# The Effect of Information on Auction Outcomes: A Large Scale Field Experiment*

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**Abstract**

We study the effect of information on market outcomes using a field experiment. By randomly manipulating the availability of information about wholesale automobile quality, we measure the effect of information on market outcomes. As the theoretical literature predicts, more information increases expected revenues. However, the biggest gains in revenue are for the lowest and highest quality grades of automobiles. This suggests that the increase in revenues is due to better matching of buyers to vehicles, and is less a consequence of lower information rents. Finally, we quantify the value of gathering information and releasing it to buyers in this setup. *JEL* classifications C93, D44, D82, L15

** VERY PRELIMINARY AND INCOMPLETE **

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# 1 Introduction

It is generally accepted that the efficiency of markets critically depends on its participants having full information about the nature of the goods and services being traded.[1] This condition, however, is often not satisfied at the onset. Indeed, in labor markets, resale markets, housing markets, health care markets and markets for corporate securities, some market participants have better information than others about the value of the good or service being traded. Furthermore, market participants may have control over how much information to release, or how much information to acquire.

This paper studies the effects of information on market outcomes. In particular, we investigate the wholesale market for used automobiles where trade between car dealers is facilitated through auctions. In these markets, sellers will typically have more information about the condition of the used vehicle than buyers do, and the sellers can often control the amount of information that they choose to release to potential buyers. Using a randomized field experiment, we are able to precisely document how more information affects auction outcomes. We are also able to quantify the changes in consummated trades, in expected revenues, and how these differ across quality levels of the cars that are sold. The results suggest that ex ante information plays an important role in matching buyers with goods, resulting in higher levels of effective competition and increased efficiency.

Auctions are one of many ways in which markets can operate and they account for a sizeable number of transactions. In the past two decades alone the use of auctions has seen tremendous growth both in the public sector (e.g., spectrum auctions) and private sectors (e.g., eBay, internet ads, and more). As a consequence, many academics and practitioners have focused attention on the design of auctions to achieve efficient allocations, to maximize revenues, or both. Though much of the discussion and analysis has focused on the auction's rules (open or sealed, first or second price, free entry or invited bidders, etc.), one dimension of auction design that has received less attention is how much information the bidders should receive.

The theoretical literature on how information affects auction outcomes started with the celebrated "linkage principle" (Milgrom and Weber, 1982) Under rather standard conditions, if the seller releases more information then his expected revenue from the auction will increase. Two policy conclusions emerge: First, for many items it is in the seller's best interest to commit to release as much credible information as he can. Second, auction formats that themselves cause information to be released (e.g. open auctions) will generate higher expected revenues as compared to auctions that do not reveal information (closed auctions.) A simplified explanation of the linkage principle is that with more information available, bidders have more aligned views of the object's value. This causes them to bid more competitively, and as a result expected revenues increase.[2]

[1] It is also well known that in some cases, more information can hamper the efficiency of markets. See, e.g., the seminal work of Hirshleifer (1971).

[2] The intuition of the linkage principle is a bit subtle and is discussed in section 2.3. Some conditions, however,

Aside from bidders *within* an auction bidding more competitively, revealing information ex ante may cause a more basic form of competition that, to the best of our knowledge, has not been explored in the theoretical literature. Namely, if several heterogeneous goods will be auctioned off simultaneously, then the release of information before the auctions are administered will help bidders choose which auctions to participate in. Put simply, information can facilitate better matching between buyers and the goods they desire most. In turn, this will intensify the effective competition in any given auction by increasing the number of high-value bidders, and as a consequence this will increase both the amount of efficient transactions and the expected revenue for sellers.

This simple yet novel insight has broader applications beyond auctions, and should generally apply to markets at large. That is, if heterogeneous participants can sort into markets for heterogeneous goods then better ex ante information will help them sort into markets for which they have the most value, and in turn, *effective* competition will intensify in all markets. For example, if a firm posts vacancies for two positions that share some similarities, they will have a more refined pool of applicants that better fit each position of they release more information that distinguishes the two positions in terms of requirements, skills and job descriptions.

Due to the challenge of testing how variation in information affects markets in general, and auctions in particular, there have been few empirical studies that address this important question. Two notable ones are Kagel et al. (1985) and De Silva et al. (2008). Kagel et al. develop laboratory experiments that indirectly test the linkage principle. By manipulating the auction formats (open versus closed), they show that formats in which more information is released do indeed result in higher average revenues.[3] De Silva et al. exploit a policy change in the laws of the state of Oklahoma that led to the release of internal estimates of the costs to complete highway construction projects. They show that average bids fell after the change in policy, consistent with the prediction of the linkage principle (since this is a "reverse" auction, a drop in cost-bids is like an increase in revenue.)

Our paper contributes to this empirical agenda in an important way by implementing a randomized field experiment in which we are able to manipulate the amount of information that bidders observe, yet all other aspects of the auction remain fixed. Furthermore, the information we release has a clear ranking of quality, which in turn allows us not only to test whether average revenues change, but also measure how the average revenues change for each quality rank. This level of detail guided the construction of the theoretical contribution of our paper regarding the matching role that information revelation plays.

Our results strongly support the hypothesis that more information will increase the average revenues obtained by the sellers. More interestingly, the increase in expected revenues holds true across all quality levels. That is, it is not the case that sellers of low quality vehicles will obtained lower expected revenues, while on average expected revenues will increase. Instead, all quality

cause the linkage principle to fail. See Board (2009) for an excellent exposition of the issues.

[3] Qualifications...Goeree and Offerman (2003)...

levels show at least a weak increase in expected revenues, with the strongest effect for the very best and very worse quality levels. These results suggest that the main driver behind the increase in expected revenues is an increase in effective competition at all quality grades, suggesting a better match between buyers and types of vehicles.

The paper proceeds as follows: Section 2 describes the industry, the details of wholesale automobile actions, and the information provided to bidders. Section 3 discusses the theoretical implications of information revelation in auctions. Section 4 describes the data and the experimental design, and section 5 presents the experimental results. Section 6 offers a discussion of the results and concludes.

# 2 Wholesale Auto Auctions

The U.S. retail market for used cars is sizeable. Estimates place used car sales at more than 30 million cars in 2008, most of which were sold by franchise or independent dealers.[4] Dealers of used cars sell on the retail market and generally purchase their inventory of used cars either from trade-ins, or from the wholesale market for used automobiles.

A prominent source of used vehicles comes from wholesale automobile auctions. In fact, according to the National Automobile Dealer Association (NADA), 35% of all used vehicles sold by new car dealers in 2008 were sourced in such auctions (see NADA DATA, 2009)[5]. Most auctions are administered by a few prominent auction houses that specialize in this market, one of which provided the data for this study.

## 2.1 The Auction Process

The buyers in our auction are exclusively dealers, while the sellers mainly belong to one of three categories: dealers who wish to change there inventories; owners of large fleets such as rental car agencies who periodically turn over their inventories; and financial lease agencies who sell vehicles for which a lease contract had ended. Sellers bring their vehicles to the auction one or more days in advance of the actual auction where they are registered and assigned a "lane" number and a "run" number. On the day of the auction the vehicles are lined up in several (up to 12) lanes, according to the registered numbers.[6] Several thousands of vehicles will be auctioned off during a sale day.

Before the auction day begins, potential bidders receive information about the lane and run numbers of each car that will be sold at the auction, as well as basic information about the vehicle such as make, model, year, color, mileage and other features. This allows buyers to

[4] **** refer to NADA, NIADA and other sources if possible.

[5] This is available at http://www.nada.org/Publications/NADADATA.

[6] For example, a vehicle with a lane-run number of 9-132 will be auctioned in lane 9, and will be the 132$^{\text{nd}}$ vehicle in the lane.

determine which cars they want to bid on. The information is available online before the auction commences, and a printout is prepared for buyers on the morning of the auction.

