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New Evidence on Price Anomalies in Sequential Auctions: Used Cars in New Jersey

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Abstract. In this paper the sequence of winning bids in the public auction of used cars in New Jersey is examined for the presence of price anomalies. Unlike many studies of heterogeneous objects where the effect of the order of sale on the price may not be credibly identified, the effect of the order is identified here because the items are randomly selected for sale. In a further contrast to many other studies, these data indicate that the prices tend to increase as the auction proceeds. The data also indicate that once several items have been sold, there is no change in the bidding behavior or further increase in prices.

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1. Introduction

Robert Weber (1983) showed that in sequential auctions of identical objects with risk neutral bidders and independent private values, the expected sale price is equal in all stages of the auction. Milgrom and Weber (1982) argued that if the bidders have affiliated common values, then the sales price should increase as the auction progresses. They asserted that this effect is a consequence of a reduction in the winner's curse, since the early stages of the auction reveal information about the object's value. In contrast, Ashenfelter (1989) found that prices of identical wine bottles in four different auction houses tended to decrease as the auction progressed. This finding revealed a puzzle that was later referred to as the "declining price anomaly" and which has been documented in several studies.[2]

In this paper the outcome of sequential English oral auctions is empirically tested with a car auction data set that I collected during the years 2001-02 from the New Jersey Distribution and Support Services in Trenton. Distribution and Support Services sells surplus personal and government property either through public oral English auctions or sealed bid auctions.

Two key problems arise in the design of a study of the declining price anomaly: the need to control for the heterogeneity in the objects sold and the problem of unsold objects. Either problem can severely bias the key findings. Compared to other empirical investigations that appear in the literature, the data I have collected are unique because randomly assigned objects are auctioned and there is no reserve price, which means the object is always sold. In addition, all the auctions are held at the same place with the same auctioneer, which eliminates differences due to different auction houses and different markets.

Unlike other studies, these data show that the price increases as the auction progresses; namely, each object sold increases the next object's sales price. Furthermore, it is evident that the prices tend to increase only during the first half of each auction and there is no anomalous result in the second half of each auction. I hypothesize that this price pattern is related to bidders' behavior due to unfamiliarity

[2] See appendix for a literature survey.

with the auction mechanism and test this hypothesis using the number of bids as a measure of "warming up" or competitive behavior. For instance, when the first several items sold in each auction are excluded from the data, there is no increasing price pattern. Hence, it appears that the anomalous results are obtained only locally.

With some modifications these empirical results are consistent with Milgrom and Weber's (1982) predictions when the agents have affiliated common values.[3] However, after the order parameter shape is identified it is shown that the increasing pattern occurs only at the beginning of each auction, and after a few items the pattern is constant. This might suggest that returns to information revelation have been exhausted at this point and agents have all the information they need about the common component of the objects. On the other hand, if agents have private values, then the initial results indicate an increasing price "anomaly." In this instance, however, the price pattern might be best explained by an insufficient opportunity for the bidders to warm up.

The paper is organized as follows. In the next section I provide an example that demonstrates the order independence in sequential auctions of heterogeneous goods. I demonstrate that unlike the conclusion in Beggs and Graddy (1997), there are no differences in the expected selling price in different stages of the auction. The expected revenue of the auctioneer will be the same regardless of the sequence of sale. In section three I will describe the data that will be used to test for the declining price anomaly. In the fourth part of the paper it will be demonstrated that, although the objects were randomly assigned, there is an increasing price pattern. Section five will demonstrate that the increasing price pattern happens only on the first part of the auction and that in the second part there is no anomaly. The increasing price phenomena will be related to agents' bidding behavior and evidence will be provided that the increasing part of the auction correlates with agents "warming up" as the auction progresses. A final section offers some concluding remarks.

[3] The Milgrom and Weber model assumes identical goods, so bids on the first item reveal information about subsequent items. In my data the items are heterogeneous, so the information revealed during the first stages might be related to aggregate demand, common quality due to the same source of the cars, or any other form of uncertainty that affects the price and is common to all cars.

2. Order Independence Within Heterogeneous Goods

In this section I will provide an example that demonstrates the order independence when selling heterogeneous goods. Consider the following simple model[4] which is a variant of Beggs and Graddy (1997) model. Suppose that there are two objects for sale and three risk neutral bidders. The bidders have unit demand and the items are heterogeneous in the sense that if good 1, the high valuation good, is worth *v* to a buyer, the second good is worth *tv*, where $0<t<1$. For simplicity I assume that $v \in \{0,1\}$ and that Pr(v=1)=p, which mean that the probability of having a valuation of 1 is p. Suppose that goods auctioned sequentially using a second price sealed bid auction and that the values drown independently. In order to demonstrate the order independence within heterogeneous good we separate the example into two cases.

Case 1: Good 1 auctioned first (the high valuation good).

Let $F(b)$ be the cumulative density function of a buyer's bid for good 1 if his valuation is 1.[5] Then a buyer with valuation v=1 chooses b to maximize:

$$(1-p)^2 1+2p(1-p)[\int_0^b (1-x)dF(x)+(1-F(b))t]+p^2[\int_0^b (1-x)dF^2(x)]$$

Differentiating with respect to b and setting to zero, we obtain:

$$F(b)=\frac{(t-(1-b))(1-p)}{p(1-b)} \text{ and } f(b)=\frac{(1-p)t}{p(1-b)^2} \text{ where } 1-t\le b\le 1-(1-p)t$$

Thus the lowest bid for a high value bidder in the first round will be 1-t and the highest bid 1-$(1$-$p)t$. The expected selling price in the first round is:

$$3p^2(1-p)\int_{1-t}^{1-(1-p)t} 2x(1-F(x))dF(x)+$$
$$+p^3\int_{1-t}^{1-(1-p)t} 6xF(x)(1-F(x))dF(x)=p^2(3pt-3t-2p+3)$$

And in the second round is p^3t.

Case 2: Good 2 (the low valuation good) is auctioned first.

Note that if a buyer with v=1 wins good 2, he will still be willing to pay up to 1-t for good 1.[6] Therefore, a high valuation bidder will bid 1-t in the second round regardless

[4] I am grateful for Eric Maskin for suggesting and finding the equilibrium strategies in this model.
[5] The bidding strategy for a bidder with 0 valuations will be to bid 0 in both rounds.
[6] We assume no disposal cost. This is not a violation to the unit demand assumption because eventually no one will have more than one unit. We need this assumption to ensure the existence of an equilibrium.

the first round outcome. Let *G(b)* be the cumulative density function of a buyer bid for good 2 if *v*=1. Then a buyer with *v*=1 will choose *b* to maximize:

$$(1-p)^2 1 + 2p(1-p)[\int_0^b (t-x)\,dG(x) + (1-G(b))(1-t)]$$
$$+\ p^2[\int_0^b (t-x)\,dG^2(x)]$$

Differentiating with respect to *b* and setting derivatives to zero we obtain:

$$G(b) = \frac{b(1-p)}{p(t-b)} \text{ and } g(b) = \frac{(1-p)t}{p(t-b)^2} \text{ where } 0 \le b \le pt$$

In this case the expected selling price in the first stage will be:

$$3p^2(1-p)\int_0^{pt} 2x(1-G(x))\,dG(x) + p^3\int_0^{pt} 6xG(x)(1-G(x))\,dG(x) = p^3 t$$

And in the second stage the expected selling price will be:

$$p^2(3-2p-3t+3pt)$$

As we can see the expected selling prices of each item is the same no meter what its place in the sequence. When the order is randomize (which mean that with probability 0.5 the high valuation item will be sold first) the expected selling is equal in both rounds. This example demonstrates the order independence in heterogeneous goods.

