Center for Economic Institutions

Working Paper Series

No. 2010-4

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November 2010

Center for Economic Institutions

Working Paper Series

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Paper for Discussion: first draft, 19 December 2009; this draft, November 27, 2010.

IS THE 'LINKAGE PRINCIPLE' VALID?: EVIDENCE FROM THE FIELD

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We present field evidence involving experienced bidders that supports the linkage principle—specifically, the prediction that in affiliated-values auction environments the expected revenues generated at open-outcry, ascending-bid (English) auctions are higher than those under other auction formats that reveal less information to participants. Using field data from a large seller of automobiles which experimented with different selling formats, we find that the seller's average revenues were significantly higher under an English auction than under a dynamic Internet auction that revealed far less information to bidders.

1. Introduction and Motivation. In an influential and classic paper, Milgrom and Weber [1982] derived a powerful result, and coined the term *linkage principle* to describe it. Simply put, in auction environments having affiliated values, the linkage principle states that a seller can expect to increase revenues by providing more information to bidders, both before and during the auction. An implication of the linkage principle is that open-outcry, ascending-price auctions (often referred to as *English* auctions) will, on average, earn more revenue for the seller than sealed-bid auctions, under which no information is released, or similar auction formats that reveal less information to potential buyers. According to Perry and Reny [1999], "the linkage principle has come to be considered one of *the* fundamental lessons provided by auction theory."

Well-known exceptions to the linkage principle exist: for example, within independent private-values environments, the celebrated *Revenue Equivalence Theorem*, first outlined by Vickrey [1961, 1962] and then proven by Riley and Samuelson [1981] as well as Myerson [1981], states that any auction format that has the same probability of assigning a winning bidder generates the same expected revenue to the seller. In particular, the Revenue Equivalence Theorem predicts that the expected revenues earned by the seller at sealed-bid auctions will be the same as those earned at English auctions, at least when the distribution from which the values are drawn is the same for all potential buyers, who are also risk-neutral.

Thus, the presence of some degree of dependence, or a *common-value component*, in the signals of potential buyers is critical to the validity of the linkage principle. The affiliated-values model is a generalization of the common-value model developed by Wilson [1977]. Under affiliation, the conditional expectation of any monotonic function of the signals of all bidders is an increasing function of any individual bidder's own signal. When the signals of bidders are dependent in this manner, information released by the seller or information the seller provides concerning the bids made by other participants (by virtue of the seller's choice of auction format) helps bidders refine their beliefs concerning the true value of the object for sale, which in turn induces them to bid more aggressively than they would in the absence of such information.

While one can imagine circumstances under which the release of information could adversely affect the outcome at an auction (for example, if the seller released information concerning problems with the object for sale, or when low bids by some bidders convince other bidders that the item is worth less than they originally thought), the remarkable feature of the linkage principle is that, *ex ante*, providing more information raises the expected revenues to the seller. Milgrom and Weber [1982] have summarized the implications of the linkage principle succinctly: "honesty is the best policy."

JEL classification:C14, D44, L1

Keywords and phrases: revenue comparison, auction choice, linkage principle, used-car auctions

The linkage principle can fail for other reasons. For example, Perry and Reny [1999] have presented a counter-example to the linkage principle in a multi-unit auction. Another reason why the linkage principle may fail is when bidders collude. In general, collusion is easier to sustain in environments that are rich in information than when little information is released: English auctions release more information than sealed-bid ones, or other less open auction formats.

To our knowledge, the specific implication of the linkage principle that English auctions should, on average, generate higher revenues than sealed-bid ones, or other less open auction formats, has never been subjected to a direct empirical test, at least not using data from "the field." All of the empirical tests that we know of have been conducted using controlled laboratory experiments. In an important series of papers, Kagel and Levin [1986] and Levin et al. [1996] analyzed the behavior of laboratory subjects at English and sealed bid auctions in situations where a common-value component existed in their experimentally-generated values.

The results of these experiments, summarized in Kagel and Levin [2002], are mixed. For relatively inexperienced subjects, they found a pronounced "winner's curse" caused by overbidding at sealed-bid auctions relative to English ones. On average, the overbidding caused the seller's revenues to be higher at sealed-bid auctions than at English auctions, contrary to the prediction of the linkage principle. However, in experiments involving experienced bidders, the winner's curse was ameliorated and the English auctions generated higher expected revenues than the sealed-bid ones, a finding consistent with the linkage principle.

We present an empirical analysis of (uncontrolled) field experiments conducted by a large rental car company that sells hundreds of unwanted, used cars each month.[1] The rental car company is obviously quite interested in adopting a selling mechanism or an auction format that maximizes the revenues it can earn from the sale of its unwanted inventory of used cars.

While there are certainly individual-specific, private-value components in any automobile purchase ("I *really* want that pink *Cadillac* over there, you know, the one with the cream leather seats, because … "), common-value elements must surely exist, too. Specifically, a pre-owned vehicle's true quality is uncertain because the intensity with which it has been used and the care shown it by previous drivers are unknown. This unknown quality is basically the same to all potential buyers, but will remain undiscovered until the vehicle has exchanged hands and the new owner has experienced it on the road. In short, we do not think it unreasonable to assume affiliation among the signals of potential buyers of used cars.

At any given point in time, the rental car company's fleet contains more than $30,000$ vehicles; over the last decade, the company has sold approximately 400 vehicles each month. During this period, the company has sold used cars under four different selling mechanisms: first, at open-outcry, ascending-price auctions conducted by the rental car company at individual car rental outlets; second, at computerized Internet auctions held in cyberspace; third, at open-outcry, ascending-price auctions conducted by a large auction house at a central location; and, fourth, through bilateral bargaining between company managers and individual customers who have rented cars under long-term rental contracts. We refer to these different methods of selling used cars as *sales regimes* and our analysis is focused on the simple question of determining which of these sales regimes yielded the highest average revenue to the rental car company.

Prior to developing its own specialized Internet auction software, the rental car company sold most used cars at open-outcry, ascending-price auctions conducted at individual car rental outlets; in addition, a relatively few used cars were sold directly to individual customers who had rented vehicles under long-term rental contracts after informal bilateral bargaining with the customer. However, in 2002, the rental car company began to suspect that collusion among some participants at some of its English auctions. The rental car company then invested in developing a unique auction format for selling used cars online. The participants

[1]The rental car company which provided us the data has requested that it remain anonymous. In addition, we are restricted from providing information that could identify the company as well as any individual vehicles, customers, or bidders.

under this Internet-auction selling mechanism were strictly anonymous. Over the course of an Internet auction, which was two minutes in duration, an individual bidder would only see a single piece of information: whether his bid was the highest competing bid at the auction. Participants could not observe the bids of their opponents. In fact, an individual bidder did not even know what the highest bid was at any time during the auction, unless the bidder himself had the current highest bid.

By 2007, the volume of vehicles the company was selling at its Internet auctions was so large that the enterprise began to occupy too much of its managers’ time; management began to regard the Internet auctions as a distraction from their main business—renting cars. Thus, the company decided to contract with a large, prominent auction house to sell the used cars. The auction house employs an open-outcry, ascending-bid auction that is virtually identical to an economist’s notion of an English auction. In particular, unlike the company’s Internet auctions, a bidder at an English auction conducted by the auction house could see the other participating bidders as well as their bids at each stage in the auction, including the highest bid at any point in the auction. The auction house charges a variable commission rate for its services, but the average commission rate is approximately ten percent of a vehicle’s gross selling price.

We have analyzed empirically the traded prices received by the rental car company (including prices net of commission in the case of sales by the auction house) over the period 2002 to 2008 under the four different selling mechanisms. We have compared revenues for specific vehicle classes and individual makes/models of vehicles for which we have the largest number of observations. While in each month the company sells a large number of vehicles in total, the numbers of vehicles sold for specific makes and models in any given month are insufficient to employ a “regression discontinuity” approach where net revenues for a specific makes/models are compared just before and just after the transition from one sales regime to another, such as the transition from the company’s Internet auctions to sales through the auction house, which began on 1 January 2008.

Instead, we have averaged prices over the much larger numbers of vehicles sold during entire sales regimes, not just the much smaller numbers of vehicles sold around sales-regime transitions. We justify this approach by noting that, during the period of our analysis, there were no sigificant “macro shocks” or inflation in the used-car market in the country where the rental company operates, something we shall document in section 3. In addition, no significant changes occurred in the engine or other features and characteristics of the specific car models we analyzed. Thus, we feel we can rule-out these explanations for the significant shifts in prices across different sales regimes. In short, we believe that a simple comparison of average prices received for specific high-volume vehicle makes and models provides an appropriate basis for measuring the effect of the sales regime and selling mechanism on revenues earned by the seller.

In general, our empirical findings are consistent with the prediction of the linkage principle. Specifically, comparing traded prices for mid-sized vehicles under the two main sales regimes, where the vast majority of our observations exist (the company’s own Internet auctions and the English auctions conducted by the auction house), *net* revenues earned by the rental car company were, on average, significantly higher at the English auction than at the Internet auctions that released less information. However, we found that revenues earned at the English auctions conducted by the rental car company were, on average, significantly *lower* than either of these two sales regimes. This evidence suggests that the rental car company was correct in suspecting that bidder collusion was at play at the English auctions conducted at the individual car rental outlets, and this suspected collusion led to lower average prices than those earned under the other sales regimes.