At the end of each lane is an auction block where the auctioneer conducts the auction, one car at a time for that lane, so that up to 12 auctions can occur simultaneously. The vehicle which is next in line to be sold is slowly driven[7] to the auction block where it stops, amid several potential buyers, and is left idling as the auctioneer begins the auction. The auction is an ascending oral (English) auction that lasts for about 45 seconds.[8] The auction ends when no bidder is willing to raise the price, and if the price exceeds the seller's reserve price then the sale is consummated. Otherwise, the vehicle either returns to the seller's lot or is left at the auction lot for a subsequent sale day.

There is a major difference between the way fleet-sellers and dealer-sellers set reserve prices. Fleet-sellers will sell a large number of cars in one sale day (we witnessed one lease agency bringing in over 800 cars), and will have a representative sitting with the auctioneer and determining in real time whether or not to accept the highest bid. This suggests that the reserve price may have some real-time input. Dealer-sellers, however, bring in a handful of cars and are seldom present at their cars' auctions. They determine their reserve prices in advance and convey it secretly to the auction house. The auction house will then inform the high bidder if the sale is accepted.

There are two distinct classes of bidders at the auction. "Lane" bidders are those bidders who are physically present at the auction and can visually inspect the car from up close. Prior to the bidding, vehicles are parked outside so that potential bidders who arrive early enough can examine their exterior condition. The second class of bidders are "online" bidders who are able to participate in the auction through an Internet webcast, which provides streaming audio and video of the auction in real-time. These bidders have online access to basic information about the vehicle, e.g., make, model, year, color, mileage and other features.

## 2.2 Information and Standardized Condition Reports

As the description above suggests, buyers have some information about the vehicle at the time of the auction, including both basic information and, for the lane bidders, a close visual inspection of the car (including listening to the engine of those cars that can be driven.) Since it is not possible to perform a serious inspection of the vehicles by the potential buyers (not to mention the disadvantage of the online bidders who cannot themselves see the vehicles in any detail), there is residual uncertainty about vehicle's quality. As a response, many auction houses offer some form of condition reports that describe in more detail what the condition of the vehicle is. Historically, fleet-sellers have requested some tailor-made condition reports for the vehicles they

[7] Some cars that are not in driving condition are towed.

[8] Interestingly, the auctioneer begins at a very high price, often above the winning bid, and then works his way down until some bidder signals his willingness to buy. This sounds like a Dutch auction but it is not: the first bid is not the winning bid, but instead determines the start of the ascending bid process. This procedure has been in place for decades (see Genesove, 1995 p.26), and we have been told that it is also common in livestock auctions. We were unable to get an answer as to why this procedure is used.

sell, but dealer-sellers have not followed suit. Also, the output from these tailor-made reports was not standard, and buyers were not always pleased with the representation of the information.

In response, the auction house from which this paper's data originates had developed a Standard Condition Report (SCR) that is aimed at offering a standard set of inspections, and a standard way in which to present the information. The SCR is based on a detailed inspection of the vehicle's exterior, documenting all imperfections (including whether there is an additional layer of paint that implies some previous damage.) The interior condition is also carefully documented, as is any visual damage to the chassis. The inspections do not include the mechanical condition of the car but the technician who executes the inspection documents whether the engine has any peculiar sounds. The technician enters all of the information through a computerized hand-held device that registers the information on a central computer, and creates a standardized report.

The SCR is then posted online in a standard one-page format. Aside from documenting a detailed summary of the inspection, two other summary statistics are generated. First, a "condition grade" (CG) is calculated based on the input of the inspection.[9] The grading system is from 1 through 5, with increments of 0.1, where a CG = 1 is considered "rough", and a CG = 5 is considered "clean". Second, the SCR calculates the expected number of labor hours needed for a body-shop technician to correct the reported damage, as well as the cost of the materials needed. Using a standard hourly labor rate this translates into the cost of bringing the vehicle to a condition where exterior and interior damage are no longer noticeable. Hence, both the CG and the estimated costs are standardized measures of vehicle quality.

# 3 The Effect of Quality Information: Theory

A question that has been troubling the auction house is whether the information revealed by the SCR is valuable to the buyers, and if in turn, it translates into more consummated sales and higher expected revenues for the sellers. (The fees collected by the auction house depend both on whether a sale occurred and on the sale price.)

## 3.1 The Linkage Principle

The question of how more information affects auction outcomes is addressed by the well known "linkage principle" that was demonstrated in the seminal work of Milgrom and Weber (1982) (henceforth, MW). In an affiliated values auction model, MW show that if the seller releases more information to the bidders about the good he is selling then the expected revenue of the auction will go up.[10] The intuition for this result is not straightforward, yet it mostly follows

[9]**** refer to Genesove and Overby who also mention CRs. Explain how SCRs differ due to standardizations.

[10]To be precise, the information revealed must be affiliated. That is, once it is revealed, the valuations of the bidders move closer to each other in a statistical sense.

from creating more competition. Namely, by offering more information, the assessments of the bidders become more congruent, resulting in lower "information rents" for the winning bidder.[11]

It is important to note that the linkage principle derived in MW does not always extend to an auction environment in which multiple units of a good are being sold at once, as shown by Perry and Reny (1999). In many ways, the auction setting that we study is closer to the environment of Perry and Reny, and hence it is not clear what the effect of more information will be on auction outcomes.

When they do apply, the empirical implications of the linkage principle go beyond simply stating that more information will increase expected revenues, or that, as a consequence, the revenue ranking of auction formats will relate to the amount of information revealed during the auction. Another implication of the linkage principle is that, given a fixed set of bidders, if the information revealed is favorable then the expected revenue should increase, while if the information revealed is unfavorable then expected revenue should decrease.[12] Hence, if the assumptions under which the linkage principle is true are satisfied, then the introduction of SCRs imply two empirical predictions:

**LP1** Expected revenues should increase.

**LP2** For vehicles whose reported SCRs reveal high (low) CGs, revenues should be higher (lower) than for vehicles for which SCRs are not revealed.

## 3.2 Information as a Matching Mechanism

The model used by MW to derive the linkage principle assumes that the set of bidders at the auction is fixed. It may be, however, that the environment of our study is one where the bidders who appear at any given vehicle auction depend on the results of the SCR, in which case the assumption of a fixed set of bidders per auction is violated.

In discussion with industry participants, it seems that used car dealers specialize in the type of vehicles they sell, making such an endogenous selection plausible. Furthermore, these dealers are quite experienced so that when they show up and see a vehicle, they have a pretty good idea of its condition as measured by the CG.

For example, consider "low-type" ($L$) dealers in a low-income neighborhoods who specialize in older and rougher vehicles with worse CGs, while "high-type" ($H$) dealers in a high-income neighborhoods specializes in newer and cleaner cars with higher CGs. This would just reflect the preferences of the residents in their respective neighborhoods: everyone prefers a vehicle in better condition, but low-income people are less picky and less sensitive due to income constraints while

[11] See, e.g., Klemperer (1999) for a simple intuition.

[12] Still, expected revenue increases when information is revealed. Above and beyond shifting willingness to pay, which as the above discussion suggests is a wash, affiliation causes updated bidder valuations to move closer, creating more competition and less information rents.

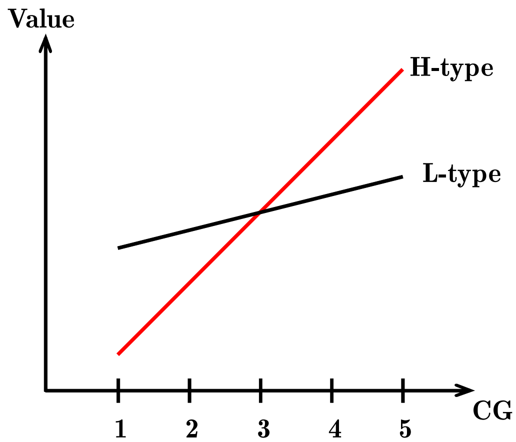


Figure 1: Heterogeneous Bidders: An Example

high-income people are pickier and will pay more for better cars. The resulting values for grades can be represented by Figure 1.

