# Bid Takers or Market Makers?
# The Effect of Auctioneers on Auction Outcomes*


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**April, 2014**


**Abstract**

Auction design has been studied extensively; however, within a given design, does the *process* of how an auction is conducted matter as well? We address this question by looking for systematic heterogeneity in the performance of auctioneers in English auctions. We analyze over 850,000 wholesale used-car auctions and find significant differences across auctioneers in outcomes for otherwise similar cars. The performance heterogeneities are stable across time and correlate with subjective evaluations by the auction house. We discuss the mechanisms driving differential performance and find evidence suggesting a role for tactics that generate bidder excitement or urgency.



* We benefited from the comments of seminar participants at UC Berkeley, Boston University, University of Chicago, Colgate, Cornell, MIT, Queen's University, RAND, Toronto, Wisconsin-Madison, the Bank of Italy, and conference participants at the 2014 ASSA Meetings, 2014 NBER IO Winter Meeting, the 2013 IZA Workshop on Behavioral Economics, the 2013 European Behavioral Economics Meeting, the 2013 NBER Summer Institute, the 2013 Stanford Institute for Theoretical Economics, and the 2013 FTC Microeconomics Conference. Special thanks to Jennifer Brown, Eric Budish, James Roberts and Tim Van Dam for helpful comments and suggestions; and to Barb Richards of the Canadian Auction College for allowing one of the authors to attend auctioneer college classes.

## 1. Introduction

Auctions are central features of many important markets, such as those for radio spectrum bands, used industrial machinery, livestock, used cars, antiques, government-owned property, procurement, debt instruments, charity, and real estate. It is therefore not surprising that economists have developed a large body of research on the functioning of auctions. Much of this work has focused on exploring the effects of different auction structures, comparing common designs such as English, Dutch, first-price sealed-bid, and second-price auctions, and assessing their revenue generation and efficiency. The literature has paid particular attention to how the performance of different auction designs may depend on the underlying distributions of product valuations and the level of information available to market participants.[1]

Although this large literature has explored the importance of auction structure to outcomes, the *process* of running an auction (conditional on the auction design) has received much less attention. For example, the basic structure of a common English auction is that there is some form of open outcry, ascending prices, and the highest bidder wins. Within that basic structure, however, there are a range of process features that could affect relevant outcomes, including the level of the opening bid, pattern and pace of price adjustments, and so on. In particular, over $250 billion worth of goods are transacted each year through live auctions (National Auctioneer Association, 2010) with human auctioneers who have some ability to affect the process by which items are sold. In this paper, we test whether differences in auction process—through the channel of auctioneer difference—meaningfully impact auction outcomes.

Models of auctions largely abstract from the role of the auctioneer. In particular, Milgrom and Weber (1982) modeled English auctions assuming that prices rise continuously from a low level and that all participants hold down a button and can be observed dropping out of the auction at some point when the price rises too high. Within that structure, there is no role for an auctioneer and the focus naturally becomes on the information structure (e.g., private vs. common signals) of the bidders in the auction. But as Milgrom and Weber themselves highlight, auctions are rich environments and many real-world ascending-bid auctions involve human auctioneers who are typically experienced professionals. These auctioneers may influence the process of an auction by choosing opening bid amounts, changing the pace of price adjustment, and deciding when to stop the bidding. In addition, many auctioneers (especially in the U.S.) interact with buyers and call out bids in a fast-paced, rhythmic chant, attempting to create a sense of urgency and excitement among bidders.[2]

[1] An overview of auction theory can be found in Bulow and Roberts (1989), Klemperer (2004), and Milgrom (2004).
[2] To our knowledge, the only two studies examining auctioneers are Capizzani (2008), who presented experimental evidence regarding the presence of a live auctioneer whose only role was to choose the public-information structure, and Cassady (1967), who provided a detailed qualitative description of auctions and auctioneers. Note, moreover, that much of the literature uses the term "auctioneer" to refer to the auction house or platform (Hossain, Khalil, and

We study the role that auctioneers play in auction outcomes in the context of wholesale used-car auctions, which we believe is a market well suited to studying auctioneer effects. More than 10 million used cars are traded in the U.S. at wholesale auctions each year (Manheim, 2011), totaling over $80 billion in sales (NAAA, 2009). The structure of these auctions is an ascending auction (English-style) with a live auctioneer and no pre-determined time limits. Cassady (1967) argues that this is the format in which the auctioneer has the most potential to influence the sale, making this a good setting to begin to more systematically study the importance of auction process. Because both buyers and sellers in these wholesale auctions are professionals trading in high-value goods, we expect all participants to have strong incentives and an understanding of auctions.

Our data include over 850,000 cars auctioned by 60 auctioneers between 2007 and 2013 at the largest location of a leading operator of used-car auctions in the U.S. Our primary measure of auctioneer performance is each auctioneer's conversion rate, defined as the fraction of auctions that end in a sale.[3] The sellers of cars in the auctions that we study set reservation prices that are binding often enough that a car going through the auction block has on average about a 50% chance of selling. The auction company and its auctioneers make it clear that the primary goal for an auctioneer is to maximize the probability of each car selling. Our main question of interest is whether the probability that a given auction will result in a sale is affected by the particular auctioneer for that car. In addition to our primary measure of conversion rates, we also investigate secondary performance metrics such as price, high bid, and speed of sale.

Cars are not randomly assigned to auctioneers in these wholesale auctions, which presents an obvious challenge to the identification of auctioneer heterogeneity. In particular, more experienced auctioneers are more likely to run auctions for newer, higher-valued cars. Fortunately, however, each of the auctioneers in our sample has auctioned a very large number of cars and faced substantial variation in their sample of cars. Our primary identification strategy exploits that fact by controlling for a rich set of observable factors at our disposal, including day effects, seller effects, and car-type effects. We argue that the process by which cars are assigned to lanes and these additional controls are likely to capture much if not all of non-random assignment that occurs in this marketplace. We also provide additional robustness tests, including exploiting shift changes as a way to identify the causal impact of auctioneers on outcomes.

We find significant dispersion in auctioneers' fixed effects for our performance measures. In our preferred specification, a one-standard deviation increase in auctioneer performance corresponds to an increase in the probability of sale of 2.3 percentage points (about a 4.3% increase over an average

Shum, 2013), or, in some cases, the seller. In this paper we reserve the term auctioneer strictly for the person calling out bids at a live auction, and the term seller strictly for the owner of the car who brings it to the auction house.

[3] Throughout, we use the terms "conversion rate" and "probability of sale" interchangeably.

conversion rate of 0.53). For our secondary outcome measures, we estimate that a one-standard deviation increase in performance equates to an increase in residual sales price by $41.8 (the average sales price is $15,141), high bid by $88, and an increase in speed of sale by 6.1 seconds (the average length of sale is 103 seconds). We apply an Empirical Bayes shrinkage correction to account for the fact that each auctioneer's effect is measured with noise and find that the estimated effects change very little. This indicates that our statistical power is such that the noise in our estimates is small relative to our effect sizes and that the heterogeneity that we find is not merely due to sampling variation.

