A Field Experiment of Jump Bidding in Online Automobile Auctions[1]

David Grether

Division of Humanities and Social Sciences, California Institute of Technology

David Porter

Economic Science Institute, Chapman University

Matthew Shum

Division of Humanities and Social Sciences, California Institute of Technology

July 2012

Abstract: We run a large field experiment with an online company specializing in selling used automobiles via ascending auctions. We manipulate experimentally the possible amounts which bidders can bid above the current standing price. We find evidence of revenue non-equivalence across different jump-size treatments. Strategic models of jump bidding generally predict a dampening of seller revenue as jump-bidding is facilitated. Using two diverse auction sites, one in New York and one in Texas, we find evidence consistent with strategic jump bidding behavior in New York but not in Texas. This difference in findings between the two markets appears partly attributable to the more prominent presence in the Texas market of sellers who are car dealers willing to withdraw their cars if their reserve prices are not met.

---

[1] We thank the Gordon and Betty Moore Foundation for a grant which facilitated this research. We also thank Amit Gandhi, Yaron Raviv, Jimmy Roberts, Tom Ruchti, Artie Zillante, and seminar participants at Florida State and Chapman universities for helpful comments.

1. Introduction

In this paper we report the results of a large scale field experiment in which a major firm in online automobile auctions allowed us to change some of the parameters of the auctions. In these experiments, we introduce manipulations to examine bidders' behavior and market outcomes with different menus of bid level choices. The manipulations allow us to study *jump bidding*, that is bidders choosing to submit bids that exceed the minimum bidding increment.

Jump bidding is an endemic feature of real-world ascending ("English") auctions; this includes the famous FCC wireless spectrum auctions[2] that the US government has been running regularly for almost twenty years, online (eBay) auctions, and also conventional art and antiquities auctions run by Sotheby's and Christies for hundreds of years. At the same time, jump bidding has also been observed in many experimental implementations of ascending auctions (McCabe et. al. (1990), Banks et al. (2003), Coppinger et al. (1980) and Lucking-Reiley (1999)).

The prevalence of jump-bidding presents a puzzle for standard auction theory.[3] In the independent private values (IPV) setting, researchers have long recognized the strategic equivalence of ascending and second-price (Vickrey) auctions; to wit, the celebrated bidding outcome in second-price auctions – that it is a dominant strategy for bidders to bid their true valuations (Vickrey (1961), McAfee and McMillan (1987), Milgrom and Weber (1982))– can be translated into an analogous strategy for ascending auctions: bidders should stay active in the auction by submitting bids just marginally above the standing bid, until the standing bid surpasses their true valuations. As mentioned above however, observed bidding behavior deviates substantially from this "straightforward bidding" benchmark, due mainly to jump-bidding. As a result, there is a small but growing theoretical literature to explain jump bidding. In this paper, we examine this bidding behavior by executing a number of field experiments in which we manipulate the amounts with which bidders can jump-bid. As far as we are aware, this

[2] See Isaac, Salmon and Zillante (2007), Plott and Salmon (2004) and Cramton (1997) for details of this behavior.

[3] For book-length treatments of auction theory, see Milgrom (2004) and Krishna (2002).

is the first paper in which field experiments are employed to assess the revenue effects of jump-bidding.[4]

Existing literature: jump-bidding

One standard model of English auctions – and one in which the equivalence between second-price and English auctions holds in the independent private values setting – is the so-called "button" or clock auction (Milgrom and Weber (1982)), in which the price is set by a clock which rises automatically, and bidders indicate their willingness to pay the current price by holding down a button. Once a bidder releases his button, however, he "drops out" of the auction, and can no longer re-enter.

While analytically attractive, this clock auction is, however, not the typical auction form used in practice. In the typical ascending bid auction, there is no "clock", and the price sequence forms endogenously, consisting of bid amounts which are chosen by the individual bidders; hence, at any moment during the auction, bidders can submit bids which exceed the minimum acceptable bid (that is, jump), instead of simply deciding whether to stay in or drop out at the current price.

In this setup, Avery (1998) analyzes bidders' strategic incentives to jump, as a means for intimidating rivals. Avery constructs an equilibrium signaling model with jump bidding. In a two-stage setting in which a preliminary jump-bidding stage is followed by a traditional open-exit "clock" auction, Avery shows that there is a continuum of equilibria involving jump-bidding in which the seller's expected revenue is bounded above by the revenue in the straightforward equilibrium, which has no jump bidding. In this setting, the ability to jump-bid allows the competing bidders to coordinate on asymmetric strategies in the second-stage auction: a bidder with more favorable information, by jumping aggressively in the initial stage, signals his more favorable information and, at the same time, "selects" to play a more aggressive strategy in the second stage, and intimidates his rivals to adopt more passive bidding strategies in the second

---

[4] Lucking-Reiley (1999), in his field experiments with Magic cards, did increase the bid increment size of higher priced cards at the request of bidders. However, this was not a systematic treatment in his study.

stage. Importantly for our empirical analysis, the asymmetric equilibria selected by the jumping behavior Pareto-dominate the symmetric equilibrium, thus *decreasing seller revenue* on average. Significantly, this revenue-dampening effect counteracts the well-known "linkage principle",[5] whereby open auctions (such as the ascending auction) yield greater expected seller revenue than sealed-bid auctions, in an affiliated-value setup.

This revenue-dampening effect of jump-bidding has also been derived in other settings, including Daniel and Hirschleifer (1997), Easley and Tenorio (2004), Hoerner and Sahuguet (2007), and Isaac, Salmon and Zillante (2007). Particularly, the latter paper contains a model of "notch-bidding"[6], in which the presence of jump increments allows strategic bidders to lower the price at which they obtain the object (relative to the "straightforward bidding" benchmark), thus dampening seller revenue.

2. Field experiments: Used-car Auctions at copart.com

The practical importance of jump bidding and its effects on auction revenues are empirical questions. However, testing hypotheses about jump-bidding is difficult using field data, mainly due to data requirements.[7] In order to isolate jumps, the complete sequence of bids observed in an ascending auction must be recorded and available to the researcher. However, in the majority of real-world ascending auctions, typically only the final bid submitted by each participating bidder is recorded, making such data inappropriate for testing theories of jump-bidding.[8]

We designed a set of unique field experiments[9] using an online ascending auction for automobiles. Specifically, we created an experiment with Copart Inc., a publicly-traded

---

5 cf. Krishna (2002), Milgrom (2004)

6 To stop a competitor from bidding again, the notch bid is the value of the bidder you want to block minus the increment plus ε.

7 See Ashenfelter and Graddy (2003) and Hendricks and Porter (2007) for surveys of the empirical auction literature.

8 This is true in typical data from online auction sites (such as eBay; see, e.g. Song (2004), Lewis (2011)), as well as from timber auctions run by the US Forest Service (Haile and Tamer (2003), Aradillas-Lopez, Gandhi, and Quint (2011)). See Athey and Haile (2002) for additional discussion of inferential difficulties with ascending auction data.

9 cf. Harrison and List (2004).

(NASDAQ: CPRT) company which is the largest auction house for salvage vehicles in the world. In these auctions, we manipulated the way bidders could engage in jump-bidding, by restricting the maximum amount that bids could be submitted above the current standing price. Before describing our experimental design in detail, we begin with a description of Copart and its online auction mechanism.

Copart sells well-over a million cars annually through its on-line virtual auction. On average, each business day, Copart auctions around 5,000 vehicles on its site. Copart is an intermediary that obtains the vehicles from governments, charities, finance companies, banks, dealers, fleets, rental car companies and the insurance industry. Copart has over 150 facilities throughout the United States, Canada and the United Kingdom. Buyers are from around world and auctions are conducted each business day at various Copart facilities. Our experiments utilize Copart's largest auction yard (in Houston, Texas) and another geographically different yard in upstate New York to examine the effect of jump bidding restrictions on observed auction outcomes. Given the large scale of the auctions run by Copart, any systematic effects of jump bidding on revenues is likely to be economically meaningful.