If this is the case then the information revealed by the SCRs may increase expected revenues for a different reason than that of the linkage principle. Namely, the information will reveal to buyers the CGs of cars ex ante that are selling in different lane/run numbers, and will help buyers focus on the cars that they are interested in. This in turn implies that for any given CG, there will be better matching of buyers to vehicles, and in turn, the vehicles will be more likely to sell at the market price perceived by the seller (which will of course determine the reservation price.)

We illustrate this point with a very basic example.[13] Consider two cars, one beaten-up ($B$) and the other clean ($C$) that are for sale. Imagine that there are four bidders, two of each type. Each type values clean cars more than rough cars, but the the low ($L$) type bidders value $B$ cars more than high ($H$) types do, while the $H$ type bidders value $C$ cars more than $L$ types do. For example, $L$ types sell in neighborhoods that are less sensitive to quality due to their limited resources, but they really need a car, while $H$ types sell in neighborhoods that are much more sensitive to quality, but are not too keen to drive in cars of low grades. Specifically, let the value of bidder $i \in \{1,2\}$ of type $t \in \{L,H\}$ for grade $g \in \{B,C\}$ be $v_{ti}^g = v_t^g + \varepsilon_i$, where $v_H^B < v_L^B < v_L^C < v_H^C$, and $\varepsilon_i$ is uniformly distributed over $[-\overline{\varepsilon}, \overline{\varepsilon}]$, with $\overline{\varepsilon}$ being very small.[14] Now assume that the two cars of different grade are selling at two distinct platforms simultaneously, but the four potential bidders do not know which car is which grade. Hence, they randomly decide

[13] Developing and analyzing a more general formal model is beyond the scope of this paper as it would be quite a long stand-alone exercise.

[14] Small enough guarantee that for any realization of the idiosyncratic noise $\varepsilon$, each of the inequalities is preserved when the noise is added.

which platform to go to. This simple example yields sixteen outcomes with equal probabilities,[15] and the expected revenue from an ascending auction (with no reserve price) will approximately[16] be

$$E[R|\text{no information}] = \frac{1}{4}v_H^C + \frac{7}{16}v_L^C + \frac{1}{4}v_L^B + \frac{7}{16}v_H^B.$$

The first two terms make up the expected revenue on the $C$ car and the last two terms make up the expected revenue of the $B$ car. Now imagine that the seller announces which car will sell on which platform. In this case it is easy to see that in equilibrium the bidders will sort themselves by type: $L$ types will flock to the $B$ car since they know that they cannot win a $C$ car and similarly, $H$ types will flock to the $C$ car.[17] Expected revenues will then approximately be

$$E[R|\text{information}] = v_H^C + v_{iL}^B > E[R|\text{no information}].$$

The expected revenue in each auction is equal to the expected value of the bidder who values that grade the most. This simple "market matching" theory offers a straightforward prediction:

**MM1** Expected revenues should increase for any given CG level and total expected revenues should therefore increase.

The simple example used to illustrate the matching role of information had only two grades: $B$ and $C$. We can think of these as corresponding to CGs of 1 and  respectively and the valuations depicted in Figure 1 would result in the values $v_H^B < v_L^B < v_L^C < v_H^C$. Now imagine that we introduce a "middle" range car $M$ that corresponds to a CG of 3. Looking back at Figure 1, this is the area of quality for which the two types do not differ much, implying that when any two bidders show up, the price will be less sensitive to the types of he bidders. This is in sharp contrast to the $B$ and $C$ cars: for a $B$ car the price will be significantly higher when two $L$-types show up than it would when one $L$-type and one $H$-type show up (similarly, for a $C$ car when two $H$-types show up). This lads  a second prediction of the market-matching effect:

**MM2** Expected revenues should increase more for more extreme CG's.

Of course, MM2 is a consequence of the kind of heterogeneity that we introduce: the difference in types' valuations is increasing as we move toward the extreme values of the CGs. For this industry we believe that the assumption is warranted since the kind of heterogeneity of consumers who are represented by dealers is very much in the spirit of our example above. One can introduce

[15] The probability of any bidder arriving at any auction is $\frac{1}{2}$, so there are 16 configurations of who shows up at which auction. E.g., with probability $\frac{1}{16}$ all four arrive at the $B$ auction, and with probability $\frac{5}{16}$ there is no more than one bidder at the $B$ auction.

[16] This is approximate because we need to calculate the expected second order statistic from each configuration. With $\varepsilon$ small this is approximately equal to the value of the $v$'s.

[17] If they sort in the opposite way then it cannot be an equilibrium: If the $L$-types intend to go the $C$ car and the $H$-types intend to go the $B$ car, then each type wants to change their choice and go to the other auction. If there is one of each type in each auction, then the "mismatched" type would prefer to switch auctions and have a chance at winning.

more types that "lie between" the two types depicted in Figure 1 and the implications would hold as long as the $L$-type values $GC = 1$ more than any other type and the $H$-type values $CG = 5$ more than any other type. In other words, as long as heterogeneity is most pronounced at the extremes then MM2 would arise as a consequence of better matching.

# 4 Data

## 4.1 Experimental Design

The purpose of the experiment was to measure the treatment effect of SCRs on expected auction revenue, probability of sale, and auction price for cars that were consigned to the auction by used car dealers. Our basic approach was as following: We inspected a subset of all dealer-consigned cars at one auction location over the course of 19 weeks using the SCR inspection procedure. Inspected cars were randomly assigned to one of two conditions. In the treatment condition, the SCR of an inspected car was made available to buyers (and sellers). In the control condition, the SCR was withheld from buyer and sellers; only the researchers knew that these cars had been inspected.

Due to a limited number of certified vehicle inspectors we did not inspect all dealer-consigned cars during the 19 weeks. Specifically, out of approximately 1500 dealer consigned vehicles each week, we inspected between 150 and 600 cars per week, depending on the number of inspectors who were available to us (see Table 11). In total, we inspected 8096 cars, 3977 of which were in the control group (SCR not reported) and 4119 were in the treatment group (SCR reported).

The number of inspected cars depended on the number of available inspectors during that week (between 3 and 12). For an auction that was conducted on Wednesday of a given week, we designating for inspections all cars that were checked in starting Friday morning of the prior week. Since we knew the number of available inspectors for that week, we could estimate how many cars they could inspect by Tuesday (the day before the auction). We kept designating all cars that were checked in until we reached the number of cars that we estimated could be inspected in time for the auction. Once we reached that number we no longer designated checked-in cars for inspection. On days with many inspectors, we inspected all cars that were checked in until mid-day Tuesday. On days with few inspectors we stopped assigning cars to be inspected at some time on Monday.

We assigned cars to treatment and control groups during the check-in process. Cars whose VIN (Vehicle Identification Number) ended in an even digit were assigned to the treatment group. Cars whose VIN ended in an odd digit were assigned to the control group. While the first digits of a VIN number designate manufacturers, country of origin, make, model, model-year, as well as some trim-level information, the later digits are assigned sequentially as vehicles are produced. Hence, the last digit of the VIN is a good randomization device: Whether the digit is even or odd is unrelated to the type of car sold and to the condition of the vehicle. Also, even and odd digits are equally represented in the population of produced cars. We thus expected an approximately even split between treatment and control groups. Consistent with this, the randomization procedure assigned 49.1% of cars to the control group and 50.9% to the treatment group.[18]

Our experiment covers two periods: Weeks 21-30 and weeks 31-39 of 2008. These periods differ in how buyers were made aware of SCRs. During weeks 21-30 the wide availability of SCRs was not explicitly publicized. As discussed in the previous section, SCRs are only available online, but not on the vehicles as they run through auction lanes. Hence, during the first half of the experiment a dealer would only learn about the availability of SCRs if that dealer used the auction house's website to preview cars that would be offered for sale on auction day. A dealer who learned about available cars only on-site on the day of the auction would not know that some of the cars had SCRs. Moreover, if dealers who logged on the day before to see which vehicles are available for sale did not have a habit of searching for SCRs (since these rarely existed for dealer-consigned cars) then they too would not be aware of the SCRs.