These effect sizes suggest that auctioneers can have meaningful economic impacts on auction outcomes. For example, we estimate that auctioneers at the top of the distribution of conversion rates may generate revenues on the order of $25,000 per year higher for the auction house than those at the bottom of the distribution. We also find that these performance enhancements in conversion rates due to higher-ability auctioneers are generally comparable to those found in studies that estimate the effects of changes in auction design, information structure, and broader macroeconomic factors on similar outcomes (Hortacsu, Matvos, Syverson, and Venkataraman, 2013; Tadelis and Zettelmeyer, 2011). The improvements in price are comparable to the theoretical benchmarks of designing the auction optimally (Bulow and Klemperer 1996) or of increasing the number of bidders (Coey, Larsen and Sweeney 2014).

A number of additional analyses and robustness checks support our findings that some auctioneers indeed outperform others. First, the performance heterogeneity for conversion rates and time on the block is persistent over time: on average, auctioneers who achieved higher conversion rates or faster sales in the first half of our sample (2007-2009) also performed better in the second half (2010-2013). Second, the different performance metrics are correlated at the individual level in that auctioneers with higher conversion rates also achieve higher prices and are typically faster. We also find that these objective performance metrics are correlated with subjective evaluations of auctioneers that were made available to us by the auction house. Our metrics, finally, are predictive of which auctioneers left the company during a period of downsizing.

These results suggest that the way in which an auction is run can have a nontrivial impact on outcomes, and in particular, human auctioneers do not simply call out prices and recognize bids. It is also important to bear in mind that these wholesale auto auction environments involve large stakes and are conducted with professionals who often have substantial auction experience. To us this suggests that auctioneer effects are not a quirk related to unfamiliarity with auctions, but rather a fundamental feature of well-established and well-functioning auction environments. The fact that we observe substantial and persistent heterogeneity across a pool of professional auctioneers also suggests that auction houses have not found ways to transfer these successful practices throughout their auctions.

Having documented that auctioneers vary systematically in their effects on auction outcomes, a natural next step is to explore the mechanisms at play in generating these differences. Deeper explorations of specific auction processes should be an interesting avenue for future studies and we suspect that experimental methods are likely to be a primary avenue for exploring these issues. As a first step to better understanding the mechanisms at play in auctioneer success, we lay out six classes of potential mechanisms. We consider the possibility that auctioneers differ in their ability to 1) convey information about car quality, 2) convince sellers to lower their reservation values and accept auction outcomes, 3) generate patterns of bids that reveal more information about the range of bidder valuations, 4) help reduce search frictions and match buyers to appropriate cars, 5) facilitate bargaining, and 6) exploit behavioral biases related to issues such as excitement in auctions. These mechanisms are difficult to disentangle, because they are not mutually exclusive and frequently observationally equivalent. Nonetheless, we present qualitative evidence from surveys of auctioneers and also discuss patterns in our data that provide suggestive evidence about these mechanisms.

We can conclude with relative certainty that auctioneers in this setting do not convey information about the quality of cars, and we also find little support for the idea that they are primarily trying to persuade sellers to lower their reservation values. We have less conclusive results about the other mechanisms that relate to changing buyer values, but the evidence supports the idea that part of the difference in auctioneer abilities arises because some auctioneers are better at creating urgency, excitement and competitive arousal among buyers. In particular, industry participants often report that successful auctioneers use speed and pacing of auctions to affect the level of excitement in ways that increase bidding, and that specific mechanism appears to be consistent with our findings that auctioneers who run faster-paced auctions are somewhat more likely to achieve sales and higher prices.

In showing that auctioneer heterogeneity resides at least in part in the ability to generate excitement among bidders, this paper contributes to a small but growing literature exploring behavioral factors in auction environments such as auction fever or overbidding (Ockenfels, Reiley, and Sadrieh, 2007; Podwol and Schneider, 2011; Malmendier and Szeidl, 2008). In the literature, auction fever—also referred to as competitive arousal or bidding frenzy—encompasses many behaviors, such as rivalry or spite (Morgan, Steiglitz, and Reis, 2003; Ku, Malhorta, and Murnigham, 2005; Cooper and Fang, 2008); endowment effects (Heyman, Orhun, and Ariely, 2004; Dodonova and Khoroshilov, 2009); utility of winning (Cooper and Fang, 2008); regret/fear of losing (Cramton, Filiz-Ozbay, Ozbay, and Sujarittanonta, 2012; Filiz-Ozbay and Ozbay, 2007); uniqueness of being first (Ku, Malhorta, and Murnigham, 2005); and irrational limited attention (Lee and Malmendier, 2011). Documenting the relevance of behavioral factors in auctions is particularly significant in our context where actors are informed professionals, as in Goldreich (2004). Our suggestive evidence that the pace of auctions may be important is also related to work in psychology, for example, suggesting that thought speed can have an impact on mood (Pronin and Wegner, 2006). Ku, Malhotra, and Murnigham (2005) also studied how time pressure can affect bidding, and Malhorta (2010) found, in a field experiment, that the combination of rivalry effects and time pressure is particularly strong in leading to additional bidding.

The results here also provide new insights about how these complex auction interactions unfold. This can inform auction design theory on how specific auction processes may affect, for example, revenue equivalence and the strategic equivalence among auction structures. We suggest that there are important dynamics at play in English auctions that are not captured by the classic framework and as such point to the importance of existing work on expanding models (Harstad and Rothkopf, 2000) and econometric approaches (Haile and Tamer, 2003) to account for the richness of real auction environments.

In documenting the heterogeneous performance of auctioneers, finally, we also contribute to the literature that has explored the impact of single individuals on organizational outcomes in several contexts (e.g. in CEOs and bosses, judges, teachers, scientists, and political leaders).[4] The evidence here is from a context where we would not expect to see meaningful individual heterogeneity; in particular, the competition among buyers generated by the bidding system, and the sophistication of the agents who have more information about the good than the auctioneers, play against finding any significant and heterogeneous impact of auctioneers. Although auctioneer heterogeneity is somewhat smaller than performance heterogeneities in other contexts, it is striking that we do find statistically and economically significant auctioneer differences.

The rest of the paper proceeds as follows. Section 2 discusses the data and offers detail on the institutional context. The empirical strategy and our main results are reported and discussed in Section 3. Section 4 is dedicated to exploring the mechanisms behind the heterogeneity across auctioneers. Finally, Section 5 offers concluding remarks.

## 2. Institutional Details and Data

The company for which we have data specializes in providing auction services for the wholesale used car market. This company has many auction facilities around the U.S., where each facility holds an auction once or twice per week. Bidders at these auctions are licensed used-car dealers who typically plan to sell the cars they purchase on their personal used-car lots. The cars being sold come from two basic sources: "dealer" sellers and "fleet/lease" sellers. The dealer sales are cars being sold by retail car dealers and are primarily cars which were received as trade-ins that the dealer did not want to sell on his or her own lot.

[4] See, for example, Abrams, Bertrand and Mullainathan (2013); Azoulay, Graff Zivin and Wang (2010); Bertrand and Schoar (2003); Chetty, Friedman, Hilger, and Saez (2010); Galasso and Schankerman (2013); Hanushek (2011); Jones and Olken (2005); Lazear, Shaw, and Stanton (2012); Malmendier and Tate (2009).