In the case of bilateral bargaining between company managers and individual customers who had rented them under long-term rental contracts, the average prices received were less than at the Internet auctions and less than the average net prices received from the auction house, but more than the average prices received at the English auctions conducted by the rental car company. This finding is also consistent with the possible existence of collusion at the English auctions conducted by the rental car company.

We also found, however, that when we analyzed specific makes/models of cars (and we considered three for which we have the largest number of observations) the rankings of the four sales regimes differed across the three models. For car Model A (again the specific make/model has been suppressed due to confidentiality restrictions imposed by the rental car company), the average price earned was highest under the English auction conducted by the auction house (again, net of commmission), followed by bilateral bargaining, then the Internet auctions; the lowest average revenues obtained at the English auctions conducted by the rental car company. For car Model B, the average revenues under Internet auctions, English auctions conducted by the auction house, and bilateral bargaining were about the same and not significantly different from one another, but all three of these sales regimes generated higher revenues, on average, than did the English auctions conducted by the rental car company: the differences were significant at conventional p-values. For car Model C, there were not enough observations for the auctions conducted by the rental car company or under bilateral bargaining to draw any statistically reliable conclusions, but the average net revenues earned at the English auctions conducted by the auction house were significantly greater than those at the Internet auctions; the difference was statistically significant at conventional p-values.

Overall, these findings support the conclusion that bidder collusion was a distinct possibility at the English auctions conducted by the rental car company, and this could explain why this open-outcry auction format generated lower average prices than the rental car company's reduced-information Internet auction format, a result that would be inconsistent with the linkage principle, at least when collusion is ignored. Thus, when cooperation among potential buyers is present, reducing bidder information in the way the rental car company did at its Internet auctions can be an effective way to thwart collusion and, thus, increase average revenues. Nevertheless, other means of policing or thwarting collusion may exist, too. We do not know how the auction house, which also operates an open-outcry auction, succeeded in thwarting collusion, but we found that this selling mechanism resulted in the highest average net revenues to the rental car company, consistent with the predictions of the linkage principle. Another possible explanation for the higher average revenues from the auction house could, however, be demand aggregation: the auction house may have succeeded in attracting more bidders than were present under the other sales regimes. In the conclusion, we discuss reasons why we do not think that the somewhat larger number of bidders who participated at the auction-house auctions could explain the significantly greater average sales prices under this sales regime.

Overall, the single most important message to take from our analysis is the following conclusion: consistent with the prediction of the linkage principle, the average traded price of vehicles was significantly higher at the open-outcry, ascending-price auctions conducted by the auction house than the closed Internet auction implemented by the rental car company. The Internet auctions may have been successful in thwarting the collusion potentially present at the English auctions conducted by the rental car company at each of its car rental outlets. If there were any collusion by participants at the English auctions conducted by the auction house, then it does not appear to have been successful because the average prices are the highest under this sales regime—especially when we consider the *gross* traded price and not the *net* traded price actually received by the car rental company.

We believe our findings are significant because they represent the first empirical test of the linkage principle that we know of using field data concerning experienced bidders. Our findings are consistent with the evidence found by Kagel et al. [1987] concerning experienced bidders in laboratory experiments. After we completed this paper, we became aware of a paper by Tadelis and Zettelmeyer [2010], who reported results from a controlled experiment conducted at a different rental car company and designed to test a different implication of the linkage principle—viz., whether the *ex ante* release of information concerning the mechanical conditions and repair histories of vehicles being sold at wholesale automobile auctions increased the average traded price. Tadelis and Zettlemeyer found that this information release did increase average traded prices, which is also consistent with the linkage principle. However, in their research, they did not undertake experiments that show the effect of the selling mechanism on average traded prices, the main contribution of this paper.

The remainder of our paper is in three sections: in section 2, we describe in some detail the four sales regimes as well as the data, while in section 3, we presents a summary of our empirical analysis and, in section 4, we summarize and conclude our research.

2. Data. During the period for which we have data, from the last quarter of 2002 onward, essentially four different sales regimes existed in the rental car company we are studying. For lack of imagination, but for parsimony, we refer to them in order as Regimes 1, 2, 3 and 4, respectively. For ease of reference by the reader, in table 1, we provide summary descriptions of the sales regimes.

TABLE 1
Description of Sales Regimes

Sales Regime	Description
Regime 1	English auctions conducted by rental car company at individual rental outlets.
Regime 2	Internet auctions conducted in cyberspace by rental car company.
Regime 3	English auctions conducted by auction house at large central site.
Regime 4	Bilateral bargaining between company managers and individual customers.

Like many companies, the one whose practices we are studying started small. Thus, Regime 1 was the traditional way in which to sell used cars—at English auction. These English auctions were conducted at each of the rental outlets of the company, so competition was probably not high. Because the control methods in the early life of the company did not involve computers, the data from this period are scant. Even when computers were introduced, for reservations and so forth, this did not trickle down to selling vehicles until much later in the company's history. In any case, we really only have part of one year's data concerning this period. In addition, the organization of auctions during this regime was less than optimal, dictated more by tradition and the personality of the manager than by thoughtful purpose. Specifically, within the company, it was believed by some that collusion among potential buyers was possibly preventing the company from getting the fair value for its used cars.

In response to this situation, at the beginning of 2003, the company implemented Regime 2, which involved conducting electronic auctions over the Internet. These electronic auctions were held at pre-announced times each month; vehicles were sold one at a time in a particular order over the Internet at auctions lasting exactly two minutes each.[2] At these auctions, a potential buyer could submit as many bids as he liked. However, the only information available to any participant was whether he was the highest bidder. Specifically, none of the participants knew how many bidders were active at the auction. Because of these institutional features, unlike at the electronic auctions used by eBay, referred to as the *California auction* format by Steiglitz [2007], it was virtually impossible to snipe effectively: except for the current highest bidder, none of the other participants knew what the current price was, so only a lucky sniper could sneak in at the last second to "steal" a vehicle away from the existing highest bidder.[3] At the end of the auction, the highest bid-

[2]In practice, the time stamps in the electronic files document that some of the auctions were, in fact, as long as 121 seconds, but we believe that this heterogeneity is unimportant.

[3]Sniping at auctions refers to the practice of observing a timed online auction, such as those electronic auctions organized by eBay, and then placing a winning bid at the last possible moment, typically in the final seconds of the auction. Because opponents cannot always respond in time, a sniper may win the object at a price lower than were the sniped bid submitted earlier in the auction. On the Amazon electronic auction site, any bid submitted in the last ten minutes of the auction prolongs the end of the auction by another ten minutes, making it impossible to snipe; for more on this, see Bajari and Hortaçsu [2004] or Roth and Ockenfels [2006]. At both eBay and Amazon auctions, the current price is known to all, unlike at the Internet auctions we study, where it is known only to one participant—the current highest bidder.

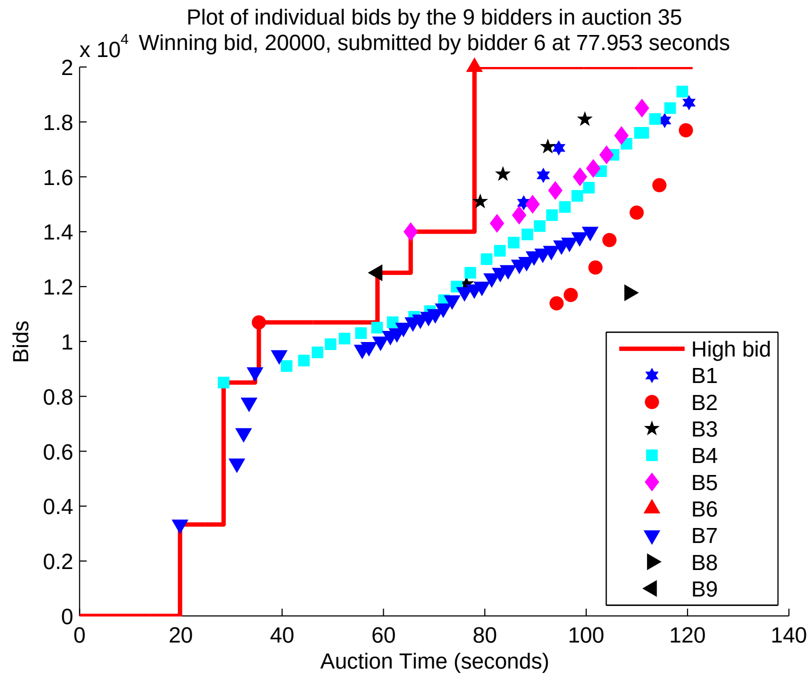

FIG 1. *Sequence of Bids Observed at a Representative Internet Auction*

der won, and paid what he bid. Thus, the pricing rule at these auctions was first-price (pay-your-bid) rather than second-price. Because of bid increments, the pricing rule at California auctions is an hybrid between the first-price and second-price auctions; for more on the importance of bid increments at California auctions, see Hickman [in press]. In short, the electronic auctions conducted by the rental car company were really nothing like the well-known California auctions conducted by eBay.

