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Comments
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Intimidation or Impatience? Jump Bidding in On-line Ascending Automobile Auctions[1]

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Abstract: We run a large field experiment with an online company specializing in selling used automobiles via ascending auctions. We manipulate experimentally the maximum amount which bidders can bid above the current standing price, thus affecting the ease with which bidders can engage in jump bidding. We test between the intimidation vs. costly bidding hypotheses of jump bidding by looking at the effect of these jump-bidding restrictions on average seller revenue. We find evidence consistent with costly bidding in one market (Texas), but intimidation in the other market (New York). This difference in findings between the two markets appears partly attributable to the more prominent presence of sellers who are car dealers in the Texas market.

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1. Introduction

The development and application of auction theory has been one of the most prominent achievements in economics over the last few decades (at least since Vickrey, 1961). For book length treatments of auction theory see Milgrom (2004) and Krishna (2002). Along with theoretical literature there has been a growing empirical literature on auctions (for surveys see Ashenfelter and Graddy (2003) and Hendricks and Porter (2007)). 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 test theories of why bidders engage in *jump bidding* – that is, why bidders choose to submit a bid which exceeds 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] which 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. 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 anomalous

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

jump-bidding.   As a result, there is a small but growing theoretical literature to explain jump bidding.   In this paper, we attempt to discriminate between these theories by executing a number of field experiments in which we manipulate the ease with which bidders can jump-bid. As far as we are aware, this is the first paper in which field experiments are employed to assess explanations of jump-bidding.[3]

Background: 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, there are two compelling explanations for jump bidding which have been emphasized in the literature.[4]   First, bidders may jump in order to *signal* one's high valuation, and thereby eliminate competition by *intimidating* rivals.   Second, bidders may be *impatient* and face *time costs* of bidding, so that they jump in order to shorten the auction and, thereby, avoid the bidding costs.

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[3] 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.

[4] Raviv (2007) contains a discussion and comparison of the models of jump bidding which have been proposed in the literature.

These two explanations have different implications on seller revenue, which forms the basic premise for our empirical work below. Intuitively, intimidative jump bidding benefits buyers by reducing competition, which will lower seller revenue. On the other hand, when bidders are impatient, opportunities to end the auction sooner by jump bidding should, all else equal, not change the allocation of the auction, but raises bidders' willingness-to-pay, thus enhancing seller revenue. Next, we examine the intimidation and impatience hypotheses of jump bidding more closely.

Jump-bidding for signalling and intimidation. Avery (1998) 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 are 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 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.[5]

Jump-bidding to overcome impatience. Another important explanation for jump bidding in the existing literature is that bidding in ascending auctions involves time costs which are absent in simultaneous sealed-bid auctions. Several authors have introduced the idea of *bidding costs* that are incurred by all bidders, and which must be incurred for each submitted bid.. Bidding costs do seem plausible in many bidding environments, and can be motivated by bidders' cost of time or simple impatience. For models in this vein, see Daniel and Hirschleifer (1997), Easley and

[5] As Avery notes, this effect counteracts the "linkage principle", whereby open auctions (such as the ascending auction) yield greater expected seller revenue than sealed-bid auctions, in an affiliated-value setup.

Tenorio (2004), Hoerner and Sahuguet (2007), and Isaac, Salmon and Zillante (2007). Time costs introduce a "war of attrition" component to ascending auctions and, in such a setting, bidders benefit from the ability to jump-bid, because auctions end sooner.

Generally, jump-bidding arising from bidder impatience or bidding costs tends to increase seller revenue. Milgrom (2004, pp. 128-132) provides a version of this argument. Essentially, any IPV auction, no matter whether bidding costs are present and no matter whether jumping is allowed, is *payoff-equivalent* to the standard sealed-bid second-price auction. That is, the presence of bidding costs or the ability to jump-bid does not affect the equilibrium allocation of the object (which always goes to the bidder with the highest valuation), but only the equilibrium transfers (prices) paid by the bidders. However, when bidding costs are present, the ability to jump-bid increases the total surplus; because the auction can end sooner, costly bidding can be avoided. Because seller revenue is the residual from total surplus minus bidders' payoff, then, it must be higher when jumping is allowed.[6] Correspondingly, both the costly bidding model in Daniel and Hirschleifer (1997) and the bidder impatience model in Isaac, Salmon and Zillante (2007) are characterized by higher seller revenues as bidders are allowed to submit jump bids and hence end the auction sooner.[7] Experimental evidence reported in Isaac, Salmon, and Zillante (2005) confirm that, indeed, revenues in ascending auctions fall when bidders are forced to bid straightforwardly (and not allowed to jump).[8]