We use data from 24 auctions – 13 run under the company's baseline parameters, and 11 run under altered parameters introduced by us. The volume varies across the sales, but each auction has approximately 500 vehicles offered for sale. The scale of the experiment is comparable to that of the sequencing experiments with used car auctions reported in Grether and Plott (2009). Relatedly, Tadelis and Zettelmeyer (2009), use field experiments with a used automobile auction company to explore how providing more information (in the form of “Standardized Condition Reports” describing a used car's condition) to bidders affects auction outcomes, particularly revenues.

Copart Auctions: main features

Here we describe the important features of the ascending auctions run by Copart. In order to participate, a buyer must first register an account to access the system. There are many types of buyers from around the world that participate in these auctions (auto parts dismantlers, re-builders, used car dealers, wrecking yards, and the public). This is a very international market of heterogeneous buyers. After buyers have registered, they are able to access the "current sales" button to view all of the auctions occurring that day, the locations of the auctions, and the start times. Buyers can join an auction at any time. Buyers can also view vehicles in upcoming auctions. Each auction shows pictures of the vehicle up for auction, its make, model and year, along with the list of details shown in Table 1. Figure 1 shows a typical auction screen from the Copart auction site.

The Copart bidding process begins with a Preliminary Bidding (proxy bids) stage. The Preliminary Bidding process, which ends 60 minutes before the start of the virtual auction, allows participants from around the world to preview vehicles for sale in each of Copart's facilities in person or over the Internet. Using Preliminary Bidding, participants enter the maximum price (called the "Bid4U Max") they are willing to pay for a specific vehicle and the software incrementally bids for the vehicle on their behalf. In the Preliminary Bidding Stage, all of the preliminary bids are incremented until only the highest preliminary bid is left. When the on-line bidding begins, the opening price is set equal to the second highest Preliminary bid plus one increment. As the on-line bidding process starts, the remaining (highest) preliminary bidder has their bid controlled by Copart software which automatically bids one bid increment above the current high bid (standing bid) for the vehicle, until their chosen "Bid4U Max" is reached. Bidders in the on-line auction are not informed if a bid is coming from the preliminary bidder or not.

The car to be auctioned is called a *lot* and is sold sequentially in *lanes* at each facility called a *yard*. Once the starting price is determined, the *bid increment* is set based on the current bid.

Table 2 shows how the bid increments change during the course of an auction, depending on the level of the current (or "standing") bid.

Once the auction is underway, bidders can submit bids in real time that are equal to one of the following options:

(i) the current bid plus the minimum increment; or
(ii) the current bid plus 5 times the minimum increment; or
(iii) the current bid plus 10 times the minimum increment.

As shown in Figure 1, the buttons for the different bid choices available to the bidders are located prominently on the lower right-hand side of the bidder screen.

Once a bidder submits one of these three bids it becomes the new standing bid and if no new standing bid is made in two seconds, then there is a five second count down displayed on the bidder screen. If no new standing bid is provided in those five seconds the auction ends. Thus, if no bid is received in seven seconds the auction is over. In our data the actual median time between bids is about one second with the average time approximately 2.5 seconds. The distribution of interbid times is bimodal with a large mode at zero (presumably the automatic increments for the winning preliminary bidder) and a second smaller mode at 7 seconds. Histograms of the distribution of interbid times for the New York and Texas yards are presented in, respectively, Figures 2 and 3. In some cases the time between bids exceeds seven seconds, but is never greater than eleven seconds. These longer intervals are caused by delays due to the online bidding environment. These auctions move quickly with most taking less than one minute.

Sellers in these auctions include insurance companies, dealers, charities, rental car companies, governmental units and single car sellers. Sellers in Copart auctions can and typically do set a *secret reserve price*[10]; called a minimum bid which is unobserved to bidders at the time they choose their bids, such that if the highest bid in the auction falls below it, the seller has the

[10] If there is no minimum bid required, this is listed as a "pure sale" in the auction. If there is a minimum bid required, it is always secret to the bidders (but they know that there is a reserve price on the lot).

option to not sell to the highest bidder.[11] Importantly, if the minimum bid is met during the course of the virtual auction, an announcement is made that the lot is "*sellin' all the way*".

If the bidding does not reach the reserve price the seller may negotiate with the high bidder or in some cases with the second highest bidder. Copart's new revised auction site specifically highlights this feature noting that bidders may engage in negotiations with sellers who "reveal or eliminate their minimum bid requirement to speed up the final sale to you." As we will see below, these aspects of the auction interact in interesting and – from our point of view -- unforeseen ways with the jump-bidding manipulations in our field experiment.

Experimental Design: interventions in bid increments

In our field experiment we manipulated the *size of the jumps* that bidders could choose when submitting their bid. As we noted above, the standard Copart auction rules allow bidders to submit jump-bids which are either 5 or 10 times the bid increment above the current bid. We call this the *baseline treatment*, and denote it by (1,5,10). We introduced two contrasting treatments. First, we have a *limited jump-size treatment* which restricts jump bids to only 2 or 3 times the bid increment above the current bid. We denote this treatment by (1,2,3). Second, we have an *enhanced jump-size treatment* which allows bidders to bid 10 or 20 twenty times the bid increment above the current bid.[12] This treatment is referred to as (1,10,20). In the enhanced (limited) jump-size treatment, it is easier (harder) for bidders to jump, in the sense that a desired bid level \$X(>0) above the current standing bid is easier (harder) to achieve under the enhanced (limited) treatment than under the other treatments.

Two Copart yards – in Houston, Texas and upstate New York -- were used in our study. The Texas yard has greater volume with two sales per week while the New York yard and all the other company yards have weekly sales. The volume per sale varies, but averages around 500

---

11 Secret reserve prices are actually commonly observed in real-world auctions, but not completely understood from an auction-theoretic point of view. See Bajari and Hortacsu (2003) and Katkar and Reiley (2006) for empirical and experimental work exploring secret reserve prices, and Elyakime et al.(1994), Vincent (1995) for theoretical analyses.

12 We had initially proposed a treatment that eliminated jumps completely (ie. "(1,1,1)"), but this was not feasible due to software limitations in Copart's online bidding system.

vehicles per sale. At both yards insurance companies are the owners of around 40% of the vehicles offered for sale. At the New York site, the other main sources of vehicles are governments and municipalities (20 %) and charities (18 %). Notably, used car dealers account for only about 10% of sales in New York. The seller mix at the Texas site, however, is quite different; dealers have the most prominent presence there, and account for 45% of the lots offered for sale. Below, we will attribute some of the observed differences in seller behavior between the Texas and New York sales to these differences in seller populations between the two sites.

Table 3 lists the sequence of our treatments by date and yard. For each lot there is information about the item and summary bid data. The information on the lot includes the description (make, model year), damage including repair cost (seller's estimate), mileage, title type and state of registration and the number of times the lot has been previously auctioned. In our empirical work below, these are the main variables used to control for heterogeneity across lots. Since these are virtual auctions and, for the most part, bidders are offsite and do not have the opportunity to inspect vehicles physically before bidding, we believe that these variables capture practically all heterogeneity observed by bidders before they bid.

Information about the auction includes the minimum bid, the starting bid, number of bids and jump bids, the high bid, the selling price (listed as zero if the seller did not accept the price), the high bidder (coded) including the state and nationality of the high bidder and the seller's identity (coded) and the type of the seller. The final sale price may differ from the high bid as a result of negotiations between the seller and the first or second highest bidder. In addition, for each lot we observe the complete sequence of bids and bidder identities, allowing us to determine accurately whether a bidder jumped (i.e., submitted a bid more than one increment above the standing bid), and the amount of the jump.

3. Empirical results

In this section we present and discuss the main findings from our field experiments. As discussed above, our main goal going into the project was to understand the revenue effects of jump-bidding in ascending auctions. However, as will be apparent below, there were some additional features of the auction which we did not anticipate, and which end up playing an important role in interpreting the empirical results. We begin with some discussion of general trends in the data, followed by a more specific regression-based analysis.