By eliminating a public forum in which signals could be discreetly exchanged and in which cooperative behavior could be monitored (and, thus, potentially enforced) by the colluders, the rental car company believed it could thwart uncompetitive behavior among the potential buyers. What made these first-price auctions different from other first-price auctions typically used is that a bidder could, by trial-and-error, discover what the highest current tender was. By allowing participants to increase their bids sequentially, some information release was permitted, unlike in the models of standard first-price auctions studied by Milgrom and Weber [1982].

The company also restricted who could participate at the Internet auctions. In particular, only a set of 95 used-car dealers were given computer accounts. These dealers were obvious resellers of pre-owned vehicles: historically, they had purchased many vehicles from the rental car company, solely for the purpose of resale.

Because the Internet auctions were electronic, data collection was relatively easy. Essentially, we have access to virtually every piece of relevant information concerning the auctions. The only exception is a three-month period in 2004, during which the company was unable to provide us access to any transaction data. We do not believe there is any hidden agenda here: the most likely explanation is that the data were simply lost in a computer crash.

In figure 1, we present a graph of the sequence of bids observed at a representative Internet auction. There were nine bidders participating at this auction, which lasted two minutes. The solid line plots the highest bid received at each instant, and the various symbols plot the actual bids submitted by the nine bidders. Three of the bidders—6, 8, and 9—tendered only a single bid at the auction. Bidder 6 submitted the highest bid $20,000$ at the 77.953-second mark of the auction. This remained the highest bid for the remainder of the two minute auction and, consequently, bidder 6 won the auction and paid $20,000$.

It is quite unusual to see the large number of “dominated” bids being placed at this auction. Of course, this occurs because of the limited information that the auctioneer provides to the bidders. As we noted, no bidder can observe the number of other bidders or the bids they have placed in the auction: the only information a bidder observes is whether his bid is the highest. Consequently, we see obvious “testing strategies”’ being used by the other six bidders, who gradually increased their bids in an attempt to become the high bidder and possibly also to learn what the high bid was at that moment of the auction. It is, however, evident that several bidders never succeeded in learning what the high bid was since their bids were always below the high bid at the auction. Examples include bidders 2 and 3, whose bids are plotted as circles as well as five-pointed stars, respectively, in figure 1.

Clearly, the Internet auction provides more information to bidders than what they would receive at a single-shot sealed-bid auction. In particular, a bidder can start out with low bids and increase them gradually in attempt to learn what the high bid is. But, as we see in figure 1, this strategy is not always successful. In fact, most of the bidders who won most frequently at the Internet auctions placed only a small number of bids, often just a single bid very close to the end of the auction. This strategy is similar to the type of bid sniping observed at eBay auctions, but not as effective.

It is also clear that the information provided to bidders at the Internet auction is less than what they would observe at an English auction, such as the auctions conducted by the auction house where all bidders see all bids placed by other bidders, including the winning bid. Furthermore, bidders can also potentially know the identities of the competing bidders because they are physically present and are calling out their bids on the auction floor. Thus, the information provided to bidders at the Internet auction is greater than the information provided at a sealed-bid auction, but less than the information provided at an English auction. If bidders are not colluding and their values are affiliated, then the linkage principle predicts that the English auction should generate higher expected revenues to the seller than the Internet auction, but the Internet auction should generate higher expected revenues than a sealed-bid auction.

Unfortunately, the rental car company did not sell any of its vehicles at sealed-bid auctions, so we are unable to test the latter implication of the linkage principle. However, our intuition is that the value of using “testing strategies”’ and attempting to learn the value of the high bid is limited in these fast-moving auctions. We conjecture that the Internet auctions are “strategically close” to sealed-bid auctions in the sense that expected revenues are not much higher than those that would obtain at sealed-bid auctions. In separate work, we plan to test this conjecture by solving a model of equilibrium bidding strategies at the Internet auction and comparing expected revenues to those that arise at a sealed-bid auction. To our knowledge, the Internet auction used by the rental car company is a unique auction institution that has never been analyzed either theoretically or empirically in the previous literature concerning auctions.

By 2007, conducting the electronic auctions had become a distraction to managing the company: the auctions were occupying too much time. Thus, management sought to exit this business. What the rental car company did was hire an auction house to conduct the sales on its behalf. In return, the firm selling the vehicles would receive a commission that varied according to the make of vehicle; the average commission rate was about ten percent of the gross sales price. We refer to this period, which began on 1 January 2008, as Regime 3.

The auction house chose to sell the vehicles using the auction format that used-car dealers know best—the

English auction format, a second-price rule. Because the auction house is rewarded using a commission, this firm presumably had an incentive to design the auctions in a better way than had been done under Regime 1. While the rental car company has been quite generous with providing us information and in answering our questions, we have no close relationship with the auction house. One of the authors has attended several Regime 3 auctions. From this field research, we see no obvious differences from other English auctions used to sell pre-owned vehicles. Of course, none of the authors observed the Regime 1 English auctions, so we cannot make direct comparisons between the Regime 1 and 3 auctions.

The information gathered under Regime 3 is quite different. Under its contract with the rental car company, the auction house is only required to report the date and time of an auction as well as the winning bid received for each vehicle sold as listed on a manifest. We know from the auction house that the potential buyers under Regime 3 are the dealers who participated under Regime 2, plus any private buyers who also want to participate. It seems unlikely that any additional used-car dealers also chose to participate because the rental car company was quite inclusive when it assigned computer accounts under Regime 2 for the most obvious reason: it wanted to sell its used cars, and believed the more potential participants the higher the price. Presumably, the rental car company excluded private buyers under Regime 2 because it would have been an administrative nightmare to deal with a large number of potentially inexperienced bidders trading over the Internet.[4]

At the same time the auction house has been conducting auctions, the rental car company has also pursued a fourth way to sell vehicles—bilateral bargaining. Like most rental car companies, the one we are studying rents to customers who only need vehicles for short periods of time, such as travellers arriving at airports. But the firm also leases vehicles for long periods (for example, one to three years) to other clients. The “demographics” of the inventory of vehicles sold under bilateral bargaining are essentially representative of the fleet at large. What differs are the buyers. Many of those who purchased vehicles from the rental car company under Regime 4 were long-term clients who had previously held leases of a year or more, and presumably knew well the vehicles they were purchasing. Some of these clients had other contracts with the firm. Why bring this up? Well, some of these long-term lessees have better bargaining positions than do the bidders at auctions. Of course, the rental car company is in a strong position as well: those vehicles not sold under bargaining can always be sold at auction.

Note, too, that it seems plausible that higher quality vehicles are sold under bargaining than at auction: of the long-term lessees looking to purchase a vehicle, those who have had good experiences with their vehicles (so the high-quality vehicles) would be more likely to offer high prices, which the rental car company is more likely to accept, leaving the remainder to be sold at auction. This sort of adverse selection problem is similar to that first described by Akerlof [1970].

The information gathered under Regime 4 is basically the same as that under Regime 3. Specifically, the date and time of an auction as well as the winning bid received for each vehicle sold as listed on a manifest; a winner identification number also exists as well.

We organized all of the data concerning the $30,621$ sales that we acquired from the rental car company into a dataset. Because different amounts and kinds of information were generated under the different selling mechanism, in making empirical comparisons across the different selling mechanism, we are constrained by the least-complete data-collection scheme. Specifically, the only information we have that is comparable across all of the selling regimes is the following:

1) date of sale;
2) vehicle identification number;
3) vehicle model;

[4] As we shall describe below, even some of the experienced participants made costly errors, albeit infrequently.

4) vehicle age;
5) purchase price of vehicle;[5]
6) sale price of vehicle;
7) type of sale;
8) identification number of winner for Regimes 2, 3, and 4.[6]

For some vehicles, we have an odometer reading for the vehicle and know whether that vehicle has been in an accident, but these data are unavailable for *many* vehicles. Specifically, we have no odometer readings for vehicles sold under Regime 1, and nearly fifteen percent of the vehicles sold under the other regimes have missing odometer readings as well. The information concerning accidents is reliable for around fifteen percent of the observations in Regimes 2, 3, and 4; it is non-existent under Regime 1. Put another way, if we constrain ourselves to observations that have complete mileage and accident histories, then the remaining samples are extremely small.

Under Regime 2, we know the complete bidding histories of all participants, but no other such information exists for Regimes 1, 3, and 4. At none of the auctions did a reserve price exist. None of the vehicles went unsold. However, under Regime 2, some bidders made errors. Let us explain: infrequently, a bidder made a keystroke error, which resulted in his winning the auction at a ridiculously high price—e.g., several hundreds of thousands of dollars for a vehicle worth less than ten thousand dollars. At the close of the auction, this mistake was realized. At this point, the company, voided the sale, and resold the vehicle at a later auction. The practical importance of such cases is trivially small.

3. Empirical Results. While we have data concerning the sales of nearly $31,000$ vehicles, most of these data are not strictly comparable with one another. In addition, as was alluded to above, trying to control for differences in observed covariates collected across each of the regimes is difficult because different types of information were gathered under the four regimes. Thus, in order to avoid the potential biases that can arise when, for example, comparing the sale of a *Mercury Sable* with the sale of a *Jeep Cherokee* (viz., comparing apples and oranges), we have chosen to focus on relatively homogeneous products. Of course, there are limits to how fine we can go; these limits are largely determined by the information provided us by the rental car company concerning models. Note, too, that by restricting ourselves in this way, we have also reduced the potential samples sizes in our analysis: we must trade-off decreased bias with increased sampling variation.