This distinction between the revenue-enhancing versus revenue-decreasing effects of jump-bidding is a crucial distinction between the impatience vs. intimidation explanations of jump-bidding, and will be an important focus of our empirical analysis below. Formally, the Avery and Milgrom models, which are the main models we consider here for, respectively, the

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6 Obviously, we are assuming here that the seller is not impatient, and does not likely incur time costs proportional to the length of the auction.

7 Indeed, certain features of eBay auctions, such as proxy bidding and the "buy it now" option, can be interpreted as attempts by sellers to reduce bidding costs or shorten auction length which, accordingly, should lead to higher expected revenue.

8 Also, Roberts and Sweeting (2010) describe a (non-auction) sequential bidding procedure in which revenues can increase when jump bidding is allowed.

intimidation and costly bidding stories of jump bidding, differ in their informational assumptions: Avery assumes that bidders' valuations are affiliated, while Milgrom maintains an IPV assumption. Hence, strictly speaking, testing between these two models is actually a joint test of both IPV vs. affiliated values as well as intimidation vs. costly bidding.[9] Nevertheless, the competing hypotheses that intimidative bidding lowers seller revenue, while allowing impatient bidders to jump raises revenue, have intuitive appeal, and in what follows we will emphasize this distinction between the models rather than the differences in informational assumptions..

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

The empirical importance of jump bidding, coupled with the contrasting revenue implications of some key explanations, call out for empirical work to determine the explanations for real-world jump-bidding behavior. However, testing hypotheses about jump-bidding is difficult using field data, mainly due to data requirements. 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.[10]

For these reasons, we design a set of unique *field experiments*[11] using an online ascending auction for automobiles, in order to evaluate the various explanations for jump-bidding described above. Specifically, we created an experiment with Copart Inc., the largest auction house for salvage vehicles in the world. In these auctions, we manipulated the ease with which bidders could engage in jump-bidding, by restricting the maximum amount of the bid that could be

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9 Indeed, Raviv (2007) uses this distinction as the basis for a test of common vs. private values in open-outcry car auctions in New Jersey.

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

11 See Harrison and List (2004) for a discussion on the use of field experiments.

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 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. Following this, the buyer will be able to access the "current sales" button to view all of the auctions going on 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 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 bidders with higher limit prices) 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.

In addition, Copart's auctions have two distinctive features.. First, for most lots offered for sale there is a *secret reserve price*[12]; that is, 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 option to not sell to the highest bidder.[13] 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*".

Second, 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 unforeseen) ways with the experimental jump-bidding manipulations in our field experiments.

Experimental Design: interventions in bid increments

The goal of our interventions in our field experiments was to change the ease with which bidders could jump-bid; that is, how easy it was for bidders to submit bids which were substantially larger than the current standing bid. To wit, 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

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12 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).

13 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.

times the bid increment above the current bid.[14] 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 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. 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, for some of the sales, 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 teach lot we observe the complete sequence of bids and bidder identities, allowing us to

[14] 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.

determine accurately whether a bidder jumped (ie., 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 test between two compelling explanations of jump-bidding in ascending auctions: signaling/intimidation vs. bidder impatience. 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. These figures are consistent with jump bids being mistakes (for bidders who jump the modal number of jump bids is one).

Second, looking at average price with the three treatments do 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[15] 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.

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-- quite modest numbers.