Beggs and Graddy demonstrate that under their model, even if one control for the presale estimator and bidders are risk neutral, if the objects are ordered by declining valuations, the price received relative to the estimated price declines as the auction progresses. This can give the appearance of the declining price anomaly when it does not exist even when the presale estimator has been controlled for. This problem is eliminating, as the above model demonstrate, if the items are auction randomly.

Another point of interest is that unlike the Beggs and Graddy model, where the auctioneer will maximize his revenue when he sells the items in declining order of presale valuation,[7] there is no difference in the current example, and the expected selling price for each item is the same in each stage. The differences in the outcomes are due to the different assumptions of the models. Beggs and Graddy could not solve their model for more than two bidders, when the sell is in increase valuation pattern,

[7] At least in the case of 2 bidders and 2 items. When there are more than two bidders Beggs and Graddy could not solve the auction game when items sold in an ascending pattern.

and says that “with more than two bidders, even the existence of equilibrium is problematic.” I overcome this problem by assuming the free disposal and the participation in the second stage by the winner in the first stage, if the auction is in increase pattern and the winner in the first stage has high valuation. The external validity of their conclusion, that the auctioneer will maximize his revenue when he sells the item in descending order, seems somewhat problematic since they rely on the two bidders-two items example.

3. The Data

I collected the auction data in 2001-02 from the New Jersey Distribution and Support Services (DSS) in Trenton, New Jersey. DSS sells surplus personal and government property through both 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 before bidding. This can be done the day before the auction and on the day of the auction until 9 am, when the auction begins. Each car that is auctioned is driven through a large warehouse, stopped in front of the auctioneer and then the bidding process over this car starts. After the car is sold it is driven to the parking lot and then 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 $25 increments. 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. If so desired, the item can be purchased outright on the auction day. Alternatively, the balance may be paid and the item picked up the following week.

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 including: bad transmission, rear axle bent, no VIN (Vehicle Identification Number) plate on door, no power steering, etc. The coordinator of operations at DSS, Anthony C. Pagano, 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 verify empirically below), 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 estimated market value of each car. Kelly Blue Book (KBB henceforth) is a website that, among other things, provides market value estimates for cars. 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 the data about resold cars. During the week after each auction I collected the official list of winning bids from DSS to compare with my notes.

Compared to other empirical investigations of the sale of heterogeneous objects that appear in the literature, this data set is unique because it has the following properties:

1) Randomly assigned objects are auctioned. This property of the auction system is very important and has the flavor of randomization in field experiments. As pointed out by Beggs and Graddy (1997), even if bidders are risk neutral, if the objects are ordered by declining valuations, the price received relative to the estimated price declines as the auction progresses. This can give the appearance of the declining price anomaly when it does not exist even when the presale estimator has been controlled for.

2) There are no reserve prices or secret reserve prices, and therefore there is a 100% sales rate. It is well known that in art auctions the sales rate is typically less than 100% and sometimes much less. Ashenfelter and Graddy (2001) estimate that between 1982 and 1994 the sales rate for contemporary art varied between 52% and 91% in different auctions. Genesove (1995) found that in wholesale automobile auctions the average sales rate for used cars was between 32% and 42%. Selection bias problems are avoided because all the items are sold and there is no reserve price.

3) All the auctions are held at the same place with the same auctioneer, which avoids differences due to different auction houses and different markets. Pesando (1993)

demonstrates that these differences may be significant. The differences between auction dates will be captured with a dummy for each auction.

4) Supply is known ex ante. As shown by Jeitschko (1999), uncertain supply, like there is in wholesale agricultural markets and harbor fish markets, can yield either declining prices or increasing prices if it becomes known that supply falls short of expectations.

Table 1 gives summary statistics from the six different auctions. The minimum and maximum presale estimates for the cars sold in a particular auction are in the first and second row, respectively. As mentioned above, the KBB private party valuation is used as the presale car value. The mean presale estimator in each auction is in the third row, while the next three rows show information about the minimum winning bid (in three of the auctions agents got operable cars for only fifty dollars), maximum winning bid and average winning bid in each auction.

As one can see, the mean winning bid is less than the mean estimate. There several potential reasons for this. First I am using the private party estimate as the presale expected market value. If bidders react to the trade-in price instead, which is lower, we will not observe these differences. Another explanation is that bidder strategy is to bid a fraction of the presale estimate because of the uncertainty and the desire to make a profit. I will elaborate on these issues later when I explain the coefficients of the regression.

The mean number of bids describes the average of the number of bids before the winning bid in each auction. The next three rows divide the cars according to their condition as defined in the KBB estimator. The main parameters that determine the car's estimated market value in the KBB are: make, model, year, mileage and condition of the car. One problem that arises is how to evaluate the cars in poor condition, because KBB does not include information about such cars. In order to address this issue, I assume that the presale value of a car in poor condition is some constant fraction of the presale value of an identical car (in terms of model, make, year and mileage) in fair condition. To avoid problems of endogeneity I will run all regressions with and without the cars in poor condition.

[Table 1 here]

4. Increasing Price "Anomaly"?

There are two main ways to test for the declining price anomaly. The first is by examining an auction of identical objects (as in the case of identical bottles of wine). That type of auction, however, is rare. The second way to demonstrate the anomaly is to examine sequential auctions of randomly assigned objects. The random assignment implies no correlation between the order in which the object is auctioned and its presale estimated value. The DSS auctions are an example of the second type of auction. In order to see if the anomaly exists, researchers usually regress (in the case of heterogeneous objects) the winning bid or the log of the winning bid on a set of covariates along with the order in which the items were auctioned off. This empirical framework will be used here as well.

Table 2 shows the preliminary regression analysis. Each column corresponds to a different auction date. The model that I am estimating is:

$$\ln bid = \alpha_0 + \alpha_1 year + \alpha_2 \ln KBB + \alpha_3 I_{POOR} \ln KBB + \alpha_4 mileage + \alpha_5 order$$

where *bid* is the winning bid; *year* is the number of years the car has been used (2001/02 minus the manufacture year); *LKBB* is the log of the presale estimator; *LPoordum* is the product of a dummy variable for poor cars and the log of the presale value of a similar car in fair condition; *Mileage* is the mileage that appears on the odometer; and *Order* is the order in which the car was auctioned. The second model is the same regression equation but with the level instead of logs in the winning bid and the KBB variables.