As we analyzed auction outcomes after the first eight weeks of the experiment we found little evidence that cars with SCRs were more likely to sell or sold at higher prices (we will present these results in detail later). This could mean that the information contained in SCRs had no effect, however, it could also mean that dealers did not know that SCRs were now available for a significant number of dealer-consigned cars. Hence, starting in week 31 we sent an E-mail to all buyers informing them that they could find SCRs for some of the dealer-consigned cars on the auction house's website prior to the auction day. These E-mails were sent once a week until the end of the experiment.

## 4.2 Auction and inspection data

The experiment yielded data on 8096 dealer-consigned and inspected cars, 3977 of which were in the control group and 4119 were in the treatment group. For each consigned car we have detailed information on the car, the outcome of the inspection (the SCR), the outcome of the auction, and some data about the auction participants.

Specifically, we observe the specific car that was consigned at the level of a model – model-year – body type – engine – trim level (e.g. a Honda Accord, 1999, 4-door, V6, EX trim). We also observe the mileage of the car. More detailed information about the condition of the car comes from the SCR as described in section 2.2. We use two key measures. The first measure is the CG , a number between 1 (rough) and 5 (clean). The second measure is the estimated cost to fix the damage detailed in the SCR. This includes the auction house's estimates of both part and labor costs and is reported in dollars.

We observe a unique seller ID that allows us to identify whether different cars were consigned by the same seller. The data reports whether a car was sold during the auction. If the car was

[18] We cannot reject the hypothesis that our randomization procedure assigned an equal proportion of cars to treatment and control groups (at a 5% significance level).

sold, we observe the auction price and a unique buyer ID that allows us to identify whether different cars were purchased by the same buyer. Finally, we know the average auction price for cars of the same car type that sold at any of auction house's locations nationwide during the prior week (henceforth "National Auction Price" or NAP). This allows us to construct a useful normalization of price that is independent of the type of car. Summary statistics are reported in Table 12.

### 4.3 Randomization check

We compare the treatment and control groups on a variety of observable characteristics. Specifically, if the randomization worked as intended, the distribution of condition grades, repair costs, mileage, vehicle age (model year), and national auction prices in the prior week should be comparable across control and treatment groups. We use a Kolmogorov-Smirnov test for equality of distribution functions. The results are reported in Table 1.

Table 1: Kolmogorov-Smirnov test for equality of distribution functions

| Variable | D | p-value |
|---|---|---|
| Condition grade | 0.0142 | 0.81 |
| Repair costs | 0.0302 | 0.05 |
| Mileage | 0.0170 | 0.60 |
| Model Year | 0.0165 | 0.64 |
| National Auction Price | 0.0183 | 0.94 |

For all five measure we fail to reject the hypothesis that the distribution functions are the same. However, the test statistic for repair costs is just above the critical level, indicating that repair cost may have a different distribution between control and treatment groups. To investigate this further, we compare the means of repair costs across the two conditions. Repair costs for the control group are on average \$1382, for the treatment group the cost are \$1316. We will take account of this \$66 difference when interpreting our auction price results.

## 5 Results

The results are organized into three parts. First, we report the basic findings of our experiment. Second, we report some supporting evidence for our interpretation of the results by looking at the behavior of online bidders. Finally, we show how out results vary by condition grade, which can help distinguish between the simple market matching story and the linkage principle.

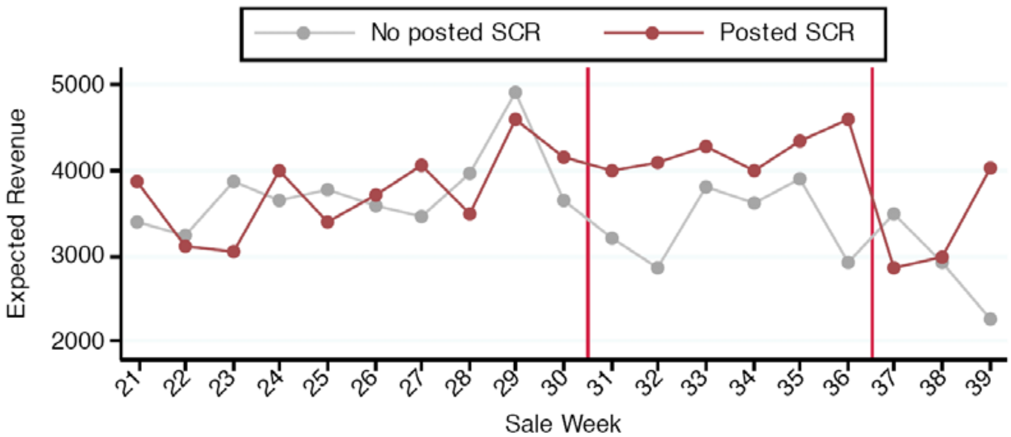


Figure 2: Expected auction revenue by experimental condition and week

## 5.1 Basic findings

We begin this section by reporting expected auction revenues for cars in the two experimental conditions. Next we decompose revenues into the probability of sale and auction prices. We then address two alternative explanations for our results.

### 5.1.1 Expected revenues

The weekly expected auction revenue during our experiment is shown in Figure 2. The figure shows the expected revenue per dealer-consigned car, which varies around a mean of \$3700 (the probability of sale for the entire sample is 43% and the average auction price for a sold car is \$8600).

The figure distinguishes between weeks 21 to 30 (during which we did not publicize the existence of SCRs), and weeks 31-39 (during which we sent weekly E-mails mentioning that SCRs for dealer-consigned cars could be found online). We have also highlighted two shocks that occurred in weeks 37 and 38: First, the auction was affected by the landfall of Hurricane Ike which disrupted Texas, the key market for the auction location where we did our experiment. Second, the auction was affected by the collapse of Lehman Brothers, which decreased auto sales nationally. While these events affected sales at our auction location, we do not have a strong a-priori reason to believe that cars in our two experimental conditions would have been differentially affected. For this reason we treat weeks 31 to 39 as one sample.

Our first findings are summarized in Table 2. Before we publicized the existence of SCRs (weeks 21-30), the expected revenue per consigned car was \$3677 for cars without a posted SCR and \$3690 for cars with a posted SCR. The difference of \$12.8 is not statistically significant at any conventional level (using a t-test). Our results changed once we started sending weekly e-mails mentioning that SCRs for dealer-consigned cars could be found online (weeks 31-39). During this period, the expected revenue per consigned car was \$3262 for cars without a posted SCR and \$3888 for cars with a posted SCR. The expected revenue difference of \$626.1 (or 19.2%) is highly statistically significant (p-value $< 0.01$). This suggests that SCRs increased expected auction revenues once buyers became aware that SCRs could be found online.

Table 2: Auction revenue by experimental condition for weeks 21-30 and weeks 31-39

| | No posted SCR | Posted SCR | Difference | % Difference | t-statistic | p-value |
|---|---|---|---|---|---|---|
| Weeks 21-30 | \$3,677.3<br>2,602 cars | \$3,690.1<br>2,798 cars | \$12.8 | 0.35% | 0.082 | 0.94 |
| Weeks 31-39 | \$3,261.8<br>1,375 cars | \$3,887.8<br>1,321 cars | \$626.1 | 19.2% | 2.89 | 0.004 |

#### 5.1.2 Probability of Sale and Prices

We can decompose the difference in expected revenues between cars with and without posted SCRs into differences in the probability of sale and differences in auction prices. Table 3 shows that during weeks 21-30, cars with and without a posted SCR were equally likely to sell; approximately 43% of cars sold in either condition. During weeks 31-39, cars with a posted SCR were 6.3 percentage points (or 16%) more likely to sell than cars without a posted SCR. This difference is highly statistically significantly different from 0 (using a test of proportions with p-value $< 0.01$).

Table 3: Sales probability by experimental condition

| | No posted SCR | Posted SCR | Difference | % Difference | z-statistic | p-value |
|---|---|---|---|---|---|---|
| Weeks 21-30 | 43.1%<br>2,602 cars | 43.6%<br>2,798 cars | 0.6% | 1.39% | 0.41 | 0.68 |
| Weeks 31-39 | 39.2%<br>1,375 cars | 45.5%<br>1,321 cars | 6.3% | 16.1% | 3.31 | 0.001 |

Prices in the two experimental conditions were not significantly different, in either period. Table 4 shows these results.

