bidder is legally bound to go through with the purchase.[6] The history of bids is publicly available, although only the five latest bids are shown, together with the username of the user placing the bid, the time at which the bid was placed as well as the bid itself. Once the auction ends, all information regarding the vehicle is removed, including the final five bids.

Every automobile listed for auction is carefully reviewed by a KVD mechanic, either in-house or affiliated, and a summary of the review together with detailed technical information is made available to the public at the start of each auction. The information is provided in a standardized format and can be broadly categorized into technical, legal and qualitative; Technical and legal information is taken from the Swedish Transport Agency's vehicle register, containing information about the bodywork, engine, size as well as the MOT period and tax details. The qualitative information contains the mechanic's assessment of the different parts of the vehicle including an overall vehicle assessment and more detailed assessments of the bodywork, engine, breaks, gearbox and interior. Each vehicle is located at one of roughly 15 locations in Sweden and anyone interested may go and test-drive the given vehicle on prespecified dates. Sometimes prespecified dates are not given, in which case one has to call and make an appointment.

The exact time at which an auction ends is not known in advance; every vehicle is listed with a so-called "countdown time" at which a 3-minute timer starts and proceeds to reset until no new bid is placed within a consecutive 3-minute period.[7] Once the 3-minute period passes with no new bid being placed, the auction ends and the item is suspended. Every vehicle has a secret reserve price[8] and if the winning bid is above this reserve price, it is automatically accepted and

[2]The sequential nature is such that, depending on popularity, a given auction may not end until the next one begins. This means there are periods when multiple auctions are underway simultaneously.

[3]Roughly $70 at an exchange rate of 7 SEK/USD.

[4]The site also offers an automated, or proxy, bidding service at no extra cost. Any user interested in using the service, merely states the maximum price he or she is willing to pay and the proxy bidding system automatically places bids until you have either won the auction or the currently highest bid has exceeded your maximum limit. Should the same bid be placed by two users, either automated or human, it is the bid that was placed first that is counted. For a more detailed discussion on the mechanics of proxy bidding see e.g. Bajari & Hortaçsu (2003).

[5]Instead the user has to contact KVD directly and ask for the bids to be withdrawn.

[6]This means that should you decide to back out after having won the auction, you will have to pay a fee for that particular auction as well as costs incurred by the seller in putting the vehicle up for auction again. While this means that one does not actually have to purchase the vehicle and incur the entire cost, the cost of compensating the seller for loss of business may still turn out to be significant.

[7]This is called a "soft" close in the literature. Online auction house eBay on the other hand has a "hard" close whereby the auction ends at a prespecified time.

[8]An item's reserve price is not fully secret as there is a publicly available "Yes/No" indicator which lets bidders know whether the reserve price has been reached or not during the entire auction. Due to data collection issues, I

the winning bid, together with the vehicle name, winner's username, winning bid and ID number of the vehicle, is posted online for 10 days. Should the reserve price not be reached, the seller is free to choose whether to sell the vehicle at the highest achieved bid or to withdraw the item and attempt to resell it at a later date.

A much more thorough description of the vehicle data provided for each auction can be found in the appendix.

2.2 Descriptive Statistics

From Table 1, we see that the sample of data used in this study is comprised of roughly ten thousand automobile auctions collected from Swedish online auction house KVD between October 7th 2011 and July 18th 2012.

INSERT TABLE 1 ABOUT HERE

The number of unique bids submitted in these auctions is roughly 470 000 with 108 686 bids being "final", or dropout bids. Although dropout bids may not correspond to the actual unobserved dropout bid, in this study I use the final bid at which a bidder was active as that bidder's dropout bid. These bids were placed by 24 586 unique bidders, with, on average, almost 11 bidders participating per auction. Some auctions were more popular than others, with the most popular having attracted 33 unique bidders and the least popular seeing only a couple of bidders.[9] Having only one observable bidder does not necessarily imply that the automobile being auctioned is unattractive; the majority of auctions that attracted only one observable bidder were auctions in which the first bid was also the winning bid, that is, the initial bidder submitted a high first bid, or "jump" bid. As such bids cannot be considered to be dropout bids, auctions with only a single participating bidder have been excluded from the sample.

The average price at which a bidder drops out is roughly 76 000 SEK, with bidders having dropped out as low as 200 SEK and as high as 523 000 SEK. The average winning bid is roughly 105 000 SEK whereas the average appraised value of an automobile is just over 144 000 SEK. While this gap between winning bids and appraisal values may suggest that cars are being sold at a discount, this is not obvious because of how the appraisal is conducted - the appraised value is that of an identical vehicle in flawless condition. The sample contains all manner of automobiles, ranging from older models to newer or more luxurious makes with appraisals ranging from 10 000 SEK to 775 000 SEK. In a few cases high-performance sports cars such as Ferraris, Maseratis and Lamborghinis have been auctioned during the sample period. As these vehicles differ significantly as compared to the average car, both in terms of characteristics and price, these have been excluded from the sample.

Looking at bidder experience we see that over the sample, the average bidder participates in around 4 auctions with the average number of wins being 0.29, suggesting that the majority of bidders walk away from this sample of auctions empty-handed. Not only that, but it suggests that there are a number of bidders that are buying significantly more than one vehicle. The highest number of wins sustained by a single bidder during the period was 87 whereas the bidder that

do not observe the reserve price signal in my data.

[9] On very rare occasions, there have been auctions in which not a single bid was placed. As the model presented in Section 3 requires at least one observable dropout bid to estimate, such auctions have been excluded from the sample.

was most active in terms of participation, participated in 853 auctions. The average cumulative experience variables, which give the number of auctions won or participated in from the sample period until the present auction, are less instructive as they are heavily influenced by the most active bidders, both in terms of participation and in terms of winning.

2.3 Reduced Form Evidence

As pointed out by Bajari and Hortaçsu (2003), one of the implications of the Milgrom and Weber (1982) model, describing both first and second-price common value auctions, is that the possibility of overpaying (or suffering the winner's curse) increases with the number of bidders participating in the auction. That is, as a bidder you are more likely to overpay when you are facing many competing bidders than when only facing a handful. To reduce the chances of overpaying, the bidders should lower, or "shade" their bids, with the degree of shading increasing in the number of auction participants.

Despite these predictions, there are a number of studies suggesting that bidders in actual fact fail to account for the winner's curse by not lowering their bids enough, both in real life auctions (e.g. Capen, Clapp and Campbell, 1971) and classroom experiments (e.g. Bazerman and Samuelson, 1983). However, in a number of classroom experiments, it has been found that although there is an overall failure to account for the winner's curse, participants' judgment does improve as the experience of the participant increases (Kagel and Levin, 1986, Weiner et al., 1987). With every additional auction, bidders shade more and more approaching the bids one would theoretically expect. This suggests that if we were to look at more experienced auction participants in real-world auction data, we may find that they shade their bids more than do less experienced players or, at the very least, that experience doesn't make a difference.

INSERT TABLE 2 ABOUT HERE

The results of simple, reduced-form Ordinary Least Squares (OLS) regressions of the number of bidders, the experience of a given bidder as measured by the cumulative number of wins or cumulative auction participation, on logarithmized dropout prices[10] presented in Table 2 suggest that, as in Bajari and Hortaçsu (2003), average bids decline with the number of bidders participating in the auction. This is consistent with bidders accounting for the winner's curse and lowering their bids more and more with each additional participating bidder. However, we also see that the more experience the bidder has the less he lowers his bid with every new participating bidder; experience has a positive effect on bid shading as measured by the positive and statistically significant interaction terms. Taken at face value, this would contradict an improvement in judgment of more experienced bidders in accounting for the winner's curse. If anything, it would suggest that more experienced bidders are getting even worse. Alternatively however, it may be the case that the degree to which bidders with little or no experience lower their bids is too high to begin with, with inexperienced bidders lowering their bids too much. Experienced bidders may realize that they were lowering their bids too far and instead increase their bids to equilibrium levels. This alternative explanation however contradicts a large body of existing evidence which suggests that the degree of shading is lower, rather than higher, than one would expect (e.g. Capen, Clapp and Campbell, 1971) with bidders tending to suffer the winner's curse.

[10] Dropout prizes are logarithmized to ensure consistency between the reduced form specifications and the log-normal specification of the Hong and Shum (2003) model. The results remain qualitatively the same if one instead uses dropout prices normalized by appraisal value.

A concern with the reduced form specification is that, not only is the number of bidders an endogenous variable, but that the two measures of experience are as well, rendering OLS estimates biased and inconsistent. It is not unlikely that the number of times a given bidder participates is related to that bidder's participation cost; bidders with lower participation costs are more likely to participate more frequently perhaps in the hope of winning their preferred car at a bargain price, whereas a bidder with high participation costs is more likely to participate less and pay a little extra to avoid participating again in the future. Similarly, the number of times a bidder wins is likely driven by the demand of that particular bidder; a private individual will not be looking to buy more than one or two cars whereas a professional dealer or trader is likely to have a much higher demand, potentially leading them to be more aggressive and win more auctions.

To account for the potential endogeneity of the number of participating bidders as well as bidder experience, I instrument the endogenous variables in the reduced form analysis; to instrument for the number of bidders in an auction, I proceed in a manner similar to Bajari and Hortaçsu (2003) who use the auction's reserve price, or minimal accepted bid normalized by the item's book value. As I do not observe the reserve price and, due to data collection issues do not have access to the public signal of whether the secret reserve price has been surpassed, I instrument using the first observed bid in the auction. In some sense, the first bid in the auction becomes an effective public reserve price for potential bidders that have not yet decided to enter the auction. If the smallest placed bid is \$10, the effective public reserve price for bidders that are yet undecided, or have only just entered the market, is at least \$10. However, if an aggressive bidder decided to place a jump bid at the very start of the auction to say \$5000 dollars, then the effective reserve price for undecided bidders is instead at least \$5000.

To instrument for bidder experience, as measured by the cumulative number of wins or cumulative auction participation, I use the bidder's percentual participation rate of the auctions having occurred to date, with the interaction term between experience and the number of bidders being instrumented by the product of the two individual instruments.

From Table 2, we see that after instrumenting, both effects persist and are now stronger; average bids decline with the number of bidders participating in the auction and experience has a positive effect on bid shading. In the remaining sections of the paper, I try to show why this somewhat surprising behavior is rational and does not contradict behavior accounting for the winner's curse.

3 Model

In this section, I present the asymmetric ascending auction model of Hong and Shum (2003). The choice of model used in this study is driven by a number of different considerations, both empirical and theoretical.

