WORKING PAPER SERIES

The Role of the Bidding Process in Price Determination: Jump Bidding in Sequential English Auctions

Yaron Raviv

WP 2004-11

CLAREMONT MCKENNA COLLEGE

500 East 9th Street
Claremont, CA 91711
Phone: (909) 607-3203
Fax: (909) 621-8249

The Role of the Bidding Process in Price Determination: Jump biddings in Sequential English Auctions

Yaron Raviv[1]

October 15, 2004

Abstract. I study the sequence of bidding in an open-outcry English auction to examine how the strategic bidding process affects price determination. I do this by studying the anomalous nature of "jump bidding" in data I have collected from a series of public auctions of used cars in New Jersey. Jump bidding occur when a new offer is submitted that is above the old offer plus the minimum bid increment permitted. I find that jump biddings are an empirical regularity in all items sold. The jumps are a function of the presale estimate of the item's price but are not affected by the selling order. I suggest a way to use the Jump Biddings to determine whether an open-outcry auction is best interpreted with models that assume private-or common-item valuations, and conclude that these auctions are consistent with the common values interpretation.

JEL Classification: D44
Keywords: Auction

[1] Department of Economics, Claremont McKenna College, 109 Bauer Center, Claremont CA 91711. I am greatly indebted to Orley Ashenfelter and Han Hong. I would also like to thank Gad Levanon, Andrea Podhorsky, Ryan Quillian, Joydeep Roy, Gabor Virag and participants in seminars at Princeton University, Tel-Aviv University, Claremont McKenna College and Ben-Gurion University. Any errors are mine.

1. Introduction

Standard auction theory predicts that, in a private value English oral auction, the winner will be the bidder with the highest valuation for the object, and the selling price will be the second-highest valuation. In those auctions, a reasonable strategy for a bidder would be to increase each bid by the minimum bid increment. This solution is referred to as the "ratchet solution," "straightforward bidding" or as "pedestrian bidding." Jump biddings occur when a new offer is submitted that is above the old offer plus the minimum bid increment permitted.

In this paper, I study the sequence of bidding in an open-outcry English auction to examine how the strategic bidding process affects price determination. I do this by studying the nature of jump biddings in data I have collected from a series of public auctions of used cars in New Jersey. The auction literature has not fully addressed and characterized jump biddings in English auctions.

In order to characterize jump biddings, and because the auctions I study have no seller's reserve price, I define the "First Jump" as the first offer submitted by any bidder. The "Second Jump" is the difference between the second offer submitted by a bidder and the first offer. The "Last Jump" is the difference between the winning bid and the previous offer. I further define the "Average Jump"[2] of all jumps excluding the First and Last jumps. Figure 1 describes these variables graphically.

I find that jump biddings are a widespread empirical regularity in the sale of all items. The jumps depend on the presale estimate of the item's price and are not affected by the selling order. For almost all items, bidders use jump biddings to increase the current offer. Furthermore, on average, the First Jump is greater than the Second Jump, which is greater than the Average Jump, which is greater than the Last Jump. I offer several explanations for the existence of jump biddings.

These findings suggest that there is some strategic bidding behavior in the way bidders advance their bids. Bidders consider the way the auction progresses, which implies that a bidder's strategy includes not only the stopping point along the bidding

[2] Qualitatively, the results are the same when I define the Average Jump as the average of all jumps excluding the First, Second and Last jumps.

path, but also the precise nature of the path that led there. I suggest a way to use the jump biddings to determine whether an open-outcry auction is best interpreted with models that assume private- or common-item valuations, and conclude that these auctions are consistent with the common value interpretation. Under the assumption of independent private values, the bidding history should not affect the point at which a bidder drops out. This is not the case in a common value auction, in which each stage of the auction is used as a device for signaling. The selling price in an English auction with common values will be path dependent. Hence, a simple test of the effect of the First Jump on the selling price determines the type of the auction.

The paper is organized as follows. In the next section I will survey the literature. Section 3 describes the data I have collected and the nature of the auctions. Section 4 shows that, although the presale estimate and other characteristics affect the size of the jumps, the order in which the cars are introduced does not. In Section 5, I analyze the relation between jump biddings and the selling price, and propose a method to evaluate alternative assumptions about item valuations. The final section offers concluding remarks.

2. Literature Survey

The literature on bidding pattern in ascending auctions is divided into three parts. First is theoretical papers that usually demonstrate the condition under which straightforward bidding is equilibrium and when we expect jump bidding. The lack of any model of English auction with affiliated values and discrete bid levels is noticeable. Second is the experimental literature that demonstrates the existence of jump bidding, sometimes with a model that supports jump bidding. Third is empirical literature that demonstrates the existence of the jumps as well. The current paper is fills the gap by reporting and then analyzing jump bidding in a regular sequential open outcry English auction.

Rothkopf and Harstad (1994) explored the role of discrete bid levels in oral auctions. They addressed the question of when it is optimal to skip a bid level. They demonstrated that, in a two-bidder game with private valuations drawn from no increasing distributions, “pedestrian bidding” by both bidders is equilibrium as long as the interval between allowed bids is not too big.

Daniel and Hirshleifer (1998) (DH hereafter) demonstrated that, when a single good is auctioned to two bidders with private values, if there is a cost to submit a bid, such a cost can lead to jump bids equilibrium. They demonstrated also that the jump between the first and the second bid is increasing in the first bid. The setup in the model is different from the usual English auction because there is no auctioneer in takeover contests.

Macskasi (2000) extended the model of DH to three players. Again, the motivation for the jump is a positive bidding cost, and the game is over after, at most, three positive bids. Under the suggested equilibrium, jump bids favor the bidders.

Easley and Tenorio (1999) argued that the cost associated with entering on-line bids and the uncertainty about future entry can explain jump bidding in an ascending-price Internet auction. The model is similar to that of DH, with the difference that, even if bidders pass they will suffer the cost. The motivation for the jump is bidding costs and the use of the jumps as signals. The model involves two identical risk-neutral bidders with private valuation who will potentially compete over one unit. There is demand uncertainty and with probability q the opponent will not find the auction. They found that, when costs are zero, the ratchet solution is equilibrium. When costs are positive, the item can be sold only after one or two stages or remain unsold. They examined their model assumption using Yankee-type Internet auctions[3] and found that jump bidding is more likely earlier in the auction and that the incentive for jump bidding increased as competition became stronger. They also found that jump bidders placed fewer bids and that increased early jump bidding in auctions reduced the total bids placed.

Avery (1998) has shown that a jump bid may be used to intimidate one’s opponents and serves as a correlating device among bidders. The choice of bids allows bidders to communicate within the auction, and the jump can signal aggressive behavior. The message of aggressiveness discourages competition because it suggests that the

[3] This format is a variation of multi unit ascending auction that have the following properties: several identical goods are auction, each bidder may buy more than one unit but all units must demand at the same price, there is a time limit to the bidding process, the winning bidders pay their own prices, and ties broken on quantity first then time basis.

bidder values the good more than everybody else and that, if the opponent wins, he probably overbid. The model involves two risk-neutral bidders competing in a single English auction with affiliated valuation and signals and describes a public auction as a two-stage game. In the first stage, bidders can use their initial bid, 0, or a cutoff point, K, to communicate through jump. This communication has a cost because the initial bid may win the auction. In the second stage, the players proceed as in an ordinary open-exit auction, in which their initial bids serve to select their subsequent bidding strategies. Adding signaling stages to the game will reduce the average price and the set of equilibrium produce exactly the set of expected prices between the first-price and second-price auction.

Isaac et al (2003, a) provided a dynamic model of bidding in ascending auctions. They solved the model using backward induction and dynamic programming to obtain the solution for two risk-neutral bidders with private valuations that draw their values from a uniform or normal distribution. They found that jump bidding occurs in equilibrium, is of moderate size, and is motivated by impatience and a combination of distribution and discreteness reasons. In addition, there is a convergence to the straightforward bidding, and the expected revenue in the straightforward bidding is slightly higher. The authors provided evidence from the FCC auction to the existence of jump biddings. Table 1 summarizes the different models' predictions and assumptions.