[Table 2 here]

It is apparent that *LKBB* and *Lpoordum* are significantly different from zero in all the regressions. In addition, *Year* and *Mileage* are also significant in some of the above regressions, which suggest that an individual's bidding strategy is most likely a function of a car's year and mileage. The most relevant variable to our analysis, the *order*, has a positive sign in each regression, which suggests that when the regression combining all the observations is run, the order coefficient will be positive and significant. Similar results (with respect to the *order*) are obtained when the same regression is run in levels instead of logs in the winning bid and presale estimator (KBB).

In Table 3 regressions without covariates are presented that use all observations in the "all cars" section and only the fair and good condition cars in the "without poor" section. All the regressions include auction dummies, an intercept, and the *order* variable. If the regression is titled "Log bid," the winning bid and the presale estimator are in logs. When the regression is titled "Bid," the dollar amount of the winning bid is used as well as the presale estimator.

[Table 3 here]

Table 3 shows that using the same empirical methods as in Beggs and Graddy (1997) or in Ashenfelter and Genesove (1992); for example, I find that the *order* coefficient is positive and significant. On average, each unit sold added $4.26 to the next car's sales price or 0.33% to its value. When I control for the presale estimator, the coefficient is still significant although it is smaller. Each unit sold adds $2.70 (or 0.25%) to the next car's sales price on average. From the KBB and *LKBB* coefficients we can see that in the log model the elasticity of the winning bid with respect to the presale estimate is 1.05, which means that, on average, if the presale value of the car is doubled, the winning bid is expected to approximately double. In the level model, on average, the winning bid is 0.54 times the value of the presale value, and a poor condition car is devalued by 17% compared to a fair condition car with the same characteristics.

In Table 4, I check the sensitivity of the results by adding covariates. I am running two types of models using two types of data sets and using two measures for the order in which the cars were auctioned. The two models are in the form:

$$y_{ij} = \alpha_0 + \alpha_1 year_{ij} + \alpha_2 poordum_{ij} + \alpha_3 mileage + \alpha_4 order_{ij} + \alpha_5 kbb_{ij} + \\ + I_j(\alpha_6 + \alpha_7 year_{ij} + \alpha_8 poordum_{ij} + \alpha_9 mileage_{ij} + \alpha_{10} kbb_{ij})$$

in the case of levels (KBB, winning bid), and in logs (log of KBB, *LKBB*, and log winning bid). The variable I_j is a dummy that is one if the observation belongs to the j-th auction. All the other variables are defined as before. I also run the same regression without poor condition cars (when there is no coefficient in the poor dummy place). I use two types of order measures. The first is *Order*, which is the place in the sequence that the car auctioned. The second is Seq, a dummy that is 0 if the observation belongs to the first half of the auction and 1 otherwise. I am using this variable to minimize the effect of different sequence lengths of the different auctions. I also constructed other measures of order, such as the fraction of cars already sold (*order* divided by the total number of cars). Qualitatively, the same results are obtained using this variable. The regressions titled LKBB Order, for example, are estimates of the model with logs using the *order* variable, while the regressions titled KBB Seq are the regressions using the values (and not logs) of the winning bid, presale estimator and the Seq variable. Interactions are the covariate's interaction with the auction dummies (for example, auction*year).

In all the specifications, the *order* and *seq* variables are positive and significant. There is not much difference in the parameter estimates when we exclude the poor condition cars. On average, each car sold increases the value of the next car by 0.2%, or, if we used the level model, each car sold adds $2.33, on average, to the next car's value. When we used the seq variable, we can conclude that on average, cars that sold in the first half of the auction sold for 12.3% less than cars in the second half, or in dollar terms, cars that sold in the second half of the auction sold on average for $122.57 more than in the first half after we control for the covariates. From tables 3 and 4 I conclude that my data set suggests an increasing price pattern.

[Table 4 here]

Next, I will show that there is no correlation between the presale estimator and the order in which the cars were auctioned. One piece of evidence is that I asked the people that operate the auction if the cars are auctioned in some specific order and specifically if there is a connection between the cars' presale value and the order in which they are sold. Their answer was that there is no order in the way the cars are introduced into the auction. The correlation between the *order* and the presale estimator is only 0.0173, while it is 0.0503 between the presale estimator and the Seq variable. To examine this issue more thoroughly, I also perform a two-regression procedure. First, I regress the presale estimator on the *Order* and Seq variables separately in each auction and on all the auctions together. Second, a probit regression is run in which Seq is the dependent variable and the presale estimator is one of the explanatory variables. I did this for all the auctions individually and then combined. The results in the two cases are similar. There is no correlation between the orders the cars were auctioned and the presale estimator.

In Table 5 we can see the results of regressing the presale estimator on the order.

[Table 5 here]

What this table shows is that there is no significant correlation between the order and the presale estimator. In three auctions—one, three, and six—there is a positive correlation between *order* and the presale estimator. In those auctions, expensive cars were auctioned late in the auction and cheap cars early, although the result is only significant in auction one. In the other three auctions there is a negative relation although again it is significant only in auction five. This suggests that when we aggregate this data we will get no significant relationship between the presale estimator and the order in which the car was auctioned. We obtain the same results when we exclude the cars in poor condition from the regression. I performed the same procedure using the Seq variable instead of the Order variable and then ran probit regressions. The results are similar: the presale estimator has no significant effect on the probability that a car will be auctioned in the second half of an auction.

Table 6 describes the results of a regression of the presale estimator on the order variable. In columns one and two I use the order variable in the regression while in columns 3 and 4 I use the Seq variable. In the last two columns I regress the *order* on the presale estimate. It can be observed that in the two specifications there is no significant correlation between the presale estimator and the order in which the car is auctioned. The same results are obtained when I add variables (like *year* and *mileage*, for example) and exclude the cars in poor condition from the sample.

[Table 6 here]

[Table 7 here]

In Table 7, I use a probit model. The dependent variable is Seq, a dummy variable that is equal to 1 if the observation belongs to the second half of the auction. It can be concluded from Table 7 that the probability of belonging to second half of each auction is not affected by the presale estimator value. Thus, KBB is not significant in any of the regressions. As the results from the last three tables indicate, one can conclude that there is no correlation between the presale car value and the order in which it was introduced into the auction.

5. The Connection between “Warm Up” and Price Pattern

In the previous section I provided evidence for an increasing price as the auction progresses after controlling for the presale estimator and other relevant covariates. The results were robust to several measures of order and to the two types of theoretical models used in the literature. There is no significant relationship between the order and the presale estimator, which implies random assignment of objects. In this section I continue to examine the data in order to reveal more precisely the shape of this increasing price “anomaly.”