The focus of this study is to determine whether experience gained by either participating in, or winning an automobile auction can help in explaining why more experienced bidders seem to lower, or shade, their bids less than do bidders with little or no experience. By its very nature, this problem is about determining whether asymmetries in experience affect bidder behavior, something easily incorporated into the general asymmetric framework of the Hong and Shum (2003) model. Furthermore, incorporating both private value and common value components, the model is very well suited to study automobile auctions, likely incorporating both types of components.

Despite there being a wide range of models proposed to study data from online auction house eBay, these models are theoretically unsuitable due to the nature of the auctions' ending rules. eBay

auctions have a predetermined ending time publicly displayed to all bidders, something known as a "hard" close. The auctions studied in this paper end only after a period of inactivity, something known instead as a "soft" close. This difference is seemingly small, but does have implications for how bidders of the two types of auctions will behave in equilibrium; eBay auctions are prone to a phenomenon known as "sniping" whereby the majority of bids are submitted very close to the end of the auction, something that looses strategic value in "soft"-close auctions.[11] For a more extensive discussion on sniping and auction ending rules see e.g. Roth and Ockenfels (2002).

3.1 Equilibrium Bidding

Consider an auction with N known bidders. The auction proceeds in rounds with a new bidder dropping out irrevocably in every round k. Let bidders be indexed by the round in which they drop out;[12] bidder N drops out in round 0, at price P_0, and bidder $N-k$ drops out in round k at price P_k, with bidder 1 finally winning the auction at the final observed dropout price P_{N-2}.

Each bidder $i = 1, ..., N$ attaches a value of V_i to the object being auctioned. The valuation is unobservable to each bidder and instead, each bidder observes a private, noisy signal X_i about their value V_i.

In round k, as the $N-k+1^{st}$ bidder has already dropped out, the remaining $N-k$ bidders can invert the dropout price P_{N-k+1} to learn the private information X_{N-k+1} of that bidder. In common value auctions, this information is useful to the remaining bidders as they can use it to update their beliefs about their own valuation.

A Bayesian-Nash equilibrium of the asymmetric ascending auction game is given by bid functions $\beta_i^k(X_i; \Omega_k)$ for each bidder $i = 1, ..., N$ and every round of the auction k. Each bid function $\beta_i^k(X_i; \Omega_k)$ determines the price above which player i should drop out in round k given the player's private signal X_i and Ω_k, the collection of $k-1$ signals observed prior to round k.[13] Denote the collection of equilibrium bid functions for player i as

$$\mathbb{B}_i = \left\{\beta_i^0(X_i; \Omega_0), ..., \beta_i^{N-2}(X_i; \Omega_{N-2})\right\}$$

Assume that for all bidders $i = 1, ..., N$ the bidding functions $\mathbb{B}_j$ of all other players $j \neq i$ are common knowledge.

Assume further that

(A1) The conditional expectation $E[V_i|X_1, ..., X_N]$ is strictly increasing in signals X_i for each bidder $i = 1, .., N$

(A2) The solution of the $N-k$ unknown variables, $X_1, ..., X_{N-k}$, in the equation system given by

$$\begin{aligned} E[V_1|X_1, ..., X_{N-k}; X_{N-k+1}, ..., X_N] &= P \\ &\vdots \\ E[V_{N-k}|X_1, ..., X_{N-k}; X_{N-k+1}, ..., X_N] &= P \end{aligned}$$

[11] Sniping is the practice of trying to place a bid as late as possible so as to avoid revealing private information to other participants. As there is no predetermined or fixed ending time in soft-close auctions, no matter what time you choose to submit your bid, there will always be a minimum amount of time remaining until the auction ends.

[12] This is done without loss of generality.

[13] One can think of Ω_k as being either the collection of $k-1$ dropout prices or inverted private signals of the $k-1$ bidders that have dropped out prior to round k.

is unique and strictly increasing in the given parameter P, for all possible realizations of $X_{N-k+1}, ..., X_N$.

Proposition 1 (Hong and Shum, 2003) Given assumptions A1 and A2, there exists an increasing-strategy Bayesian-Nash Equilibrium of the asymmetric English auction for which the strategies are defined recursively. In round k:

$$\beta_i^k (X_i; \Omega_k) = E\left[V_i | X_i; X_j = \left(\beta_j^k\right)^{-1}\left(\beta_i^k (X_i; \Omega_k)\right), j = 1, ..., N, j \neq i, \Omega_k\right]$$

for the bidders $i = 1, ..., N-k$ remaining active in round k, where Ω_k denotes the public information set consisting of the signals of the bidders $N-k+1, ..., N$ who have dropped out prior to round k, i.e.,

$$\Omega_k = \left\{X_j = \left(\beta_j^{N-j}\right)^{-1}(P_{N-j}), j = N-k+1, ..., N\right\}$$

Proof: See Hong and Shum (2003), p331.

Let the valuation of bidder i have a multiplicative form given by $V_i = A_i \times V$ where A_i is a bidder-specific private value component and V is a component common to all bidders in the auction. Let A_i and V, both unobserved by all bidders, be independently log-normally distributed;[14]

$$\begin{aligned} \ln V &= v = & m + \varepsilon_v \sim N\left(m, r_0^2\right) \\ \ln A_i &= a_i = & \bar{a}_i + \varepsilon_{a_i} \sim N\left(\bar{a}_i, t_i^2\right) \end{aligned}$$

The mean parameters, $\bar{a}_i$, m, can be thought of as governing the magnitude of the average bid within auctions whereas t_i^2 can be thought of as governing the dispersion of those bids. The variance of the common value component r_0^2, governs the dispersion of bids across auctions.

Each bidder observes a private noisy signal X_i of the value V_i, given by $X_i = V_i \exp\{s_i e_i\}$, where e_i is a normally distributed unobserved error term with a mean of zero and variance of one. The variance of the noise, s_i^2, can be thought of as the informativeness or accuracy of signal X_i. Let the parameters

$$\left\{\{\bar{a}_i\}_{i=1}^N, \left\{t_i^2\right\}_{i=1}^N, m, r_0^2, \left\{s_i^2\right\}_{i=1}^N\right\}$$

be denoted by θ and assumed to be common knowledge among all bidders.

Under the assumption of log-normality of the errors, the conditional expectation given under A1 will have the general form given by

$$E\left[V_i | X_1, ..., X_{N-k}; X_{N-k+1}, ..., X_N\right] = \exp\left\{E\left(v_i | x_1, ..., x_N\right) + \frac{1}{2} Var\left(v_i | x_1, ..., x_N\right)\right\} \quad (1)$$

Let us denote the marginal mean-vector, variance-covariance matrix of the valuation of bidder $i = 1, ..., N$ and the signals of all bidders $(v_i, (x_1, ..., x_N))$ by $\left(u_i, \mu^{*'}\right)$ and $\Sigma_i = \begin{bmatrix} \sigma_i^2 & \sigma_i^* \\ \sigma_i^* & \Sigma^* \end{bmatrix}$ respectively. We can then rewrite the conditional expectation in the exponential term of equation (1) as

$$E\left(v_i | \mathbf{x} = (x_1, ..., x_N)'\right) = \left(u_i - \mu^{*'} \Sigma^{*-1} \sigma_i^*\right) + x' \Sigma^{*-1} \sigma_i^* \quad (2)$$

[14] By lemma 1 of Hong and Shum (2003), p335, this log-normal log-additive specification satisfies assumptions A1 and A2, ensuring existence of an increasing-strategy Bayesian-Nash Equilibrium of the asymmetric English auction.

and the conditional variance in the exponential term of equation (1) as

$$Var\left(v_i | x = (x_1, ..., x_N)'\right) = \sigma_i^2 - \sigma_i^{*'} \Sigma^{*-1} \sigma_i^* \tag{3}$$

For round k, let us partition the vector of signals $(x_1, ..., x_N)$ into an $(N-k) \times 1$ vector of signals of bidders that remain active, x_r^k, and a $k \times 1$ vector of signals of bidders that have dropped out, x_d^k - that is let $x = \left(x_r^k, x_d^k\right)$.

Similarly, let us partition the variance-covariance matrix of the signals as $\Sigma^{*-1} = \begin{bmatrix} \Sigma_{k,1}^{*-1} \\ \Sigma_{k,2}^{*-1} \end{bmatrix}$ where $\Sigma_{k,1}^{*-1}$ is an $(N-k) \times N$ matrix pertaining to the bidders active in round k and $\Sigma_{k,2}^{*-1}$ a $k \times N$ matrix pertaining to the bidders that have dropped out prior to round k.

Substituting expressions (2) and (3) into the equation given by (1), we get

$$\exp\left\{\left(u_i - \mu^{*'} \Sigma^{*-1} \sigma_i^*\right) + \sigma_i^{*'} \Sigma_{k,1}^{*-1'} x_r^k + \sigma_i^{*'} \Sigma_{k,2}^{*-1'} x_d^k + \frac{1}{2}\left(\sigma_i^2 - \sigma_i^{*'} \Sigma^{*-1} \sigma_i^*\right)\right\} \tag{4}$$

for the $i = 1, ..., N-k$ bidders still active in round k.

Letting $\ln P = p$, l_k be a $k \times 1$ vector of ones, $u_k = [u_1, ..., u_{N-k}]'$, $\Gamma_k = \left[\sigma_1^2, ..., \sigma_{N-k}^2\right]'$, $\Lambda_k = \left[\sigma_1^*, ..., \sigma_{N-k}^*\right]'$ and logarithmizing both sides, we can write a system of equations analogous to the one given under assumption A2 for the log-normal case as

$$u_k - \Lambda_k \Sigma^{*-1} \mu^* + \Lambda_k \Sigma_{k,1}^{*-1'} x_r^k + \Lambda_k \Sigma_{k,2}^{*-1'} x_d^k + \frac{1}{2}\left(\Gamma_k - diag\left(\Lambda_k \Sigma^{*-1} \Lambda_k'\right)\right) = p \times l_k \tag{5}$$

From this system of equations we can obtain the set of $(N-k)$ round k log-inverse bid functions by solving for x_r^k, the vector of signals of those bidders that remain active, as

$$x_r^k = A^k p - D^k x_d^k - C^k \tag{6}$$

where

$$\begin{aligned} A^k &= \left(\Lambda_k \Sigma_{k,1}^{*-1'}\right)^{-1} l_k \\ C^k &= \frac{1}{2}\left(\Lambda_k \Sigma_{k,1}^{*-1'}\right)^{-1}\left(\Gamma_k - diag\left(\Lambda_k \Sigma^{*-1} \Lambda_k'\right) + 2u_k - 2\Lambda_k \Sigma^{*-1} \mu^*\right) \\ D^k &= \left(\Lambda_k \Sigma_{k,1}^{*-1'}\right)^{-1}\left(\Lambda_k \Sigma_{k,2}^{*-1'}\right) \end{aligned}$$

For each bidder $i = 1, ..., N-k$ active in round k this gives the inverse bid function as

$$x_i = \left(b_i^k\right)^{-1}\left(b_i^k\left(x_i; x_d^k\right)\right) = A_i^k p - D_i^k x_d^k - C_i^k \tag{7}$$

and consequently, the log-bid function as

$$\ln \beta_i^k\left(\exp\left\{x_i\right\}; \Omega_k\right) = b_i^k\left(x_i; x_d^k\right) = \frac{1}{A_i^k}\left(x_{r,i}^k + D_i^k x_d^k + C_i^k\right) \tag{8}$$

3.2 The Likelihood Function

Although a full derivation of the likelihood function for the observed dropout price vector can be found in Hong and Shum (2003), I present a concise summary below in order to clarify certain

restrictions that need to be placed on private signals to ensure consistency with the equilibrium bidding strategies and the observed dropout order.