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*.[16] 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

15 A re-auctioned lot is a lot that was previously offered in an earlier auction but not sold.

16 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.

lasting under a minute, so that it is possible that bidders may accidentally bid against themselves ("tremble"). This explanation is plausible for much of the repeat bidding at 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. However, some buyers bid against themselves several hundred times in one day (the maximum number of times we observe this is 811!).

The timing of the repeat bids may provide some explanation for them. Recall that if no new bid is received for two seconds, the message "going once, two times, etc." is given until a new bid is received or the sale ends if the time without a bid reaches 11 seconds. Repeat bids occur with a longer lag, with a longer time interval from the preceding bid, than other 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). Recall that, if the bidding starts above the secret reserve price or goes above it during the bidding, a "selling all the way" announcement is made 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 their bids on the vehicles of a few sellers. This suggests, but hardly proves, that the repeat bidders are simply hurrying things along, which is consistent with *impatience* as a primary motivating factor in these auctions. While the auctions do move quickly, with most lasting under one minute, each weekday there are many of these auctions at sites all over North America, each with on order of 500 vehicles put up for bids. A bidder interested in one or more of the cars being sold must somehow manage to monitor the sale (or submit a maximum willingness to pay prior to the auction). Submitting jump bids or repeatedly clicking and, thus, raising your own bids, can be useful ways of hurrying things along. Along these lines, this type of jump bidding decreases substantially once the secret reserve price is met.

Regression results: testing intimidation vs. impatience

Next, we discuss results from regressions to distinguish more narrowly between the intimidation versus impatience stories of jump bidding. As we discussed before, 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, while the opposite obtains if impatient bidders simply jump in order to “speed up the clock” and end the auction sooner.

The 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, 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 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 40.7% of the time, and withdraw the car 36.3%. When the final bid exceeds the minimum bid, however, sellers sell the car 85.4% of the time. The 14.6% no sales, even when the final bid exceeds the minimum bid arises from buyers reneging their winning bid.[17] 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. 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.[18]

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[17] Buyers that renege on their bid must pay a penalty.

[18] 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

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 \$816, not a small amount. This is not consistent with the intimidation story, which would predict higher revenues for the seller when jump bidding is restricted, but rather with the impatience story.

In the New York sales, however, we find that LARGEJUMP has a negative and significant effect on the final sales prices (implying a substantial \$1,114 decrease 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.

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.

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withdraw the car. The minimum bid plays the role of the instrument included in the selection equation, which is excluded from the price regression. The validity of this instrument relies on an assumption that the minimum bid is not correlated with any other unobservables which may affect final prices (such as a seller's private information). This is partly justified because, for the most part, the minimum bid is secret (unknown to bidders) , which lessens its direct effect on prices.

Why are Texas and New York different? The results here beg the question, as to 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 are insurance companies, who are disposing of vehicles which have been "totaled"; in both markets, insurance companies account for around 40% of the cars sold.

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 8, 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 (59%) of their cars at the high bid in the auction, and negotiate on only around 35% of sales. Dealers sell only a quarter (24%) at the high bid, and negotiate around 30% of their sales. Moreover, dealers withdraw (and presumably resell at a later date) 43% 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 76% (=1093/1430) of the cars sold by dealers, but only 24% 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. At the same time, the longer duration of the Texas auctions may also lead to greater bidder impatience, so that restrictions in jump bidding (as in the SMALLJUMP treatments) lead to lower surplus and, therefore, lower seller revenue, which is what we find.

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 invite bidders to engage in intimidating behavior, leading to lower seller-revenue; this is what we find.

Caveat: Non-monotonic effects of jumpsize 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 jumpsize (SMALLJUMP) reduces revenues relative to the baseline, but we don't find that, symmetrically, increasing the jumpsize (LARGEJUMP) increases revenues. Similarly, for New York, increasing the jumpsize (LARGEJUMP) reduces revenues, but decreasing the jumpsize (SMALLJUMP) doesn't increase revenues. The revenue effects do not appear to be monotonic, at least in the range of jumpsizes which we consider in our experiments. This may suggest that, to a first-order, the baseline jumpsizes 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? Two of the leading explanations are (i) strategic signaling and intimidation; and (ii) impatience. 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 which over 15,000 vehicles were auctioned.