Table 8 reports regression results that shed light on the shape of the price trend as the auction progresses. I introduce an order-squared variable to determine whether the order variable’s effect is non-linear. In the first column, log of the winning bid is used as the dependent variable, and in the second column winning bid is used as the dependent variable. In those two columns I add order squared. I find that the order-squared variable is negative and significant, which suggests that after a certain point in the auction there is a decline in the price pattern with respect to the order. I also run the same regression without the poor condition cars and get the same results. The next three columns report regression results with the data set divided into two data sets. The first, Seq=0, runs the above regression on the first half of each auction. The second, Seq=1, uses the second half of each auction to run the above regression. In both columns the dependent variable is log of the winning bid. Similar results are obtained by using winning bid as the dependent variable and when I exclude the cars in poor condition from the sample.

When I run the regression using the second half (Seq=1) there is no anomaly. In fact, the order coefficient is negative (-0.0008) although not significant. So one cannot reject the null hypothesis that the order coefficient is 0 in the second half. This result is also obtained when I exclude the cars in poor condition. In the first part of the auctions, however, the order coefficient is positive (0.004) and significant. In the last column I run the same regression model with the order squared variable in order to see if there is non-linearity in the order variable in the first half of the auctions. The results indicate that there is no non-linearity in the order parameter (at least not in a form of second degree polynomial). Again, although the squared order parameter is negative (-0.00013), it is not significant. Therefore a linear function with a positive slope relates the order to the winning bid in the first half of the auctions.

[Table 8 here]
[Figure 1 here]
[Table 9 here]

In figure 1, I summarize the findings. If I fix all the other factors that affect the winning bid and check the effect of the order on the winning bid, I find that in the first part of these auctions the winning bid follows a linear increasing trend. During the second part of these auctions there appears to be no connection between the order and the winning bid—the order does not affect the winning bid. The order stops affecting the price trend in the first half of the auctions. I will use the number of bids to identify and relate the price pattern to the agent's behavior.

The reason for using the number of bids before the winning bid in order to characterize the agent behavior is as follows. Usually, under the standard assumptions, the level of competition is increasing in the number of bidders. This is true specifically in sealed bid auctions. In open outcry auctions, like the one my data come from, this information is not usually available to the researcher 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. In order to measure the level of competition we must instrument with an observable variable and this is the reason for using the Number of Bids in this role. If the competition structure is the same across all auctions and within each auction, namely, in each stage the same number of agents, on average, competes over the object, then the Number of Bids can be used as a measure for competitive behavior or a measure of being "warmed up." If two similar cars sell for the same price in two different stages of the auction, but the car in the second stage received more bids, then we can argue that there was more competitive behavior in the second stage. If, for example, two cars sold for $1000 each, but the first car's bidding history was 500, 1000, while the second car's bidding history was 100, 200, 300,…1000, I claim that in the latter stage bidders' behavior indicated that they were more "warmed up."

In Table 9, I report results of regressing the number of bids until the winning bid on several covariates. I report the Negative Binomial regression results although I find very similar results when I use other distributions including Gamma, Inverse Gauss and Poisson. The Negative Binomial has the best goodness-of-fit measures. I use the presale estimate (KBB) as one of the independent variables. I run the same regressions and use the winning bid instead and get similar results. However, there may be an endogeneity problem with using the winning bid as one of the explanatory variables for the number of bids so I do not reporting these results here, even though they were almost identical in all of the specifications.

Column one of Table 9 shows the results for the regression of the Number of Bids variable on the presale estimator, *order* and dummy variables for the different auctions. The Negative Binomial regression model was used. The first column shows that the order is positive and significant. This suggests that all else equal, cars offered at the end of the auction will tend to receive on average more bids than cars offered at the beginning. To find the exact effect, just to fix ideas, I will check the effect of the order in the first auction. I will assign the variables their means; if the number of cars auctioned in the first auction is 100 and the average presale estimator was $2386.3, then I get that each unit sold increases the number of bids by 0.0178. This result (the positive and significant order coefficient) is robust to the introduction of other covariates like the *year* and *mileage* and excluding the poor cars from the sample. I repeat the same procedure as I did with the winning bid parameter in order to identify the exact shape of the order coefficient. In column two I introduce an order square parameter into the regression. The SAS package reports the above estimator (-0.0000) and a p-value of 0.1611. In column three I run the regression only on the first part of each auction. Again, the order coefficient is positive, significant and larger in size than in the first column. I do the same on the second part of each auction in column four. The order coefficient is now negative although not significant. I find that there is a similarity between the results obtained from regressing the number of bids on the order and regressing the winning bid on order. When I summarize the results pictorially then Figure 1 would summarize my finding. I simply use the number of bids instead of winning bid.

The last column of Table 9 excludes the first 10 observations of each auction. The order coefficient is still positive but smaller in magnitude than in the first regression. The p-value of the order coefficient is 0.1017. When I continue to exclude observations then the order coefficient gets smaller in size and becomes insignificant in general (when I exclude the first 12 observations the order coefficient is 0.0017 and the p-value is 0.0897). If I exclude the first 13 observations of each auction, the order coefficient is no longer significant at 10% level. Hence, we may conclude that if my previous assumption about the competition structure is valid, then after the first thirteen observations in each auction, there is no change in the competitive behavior and agents are already "warmed up." Hence it seems as though during the early stages of the auctions, agents hesitate and so are less competitive. This hesitation vanishes roughly after the first 13 items are auctioned off. To put things in perspective, in all these auctions the first item is auctioned at nine am sharp and the first 10 items are auctioned in less than fifteen minutes. If agents arrive to this warehouse for the first time and it takes a few minutes to adjust to the auction, or agents are just a little "sleepy" in the beginning, then the above results.

In Table 10 the results are shown for the regression of the winning bid and log of winning bid on the same covariates used in Table 4. This time, in the first two columns I exclude the first ten observations in each auction, and in the last two columns I exclude the first twenty cars in each auction. I regress the two models I used previously using these sub-samples. In columns one and three I am using the model in levels (KBB) in which the dependent variable is the winning bid, while in columns two and four I am using the log of winning bid as dependent variable and *LKBB* as one of the covariates.

When winning bid is used as the dependent variable and I exclude the first ten observations in each auction (or more), the order coefficient is no longer significant. The magnitude and the significance level of this coefficient decline with the number of observations excluded. Thus, in this model there is no anomaly after the first ten items are auctioned.

[Table 10 here]

When I exclude the first ten observations from the sample and the model with log of winning bid as dependent variable is being used, the order coefficient is still significant. If I exclude the first twenty observations then the size of the coefficient goes down and it is no longer significant. It stops being significant, at 10 percent significance level, after we exclude the first 18 observations in each auction. In this model there is no anomaly after approximately the first 18 items auctioned.

6. Conclusions

In this paper I test the declining price anomaly. I collected data about car auctions that are conducted by the state of New Jersey. The fact that the cars were randomly assigned to the auction eliminated the problem of heterogeneity among objects and allowed me to test the declining price anomaly hypothesis. When I used the same empirical strategy that was utilized in previous research papers, I found that the price pattern increased as the auction progressed, namely each object sold increase the next object's sales price. This result was robust to several specifications.