[Table 1 here]

The empirical and experimental literature on jump bidding is quite narrow. Plott and Salmon (2002) developed a model of the behavior of bidders in simultaneous ascending auctions, in each round, based on surplus maximization and bid minimization. The purpose is to give the auctioneer an idea of the bidders' valuation during the auction process. They demonstrated that the model is valid in an experimental setting and also in the United Kingdom third generation mobile auction. The authors observed jump bids but concluded that their influence is only on speed and not on final prices or allocation.

Isaac et al. (2003, b) used economic experiments to empirically determine which of three alternative models described bidding behavior in a non clock ascending auction. They found that their model was superior and rejected the straightforward bidding because they observed jump biddings. They rejected DH's model because it predicted that the auction would end in the first or second stage. They claimed that, under a signaling model (like Avery's), the expected selling price should be lower because this is the only reason to engage in signaling. If the revenues are not lower it is an evidence of model rejection.

Isaac and Schinier (2003) analyzed data from three silent auction[4] field sessions. Their focus was on descriptive statistics and a parametric model of jump bidding. They also conducted a laboratory experiment. They found that bidders never jumped their own bids, seldom bid over publicly stated market values, and frequently submitted jump bids. In addition, they found that the number of bidders has a negative effect on the magnitude of the jump bids.

Borgers and Dustmann (2002) analyzed the United Kingdom's sale of licenses for third-generation mobile telephone services. This auction was organized as a simultaneous ascending auction in which each competitor could win only one item and the auction stopped when bidding on all licenses had stopped. They focused on the hypothesis of straightforward bidding under private values and described systematic deviations from this benchmark hypothesis. The deviations concerned mostly how bidders chose whether to bid for a large or small license. They also found that, although the majority of bids in the auction were the lowest admissible bids, there were a significant number of jump bids. The motivation they offered for the jumps was that bidders try to avoid ties and try to speed up the auction. They reported that jump bids in early rounds were larger than in the later rounds.

Betton and Eckbo (2000) examined a sample of tender offers. When the bid contest lasted more than two stages, they found that the expected time to the second bid was 15 days and that the median jump bidding from the first offer to the second offer was 10%. The setting of tender offers is different, theoretically and in practice, from an oral English auction for several reasons. Hirshleifer and Png (1990), for example,

---

[4] A silent auction is a simultaneous ascending first price auction where usually donated items are placed in a central location with a bid sheet and a starting bid. This institution usually used by churches and other non-profit organization for fund raising.

demonstrated that, when there is a cost to make and revise a takeover bid, the theoretical equivalence between an English auction and a takeover target breaks down.

Haile and Tamer (2003) documented jump biddings in a regular English auction and reported that the gap between first- and second-highest bids is usually above the minimum bid increment allowed.

3. The Data

I collected the auction data in 2001-02 from the New Jersey Distribution and Support Services (DSS) in Trenton, New Jersey.[5] DSS sells surplus personal and government property through public oral English auctions and sealed-bid auctions. The open English oral auctions of cars are usually held on Saturdays once a month. Bidders can physically inspect the items the day before the auction and on the day of the auction until 9 A.M., when the auction begins. Each car that is auctioned is driven through a large warehouse and stopped in front of the auctioneer, and then the bidding process begins. The auctioneer stands up at the front and simply receiving shouted bids without offering any guidance. After the car is sold, it is driven to the parking lot, and a new car is auctioned off. The average time required to sell a car is between 1 and 2 minutes. Bids on operable vehicle units are only accepted in multiples of $25. At the time of sale, successful bidders are required to make a deposit in cash, bank money order, or certified check for $150 or 10% of the total amount of the bid, whichever is greater. If the high bidder fails to place the deposit, the vehicle is immediately resold.

The DSS reveals all information available about the car's condition such as model, year, mileage and the source of the vehicle (Turnpike Authority, criminal justice seizure, Transportation Department, taxation seizure, etc.). The state also reveals all the mechanical information known about the vehicle's condition, for example whether it has

[5] For further information, see Raviv (2003).

bad transmission, bent rear axle, no vehicle identification number plate on the door, no power steering, etc. The coordinator of operations at DSS has stated that all the information known about the vehicles is made available to the bidders and that the cars are auctioned in random order (which I verified empirically in Raviv (2003)), so that there is no correlation between a cars' presale value and the sequence in which it is auctioned off.

The day before each auction, I collected data on each vehicle's condition. On the same day, I gathered the Kelly Blue Book (KBB) estimated market value of each car. KBB is a company that, among other things, provides market value estimates for cars on it Website. On the day of the auction, I collected the following data: the sequence in which the vehicles were auctioned, all the bids that each car received up to (and including) the winning bid, and data about the resold cars. During the week after each auction, I collected the official list of winning bids from DSS to compare with my notes.

Table 2 gives summary statistics from the different auctions. In the first and second columns, the presale estimator (the price from KBB) and the price for which the item was sold are reported. The mean of the presale estimator was $2,662.19, and it was above the mean of the winning bids, which was $1,520.42. It appears that some of the cars were sold quite cheaply. Some bidders bought operable cars for as little as $50. The car with the highest presale value ($15,265) was a 1986 Porsche with 77,000 miles on its odometer. This car was eventually sold for $3,400. Although the governor of New Jersey's car, a 1998 Buick Ultra, had a presale estimator of $11,270, it was sold for $8,650 and was the most expensive item sold in the auctions. To examine the jump bidding characteristics, I define four new variables. "First Jump" is the first offer submitted by a bidder. "Second Jump" is the difference between the second offer and the first offer. "Last Jump" is the difference between the winning bid and the previous bid. "Average Jump" is defined as the last offer before the wining bid minus the First Jump divided by n–2, where n is the total number of bids made on the car.

[Table 2 here]

The mean number of bids is the average number of bids each item received before it was sold. The mean of this variable is 11.39, which indicates that it took, on average, 11.39 rounds for an item to be sold. The minimum of this variable is 1, which means that some of the cars were won by the first bidder. Figures 2 through 5 show the empirical distribution of the First, Second, Average, and Last Jumps.

Figure 2 shows the empirical distribution of the First Jump variable. The size of the First Jump is on the x-axis, and the frequency is on the y-axis. For example, for almost 200 cars, the First Jump was $500. Because it is a logarithmic scale, the frequency determines the scale of the x-axis. For example, the First Jump was $100 96 times and $200 101 times. Because First Jump was never between $100 and $200 for any of the items sold, these two values are juxtaposed in the chart. On the other hand, one car received a first bid of $75. This number appears on the chart because, to make the chart clear, the First Jump values are reported on the chart scale in two-value increments.

[Figure 2 here]

Figure 3 shows the empirical distribution of the Second Jump variable. Again, because it is a logarithmic scale, the values of this variable determine the scale of the x-axis. If, for example, none of the cars receives $75 as Second Jump, this value is absent from the chart scale. We can see that the difference between the first and second bids was usually $100. For almost 100 cars, the Second Jump was $50.

[Figure 3 here]

Figure 4 shows the empirical distribution of the Average Jump. The value of the Average Jump variable appears on the x-axis, its frequency on the y-axis. The minimum Average Jump is $25, which occurs 22 times. The scale, again, is a logarithmic scale. The Average Jump was $50 68 times, and it was $75 25 times. The most-frequent Average Jump (95 times) was $100.

[Figure 4 here]

Figure 5 shows the empirical distribution of the Last Jump. The value of the Last Jump, which is the difference between the winning bid and the preceding bid, appears on the x-axis, with the frequency on the y-axis. We can see that the most frequent event is that the winner increases the current bid by $50, which is the case for 369 cars.