The fleet/lease sales represent cars sold by rental car companies, leasing companies, or company fleets and are typically sold in large volumes with low reservation prices.[5] On an auction day, cars run through one of multiple lanes which operate simultaneously. The buyers bid for cars in a standard ascending-price (i.e., English) auction which typically lasts between one and two minutes. At the auction house which serves as our primary source of data, the seller of the car is usually present at the sale and decides whether or not to accept the high bid.[6] Therefore, the highest bidder receives the car as long as the auction price exceeds the seller's privately known reserve price. The high bidder can personally take it back to his or her used-car lot or arrange delivery through independent agencies which operate at the auctions. If the final bid does not exceed the seller's reserve price, the seller can either leave the car at the auction house to be sold at some future sale or remove the car to his or her own car lot.[7]

Wholesale used-car auctions are conducted by professional auctioneers. Most of them have some formal training from one of many auctioneer schools located nationwide, the existence of which is by itself suggestive that auctioneer skills and training may matter.[8] Auctioneers also tend to learn the trade through an apprenticeship system and many come from families with long histories as auctioneers. Top auctioneers in the profession are granted awards.[9] Section 4 discusses the characteristics and tools of an auctioneer that are considered important.

The auctioneers at the locations we study here work as independent contractors and receive a fixed daily wage for each auction day they work. The auction house periodically uses small bonus incentives tied to targets like the fraction of cars sold in a lane per day. The auctioneers, however, have no commission incentives on any particular car they auction. The auction house tells us they use this compensation design in part so that the auctioneers are not seen by the bidders as agents of the seller, but rather as independent market makers.

[5] Our analysis uses only cars sold by "dealer" sellers. The two primary reasons for this restriction are, first, that fleet/lease companies set low or no reservation prices and thus sell nearly all of their cars. This results in us having little if any variation in our primary performance metric (conversion rates). Second, and just as importantly for our identification, because fleet/lease companies are selling a large volume of cars, they tend to either bring their own auctioneer with them to the auction or have a relationship with one particular auctioneer that is used week after week. Thus, even if variation in performance existed, we would be unable in many cases to disentangle an auctioneer effect from a seller effect in the fleet/lease sample.

[6] At many other auto auction houses, the seller is not necessarily present for the sale and, when this is the case, either reports a secret reserve price to the auction house before the sale takes place or requests to be notified of the high bid by phone after the sale in order to be given the chance to accept or reject the final bid. See Larsen (2014).

[7] Much of the industry facilitates bargaining between the seller and the high bidder when the final bid fails to exceed the reserve. The auction house from which our primary dataset comes does not formally facilitate such bargaining, although it does occur on occasion. When it occurs, it typically occurs quickly on the auction block rather than over the phone as in Larsen (2014), and data on when bargaining occurred is unavailable.

[8] The National Auctioneers Association website (www.auctioneers.org) lists 29 schools, and additional schools are listed elsewhere.

[9] For example, the World Auto Auctioneer Championship has been held annually since 1989.

On the auction day the auctioneers are assigned to specific lanes. Typically, dealer lanes are filled on a first-come, first-served basis and the auction house will simultaneously run multiple lanes of dealer-car auctions. For example, a dealer may bring in five cars the day before the auction and be slotted into lane 15, with run numbers 26-30; another dealer may then arrive with three cars and be given run numbers 31-33 in lane 15. On average, 200-300 cars are auctioned off in each lane in a given day. The median seller in a lane on a given day represents only 6.4% of cars being auctioned in that lane on that day.

Although the method for assigning dealer cars to lanes produces a large amount of random variation in what cars an auctioneer will end up auctioning, the process is not entirely random. For example, larger dealers can often influence the choice of lane, timing of their run through the lane, or even which auctioneer is assigned to their lane.[10] For this reason, it is important that we control for features of a car (e.g. seller effects) in our empirical strategy. We will argue that the allocation of cars to auctioneers is conditionally random after controlling for a set of important car characteristics and provide several robustness checks to help assess this identifying assumption.

We have access to information on all cars auctioned between January 2007 and June 2013 at the largest facility operated by the auction company for which we have data. We take steps to clean the data before running analyses. As explained above, we restrict attention to dealer cars. We drop a small number of observations with missing data or nonsensical values. We exclude observations having outlier values on our key variables (e.g. cars that sold for less than $100 or for more than $75,000). We then restrict the sample to auctions conducted on two specific days of the week (there are occasionally small specialty auctions conducted on other days of the week). We eliminate rerun auctions.[11] Lastly, we reduce the sample to the 60 auctioneers who auctioned off at least 5,000 cars during our sample period. This limits the sample of auctioneers to those that worked "full time" for at least a year or two during our sample period. Within these remaining 60 auctioneers, the median auctioneer performed just over 13,000 auctions during our sample period while the busiest auctioneer performed approximately 30,000 auctions.

Our final dataset contains information on 859,239 cars. For each car we observe the make, model, body style, model year, date and time at which it was auctioned, and odometer mileage as well as an identifier for the seller of the car. We also observe whether the car sold, the sales price if sold, the highest bid if not sold, the amount of time spent auctioning off the car, and the lane in which the car was sold.

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[10] In written correspondence with the general manager of the auction facility for which we have data, we asked whether auctioneers are randomly assigned to the dealer lanes. The response was, "Sometimes it is by dealer request. We try and discourage that, because we want 40 great auctioneers..."

[11] If a car does not sell, sometimes it will be put through the lane one more time at the end of the day with a group of other cars that did not sell. We restrict the sample to the first time a car went through the lane on a given day.

Lastly, auctioneer identifiers let us detect the specific auctioneer who was on the block in a given lane for a given car.[12]

Table 1 reports some basic descriptive statistics on our sample of used cars. The average car is 4.4 years old and has about 56,000 miles. Approximately 53% of cars sell.[13] The mean sales price for sold cars is slightly above $15,000. For cars that sold, we also have a wholesale, "blue book"-type value that is created by the auction house. This allows us to create a variable that we call "residual price" which is the actual price the car sold for minus the company's expected price of the vehicle. We find a positive residual of approximately $375 for the cars in our sample. We also have a variable that indicates the highest bid made on the car. Unlike the sale price and residual price, this variable is available for cars that sold and cars that did not sale (it is equal to sale price for cars that sold). We see an average high bid of approximately $15,500 for the cars in our sample. Lastly, on average car auctions last 1 minute and 43 seconds.[14]

We consider four main performance measures for auctioneers: a) conversion rates (fraction of cars that sold), b) the price of cars conditional on selling, c) the highest bid for each car, and d) the time that each car is on the block. Conversion rate is the primary outcome measure of interest. The auction company earns a flat commission fee when cars transact at the auction with very small additional fees for higher-valued vehicles. As we document below, the sellers of cars often set binding reservation values, so that substantial fractions of the cars running through the lanes each day do not sell. From a seller's perspective, both conversion rates and to a larger extent prices are important outcomes. However, the company also needs to attract buyers, therefore high prices, in and of themselves, are not the company's primary goal. The speed at which a car is sold is also of interest to the auction house as faster sales imply more cars can get through the lanes of the auction house on a given day as opposed to remaining unsold in inventory to be sold at a later date.

[12] At some auctions, there is also a "ringman" on the floor of the auction who assists the auctioneer in identifying bids and energizing the crowd. The auction facility for which we have data does not use a ringman.