I identify exactly the shape of the order parameter and conclude that the increasing price pattern appears only on the first half of each auction and there is no anomaly in the second half of the auctions.

At this point I tried to relate the price pattern to agents' behavior by using the number of bids variable as a measure of competitive or "warmed up" behavior. The results paralleled my previous finding in the sense that the order-winning bid regression pattern was similar to the order-number of bids pattern. In the number of bids regressions, again, the order was positive and significant, which suggests that the aggressiveness of the bidding behavior increases as the auction progresses. When I separate the data into two sub-samples, as before, the order coefficient was positive and significant only on the first half of the auctions. The order stopped affecting the number of bids approximately after the first twelve items were sold. It takes the agents approximately fifteen minutes to warm up and then bidding behavior does not change as the auction progresses.

In both the models I used I found that if the first ten items auctioned in each auction are excluded there was no “increasing price anomaly” when I used the levels model. If I used the logs model then this happened after I excluded the first eighteen items. I therefore conclude that if the agents have private valuations then the results are such because the agents are not “warmed up” in the beginning of each auction. After a short period of time there is no change in bidding behavior and no anomaly in the price pattern.

This paper is an empirical paper and therefore the issue of precisely identifying the agent’s valuations was postponed. However, the results are noteworthy regardless of the valuations. For instance, if the agents have affiliated common values, then the initially increasing price pattern would fit the theory. However, after the order parameter shape is identified it is shown that the increasing pattern occurs only at the beginning of each auction, and after few items the pattern is constant. This might suggest that returns to information revelation have been exhausted at this point and agents have all the information they need about the common component of the objects. However, if agents have private values then the initial results indicate an increasing price “anomaly.” In this instance, however, the prices pattern might be best explained by an insufficiently opportunity for the bidders to warm up.

I think my findings are most closely related to Ginsburgh (1998), who shows that in the case of the wine auction there is no anomaly and the price decline is due to absentee bidders who win the first items. In my case, under the assumption of independent private values, there is no anomaly either and the results about the “anomaly” are obtained because the first few items are sold particularly cheaply because agents are not “warmed up” at the beginning of the auction. I suggest that other researchers who estimate the effect of the order (or any other sequential variable) on price (or any other variable) and find any results to carefully check them. Those results might be obtained because of outlier observations, located in a special place in the sequence (beginning the end or even in the middle) affected the whole data set and determined the regression coefficients.

Beggs and Graddy (1997) found that under their assumptions, the auctioneer would maximize his expected profit by auctioning the items in a declining pattern. Under certain assumptions, this might be true; however, if there is a reason for agents not to be "warmed up" at the beginning of the auction due to environmental reasons (i.e. they have never been in a auction before, they have just arrived, it is too early in the morning, etc.,) then the optimal strategy for the auctioneer will be to devote a couple of minutes to auctioning less important items just to "warm up" the crowd.

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Appendix: Literature Survey

Since Ashenfelter (1989), theoretical and empirical research has been conducted to study sequential auctions and the declining price anomaly. The literature is divided into several parts. First are papers providing theoretical explanations of the phenomenon, some with empirical findings demonstrating the declining price anomaly. Second are empirical investigations of sequential auctions, wherein the anomaly is present; some of these papers provide an empirical explanation of the phenomenon. Third, with much less volume, is empirical evidence of an increasing price trend in sequential auctions; some of these papers provide a theoretical explanation for their findings.

McAfee and Vincent (1993) tried to explain the anomaly and show that the presence of risk-averse bidders can explain this pattern. In this sense, earlier bids will be equal to expected late bids plus some risk premium due to the unknown future price. The intuition is as follows. A player submitting a bid in the first of two period auctions uses the expected utility of the second auction to assess the cost of losing in the first period. The randomness of utility from the final auction reduces risk-averse bidders' value and therefore increases the bids they are willing to make in the first period. For these results it is necessary to have non-decreasing absolute risk aversion. When this is not the case (it does not seem to characterize individual attitudes towards risk), the outcome of a sequential auction might be inefficient. They verified the anomaly using data from wine auctions conducted by Christies in Chicago in 1987.

Engelbrecht-Wiggans (1994) showed that, in sequential auctions with a large number of stochastically equivalent objects, prices will, on average, have a downward trend. He approximated an English auction with a second-price sealed-bid auction and assumed that bidders do not know their valuation of the j+1 object in stage j. Two examples are provided. For the uniform cases, the expected prices decrease (except in trivial cases, such as when there are two objects and three bidders). For the exponential cases, the expected price trend increases (due to unbounded support). For a sufficiently large number of objects with bounded independent values, the average price trend will be downward.

Bernhardt and Scoones (1994) showed that, if there are two objects auctioned sequentially in a second-price sealed-bid auction with private values, and if the bidders do not know their valuation for the second object before the end of the first stage (only its distribution), then we will find, on average, declining prices. The intuition is that bidders recognize in the first stage that, if they do not win, then all other bidders expect the same profit from the second object. Since this option value is the same for all first auction participants, all discounts their bid by the same amount. In Weber's model of identical items, the strategy calls for agents to bid less then their valuation to account for the option value of participating in subsequent auctions. High-valuation bidders have a high-value option (because the goods are identical), and the outcome is a martingale. In the above model, the bidders with high valuation determine the price of the first object. These bidders' discounts are what lead the expected price to fall in later auctions.

Black and De Meza (1992) argued that assuming that the first-round winner is given an option to purchase further units at the same price might also explain a decreasing price path. This option value declines as the auction progresses.

Pezanis-Christou (2001) explained the declining price by considering different types of buyers and supply conditions. He checked the price trends in Dutch fish auctions with two types of buyers (retailers and wholesalers) and different supply conditions in different months. In each auction, there was also a supply uncertainty. He found that, when supply is short, buyer's asymmetries (in demand) do not affect the price trend, and prices decline. When supply is regular, if retailers bid before wholesalers, there is a downward-sloping price trend. When there is no difference in time purchasing, price trends are hump shaped. He concludes that, although different types of buyers pay different prices, their asymmetric preferences and behaviors do not interfere much with the formation of price trends.

Von Der Fehr (1994) showed that, even if bidders are risk neutral, when they value their time, and the first stage reveals the bidders' valuations, we expect a decline in the second-stage selling price. The model is an independent private values English auction of two units. The first stage reveals bidders' valuations. A random fraction of the participants suffers positive participation cost. In this case, there will be, on average, a declining price.

Branco (1997) demonstrated through an example that, in a two-unit sequential ascending price auction, in which some of the bidders have super additive values, the expected price declines from the first stage to the second. The model invovolves two bidders with bundle demand and two bidders with unit demand, but for different units. The utility for the bundle bidders is q/2 if they receive one unit and q+a if they receive two units. The intuition for these results is that both bundle bidders will bid more aggressively in the first stage, whereas only the winner will bid aggressively in the second stage. The unit-demand bidders have the same bidding strategy in both stages, hence the declining price pattern.