One problem in concluding that transaction prices did not differ between experimental conditions is that the variance of prices of sold cars is very high. This is because the auction location sells everything from 11 year old small cars to current model year luxury cars. Ideally, we would like to specify prices relative to the typical price for cars of the same car type, i.e. of the same make, model, and model-year. Fortunately, we know the average auction price for cars of the same car type that sold at any of the auction house's locations during the prior week, what we refer to as the National Auction Price (NAP). We use this measure to construct a normalized

Table 4: Transaction prices by experimental condition

| | No posted SCR | Posted SCR | Difference | % Difference | t-statistic | p-value |
|---|---|---|---|---|---|---|
| Weeks 21-30 | \$8651.4<br>1,106 cars | \$8582.7<br>1,203 cars | \$-68.7 | -0.8% | -0.279 | 0.78 |
| Weeks 31-39 | \$8446.0<br>531 cars | \$8704.7<br>590 cars | \$258.7 | 3.1% | 0.75 | 0.45 |

price for each car in the sample, specifically, the price of the car divided by the NAP. This normalized price allows us to reevaluate whether there are price differences between experimental conditions. Table 5 shows these results.

Table 5: Transaction prices / NAP by experimental condition

| | No posted SCR | Posted SCR | Difference | % Difference | t-statistic | p-value |
|---|---|---|---|---|---|---|
| Weeks 21-30 | 1.064<br>1,106 cars | 1.059<br>1,203 cars | -0.005 | -0.5% | -0.5 | 0.62 |
| Weeks 31-39 | 1.035<br>531 cars | 1.055<br>590 cars | 0.02 | 1.9% | 1.61 | 0.11 |

The findings suggest that after week 31, prices were higher by 1.9% for cars with a posted SCR relative to cars without a posted SCR. The difference, however is only marginally significant (p-value 0.11).

Overall, the decomposition suggests that most of the effect of SCRs on expected auction revenue comes from an increased probability of sale; transaction prices did increase, but only by little.

### 5.1.3 Alternative explanations and robustness

To conclude that the increase in auction revenue due to SCRs is attributable to the information revealed in the reports we need to rule out an alternative explanation for why SCRs increased revenues. We also want to revisit our randomization procedure by checking whether our findings are robust to the inclusion of fixed effects.

#### Substitution

Suppose that the e-mails that buyers received from week 31 onwards focused buyers' attention on cars with SCR without affecting their willingness to pay for cars with posted SCRs relative to cars without posted SCRs. This might have lead to an increase in the number of bidders for cars with posted SCRs and a decrease in the number of bidders for cars without posted SCRs. The larger number of buyers for cars with posted SCRs could have made it more likely that reserve prices were met and this would have increase the probability of sales. Specifically, consider the sales percentages in Table 3. The probability of sale was 43% in weeks 21-30 for both conditions. In weeks 31-39 the *average* probability of sale remained at 43% but cars without a posted SCR sold 39% of the time while cars with a posted SCR sold 45.5% of the time. Could it be that the SCR simply made buyers substitute from cars without posted SCRs to cars with posted SCRs without changing their willingness to pay? Or could it be that SCRs *did* increase buyers' willingness to pay *relative to* cars without a posted SCR but that overall demand for cars at the auction fell from weeks 21-30 to weeks 31-39?

To answer these questions we need an estimate of the secular trend in the probability of sale for our sample period, i.e. we need to know what the sales of cars without a posted SCR would have been if demand for cars at auction had stayed the same from weeks 21-30 to weeks 31-39. This is particularly important because during weeks 21-30 the stock market was declining steadily (the DOW dropped by about 15%) and during week 38 Lehman Brothers crashed. Arguably, market demand may have reacted to these events.

To find such a trend we use cars that were not part of our experiment, namely the cars offered for sale by fleet-sellers. For these cars there was no change in available information due to our experiment. In using fleet-seller consigned cars to establish a secular trend for the probability of sale of dealer consigned cars, we assume that their demand conditions are affected similarly to the demand for dealer consigned cars. This assumption is not unreasonable: While fleet-seller consigned cars are on average somewhat newer, the overlap in age and condition between fleet-seller and dealer consigned cars is high.

{XXX Add evidence of the overlap of these two groups of cars. }

{XXX try to check for a trend in the probability of sale before week 21 if we can get the data.}

The probability of sale for fleet-seller consigned cars is 66.94% in weeks 21-30 (14,161 cars) and 59.75% in weeks 31-39 (13,332 cars). This means the sales probability for fleet-seller consigned cars decreased by 7 percentage points, suggesting that demand for cars at auction decreased from week 21-30 to 31-30. Adding fleet-seller consigned cars to our sample allows us to use a difference-in-differences linear probability regression that estimates the change over time in the probability of sale for cars with and without a posted SCR relative to fleet-seller consigned cars. The results are in Table 6.

The constant in this regression is the probability of sale for fleet-seller consigned cars during weeks 21-30. The coefficient on *Week 31-39* is the change in the probability of sale for fleet-seller consigned cars relative to weeks 21-30 and is our estimate of the secular trend. The variables of interest are the interaction between *Week 31-39* and the two dealer consigned car conditions. The coefficient on *Week 31-39 * Dealer-consigned car, no posted SCR* is 0.031 and is not significantly different from 0 at a 5% level. This means that we cannot reject the hypothesis that the probability of sale for dealer consigned cars was unchanged between weeks 21-30 and weeks 31-39. In contrast, the coefficient on *Week 31-39 * Dealer-consigned car, posted SCR* at

Table 6: Linear probability model: diff-in-diff specification

| Dependent Variable: Sold | |
|---|---|
| Dealer-consigned car, no posted SCR | -.24** |
| | (.01) |
| Dealer-consigned car, posted SCR | -.23** |
| | (.01) |
| Week 31-39 | -.07** |
| | (.0058) |
| Week 31-39 * Dealer-consigned car, no posted SCR | .031+ |
| | (.017) |
| Week 31-39 * Dealer-consigned car, posted SCR | .089** |
| | (.018) |
| Constant | .67** |
| | (.004) |
| Observations | 35589 |
| R-squared | 0.034 |

* significant at 5%; ** significant at 1%; + significant at 10% level. Robust SEs in parentheses.

0.089 is significantly different from 0 (p-value $< 0.01$). The interpretation of these results is as follows: Under the maintained assumption that the demand conditions of fleet-seller consigned cars change similarly to the demand conditions for dealer consigned cars, we find no evidence that the e-mails sent out starting in week 31 led dealers to substitute from cars without posted SCRs to cars with posted SCRs. Instead, it seems that the probability of sale for cars without posted SCRs was unchanged (relative to fleet-seller consigned cars) while the probability of sale for cars with posted SCRs increased.

One remaining concern is that there may have been substitution between fleet-seller consigned cars and dealer-consigned cars with a posted SCR. If so, controlling for the secular trend by using the change in probability of sale of fleet-seller consigned cars would no longer be valid. To address this concern we constructed a sample of buyers who only purchased fleet-seller consigned cars during weeks 21-30. 616 dealers fall in this category, a large fraction of the 1670 dealers who purchased at least one car (fleet-seller or dealer consigned) during our experimental period. If there is substitution between fleet-seller consigned cars and dealer consigned cars with a posted SCR, we should find that these 616 dealer—if they purchased *any* dealer consigned cars during weeks 31-39—should be more likely to buy cars with a posted SCR than without a posted SCR. We find no evidence of such behavior: Dealers who only purchased fleet-seller consigned cars during weeks 21-30 purchased 48 dealer consigned cars with a posted SCR and 53 dealer consigned cars without a posted cars after we started publicizing SCRs by E-mail (i.e. during weeks 31-39).

We conclude that substitution is unlikely to explain why SCRs increase expected auction revenue.