Initial results

Summary statistics for the two yards and the three treatment conditions are given in Table 4. First, we confirm that the treatments are *effective* in that the proportion of jumps in both the limited and enhanced jump-size treatments are significantly different from the proportions in the baseline (1,5,10) treatment. The observed treatment effects are sensible with the number of jumps increasing when the jump size is restricted, and falling when the jump size is increased. The actual number of jumps varies somewhat across the auction sites. At the New York location approximately 1.3 percent of the bids are jumps with roughly six percent of the buyers jumping at least once. Jump bids are more frequent at the Texas site with about nine percent of the bidders jumping at least once and jump bids accounting for approximately 2.5 percent of the bids.

Second, looking at average prices with the three treatments does not reveal any substantial revenue effects of changing the allowable jump sizes. The average high bid does not vary significantly nor does the average sale price (conditional on the vehicle being sold). Moreover, the auctions in Texas take about twice as long as those at the New York yard, and the high bids are roughly twice those at New York.

The proportion sold decreases at the Texas site when jumps are restricted and at the New York yard when the jumps are larger. Thus, the overall revenue effects are ambiguous and not consistent across the two locations. Variation in the composition of the seller groups may account for some of these differences between the two sites. While insurance companies in our sample sell about 90-95 percent of their cars at auction, dealer sales rates are mainly in the 60 percent range. The re-auctioning[13] of cars at the Texas site is about twice the rate observed at the New York site. Looking at the number of times a vehicle has been auctioned, the median is one in New York and two in Texas and the numbers are about double at the quartiles and, at the 99th percentile: 7 for New York and 14 for Texas. In the New York auctions the high bids usually exceed or meet the reserve prices (72.3 percent of the time), while in Texas the situation is almost the reverse with high bids being less than the reserve in 68.5 percent of the auctions.

Theories of strategic jump bidding often have equilibria with the bidding starting and ending with jump bids. In our data this does not happen. The fraction of first bids that are jumps is somewhat higher than the overall jump rates at both locations (0.022 in New York and 0.036 at the Texas site). At the New York site the proportion of final bids that are jumps is about the same (1.5 percent) as the overall proportion of jump bids. In Texas, final bids are more likely to be jumps with about 3.2% of the sales ending with jumps. At both locations the 'winning bids' are likely to come from bidders who jumped at some time during the bidding on the lot. In New York about 4 percent and in Texas 11 percent of the high bids were made by bidders who jumped during the auction on that lot. All in all, these are very modest figures, and provide scant confirmation of one important empirical implication of strategic jump bidding.

Detour: Repeat-bidding. Before moving on to regression results which show how robust these findings are to various controls, we discuss a particularly striking bidding phenomenon which we observed in Copart auctions, which appears anomalous at first glance – that of *repeat bidding*.[14] We say that a buyer engages in repeat bidding when he/she submits two consecutive bids. Thus, repeat bidders are *raising their own bids*. These auctions move very fast with the typical lot lasting under a minute, so that it is possible that bidders may accidentally and mistakenly bid against themselves ("tremble"). This explanation is plausible for much of the repeat bidding at

[13] A re-auctioned lot is a lot that was previously offered in an earlier auction but not sold.
[14] In the history of the Copart auctions, repeat bidding at one time was not allowed. However, an uproar by the bidders caused Copart to allow such bidding to be part of its current design.

the New York site. There, most bidders who repeat-bid do so only once or twice in a weekly sale, and the most frequent do so on the order of only 10 to 20 times. The fraction of repeat bids is generally less than 2% of the bids. In Texas, however, the proportion of repeat bids is much higher, ranging from 18% to over 24%. Most buyers either do not repeat bid or do so only occasionally.[15]

While puzzling at first glance, the repeat bids may be (partially) explained by examining their timing patterns. Repeat bids occur with a longer lag, i.e. with a longer time interval from the preceding bid, than non-repeat bids. At a typical sale, the median time interval between repeat bids is six seconds while it is only two seconds for the non-repeating bids. Recall that reserve pries at Copart auctions are secret (that is, unknown by bidders when they choose their bids). Moreover, if the bidding starts above the secret reserve price or goes above it during the bidding, an audible announcement that the lot is "selling all the way" is emitted on the web site. However, *virtually all of the repeat bids take place below the reserve price*. At the Texas site the proportion of bids that are repeats drops by more than half when the minimum bid is passed. (The proportion of jump bids also drops, but by a lesser amount.) This suggests that repeat bidding (and, to a lesser extent jump bidding) may be symptomatic of a kind of search behavior by which bidders try to discover the reserve price, but do not want to risk going over it.

Another possibility is that some of the repeat bids are shills working with specific sellers. We have no robust statistical evidence for this story, but rather a colorful anecdote. Namely, the individual buyer in Texas mentioned above who submitted 811 repeat-bids in one day was the high bidder (hence, "won") 75 auctions over the course of two consecutive sales, but failed to obtain any of these cars – that is, in each of the 75 cases, the seller declined to sell the car to this individual. This buyer certainly looked like a shill bidder.

More broadly, however, we looked at the identities of the sellers whose vehicles had repeat bids, and we did not find any particular pattern. Also, the frequent repeat bidders did not concentrate

[15] However, some buyers bid against themselves several hundred times in one day (the maximum number of times we observe this is 811!).

their bids on the vehicles of a few sellers. In addition, this type of jump bidding decreases substantially once the secret reserve price is met. For these reasons, we do not believe shill bidding to be widely prevalent in these auctions.

Regression results: revenue effects

The main empirical implication we focus on is that, if bidders jump to intimidate rivals, we should see a detrimental effect of jump bidding on sellers' revenues. The revenue results from the lot-level regressions are shown in Table 5. As controls, we included the car's odometer reading ("Odometer"), a dummy for whether this reading represents the actual mileage ("Actual odometer"), the number of bidders ("# buyers"), the seller's estimated value ("seller book value"), and dummies for the lane, make, week, and day of the week of the auction. We did not include time (e.g. week or day) dummies for the New York yard as there was only one sale each week. (We did experiment with various time trends and functions of mileage and found no substantive changes in the results.) The main coefficients of interest are those on SMALLJUMP and LARGEJUMP which are, respectively, indicators for the 1,2,3 and 1,10,20 experimental treatments. (The excluded category is when the increments are 1,5,10).

For the Texas sales, the regression results in Table 5 show that restrictions on jump-bidding have little effect on the high bids in the auctions. However, for the New York sales the coefficient of SMALL JUMP is positive and marginally significant, indicating that restricting jump-bidding increases slightly (by around $170) the high bid in the auctions. This is consistent with the "jump-bidding as intimidation" hypothesis, and suggests that auctions are more competitive when jump-bidding is restricted, leading to higher potential revenue for the sellers. The results are basically the same if the dependent variable is final sale price, conditional on being sold (columns B and D in Table 5).

Confounding effects: seller strategic behavior. The picture presented in the regressions so far is incomplete. As we discussed before, due to the prevalent use of secret reserve prices, sellers are not required to sell the car at the high bid. Table 6 presents some summary statistics describing seller behavior. Obviously, we see that seller behavior varies substantially depending on whether the minimum bid (i.e., secret reserve price) is exceeded in the auction. For the Texas sales, we see that when the final bid is below the minimum bid, sellers sell the car at the final bid only 40.8% of the time, and withdraw the car 36.3%. When the final bid exceeds the minimum bid, however, sellers sell the car 85.2% of the time. The 4.4% no sales, even when the final bid exceeds the minimum bid arises from buyers reneging their winning bid.[16] When a buyer reneges, the seller can negotiate with the second highest bidder to sell the lot. This results in sales 70% of the time. Similar figures hold for the New York sales.

Motivated by these numbers, we next consider regression specifications which jointly model the final sales prices along with the seller's decision of whether or not to sell the car. Since the final sales prices is equal to zero for lots which the seller decides to withdraw, we augment the price regression with a second "selection" equation which explains the seller's decision to sell (vs. withdraw) the car. The specification of this two-equation model is:

$$FSP_{it} = \begin{cases} X_{it}\beta + \varepsilon_{it} & if\ SOLD_{it} = 1 \\ 0 & otherwise; \end{cases}$$

$$SOLD_{it} = \begin{cases} 1 & if\ Z_{it}\gamma + \eta_{it} \geq 0 \\ 0 & otherwise; \end{cases}$$

$$(\varepsilon_{it}, \eta_{it}) \sim N(0,0,1,1,\rho)$$

In the above, the subscript "*it*" denotes lot *i* in sale *t*, and FSP_{it} and $SOLD_{it}$ denote, respectively, the final sales price for lot *i* in sale *t* and whether the seller of this lot decided to sell it (rather than withdraw the lot for a later sale). By estimating such a model, we allow for common unobservables – presumably unobserved characteristics of a car – which affect both the bids placed on the car as well as the sellers' decisions to withdraw the car.