Over thirty-seven percent ($11,504$ of $30,621$) of the sales in our dataset involved mid-sized vehicles of various models. Thus, we focused on those first.

In table 2, we report the sample descriptive statistics for mid-sized vehicles under the four regimes. Switching from the English auctions of Regime 1 to the Internet auctions of Regime 2 probably made profits for the rental car company: in real terms, the average traded price rose around 14.7 percent.[7] We say “probably” because we do not know what it costs to run either of these auctions, but a nearly fifteen percent improvement is substantial, and impressive. This increase also supports the hunch that some within the rental car company had; viz., collusion among potential buyers was likely a problem under Regime 1.

When the company switched to Regime 3, where the auction house conducted English auction the average traded price rose around 4.7 percent over its Regime 2 counterpart. As was noted above, the rental car company pays auction house a commission for conducting the auction which averages out to be about ten percent of the gross revenues. It is important to note that the price data we received from the auction house

[5] For around 0.15 percent of the vehicles in the dataset, the initial purchase price is unknown.

[6] For around five percent of these sales, the identity of the winner is unknown. Also, under Regime 3, the winner is listed as 16, the firm who conducted the auctions, rather than the actual winner.

[7] We made the CPI 1.00 for July 2005, around the midpoint of our sample.

TABLE 2
Sample Descriptive Statistics—All Regimes; Mid-Sized Vehicles

Variable	Statistic	Regime 1 English Auctions Rental Car Company	Regime 2 Internet Auctions Rental Car Company	Regime 3 English Auctions Auction House	Regime 4 Bilateral Bargaining
Traded Price	Mean	6261.68	7255.08	7605.51	7088.77
	St.Dev.	1730.93	2188.96	2020.30	2751.28
	Median	6253.11	7183.07	7770.44	6001.87
	Lower Quartile	5056.26	6011.54	6573.84	5048.80
	Upper Quartile	7518.28	8279.73	8787.28	9569.29
Age (in days)	Mean	1180.24	1080.20	1120.58	1135.65
	St.Dev.	206.46	179.43	135.32	163.73
	Median	1170	1178	1102	1105
	Lower Quartile	1140	972	1041	1047
	Upper Quartile	1200	1141	1147	1144
	Sample Size	246	6,214	4,208	835

are *net* of that commission, the rate of which varies from vehicle to vehicle. Thus, under Regime 3, the rental car company does not have to incur selling costs, such as those incurred when running the Internet auctions under Regime 2: all auction-related costs under Regime 3 are borne by the auction house. In short, while this increase in prices is relatively small, it is a lower bound on the profit that the rental car company is making by switching auction formats and pricing rules.

The average traded price under bilateral bargain, Regime 4, is less than either the Regime 2 average or the average net traded price under Regime 3, and negotiations are not without costs either. Unfortunately, the magnitudes of these negotiation costs are unknown to us and, perhaps, the rental car company as well, so we cannot put a firm figure one the average difference, but do know that, under Regime 3, the rental car company is doing better than under negotiation.

While these differences are obviously economically important, the question of whether any one is statistically significant remains. Conventional standard errors for the sample means can be calculated using the information provided in the table; i.e., simply divide the reported standard deviation under each regime by the square root of the sample size reported for that regime to get the standard error. We also calculated the asymptotic test statistics for each of the pair-wise differences: the p-values are uniformly below 0.01, so the differences are unlikely the result of sampling errors.

The main point to take from this part of the analysis is the following revenue ranking:

$$\text{English Auction (auction house)} > \text{First-Price Auction (auction house)} > \\ \text{Bilateral Bargaining} > \text{English Auction (rental car company).}$$

Thus, our findings are mixed: the English auctions conducted by the auction house generated the highest average traded prices, but those conducted by the rental care company generated the lowest average traded pricess. If, however, we assume that the English auctions conducted by the rental car company reflect the effects of collusion and the other auctions are unaffected by collusion, then the first inequality is consistent with the linkage principle. To wit, as Milgrom and Weber [1982] as well as Ausubel [2004] have counselled, information release matters and, as Bulow and Klemperer [1996] have predicted, auctions (appropriately designed) are better for the seller than negotiation, the second inequality.

The rental car company appears to have made a wise decision when it switched from the English auction used in Regime 1. However, without knowing the magnitude of the costs involved in conducting the Regime 2 Internet auctions, it is impossible to know whether the switch to Regime 2 from Regime 1 was profitable.

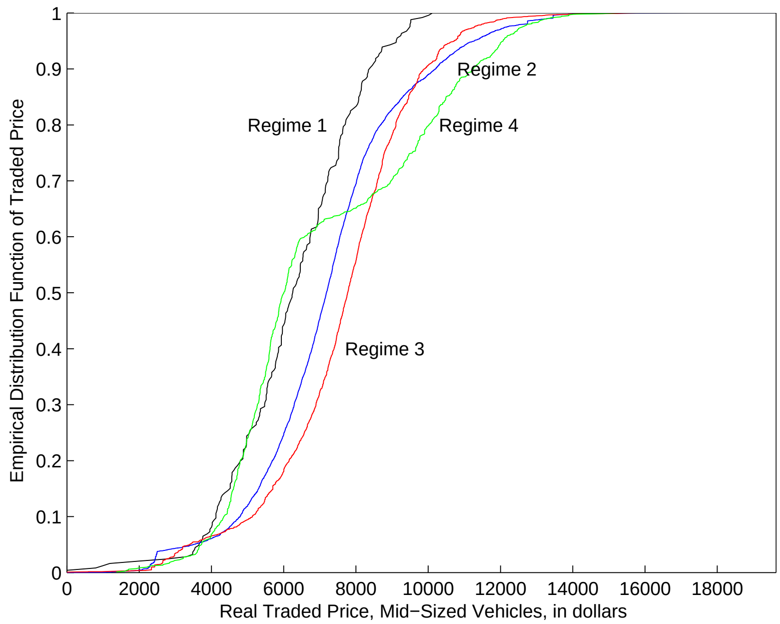

FIG 2. *Empirical Distribution Functions of Traded Prices—Mid-Sized Vehicles*

We have been unable to obtain from the rental car company usable data to estimate the costs of conducting the Internet auctions. On the other hand, because the prices at the Regime 3 auctions are net of commissions, which means no other costs were incurred to sell the unwanted vehicles, and because the average price at Regime 3 auctions is greater than those at either Regime 1 or Regime 2 auctions, this last change was certainly profitable.

In figure 2, we depict the empirical distribution functions (EDFs) of traded prices under the four regimes. Except at the very top end, above about the 85^{th} percentile, the EDF of Regime 3 is to the right of that of Regime 2. When, however, Milgrom and Weber [1982] used the linkage principle to prove the revenue ranking of the auction formats and pricing rules, they did not characterize the effect that the formats and rules have on the distributions of traded prices, just the averages of traded prices.

We note, however, that in single-object models, within the symmetric independent private-value paradigm, with risk-neutral bidders, the Revenue Equivalence Theorem holds. In addition, the distribution of winning bids at first-price auctions and that at second-price auctions can be ranked in terms of second-order stochastic dominance. Specifically, the latter involves a mean-preserving spread of the former. Within the Milgrom–Weber model, with affiliated signals, we know of no formal result along these lines. Nevertheless, under affiliation, the right tail of the winning bid distribution at a second-price auction is likely longer than that at a first-price auction, suggesting an inconsistency between the data and the theory.

Of course, the reader may worry that contamination, in the form of mis-reported traded prices or mis-classified vehicles, could affect our empirical results because, as an estimator, the sample mean has a very low breakdown point; see, for example, Huber [1981] as well as Belsley et al. [1980]. Contamination also

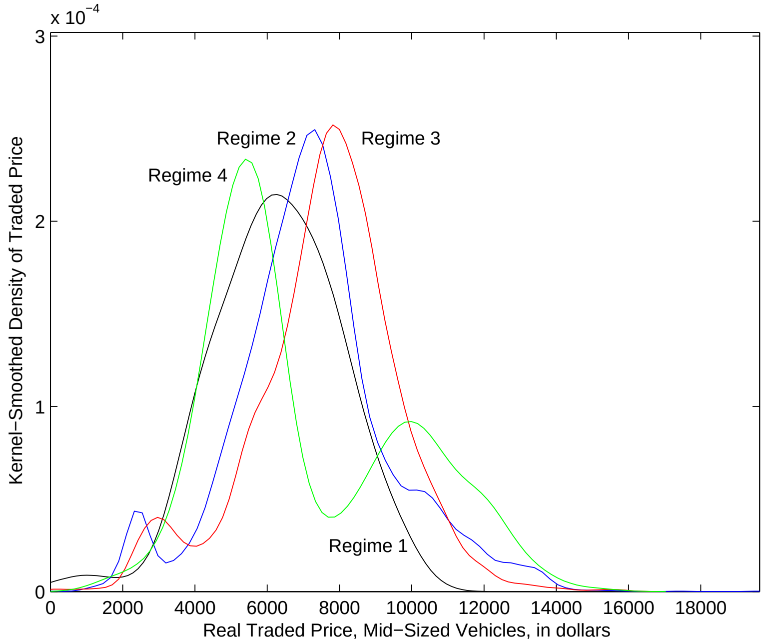

FIG 3. *Estimated Kernel-Smoothed Densities of Traded Prices—Mid-Sized Vehicles*

has implications for what can learned from the data, as was noted out by Horowitz and Manski [1997].