**Randomization check**

Previously, we compared the treatment and control groups on a variety of observable characteristics to make sure that the randomization worked as intended. A second approach to checking whether our procedure yielded a random assignment to treatment and control groups is to analyze whether our basic results change as we control for a variety of fixed effects. Specifically, we regress auction revenue on the treatment, controlling for seller fixed effects (267), week fixed effects (9), model year fixed effects (12), and condition grade fixed effects (5).

Table 13 shows the regression results. For comparison, we also report the treatment effect without fixed effects (which is also in Table 2). The point estimate of the treatment effect drops from \$626 to \$439. However, we can't reject the hypothesis that the treatment effect is unchanged by the inclusion of the extensive set of fixed effects. The point estimate in the fixed effect specification is somewhat less precisely estimated but is still significant at a 6% level. These results provide no evidence that our procedure yielded a non-random assignment to treatment and control groups.

## 5.2 Online Transactions

We have argued that SCRs did not increase expected auction revenue during weeks 21-30 because dealers during that period were not aware that SCRs had been posted for many dealer consigned cars. One way to test this argument is to look at the behavior of dealers for whom we know that they must have been aware of SCRs even during weeks 21-30. If these dealers behave no differently before and after week 31, this supports our argument that the effectiveness of SCRs during weeks 31-39 was tied to dealers knowing about them.

To identify a set of dealers who must have been aware of SCRs even during weeks 21-30 we make use of the auction house's online bidding feature. Clearly, dealers who bid online must have know about SCRs because the SCRs are listed on the page that is used to start online bidding. Furthermore, for these online dealers this is the only source of information that puts them on some equal footing with the on-site lane bidders.

Online bidding was relatively rare at the time of our experiment. Of the 8,096 dealer consigned cars that were up for auction between week 21 and week 39, only 243 (3%) received an online bid. The 8,096 cars up for auction yielded 3,482 sales. Of these sold cars, only 137 (3.9%) received the winning bid from an online bidder.

In the following we look at three measures of online behavior as a function of whether we posted a SCR or not. First, what percentage of vehicles received an online bid? Second, for what percentage of sold vehicles was the winning bid placed online? Third, what is the expected number of online bidders? We will compare all three measures for weeks 21-30 and 31-39.

Table 7 shows the percentage of vehicles that received an online bid by week and by whether a SCR was posted. Over the entire experimental period, 3.45% of cars with a posted SCR received an online bid, compared to 2.54% of cars without a posted SCR. This 36% difference in the probability of receiving a bid is statistically significant (using a test of proportions and a 5% significance level). The key comparison is whether a similar difference already existed in weeks 21-30 or whether it was mostly driven by dealer behavior in weeks 31-39. We find that a posted SCR increased the probability of receiving an online bid by 30% during weeks 21-30. This suggests that an SCR had a meaningful effect on dealer behavior during weeks 21-30 for dealers who knew about its existence.

Table 7: Percentage of dealer-consigned cars which received an online bid

| | No posted SCR | Posted SCR | Difference | % Difference | z-statistic | p-value |
|---|---|---|---|---|---|---|
| All weeks | 2.54%<br>3,977 cars | 3.45 %<br>4,119 cars | 0.91% | 35.8% | 2.39 | 0.017 |
| Weeks 21-30 | 2.69%<br>2,602 cars | 3.50%<br>2,798 cars | 0.81% | 30.2% | 1.72 | 0.086 |
| Weeks 31-39 | 2.25%<br>1,375 cars | 3.33%<br>1,321 cars | 1.08% | 47.7% | 1.70 | 0.089 |

We find a similar result in Table 8, which shows the percentage of sold vehicles for which the winning bid was placed online. Over all weeks, the winning bids of 4.7% of cars with a posted SCR was places online, compared to 3.07% of cars without a posted SCR. This 53% difference is statistically significant (using a test of proportions and a 5% significance level). As before, much of the SCR effect is already present during weeks 21-30 (although the SCR effect is a bit smaller and statistically weaker than in the overall sample).

Table 8: Percentage of sold dealer-consigned car with where winning bid was placed online

| | No posted SCR | Posted SCR | Difference | % Difference | z-statistic | p-value |
|---|---|---|---|---|---|---|
| All weeks | 3.07%<br>1,660 cars | 4.72 %<br>1,822 cars | 1.65% | 53.6% | 2.50 | 0.01 |
| Weeks 21-30 | 3.21%<br>1,121 cars | 4.5%<br>1,221 cars | 1.29% | 40.3% | 1.62 | 0.11 |
| Weeks 31-39 | 2.78%<br>539 cars | 5.15%<br>601 cars | 2.37% | 85.3% | 2.03 | 0.04 |

Our final online result is in Table 9, which shows the expected number of online bidders per 100 auctions. We find that over all weeks of the experiment, more online bidders participated in auctions for cars with a posted SCR (4.73 per 100 auctions) than for cars without a posted SCR (3.65 per 100 auctions). As for the previous two measures, the SCR effect seems to be present already in weeks 21-30 (although the SCR effect is a bit smaller and statistically weaker than in the overall sample).

Table 9: Expected number of online bidders per 100 auctions

| | No posted SCR | Posted SCR | Difference | % Difference | t-statistic | p-value |
|---|---|---|---|---|---|---|
| All weeks | 3.65<br>3,977 cars | 4.73<br>4,119 cars | 1.08 | 29.8% | 2.21 | 0.027 |
| Weeks 21-30 | 3.77<br>2,602 cars | 4.72<br>2,798 cars | 0.95 | 25.3% | 1.57 | 0.12 |
| Weeks 31-39 | 3.42<br>1,375 cars | 4.77<br>1,321 cars | 1.35 | 39.5% | 1.60 | 0.11 |

Given that online dealers knew about SCRs from the beginning (week 21) of the experiment, and given that the effect of a posted SCR barely changes between weeks 21-30 and 31-39, we conclude that the effectiveness of SCRs we observe offline during weeks 31-39 is most likely to be tied to dealers knowing about SCRs.

## 5.3 Transactions by Quality Grades

We now investigate whether the effect of a posted SCR on auction outcomes differs by the condition of the vehicle. The basic auction expected revenue results are shown in Figure 3. Not surprisingly, expected revenues generally increase with condition grade. Notice also that a posted SCR does not affect expected auction revenues in weeks 21-30; this is consistent with out earlier findings. The two most important result in the figure are that an SCR has the largest effect for cars high condition grades, i.e. cars that are in very good condition, and that SCRs do not have a negative effect for the very worse grades. In fact, the effect is slightly positive. This suggests that market matching is likely to be an important consequence of the SCRs.

Another way to look at expected auction revenues is to normalize revenues by the National Auction Price of the consigned car. This reduces the variance in the expected auction revenue measure. Figure 3 shows the result. A similar pattern emerges, except that SCRs seem to have a non-negative effect across *all* condition grades, again consistent with a market matching story.

To assess the statistical significance of these results, we use a t-test to compare auction revenues (normalized by NAP) by condition grade during weeks 31-39 (see Table 10). The small cell sizes for each condition grade allow us to conclude only for grades 1 and 5 that a posted SCR is associated with higher expected auction revenues. There is weak evidence that a posted SCR is associated with higher expected auction revenues for grades 2 and 4. The effect for condition grade 3 is clearly too small to consider as different from 0.