In our specification of this generalized selection model, we use additional seller characteristics – specifically, dummies for whether the seller is a dealer, or an insurance company – as

[16] Buyers that renege on their bid must pay a penalty of $400 or 10% of the sales price, whichever is greater.

instruments which enter the selection equation (so are elements in Z_{it}), but are excluded from the price regression (are not elements in X_{it}). Estimates from this augmented model – obtained using Heckman's two-step method – are presented in Table 7 for, respectively, the Texas and New York sales.

The results from this specification are quite different from the results presented earlier. Specifically, for the Texas sales, we find that SMALLJUMP now has a negative and significant effect on the final sale price: restricting jump bidding reduces, on average, the final sales price by $1,013, not a small amount. This is not consistent with the strategic implications of jump bidding, which would predict higher revenues for the seller when jump bidding is restricted.

In the New York sales, however, we find that LARGEJUMP has a negative and significant effect on the final sales prices (implying a $434decrease in the prices on average). This supports the intimidative bidding hypothesis. Apparently, then, our evidence suggests that jump bidding may have an intimidation component in New York, but not in Texas.

The selection equations, which explain whether a lot is sold at the high bid (vs. withdrawn or negotiated by the seller), are reported in Columns B and D in Table 7. Not surprisingly, the results here mirror those in Columns B and D in Table 5: we see that in Texas, SMALLJUMP also has a significantly negative effect on the propensity that a car is sold, but in New York, it is LARGEJUMP that has the significantly negative effect.

Among the other variables, we note that the seller characteristics ("Insurance firm" and "Dealer") affect the probability of a sale significantly. *Ceteris paribus*, in both the New York and Texas yards, sellers who are insurance companies are much more likely to part with their cars at the highest bid, while dealers are less likely to do so. These results highlight an important behavioral difference between these two types of sellers, which we will return to below.

Taken together, these results suggest some striking differences between the Texas and New York sales: restricting jump bidding in Texas (resp. enhancing jump bidding in New York) tends to lower the high bids, which are less likely to attain the seller's minimum, and hence trigger the seller to either withdraw the car, or negotiate with the high bidder for a higher price. In net, however, this compensating behavior of the seller is not enough to equalize revenue across the different treatments; the average revenue in auctions where jump bidding is restricted in Texas (resp. enhanced in New York) is still lower.

Remarks: instrument validity

While these results from the selection model are quite striking, and plausible, they depend importantly on the validity of the instruments in the selection model. On the one hand, these instruments satisfy the exclusion restriction because seller type is not known by the bidders at the time of bidding (but only known once a bidder wins the car); hence, they should not affect their bids.[17] At the same time, seller type must be orthogonal to the unobservable ε_{it}, which encompasses car characteristics unobserved by the researcher, but observed by buyers and incorporated into the final sales price. Of course, this cannot be verified directly, but Table 8 shows how the *observed* car characteristics vary across different seller types. Furthermore, as we remarked earlier, unobserved car characteristics may not be as important of a concern in the setting we consider, because these are virtual auctions in which bidders do not have the opportunity to inspect the cars physically, thus limiting their information on a car's characteristics to the variables listed in the online description, which are the variables which we include as controls in the regressions (and are summarized in Table 8).

Another reason that seller type may fail the exclusion restriction is because dealers and insurance companies differ in how they set their reserve prices which, in turn, affects bidding behavior; namely, if the reserve price is very low (or even zero), then the high-bid in the auction is more likely to exceed the reserve price, which makes the seller reluctant to withdraw the lot (so that $SOLD_{it}=1$ for this lot). Indeed, Table 8 also shows that dealers tend to set high reserve prices, In

[17] We have also considered alternative specifications where we used the sellers' minimum bid (their secret reserve price) as the instrument, and the results are very similar to those reported in Table 7.

Table 9, we find that for insurance companies, the high bid exceeds the reserve price 67% of the time (2835 of 4221) while for dealers it only occurs 14% for the time (364 of 2522). Furthermore, from Table 9, we find that for car dealers, when the high bid is less than the reserve price 47% of the cars are withdrawn (1014 of 2158), while only 8% (30 of 364) are withdrawn when the reserve price is met. To examine these issues, we also re-ran the selection model separately for the two subsamples of lots where the high-bid exceeded, and did not exceed, the reserve price. The main results are qualitatively unchanged in these regressions, albeit the significance of the coefficients on the jumpsize indicators is reduced, due to the smaller sample sizes (see the Appendix for these results).

Why are Texas and New York different? What factors drive the difference in the results between the Texas and New York sales? As mentioned above, an important difference between the two markets is the *seller mix*: specifically, car dealers are more prominent in the Texas market, accounting for around 45% of the cars sold, while dealers are account for only 10% of the cars sold in New York. The other major group of sellers in these auctions is insurance companies, who are disposing of vehicles which have been "totaled"; in both markets, insurance companies account for around 40% of the cars sold. At the same time, the results in Table 7 also showed that these two types of sellers behave quite differently, especially in their willingness to sell the car to the highest bidder in the auction.

A priori, one might expect dealers to behave more strategically; because they arguably have lower costs of holding inventory than insurance companies, they may be more inclined to use the particular institutions of the Copart auctions – such as the secret reserve prices and opportunities for renegotiation or withdrawing their cars – to their advantage. We examine this hypothesis more formally; for a subset of the sales in both New York and Texas, we were able to obtain, in addition to the sellers' identity codes, their classification by types. In Table 9, we present the same type of figures as in the Table 6, but now broken down by lot sold by car dealers versus insurance companies. The difference in seller behavior between these two groups is very striking. First, across all sales, we see that insurance companies sell the majority (84%) of their cars at the high bid in the auction, and negotiate on only around 12% of sales. Dealers sell only a quarter (27%) at the high bid, and negotiate around 31% of their sales. Moreover, dealers withdraw (and presumably resell at a later date) 42% of their cars. Grether and Plott (2009) observed similar behavior with dealers selling a substantially smaller fraction of vehicles brought to auctions than the large sellers (banks and finance companies in their data).

Dealers are able to engage in such extensive negotiation and withdrawing behavior by manipulating the secret reserve price. We see that the high bid in the auction fails to exceed the minimum bid for about 86% (=21583/2522) of the cars sold by dealers, but only 33% of the time for cars sold by insurance companies. Regressions (not reported) confirm that, indeed, controlling for car characteristics, dealers set minimum bids systematically higher than do insurance companies.

The findings provide at least a partial reconciliation of the earlier regression results. The greater dealer presence in the Texas sales, and their more strategic behavior, limit the scope and effectiveness of bidder strategies that reduce seller revenue. That is, strategic sellers can counteract tendencies towards lower revenue by setting higher minimum bids and engaging in post-auction price negotiation, which may explain why we don't see evidence of dampened seller revenue in the LARGEJUMP treatments in Texas.

The opposite is true in the New York sales. Here, sellers are less strategic, so that enhanced opportunities to jump-bid (as in the LARGEJUMP treatments) may augment the scope for bidders to engage in intimidating behavior, leading to lower seller-revenue; this is what we find.

Caveat: Non-monotonic effects of jump-size on seller revenue. We end our analysis with a caveat of sorts. It is noteworthy that we find *asymmetric* and *non-monotonic* effects of the jump-bidding treatments on seller revenue in both markets. That is, for Texas, we find that restricting the jump size (SMALLJUMP) reduces revenues relative to the baseline, but we don't find that, symmetrically, increasing the jump size (LARGEJUMP) increases revenues. Similarly, for New York, increasing the jump size (LARGEJUMP) reduces revenues, but decreasing the jump size (SMALLJUMP) doesn't increase revenues. The revenue effects do not appear to be monotonic, at least in the range of jump sizes which we consider in our experiments. This may suggest that, to a first-order, the baseline jump sizes are close to optimal, to maximizing expected seller revenue; hence, changes from the baseline either reduce revenue, or have no significant effect. This interpretation may imply that perhaps treatments involving larger changes in jump sizes may be needed to better understand the effects of jump bidding opportunities on seller revenue in these auctions.