[13] Sellers either provide the auction house with a reservation price ahead of time or, more frequently, they sit by the auctioneer during the auction of their cars. Thus, the seller often makes a decision on the block as to whether or not the highest bid is more than their reservation price. We unfortunately do not have any consistent data for the reservation prices set by sellers.

[14] Time on the block is calculated by subtracting the starting time stamps from consecutive car auctions on each auction lane to determine the duration of each auction. It has a smaller number of observations than the other variables because we set time on the block equal to missing if the time taken to sell the car is in the bottom or top 5 percentile. The reason we make this restriction is because cars that take a very long (or short) time to sale may have had other factors outside of the control of the auctioneer influence the time on the block. For example, waiting for the seller, getting the information coded into the computer, or waiting for the next car to be driven into the lane can cause an auction to last much longer than normal.

We specifically discussed these performance measures with the general manager of the auction facility for which we have data. It is clear that conversion rate is the most important objective to them.[15] The general manager wrote, “Conversion rate pays the bills. Sales price and speed are generally the parents of conversion rate.” The manager indicated that as long as a car sells, the company is somewhat indifferent regarding the price, in the same way that a stock exchange ultimately does not care if a stock price goes up or down because they are catering to both buyers and sellers. He further specified that although speed is important (because it allows them to sell cars more quickly on a given day), he sees speed as primarily an input into whether a car sells or not. Specifically, he said, “Speed tends to sell and sell for a higher price. It puts adrenaline into the mix for the buyer.” Based on these conversations regarding what makes a “good” auctioneer for this particular company, our focus in the empirical section below is primarily on the probability-of-sale metric.

However, we also provide results on price, highest bid, and speed. It is worth noting that these additional metrics are problematic in certain ways. For example, the sale price variable may not provide a good metric for the quality of an auctioneer because it is only available for a selected part of the sample (i.e. the cars that sold). A high-quality auctioneer that is able to sell more cars could theoretically call lower prices on average than a low-quality auctioneer. This could happen if the marginal cars that a high-quality auctioneer is able to sell are of lower value or have systematically worse unobservables (using residual prices would take care of the former, but not the latter issue). Using the highest bid (which is available even for cars that did not sell) may help to address this selection problem. However, the high bid may be problematic in other ways. For example, a high-quality auctioneer may be more experienced and know when to shut down an auction early because the reserve price that the dealer has set is extremely unlikely to be met given how bids are coming in. As a consequence, high-ability auctioneers may have several high bids that are low and as such, high-ability auctioneers may on average get lower bids than low-ability auctioneers. Overall, we think there is some value to generating results for outcome measures such as residual price and high bid in addition to our primary measure of conversion rates. We are, however, somewhat cautious in how we interpret these results because they could be prone to the biases discussed above and are not the primary objective of the auctioneer or the auction house.

[15] The recent discussion of the wholesale auto auction industry in Treece (2013) explains the importance of conversion rates to auction houses and also highlights the important role a good auctioneer can play in increasing conversion.

## 3. Empirical analysis

### 3.1 Identification strategy

One measure of auctioneer heterogeneity would be to simply calculate the average conversion rate for each auctioneer in our dataset. Analyzing the variation in these averages across auctioneers could provide an indication for the degree to which an auctioneer can impact auction outcomes. Following the discussion of how auctioneers are allocated to lanes reported in the previous section, a concern with this approach is that these raw comparisons may result in performance dispersion that is due to omitted variables and not differential auctioneer ability. Thus, our first and primary method for overcoming this threat to identification is to control for a rich set of observable factors about each auction. Given the quasi-random process in the way that most sellers and auctioneers are matched, we argue that controlling for variables such as day effects, seller effects, and car-type effects addresses non-random assignment.

Our main analyses of auctioneer heterogeneity are based on estimation of versions of the following regression model:

$$Y_i = \alpha + \beta_k + X_i{}'\gamma + \varepsilon_{ik}. \qquad (1)$$

$Y_{ik}$ is an indicator for whether the car sold (or one of our secondary performance metrics). Individual cars are indexed by $i$ and auctioneers by *k*. The vector $X_i$ includes, depending on the specification, fixed effects for various characteristics of car $i$ (sellers, auction day, lane number, etc.). The estimates of interest are the $\hat{\beta}_k$s, the auctioneer effects.

Because the individual $\hat{\beta}$s will depend on which auctioneer is excluded from the regression as the baseline, it is useful to have a normalization so that auctioneer effects are not sensitive to this specification issue. We thus compute:

$$\hat{\beta}_{norm,k} = \hat{\beta}_k - \frac{1}{M}\sum_{j=2}^{M} \hat{\beta}_j \text{ for } k = 2, \ldots M;$$

$$(2)$$

$$\hat{\beta}_{norm,1} = 0 - \frac{1}{M}\sum_{j=2}^{M} \hat{\beta}_j,$$

where *k = 1* denotes the omitted auctioneer in Equation (1).

Our interest is in understanding whether there is substantial heterogeneity in these normalized auctioneer effects. Statistically our question of interest is whether the $\beta$ coefficients are jointly different from zero, which can be addressed through standard metrics such as $F$-tests. It is, however, also very useful to be able to talk about the economic magnitude of our findings by focusing on measures such as the spread between auctioneers with high effects versus those with low effects. A challenge here is that even if there is no meaningful underlying heterogeneity in auctioneer ability, we would still expect random sampling variation to generate some degree of dispersion between our estimates of the best auctioneer and the worst auctioneer. This would especially be an issue if our effects were being estimated off of a smaller sample size. We therefore also perform analyses using a Bayesian shrinkage procedure which corrects for sampling variation and has been used in many other settings such as evaluating differences in teacher quality and organizational productivity.[16] Specifically, we calculate:

$$\hat{\beta}_{norm-shrink,k} = \lambda_k \hat{\beta}_{norm,k} + (1-\lambda_k)\frac{1}{M}\sum_{j=1}^{M}\hat{\beta}_{norm,j}, \qquad (3)$$

with $\lambda_k = \frac{\theta}{\theta+\sigma_k^2}$., where $\theta$ is the variance of the 60 normalized estimates and $\sigma_k^2$ is the square of the estimated standard error of each $\hat{\beta}_{norm,k}$. Because the effects are normalized, $\sum_{j=1}^{M}\hat{\beta}_{norm,j} = 0$ by construction; thus the shrinkage estimator reduces to $\frac{\theta}{\theta+\sigma_k^2}\hat{\beta}_{norm,k}$ for each $k$.

### 3.2 Heterogeneity in auctioneer performance

We begin by estimating the model in Equation (1) using probability of sale as the outcome of interest. We estimate eight different specifications, where each specification adds additional controls. The first specification includes no controls (just the auctioneer fixed effects). The first column in Table 2 provides the standard deviation of the auctioneer fixed effects for the various specifications using probability of sale as the outcome of interest. Specification 1 (raw values) suggests that the standard deviation in auctioneers' ability to sell cars is .051. Taken literally, this suggests that a one standard deviation improvement in auctioneer ability translates into a 5.1 percentage point higher probabiliy of sale (off a base of 53%). The solid line in Figure 1 graphically presents these raw auctioneer effects by ranking the 60 auctioneers from worst to best and plotting their associated fixed effects. There is a remarkable amount of variation across auctioneers with the two highest-performing auctioneers being able to sell cars at more than a 10 percentage point higher rate than average.