[Figure 5 here]

We can conclude the following from the above charts and table. First, jump biddings are important phenomena. Of the four variables described above, all of them are significantly above the minimum bid increment. Bidders use jumps to advance their bids in all the auction stages. In addition, there is a pattern, on average, that the First Jump is greater then the Second Jump, which is greater then the Average Jump, which is greater then the Last Jump.[6] The question that arises is, "Why do jump biddings exist?" It does not seem rational for bidders to progress and submit offers that are above the minimum bid increment (the ratchet solution). This paradox is noticeable in the Last Jump chart. For more than 150 cars that were auctioned, the winning bid was increased by $100 or more when it could have been increased by only $25. The winner did not know when he bid that he would win, but it is still puzzling.

There might be several explanations for the jump bidding phenomenon.

1) Agents value their time: In this sense, a bidder will immediately jump to the lower bound of the valuation support (which explains the First Jump phenomena), and they might then progress in steps that are above the minimum bid increment. In addition, if there is a social pressure to finish the auction fast, bidders will feel uncomfortable to advance their bids by the minimum bid increment in the beginning and proceed instead in bigger steps.
2) Comfort: It is easy to work with round numbers. It is easier for some of the agents to add 100 than increments of 25 or 75. As we can see from the figures describing the Second Jump, Average Jump and Last Jump, there are spikes at $100 and $50. In addition, none of the items had a second jump of $75 or $125.
3) Signaling and threat: As pointing out by Avery (1998), under affiliated values paradigm, jumps may signal to and coordinate with opponents about an agent's valuation. In addition, jumps may signal that an agent is a strong candidate and will bid aggressively to win the object.
4) Distribution: We can observe a rational jump bidding because of distribution of the valuation. If, for example, the distribution is increased above the support in a two-bidder game with private values, we may observe optimal jump biddings.

[6] This relationship holds not only when I look at the averages. When I examine within each item, the First Jump is greater than or equal to the Second Jump for 99% of the items sold, the Second Jump is greater than or equal to the Average Jump for 95% of the items sold, and the Average Jump is greater than or equal to the Last Jump for 95% of the items sold. There is equality between the First and the Second Jumps for 13% of the items, between the Average Jump and Second Jump for 28% of the items, and between the Average Jump and Last Jump for 24% of the items sold. This pattern is justified because the probability of winning with jump bidding, and pay too much, increasing with the auction progress.

Also, it is easy to demonstrate that, even with uniform distribution of valuation, an optimal jump bidding may occur when the auction progresses only in discrete steps (Rothkopf et al., 1994).

5) Agents: It might be the case that people participating in these auctions are following the orders of their employees. For example, a worker in a dealership might have instructions to bid a maximum of $x on an item, but have no instructions about the bidding process.
6) Bounded rationality: People might behave sub optimally and deviate from optimal behavior as predicted by the theory.

4. Initial Regression Analysis

To explore the relationship between jump biddings and car characteristics, an ordinary least squares (OLS) regression is applied. Table 3 shows the regression results of the different types of jumps on a variety of explanatory variables. Each column corresponds to a different jump bidding variable. The explanatory variables in the models are the presale estimator (Estimator), the number of years the car has been used (Year) (2001/02 minus the manufacture year), the mileage that appears on the odometer divided by 10,000 (Mileage), the order in which the car was auctioned divided by the total number of cars in the particular auction[7] (Order), and a dummy variable equal to 1 if the car was in poor condition (Poor) and 0 otherwise. In addition, there are fixed-effects dummies for the different auctions (Auction dummies).

[Table 3 here]

In the first four columns, I run the regression using all observations, whereas in the last two columns I use only the items that received more than one offer.[8] The constant is significant in all specifications and keeps the same pattern as in the means: First Jump is greater then the Second Jump, which is greater then the Average Jump, which is greater then the Last Jump. The Year variable is significant and with the "right sign" only

[7] I define the order in this way to control for the different number of items in each auction.
[8] There is no difference in the Second Jump and Average Jump variables because these variables are defined only for items receiving more than one and two offers, respectively.

in the First Jump variable. On average, each additional year the car has been used will reduce the First Jump (offer) by $45. It is not significant in the Second Jump, Average Jump, or Last Jump variables. The Mileage is negative and significant in all of the specifications except the Last Jump. Another point of interest is that unlike the selling price, the order the object is auctioned has no effect on the jump biddings. The condition of the car (Poor) has no effect on the jump variables either. This could be because the presale estimator already captures this information.

The fact that the presale estimator and other measure condition affect all the jump bidding variables suggests that there is some strategic behavior in the way bidders advance their bids. If one believes that the bidders arrive at the auction place with just a number that they plan to stop at and do not consider the process leading up to this number (like in the usual model of the English oral auction with the continuous clock mechanism), those initial findings will dismiss these beliefs. If there was not some strategic behavior in the bidding process, none of the covariates that appear in the regression except the constant should be statistically different from zero.

In the last two columns, I repeat the analysis, but this time I exclude the items that received only one offer, because in those cases, the First Jump and the Last Jump are the same. The mean of the offers ending in the first round was $248.75, which is far above the mean of the Last Jump variable. In addition, there were two outliers with respect to the Last Jump variable, but not an outlier with respect to the First Jump variable (rounds that end in the first offer and items sold for $500 and $1800, respectively). What we can see from the regression analyses in columns four and five is that, while the First Jump regression coefficients and R^2 do not change by much, there is a huge increase in the R^2 for the Last Jump regression because the two outliers are excluded. This leads me to conclude that the items sold after one round should be classified as a First Jump and not Last Jump.[9]

As a robustness check, and because I do not know the true theoretical model that governs the jumps, I run the same regressions, this time with log of the monetary

[9]Bidders in stage 0 do not know that the auction will end after one round. They know however that the next stage is the First Jump.

variables (the presale estimator and the different jump variables) instead of levels. The results, showed in Table 3A, are qualitatively very similar.

[Table 3A here]

5. Common Values or Private Values?

It is reasonable to assume that used car auctions are common value auctions, and in this section I will demonstrate that we cannot reject the hypothesis that the data are consistent with models assuming common valuations. The method I will use to distinguish between the common and private value paradigms in oral English auctions is different from the method usually suggested in the literature because the information available to the researcher in those auctions is different from the information available in sealed-bid auctions. First, even if the attendant number of bidders could be controlled for, the active number of bidders cannot. Second, information about each candidate bidding in each stage is not available. In addition, I will demonstrate that there is a positive relationship between jump biddings, which again suggests some strategic behavior during the auction process.

In Table 4, I report the results demonstrating the positive relationship between the jump biddings. Each column in the table corresponds to a different regression. When the column title is Average Jump, for example, it means that it was the dependent variable in that regression. All regressions include a constant, the presale estimator, the year of manufacture, the mileage as it appears on the odometer, the order the car was sold, and a dummy variable for the specific auction. Similar results were obtained when any subset of this model was applied. I report only the jump variable coefficients from those regressions because they are my main interest and it saves space.

[Table 4 here]

The first column indicates that the size of the First Jump affects the size of the Second Jump,[10] with an increase in the First Jump leading to an increase in the Second

[10] Daniel and Hirshleifer (1998) provide a model for sequential bidding when there is a cost associated with submitting or revising a bid. Proposition 2 of their paper states that the jump between the first and the second bid is increasing in the initial bid for all identically distributed valuation densities satisfying some regular restriction on the density function. In our notation, the proposition states that we expect to have a

Jump. Although the effect is not big, it is positive and significant. We can conclude also that this phenomenon is not unique to the first stage. The same effect occurs when the Second Jump is a covariate in the Average Jump regression and when the Average Jump is a covariate in the Last Jump regression. In addition, the First Jump has a positive influence on the Last and Average Jumps. When the First and Second Jumps are introduced (in the Average Jump regression), the effect of the First Jump diminishes and becomes significant only at 10% significance level. Looking at the R^2, it can also be concluded that the best predictor for each jump variable is the variable that immediately precedes it (i.e. the Second Jump for the Average Jump and the Average Jump for the Last Jump). The predicting power declines with the distance between the variables. Again, as a robustness check I run the same regressions with log instead of levels. The results, showed in Table 4A, are qualitatively very similar.