The log-bidding functions in (8), relate all bidders' signals to their equilibrium dropout prices for each round k. In the data we do not observe dropout prices for all bidders in every round, instead observing only the dropout price for bidder $N-k$, the bidder that actually does drop out during that round.[15] This means that only the equations relating the observed dropout prices to unobserved private signals are used in the likelihood function. Let the bid functions of bidders dropping out in round k be denoted

$$b_{N-k}^{k}\left(x_{N-k};x_{d}^{k}\right)=\frac{1}{A_{N-k}^{k}}\left(x_{N-k}+D_{N-k}^{k}x_{d}^{k}+C_{N-k}^{k}\right)\qquad\forall k=1,...,N-2 \tag{9}$$

Letting

$$\begin{aligned}\mathcal{F}&=\left(\frac{C_{N}^{0}}{A_{N}^{0}},...,\frac{C_{2}^{N-2}}{A_{2}^{N-2}}\right)'\\ \mathcal{G}_{i}&=\left(\underbrace{0,...,0}_{N-i-2},\frac{1}{A_{N-i}^{i}},\frac{D_{N-i}^{i}}{A_{N-i}^{i}}\right)\\ \mathcal{G}&=\left(\mathcal{G}_{0}',...,\mathcal{G}_{N-2}'\right)'\end{aligned}$$

we can write the vector of dropout bids as

$$\mathcal{P}=\mathcal{G}\left(x_{2},...,x_{N}\right)'+\mathcal{F} \tag{10}$$

In deriving the likelihood function for the asymmetric ascending English auction, Hong and Shum (2003) point out that one must condition on the observed dropout order of bidders in an asymmetric ascending auction model. This implies a constraint on the log-signals $(x_1,...,x_N)$, confining them to some region $\Im_1(\theta)\subset R^N$. Furthermore, although we observe the identity of the winning bidder, we, unsurprisingly, do not observe the winning bidder's dropout bid. This means we need to put a restriction on the signal of the winning bidder that is consistent with his winning the auction but never revealing his dropout price. This also restricts the signal of the winning bidder to a region $\Im_2(x_2,...,x_N;\theta)\subset R^N$ that is consistent with bidder 1 having won the auction. In essence, these restrictions ensure that dropout prices are increasing given the model parameters θ.

Let $\Pr\left(\Im_2\left(\mathcal{G}^{-1}\left(\mathcal{P}-\mathcal{F}\right);\theta\right);\theta\right)$ denote the probability that the signal of the winning bidder is consistent with bidder 1 having won the auction, that is $x_1\in\Im_2(\theta)$, conditional on the observed dropout vector $\mathcal{P}$ and let $\Pr\left(\Im_1(\theta);\theta\right)$ denote the probability that $(x_1,...,x_N)\in\Im_1(\theta)$.

Defining $\mu_2^*(\theta)$ as the $N-1$ sub-vector of μ^* and $\Sigma_2^*(\theta)$ the $(N-1)\times(N-1)$ sub-matrix of Σ^* corresponding to bidders $2,...,N$, let

$$\begin{aligned}\mu_p(\theta)&=\mathcal{F}(\theta)+\mathcal{G}(\theta)\,\mu_2^*(\theta)\\ \Sigma_p(\theta)&=\mathcal{G}(\theta)\,\Sigma_2^*(\theta)\,\mathcal{G}(\theta)'\end{aligned}$$

[15] The player that finally drops out during round k will be the player with the lowest dropout price during that specific round.

The authors show that the likelihood function for a given auction can be written as

$$L(\mathcal{P}|\theta) = \frac{f(\mathcal{P};\theta)\Pr\left(\Im_2\left(\mathcal{G}^{-1}(\mathcal{P}-\mathcal{F});\theta\right);\theta\right)}{\Pr\left(\Im_1(\theta);\theta\right)} \tag{11}$$

which resembles a truncated multivariate normal likelihood function, where

$$f(\mathcal{P};\theta) = (2\pi)^{-(N-1)/2}\left|\Sigma_p(\theta)\right|^{-1/2}\exp\left[-\frac{1}{2}\left(\mathcal{P}-\mu_p(\theta)\right)'\Sigma_p^{-1}(\theta)\times\left(\mathcal{P}-\mu_p(\theta)\right)\right]$$

and $f(\cdot;\theta)$ is an $N-1$-variate normal distribution with mean and variance given by $\mu_p(\theta)$ and $\Sigma_p(\theta)$ above.

Despite being able to explicitly derive the likelihood function, it is difficult to implement because of the need to calculate the multivariate integral in $\Pr(\Im_1(\theta);\theta)$.[16] This is why, I, as well as Hong and Shum (2003), use simulation based estimation methods to estimate the asymmetric ascending English auction model.

4 Identification

The focus of this study is to determine whether experience gained by either participating in, or winning an automobile auction can help in explaining why more experienced bidders seem to lower, or shade, their bids less than do bidders with little or no experience. Intuitively, we may expect that participating in many auctions over a longer period of time would give even the most inexperienced bidder a better understanding of how others value a certain brand or make of car. However, we may also expect winning an auction to convey more experience to the bidder than does participation alone; through participation one may be able to learn about the distribution of equilibrium bids or what characteristics bidders seem to value. Winning on the other hand, reveals not only technical details one may not have been aware of, despite the public information available, but also for example the true resale value on the secondary market once one has attempted to resell the vehicle. It has also been suggested in the literature that bidders may get a better understanding of their own valuation as they participate in auctions (e.g. as in Hossain, 2008).

Due to the overall complexity of the model presented in this paper, it is not obvious which parameters should be used to capture the desired effect or how the parameter of interest will affect bidder behavior. The most natural candidate to capture the effect of experience on value assessment is the variance of the noise, s_i^2, as opposed to the variance of the private value component t_i^2 or the variance of the common value component r_0^2; the variance of the private value component t_i^2 can be thought of as governing the dispersion of idiosyncratic bidder tastes such as preferences for red over blue cars, something unlikely to be affected by experience. The variance of the common value component r_0^2, on the other hand, governs dispersion of what can be thought of as an "intrinsic" car value, such as the remaining life-time usage of the car, something that is unique to a given car and will also not be influenced by the experience of an individual bidder.

Although it would have been instructive to discuss how a change in the variance of the noise, s_i^2, affects bidding behavior through its affect on the bidding functions of participating bidders, the overall effect will largely depend on the entire set of model parameters. This is why I save such a discussion until presenting the results, at which point I will be able to describe the effect given the model configuration estimated from the data.

[16] By Corollary 3 in Hong and Shum (2003) p340, the support of the dropout prices $\mathcal{P}(\theta)$ does not depend on the model parameters θ, thereby not violating regularity conditions necessary for deriving asymptotic normality of the Maximum Likelihood Estimator.

Parametrization

To parametrize the different model primitives, let us first partition the model parameter vector θ into vectors of parameters corresponding to each of the five model primitives $\{\bar{a}, t^2, m, r_0^2, s^2\}$;

$$\theta = (\theta_a, \theta_t, \theta_m, \theta_r, \theta_s)$$

Analogously, partition the vector of explanatory variables, z_k^t, of the bidder having dropped out in round k of auction t as

$$z_k^t = \left(z_{k,a}^t, z_{k,t}^t, z_{k,m}^t, z_{k,r}^t, z_{k,s}^t\right)$$

To capture the effect of experience on the dispersion of an individual bidder's signal X_i, let the standard deviation of the signal noise of the bidder dropping out in round k in auction t, s_k^t, be an exponential function of a given bidder's cumulative experience, ξ_i^t;[17]

$$s_k^t = \exp\left\{\frac{1}{2} \times z_{k,s}^t \theta_s'\right\}$$

The vector of variables $z_{s,i}^t$ used is a constant term and a cumulative experience variable ξ_i^t which will measure, depending on the specification, either the number of unique auctions bidder i has won or the number of unique auctions bidder i has participated in up to his participation in auction t. Winning the auction is analogous to placing the highest bid, whereas participating in an auction is analogous to placing at least one bid during the entire auction.

The mean value of the private value component is parametrized linearly as

$$\bar{a}_k^t = z_{k,a}^t \theta_a'$$

Identification of private value components comes from both within auction and inter-auction variation and is identified through bidder specific covariates. If no bidder specific covariates are available, then the two parameters governing the mean private value and the mean common value components, $\bar{a}_k^t$ and m^t, are not separately identified.[18]

The vector of variables $z_{k,a}^t$ used is going to be a constant term, as well as the total, rather than cumulative, experience of a given bidder ξ_i^T given by either the total number of unique auctions the bidder has participated in during the entire sample period, or the total number of auctions the bidder has won during the sample period. Bidders' overall experience is included to account, albeit in a reduced form manner, for not being able to observe participation costs or demand of different bidders. It is likely that bidders with very high levels of participation have low participation costs, be it in the form of information acquisition costs or opportunity cost of time, as compared to bidders that participate infrequently.[19] Frequent winners of auction may different among other dimensions to frequent auction participants; a bidder that exits the market after having won a single auction is likely to be a private individual that wanted to either replace an existing car, or buy a second car. On the other hand, bidders buying more than two or three cars are much more likely to be dealers or traders looking to resell the car on the secondary market. Although

[17] The term $\frac{1}{2}$ is added for convenience and disappears once the standard deviation is squared. The exponential form is also used by Hong and Shum (2003) and ensures non-negativity of the standard deviation.

[18] In general, the constant terms in the parametrization of the mean private value and the mean common value components, $\bar{a}_k^t$ and m^t, are not separately identified.

[19] In dynamic sequential auction models (e.g. Sailer, 2006), participation costs are positively related to bids i.e. higher participation costs cause more aggressive bidding because the bidder would rather pay a little more in the current auction to avoid participating again in the future.

imperfect, the total experience of a given bidder as measured by either the total number of times the given bidder participated or won an auction should help control for these differences across bidders.