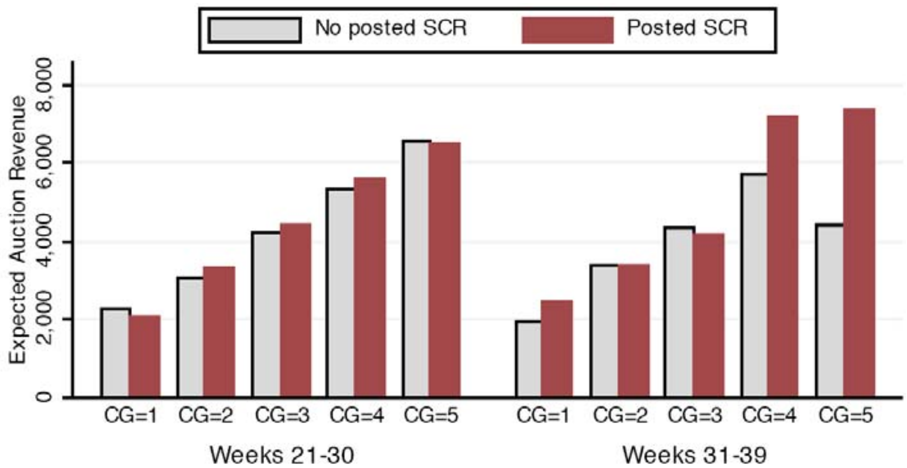


Figure 3: Expected auction revenue by condition grade and experimental condition

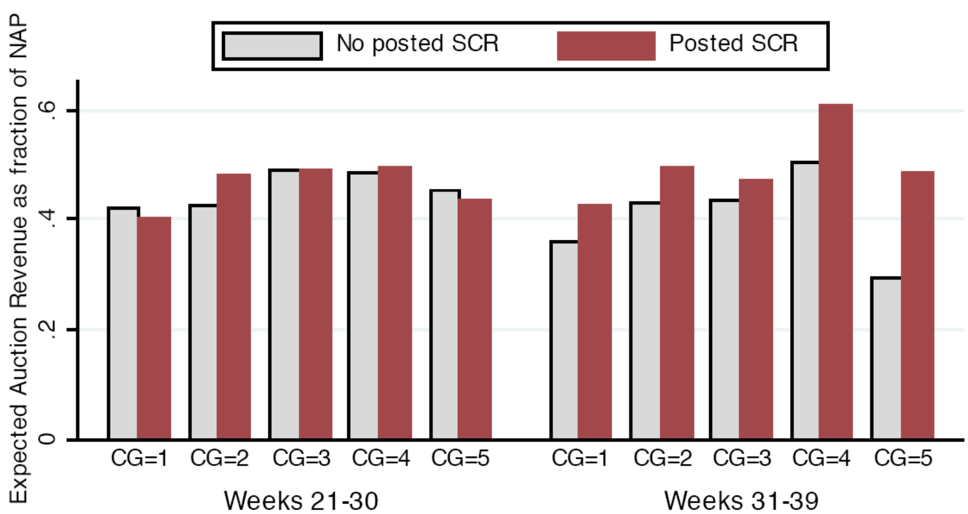


Figure 4: Expected auction revenue / NAP by condition grade and experimental condition

Table 10: Expected auction revenue / NAP by condition grade, weeks 31-39

| Condition Grade | # of Cars | No posted SCR | Posted SCR | Difference | % Difference | t-statistic | p-value |
|---|---|---|---|---|---|---|---|
| 1 | 1070 | 0.361 | 0.425 | 0.064 | 17.7 % | 2.02 | 0.044 |
| 2 | 483 | 0.428 | 0.496 | 0.068 | 15.9 % | 1.39 | 0.16 |
| 3 | 644 | 0.436 | 0.472 | 0.035 | 8.0 % | 0.82 | 0.41 |
| 4 | 254 | 0.504 | 0.609 | 0.104 | 20.6 % | 1.56 | 0.12 |
| 5 | 245 | 0.293 | 0.483 | 0.191 | 65.2 % | 2.98 | 0.003 |

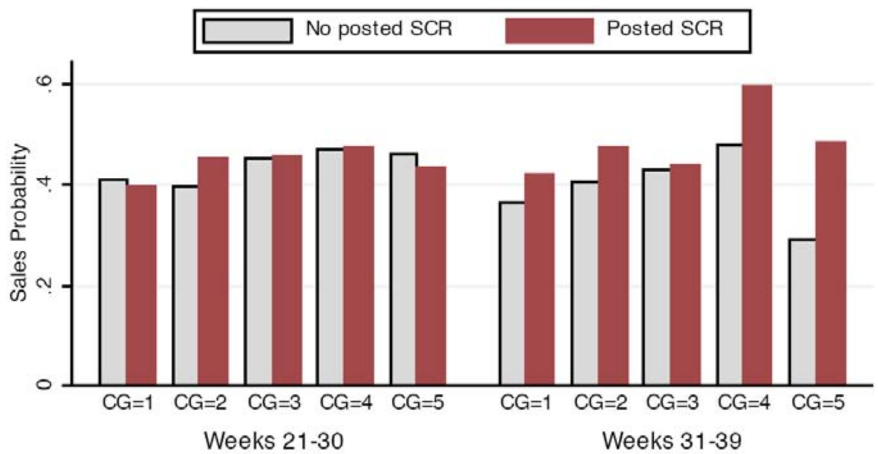


Figure 5: Sales probability by condition grade and experimental condition

We can decompose the auction revenue effect into a sales probability and price effect. As Figures 5 and 6 show, most of the difference in expected auction revenues comes from differences in sales probabilities not from differences in auction prices. This is true regardless of condition grade.

SCRs contain an estimate of the labor and parts cost required to fix damage on the inspected vehicle. These yield a different estimate of the condition of a vehicle than the condition grade. For example, as a rule the AH will not award a car a condition grade above 3 if any sheet metal of the car has been repainted. Now suppose that a car has had some parts of it sheet metal repainted but the car has no damage otherwise. Then the repair cost estimate is zero but the condition grade is 3.

Since the measure are not perfectly correlated, but the repair costs give dealers useful information about the condition of the vehicle, we can also investigate whether the effect of a posted SCR on auction outcomes differs by the estimated repair costs of the vehicle. We create repair cost quintiles (to stay with the condition grade ordering we define 1 as high repair cost and 5

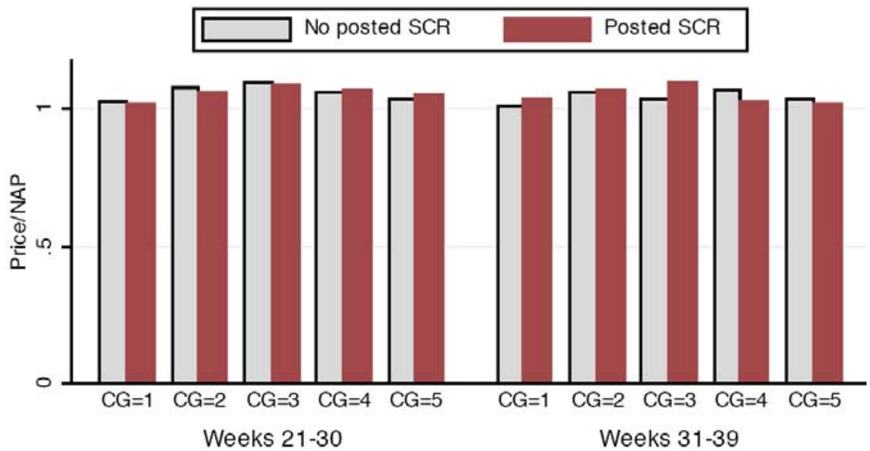


Figure 6: Price/NAP by condition grade and experimental condition

as low repair cost). Figure 7 shows the effect of SCR on expected auction (divided by NAP) by repair cost quintile.

Similar to our findings about condition grades, we find that expected auction revenues are generally higher for cars with a posted SCR in weeks 31-39. However, we don't find evidence that the effect is largest for cars with low repair costs (as we did not cars with high condition grades). There is also no evidence that a posted SCR reduces expected auction revenues for cars with high estimated repair costs. In fact, the results point to the opposite.

# 6 Discussion

- Linkage may be there but market matching seems to overcome the negative effect that low CGs may have
- If reserve prices are set close to the higher end of the valuations (can always come back) then the effect will be mostly on the likelihood of a sale and less on the price, which is what we get.
- Our sellers set their reserve price without knowing that their cars will have SCRs. If the sellers respond with changing reserve prices then by revealed preferences it must be that expected revenue is higher still.