Rothkopf and Harstad (1994) provide a model of an independent private value English auction with a discrete bid increment. In their model, bidders draw their values from nonincreasing distributions (e.g., uniform or exponential), and the pedestrian bidding by the bidders is equilibrium. Therefore, my findings so far refute their model's assumptions. The fact that there are jump biddings implies that the assumption of the independent private values or of non increasing distribution is not appropriate to my data.

The results presented in Table 4 and Table 4A support the claim that there is some strategic bidding behavior in the auction process and that some of the jump variables affect other jump variables. Natural question that arise at this point is whether jump biddings have a real effect on the auction outcome and they affect the winning bid. Avery (1998) solved the English auction game of two risk-neutral bidders with affiliated common values. He found that, under the proposed equilibrium, jump biddings may be employed to intimidate one's opponents and serve as a correlating device between bidders. The fact that the jumps are used as a correlating device suggests that the selling price might be path dependent. In other words, the jumps might affect the winning bid outcome. If one thinks, on the other hand, about the private value paradigm, the jumps should have no real effect on the winning bid. In that sense, the history of the bids will

---

positive significant sign on the First Jump variable when running a regression with the Second Jump as a dependent variable.

not affect the winning bid because there is no winner's curse in a private value auction. A reasonable strategy, under the regular assumption of a private value auction game, is to advance the bid as long as the opponent's current bid is below the valuation, no matter what the history is. Hence, we might have a test that will allow us to distinguish between common value and private value auctions. If the jumps affect the selling price of the good after controlling for all the other relevant covariates, we cannot reject the hypothesis that the auction involves a common value between bidders because the selling price is path dependent.

Table 5 shows the regression results. The sample includes items receiving more than a one offer, although similar results were obtained using the whole sample. All regressions include fixed-effect auction dummies and interaction variables between the auction dummies and the other covariates (which are not reported here to save space). Similar results are obtained when the log of the variables is used instead of the variables' level and when the model that is being used is a subset of the above model.

Table 5 shows that each of the jump variables is statistically significant and has prediction power for the selling price of the good. The goodness of fit is varied between the jump variables, and the best fit is for the First Jump. The First Jump is correlated with the selling price, which means that if there is causality between the First Jump and the selling price then the selling price is path dependent. This might lead to the conclusion that the auction data came from a common value auction.

[Table 5 here]

Again, as a robustness check I run the same regressions with logs instead of levels. The results, showed in Table 5A, are qualitatively very similar.

I used the term correlation and not causation because there might be an endogeneity problem in the last regression and maybe the direction of causality is from the selling price to the First Jump. If this is the case we cannot conclude that there is a path dependency. First, to perform a Hausmann test to check for endogeneity, I had to find an instrument that is correlated with the First Jump, for example, but not with the winning bid. I have been unable to find such a variable, but even if I could, the problem would not be solved. We can demonstrate exogeneity by two means: statistical tests, when we have an instrument, and context. In our auction, for example, it is obvious from the context that all the covariates except the jump variables are exogenous: the year of manufacture, the mileage, and the condition of the car affect the selling price and not vice versa. In the relationship between the First Jump and the winning bid, we are interested in endogeneity in the causality sense. Does the First Jump affect the winning bid or does the winning bid cause the size of the First Jump? If the First Jump affects the winning bid, then we can be sure that the auction process is path dependent, and hence that is a common value auction.

Although the First Jump happens before the final bids and might be considered to be predetermined, one can claim that a bidder's strategy will be to bid a constant fraction of his valuation as the First Jump or to randomize his First Jump where the randomization is between 0 and his valuation. If this is the case, we will observe the same results with the opposite conclusion.[11]

To be able to comment on this issue, and investigate if my data are consistent with the first model proposed, I constructed a new dummy variable. This variable equals 1 if the number of bids is even and 0 otherwise. The idea is that if the structure of the bidding process is usually the same (namely, for each item that is being sold, on average two bidders compete with each other over it), then an even number of bids means that on average the person who responded to the First Jump won the object. In that case, the winning bid is a good proxy for the first bidder valuation under the private value auction assumptions. On the other hand, when the number of bids is odd, the winning bid is only a lower bound for the first bidder valuation. If the data came from a private value auction, then when we introduce this dummy variable to the winning bids regression, it should be significantly negative. I am not reporting the results here, but in all the regression combinations I tried, with and without the First Jump and with and without the log of the variables, this variable never became significant. This led me to conclude that the auction cannot be characterized as one involving bidders with private valuations in which their First Jump is a constant fraction of their valuation.[12]

---

[11] There might be other models consistent with the private valuation model as well.

[12] Further evidence on this appears when I plot the graph describing the relation between the number of bids variable and the ratio between the difference between the winning bid and First Jump and the first bid, and the ratio between the difference between the winning bid and the First Jump and the winning bid. If the First Jump were a constant fraction of the winning bid, the slope of these curves should be 0 (because the variables are supposed to be constant). This is not the case.

The second model I consider, which is consistent with the private valuation paradigm, is one where bidders randomize their first offers. In this model, a bidder with a valuation of y will choose randomly a First Jump and will bid until his valuation. This kind of model fits the data and we cannot reject the hypothesis that the data can be characterized as a private values auction data.[13]

In addition some might claim that in this model there is a technicality problem. Because the jump variables are always less than or equal to the winning bid we might get positive and significant coefficients even when the jumps are drawn randomly. In order to deal with this claim I define a new variable: the ratio between the selling price and the presale estimator. There is no technicality in the relation between this variable and the jumps variable and no reason to predict that an increase in the jump will increase this variable. I report the results of these regressions in Table 5B (the results from regressions with logs are shown in Table 5C). Again, the results demonstrate that in both models the jumps have a positive and significant effect on the ratio. These regressions support the conclusion that the jumps have real effects on the selling price.

[Table 5B here]

[Table 5C here]

In addition to the jump bidding, there is more evidence to support the above claim that this data came from a common value auction. First, I can identify that dealers make up a part of the population involved in this auction. This might support the common value assumption, because if the dealers came from the same market and did not know the exact demand, then two dealers that buying the same car would make the same profit, hence resulting in a common value auction.[14] Additional evidence is provided in Raviv (2003), where I show (using the same data set) that the sequence of selling prices is upward sloping in the first part of the auction and then remains constant for the rest of the auction. These findings are in line with the predictions of Milgrom and Weber (1982), who demonstrate that, when the agents have affiliated common values, we expect an

---

[13] Consider, for example, the following model: bidders draw their private valuation y from a uniform (0, 1) distribution. Then they draw their First Jump x such that $x=\alpha y$ where α is drawn from a uniform (0, 1) distribution as well. In this case, when we run the simple regression model $y=a+bx$ the expected value estimator of b will be 0.75. If we take the log of the variables the expected value of b will be 0.33.

[14] It is still possible, hypothetically, for dealers to participate in a private-valuation auction. This could happen if, for example, the dealers came from different independent markets, but this seems unlikely in the case of car dealers in New Jersey.

upward-sloping price pattern. In our data, this might suggest that returns to information revelation have been exhausted at some point and that agents have all the information they need about the common component of the objects.

The method suggested above of distinguishing between common- and private-value paradigms in oral English auctions is different from what is usually suggested in the literature.[15] The way to differentiate between the two paradigms empirically usually involves all the bids submitted from all bidders (typically in sealed bid auctions) and the assumption that, with private value, we expect a monotonic increase of winning bids in the number of bidders, whereas with common value, we expect that the individual bid function may first increase (because of competition increase) but will eventually decrease (because of the winner's curse). This information is not usually available to the researcher in an oral English auction because, even if the attendant number of bidders could be controlled for, the effective number of bidders cannot. Second, information about each candidate bidding in each stage is not available. The suggested method (by relying on observable information) can help in determining the auction type.

6. Conclusions

Standard auction models describe the English oral auction as a clock auction in which an auctioneer raises the price continuously and each bidder chooses when to drop out. This description, however, prevents jump biddings from happening. When a new offer is submitted that is above the old offer plus the minimum bid increment, we refer to that as a jump bidding. This phenomenon is known to occur in reality but has not been fully documented in the auction literature. A rigorous empirical investigation of jump biddings in English auctions does not exist.