Identification of common value component will come largely from cross-sectional variation and the mean value of the common component is parametrized linearly as

$$\bar{m}^t = z_m^t \theta_m'$$

The vector of variables $z_{s,i}^t$ is going to contain a constant[20] and the appraisal value of the automobile sold in auction t. If one thinks of the common value component as some average resale price of the automobile or value of the remaining usage, then the appraisal value should capture this component. If a car has a high appraisal value, then it is likely to have a higher resale value should the winner want to resell the automobile after the auction. If this is the case bidders may bid more aggressively for a car with high appraisal value which they know fill fetch a good price should they wish to resell it in the future.

Let the remaining variance parameters, r_0^2 and t^2be both parametrized as

$$r_0 = \exp\left\{\frac{1}{2} \times \theta_r\right\}$$

and

$$t = \exp\left\{\frac{1}{2} \times \theta_t\right\}$$

That is, let the variances of the private and common value components be constant.

5 Estimation

To estimate the structural model presented in Section 3, I use the simulation technique used by Hong and Shum (2003). The technique is based on the simulation methods of Laffont, Ossard and Vuong (1995) whereby the estimator minimizes the nonlinear least squares objective function given by

$$Q_T(\theta) = \frac{1}{T}\sum_{t=1}^{T}\sum_{k=0}^{N_t-2}\left(p_k^t - m_k^t\left(z_k^t;\theta\right)\right)^2$$

where p_k^t is the k^{th} dropout price of auction $t = 1, ..., T$ and $m_k^t\left(z_k^t;\theta\right)$ the corresponding expectation, conditional on a vector of explanatory variables z_k^t.

Due to the complexity of calculating $m_k^t\left(z_k^t;\theta\right)$ it is approximated using simulation by $\tilde{m}_k^t\left(z_k^t;\theta\right)$, giving

$$Q_{S,T}(\theta) = \frac{1}{T}\sum_{t=1}^{T}\sum_{k=0}^{N_t-2}\left(p_k^t - \tilde{m}_k^t\left(z_k^t;\theta\right)\right)^2$$

where

[20]The constant in the mean of the common value component is not going to be separately identified from the constant in the mean of the private value component.

$$\tilde{m}_k^t\left(z_k^t;\theta\right)=\frac{\frac{1}{S}\sum_{s=1}^S p_k^t\left(\bar{x}_s,z_k^t;\theta\right)\mathbf{1}\left(\bar{x}_s\in\Im_{1t}\left(\theta\right)\right)}{\frac{1}{S}\sum_{s=1}^S \mathbf{1}\left(\bar{x}_s\in\Im_{1t}\left(\theta\right)\right)}$$

and $\bar{x}_s=(x_1,...,x_N)$ is the vector of signals of the bidders in order of dropping out. This objective function yields a consistent estimate of θ as $S\to\infty$.[21]

As the indicator function that the observed signals satisfy the truncation condition induces non-smoothness into the objective function, Hong and Shum (2003) replace it with an approximation utilizing an independent probit kernel-smoother;

$$\mathbf{1}\left(\bar{x}_s\in\Im_{1t}\left(\theta\right)\right)\approx\prod_{k'=0}^{N_t-2}\prod_{j=1}^{N_t-k'-1}\Phi\left(\frac{p_{k',j}\left(\bar{x}_s,z_k^t;\theta\right)-p_{k'}\left(\bar{x}_s,z_k^t;\theta\right)}{h}\right)$$

The iterated estimation and simulation of $\tilde{m}_k^t\left(z_k^t;\theta\right)$ proceeds as follows;

1. For iteration n fix θ_n
   (a) Simulate dropout prices $\tilde{m}_k^t\left(z_k^t;\theta_n\right)$ for each auction $t=1,...,T$ and each round $k=0,...,N-2$ by
      i. Drawing an $(N^t\times 1)$ random variable vector $\eta_s^t\sim N(0,1)$ for each auction $t=1,...,T$ and each simulation draw $s=1,...,S$.[22]
      ii. Generating a vector of signals $\mathbf{x}_s^t$ for each auction $t=1,...,T$ and each simulation draw $s=1,...,S$ by linearly transforming the standard normal vectors as

$$\mathbf{x}_s^t=\mu^t+\mathbf{\Lambda}\eta_s^t$$

      where $\mathbf{\Sigma}^*=\mathbf{\Lambda}\mathbf{\Lambda}'$ is the Cholesky decomposition and both μ^t and $\mathbf{\Sigma}^*$ are functions of θ_n.
      iii. Calculating $p_k^t\left(\bar{x}_s,z_k^t;\theta_n\right)\mathbf{1}\left(\bar{x}_s\in\Im_{1t}\left(\theta_n\right)\right)$ for each auction $t=1,...,T$, each round $k=0,...,N-2$ and each simulation draw $s=1,...,S$.
      iv. Calculating $\tilde{m}_k^t\left(z_k^t;\theta_n\right)$.

[21] Although the authors suggest using an adjusted objective function given by

$$\tilde{Q}_{S,T}\left(\theta\right)=\frac{1}{T}\sum_{t=1}^T\sum_{k=0}^{N_t-2}\tilde{P}_{\Im_{1t}}\left(\theta\right)\left(p_k^t-\tilde{m}_k^t\left(z_k^t;\theta\right)\right)^2$$

whereby one premultiplies the squared deviation term by $\tilde{P}_{\Im_{1t}}(\theta)$ to correct for the bias stemming from the truncation probability in the denominator of $\tilde{m}_k^t\left(z_k^t;\theta\right)$, I do not do so as I have found it to significantly complicate estimation. If one premultiplies the errors by $\tilde{P}_{\Im_{1t}}(\theta)$, the objective function has a tendency to go to zero for unreasonable parameter values that push the truncation probability $\tilde{P}_{\Im_{1t}}(\theta)$ to 0 rather than pushing the error to 0. If however, this probability is left in the denominator then as it goes to 0 it tends to increase the error, instead pushing the optimizer away from such parameter regions.

[22] The random variables are drawn only once, at the start of the estimation procedure, and kept fixed for all subsequent iterations of the objective function. This is done to eliminate "chatter" or noise caused by the simulation process itself and to ease numerical convergence (Cameron and Trivedi (2005) p394). This is also the approach used in Hong and Shum (2003).

(b) Calculate $Q_{S,T}(\theta_n)$.

2. For iteration $n+1$ fix θ_{n+1} etc.

The authors show that as $T \to \infty, S \to \infty$, $S/T \to \infty$ and $h \to 0$ that the distribution of $\hat{\theta} = \arg\min Q_{S,T}(\theta)$ is given by

$$\hat{\Sigma}^{-1/2}\sqrt{T}(\theta - \theta_0) \to N(0, I)$$

where

$$\hat{\Sigma} = \hat{\mathcal{J}}^{-1}\hat{\mathcal{H}}\hat{\mathcal{J}}^{-1}$$

and for $\tilde{\zeta}_k^t(z_k^t;\theta) = p_k^t - \tilde{m}_k^t(z_k^t;\theta)$

$$\hat{\mathcal{J}} = \frac{1}{T}\sum_{t=1}^{T}\sum_{k=0}^{N_t-2}\frac{\partial}{\partial\theta}\left(\tilde{\zeta}_k^t\left(z_k^t;\hat{\theta}\right)\frac{\partial\tilde{\zeta}_k^t\left(z_k^t;\hat{\theta}\right)}{\partial\theta}\right)$$

together with

$$\hat{\mathcal{H}} = \frac{1}{T}\sum_{t=1}^{T}\left(\left[\sum_{k=0}^{N_t-2}\tilde{\zeta}_k^t\left(z_k^t;\hat{\theta}\right)\frac{\partial\tilde{\zeta}_k^t\left(z_k^t;\hat{\theta}\right)}{\partial\theta}\right]\times\left[\sum_{k=0}^{N_t-2}\tilde{\zeta}_k^t\left(z_k^t;\hat{\theta}\right)\frac{\partial\tilde{\zeta}_k^t\left(z_k^t;\hat{\theta}\right)}{\partial\theta}\right]'\right)$$

The matrices $\hat{\mathcal{H}}$ and $\hat{\mathcal{J}}$ are evaluated numerically using center-difference approximations. All technical details pertaining to the estimation and simulation, such as the choice of bandwidth parameter h and the number of simulation draws S, can be found in the appendix.

6 Results

In this section, I present the estimation results for the model presented in Section 3.

From the reduced form evidence in Section 2, we saw, rather surprisingly, that although bidders reduce their bids on average with the number of participating bidders in an auction, more experienced bidders reduce their bids less than bidders with little or no prior experience. This suggests that rather than getting better with experience, bidders are in actual fact get worse. Alternatively however, it may be the case that the degree to which bidders with little or no experience lower their bids is too high to begin with, with inexperienced bidders lowering their bids too much. Experienced bidders may realize that they were lowering their bids too far and instead increase their bids to equilibrium levels. This alternative explanation however contradicts a large body of existing evidence which suggests that the degree of shading is lower, rather than higher, than one would expect (e.g. Capen, Clapp and Campbell, 1971) with bidders tending to suffer the winner's curse. This begs the question whether experienced bidders are really getting worse at accounting for the winner's curse, or whether there are rational reasons for their behavior which can only be captured through a structural model.

INSERT TABLE 3 ABOUT HERE

We see from main results in Table 3 that the level of experience of a given bidder i, measured by the number of auctions the bidder has won up until his participation in the current auction, has a significantly negative effect on the dispersion of his signal X_i as measured by the standard deviation of the noise, s_k^t. Put simply, more experienced bidders have more accurate signals or value estimates than do their less experienced counterparts. Due to the overall complexity of the model however, it is difficult to fully interpret these results and their implications for bidder behavior.

To overcome this difficulty, let us consider three specific cases looking at how bidding behavior is affected by differences in past auction experience and how remaining bidders adjust their bids once a bidder with an accurate signal drops out vis a vis a bidder with an inaccurate signal:

Case 1 All else equal, how do the bid functions of two bidders, one with a lot of past experience and the other with little, differ for some generic auction round k?

To simplify matters, let us consider the two extreme cases; the first case in which bidder j has won ten auctions, $\xi_j = 10$, allowing him to draw a highly accurate signal and the second case in which bidder i hasn't won a single auction, $\xi_i = 0$, allowing him instead to draw an inaccurate signal.

INSERT FIGURE 1 ABOUT HERE

If we plot the log-bid functions for these two bidders given the estimated parameters, we see from Figure 1 that the more accurate the signal, the closer you are to dropping out once the price reaches the value of your signal.[23] On the other hand, the more inaccurate a bidder's signal, the flatter the line becomes, with an intercept that will depend only on the signals of the other bidders. If your signal is highly inaccurate you will choose to completely disregard your own signal instead making your bid dependent only on your beliefs about the remaining players' signals.