In an effort to demonstrate the robustness of our results, we have reported the samples medians as well as lower and upper quartiles in table 2.[8] For example, the estimated sample median of Regime 3 is greater than that of Regime 2 at size 0.01. But this is not an implication of the linkage principle, simply corroborating evidence supporting the notion that the English auction generates more information than the sealed-bid auction, and this release of information increases the average revenues garnered under the English auction.

In figure 3, we depict the estimated kernel-smoothed densities of traded prices where we used a Gaussian kernel with the bandwith parameter recommended by Silverman [1986]—viz., $4T^{-1/5}\hat{\sigma}/3$. Here, $\hat{\sigma}$ denotes the estimated standard deviation of trade prices, while T denotes the sample size. Nothing new concerning the traded-price processes under Regimes 1, 2, and 3 is really learned from this exercise, but something interesting is revealed about the traded-price process under Regime 4. In particular, the Regime 4 estimated probability density function is distinctly bi-modal: this bi-modality is not a bi-product of smoothing as with

[8]To calculate standard errors of the sample percentiles, we used the following first-order approximation for the q^{th} population percentile $\xi^0(q)$ estimated by the sample percentile $\hat{\xi}(q)$:

$$\sqrt{T}[\hat{\xi}(q) - \xi^0(q)] \xrightarrow{\text{d}} \mathcal{N}\left(0, \frac{q(1-q)}{f^0[\xi^0(q)]^2}\right)$$

where we used $\hat{f}(w)$, the kernel-smoothed estimate of the population probability density function of traded prices $f^0(w)$, evaluated at the sample percentile $\hat{\xi}(q)$, to approximate $f^0[\xi^0(q)]$. We should note, however, that under contamination this standard error statistic is not robust, even though the sample percentiles are, because (like the sample mean) the kernel-smoothed density estimator has a very low breakdown point as well.

TABLE 3
Sample Descriptive Statistics—All Regimes; Mid-Sized, Model A

Variable	Statistic	Regime 1 English Auctions Rental Car Company	Regime 2 Internet Auctions Rental Car Company	Regime 3 English Auctions Auction House	Regime 4 Bilateral Bargaining
Traded Price	Mean	6170.98	6848.55	7600.83	7387.44
	St.Dev.	1577.97	2163.49	1783.51	2322.70
	Median	6163.95	6768.46	7725.55	6281.36
	Lower Quartile	4972.65	5466.14	6894.59	5498.22
	Upper Quartile	7342.91	8032.13	8527.45	9739.76
Age (in days)	Mean	1194.36	1080.50	1128.50	1132.66
	St.Dev.	184.52	170.51	119.83	167.06
	Median	1170	1078	1112	1107
	Lower Quartile	1140	980	1067	1045
	Upper Quartile	1200	1141	1150	1139
	Sample Size	218	2,591	1,750	321

the minor multi-modality for the Regime 2 and 3 data. Specifically, under Regime 4, there exists a low-outcome part and an high-outcome part to the estimated probability density function, suggesting that some buyers get outstanding deals, while others pay considerably more, perhaps because the vehicles are different in some way. We shall return to this later in this section.

One obvious limitation of this analysis derives from the aggregation of all mid-sized vehicles into one sample. Within the mid-sized category, however, the top three models account for over eight-five percent ($9,850$ of $11,504$) of mid-sized sales, around thirty-two percent of total sales. Thus, we next disaggregated and focused on the top three models, individually. In tables 3, 4, 5 we present descriptive statistics for the top three models of mid-sized vehicles. At the request of the rental car company, we do not refer to these models by their names, but rather by letters of the alphabet—A, B, and C.

In general, the descriptive statistics for Models A and C, under Regimes 2 and 3, are basically like those for the data concerning all mid-sized vehicles; i.e., for these models, the ranking of Regime 3 over Regime 2 remains. Because the sample sizes under Regime 1 for Models B and C are so small—6 and 4, respectively—we did not consider these samples relevant in our analysis. What is a bit puzzling is that average revenues under Regime 4 are significantly greater than those under Regime 2 for both Models A and C.

The results for Model B are quite different. For this model, the average revenues are highest under Regimes 4, and Regime 2 garners significantly greater revenues than Regime 3, although the difference is economically small—under three percent. What could be causing these differences?

One obvious, but compelling point emerges from the previous analysis: the vehicles sold could be different in ways that the potential buyers can observe, but which we (as empirical analysts) cannot. We sought to use observed covariates to control for such factors. One important source of heterogeneity is in the new vehicle itself. While new model vehicles are remarkably homogeneous by some standards, considerable variation can exist in the features those vehicles possess. For example, we may not know whether a vehicle has the optional *Powder White Pearl Paint* or a sunroof or the *Bluetooth Hands-Free Phone System*, but the purchase price will probably reflect a good portion of this heterogeneity. Thus, in order to deal with this heterogeneity, we used p_t, the real purchase price of the t^{th} vehicle, as a control for unobserved (to the analyst) features of the vehicle. While we believe that the real new-car price is a reasonable sufficient statistic for all of the unknown features of a vehicle, we should note that this data series is all we have to control for this type of heterogeneity. Also, we know that a vehicle's age is important. For all vehicles in our dataset, we know when the vehicle was bought and when it was sold—vehicle age, in days, which we then converted

TABLE 4
Sample Descriptive Statistics—All Regimes; Mid-Sized, Model B

		Regime 1	Regime 2	Regime 3	Regime 4
Variable	Statistic	English Auctions Rental Car Company	Internet Auctions Rental Car Company	English Auctions Auction House	Bilateral Bargaining
Traded Price	Mean	7176.21	7892.92	7622.54	8054.58
	St.Dev.	2827.49	1767.16	2242.13	3008.55
	Median	7887.69	7560.50	8000.90	6896.07
	Lower Quartile	5338.75	6802.27	6738.31	5361.17
	Upper Quartile	9409.33	8640.78	9003.58	10870.49
Age (in days)	Mean	1080.00	1110.08	1143.71	1126.15
	St.Dev.	518.57	178.96	159.09	158.63
	Median	960	1100	1105	1104
	Lower Quartile	570	1000	1052	1052
	Upper Quartile	1710	1165	1167	1144
	Sample Size	6	2,779	1,347	316

TABLE 5
Sample Descriptive Statistics—All Regimes; Mid-Sized, Model C

		Regime 1	Regime 2	Regime 3	Regime 4
Variable	Statistic	English Auctions Rental Car Company	Internet Auctions Rental Car Company	English Auctions Auction House	Bilateral Bargaining
Traded Price	Mean	6008.04	4866.86	5639.53	5053.16
	St.Dev.	3425.15	1888.64	1193.56	1384.69
	Median	7164.57	5227.72	5701.09	5403.73
	Lower Quartile	2518.01	2780.98	5290.09	4826.97
	Upper Quartile	8341.54	6178.67	6340.22	5854.04
Age (in days)	Mean	915.00	1016.39	1108.97	1384.69
	St.Dev.	90.00	159.13	148.83	198.33
	Median	960	983	1059	1478
	Lower Quartile	825	930	1003	1455
	Upper Quartile	960	1088	1119	1478
	Sample Size	4	341	145	32

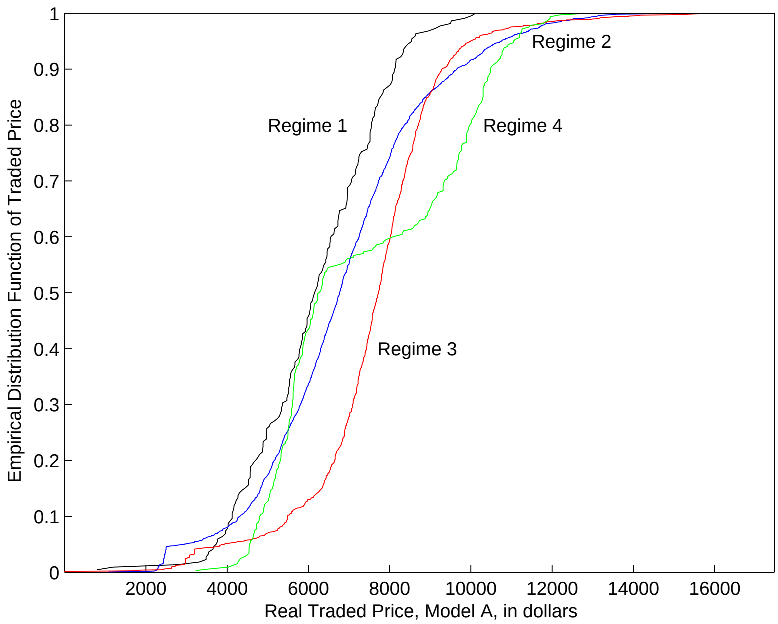

FIG 4. *Empirical Distribution Functions of Traded Prices—Mid-Sized, Model A*

to years; we denote this variable by Age. We know, too, that past usage is important. For around eighty-five percent of the vehicles sold (those under Regimes 2, 3, and 4), we know the odometer reading when the vehicle left the fleet, which we converted to tens of thousands of miles; we denote this variable by Mileage.[9]

When introducing observed covariate heterogeneity (denoted by the vector x, below) into econometric models of auctions, only certain functional forms will lead to tractable empirical specifications. In particular, two different structures have typically been used to introduce observed covariates into the valuations (denoted by Vs, below) of potential buyers. The first is an additive form, like

$$V_{nt} = g(x_t) + \varepsilon_{nt}$$

for the n^{th} potential buyer at the t^{th} sale where $g(\cdot)$ is some (typically unknown) function, while the second is a multiplicative form, like

$$V_{nt} = h(x_t)\varepsilon_{nt}$$

where $h(\cdot)$ is some (typically unknown) function. Here, ε_{nt} denotes the unobserved bidder-specific heterogeneity in valuations.