In this paper, the characteristics of bid offers and jump biddings in sequential English oral auctions is empirically examined using a car auction data set I collected during 2001 and 2002 from New Jersey DSS in Trenton. I defined four variables that measure jumps and found that jump biddings are an important real-world phenomenon.

[15] See, for example, Paarsch (1992) and Haile, Hong, and Shum (2002)

For almost all of the items sold, bidders do not follow the ratchet solution but rather use jump biddings to increase the current offer. Furthermore, there is a pattern in the jump size. On average, for each item sold, the first offer is the largest jump, and the last offer is the smallest jump. I offer several explanations for the existence of jump biddings and examine them using regression analysis. The entire set of jump variables depends on the presale estimator but not on the order the items are sold. These findings suggest that there is strategic bidding behavior in the auction process.

I use jump biddings, and specifically the First Jump, to determine whether the auction of interest is a private- or common- value auction. This approach uses the fact that selling prices in a common value auction may be path dependent, whereas in private value auctions, they are not. A simple test of the effect of the First Jump on the selling price then determines the type of the auction. I perform this test and conclude that the auctions I observed can be characterized as common value auctions. On the other hand, the data are also consistent with several private value models, since the regression analysis I performed demonstrates only correlation between the jumps and the selling price and not causation. One problem that arises if indeed there is a path dependency is that an increase in the First Jump will on average increase the winning bid. Usually, in the theoretical models that accommodate jumps, the incentive to make jump bidding is to reduce the expected selling price. If indeed there is path dependency and an increase in the first jump leads to higher selling price it does not seem rational to perform the jumps. But this is true for any jump during the auction process and the same intuitive explanation provided for the existence of jumps in general will hold for the First Jump as well. For further empirical research, I suggest testing for the effect of the first offer on the selling price when pure private value goods are being auctioned. If there is no effect, it supports the proposed test for deciding between the private and common value paradigm in an oral English auction.

In Table 1 I reviewed the main models describes bidding pattern. None of them can describe effectively the bid pattern in an open outcry English auction according to my data. Rothkopf and Harstad (1994) predict straight forward bidding under their model assumption and do not specify what type of jumps we expect to observe when we deviate from the model assumption. Although I demonstrate that there is a positive correlation between the jumps, and this finding is similar to the theoretical predictions of Daniel and Hirshleifer (1998) within the private value paradigm, their model predicts that the auction will end after two stages. This is the case also for Macskasi (2000) and Easley and Tenorio (2001). Isaac et al (2003) computed numerically an example of an English auction using backward induction and dynamic programming. They found jump bidding of moderate size with convergence to the straight forward bidding at some point of the auction. I don't find this pattern in my data though.

An extension of the Avery (1998) model to discrete bid level might yield a model that describes bidding behavior in English auctions which is closer to reality. But this task is hard to achieve since it is difficult to analyze this kind of dynamic games theoretically.

References

[1] Avery, Christopher. "Strategic Jump Bidding in English Auctions" *The Review of Economic Studies*, 1998, Volume 65, Issue 2, 185-210.

[2] Betton, Sandra and Eckbo, B. Espen,"Toeholds, Jump biddings and Expected Payoffs in Takeovers" *Review of Financial Studies*, 2000, Volume 13, Issue 4, 841-882.

[3] Tilman Borgers and Christian Dustmann "Strange Bids: Bidding Behavior in the United Kingdom's Third Generation Spectrum Auction," 2002, Working Paper, University College London

[4] Daniel, Kent D and Hirshleifer, David. "A Theory of Costly Sequential Bidding" Northwestern University, 1998, Mimeo.

[5] Robert F Easley and Rafael Tenorio "Jump Bidding Strategies in Internet Auctions"

[6] Haile, Philip, Hong, Han and Shum, Matthew. "Nonparametric Test for Common Values in First-Price Sealed-Bid Auctions" Working Paper, Princeton University.

[7] Haile, Philip and Tamer, Elie. "Inference with an Incomplete Model of English Auctions" *Journal of Political Economy*, 2003, Volume 111, 1-51.

[8] Harstad, Ronald M. and Rothkopf, Michael H. "An "Alternating Recognition" Model of English Auctions" *Management Science*, 2000, Volume 46, 1-12.

[9] Hirshleifer, David and Png, I P L. "Facilitation of Competing Bids and the Price of a Takeover Target" *Review of Financial Studies*, 1990, Volume 2, 587-606.

[10] Isaac, R. M., T. Salmon, and A. Zillante (2003, a). "A Theory of Jump Bidding in Ascending Auctions," Working paper, Florida state university.

[11] Isaac, R. M., T. Salmon, and A. Zillante (2003, b). An Experimental Test of alternative Models of Bidding in Ascending Auctions. Working paper, Florida state university

[12] Isaac, R.M., and Schinier, K. "Run Silent, Run Cheap? A Study of Charity Auction Mechanism," Working Paper, 2003, Florida State University.

[13] Macskasi, Zsolt "Jump bidding," 2000 Working Paper, Northwestern University.

[14] McMillan, John and Eiichiro, Kazumori. "Selling Online versus Offline: Theory and Evidence from Sotheby's" 2002, Stanford University, Mimeo.

[15] Milgrom, P. and Weber, R. "A Theory of Auction and Competitive Bidding" *Econometrica*, 1982, Volume 50, 1089-1122.

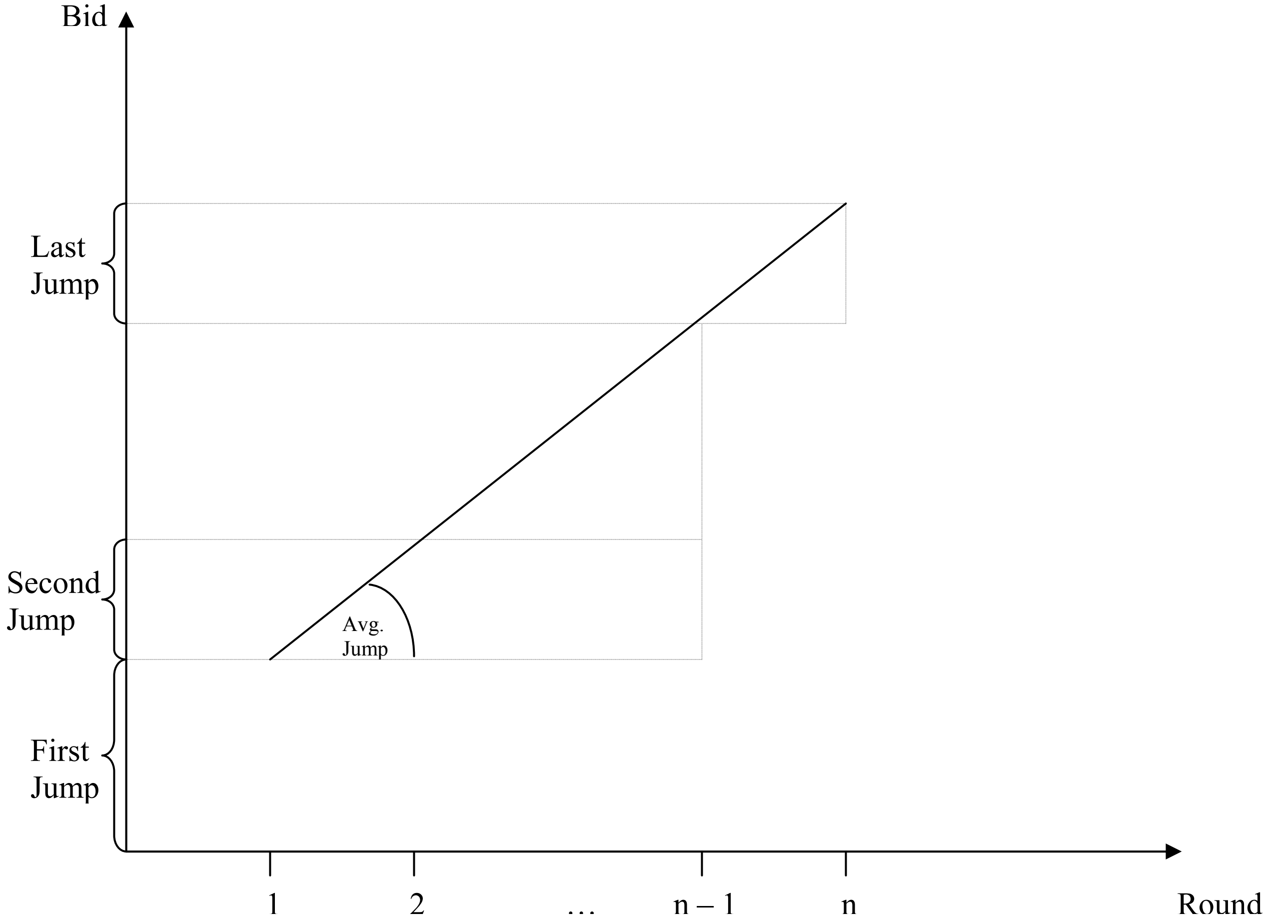
[16] Paarsch, Harry. "Deciding Between the Common and Private Value Paradigms in Empirical Models of Auctions" *Journal of Econometrics*, 1992, Volume 51, 191-215.