The concern with these raw performance measures is that unobserved assignment of cars to auctioneers could be taking place. Based on discussions with the auction house, a primary confounder with the raw data is that certain auctioneers may be systematically assigned to sellers that have lower or higher reservation values than other sellers. To control for this concern, we include seller fixed effects in the second specification.[17] Regressions including seller indicators are well-identified because, in general, a given seller is served by more than one auctioneer, and any given auctioneer is associated to more than one seller. On average, a given seller in our dataset has had one of his/her cars auctioned off by 54 of the 60 auctioneers during our sample period. Moreover, a given auctioneer in our dataset has on average auctioned off cars for 840 of the 1,087 large sellers in our data. Figure 1 illustrates how including these

[16] See, among others, Chandra, Finkelstein, Sacarny, and Syverson (2013); Jacob and Lefgren (2005); and Morris (1983).

[17] We include a dummy variable for each of 1,087 sellers who sold at least 100 cars during our sample. The omitted category includes all sellers who sold less than 100 cars during our sample period. Grouping the final 100 sellers into one omitted category makes the estimation computationally feasible.

controls significantly reduces the amount of variation across auctioneers. Table 2 indicates that the standard deviation of auctioneer fixed effects is reduced from .051 to .038 when seller fixed effects are included. One question about including these controls is whether the auctioneer fixed effects are simply dampened, or if the ranking of the auctioneers is also signficantly changed. The second column in Table 2 provides the coefficient of correlation between specification 2 (and the other specifications) and the previous specification and also t-stats in brackets. The correlation coefficient of .94 suggests that including seller fixed effects reduced the variation in auctioneer fixed effects, but did not greatly alter the rank order of the auctioneers.[18]

Almost surely due to macroeconomic factors, the probability of sale in our data changed substantially throughout the sample period. Once again, this can bias the dispersion of auctioneer fixed effects if some auctioneers worked more in certain periods during our sample than others. In Specification 3, we include time controls—both auction day (day*month*year) effects and time of day (hour-by-hour) effects. These controls also capture changes in the auction-house environment which can affect bidders' choices of which lanes and sales to participate in, such as the number of similar cars selling on a given day on in a given hour or the number of active lanes.[19] Figure 1 and Table 2 indicate that these controls reduce the amount of variation in the auctioneer fixed effects. Specification 4 includes fixed effects for the 55 lanes that operated at some point during our sample. This produces a slight decrease in the standard deviation of auctioneer fixed effects. We continue to find that the rank ordering of auctioneers is very similar from one specification to the next.

Specification 5 begins to include car characteristics in the model by adding car-make effects. Specification 6 includes age interacted with make (make*age) and also a 5th-order polynomial in the number of miles on the car's odometer. Specification 7 adds the car model into the interaction (make*model*age) as well as the miles polynomial. Specification 8 adds the body type of the car into the interaction (make*model*body*age) in addition to the miles polynomial. As can be seen in Figure 1 and in Table 2, moving from Specification 4 to Specification 8 neither impacts the standard deviation of the auctioneer effects, nor changes meaningfully the rank ordering of the estimates.[20]

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[18] The reported correlation coefficients are based on correlation of values (Pearson). Rank-correlation coefficients (Spearman) are very similar.

[19] We examined explicitly including measures of the number of similar cars, the number of active lanes, or auctioneer dummies for other auctioneers who were selling at the same time in other lanes and found that these measures captured no additional variation beyond that captured by day and hour effects.

[20] We argue that the stability of the heterogeneity between specification 4 and specification 8 provides some reassurance about the potential impact of selection effects. As has been recently argued (e.g. Oster, 2014; Altonji, Elder, and Taber, 2005), under certain assumptions, the amount of reassurance that one should take from this stability depends crucially on the change in R-squared values across these specifications. The R-squared values for the eight specifications are as follows (we omit these values from Table 2 given space constraints): .008, .074, .236, .240, .243, .252, .276, and .313. Although the largest increases in R-squared values occur between specifications 1

After including the controls mentioned above, we are left with an estimate suggesting that a one standard deviation improvement in auctioneer ability results in a 2.3 percentage point increase in the probability of selling a car (off a base of 53%). Panel B of Figure 1 provides 95% confidence intervals for each of the auctioneer fixed effects. One remaining question is how much of this variation we would expect due simply to sampling variation. To answer this question, we apply the Bayesian Shrinkage procedure discussed above to these estimates. The standard deviation that we find for Specification 8 after applying this procedure is .0220 (compared to .0228 without the shrinkage procedure). Because of the large sample of auctions for each auctioneer in our data, sampling variation is small relative to the amount of variation in the estimated fixed effects.

We now turn to the secondary performance metrics for auctioneers. The first is residual price, i.e. the price that was obtained by the auctioneer for a sold car minus the wholesale blue book value as calculated by the auction house company using nationwide data from auction sales The second is high bid, i.e. the highest bid obtained for each car whether the car sold or not. The third performance metric is the amount of time that an auctioneer takes to run an auction (in seconds).

The results for these three metrics are presented in the second, third, and fourth set of columns in Table 2. The standard deviation in raw residual price values across auctioneers is very large ($219) and even larger for high bid which is not residualized ($1936). These spreads are reduced considerably after including seller fixed effects ($56 and $982 respectively). Once again, this suggests that some nonrandom sorting of cars to auctioneers is taking place in this environment. The standard deviation for the residual price effects stabilizes after Specification 4 at about $40 whereas the high bid results continue to decrease without stabalizing to approximately $88.[21] The time-on-the-block effects are fairly stable, especially after controlling for seller fixed effects. The estimates imply that a one standard deviation increase in auctioneer speed is associated with running an auction in 6 fewer seconds (off a base of 103 seconds). The stability in these findings is an indication of speed being an individual characteristic or style which does not depend heavily on the car being auctioned off, the seller, or other environmental contingencies.

Sampling variation can explain 20-25% of the variation in the residual price effects. Specifically, the standard deviation for Specification 8 with Bayesian Shrinkage applied is $31.99 (compared to $41.78 without the shrinkage). The standard deviation for Specification 8 with Bayesian Shrinkage for high bid is $84 (compared to $87.94 without shrinkage). The time effects are not very affected by sampling variation with a standard deviation of 5.87 once shrinkage is applied (compared to 6.07 without the shrinkage).

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and 3, R-squared significantly increases from .240 in specification 4 to .313 in specification 8 while the level of auctioneer heterogeneity remains stable.

[21] It is not surprising that the residual price effects are not affected by car characteristics (make, model age) because these are almost surely being taken into consideration by the wholesale blue book value that the company creates.

### 3.3 Identifying auctioneer effects from shift changes

In this section, we propose an additional method to help overcome selection and causally identify estimates of auctioneer ability that uses natural variation associated with work shift changes. We then compare these new auctioneer estimates with the estimates from the previous section.