Under these functional-form assumptions, the Bayes–Nash equilibrium bid function is of the form

$$\beta(V_{nt}) = g(x_t) + \beta(\varepsilon_{nt})$$

[9]Some odometer readings were ridulously high, given the vehicle's age—for example, several millions of miles. Others were unusually low, again, given the vehicle's age—for example, less than ten thousand miles. While the former odometer readings are likely impossible, the latter are feasible, but we do not whether an odometer reading of 2 is really $1,000,002$ miles, or a mis-reported observations. Thus, we constrained ourselves to vehicles having mileages of less than one million and greater than ten thousand.

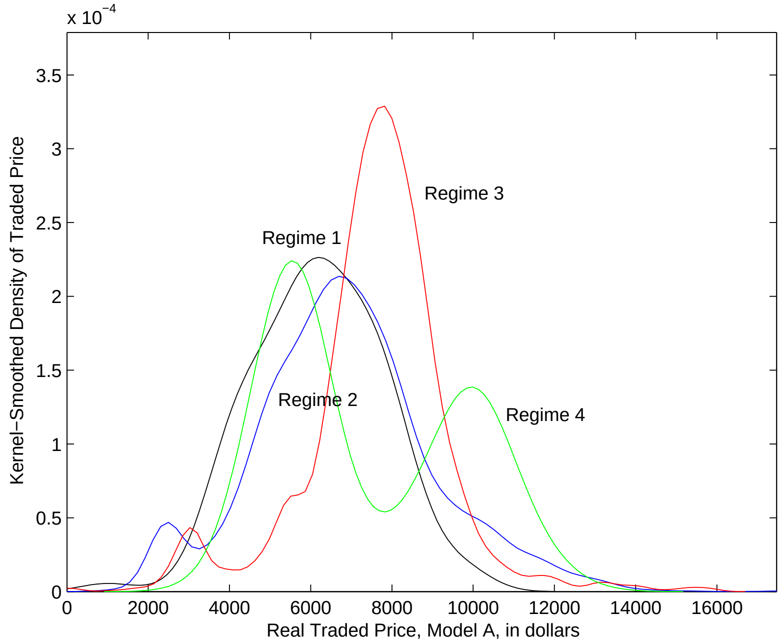

FIG 5. *Estimated Kernel-Smoothed Densities of Traded Prices—Mid-Sized, Model A*

in the first case, and

$$\beta(V_{nt}) = h(x_t)\beta(\varepsilon_{nt})$$

in the second. When it comes to implementing these specifications, researchers often assume a single-index structure, like

$$g(x) = x\theta,$$
$$\log[h(x)] = x\eta$$

where θ and η are vectors of unknown parameters conformable to x.

We imagine the following separable empirical specification relating $(p_t, \mathsf{Age}_t, \mathsf{Mileage}_t)$ to W_{it}, the traded price of the t^{th} vehicle under Regime i:

$$W_{it} = \rho_1(p_t)\rho_2(\mathsf{Age}_t)\rho_3(\mathsf{Mileage}_t)\lambda_i(S_t) \tag{3.1}$$

Here, $\rho_1(p_t)$ represents an unknown transformation of the real purchase price, $\rho_2(\mathsf{Age}_t)$ an unknown transformation of Age_t, $\rho_3(\mathsf{Mileage}_t)$ an unknown transformation of $\mathsf{Mileage}_t$, and $\lambda_i(S_t)$ an unknown transformation of the sale-t specific unobserved error term S_t. This latter transformation can vary across the selling regimes $i = 1,2,3,4$. Taking logarithms of both sides of equation (3.1) yields

$$\log W_{it} = \mu_1(p_t) + \mu_2(\mathsf{Age}_t) + \mu_3(\mathsf{Mileage}_t) + \lambda_0 + (\log[\lambda_i(S_t)] - \lambda_0) \tag{3.2}$$

where $\mu_j(\cdot)$ denotes $\log[\rho_j(\cdot)]$, $j = 1,2,3$. Here, the unknown parameter λ_0 is introduced as a centering parameter: under the null hypothesis that the selling regime does not matter, the random variable $(\log[\lambda_i(S_t)] -$

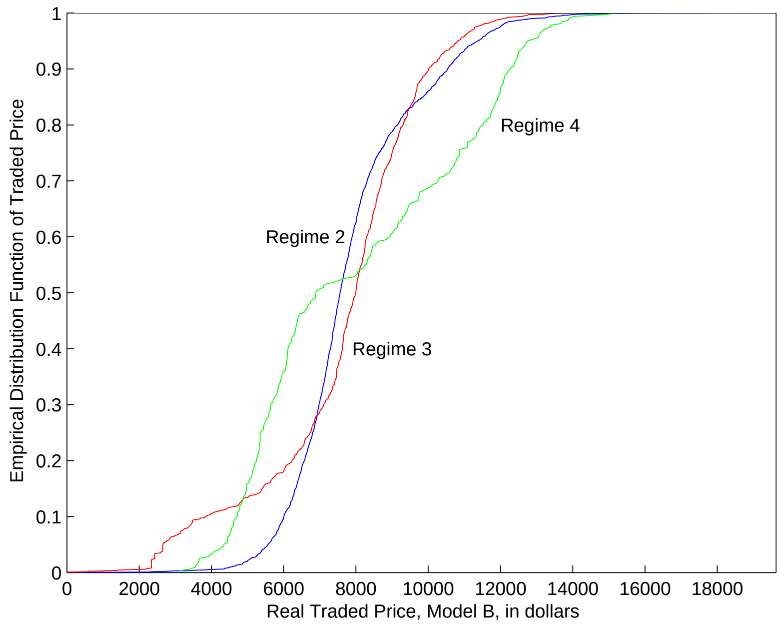

FIG 6. *Empirical Distribution Functions of Traded Prices—Mid-Sized, Model B*

λ_0), which we shall denote below as U_{it}, has mean zero and is uncorrelated with p as well as Age and Mileage.

Suppose

$$\rho_1(p) = A_1 p^{\gamma_1},$$

then

$$\mu_1(p) = \alpha_1 + \gamma_1 \log p.$$

Also, when

$$\rho_2(\mathsf{Age}) = A_2 \delta_2^{\mathsf{Age}}$$

and

$$\rho_3(\mathsf{Mileage}) = A_3 \delta_3^{\mathsf{Mileage}},$$

so constant but different “depreciation” rates with age and mileage, then

$$\mu_2(\mathsf{Age}) = \alpha_2 + \gamma_2 \mathsf{Age}$$

and

$$\mu_3(\mathsf{Mileage}) = \alpha_3 + \gamma_3 \mathsf{Mileage}.$$

We estimated the following empirical specification:

$$\log W_{it} = \gamma_0 + \gamma_1 \log p_t + \gamma_2 \mathsf{Age}_t + \gamma_3 \mathsf{Mileage}_t + U_{it} \tag{3.3}$$