4. Conclusions

In the literature on auctions, jump bidding has received substantial attention. Since jump bidding is frequently observed in practice, natural questions arise: why does it occur, and what are the revenue implications? In this paper we report the results of field experiments with the treatment variables being the sizes of allowed jump bids. One treatment restricted participants to smaller jump sizes than the company had been allowing, and the other increased the jump sizes. We analyzed data from 24 online auctions at two auction locations (New York and Houston) at which over 15,000 vehicles were auctioned.

We find that behavior is much different at the two locations we examined. In New York, where there are more insurance companies that just want to sell their inventory, there are fewer unsold lots by the sellers than in Texas. In New York, our regressions show that enhanced opportunities to jump bidding lower revenue, which is consistent models of strategic bidding. However, in Texas, where there are many dealers offering cars but selling a smaller fraction of them, the results show that restrictions on jump bidding lower revenue,. While our focus in this paper has been on bidder behavior, our results suggest that the interaction between the strategic behavior of both bidders and sellers is important in these auctions. In ongoing work, we are conducting additional field experiments to gauge the effect of seller strategies on auction outcomes.

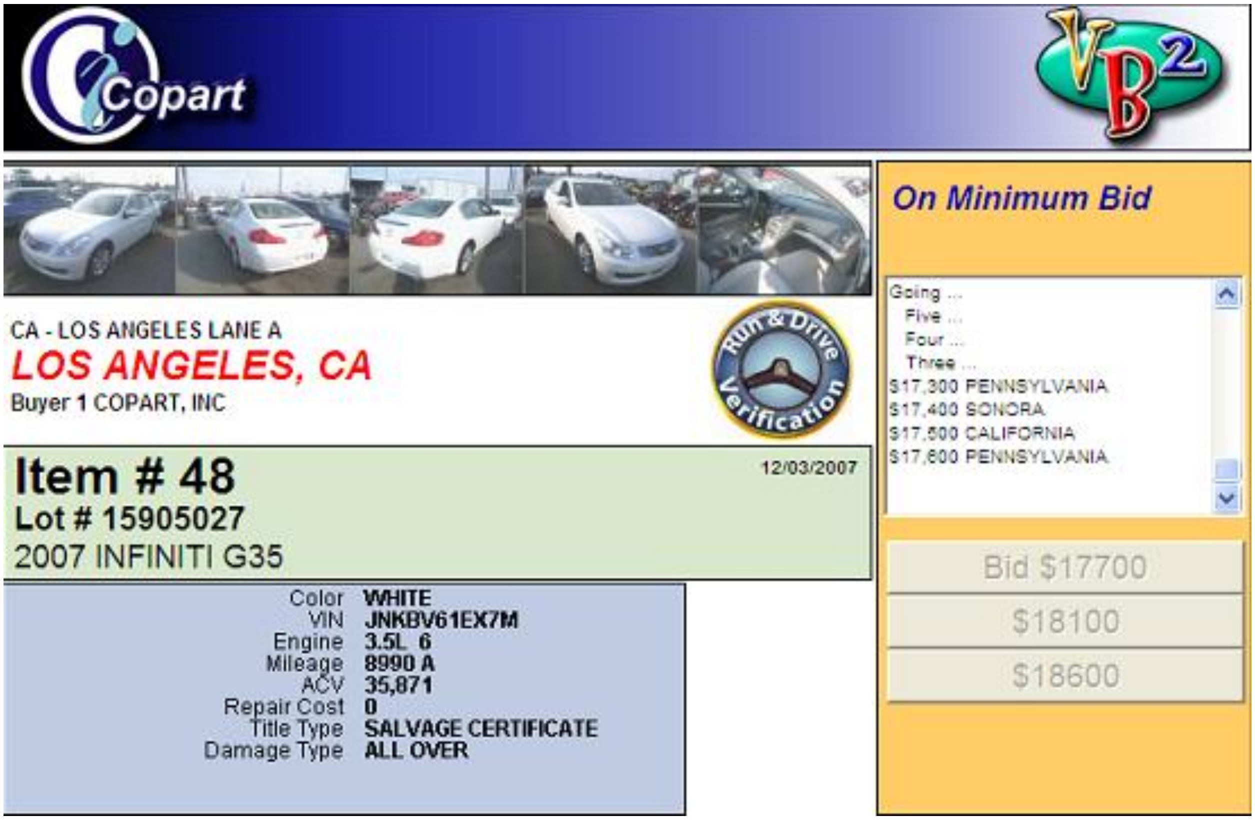

Figure 1

Screenshot of Copart Bidder Screen

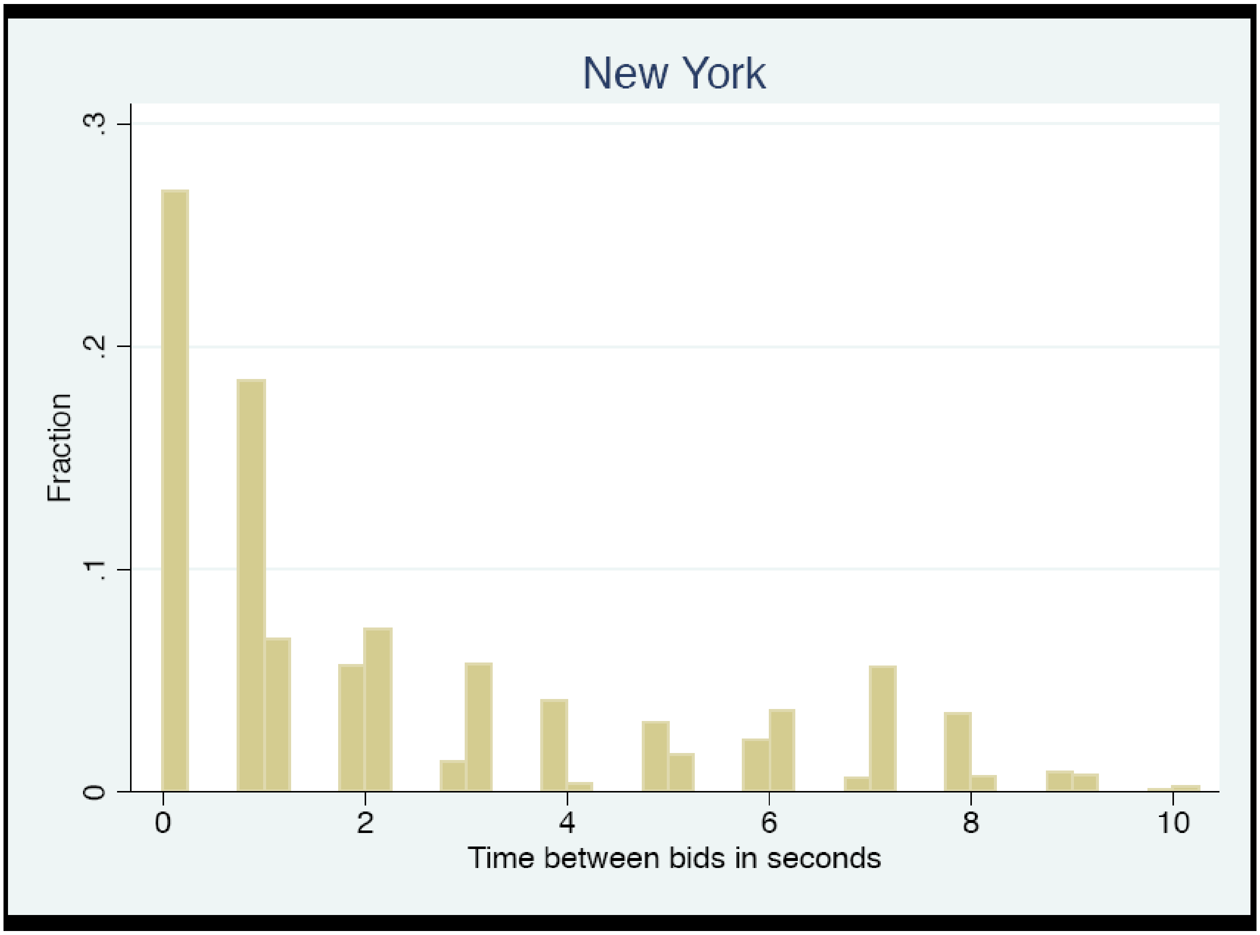

Figure 2

Interbid Times

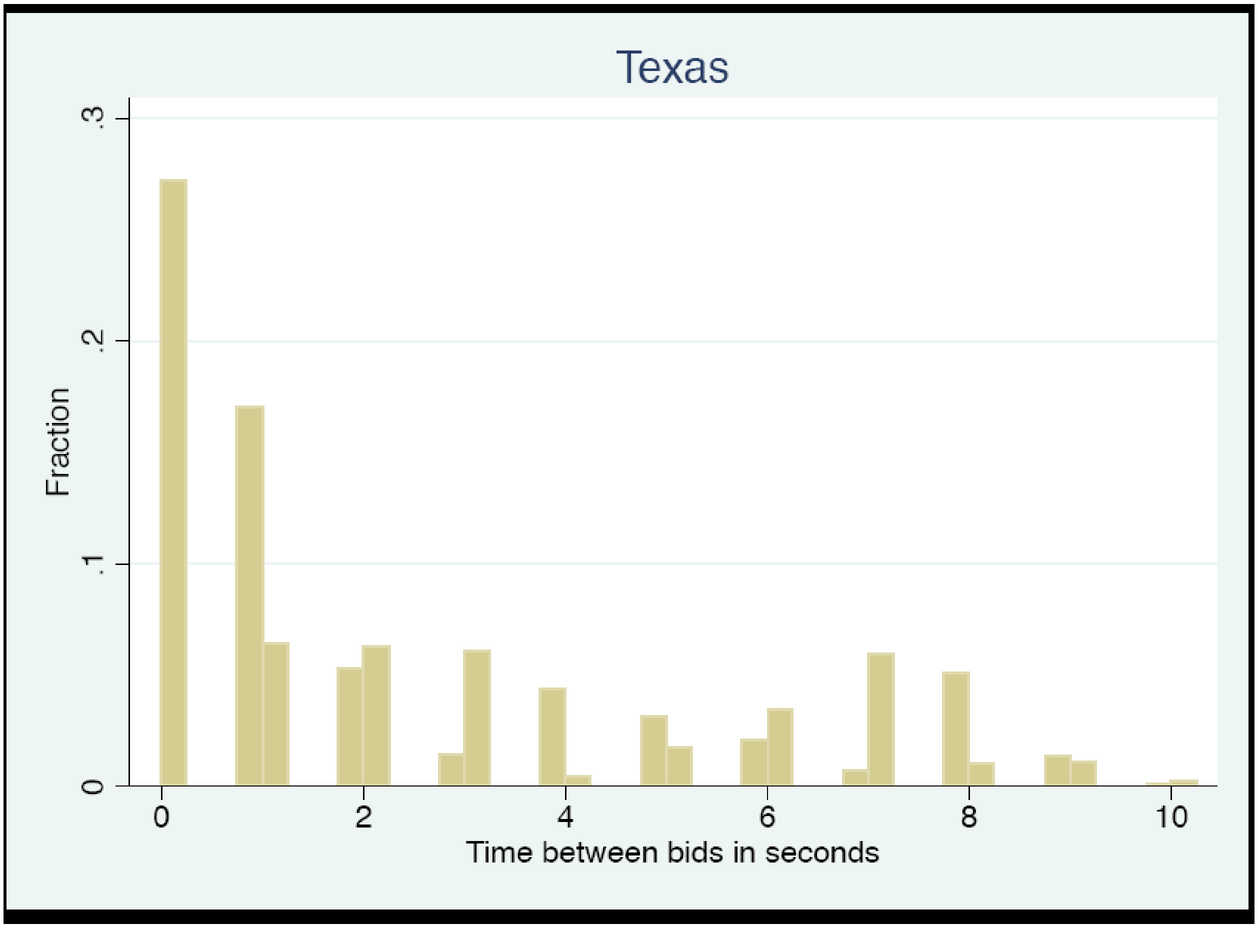

Figure 3

Interbid Times

Table 1

Lot Details and variable definitions

Actual Cash Value	***Estimated*** retail value of the lot as submitted to Copart by the seller. If the lot has been damaged, this is the value prior to the occurrence of the damage. The number is only informational.
Repair Cost	***Estimated*** cost to repair the vehicle as submitted to Copart by the seller of the vehicle.
Title State/Type	Title type denotes the ownership documents that will be transferred to the buyer.
Odometer	Odometer codes are shown to reflect the known reliability of the odometer reading.
Primary Damage	Location of the major damage on the car
Secondary Damage	Location of the minor damage on the car
VIN	Vehicle Identification Number assigned by the manufacturer.