We see from the two estimated specifications that participation and winning seem to have the same overall effect; participation, although insignificant, has a negative effect on the dispersion of noise, as does winning. However, the effect from participating in one additional auction is much lower than the effect of winning an additional auction. This does not seem unreasonable as participating in itself does not reveal as much information as having won the vehicle; through participation one may be able to learn something about the distribution of equilibrium bids or what characteristics bidders seem to value. Winning on the other hand, reveals not only technical details one may not have been aware of, despite the public information available, but also for example the true resale value on the secondary market once one has attempted to resell the vehicle.[24] In this

[23] Mathematically speaking, the slope goes towards one and the intercept goes towards zero, with the log-bid function converging towards $b_i^k\left(x_i; x_d^k\right) = x_i$

[24] In other words, the common value component is only observed after the auction has ended. This information however does not become known the instant one wins an auction. Taking oil drilling rights as an example, the value of the oil within the well will only truly become known once the well has been emptied and one knows exactly how many barrels of oil were extracted - a time consuming process. In the case of automobile auctions, additional technical information may only become known after either a thorough inspect has been done on behalf of the winner or after a certain amount of usage.

respect, perhaps unsurprisingly, one can only suffer the winner's curse having won an auction and consequently been able to observe what was previously unobservable.

Case 2 How will some bidder i, that is still active during round k, react to the dropping out of a bidder with high experience vis a vis a bidder with low experience in the previous round?

Once a bidder drops out, it is assumed that all remaining bidders are able to invert his dropout bid to learn that bidder's private signal X. Not only is it assumed that bid functions are common knowledge, but also the model parameters. While this means that bidders cannot observes all other bidders' levels of experience, and although they may not observe the exact draws from the noise distribution, all bidders would be aware which bidders have better signals and which would have worse signals as given by the dispersion parameter s_k^t. It is not unreasonable to believe that rational players put more weight on less noisy signals and less weight on more noisy signals when updating their expectations.

INSERT FIGURE 2 ABOUT HERE

Again, let us plot log-bid functions for a bidder in round $k-1$ and compare these to the updated log-bid functions of round k, given that a bidder with a very accurate signal drops out in round $k-1$ or a bidder with a very inaccurate signal drops out in round $k-1$. Consistent with the previous discussion, the implication of asymmetric signal precision suggests that indeed, the higher the level of experience of the bidder that drops out, the more the remaining bidders adjust their bids, that is the slope of the bid function decreases more for the remaining bidders if a low noise bidder drops out as compared to a high noise bidder, as seen in Figure 2.

As in Hong and Shum (2003), the estimated log-bid functions have decreasing slopes meaning bidders with high initial signals revise their estimates down as more and more information becomes available with bidders dropping out of the auction. This is consistent with bidders lowering their bids to account for the winner's curse and, as pointed out by the authors, this property is characteristic of symmetric ascending auctions.

Including total bidder experience to control for unobserved differences in bidder participation costs or bidder demand has very little effect as both total number of wins and total number of participations are both statistically and economically insignificant. Consistent with the downward sloping log-bid functions, the results suggest that bidders in the studied automobile auctions, while having asymmetric signal precision, are largely symmetric in their tastes.

Case 3 Which of two bidders, one with high experience and the other with low experience, updates their bids the most after a third bidder drops out?

Intuitively, the better a bidder's signal, the more certain that bidder should be about the value of the object being auctioned. In one extreme case, a highly experienced bidder j may know the "exact" value of the vehicle because that bidder may already have found a buyer on the secondary market guaranteeing a price P' for that specific vehicle. In this situation, the information contained in the signals of the other bidders will in no way impact the valuation of bidder j because he is happy as long as he wins the vehicle for a price below that of P'. The other extreme is an inexperienced bidder i with a very noisy signal, that once observing a more precise signal may potentially see a large change in his expectation after realizing his own signal was far too unreasonable.

INSERT FIGURE 3 ABOUT HERE

Plotted in Figure 3 are the estimated round k log-bid functions of two players, identical in every respect except for one player having won zero auctions previously, while the other having won 10 auctions previously, together with the corresponding updated round $k+1$ log-bid functions for both bidders. From Figure 3, we see that bidder i, with no experience and the more noisy signal, will adjust his bid more than bidder j that has more experience and the less noisy signal. Despite having an accurate but still imperfect signal, the more experienced bidder j will adjust his bids but due to the higher accuracy of his signal, will do so much less than bidder i who is less experienced and has a noisier signal.

In light of these results, we now see that it is perhaps not as surprising as before that more experienced bidders reduce their bids less than bidders with little or no prior experience. Being more experienced, bidders seem to have a more accurate signal about the value of the auctioned automobile and because of this, are less reliant on the private information of other, less experienced bidders. One should also distinguish between the winner's curse and signal precision, as adjustments to bids due to a better signal are not the same as changes in behavior due to accounting for the winner's curse. Firstly, in this model it is not obvious that there is bid shading, or a lowering of bids as new information enters a bidder's information set. Whether bids are adjusted up or down depends on the parameters in the model, with some parameter values allowing for positive, rather than negative adjustments to expectations. In this sense, re-conditioning on an ever expanding information set will drive the winner's curse effects whereas, as we have seen, differences in levels of signal precision change how large these adjustments are going to be. More experienced bidders, although also lowering their bids will do so less than less experienced bidders because the signals they had were better to begin with.

Despite the estimated results being rather intuitive, the effect from winning a single additional auction seems large; the variance of the signal noise for a bidder with five previous wins is close to zero, that is, the signal is highly accurate. However, taken into context, the number of bidders with this kind of experience is only 0.58% of the total number of bidders in the entire sample - one hundred seventy three individuals. Furthermore, it is not unreasonable to believe that these bidders are professional automobile traders or dealers, with a great deal of experience gained prior to ever having taken part in automobile auctions. Furthermore, it is likely that the majority of bidders do in fact have a certain degree of previous experience from participating in auctions, be it through eBay or real estate auctions. However, while experience from all types of auctions is undoubtedly valuable, each type of object has its own fundamental characteristics, all of which will take time to learn to understand and value.

7 Experience and Revenue

One of the key assumptions of the ascending auction model presented in Section 3 is that all distributional parameters are observable, that is, although bidders cannot observe exact draws from the noise distribution they do know whether bidder draws from a more or less noisy one. Knowing this, once a bidder drops out and the others are able to learn the exiting bidder's private signal, they can put more weight on signals coming from less noisy distributions when updating their own beliefs.

It is however unclear how this sort of asymmetry in signals affects revenues and whether more or less experienced bidders are preferable from a seller's point of view. To gain intuition, I simulate revenues for two opposing cases and a varying number of bidders - one in which all bidders have no previous experience and one in which all bidders have previously won a single auction. The revenues are simulated for one hundred thousand auctions using the estimated parameters of Model II of Table 3 with the appraisal value set to that of the average in the sample.

INSERT FIGURE 4 ABOUT HERE

Looking at simulated revenues in the left-most part of Figure 4 we see that, even if one could make everyone more experienced, what effect this may potentially have on revenues is ambiguous; for auctions with fewer bidders, revenues decrease when bidders are more experienced, whereas for auctions with a large number of bidders revenues tend to increase. The reason why the effect is ambiguous is more easily understood by looking at average bids across auctions with different numbers of participants in the two extreme cases when bidders are either inexperienced or experienced.

From the right-most graph of Figure 4, we see that experience has two effects on the average bid curves; firstly, the average bid curves become flatter as bidders' signals become more accurate. This is because the information of other bidders becomes less important and experienced bidders will not revise their bids downwards as much as less experienced bidders, causing a smaller fall in average bids with each additional bidder. Secondly, the intercept of the curves becomes lower or, stated differently, average bids in auctions with relatively few bidders decline with experience. The reason is that the fewer bidders there are in the auction, the less information becomes available and the lower the possibility to revise outrageous estimates during the course of the auction. This means that the more noisy the signal of a given bidder, the more likely he is to overpay if he is only facing a single competing bidder than if he were facing ten competing bidders.

If we are to put these two separate effects together, we have that in auctions with fewer, less experienced bidders, revenues are higher than if bidders were experienced because the inexperienced bidders will have less information to revise overly optimistic signals whereas experienced bidders will have less optimistic signals to begin with. In auctions with more bidders however, revenues are higher in the case with experienced bidders because if an experienced bidder draws a high accurate signal, he is not going to revise it down as much with information from others as an inexperienced bidder would.

Even assuming that we knew the average number of bidders in an auction, there would still be little that could be done from a policy point of view to change either the level of experience of different bidders.

8 Robustness

In this section I present the results of various robustness checks to make sure the main results aren't driven by outliers, the inclusion of unsuccessful auctions, the definition of experience and the dynamic nature of sequential auctions.

INSERT TABLE 4 ABOUT HERE

Winsorized Experience Although the majority of bidders only win a single auction before exiting the sample, a number of bidders have remained active throughout and won a very large number of auctions; the most successful bidder throughout the sample period won 87 auctions, followed by the second and third most successful bidders with 72 and 60 wins respectively. The fact that only roughly three percent of all bidders in the sample, that is 562 individuals, have won more than a single auction raises concerns that the results are driven by the most successful of experienced bidders. In itself, this would not contradict the fact that certain bidders get better signals as their level of experience improves but it would suggest that there is other heterogeneity among even the experienced bidders that could be driving the effect. One way to ease these concerns would be to completely remove the observations pertaining to the bidders with most wins. Doing so would result in removing bids and changing the structure of bids within most auctions so in order to avoid this, I instead winsorize the experience of a given bidder whereby I limit the cumulative number of auctions a bidder has previously won to be at most ten. The results of re-estimating the full model, as given under Model I in Table 4, with winsorized experience variables slightly changes the results, with an increase in significance and slight reduction in the coefficients of interest. Overall bidder experience, as measured by the number of cumulative auctions wins, still seems to have a negative effect on bidder valuation signal noise even after winsorizing. This seems to suggest that it is not the performance of the most successful bidders that is driving the effect, rather that experience is important for all frequent winners.

Successful Auctions So far in this study, I have made no distinction between bids made in auctions which turned out to be successful, with a sale on completion, and auctions which failed because the reserve price was not met. To make sure the experience effect isn't in some way driven by inclusion of unsuccessful auctions I remove these and re-estimate the model. From Table 4 we see the results of Model II, for which unsuccessful auctions have been excluded from the data. The number of auctions used in the estimation drops by roughly 30%, to just over seven thousand, with the results remaining largely the same as in the main specification. The effect from bidder experience becomes even more pronounced as the coefficient on the number of cumulative bidder wins becomes even more negative. The stronger effect is perhaps unsurprising given the earlier discussion on the difference in experience gained from participation alone and that gained from actually winning an auction. Although one could still "win" an unsuccessful auction, in the sense that one submits the highest bid, one would still not have the ability to physically evaluate the vehicle. In this sense, submitting the highest bid in an unsuccessful auction is likely to give a similar amount of experience as only having participated in, rather than won, a successful auction.