Pitchick and Schotter (1988) presented an experimental study of bidding behavior in sequential auctions in which there are budget constraints and perfect information. They found that the budget constraints affected bidders' behavior. The intuition behind this is that bidders may exploit the budget constraints of others by bidding up the price of goods offered early in the auction. This relatively high price for early goods depletes the winner's budget. A later good can then be won at a relatively low price. They tested several hypotheses, among them that, under a second-price auction, the price of a good sold first is higher than that same good sold second. They could not reject this hypothesis.

Empirical research has also been conducted to test the declining price anomaly. Ashenfelter and Genesove (1992) compared prices paid for identical condominium units in face-to-face bargaining with prices paid in an auction. They found that the auction price was higher than the face-to-face price and depended on the order in which the units were auctioned. They regressed the logarithm of the winning bid on dummy variables that indicated the unit type and the order in which the unit was sold. They found that the winning bid declined about 0.27% with each unit sold. When they regressed the order in which the units were auctioned on the prices received in face-to-face bargaining, they found that the coefficient of the order was not significant, which suggests that the decline in price was not due to quality differences between the units sold.

Another explanation relates the price decline to the heterogeneity of objects. Beggs and Graddy (1997), for instance, found declining values and the "afternoon effect" in art auctions. The winning bid had a tendency to decline relative to the estimated market value as the auction progressed. They used two data sets, one for contemporary art and the other for impressionist and modern art. For each data set they ran two linear regressions, one with covariates and the other without. They used the log of the bid price as the dependent variable. When they used the presale estimate as the explanatory variable, it was also in logs. For the regression without covariates, the results for the two data sets were similar, and they found that the bid price decreased about 0.5% per unit sold; when they controlled for the presale value estimator it declined by 0.09%. When covariates were used, such as painting date, length, width, and whether the piece was signed, the order coefficient was significantly negative (-0.05% on average) in most of the specifications, especially when the presale value estimate was used. They showed theoretically that, in an auction ordered by declining valuations, even with risk-neutral bidders, the price received relative to the estimate for later items in the auction should be less than the price relative to the estimate for earlier items.

Ginsburgh (1998) showed that in the case of the wine auctions, there is no anomaly and the price decline is merely due to absentee bidders. He collected data on auctions conducted at Christie’s in London in December 1995 and January and February 1996. He separated the decline into three components: option effect, quality and quantity effect, and absentee bidder’s effect. He found that the most important components of the decline were due to absentee bidders who won the lots. When he checked the price pattern involving bidders present in the auction room, there were no decline prices.

Van Den Berg et al. (2001) used data from Dutch Dutch auctions of roses to examine the declining price anomaly. They used two types of models, one of which was a fixed-effect panel estimate, and verified the declining pattern as well.

Engelbrecht-Wiggans and Kahn (1999) used data from dairy cattle auctions and verified the existence of the “declining price anomaly.” They argued that the crucial feature driving the price declines in the model is auction participants’ limited capacity for purchases, which in turn decreases competition for the final units in the auction. They examined 18 local auctions that took place between 1987 and 1988. In most of the regressions, they used item remaining as a measure of the order and usually estimated a level model. The items were not randomly assigned to the auctions, and they found, after controlling for presale estimator (which was not available to the bidders), that each unit sold decreased the next unit price by $1.47, on average.

Although most papers that have tried to empirically analyze sequential English auctions have found a declining price pattern, some papers have found an increasing price pattern. Gandal (1997), for instance, found evidence of an increase in prices over time through examination of the auction of 17 cable television licenses in Israel. The deadlines for bids were on four different dates and there were total of 38 bids. Interdependent licenses are those that share a common border in a metropolitan area and have populations of the same order of magnitude. The winner in these auctions is the bidder who offers the cheapest subscriber fee package. He found that, among the interdependent licenses, the license price (subscriber fees) fell as time progressed. He estimated a linear regression in which the dependent variable was the subscriber fee and one of the explanatory variables was a dummy for the date. He found a significant coefficient of –0.6, which suggests that, all other things being equal, subscriber fees per channel will fall by 0.6 with each deadline (the average price per channel was 1.83 Israeli shekels). He attributed the decline to increasing returns to scale in the cable industry. It is hard to make any conclusions about price pattern in English auctions from this paper because of the low number of observations, the fact that objects were not randomly assigned, and the fact that the auction was not an English oral auction**.**

Deltas and Kosmopoulou (2000) found evidence of an increasing price pattern in an auction of rare books. Because the books were organized in alphabetical order, they assumed random assignment and therefore no correlation between presale estimated value of the items and the order in which they were auctioned. They showed that when lots of books were divided into four groups, the mean winning bid tended to increase with the quartile of the lots.

Katzman (1999) examined theoretically the sequence of two second price auctions in which individuals had diminishing marginal valuations for both objects and independent private values. In this setup, the expected price pattern was increasing (sub martingale). Milgrom and Weber (1982) found that the price sequence is martingale when there is unit demand. If bidders expected the second round to be below the first, they would bid less aggressively than equilibrium call in the first stage. If bidders expected the second round price to be higher, they would bid more aggressively in the first round. The tradeoff between these two forces resulted in constant expectation of prices equilibrium. In the multi demand model, a martingale resulted only when the winners in both stages differed from each other. When the same bidder won both stages, the expected price pattern was upward hence the overall expected price pattern was increasing. The reason for that was that bidders shaded their high valuation on the first stage and bid their high valuation on the second stage. If the same bidder won both stages, the second order statistic was higher in the last stage.

Table 1: Summary statistics of the different auctions

Auction:	**1**	**2**	**3**	**4**	**5**	**6**
Min car Estimate	375	425	400	400	375	575
Max car estimate	7885	7335	15265	6730	8955	8945
Mean estimate	2386.3 (1593.32)	2873.63 (1334.37)	2369.36 (2015.1)	2774.12 (1369.07)	2818.84 (1334.02)	3471.42 (1862.12)
Min win bid	50	175	50	50	350	400
Max win bid	8350	4400	6200	4000	4250	5400
Mean win bid	1223.75 (1271.18)	1621.88 (959.69)	1454.77 (1130.3)	1188.16 (858.45)	1660.14 (827.48)	2123 (1285.52)
Mean number of bids	9.91 (8.05)	10.14 (5.13)	11.15 (6.62)	10.04 (7.39)	13.27 (7.54)	13.28 (6.30)
Condition:						
Percent good	19	35	46.36	42.11	51.43	38.67
Percent fair	59	41.25	45.45	39.47	35.71	41.33
Percent poor	22	23.75	8.18	18.42	12.86	20
N	100	80	110	114	70	75

Note: Standard errors are in parentheses.