[17] Charles R. Plott and Timothy C. Salmon "The Simultaneous Ascending Auction: Dynamics of Price Adjustment in Experiment and in the U.K. 3G Spectrum Auction," Journal of Economic Behavior and organization, Forthcoming

[18] Raviv, Yaron. "New Evidence on Price Anomalies in Sequential Auctions: Used Cars in New Jersey" Princeton University, November 2003, Mimeo.

[19] Rothkopf, Michael H. and Harstad, Ronald M. "On the Role of Discrete Bid Levels in Oral Auctions" *European Journal of Operational Research*, 1994, Volume 74, 572-581.

Figure 1: Pictorial Description of the Jump Variables



This drawing describes graphically the four different jump variables for an item that has been sold after n rounds. On the x-axis is the stage of the auction. Round 1 is the first offer by any bidder, round 2 is the counter offer by the next bidder, etc. The first offer is the First Jump. The difference between the first offer and the second bid is the Second Jump. The difference between the winning bid and the preceding bid is the Last Jump. The Average Jump is last offer before the wining bid minus the First Jump divided by n-2, and it is the slope of the linear curve connecting the first bid and the bid before the winning offer.

Table 1: Models Describes Bidding Pattern

Model *	Auction Format	Reasons for Jumps	Predictions	Data Support
Rothkopf and Harstad (1994)	English auction discrete bid level	Increase distribution, large interval, discreteness	Straight forward bidding	
Daniel and Hirshleifer (1998)	Takeover contest, cost to submit bids	Cost and signaling	Jump bidding, contest end after max two active stage	
Macskasi[a] (2000)	Takeover contest, cost to submit bid	Cost and signaling	Jump bidding, contest end after max three active stage	
Easley and Tenorio[b] (2001)	Ascending Internet auction, random demand	Cost and signaling	Straightforward bidding with 0 costs, the game over after 1 or 2 rounds if the item sold.	Yankee type internet auctions
Avery[c] (1998)	2 stage English auction	Signaling	If both players chose the same in the first stage than a regular clock English auction. expected prices between the first and second price auction	
Isaac et al (2003)	English auction with Discrete bid levels	Distribution and discreteness	Jump bidding of moderate size, convergence to straight forward bidding	Experiment
Plott and Salmon (2002)	simultaneous ascending auctions	None	surplus maximization and bid minimization, straightforward bidding	FCC and 3GUK auctions

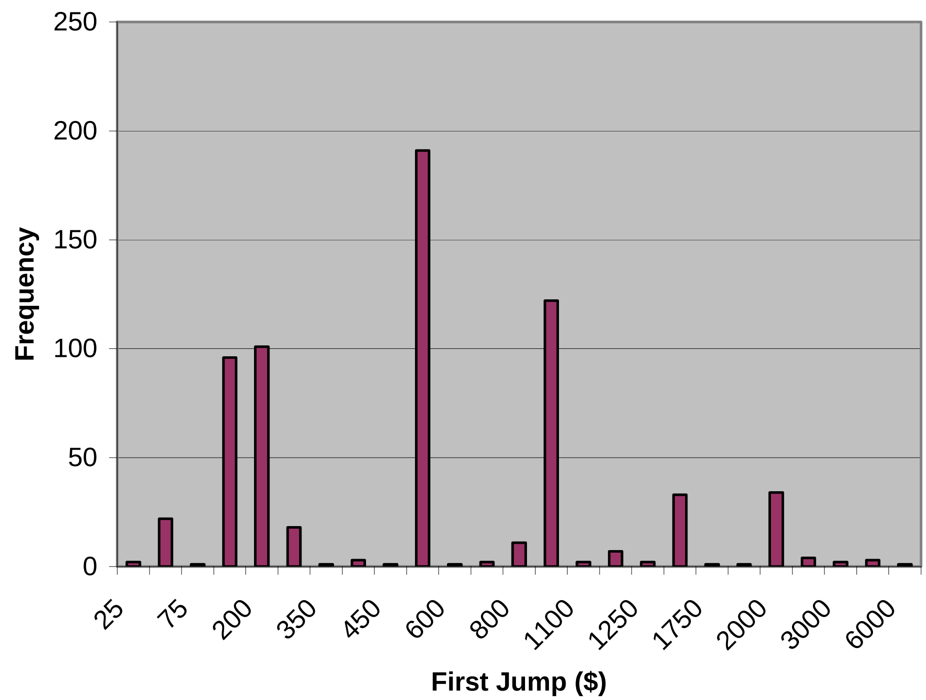
*All models assume two risk neutrality bidders with private valuation and a unit demand. [a] This model is an extension of DH to three bidders. [b] This model is with the same assumptions as DH beside random demand and cost for each round of participation. [c] This model assumed affiliated valuation and signals.

Table 2: Summary Statistics

	Presale Estimator	Price	First Jump	Second Jump	Average Jump	Last Jump	Number of Bids
Mean	2662.19 (1634.84)	1520.42 (1168.18)	656.91 (626.10)	121.44 (107.08)	81.89 (37.38)	62.51 (76.41)	11.39 (7.13)
Minimum	318.75	50	25	25	25	25	1
Maximum	15265	8650	6000	1000	533.33	1800	49
Observations	678	683	662	633	610	637	641

Standard errors are in parentheses.