Body Style	Body Style is the manufacturer's designation of the vehicle's configuration
Color	Color listed on this site is the common color name that reasonably represents the exterior color of the vehicle.
Engine	Engine is the motor
Drive and Cylinders	Manufacturer's designation of the vehicle's power train.
Fuel	Designates the fuel type used by the engine as designated by the VIN.
Keys	Indicates whether Copart is in possession of the keys to the lot.

Table 2

Minimum Bid Increments

Bid Range	Minimum Increment
$0 - $5	$1
$5 - $40	$5
$40 - $100	$10
$100 - $1,000	$25
$1,000 - $5,000	$50
$5,000 - $25,000	$100
$25,000 - $50,000	$250
$50,000 - $100,000	$500
$100,000 - $10,000,000	$1,000

Table 3

Treatment Application

Yard	Date	Treatment	# of Lots in Sample
Texas	2/19/10	1,5,10 (benchmark)	408
Texas	2/23/10	1,2,3 (restricted)	497
Texas	2/26/10	1,5,10 (benchmark)	560
Texas	3/2/10	1,5,10 (benchmark)	490
Texas	3/5/10	1,2,3 (restricted)	549
Texas	4/20/10	1,5,10 (benchmark)	515
Texas	4/23/10	1,2,3 (restricted)	727
Texas	4/27/10	1,2,3 (restricted)	486
Texas	4/30/10	1,5,10 (benchmark)	642
New York	5/19/10	1,5,10 (benchmark)	714
Texas	5/25/10	1,5,10 (benchmark)	689
New York	5/26/10	1,2,3 (restricted)	658
Texas	5/28/10	1,10,20 (enhanced)	689
Texas	6/1/10	1,10,20 (enhanced)	538
New York	6/2/10	1,5,10 (benchmark)	586
Texas	6/4/10	1,5,10 (benchmark)	527
New York	8/11/10	1,5,10 (benchmark)	549
Texas	8/17/10	1,5,10 (benchmark)	613
New York	8/18/10	1,10,20 (enhanced)	549
Texas	8/20/10	1,10,20 (enhanced)	703
Texas	8/24/10	1,10,20 (enhanced)	450
New York	8/25/10	1,10,20 (enhanced)	551
Texas	8/27/10	1,5,10 (benchmark)	746
New York	9/1/10	1,5,10 (benchmark)	577

Table 4

Average Bidding Behavior for each Yard/Lot/Treatment

Yard	# of Bidders	# of Bids	High Bid	Frequency of Jump Bids	Frequency of Repeat-bidding	Size of Jumps	Proportio n Sold	Time in Seconds
Texas (1,5,10)	4.23	23.8	5330	.024	.193	460	.765	81.63
Texas (1,2,3)	4.52 (.01)	26.2 (.00)	5501 (.36)	.035 (.00)	.184 (.00)	187 (.00)	.676 (.00)	87.12 (.00)
Texas (1,10,20)	4.23 (.90)	26.0 (.00)	5196 (.17)	.023 (.00)	.192 (.54)	923 (.00)	.759 (.30)	86.25 (.00)
New York (1,5,10)	3.02	10.4	2372	.013	.014	356	.918	43.86
New York (1,2,3)	2.87 (.08)	11.3 (.12)	2731 (.06)	.019 (.00)	.014 (.53)	154 (.00)	.926 (.64)	44.51 (.65)
New York (1,10,20)	3.21 (.01)	11.3 (.06)	2318 (.73)	.003 (00)	.013 (.73)	508 (.00)	.850 (.00)	46.03 (.07)

Figures in parentheses are significance levels for testing equality with baseline (1,5,10).