We find that behavior is much different at the two yards 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 with the intimidation explanation. 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, which is consistent with the impatience explanation. 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

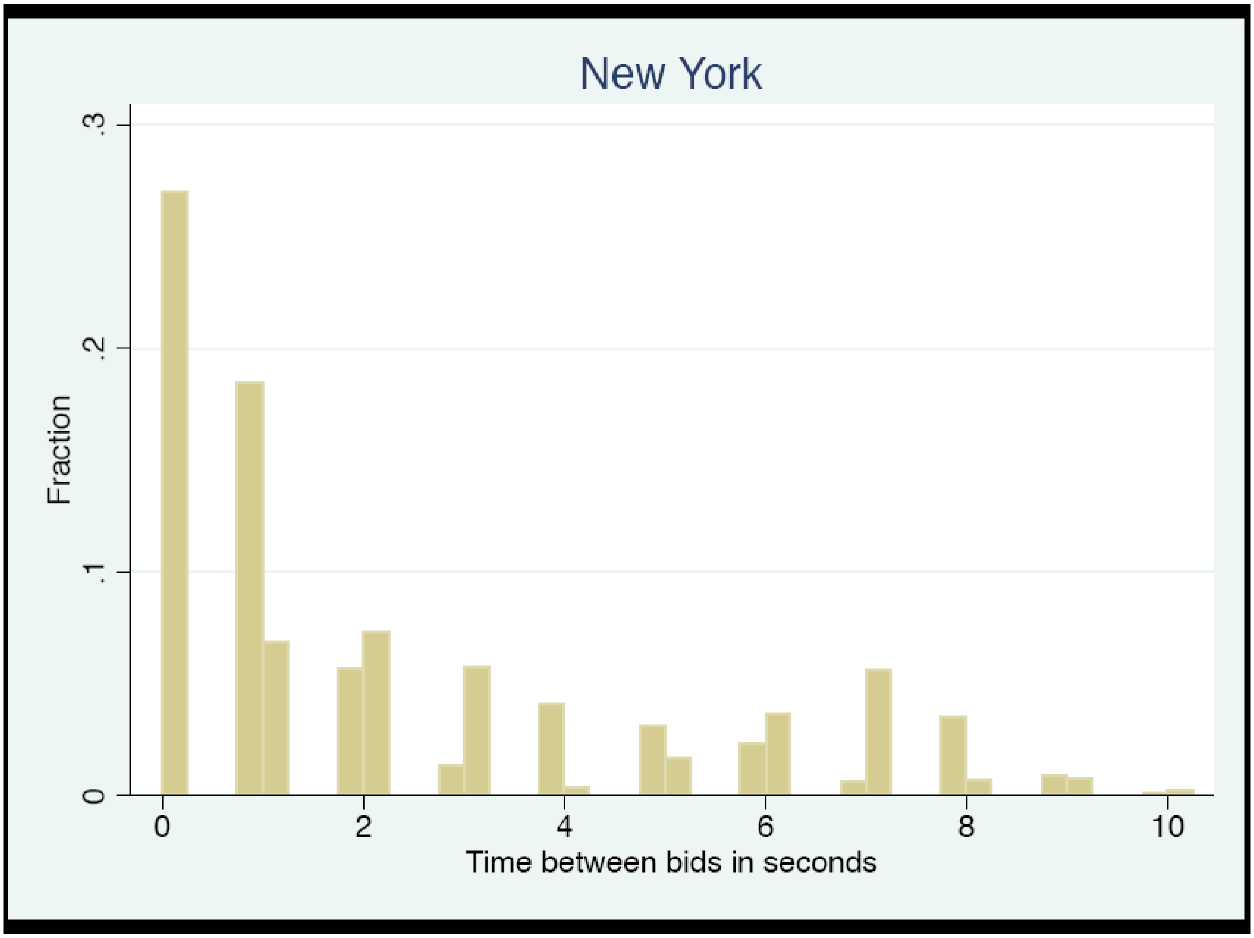

Figure 2

Interbid Times

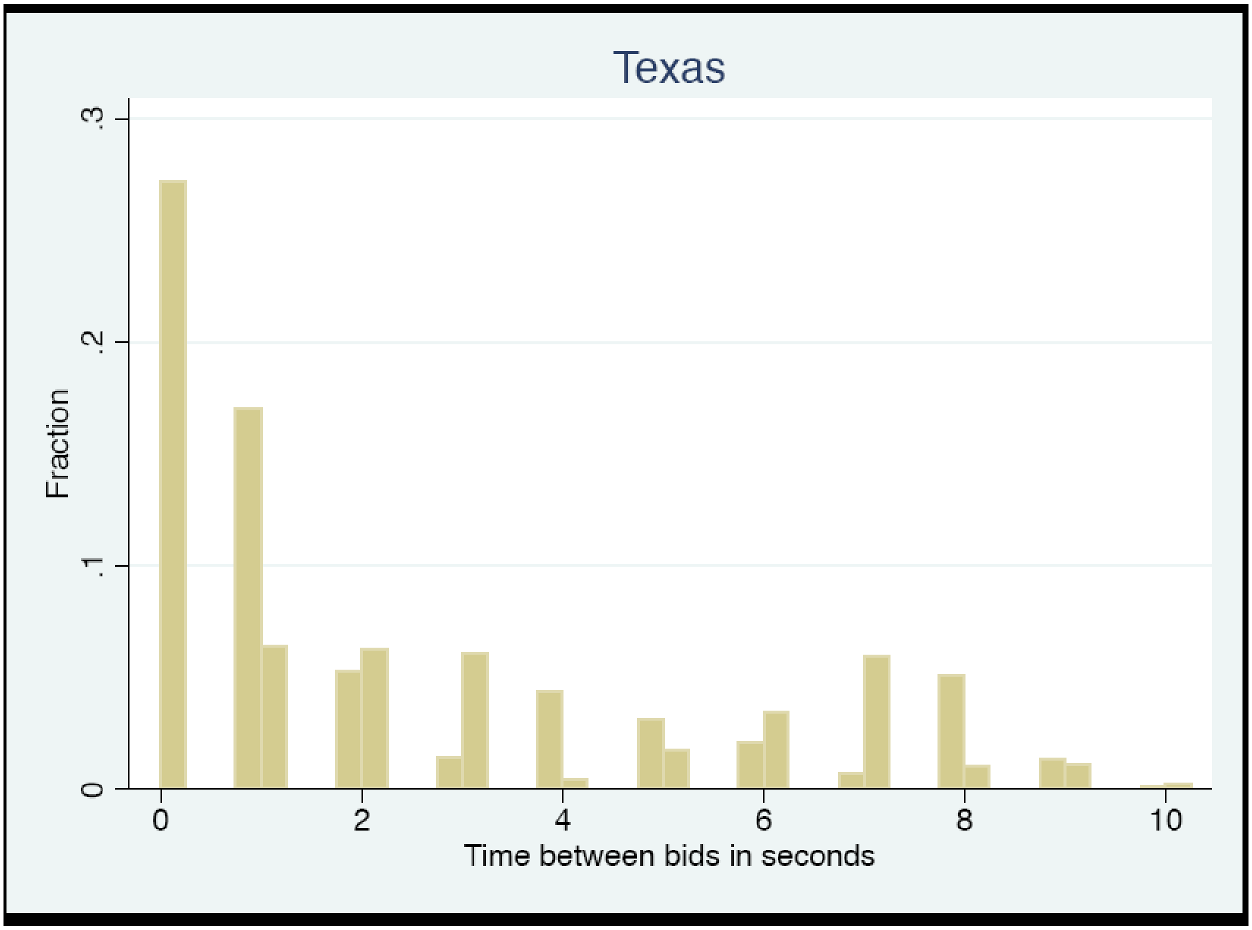

Figure 3

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	High Bid	Frequency of Jump Bids	Frequency of Repeat-bidding	Size of Jumps	Proportion Sold	Time in Seconds
Texas (1,5,10)	4.28	5401	.024	.193	460	.765	81.63
Texas (1,2,3)	4.52 (.01)	5638 (.23)	.035 (.00)	.184 (.00)	187 (.00)	.676 (.00)	87.12 (.00)
Texas (1,10,20)	4.17 (.22)	5345 (.77)	.023 (.00)	.192 (.54)	923 (.00)	.779 (.30)	86.25 (.00)
New York (1,5,10)	3.02	2372	.015	.014	356	.918	43.86
New York (1,2,3)	2.87 (.08)	2731 (.06)	.019 (.01)	.014 (.47)	154 (.08)	.926 (.52)	44.51 (.65)
New York (1,10,20)	3.21 (.01)	2318 (.73)	.006 (00)	.013 (.77)	508 (.00)	.860 (.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[19]

	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

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

Table 6 Seller Behavior