Figure 2: Empirical Distribution of First Jump



\

Figure 3: Empirical Distribution of Second Jump

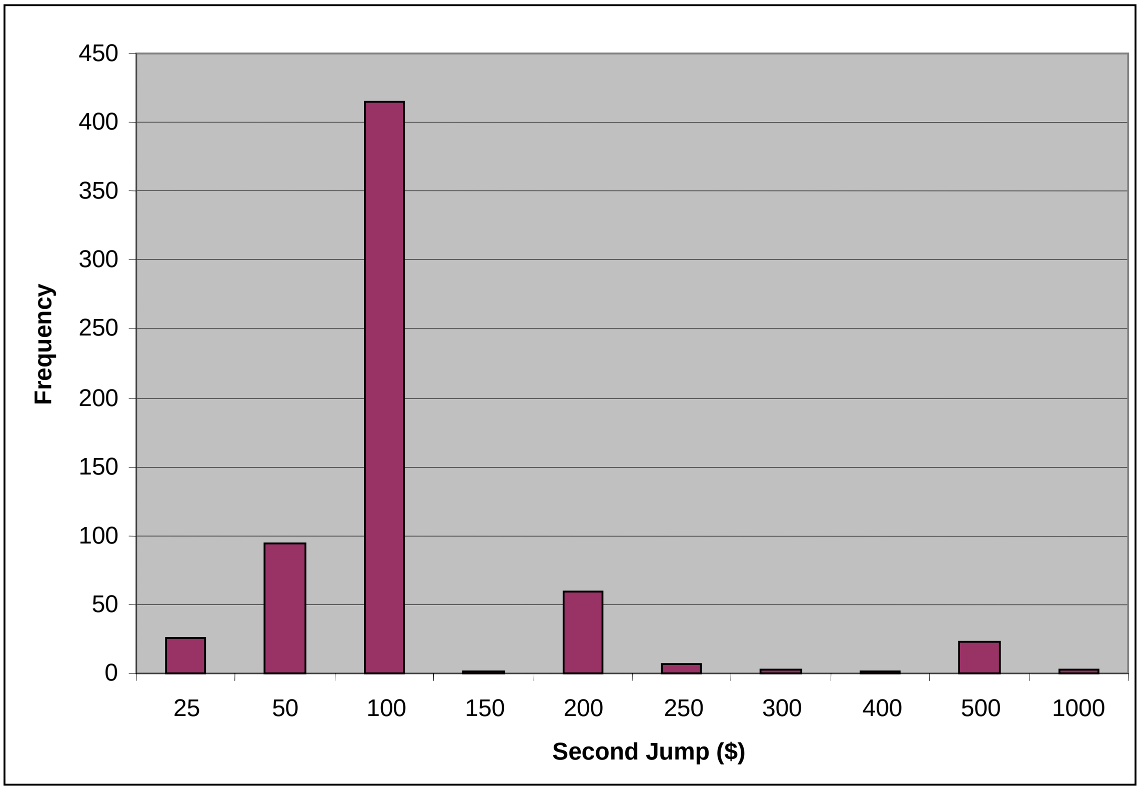


Figure 4: Empirical Distribution of Average Jump

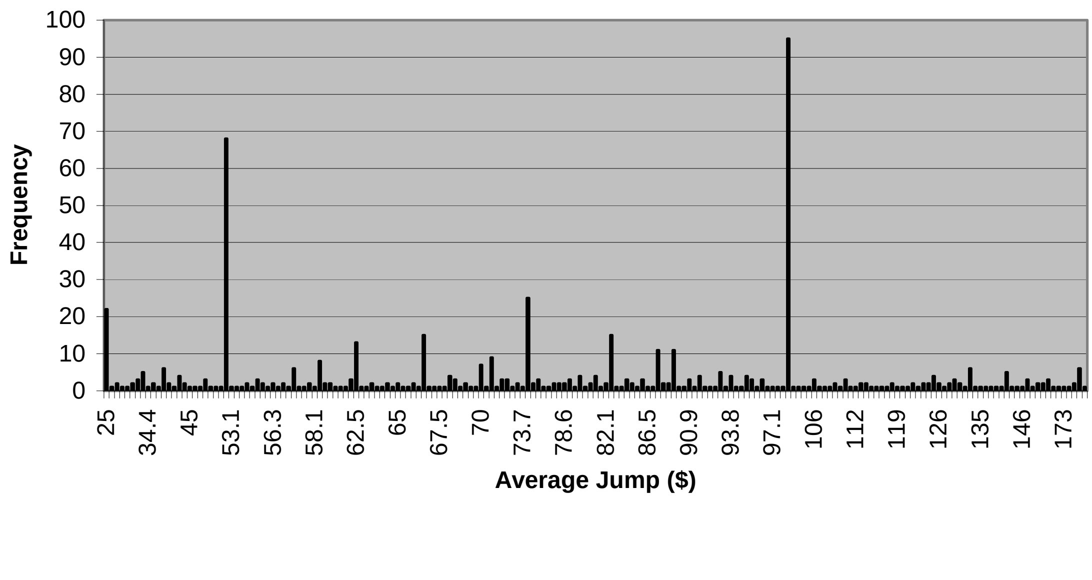


Figure 5: Empirical Distribution of Last Jump

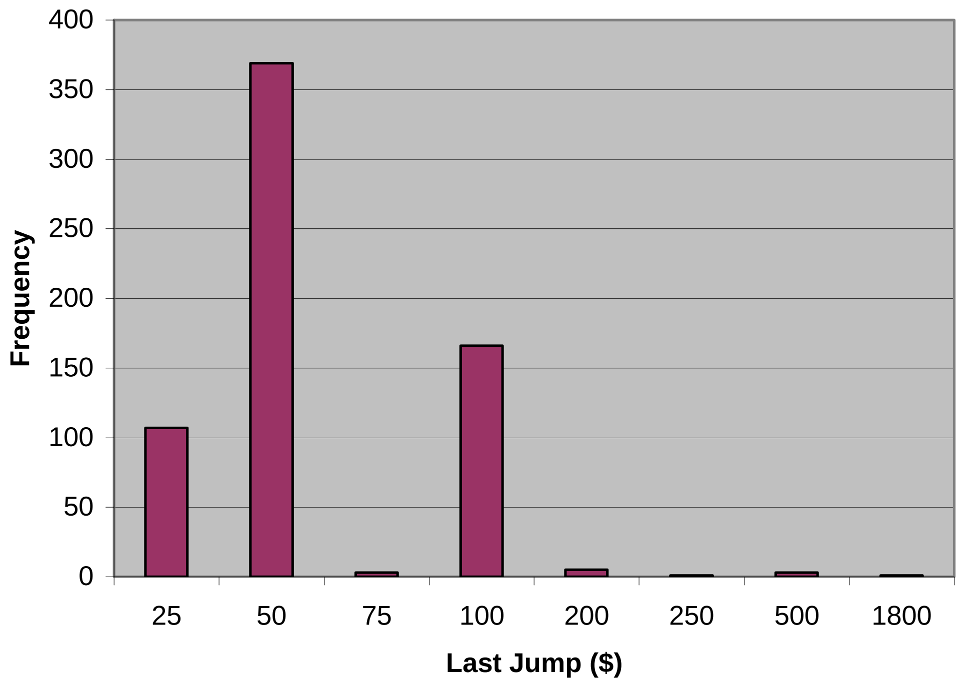


Table 3: OLS Regression Results

	First Jump	Second Jump	Average Jump	Last Jump	First Jump n>1	Last Jump n>1
Constant	914.41	93.41	66.729	58.11	932.16	44.26
	(115.57)	(27.75)	(9.27)	(22.187)	(117.64)	(7.36)
Year	-45.85	-2.559	-0.539	-0.569	-46.37	0.186
	(6.10)	(1.459)	(0.4829)	(1.15)	(6.19)	(0.384)
Mileage	-17.42	-1.79	-1.11	-0.484	-18.177	-0.422
	(3.92)	(0.94)	(0.319)	(0.763)	(4.003)	(0.253)
Estimator	0.2016	0.0248	0.0098	0.004	0.2038	0.0061
	(0.0122)	(0.0029)	(0.0009)	(0.0023)	(0.0124)	(0.0007)
Order	46.60	17.175	6.817	18.04	35.11	2.33
	(55.24)	(13.297)	(4.42)	(10.61)	(56.53)	(3.52)
Poor	-77.00	-18.039	-3.46	-4.087	-92.97	0.626
	(43.92)	(10.897)	(3.67)	(8.697)	(46.03)	(2.88)
Observations	655	627	605	632	635	630
R^2	0.5980	0.2427	0.3349	0.0444	0.5959	0.2078

Standard errors are in parentheses. All the regressions include auction dummies fixed effects. Mileage is the mileage that appears on the odometer divided by 10000 and Order is the order the car was auctioned divided by the total number of cars in the particular auction.