On a typical auction date, two auctioneers will be assigned to work on each lane. These two auctioneers will take turns auctioning off cars in that lane. Auctioneers may switch at any time, but we observe that auctioneers typically switch roughly every 30 or 60 minutes in what are regular shift-length norms. In particular, we see very few instances of an auctioneer who is on the block for much longer than 60 minutes at a time (Appendix Figure A.1).

We can exploit the variation in auctioneers that occurs within a lane on a given day by including lane*day fixed effects when estimating auctioneer ability.[22] By looking within a lane on a given day, we are able to control for additional unobserved factors that may exist (number of buyers at the auction located near a given lane, unobserved characteristics about the cars/sellers assigned to that lane, etc.) when estimating auctioneer fixed effects.

We estimate the model in Equation (1) while controlling for seller, time of day, and 13,687 lane*day fixed effects. Figure 2 provides scatter plots of the estimates from Specification 8 in the previous section and the estimates using the specification described here for each of the four performance metrics. The estimates that we find are strongly correlated across identification strategies: the t-stats for probability of sale, residual price, high bid, and time on the block are 18.9, 6.51, 3.60, and 15.46 respectively. A common pattern that we find in these results and others to follow is that the results for probability of sale (and also speed) appear to be very robust and stable while the price results (residual price and high bid) are often less stable and robust. This could simply be a result of the price effects being small (and thus the noise to signal ratio is high) or could also be related to the concerns that we discussed above about how the price results may not reflect accurate auctioneer ability. Overall, however, finding similar estimates when looking within a lane*day lends additional credibility to the estimates found in the previous section.

### 3.4 Stability of heterogeneity over time

If these estimated effects reflect persistent differences in auctioneer abilities, then we would expect them to be fairly stable over time. In particular, an auctioneer who performed better than average in the first half of our sample (2007-2009) should also perform better than average in the second half of our sample (2010-2013). In Figure 3 we plot the fixed effects for the 49 auctioneers who were full-time employees in

[22] One might be tempted to use a regression discontinuity design based on shift changes. However, because changes can occur endogenously (perhaps an auctioneer feels like he/she underperformed on the last couple of auctions and then decides to switch) and because switches likely occur at the same time as the cars being sold switch from one seller to the next, we are hesitant to try to identify the effects out of discontinuous work shift changes.

both the first and second half of our sample period. We find a strong, positive correlation with probability of sale (t-stat = 4.91) and time fixed effects (t-stat = 7.32) between the two sample periods. We find a positive correlation for high bid (t-stat = 2.90) but no persistent effect for residual price, suggesting once again that the price effects are not as well identified and stable. The persistence of the probability of sale and speed effects, however, suggests that on these dimensions we are detecting features of the auctioneers that are stable and robust across time.

### 3.5 Correlation between performance measures

As discussed earlier, the primary objective of auctioneers as seen by the auction house is to maximize the probability of selling a car. However, it is informative to consider how auctioneers who excel in selling a large fraction of their cars perform in the other metrics (residual price, high bid, and speed).[23] It is possible that the individual auctioneers who have the best performance for the probability of sale achieve this at the cost of one of the other metrics. For example, perhaps it is auctioneers who go really slow and take a lot of time to do the auction that are able to acheive better conversion rates. Conversely, a finding of a positive correlation between conversion rates, prices, and speed would be further evidence of the existence of differences in auctioneer ability.

A concern with correlating the time-on-the-block effects with other outcomes is that there may be a mechanical bias. The average time on the block for cars that sell is approximately 11 seconds longer than the time on the block when the car does not sell. This may be in part due to the extra recording time that is required when a sale occurs. Thus, if an auctioneer is able to obtain a higher probability of sale than another auctioneer, he/she may mechanically have a longer time on the block as well. In order to avoid this bias, we produce and use time on the block fixed effects for each auctioneer based only on cars that sold rather than all cars. Thus, we are able to obtain a measure of how fast an auctioneer typically performs auctions that is uncorrelated with the conversion rate of the auctioneer. Appendix Figure 2 illustrates that the time-on-the-block fixed effects using only cars that sold are highly correlated with the time-on-the-block fixed effects when using all auctions (t-stat = 22.00). An auctioneer's fixed effects for time-on-block for sold cars also correlates strongly with his fixed effect for time-on-block for unsold cars (Figure A.2 Panel B). This suggests that time-on-block likely reflects systematic differences across auctioneers in the speed with which they conduct their auctions, regardless of the auction outcome, and that the specific time-on-the-block effects that we use is not going to be very relevant. From this point on we will always use the time-on-the-block fixed effects from only sold cars in order to avoid bias when computing correlations.

[23] Correlating these measures may provide insight into the possible mechanisms that the best auctioneers may be using and will be discussed in further detail in Section 4.

Using Specification 8 from Section 3.2, Panels A-F of Figure 4 provide all possible correlations between our four performance metrics. We find a positive correlation between probability of sale and residual price and high bid (t-stats = 3.29 and 1.40 respectively). This suggests that the same auctioneers who have higher conversion rates also obtain higher prices and bids on average. We also find that speed is correlated with probability of sale. Specifically, auctioneers that run auctions faster (and thus have a *small* time-on-the-block fixed effect) sell more cars (t = 1.62) and obtain higher residual prices (t = 2.52) and high bids (t = 1.98).[24] Although the statistical power to identify these correlations is somewhat limited, we find no evidence that auctioneers who are doing well on their main objective (maximizing probability of sale) are doing so at a cost to secondary objectives. If anything, we find that auctioneers who are better in one dimension are better in the other dimensions as well. This supports the statement made by the auction house's general manager that "sales price and speed are generally the parents of conversion rate" and is something to which we will also refer when discussing potential mechanisms for these effects in the next section.

### 3.6 Comparing estimates with auction-house evaluations and termination decisions

To what extent do our estimated performance differences relate to decisions made by the auction house, such as evaluation and staffing? At our request, the auction company produced evaluations for the 41 full-time auctioneers working in the Fall of 2012 (prior to them seeing any auctioneer-specific results generated by us). These evaluations were based on a multidimensional subjective assessment by a panel of three senior auctioneers. This panel considered a range of inputs of their own choosing in order to produce a summary metric in 0.1 increments which we place on a scale from 0 (worst) to 1 (best).[25] In Figure 5 we correlate the company's subjective rankings with our estimated fixed effects (once again using the full model from Specification 8 in Table 2). Panels A through D provide correlations between the subjective evaluations and fixed effects for probability of sale, residual price, high bid, and speed respectively. We find significant correlations between their measure of who the best auctioneers are and our measure of auctioneers who have a high probability of sale (t-stat = 4.62), who obtain high prices (t-stat = 2.09), high bids (0.78), and who conduct fast auctions (t-stat = -2.03). The correlations that we find, especially with the probability-of-sale metric, are remarkably strong. They lend additional credibility to the idea that we are identifying true economically relevant differences in auctioneer ability.