Texas			New York		
	# lots	%		# lots	%
All lots:			**All lots:**		
Sell at high bid	6321	54.8	Sell at high bid	3269	78.1
Negotiate price	2189	19	Negotiate price	505	12.1
Withdraw	3026	26.2	Withdraw	410	9.8
Total:	*11536*		*Total:*	*4184*	
Lots with high bid < minimum bid:			**Lots with high bid < minimum bid:**		
Sell at high bid	3221	40.7	Sell at high bid	495	42.8
Negotiate price	1818	23	Negotiate price	401	34.7
Withdraw	2868	36.3	Withdraw	261	22.6
Total:	*7907*		*Total:*	*1157*	
Lots with high bid > minimum bid:			**Lots with high bid > minimum bid:**		
Sell at high bid	3100	85.4	Sell at high bid	2774	91.6
Negotiate price	371	10.2	Negotiate price	104	3.4
Withdraw	158	4.4	Withdraw	149	4.9
Total:	*3629*		*Total:*	*3027*	

Table 7 Heckman Selection Model results for New York and Texas Sales[20]

	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	0.5640 (1.23)	0.1364 (1.84)*	-0.8404 (2.39)**	-0.2488 (4.68)***
LARGEJUMP	-1.1092 (2.16)**	-0.3685 (5.48)***	0.0949 (0.34)	0.0499 (1.12)
Odometer	-0.0427 (1.35)	-0.0050 (1.08)	0.0074 (0.63)	0.0071 (3.09)***
Actual odometer	0.5561 (1.26)	0.0547 (0.80)	1.3109 (6.73)***	0.2207 (7.16)***
#buyers	0.1475 (1.43)		0.1114 (2.95)**	
Seller book value	0.2795 (11.95)***	0.0283 (6.97)***	0.2142 (23.89)***	0.0300 (17.94)***