Delayed Learning In order to measure the degree of experience a bidder has, I have used the cumulative number of auctions the bidder has won up until his participation in any given auction. This however means that a bidder's level of experience increases immediately after each win, something that is unlikely to actually happen. It is not obvious how long it truly takes for someone to gain experience from either participating or winning an auction but it is not unlikely that some experience is gained during the auction itself whereas some experience only comes later. To account for this effect and check the robustness of the results with respect to the timing of experience, I delay the entire gain in experience from an extra win by five days, that is, if I win an auction on a Monday at noon, then the full gain in experience will come at noon on Saturday.[25]

[25]Although it may seem rather arbitrary, five days would be roughly the amount of time one would need to fully

Under Model III of Table 4 we see the results of this exercise and can conclude that, despite delaying learning for five days, there is still a negative effect on signal noise from increased bidder experience.

Controlling for Dynamics Every week, roughly three to four hundred automobiles are auctioned on KVD. The vehicles that are to be auctioned a given week are listed on the Friday before, making the entire week's set of potential auctions publicly available to everyone by Friday evening. This, together with the fact that auctions are conducted sequentially, means that a bidder's strategic behavior may change depending on how many cars remain to be auctioned that given week and how many of those the bidder would find worthwhile bidding on. In other words, the time of the week together with that week's choice of auctions affects the bidder's outside option, that is the "value" of not winning a given auction. The higher the value of the outside option, the less aggressive the bidder can be as the value of not winning is high whereas, on the other hand, the lower the outside option, the worse off the bidder is from not having won an auction and the more aggressive he may choose to be. To account for these potential effects, albeit in a reduced form manner, I add additional variables into the mean private valuation $\bar{a}_k^t$ to control for the number of parallel auctions a given bidder is participating in as well as into the mean common value component $\bar{m}^t$ to control for the number of auctions during a given week and the number of active auction participants during a given week. From the results of Model IV in Table 4, we see that although the coefficient of interest falls in magnitude, the qualitative results still remain the same as in the main specification.

It is not unlikely that there are other dynamic mechanisms that are affecting bidder behavior, especially the behavior of the more experienced bidders; if the bidders with the most experience also happen to be dealers with inventory, then current inventory or inventory constraints may have an impact on how frequently they purchase as well as how aggressively they bid. For example, in their paper, Jofre-Bonet and Pesendorfer (2003) provide a dynamic auction model with capacity constraints and show that capacity constrained firms bid less aggressively in highway procurement auctions. If the number of previous purchases is somehow related to current car dealer inventory then the effect captured in the model may be due to these types of mechanisms rather than learning and experience effects although why this would result in increased bidder aggression is unclear. Furthermore, even if winning, or for that matter participating in, an auction does contribute with valuable experience it has previously been suggested that experience deteriorates with time; Benkard (2000) documents that the number of man-hours required to construct an aircraft falls the more units are produced a given year but increases again after particularly unproductive years and shows that this effect is consistent with a depreciation of past experience. This would suggest that there be a much more complex effect from experience that is not captured in the results of this paper.

9 Conclusion

Auctions can simplistically be divided into two paradigms - the independent private value auction in which bidders' valuations are only known to the bidders themselves and do not depend on how other bidders value the object, and the common value auction. In common value auctions, the

complete the purchase of the car and have the chance to drive it in normal conditions (as compared to for example a limited test-drive).

object being auctioned has the same value to all participants, although no bidder truly knows what that value is. Instead, bidders rely on private estimates to guide their bidding. If a bidder should win, but fail to take into account that the bidding behavior of other bidders is informative, he will realize his estimate was the most optimistic and that he has overpaid, or suffered the winner's curse. As pointed out by Bajari and Hortaçsu (2003), one of the implications of the seminal Milgrom and Weber (1982) common value auctions model is that to reduce the chances of overpaying, the bidders should lower, or "shade" their bids, with the degree of shading increasing in the number of auction participants.

In this paper, I present evidence from roughly ten thousand Swedish online automobile auctions consistent with bidders accounting for the winner's curse and lowering their bids more and more with each additional participating bidder. However, perhaps more surprisingly, I also find evidence that the more experience a bidder has, the less he lowers his bid with every new participating bidder; experience seems to have a has a positive effect on bid shading.

There are a number of studies suggesting that bidders in actual fact fail to fully account for the winner's curse by not lowering their bids enough. Through more experience however, bidders judgment has been found to improve and bid shading increases to levels more consistent with theoretical predictions. This begs the question of whether experienced bidders are actually getting worse at accounting for the winner's curse, or whether there are rational reasons for their behavior which can only be captured through a structural model.

I have used the asymmetric ascending auction model of Hong and Shum (2003) to show that more experienced bidders shading their bids less is consistent with these bidders having more accurate value signals than bidders with little or no previous experience. Bidders with accurate signals pertaining to their valuation of the auctioned automobile, are shown to shade their bids less than bidders with inaccurate signals. In the extreme cases, bidders with perfect signals will not shade at all whereas bidders with fully noisy signals will choose to disregard their private information altogether. Furthermore, when a bidder with an accurate signal drops out, the remaining bidders update their bids more than when a bidder with an inaccurate signal drops out suggesting quite reasonably that active bidders put more weight on the private information of dropped out bidders with accurate signals.

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Appendix

Estimation details

Optimizer Starting Values, θ_0 For estimation of the full model, starting values are taken to be the parameter estimates from estimating a model using a subsample of 100 auctions from the start of the sample period, a vector of zeros as starting values and fifty simulation draws. Although estiamtion does not seem to be sensitive to the initial starting parameters, picking sensible parameters from the beginning greatly improves convergence and estimation time. The values themselves, are given below;

a_0	a_1	t_0	m_0	r_0	s_0	s_1
9.9258	-0.0010	-1.6929	8.46e-06	-2.1139	1.6899	-1.7316

Optimizer I have used three different optimizers in estimating the model; Firstly, I have used the Knitro 7 optimizer in Matlab with function and parameter tolerances set to 10e-8. Secondly, as the main optimizer, I use Matlab's built-in Fminunc optimizer using automated settings with function and parameter tolerances set to 10e-8.[26] Thirdly, to find the starting values I have used Matlab's Fminsearch with function and parameter tolerances set to 10e-8, which performs very well when compared to the others if using a vector of zeros as initial starting values. Although Knitro 7 is more stable and efficient, both Knitro and Fminunc optimizers produce very similar parameter estimates.

Parallelization The nature of the optimization problem easily allows for parallel computing along one of two dimension; one can parallelize across auctions or one can parallelize across simulated draws. I parallelize across auctions, that is, each core independently calculates a predicted dropout price vector $\tilde{\mathcal{P}}^t$ for a given auction t. Alternatively one can parallelize across each independent simulation draw s, whereby one core draws a singal draw s and calculates thet predicted dropout price vector $\tilde{\mathcal{P}}^t_s$ for that given simulation. The choice between these two alternative ways of paralellizing the computation depends largely on the number of auctions T and the number of simulation draws S.[27]

Bandwidth of Probit Kernel Smoother, h I choose $h = 0.01$ as in Hong and Shum (2003). Unlike the authors however, I find that changing the bandwidth to a lower number to have very little difference on the resulting parameter estimates while increasing it to $h = 0.1$ affects both convergence and parameter results. Although convergence becomes faster, the estimated parameter values start becoming unreasonable.

Approximation Step, δ The differencing approximation step δ is set to $\delta = 0.01$.[28] The

[26] I also replace all basic Matlab functions with optimized and improved versions found in the freely available Lightspeed Toolbox by Microsoft Research.

[27] Due to the recursive nature of the model, parameter estimation becomes a time-consuming process. I believe that if one wishes to estimate either a more complex model than the one presented in this study, be it in terms of the number of observations, simulations or explanatory variables, one will most likely need to resort to cluster computing to keep estimation times reasonable.

[28] This value of the approximation step gives the most conservative standard errors. Due to the number of individual approximations that need to be made in order to calculate the standard errors, the results are quite sensitive to large changes in δ, where "large" is a hundred-fold or higher decrease in the step.

derivatives used in calculating the estimated parameters' standard errors are approximated using center differencing approximations;

$$
\begin{aligned}
\frac{\partial f(x)}{\partial x} &\approx \frac{f(x+\delta)-f(x-\delta)}{2\delta} \\
\frac{\partial^2 f(x)}{\partial x^2} &\approx \frac{f(x+\delta)+f(x-\delta)-2f(x)}{\delta^2} \\
\frac{\partial^2 f(x,y)}{\partial x \partial y} &\approx \frac{f(x+\delta,y+\delta)-f(x+\delta,y-\delta)-f(x-\delta,y+\delta)+f(x-\delta,y-\delta)}{4\delta^2}
\end{aligned}
$$

Simulation Draws, S The number of simulation draws S is set to 20. At this time, this is the maximum number of draws that gives reasonable estimation times together with a sample of roughly ten thousand auctions.

Tables and Figures

			Start	End
Sample Period			Oct. 7th 2011	Jul. 18th 2012
Nr. of Auctions				9 955
Nr. Unique Bidders				24 586
Nr. Drop-out Bids				108 686
Variable	Mean	Std.	Min.	Max.
Nr. Bidders (per Auction)	10.92	4.83	2[§]	33
Dropout Bid (SEK)	75 668	55 111	200	523 000
Winning Bid (SEK)	105 038	55 849	1 500	523 000
Appraised Auto Value (SEK)[§§]	144 637	64 168	10 000	775 000
Nr. Bidder Cumu. Wins	1.29	5.89	0	86
Nr. Bidder Cumu. Participations	31.79	81.71	0[§§§]	852
Nr. Bidder Wins	0.29	1.37	0	87
Nr. Bidder Participations	4.42	16.15	1	853

Table 1: [§]Auctions where the first bid was also the winning bid, as the starting bidder jump-bid and auctions where there were no bids not included. [§§]Appraised value given is that of an identical vehicle in brand new condition, as opposed to the replacement cost or estimated auction price. [§§§]The number of auctions a given bidder has participated in can be zero as the variable as defined as the number of auctions participated in prior to participation in the current auction. Hence, during the first auction, a given bidder will have no prior experience as measured by zero. Descriptive statistics for key variables, pertaining to ten thousand ascending online automobile auctions carried out by Swedish online auction house Kvardammen AB.