We can also relate our estimates to job termination decisions made by the company. Due to the recession that took place during our sample period, the company significantly downsized the number of

[24] Simple exploratory factor analyses show the presence of one dominant factor underlying the auctioneer fixed effects on conversion rate, residual price, high bid, and time on the block.
[25] The original scale used by the company is from 2 (worst) to 1 (best).

full-time auctioneers between the start and end of our sample. Specifically, there are 59 full-time auctioneers at the start of our sample. Of these 59 auctioneers, 18 were no longer working for the company by 2013 (and one new auctioneer was hired). This downsizing provides us with an additional test for the validity of our measure of heterogeneity in auctioneer ability and its relevance to the organization. We are interested in analyzing whether the auctioneers who stayed in the sample ("stayers") were better than the auctioneers let go during the downsizing who exited the sample ("goers").[26]

Figure 6 displays the ordered auctioneer fixed effects from the fully specified model (Specification 8) for each performance measure. The auctioneers who left the company before 2012 are those represented with red, open-circle dots. Note that many of the worst-performing auctioneers in each dimension (the left tail of auctioneers in panels A, B, and C and the right tail of auctioneers in panel D) left the firm during the downsizing. In contrast, the large majority of the best-performing auctioneers (the right tail in panels A, B, and C and the left tail in panel D) were retained by the firm. Regressions of the auctioneer fixed effects (from Specification 8 above) on a dummy for whether the auctioneer was a stayer or not imply that stayers are, on average, more likely to sell a car by 1.5 percentage points (t-stat = 2.53), have residual prices that are $25 higher (t-stat = 2.09), receive high bids that are $72.3 higher (t = 3.19), and take 6.7 fewer seconds when selling a car (t-stat = -3.36). Again, the fact that our ability measures significantly predict who exited the sample during a downturn provides evidence in favor of our metrics representing true ability.

### 3.7 Benchmarking the impact of auctioneer ability and the impact on expected revenues

Having established that heterogeneities exist among auctioneers, we now provide simple calculations, based on the point estimates from the analyses above, to compute the impact of these estimates on some relevant economic variables. On average, each full-time auctioneer performs approximately 2,000 car auctions per year of our sample. An auctioneer who moves from the 10th percentile to the 90th percentile in our probability-of-sale metric (a 5.6 percentage point increase in probability of sale off a base of 53%) will sell approximately 123 more cars each year. Assuming an average fee to the auction house of $200 for each car sold, this translates to an increase in revenue for the auction company of $24,600.[27]

[26] Unfortunately, we do not have hard data on whether the auctioneers that left the sample were fired or left voluntarily. Our discussion with the auction company suggests that the majority if not all of these auctioneers left involuntarily. To the extent that a few of the higher-performing auctioneers left on their own accord, this would bias us against finding significant differences between stayers vs. goers.

[27] These calculations are rough and ignore many other potentially important factors. For example, if the probability of sale increases, it could cause more sellers to bring their cars to this market suggesting that the value of the auctioneer is even higher. It is also possible that an auctioneer that is able to sell more cars is causing lower sales for the other auctioneers.

Similar calculations can be done for the value of auctioneers who systematically obtain higher residual prices, bids, and/or go faster. In particular, the average difference in residual prices obtained by the $90^{th}$-percentile auctioneer and the $10^{th}$-percentile auctioneer is about $96, the average difference in high bids between these two groups is $223, and the difference in time on the block is 12.6 seconds (14.7 seconds for sold cars). However, it is harder to translate these values into company profit since fees received are not primarily based on these measures.

Another way to benchmark the results is to compare our estimated effects with the impact of changes in other relevant variables in our data, as well as with results from related studies that estimate the effects of certain changes in auction design and information structure on similar outcomes. Within our data, we estimate the $90^{th}$-$10^{th}$ percentile difference in residual prices to correspond to the effect of a difference of 1,136 miles between two otherwise identical cars.[28]

As for related studies, Tadelis and Zettelmeyer (2011) estimate the impact of randomly providing additional information about car quality from a reputable source in a wholesale car auction. They find that additional information translates into a 6.3 percentage point increase in probability of sale and a $237 increase in average price. These effects are slightly bigger than those we estimate to be the difference in average probability of sale and price obtained by an auctioneer at the 10th and at the 90th percentile. Similar impacts have been found from changes in relevant economic and financial conditions at a more aggregate level; Hortaçsu, Matvos, Syverson, and Venkataraman (2013) show that a 1000-point increase in the CDS spread for an auto manufacturer is associated with a drop in average prices for that manufacturer's used cars at auctions of $68.

In addition to the above benchmarks, it is interesting to ask how important a good auctioneer is relative to the importance of optimal auction design. Optimal auction design has received a considerable amount of attention in both the theoretical and empirical literature, yet using a good auctioneer may be just as important for increasing seller revenue as is an optimal reserve price. Bulow and Klemperer (1996) demonstrated that the participation of one additional, random bidder increases seller revenue more than an optimal reserve price would. Coey, Larsen, and Sweeney (2014) present a method for calculating an upper bound for the causal effect of including an additional, random bidder on final prices and find that this effect is bounded above by $200 at wholesale used-car auctions.[29] This implies that the effect we find of moving from the $10^{th}$ percentile to the $90^{th}$ percentile auctioneer captures a substantial portion of the improvement in seller revenue which would come using an optimal reserve price.

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[28] This estimate was obtaining by running a regression of residual price on the same right-hand side variables as in Specification 8, but with miles entered linearly. The estimated coefficient on miles is -.00845.

[29] As demonstrated in Coey, Larsen and Sweeney (2014), the Bulow and Klemperer (1996) effect of adding one more random bidder to an $N$-bidder auction is given by scaling the average gap between the second and third-highest bids from $N+1$-bidder auctions by a factor of $2/(N+1)$.

## 4. Exploring the sources and mechanisms of auctioneer heterogeneity

The analyses in the previous section provide robust evidence that, even in a well-functioning auction market, individual auctioneers can significantly impact key market outcomes. This suggests that auctioneer skills are a real phenomenon. Although the primary contribution of the paper comes from documenting the systematic variance in outcomes across auctioneers, a natural next step is to explore the mechanisms that might explain why some auctioneers outperform others. Uncovering these mechanisms is an interesting avenue for a whole body of future research and will benefit from using experimental techniques in addition to observational data. However, in this section we begin to explore these potential mechanisms, noting that the nature of the available data here do not allow us to reach any fully conclusive claim about mechanisms. We begin with a short discussion of some potential sources of heterogeneity. We then present qualitative evidence from a survey prepared for this paper in which professional auctioneers were asked to comment on and rank various tools and characteristics that define an effective auctioneer. Finally, we provide and discuss quantitative evidence from our data (some of which was already presented in Section 3 above) that helps establish the potential relevance of the various mechanisms considered here.