Table 3A: OLS Regression Results

	Log First Jump	Log Second Jump	Log Average Jump	Log Last Jump	Log First Jump n>1	Log Last Jump n>1
Constant	2.128 (0.412)	1.971 (0.359)	1.963 (0.267)	1.989 (0.334)	2.092 (0.426)	1.923 (0.310)
Year	-0.094 (0.008)	-0.016 (0.007)	0.00002 (0.005)	0.005 (0.007)	-0.094 (0.008)	0.006 (0.006)
Mileage	-0.031 (0.005)	-0.014 (0.004)	-0.013 (0.003)	-0.006 (0.004)	-0.032 (0.005)	-0.007 (0.004)
Log Estimator	0.720 (0.042)	0.384 (0.037)	0.323 (0.027)	0.268 (0.034)	0.727 (0.044)	0.273 (0.032)
Order	-0.019 (0.075)	0.046 (0.065)	0.036 (0.048)	0.054 (0.060)	-0.032 (0.077)	0.020 (0.056)
Poor	-0.230 (0.060)	-0.137 (0.053)	-0.045 (0.039)	0.014 (0.049)	-0.237 (0.063)	0.028 (0.046)
Observations	655	627	605	632	635	630
R^2	0.7072	0.3768	0.4113	0.2163	0.6957	0.2391

Standard errors are in parentheses. All the regressions include auction dummies fixed effects. Mileage is the mileage that appears on the odometer divided by 10000 and Order is the order the car was auctioned divided by the total number of cars in the particular auction.

Table 4: OLS Regression Results

	Second Jump	Average Jump	Average Jump	Average Jump	Last Jump	Last Jump	Last Jump	Last Jump
First Jump	0.023 (0.009)	0.0089 (0.0031)		0.0043 (0.0024)	0.005 (0.002)			0.002 (0.002)
Second Jump			0.196 (0.010)	0.194 (0.010)		0.032 (0.009)		-0.058 (0.010)
Average Jump							0.347 (0.027)	0.453 (0.033)
Observations	627	604	604	604	604	604	604	604
R^2	0.2470	0.3429	0.5822	0.5843	0.2345	0.2419	0.3948	0.4240

Standard errors are in parentheses. All regressions include a constant, the presale estimator, the year of manufacture, the mileage as it appears on the odometer, the order the car was sold, and a dummy variable for the specific auction. Similar results are obtained when any subset of this model is applied

Table 4A: OLS Regression Results

	Log Second Jump	Log Average Jump	Log Average Jump	Log Average Jump	Log Last Jump	Log Last Jump	Log Last Jump	Log Last Jump
Log First Jump	0.074 (0.033)	0.085 (0.024)		0.044 (0.017)	0.088 (0.028)			0.033 (0.023)
Log Second Jump			0.501 (0.021)	0.496 (0.021)		0.201 (0.033)		-0.245 (0.037)
Log Average Jump							0.652 (0.039)	0.882 (0.053)
Observations	627	604	604	604	604	604	604	604
R^2	0.3752	0.4215	0.6980	0.7011	0.2624	0.2947	0.4897	0.5249

Standard errors are in parentheses. All regressions include a constant, the log of the presale estimator, the year of manufacture, the mileage as it appears on the odometer, the order the car was sold, and a dummy variable for the specific auction. Similar results are obtained when any subset of this model is applied.

Table 5: OLS Regression Results of Winning Bid

	1	2	3	4
Constant	465.12 (441.93)	572.68 (522.09)	387.17 (522.45)	535.66 (527.74)
Year	-9.21 (26.92)	-10.94 (31.81)	-5.87 (31.57)	-9.63 (32.09)
Estimator	0.375 (0.056)	0.670 (0.062)	0.708 (0.061)	0.712 (0.062)
Poor	-0.070 (0.062)	-0.150 (0.073)	-0.182 (0.076)	-0.173 (0.074)
Mileage	-37.72 (12.41)	-63.46 (14.53)	-71.02 (14.94)	-68.55 (14.63)
Order	132.37 (68.52)	120.44 (81.61)	99.95 (82.56)	118.33 (82.14)
First Jump	0.846 (0.051)			
Second Jump		1.326 (0.254)		
Average Jump			3.849 (0.779)	
Last Jump				2.507 (0.936)
Observations	635	627	605	630
R^2	0.8447	0.7826	0.7827	0.7739

Standard errors are in parentheses. The sample includes items receiving more than a single offer. Mileage is the mileage as it appears on the odometer divided by 10,000. All regressions include auction fixed-effect dummies and interaction terms between the auction dummies and the other covariates. Similar results are obtained when the log variables, instead of the variables' levels, are used and when the model used is a subset of the above model.

Table 5A: OLS Regression Results of Log Winning Bid

	1	2	3	4
Constant	2.339 (0.846)	2.995 (1.019)	2.356 (0.983)	3.383 (1.046)
Year	-0.035 (0.019)	-0.068 (0.023)	-0.069 (0.021)	-0.078 (0.023)
Log Estimator	0.352 (0.088)	0.536 (0.105)	0.571 (0.100)	0.565 (0.108)
Poor	-0.011 (0.014)	-0.013 (0.017)	-0.017 (0.017)	-0.025 (0.017)
Mileage	-0.021 (0.008)	-0.037 (0.009)	-0.040 (0.009)	-0.043 (0.009)
Order	0.152 (0.044)	0.142 (0.053)	0.130 (0.052)	0.151 (0.055)
Log First Jump	0.415 (0.022)			
Log Second Jump		0.229 (0.033)		
Log Average Jump			0.348 (0.045)	
Log Last Jump				0.158 (0.039)
Observations	635	627	604	630
R^2	0.8733	0.8171	0.8284	0.8065

Standard errors are in parentheses. The sample includes items receiving more than a single offer. Mileage is the mileage as it appears on the odometer divided by 10,000. All regressions include auction fixed-effect dummies and interaction terms between the auction dummies and the other covariates. Similar results are obtained when the model used is a subset of the above model.

Table 5B: OLS Regression Results of the Ratio between the Winning Bid and estimator

	1	2	3	4
Constant	0.516 (0.058)	0.724 (0.052)	0.679 (0.058)	0.758 (0.054)
Year	0.003 (0.003)	-0.007 (0.002)	-0.005 (0.002)	-0.008 (0.002)
Poor	-0.00002 (0.000007)	-0.00002 (0.000008)	-0.00003 (0.000008)	-0.00003 (0.000008)
Mileage	-0.006 (0.002)	-0.008 (0.002)	-0.008 (0.002)	-0.009 (0.002)
Order	0.041 (0.028)	0.051 (0.029)	0.051 (0.029)	0.054 (0.029)
First Jump	0.00012 (0.00001)			
Second Jump		0.0002 (0.00008)		
Average Jump			0.0007 (0.0002)	
Last Jump				0.00041 (0.00032)
Observations	635	627	604	630
R^2	0.2474	0.1957	0.1836	0.1869

Standard errors are in parentheses. The sample includes items receiving more than a single offer. Mileage is the mileage as it appears on the odometer divided by 10,000. All regressions include auction fixed-effect dummies. Similar results are obtained when the log variables, instead of the variables' levels.

Table 5C: OLS Regression Results of the Log Ratio between the Winning Bid and estimator

	1	2	3	4
Constant	-1.976 (0.220)	-0.814 (0.202)	-1.118 (0.228)	-0.409 (0.196)
Year	0.012 (0.006)	-0.020 (0.005)	-0.015 (0.005)	-0.025 (0.005)
Poor	-0.00005 (0.00001)	-0.00006 (0.00001)	-0.00006 (0.000015)	-0.00007 (0.00001)
Mileage	-0.009 (0.003)	-0.017 (0.004)	-0.016 (0.004)	-0.021 (0.004)
Order	0.077 (0.053)	0.083 (0.056)	0.087 (0.055)	0.091 (0.056)
Log First Jump	0.214 (0.022)			
Log Second Jump		0.133 (0.032)		
Log Average Jump			0.195 (0.042)	
Log Last Jump				0.075 (0.038)
Observations	635	627	604	630
R^2	0.3346	0.2655	0.2540	0.2515

Standard errors are in parentheses. The sample includes items receiving more than a single offer. Mileage is the mileage as it appears on the odometer divided by 10,000. All regressions include auction fixed-effect dummies.