	OLS		IV		OLS		IV	
Coefficient	Estimate	Std. Dev	Estimate	Std. Dev	Estimate	Std. Dev	Estimate	Std. Dev
Nr. Bidders	-0.0091***	0.0007	-0.2408***	0.0052	-0.009***	0.0007	-0.1735***	0.0027
Nr. Bidder Cumu. Wins					0.0099***	0.0009	-0.1383***	0.0081
Nr. Bidder Cumu. Participations	0.0006***	0.0001	-0.0237***	0.0014				
Nr. Bidders X Cumu. Wins					0.0009***	0.0001	0.0146***	0.0007
Nr. Bidders X Cumu. Participations	5.38e-06	5.06e-06	0.0026***	0.0001				
Appraised Auto Value	8.99e-06***	5.98e-08	9.58e-06***	9.13e-08	8.90e-06***	5.94e-08	9.37e-06***	7.53e-08
Constant	9.6017***	0.0127	12.2768***	0.0625	9.6121***	0.0125	11.6680***	0.0376
First Stage F-stat								
Nr. Bidders							3490.74	
Nr. Bidder Running Wins							458.58	
Nr. Bidder Running Participations								
Interaction							388.57	
#Auctions	9955		9955		9955		9955	
#Drop-out Prices	108 686		108 686		108 686		108 686	

Table 2: Results of OLS and IV regressions of log bids regressed on the number of participating bidders, cumulative experience of the bidder and the interaction between number of bidders and experience. The number of participating bidders and the cumulative experience of a bidder are treated as endogenous variables with the number of bidders being instrumented by the lowest observed bid within an auction and bidder experience is instrumented by the fraction of auctions participated in up until the current auction. Significance is given at the 10% (*), 5% (**) and 1% (***) significance levels.

Coefficient	Model I Estimate	Model I Std. Dev	Model II Estimate	Model II Std. Dev
Components of $\bar{a}$				
Constant	9.4565***	2.0899	9.5190***	2.5885
#Total Bidder Participations	-0.0004	0.0553		
#Total Bidder Wins			-0.0007	0.3491
Components of $\ln t$				
Constant	-0.1368	2.5067	-0.1940	0.2821
Components of m				
Constant§				
Appraisal Value	9.03e-06	9.07e-06	9.03e-06	1.11e-05
Components of $\ln r$				
Constant	-1.7627	1.1461	-1.1165***	0.2179
Components of $\ln s$				
Constant	3.0720***	0.7626	1.9815***	0.1330
#Bidder Cumu. Participations	-0.4927	0.8761		
#Bidder Cumu. Wins			-2.1313*	1.1351
#Auctions	9955		9955	
#Drop-out Prices	108 686		108 686	

Table 3: §Not separately identified from constant in $\bar{a}$. Number of draws S is 20, probit kernel smoother bandwidth h is 0.01, differencing-step size δ is 0.01. Results for the asymmetric ascending auction model. In model I, bidder experience is measured by the number of cumulative auctions the bidder has participated in until his participation in the the current auction whereas in Model II, bidder experience is measured by the cumulative number of auctions the bidder has won until his participation in the current auction. Bidder participation is synonymous with having placed at least one bid in a given auction while winning is synonymous with having placed the highest bid. Significance is given at the 10% (*), 5% (**) and 1% (***) significance levels.

	Model I		Model II		Model III		Model IV	
Coefficient	Estimate	Std. Dev	Estimate	Std. Dev	Estimate	Std. Dev	Estimate	Std. Dev
Components of $\bar{a}$								
Constant	9.5779***	2.6807	9.4485***	1.6088	9.7042***	2.3645	9.0890	9.5244
#Total Bidder Wins	-0.0003	0.1772	-0.0006	0.2624	-0.0002	0.2407	-0.0065	0.4657
Components of $\ln t$								
Constant	-0.3000*	0.1677	-0.1980	0.1696	-0.6431	0.5656	0.3044	0.9701
Components of m								
Constant[§]								
Appraisal Value	8.98e-06	1.30e-05	9.97e-06	6.19e-06	8.97e-06	1.23e-05	9.15e-06	1.13e-05
Components of $\ln r$								
Constant	-1.0889***	0.4421	-1.0852***	0.2616	-0.9898	0.7564	-1.1613***	0.2630
Components of $\ln s$								
Constant	1.8053***	0.4423	2.1470***	0.4077	1.2977	0.8581	2.8201***	0.2128
#Bidder Cumu. Wins	-1.7058***	0.4505	-2.1066***	0.1447	-0.4880*	0.2650	-0.7935***	0.2139
#Auctions	9955		7204		9955		9955	
#Drop-out Prices	108 686		81 702		108 686		108 686	

Table 4: Results of various robustness checks of main specification; Model I: bidders with cumulative wins greater than 10 winsorized to 10. Model II: All unsuccessful auctions dropped. Model III: Experience lagged 5 days. Model IV: Dynamic controls added (additional coefficients not reported in table).

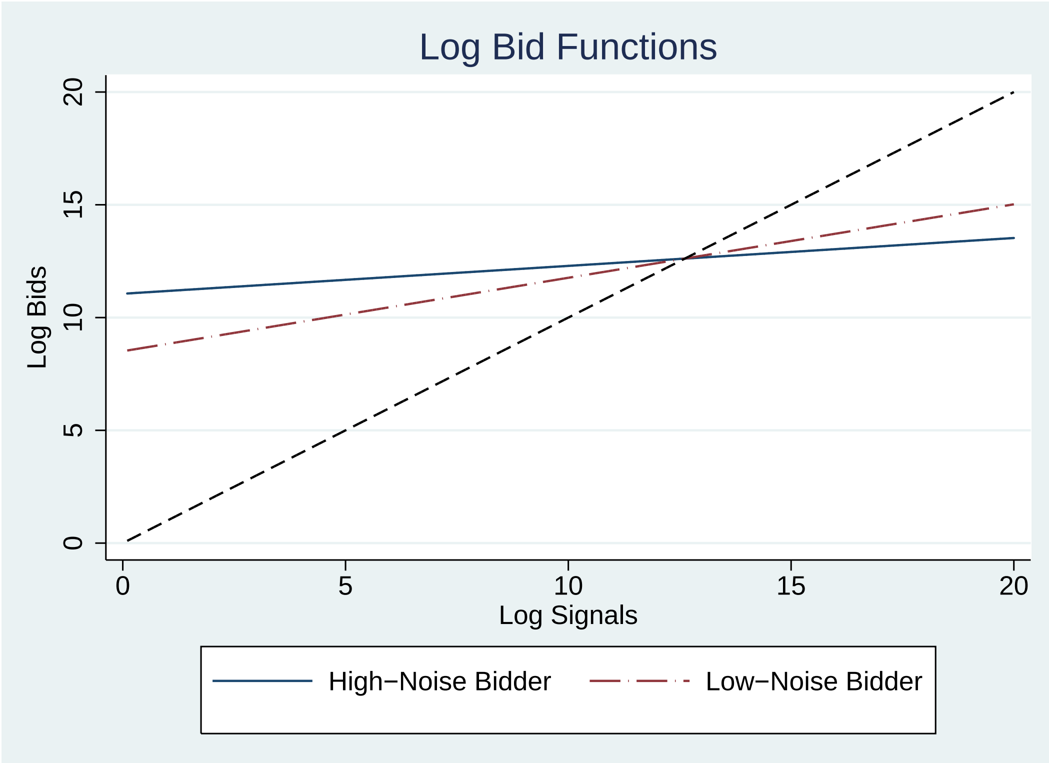

Figure 1: Estimated bid functions for two generic bidders one of which has a lot of previous experience (Low-Noise Bidder) and the other that has no previous experience (High-Noise Bidder). High experience reduces value signal noise resulting in experienced bidders bidding closer to the 45-degree line.

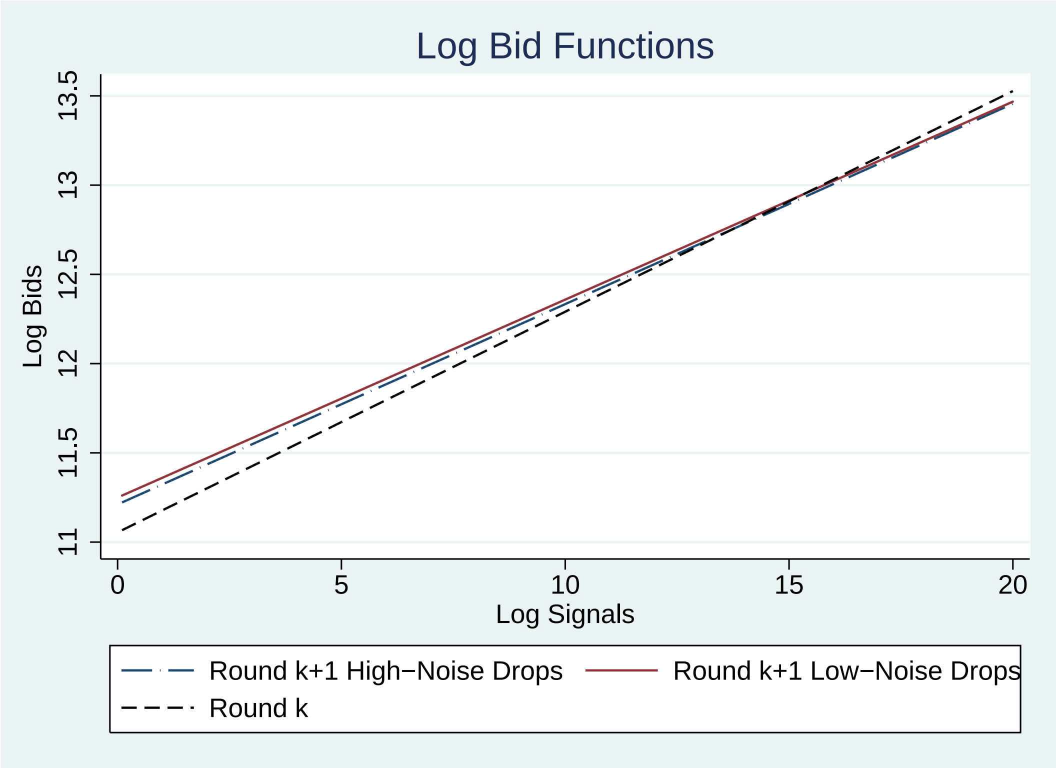

Figure 2: Estimated bid functions for round k and updated round $k+1$ of a generic bidder, one after having observed an experienced (Low-Noise) bidder drop out in round k and one after having observed an inexperienced (High-Noise) bidder drop out in round k .