Table 2: Ordinary least squares regressions for log winning bid

Auction	1	2	3	4	5	6
Intercept	0.216 (0.847)	3.393 (0.885)	0.614 (0.598)	0.924 (0.931)	0.410 (0.911)	-0.614 (0.862)
Year	-0.059 (0.021)	-0.104 (0.021)	-0.037 (0.012)	-0.075 (0.020)	0.013 (0.015)	-0.017 (0.015)
LKBB	0.972 (0.092)	0.639 (0.096)	0.909 (0.058)	0.867 (0.099)	0.871 (0.096)	1.035 (0.092)
LPoordum	-0.080 (0.016)	-0.042 (0.013)	-0.079 (0.018)	-0.091 (0.018)	-0.053 (0.014)	-0.018 (0.012)
Mileage	$-28*10^{-7}$ $(97*10^{-8})$	$-21*10^{-7}$ $(12*10^{-7})$	$-13*10^{-7}$ $(11*10^{-7})$	$-22*10^{-7}$ $(12*10^{-7})$	$-7*10^{-7}$ $(93*10^{-8})$	$-16*10^{-7}$ $(11*10^{-7})$
Order	0.0046 (0.0018)	0.0008 (0.0019)	0.0017 (0.0010)	0.0018 (0.0014)	0.0019 (0.0017)	0.0036 (0.0016)
Observations	96	77	108	112	68	73
R-squared	0.7785	0.7575	0.9024	0.7381	0.7581	0.8225

Note: Standard errors are in parentheses. The regression equation for each auction was

$$\ln bid = \alpha_0 + \alpha_1 year + \alpha_2 \ln kbb + \alpha_3 I_{POOR} \ln kbb + \alpha_4 mileage + \alpha_5 order$$

Table 3: Regression results using all the data

	All cars				Without poor	
	Log bid	**Bid**	**Log bid**	**Bid**	**Log bid**	**Bid**
Intercept	7.32 (0.115)	1968.52 (138.84)	-0.99 (0.235)	234.24 (96.21)	-0.83 (0.24)	238.26 (110.42)
Order	0.0033 (0.0013)	4.26 (1.65)	0.0025 (0.0007)	2.70 (0.953)	0.0024 (0.0007)	3.05 (1.09)
KBB				0.54 (0.016)		0.53 (0.018)
LKBB			1.05 (0.028)		1.02 (0.029)	
Poordum			-0.07 (0.006)	-0.17 (0.024)		
Auction dummies	Yes	Yes	Yes	Yes	Yes	Yes
R –squared	0.1080	0.0890	0.7751	0.7039	0.7664	0.6781
Observation	539	539	539	539	448	448

Note: Standard errors are in parentheses. Regression results of winning bids and log winning bid on the explanatory variables using the data from all the auctions together.

Table 4: Regression results using all the data with covariates

	LKBB Order		KBB Order		LKBB Seq		KBB Seq	
Intercept	-0.653 (1.166)	-0.956 (1.336)	355.26 (445.95)	193.99 (531.75)	-0.567 (1.167)	-0.76 (1.33)	482.31 (446.61)	356.81 (533.29)
LKBB	1.046 (0.123)	1.083 (0.142)			1.051 (0.123)	1.07 (0.14)		
KBB			0.642 (0.049)	0.656 (0.056)			0.642 (0.049)	0.653 (0.056)
Poordum	-0.0179 (0.0163)		-0.112 (0.042)		-0.016 (0.016)		-0.108 (0.042)	
Year	-0.017 (0.020)	-0.018 (0.022)	-4.68 (26.24)	4.943 (31.888)	-0.015 (0.020)	-0.017 (0.02)	-2.860 (26.33)	5.54 (31.98)
Order	0.0024 (0.0006)	0.0023 (0.0006)	2.332 (0.863)	2.416 (0.978)				
Seq					0.123 (0.035)	0.12 (0.036)	122.57 (47.91)	135.37 (54.33)
Mileage	$-17*10^{-7}$ $(15*10^{-7})$	$-16*10^{-7}$ $(16*10^{-7})$	-0.003 (0.002)	-0.003 (0.002)	$-16*10^{-7}$ $(15*10^{-7})$	$-17*10^{-7}$ $(16*10^{-7})$	-0.003 (0.002)	-0.003 (0.002)
Auction dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interaction	All	All	All	All	All	All	All	All
R-squared	0.8213	0.8139	0.7755	0.7593	0.8201	0.8128	0.7729	0.7568
Observations	539	448	539	448	539	448	539	448

Note: Standard errors are in parentheses. Regression results of winning bids and log winning bid on the explanatory variables using the data from all the auctions together. The level model is:

$$y_{ij} = \alpha_0 + \alpha_1 year_{ij} + \alpha_2 poordum_{ij} + \alpha_3 mileage_{ij} + \alpha_4 order_{ij} + \alpha_5 Kbb_{ij} +$$
$$+ I_j(\alpha_6 + \alpha_7 year_{ij} + \alpha_8 poordum_{ij} + \alpha_9 mileage_{ij} + \alpha_{10} Kbb_{ij})$$

Similar results obtained when we reduced the explanatory variables in the model.

Table 5: Regression results from regress KBB as dependent variable

Auction	1	2	3	4	5	6
Intercept	1663.75 (315.85)	2902.86 (308.63)	2078.34 (386.66)	2765.32 (257.25)	3349.46 (319.02)	2725.34 (404.91)
Order	12.38 (5.45)	-3.14 (6.74)	4.96 (6.04)	-0.827 (3.902)	-16.24 (7.89)	17.38 (9.37)
R-squared	0.0515	0.0028	0.0063	0.0004	0.0595	0.0456
Observations	98	80	109	113	69	74

Note: Standard errors are in parentheses.

Table 6: Regression of KBB and Order using all observations

	KBB				Order	
Intercept	2627.77 (134.68)	3246.55 (207.99)	2756.4 (99.56)	3460.42 (198.38)	46.72 (2.40)	33.94 (4.11)
Order	0.97 (2.41)	3.495 (2.483)				
Seq			163.80 (140.29)	165.39 (137.75)		
KBB					0.0003 (0.0007)	-1.80 (4.68)
Auction dummies	No	Yes	No	Yes	No	Yes
R-squared	0.0003	0.0484	0.0025	0.0474	0.0003	0.0931
Observations	539	539	539	539	539	539

Note: Standard errors are in parentheses. Dependent variable is Kelly Blue Book private party price (KBB) in the first four columns and Order in the last two. There is no significant connection between the order the vehicle sold and the Kelly Blue Book value.

Table 7: Probit regression results using Seq as dependent variable

	All cars			Without Poor cars		
Intercept	0.11 (0.10)	-0.34 (0.27)	0.08 (0.654)	0.17 (0.11)	-0.15 (0.30)	0.44 (0.72)
KBB	-0.000037 (0.000033)	$5.87*10^{-6}$ (0.000042)	-0.000039 (0.000034)	-0.000046 (0.000036)	$-16*10^{-6}$ $(44*10^{-6})$	$-48*10^{-6}$ $(37*10^{-6})$
Year		0.03 (0.02)			0.027 (0.023)	
Auction dummies	No	No	Yes	No	No	Yes
Log likelihood	-375.69	-374.11	-375.58	-311.50	-310.79	-311.20
Observation	543	543	543	451	451	451

Note: Standard errors are in parentheses. Dependent variable is Seq, a dummy that is 1 if the vehicle is sold in the second half of the auction. Qualitatively similar results obtain using log estimate instead of the estimate.