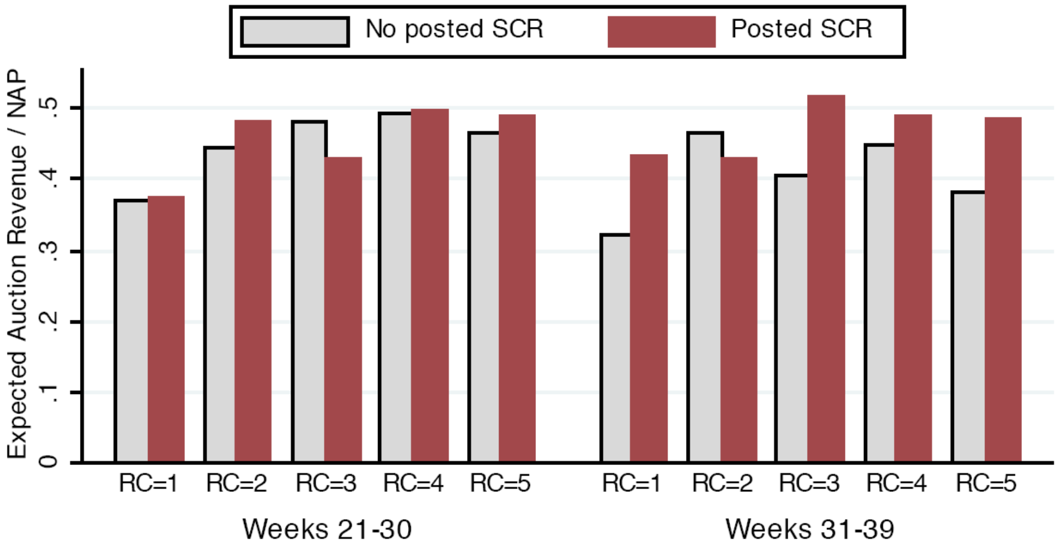


Figure 7: Expected Auction Revenue/NAP by Repair Cost and Experimental Condition

# 7 References


Board, Simon. (2009) "Revealing Information in Auctions: The Allocation Effect," *Economic Theory*, 38(1):125-135

Cutler, David M., Robert S. Huckman and Mary Beth Landrum. (2004) "The Role Of Information In Medical Markets: An Analysis Of Publicly Reported Outcomes In Cardiac Surgery," *American Economic Review Papers and Proceedings*, **94(2)**:342-346

De Silva, Dakshina G., Timothy Dunne, Anuruddha Kankanamge and Georgia Kosmopoulou (2008) "The impact of public information on bidding in highway procurement auctions," *European Economic Review* **52(1)**:150–181

Genesove, David (1993) "Adverse selection in the wholesale used car market," *Journal of Political Economy* **101(4)**:644-665.

Goeree, J.K., Offerman, T. (2003) "Competitive bidding in auctions with private and common values," *Economic Journal* **113 (4)**:598–613.

Hishleifer, Jack (1971) "The Private and Social Value of Information and the Reward to Inventive Activity." *American Economic Review*, **61(1)**:561–574.

Kagel, John .H., R.M. Harstad and Dan Levin (1987) "Information impact and allocation rules in auctions with affiliated private values: A laboratory study." *Econometrica* **55(6)**:1275–1304.

Klemperer, Paul (1999) "Auction Theory: A Guide to the Literature," *Journal of Economic Surveys* **13(3)**:227-286.

Milgrom, Paul R. *Putting Auction Theory to Work.* 2004. Cambridge University Press, New York, NY.

Milgrom, Paul R. and Robert J. Weber (1982) "A theory of auctions and competitive bidding," *Econometrica* **50 (5)**:1089–1122.

Overby, Eric and Sandy Jap (2009) "Electronic and Physical Market Channels: A Multi-Year Investigation in a Market for Products of Uncertain Quality," *Management Science*, **55(6)**:940-957.

Perry, Motty and Phillip .J. Reny (1999) "On the failure of the linkage principle in multi-unit auctions," *Econometrica* **67(4)**:895–900

Porter, Robert H. (1995) "The role of information in US offshore oil and gas lease auction," *Econometrica* **63(1)**:1–27.

# Appendix

Table 11: Dealer-consigned and inspected cars by week[†]

| Sale Week | Dealer-Consigned Total | With SCR Not reported | With SCR Reported |
|---|---|---|---|
| 21 | 1,442 | 237 | 223 |
| 22 | 1,709 | 195 | 186 |
| 23 | 1,438 | 324 | 330 |
| 24 | 1,606 | 281 | 365 |
| 25 | 1,249 | 303 | 344 |
| 26 | 1,408 | 229 | 250 |
| 27 | 1,170 | 290 | 305 |
| 28 | 1,462 | 245 | 245 |
| 29 | 1,440 | 267 | 281 |
| 30 | 1,621 | 231 | 269 |
| 31 | 1,533 | 233 | 247 |
| 32 | 1,590 | 214 | 215 |
| 33 | 1,329 | 237 | 154 |
| 34 | 1,555 | 225 | 185 |
| 35 | 1,526 | 150 | 140 |
| 36 | 1,474 | 73 | 85 |
| 37 | 1,418 | 90 | 107 |
| 38 | 1,554 | 71 | 84 |
| 39 | 1,639 | 82 | 104 |
| Total | 28,163 | 3,977 | 4,119 |

Weeks are of 2008.

Table 12: Summary Statistics

| Variable | N | mean | p50 | sd | min | max |
|---|---|---|---|---|---|---|
| Model Year | 8096 | 2003.509 | 2004 | 2.653825 | 1997 | 2009 |
| Mileage | 8096 | 76091.4 | 71340 | 45527.27 | 0 | 999999 |
| Condition Grade | 8096 | 2.419466 | 2 | 1.312998 | 1 | 5 |
| Repair Costs | 8096 | 1348.07 | 1025.12 | 1236.787 | 0 | 16110.8 |
| Sold | 8096 | .4300889 | 0 | .4951189 | 0 | 1 |
| Sales Price | 3430 | 8604.672 | 7300 | 5861.903 | 500 | 59000 |
| National Auction Price | 3430 | 8395.569 | 6975 | 5810.735 | 200 | 62000 |
| Sales Price/National Auction Price | 3430 | 1.056347 | 1.030303 | .2430727 | .2358974 | 5.6 |

Table 13: Randomization check: Expected auction revenue for weeks 31-39

| | Base result | Fixed Effects |
|---|---|---|
| Posted SCR | 626** | 439+ |
| | (217) | (226) |
| Week 32 | | -277 |
| | | (390) |
| Week 33 | | 90 |
| | | (406) |
| Week 34 | | 511 |
| | | (399) |
| Week 35 | | 489 |
| | | (435) |
| Week 36 | | 318 |
| | | (530) |
| Week 37 | | -272 |
| | | (499) |
| Week 38 | | -1120* |
| | | (536) |
| Week 39 | | -1083* |
| | | (545) |
| Condition grade=2 | | 643+ |
| | | (329) |
| Condition grade=3 | | 767* |
| | | (316) |
| Condition grade=4 | | 2344** |
| | | (432) |
| Condition grade=5 | | 1821** |
| | | (469) |
| Model year 1998 | | 1338 |
| | | (1380) |
| Model year 1999 | | 1162 |
| | | (1226) |
| Model year 2000 | | 1120 |
| | | (1212) |
| Model year 2001 | | 1540 |
| | | (1184) |
| Model year 2002 | | 2179+ |
| | | (1160) |
| Model year 2003 | | 1980+ |
| | | (1150) |
| Model year 2004 | | 2627* |
| | | (1152) |
| Model year 2005 | | 2103+ |
| | | (1155) |
| Model year 2006 | | 2867* |
| | | (1156) |
| Model year 2007 | | 3623** |
| | | (1184) |
| Model year 2008 | | 2682* |
| | | (1265) |
| Model year 2009 | | 1035 |
| | | (2245) |
| Seller fixed effects | no | yes |
| Constant | 3262** | 451 |
| | (146) | (1120) |
| Observations | 2696 | 2696 |
| R-squared | 0.003 | 0.227 |

* significant at 5%; ** significant at 1%; + significant at 10% level. Robust SEs in parentheses.