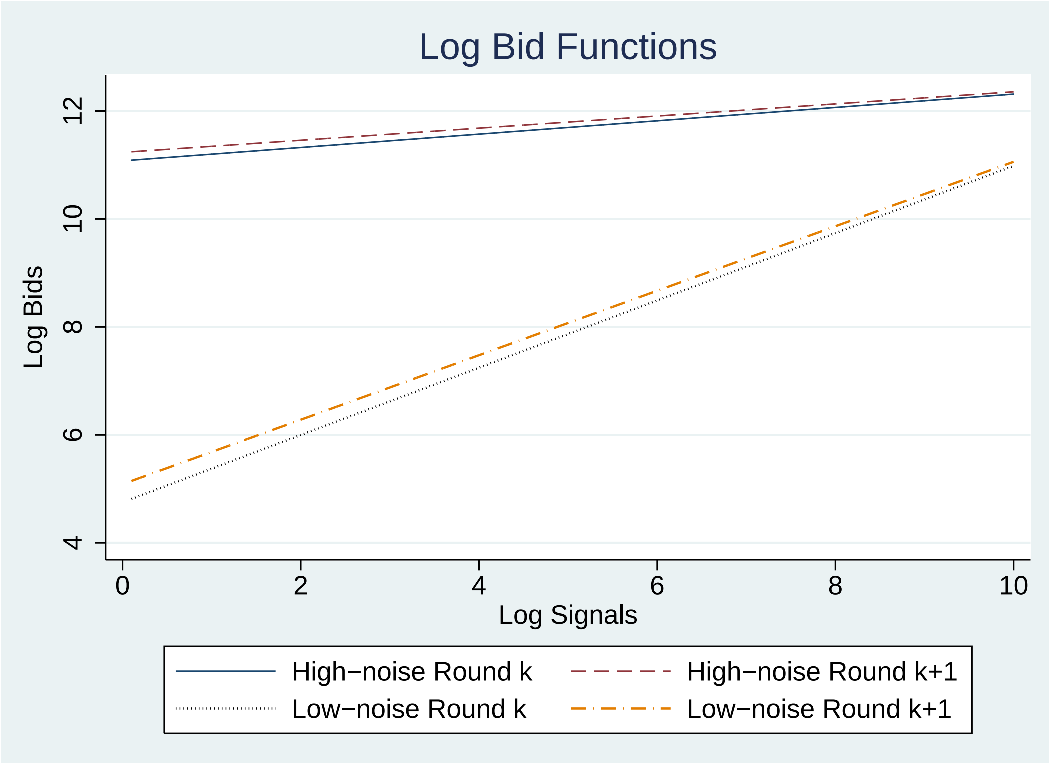

Figure 3: Estimated bid functions for rounds k and $k+1$ of two generic bidders one of which has a lot of previous experience (Low-Noise Bidder) and the other that has no previous experience (High-Noise Bidder) after having observed a generic bidder drop out in round k.

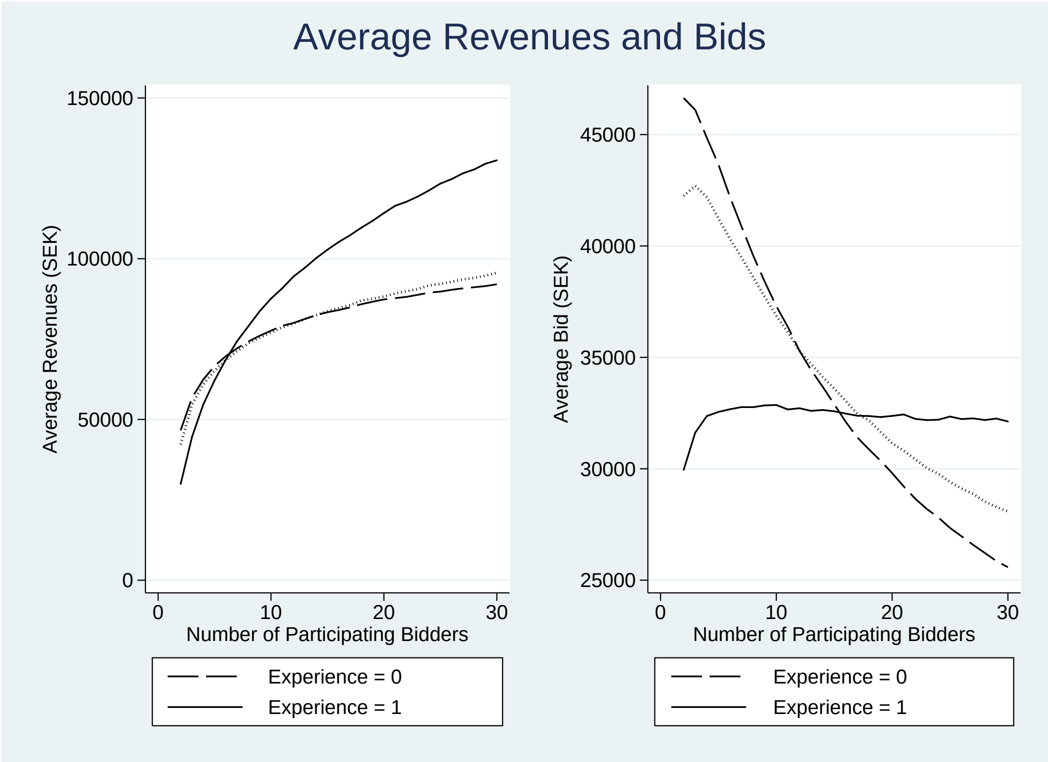

Figure 4: The left-most graph shows how the average revenues from the auction of a vehicle with an average appraisal value change with the experience of bidders and the number of participating bidders. Solid line shows average revenues in the case when all bidders have the experience of having one auction previously whereas the dashed line gives average revenues when all bidders have never won an automobile auction.The dotted line gives revenues simulated using the empirical distribution of experience. The right-most graph shows how average bids from the auction of a vehicle with an average appraisal value change with the experience of bidders and the number of participating bidders.

Data

Tables 4 through 7 below, give a brief description of all information publicly provided for each vehicle listed for auction on Kvarndammen AB (KVD).[29] Although, the format is standerdized, this does not necessarily guarantee that all details are provided without flaw. For instance, the Swedish Transport Agency's vehicle register, from which a vehicle's technical details are collected, contains more information about newer vehicles, meaning that older vehicles will may lack certain information. Furthermore, mechanics sometimes do not assess all aspects of the vehicle, rating them "Unknown" or "Untested".[30]

Transaction and Misc. Variables	Description
Transaction Price	The price paid for the vehicle in SEK, not incl. the auction fee.
Username	Username of winning bidder.
Auction Date and Time	Date and time at which the final countdown starts.
Appraised Value	The appraised value of the vehicle.
Region of Sale	The location of the warehouse at which the vehicle is situated.
Baseline Price	The appraised replacement price for the given vehicle model.
Seller Type	Broad categorization of the type of seller e.g. Fleet Owner, Insurance company or Governmental agency.
Comments	These contain detailed comments about the expert's assessment of the vehicle as well as any major/minor details of interest.

Table 5: Description of transaction and miscellenious variables provided by KVD for each vehicle auctioned. This information is listed for every vehicle auctioned from the time the vehicle is listed.

[29] This description is valid for the data collected up until Dec. 31st 2012. From Jan. 1st 2013, KVD changed the standardized format somewhat with certain information being added and other information being removed.

[30] Most often this is for vehicles that have been in a car accident and are sold as "objects for repair" or for spare parts.

Technical Variables	Description
Equipment	A detailed list of equipment available in the car e.g. GPS, Parking Assistance.
Odometer Reading	The odometer reading of the car at the time of sale in tens of kilometers.
Colour and Coating Type	Colour of the vehicle and whether the coating is matte or solid.
Engine Power (Kw and HP)	The engine size given in both KW and horse power.
Fuel type	The type of fuel the vehicle is registered to run on.
Hook	Whether the vehicle is fitted with a tow hook.
Fuel Economy	Fuel economy of the vehicle based on mixed driving conditions in litres per 100km.
CO2 Emissions	The amount of CO2 the vehicle emits is grams per kilometer.
Number of Passengers	The number of passengers the vehicle is legally registered to carry. May differ from the technical specification of the vehicle.
Number of Keys	Number of keys accompanying vehicle.
Total Allowed Weight	The total weight legally allowed for the vehicle in kilograms.
Max Allowed Load	The maximal load the vehicle is allowed to carry in kilograms.

Table 6: Description of technical variables provided by KVD for each vehicle auctioned. This information is listed for every vehicle auctioned from the time the vehicle is listed.

Legal Variables	Description
Registration and Chassis Numbers	Vehicle registration number and chassis number.
Production Month and Year	Year and month the vehicle rolled off the production line.
Date of Vehicle Registration	Year and month the vehicle was registered with the Swedish Transport Agency.
Date of Entering into Traffic	Year and month the vehicle entered into traffic in Sweden.
MOT§ Test Period	The period within a year during which a vehicle must be inspected.
Date of Last MOT Test	The date and result of last MOT inspection. A failed inspection is reported together with flaws found and date before which the problems must be resolved. A number of vehicles are banned from being in traffic.
Annual Tax	The annual road tax the owner of the vehicle has to pay. Depends on the weight, CO2 emissions, environmental classification, fuel type, municipality of registration and gearbox type.
Environmental Classification	The environmental classification of the vehicle based on EU emission standards.
Tax Deductability	Whether it is possible to deduct the annual tax if purchased for corporate use.
Imported	Whether the vehicle is imported or originally sold in Sweden.
Export Permissible	Whether the vehicle can be exported or not.
Temporary Registration Permissible	Whether it is possible to temporarily register the vehicle for export. Legally, if not possible, the vehicle cannot be driven on Swedish roads as the Swedish registration number is removed.

Table 7: §MOT, is a British terms which stands for Ministry of Transport and the MOT test is conducted to assess whether a vehicle is roadworthy. The Swedish counterpart is called the "Roadworthiness test". Description of legal and administrative variables provided by KVD for each vehicle auctioned. This information is listed for every vehicle auctioned from the time the vehicle is listed.

Quality Variables	Description
Service Book and History	Whether the car comes with its original service book and if so, an exerpt of the service history.
Bodywork, Engine, Gearbox, Brakes and Interior Ratings	Experts assessment based on a 1-5 scale with 5 being best and 1 being worst.
Vehicle Guarantee	Details of any remaining guarantees that were issued on the new vehicle.
Damage Guarantee	Details of any remaining damage guarantees that were issued on the new vehicle. If a damage guarantee still covers the vehicle one has benefits on the insurance premium one pays for the vehicle.

Table 8: Description of quality and assessment variables provided by KVD for each vehicle auctioned. This information is listed for every vehicle auctioned from the time the vehicle is listed.