Constant	-2.335 (0.63)	1.3419 (2.47)**	0.6248 (0.12)	-0.2210 (0.49)
Minimum bid		-0.0907 (10.53)***		-0.1392 (37.99)***
Selection term[21]	12.0055 (6.53)***		9.0027 (27.95)***	
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

[20] T-stats in parentheses. ***: statistically significant at 1%, **: statistically significant at 5%; * statistically significant at 10%.
[21] Inverse Mill's ratio.

Table 8 Seller Behavior: Car Dealers vs. Insurance companies

	Car Dealers			Insurance Companies	
	# lots	%		# lots	%
All lots:			**All lots:**		
Sell at high bid	343	24	Sell at high bid	3269	59
Negotiate price	472	33	Negotiate price	505	36
Withdraw	615	43	Withdraw	410	5
Total:	*1430*		*Total:*	*3215*	
Lots with high bid < minimum bid:			**Lots with high bid < minimum bid:**		
Sell at high bid	273	25	Sell at high bid	470	60
Negotiate price	262	24	Negotiate price	228	29
Withdraw	558	51	Withdraw	86	11
Total:	*1093*		*Total:*	*784*	
Lots with high bid > minimum bid:			**Lots with high bid > minimum bid:**		
Sell at high bid	67	20	Sell at high bid	1434	59
Negotiate price	212	63	Negotiate price	924	38
Withdraw	58	17	Withdraw	73	3
Total:	*337*		*Total:*	*2431*	

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