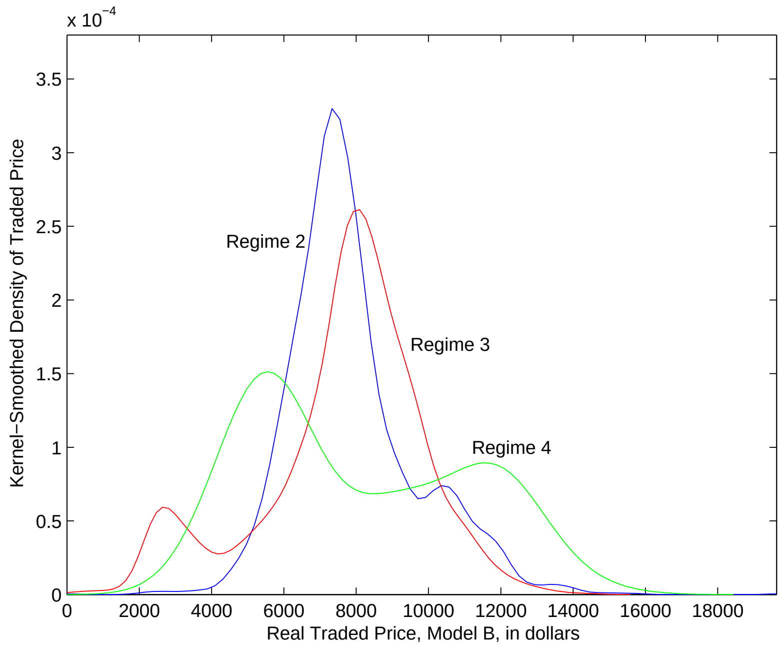

FIG 7. *Estimated Kernel-Smoothed Densities of Traded Prices—Mid-Sized, Model B*

by the method of least squares. We report our parameter estimates as well as robust standard errors in table 6. The estimated "depreciation" parameters for Age and Mileage make sense: in the first year, a vehicle is predicted to lose 22.45 percent of its value; controlling for vehicle age, an extra ten thousand miles is predicted to reduce the vehicle's value by around 2.75 percent. In figure 10, we present the EDFs of the fitted residuals (by Regime), while in figure 11, we present the estimated kernel-smoothed densities of the fitted residuals (by Regime). In table 7, we present the descriptive statistics. The most important statistic to notice in this table is the mean: under Regime 3, the average residual is positive, while under Regime 2 it is negative. The average difference in the gross traded prices is over ten percent We constructed a standard error for this difference is using the bootstrap; the p-value for the hypothesis that the mean under Regime 3 was greater than that for Regime 2 was less than 0.001. This evidence suggests that more information is released under the English auction than under the sealed-bid auction, evidence supporting the linkage principle. What remains puzzling is the fact that the variation in fitted residuals is much smaller under Regime 3 than under Regimes 2 or 4: theory would predict otherwise.

The bi-modality of traded prices under Regime 4 also represents a puzzle. Earlier, we conjectured that long-term lessees of vehicles would have better information concerning the vehicles they were purchasing. We also mentioned that some long-term clients had other contracts with the firm, so these potential buyers might have better bargaining positions than do the bidders at auctions. It seems plausible, too, that higher quality vehicles are sold under bargaining than at auction because the long-term lessees who had good experiences with their vehicles would be more likely to offer high prices, which the rental car company is more likely to accept, leaving the remainder to be sold at auction.

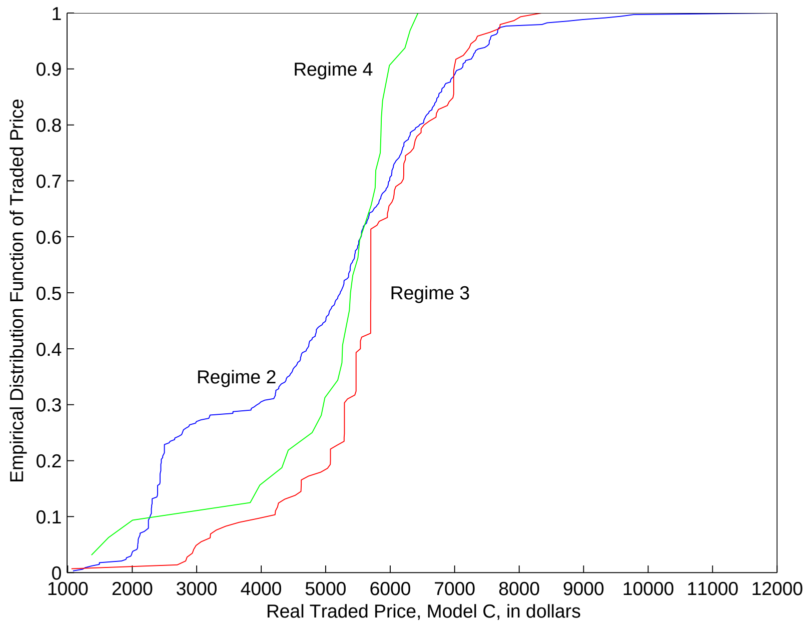

FIG 8. *Empirical Distribution Functions of Traded Prices—Mid-Sized, Model C*

While we do not know whether certain winners under Regime 4 are long-term lessees, we do know which winners are used-car dealers: basically, these are the 95 participants from the Regime 2 auctions.[10] In table 8, we present descriptive statistics concerning "Dealers" and "Non-Dealers" under Regime 4. Interestingly, on average, the Dealers paid over twenty-five percent more than the Non-Dealers for vehicles under bilateral bargaining—negotiation; the p-value of the asymptotic test statistic is less than 0.001. What is more, the bi-modality in the estimated kernel-smoothed densities remains after we control for whether a buyer is a Dealer or a Non-Dealer, as one can see from the estimated kernel-smoothed densities in figure 12.

4. Summary and Conclusions. In this paper, we have presented results derived from a unique new dataset concerning the revenues earned by a large rental car company for used cars it sold under a variety of selling mechanisms. This company experimented with several different mechanisms to dispose of unwanted vehicles, including designing a unique new "Internet auction" which, to our knowledge, has never been previously implemented, nor analyzed theoretically. Using simple empirical methods, we have analyzed these data to shed light on the effect these diffferent selling mechanisms had on the average revenues earned by the rental car company. Our empirical results are potentially subject to alternative interpretations.

On the one hand, in general, we found that the average traded prices were the highest when vehicles were sold at the auctions conducted by the auction house, which used an oral, ascending-price format—the standard English auction. On the other hand, the English auctions conducted by the rental car company itself

[10]Not all of our Regime 4 sales include a winner identification number. Hence, in the analysis reported, we have a smaller sample than we did in the analysis above.

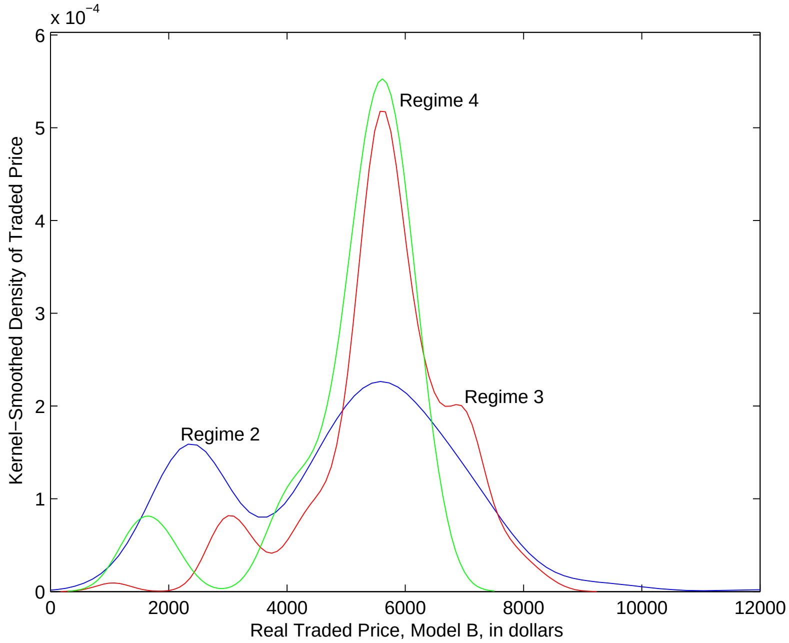

FIG 9. *Estimated Kernel-Smoothed Densities of Traded Prices—Mid-Sized, Model C*

yielded the lowest average revenues. What explains the difference?

As we noted in the introduction, the rental car company suspected collusion at the English auctions it conducted at each of its rental locations. In an attempt to thwart collusion, the company developed the Internet auction format, and this greatly reduced the information provided to participants. We found that the average traded prices the company earned at these Internet auctions were indeed greater than the those garnered at the English auctions conducted at each of its rental locations. One interpretation of this result is that the company's switch to the Internet auctions was successful in thwarting collusion, which explains the apparent violation of the linkage principle; viz., an auction format that provided *less* information to bidders actually generated *higher* average revenues to the seller.

Another potential explanation exists for the increase in average traded prices: the increase in average traded prices that the rental car company earned from its Internet auctions obtained because the number of potential buyers increased. This increased number of potential buyers alone, even in the absence of collusion, is sufficient to explain why the average traded prices earned by the company at its Internet auctions increased. Unfortuately, the data the rental car company provided us do not allow us to determine the number of potential buyers who participated at the English auctions conducted at each of its rental locations, although we do know the exact number of participants at each Internet auction. Our lack of data concerning the number of participants means that we cannot rule out the possibility that the increased average traded prices that the rental car company earned at its Internet auctions obtained mostly because of an increased number of participants and not necessarily because of collusion at the English auctions conducted at each rental location.