Table 8: Regression results obtained by adding an order squared parameter

	LKBB	KBB	Seq=0	Seq=1	Seq=0
Intercept	-0.640 (1.162)	203.58 (445.22)	0.128 (1.56)	-0.965 (1.719)	0.147 (1.559)
LKBB	1.033 (0.123)		0.946 (0.168)	1.113 (0.178)	0.936 (0.169)
KBB		0.634 (0.048)			
Poordum	-0.018 (0.016)	-0.11 (0.042)	0.003 (0.023)	-0.041 (0.022)	0.001 (0.023)
Year	-0.018 (0.020)	-6.30 (26.03)	-0.023 (0.034)	-0.020 (0.029)	-0.026 (0.034)
Order	0.0067 (0.0022)	11.05 (3.00)	0.0049 (0.0017)	-0.0008 (0.0018)	0.012 (0.006)
Order sqr	$-43*10^{-6}$ $(21*10^{-6})$	-0.085 (0.028)			-0.00013 (0.00011)
Mileage	$-16*10^{-7}$ $(15*10^{-7})$	-0.0035 (0.002)	$-19*10^{-7}$ $(24*10^{-7})$	$-17*10^{-7}$ $(22*10^{-7})$	$-17*10^{-7}$ $(24*10^{-7})$
Auctno1	0.939 (1.348)	595.59 (550.42)	-0.067 (1.826)	1.316 (1.983)	-0.110 (1.825)
Auctno2	4.09 (1.49)	1748.59 (627.84)	2.243 (1.962)	5.638 (2.327)	2.263 (1.960)
Auctno3	1.26 (1.37)	1833.06 (536.77)	0.768 (1.843)	2.042 (2.055)	0.641 (1.845)
Auctno4	1.55 (1.37)	-173.13 (552.98)	1.054 (1.880)	1.528 (1.998)	0.858 (1.887)
Auctno5	0.63 (1.71)	-22.04 (621.83)	-1.082 (2.311)	2.386 (2.757)	-1.292 (2.317)
Interaction	All	All	All	All	All
R-squared	0.8227	0.7795	0.8508	0.8233	0.8513
Observations	539	539	271	267	271

Note: Standard errors are in parentheses. The first column used log of winning bid as the dependent variable. The second column used winning bids as the dependent variable. Next we separate the data set into two data sets. The first, Seq=0, runs the above regression on the first half of each auction. The second, Seq=1, used the second half of each auction to run the above regression using log of winning bid as a dependent variable. Similar results obtained by using winning bid as the dependent variable and when we exclude the poor condition cars from the sample.

Figure 1

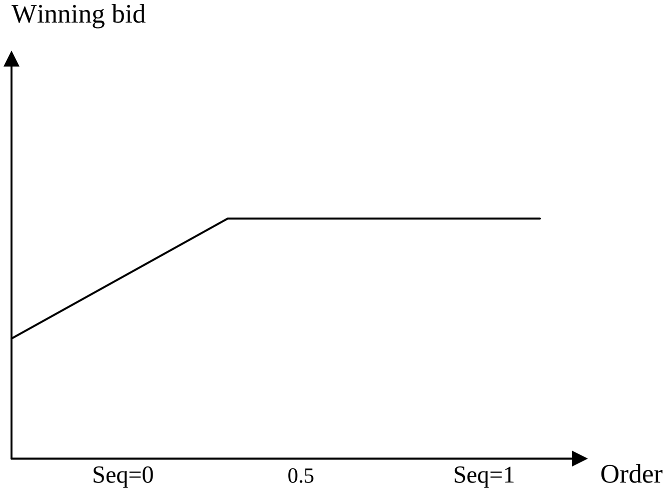

Table 9: Negative Binomial regression results for Number of Bids

	All	All	Seq=0	Seq=1	Order>10
Intercept	1.3143 (0.2758)	1.2814 (0.27)	1.1963 (0.3853)	1.6347 (0.4922)	1.5362 (0.303)
Order	0.0023 (0.0008)	0.0061 (0.0028)	0.0062 (0.0023)	-0.0009 (0.0023)	0.0016 (0.0010)
KBB	0.0002 (0.0000)	0.0002 (0.0000)	0.0002 (0.0000)	0.0002 (0.0000)	0.0002 (0.0000)
Auction dummies	Yes	Yes	Yes	Yes	Yes
Order square		-0.0000 (0.0000)			
Dispersion	0.1605 (0.0158)	0.1594 (0.0157)	0.1531 (0.0213)	0.1612 (0.0226)	0.1658 (0.0172)
Deviance	1.0232	1.0252	1.0197	1.0520	1.0325
Log Likelihood	8396.83	8397.81	4056.53	4344.68	7578.14
Observations	505	505	261	244	446

Note: Standard errors are in parentheses. Seq=0, runs the above Negative Binomial regression on the first half of each auction. The second, Seq=1, used the second half of each auction to run the above regression using number of bids until the winning bid as a dependent variable. Order>10 run the same regression on vehicles that auctioned after the first 10 vehicles was auctioned. Similar results obtained by using gamma, inverse gauss and Poisson as the dependent variable distributions.

Table 10: OLS results using bid and log bid as dependent variables

	Order>10		Order>20	
	KBB	**lKBB**	**KBB**	**lKBB**
Intercept	362.44 (465.94)	-0.749 (1.207)	252.67 (559.37)	-1.44 (1.43)
Year	-0.782 (27.13)	-0.014 (0.021)	7.26 (30.69)	-0.0002 (0.023)
KBB	0.652 (0.050)		0.65 (0.055)	
LKBB		1.055 (0.128)		1.12 (0.149)
Poor dummy	-0.118 (0.043)	-0.018 (0.016)	-0.12 (0.045)	-0.032 (0.0175)
Mileage	-0.0039 (0.0021)	$-16*10^{-6}$ ($16*10^{-6}$)	-0.003 (0.0025)	$-5*10^{-7}$ ($19*10^{-7}$)
Order	1.074 (1.034)	0.0020 (0.0007)	0.539 (1.24)	0.0010 (0.00089)
Auction dummies	Yes	Yes	Yes	Yes
Interaction	All	All	All	All
R-squared	0.7793	0.8213	0.7715	0.8275
Observations	479	479	419	419

Note: Standard errors are in parentheses. Order>10 runs OLS regression on vehicles that auctioned after the first 10 vehicles were auctioned. The first and third column used wining bid as the dependent variable. The second and fourth column used log-wining bid as the dependent variable.