Table 5 Regression results for New York and Texas Sales[18]

	New York Yard		Texas Yard	
Dependent variable:	**OLS High bid**	**OLS Final sale price>0**	**OLS High bid**	**OLS Final sale price>0**
	(A)	(B)	(C)	(D)
SMALLJUMP	0.1653 (1.82)*	0.1596 (1.73)*	0.1055 (0.74)	0.0389 (0.33)
LARGEJUMP	0.0201 (0.21)	-0.0304 (0.31)	0.0660 (0.57)	0.0375 (0.41)
Odometer	-0.004 (0.80)	-0.0063 (1.00)	0.0091 (1.87)*	-0.018 (4.81)***
Actual odometer	0.4256 (4.87)***	0.3440 (3.85)***	1.05 (13.26)***	1.0041 (16.98)***
#buyers	0.1655 (8.05)***	0.1596 (7.55)***	0.0511 (3.27)***	0.0345 (2.78)**
Seller book value	0.2638 (57.68)***	0.2679 (55.63)***	0.3435 (132.32)***	0.2717 (92.03)***
Constant	-0.1298 (0.20)	1.697 (2.12)**	0.391 (0.33)	1.3585 (0.85)
Week dummies	yes	yes	yes	yes
Day of week dummies	yes	yes	yes	yes
Make dummies	yes	yes	yes	yes
Lane dummies	yes	yes	yes	yes
Primary damage dummies	yes	yes	yes	yes
#observations	4170	3760	11499	8473

[18] T-stats in parentheses. ***: statistically significant at 1%, **: statistically significant at 5%; * statistically significant at 10%.

Table 6 Seller Behavior

	Texas Yard			New York Yard	
	# lots	%		# lots	%
All lots:			**All lots:**		
Sell at high bid	6249	54.6	Sell at high bid	3252	78.1
Negotiate price	2179	19	Negotiate price	503	12.1
Withdraw	3021	26.4	Withdraw	410	9.8
Total:	*11449*		*Total:*	*4165*	
Lots with high bid < minimum bid:			**Lots with high bid < minimum bid:**		
Sell at high bid	3227	40.8	Sell at high bid	495	42.8
Negotiate price	1809	22.9	Negotiate price	401	34.7
Withdraw	2868	36.3	Withdraw	261	22.6
Total:	*7904*		*Total:*	*1157*	
Lots with high bid > minimum bid:			**Lots with high bid > minimum bid:**		
Sell at high bid	3022	85.2	Sell at high bid	2757	91.7
Negotiate price	370	10.4	Negotiate price	102	3.4
Withdraw	153	4.4	Withdraw	149	4.9
Total:	*3545*		*Total:*	*3008*	

Table 7 Heckman Selection Model results for New York and Texas Sales[19]

	New York Yard		Texas Yard	
Dependent variable:	**Final sale price**	**Pr(Final sale price>0)**	**Final sale price**	**Pr(Final sale price>0)**
	(A)	(B)	(C)	(D)
SMALLJUMP	0.31899 (1.78)*	0.14831 (1.96)*	-1.0132 (5.16)***	-0.942 (11.59)***
LARGEJUMP	-0.4341 (2.21)**	-0.45652 (6.61)***	0.08834 (0.85)	0.08819 (1.93)*
Odometer	-0.1656 (13.58)***	-0.00364 (0.81)	-0.00188 (0.42)	0.0048 (2.08)*
Actual odometer	0.35349 (2.06)*	-0.02924 (0.41)	1.1757 (15.13)***	0.0984 (2.93)**
#buyers	0.14698 (3.96)**		0.03672 (2.78)**	
Seller book value	0.27473 (30.19)***	-0.00634 (2.03)*	0.2572 (75.65)***	-0.00908 (7.84)***
Constant	-0.99591 (0.694)	6.3722 (12.39)***	-2.9617 (1.81)*	0.1864 (0.39)
Selection term[20]	4.7177 (7.23)***		3.3112 (23.60)***	
Insurance Firm		0.81415 (10.72)***		1.2922 (23.30)***
Dealer		-0.41149 (4.83)***		-0.3319 (6.74)***
Week dummies	yes	yes	yes	yes
Day of week dummies	yes	yes	yes	yes
Make dummies	yes	yes	yes	yes
Lane dummies	yes	yes	yes	yes
Primary damage dummies	yes	yes	yes	yes
#observations	4170	4170	11499	11499

19 T-stats in parentheses. ***: statistically significant at 1%, **: statistically significant at 5%; * statistically significant at 10%.

20 Inverse Mill's ratio.

Table 8 Observed Car Characteristics Across Seller Types: Mean Values (Standard Errors)

Age	*(Years)*			
	Insurance Co.	*Dealers*	*Others*	*All*
New York	7.03 (0.15)	8.28 (0.33)	11.96 (0.20)	8.85 (0.13)
Texas	7.83 (0.07)	4.63 (0.08)	10.92 (0.16)	7.50 (0.06)
Total	7.67 (0.06)	4.81 (0.08)	11.19 (0.13)	7.73 (0.05)
Odometer reading	(miles)			
New York	67794 (1760)	92495 (5428)	118172 (2703)	87285 (1540)
Texas	89246 (974)	54379 (1128)	106196 (3336)	82370 (9921)
Total	85122 (864)	56319 (1116)	109348 (2561)	83214 (807)
Actual Odometer:	(%)			
New York	.41 (0.01)	.30 (0.08)	.17 (0.01)	.32 (0.01)
Texas	.53 (0.01)	.61 (0.01)	.28 (0.01)	.50 (0.01)
Total	.51 (0.01)	.59 (0.01)	.25 (0.01)	.47 (0.01)
Actual Cash Value	($)			
New York	10543 (255)	2564 (430)	1338 (193)	6717 (193)
Texas	9266 (123)	19923 (399)	3829 (280)	11329 (158)
Total	9512 (111)	19040 (386)	3174 (213)	10537 (136)
Have salvage title?	(%)			
New York	.86 (0.01)	.15 (0.03)	.02 (0.01)	.41 (0.01)
Texas	.85 (0.01)	.60 (0.01)	.16 (0.01)	.63 (0.004)
Total	.81 (0.01)	.58 (0.01)	.13 (0.01)	.60 (0.005)
Have estimated repair cost?	(%)			
New York	.63 (0.01)	.00 (0.00)	.05 (0.01)	.39 (0.01)
Texas	.83 (0.01)	.01 (0.002)	.09 (0.01)	.44 (0.01)
Total	.79 (0.005)	.01 (0.002)	.08 (0.01)	.43 (0.005)

Table 9 Seller Behavior: Car Dealers vs. Insurance companies

	Car	Dealers		Insurance	Companies
	# lots	%		# lots	%
All lots:			**All lots:**		
Sell at high bid	680	27	Sell at high bid	3532	84
Negotiate price	791	31	Negotiate price	519	12
Withdraw	1051	42	Withdraw	170	4
Total:	*2522*		*Total:*	*4221*	
Lots with high bid < minimum bid:			**Lots with high bid < minimum bid:**		
Sell at high bid	540	25	Sell at high bid	842	60
Negotiate price	604	28	Negotiate price	437	32
Withdraw	1014	47	Withdraw	107	8
Total:	*2158*		*Total:*	*1386*	
Lots with high bid > minimum bid:			**Lots with high bid > minimum bid:**		
Sell at high bid	144	40	Sell at high bid	2690	95
Negotiate price	190	52	Negotiate price	82	3
Withdraw	30	8	Withdraw	63	2
Total:	*364*		*Total:*	*2835*	

Appendix

Heckman Selection Model results for New York and Texas Sales with subsamples of lots with high-bid>Reserve and high-bid<Reserve