TABLE 6
Least-Squares Estimates—Regimes 2, 3, and 4; Mid-Sized Vehicles

Parameter	Estimate	Std.Error
γ_0	2.3999	0.3494
γ_1	0.7572	0.0345
γ_2	-0.2543	0.0106
γ_3	-0.0179	0.0023
$T = 9,081$	$R^2 = 0.44$	$\hat{\sigma} = 0.247$

TABLE 7
Sample Descriptive Statistics—Regimes 2, 3 and 4; Mid-Sized Vehicles

Variable	Statistic	Internet Auctions Rental Car Company	English Auctions Auction House	Bilateral Bargaining
Fitted Residuals	Mean	-0.0032	0.0032	0.0030
	St.Dev.	0.2875	0.1743	0.2822
	Median	0.0319	0.0375	0.0187
	Lower Quartile	-0.1328	-0.0389	-0.1806
	Upper Quartile	0.1884	0.1020	0.1958
	Sample Size	4557	3759	765

Similarly, the increase in average traded prices that the company earned at the English auctions conducted by the auction house could also reflect an increased number of participants, rather than providing evidence supporting the linkage principle. Unfortunately, we do not know how many bidders participated at each of the English auctions conducted by the auction house, so we cannot rule out the possibility that the increased average traded prices earned at the English auctions conducted by the auction house obtained mostly because of an increase in the number of participants, and not because of the linkage principle.

Although our results are equivocal, we believe the most likely explanation for what we have found is that the rental car company was correct: collusion did exist at the English auctions conducted at each of its rental locations. The switch to the company’s Internet auction format most likely made it very difficult, if not impossible, for bidders to collude. The Internet auctions also probably increased the number of participants at each auction, which may also explain why average traded prices increased when the company switched to the Internet auction format.

Similarly, when the company switched to the English auctions conducted by the auction house, we believe that the increase in information provided to participants at these auctions (i.e., the linkage principle) is a key reason why the average traded prices increased at these auctions. We do not believe that the increase in average traded prices obtained simply because of an increase in the number of bidders participating at the sales conducted by the auction house. While we do not know the number of participants at any given auction, we do know that the pool of *potential* buyers was larger than the pool of potential buyers at the Internet auctions conducted by the rental company where there were 91 potential buyers. However, the relative effects of competition on traded prices when the number of potential buyers is large is much smaller than when the number of potential buyers is small. Unfortunately, we have no way of knowing how many bidders actually participated (i.e., called-out bids) at the English auctions conducted by the auction house.

We believe that collusion is unlikely to have been an important problem at the English auctions conducted by the auction house, if it existed at all: with a very large number of bidders participating at each auction, it would be quite difficult to organize and to police a successful bidding cartel. Nevertheless, the following seems plausible to us: at the auctions conducted by the rental car company at each of its rental locations, the small number of potential buyers (who knew one another and who interacted regularly with one another)

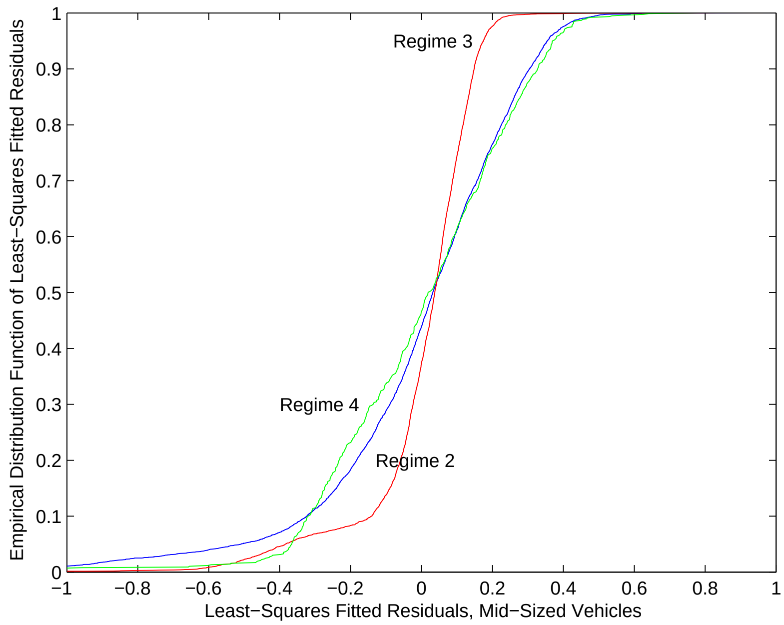

FIG 10. *Empirical Distribution Functions of Least-Squares Fitted Residuals—Mid-Sized Vehicles*

were probably able to collude successfully.

Thus, while the results of our empirical analysis are relatively unambiguous—the average traded prices earned by the rental car company at the English auctions conducted by the auction house were the highest, especially when we note consider the *gross* traded prices rather than the *net* traded prices received by the retntal car company—we cannot be absolutely certain whether the increase in average traded prices reflects primarily the linkage principle or a demand-aggregation effect (i.e., an increased number of participants at the auctions conducted by the auction house).

Acknowledgements. The authors thank Matthew Chesnes and David McArthur for exceptional research assistance. In addition, Srihari Govindan, Han Hong, Timothy P. Hubbard, Vijay Krishna, Dan Levin, David P. Porter, and Robert B. Wilson provided helpful comments and useful suggestions on earlier drafts of the paper. Paarsch gratefully acknowledges that much of the research for this paper was completed while he was a visiting research scholar at the Center for Economic Institutions in the Institute of Economic Research at Hitotsubashi University in Kunitachi, Japan.

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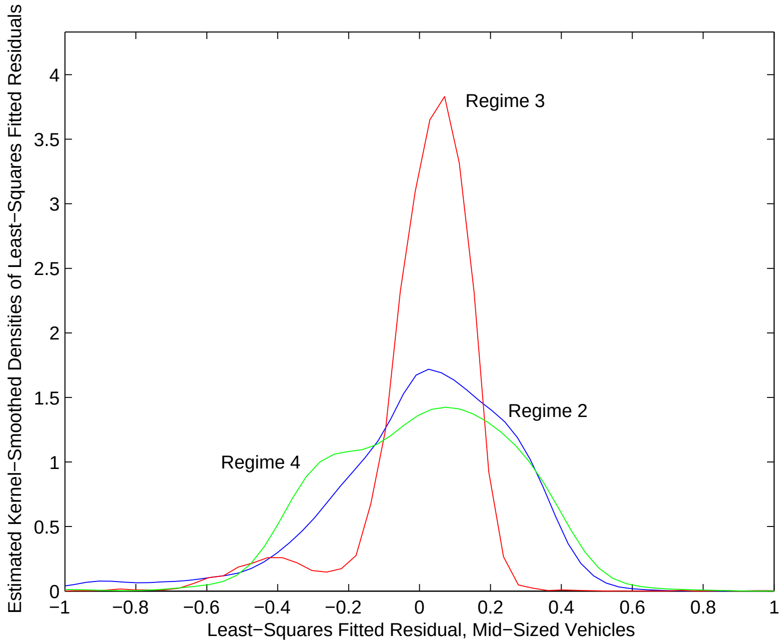

FIG 11. *Estimated Kernel-Smoothed Densities of Least-Squares Fitted Residuals—Mid-Sized Vehicles*

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TABLE 8
Sample Descriptive Statistics—Mid-Sized Vehicles, Regime 4, Dealers and Non-Dealers

Variable	Statistic	Dealers	Non-Dealers
Traded Price	Mean	7825.00	5956.57
	St.Dev.	2857.66	2135.71
	Median	6983.83	5569.03
	Lower Quartile	5360.47	4722.18
	Upper Quartile	10299.63	6315.56
Age (in days)	Mean	1144.21	1120.93
	St.Dev.	174.50	145.60
	Median	1108	1092
	Lower Quartile	1054	1041
	Upper Quartile	1143	1142
	Sample Size	508	317

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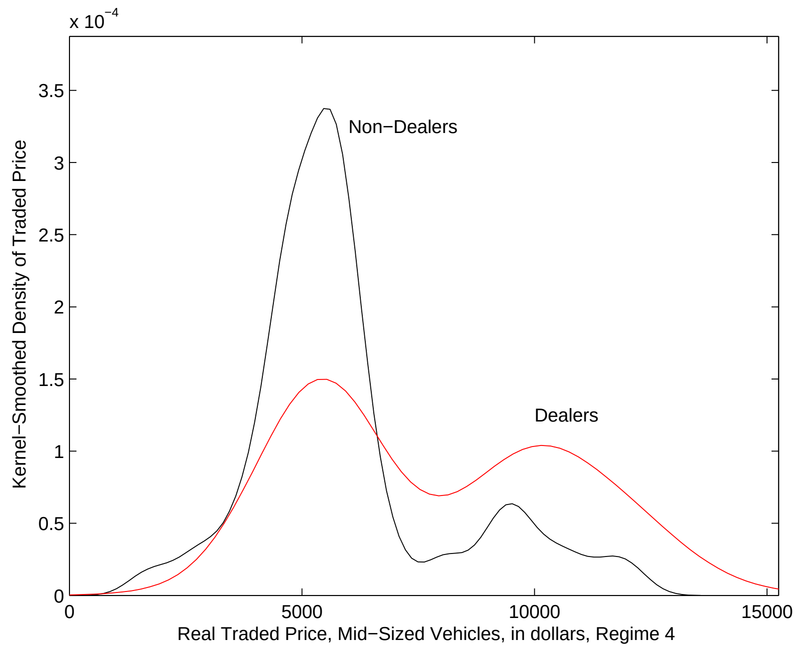

FIG 12. *Estimated Kernel-Smoothed Densities of Traded Prices—Mid-Sized, Regime 4, Dealers and Non-Dealers*