	Texas Yard				New York Yard			
	Final Sale Price		**Final Sale Price>0**		**Final Sale Price**		**Final Sale Price>0**	
Dependent variable:	**Hibid < Reserve**	**Hibid > Reserve**	**Hibid < Reserve**	**Hibid > Reserve**	**Hibid < Reserve**	**Hibid > Reserve**	**Hibid < Reserve**	**Hibid > Reserve**
Odometer	-0.01473 (0.01)	0.00539 (0.01)	0.00114 (0.00)	0.01393 (0.01)	0.03119 (0.04)	-0.02337 (0.01)	-0.00313 (0.01)	0.00072 (0.01)
Actual Odometer	1.36474 (0.12)	0.78660 (0.19)	0.16263 (0.04)	-0.14675 (0.11)	1.44976 (0.61)	0.15879 (0.19)	0.22376 (0.11)	-0.20590 (0.10)
Nojump	-1.78901 (0.31)	-0.56467 (0.45)	-0.99745 (0.09)	-0.62621 (0.29)	-0.04757 (0.74)	0.27784 (0.19)	0.15880 (0.15)	-0.02053 (0.10)
Bigjump	0.20480 (0.15)	0.07113 (0.25)	0.09861 (0.05)	0.07369 (0.15)	-0.84370 (0.67)	-0.32385 (0.22)	-0.32473 (0.11)	-0.52692 (0.10)
#buyers	0.07608 (0.02)	0.05901 (0.04)	0.02970 (0.01)	0.03313 (0,02)	-0.02405 (0.14)	0.20147 (0.05)	-0.03655 (0.03)	0.05185 (0.02)
Seller book value	0.24093 (0.00)	0.30945 (0.01)	-0.00998 (0.00)	0.00077 (0.01)	0.31876 (0.03)	0.25972 (0.01)	0.00335 (0.01)	-0.01262 (0.00)
Constant	-7.38421 (1.61)	0.91512 (3.35)	1.78342 (0.01)	0.03313 (0.90)	-7.22712 (6.04)	1.66876 (2.09)	-6.38332 (0.66)	6.58803 (0.51)
Selection term[21]			3.95680 (0.22)	4.64464 (0.91)			7.35424 (2.39)	4.63451 (0.93)
Insurance Firm			1.17093 (0.07)	1.30253 (0.13)			0.48624 (0.13)	0.95006 (0.11)
Dealer			-0.28946 (0.06)	0.76375 (0.19)			-0.24067 (0.13)	-0.35478 (0.13)

21 Inverse Mill's ratio.

References

Aradillas-Lopez, A., A. Gandhi, and D. Quint (2011), “Identification and Inference in Ascending Auctions with Correlated Private Values,” working paper, University of Wisconsin.

Ashenfelter, O. and K. Graddy (2003) "Auctions and the Price of Art," *Journal of Economic Literature*, vol. 41, no. 3

Athey, S. and P. Haile (2002), “Identification of Standard Auction Models,” *Econometrica*, 70: 2107-2140.

Avery, C. (1998) “Strategic Jump Bidding in English Auctions” *Review of Economic Studies* 65, 185-210.

Bajari, P. and A. Hortacsu (2003), “The Winner's Curse, Reserve Prices, and Endogenous Entry: Empirical Insights from *eBay* Auctions,” *RAND Journal of Economics*.

Banks, J., M. Olson, D. Porter, S. Rassenti & V. Smith (2003), ‘Theory, Experiment and the Federal Communications Commission Spectrum Auctions’, *Journal of Economic Behavior and Organization* 51(3), 303—350

Bikhchandani, S. and J. Riley (1991), “Equilibria in Open Common Value Auctions,” *Journal of Economic Theory*, 53: 101-130.

Coppinger, V., V. Smith & J. Titus (1980), ‘Incentives and Behavior in English, Dutch and Sealed-Bid Auctions’, *Economic Inquiry* 18, 1—20.

Cox, J., B. Roberson, and V. Smith. “Theory and Behavior of Single Object Auctions,” in Vernon L. Smith (ed.), *Research in Experimental Economics*, vol. 2, (Greenwich: JAI Press, 1982).

Cramton, P. (1997), “The FCC Spectrum Auctions: An Early Assessment”, *Journal of Economics and Management*. *Strategy*, 6, 431-495.

Daniel, K., and D. Hirshleifer (1998), .A Theory of Costly Sequential Bidding,. Mimeo, Kellogg Graduate School of Management, Northwestern University.

Easley, R. and R. Tenorio (2004), “Jump Bidding Strategies in Internet Auctions,” *Management Science*, 50, 1407-1419.

Elyakime, B. and J. Laffont, P. Loisel, and Q. Vuong (1994), “First-Price Sealed-Bid Auctions with Secret Reservation Prices,” *Annales d'Economie et de Statistique*, 34.

Grether, D. and C. Plott (2009) “Sequencing Strategies In Large, Competitive, Ascending Price Automobile Auctions: An Experimental Examination,” *Journal of Economic Behavior and Organization* 71(2) 75-88.

Haile, P. and E. Tamer (2003), “Inference from an Incomplete Model of English Auctions,” *Journal of Political Economy,*111: 1-51.

Harrison, G. and J. List (2004) "Field Experiments," *Journal of Economic Literature*, 42(4), 1013-1059.

Hendricks, K. and R. Porter (2007), “An Empirical Perspective on Auctions,” Handbook of Industrial Organization, volume 3, edited by M. Armstrong and R. Porter.

Hoerner, J. and N. Sahuguet (2007), “Costly Signalling in Auctions,” *Review of Economic Studies*, 74: 173-206.

Isaac, M., T. Salmon and A. Zillante (2007) "A Theory of Jump Bidding in Ascending Auctions," *Journal of Economic Behavior and Organization* 62:144-164.

Isaac, M., T. Salmon and A. Zillante (2005) "An Experimental Test of Alternative Models of Bidding in Ascending Auctions," *International Journal of Game Theory* 33: 287-313.

Katkar, R. and D.Reiley (2006), “Public vs. Secret Reserve Prices on eBay: Results from a Pokemon Field Experiments,” *Advances in Economic Analysis and Policy*, 6.

Krishna, V. (2002) *Auction Theory*. Academic Press.

Lewis, G. (2011), “Asymmetric Information, Adverse Selection and Online Disclosure: The Case of eBay Motors,” *American Economic Review*, 101(4): 1535–46.

Lucking-Reiley, D. (1999), ‘Using Field Experiments to Test Equivalence Between Auction Formats: Magic on the Internet’, *American Economic Review* 89(5), 1063—1080.

McAfee, P. and J. McMillian (1987) “Auctions and Bidding” *Journal of Economic Literature* 82 6 99-738

McCabe, K., Rassenti, S., Smith, V., 1990. Auction institutional design: theory and behavior of simultaneous multiple unit generalizations of the Dutch and English auctions. American Economic Review 80, 1276–1283.

Milgrom, P. (2004) *Putting Auction Theory to Work*. Cambridge University Press.

Milgrom, P. and R. Weber (1982), "A Theory of Auctions and Competitive Bidding," *Econometrica*. 50 1089-1122

Plott, C. and T. Salmon (2004) "The Simultaneous, Ascending Auction: Dynamics of Price Adjustment in Experiments and in the U.K. 3G Spectrum Auction." *Journal of Economic Behavior and Organization* 53(3) 353-383

Raviv, Y. (2008), "The Role of the Bidding Process in Price Determination: Jump Bidding in Sequential English Auctions." *Economic Inquiry,* 46(3) 325-341.

Roberts, J. and A. Sweeting, "When Should Sellers Use Auctions?" working paper, Duke University, Department of Economics.

Song, U. (2004), "Nonparametric Estimation of an eBay Auction Model with an Unknown Number of Bidders," working paper, University of British Columbia.

Tadelis, S. and F. Zettelmeyer (2009), "The Effect of Information on Auction Outcomes: A Large-Scale Field Experiment," working paper, UC Berkeley Haas School of Business.

Vickrey, W. (1961) "Counterspeculation, Auctions and Competitive Sealed Tenders," *Journal of Finance"* 16, 8-37.

Vincent, D. (1995): "Bidding Off the Wall: Why Reserve Prices May be Kept Secret," *Journal of Economic Theory*, 65: 575-584.