### 4.1 Potential mechanisms

We consider six broad mechanisms that could drive heterogeneity in auctioneer ability:

1. **Direct information revelation.** One way in which auctioneers could potentially affect market outcomes is by directly revealing information about the products being sold. In particular, the linkage principle (Milgrom and Weber, 1982; Milgrom, 2004) would predict that an auctioneer who could better commit to revealing truthful information about the cars being sold could expect to generate higher prices. However, it is important to note here that the predictions of information revelation require that the auctioneer have private information about the value of the good being sold, which as we discuss below is very unlikely in this market.
2. **Persuading sellers to lower reservation values.** The main effects documented in this paper concern the ability of an auctioneer to achieve a sale. One of the obvious ways in which auctioneers could differ in their ability to achieve a sale would be if they differ in an ability to persuade sellers to lower their reservation values to match the available market price. If some auctioneers have more credibility with sellers, they may be better at convincing sellers to lower reservation values and accept the outcome of the auction.[30]

[30] Note that rather than directly persuading a seller to lower the reservation price, an auctioneer may instead influence a seller's decision to accept a lower price indirectly through running an auction which has more of an

3. **Generating patterns of bids that increase revelation of bidder values.** In Milgrom and Weber's (1982) model of English auctions with affiliated values, bidders reveal something about their valuation as they are observed dropping out of the bidding, and it is this extra information that leads to predictions of higher revenues from English auctions relative to other formats. As a number of papers have highlighted, however, in real-world English auctions of the type we observe here, many potential bidders remain silent during the auction and never reveal information about their valuation (Haile and Tamer, 2003; Harstad and Rothkopf, 2000). Thus real-world English auctions may not achieve the same revenue-enhancing benefits that classic theory would predict. If some auctioneers are particularly good, however, at getting those with lower signals about the market value of the car to initially bid, they could increase the information revealed and hence raise overall prices. For example, some auctioneers may be particularly good at choosing the starting prices or bid increments that they call in a way that induces a greater number of initial bids from those with low valuations. Or, perhaps some auctioneers are better at identifying low-valuation bidders and recognizing their bids early before focusing on the bids by those who will eventually win the auction.[31]
4. **Reducing search frictions.** Much of the activity at wholesale auto auctions occurs across a range of auction lanes simultaneously. Bidders may face search costs and cognitive limits that affect their ability to process information and pay attention to the available cars up for auction. Auctioneers may then differ in their ability to help bidders "match" to cars through techniques that increase the salience of cars for bidders who are likely to value them. For example, Steve Lang, a former award-winning auctioneer who is now a buyer and seller at auto auctions and owner of a popular car blog, stated, "I'll go to my strongest buyers first. Always" (2009b), and B. J. Lewis, another award-winning auctioneer, declared, "Knowing the buyer is really important…You're not watching 20 people all at once. For example, you might know that [a dealer] buys a certain kind of car" (Reynolds, 2003).
5. **Facilitating efficient bargaining directly or through phantom bids.** In cases where the final bid from the auction does not meet the seller's secret reserve price, the auctioneer may allow a quick round of bargaining between the seller and high bidder. Although this occurs frequently at some auto auction houses (see Larsen 2014), we are informed that this event occurs rarely at the auction house from which our primary data come. An auctioneer may also facilitate agreement through a process referred to as "taking bids off the wall," "taking bids from the vending machine," or "taking phantom bids" (see Ashenfelter, 1989; and Vincent, 1995), a process in which the auctioneer acts as though the

appearance of having achieved a fair market price. We consider this case as falling into other mechanism categories because it does not involve directly influencing the seller.

[31] Identifying buyers at auctions can be particularly challenging given what one writer called the "barely discernible sign language used by the buyers" (Reynolds, 2003). Lang (2009a) similarly argued that hand signals used by bidders at auto auctions would be confusing to a lay observer.

final bidder still faces a stream of competing bids, thus signaling to the final bidder that the reserve price has not yet been met. This process could potentially encourage efficiency in cases where the seller's reservation value lies between the second and first order statistic of bidder values.[32]

6. **Exploiting behavioral biases.** A final source of heterogeneity may come from variation in the ability auctioneers have to exploit potential behavioral biases in auction settings. Auction environments are exciting and emotions may sway bidders. It could be that some auctioneers are better at generating the sort of excitement that induces "irrational exuberance" and "auction fever" (Ku, Malhorta, and Murnigham, 2005; Ockenfels, Reiley, and Sadrieh, 2007; Malmendier and Szeidl, 2008; Podwol and Schneider, 2011). Describing his experience, Steve Lang stated, "[I] may have only been 26. But when I was on the block or in the lane, I had the manipulative mind of a 62-year-old charmer and my job was to use my powers of persuasion to create the urgency to buy. An inflection of voice. The right word. The right implicit use of eye contact, hand or body gesture…" (Lang, 2010). Another possibility is that good auctioneers may be particularly skilled at "anchoring" bidders to certain reference points (e.g. prices) through the choice of the opening price, referred to as the fish price. At wholesale car auctions, the auctioneer often starts by calling out a high bid, then lowers the price until a bidder indicates a willingness to pay at that price, at which point the ascending auction begins. Of this practice, Genesove (1995) commented, "The auctioneer's initial price almost always exceeds the winning bid. What effect it has on the subsequent bidding is an open question. One auction official, otherwise quite forthcoming about the workings of the auction, avoided discussion of the initial price, aside from describing its choice as an important part of the auctioneer's art."

These mechanisms differ in their implications for efficiency and revenue improvement. Mechanisms 1, 3, 4, and 5 can all increase seller revenue as well as efficiency—increasing the likelihood that a sale occurs when the highest value bidder indeed values the car more than the seller. Mechanism 6 may improve seller revenue at the expense of bidder surplus, but both Mechanism 6 and Mechanism 2 could be paths for an auctioneer to decrease overall efficiency if the seller or buyer is actually convinced to take an action inconsistent with his or her value for the car.

There are a number of reasons why it is challenging to disentangle the importance of these potential mechanisms from observational data. For one thing, these forces do not have to be mutually exclusive in any way. For example, it could be that an auctioneer who is able to generate excitement (Mechanism 6)

[32] Ignoring jump bidding (which is rare at auto auctions because it is the auctioneer who calls out prices) and bid increments, the final price at an ascending auction with multiple bidders should be close to the second-highest willingness to pay among the bidders. When the seller's valuation of the car lies between the second and first-highest willingness to pay of bidders, the auction outcome (in the absence of phantom bids) is inefficient given that no sale occurs even thought the final bidder and the seller could have potentially agreed upon a price lying between the second and first-highest valuations.

gets more initial low bids that reveal information (Mechanism 3) to higher-value bidders. An auctioneer who generates excitement might also draw attention to the cars on his lane and get better matches (Mechanism 4) and exciting auctions with many bidders may give sellers more confidence to accept the auction price, which would look observationally a lot like Mechanism 2. Similarly, auctions which reveal more information (Mechanism 3) may last longer, just as auctions in which the auctioneer runs up the price through additional phantom bids (Mechanism 5). Another challenge is that many of the behaviors that successful auctioneers might employ could be related to different mechanisms. For example, patterns of starting prices ("fish prices") could be used to successfully induce low-value bids (Mechanism 3) or to induce anchoring (Mechanism 6), so simply observing heterogeneity in patterns of fish prices across auctioneers will not be enough information to identify a mechanism. Also, any of these mechanisms might affect auction outcomes on the intensive margin, altering outcomes for a given set of bidders, or on the extensive margin, influencing additional bidders to participate, and the two avenues are not separately identified in the available data.

Despite the challenges inherent in identifying these mechanisms in a field context, we believe that it is possible to provide a range of evidence, from both surveys and data analysis, which begins to speak to the potential relevance of these different sources of heterogeneous ability and could provide direction for future research. In the next two sub-sections we present evidence from a survey of auctioneers and then discuss observable patterns in our main data and in supplementary data which shed light on the mechanisms at play.

### 4.2 Survey evidence

Our first approach in trying to understand the mechanisms better is through an anonymous survey that the auction house conducted with 33 of their auctioneers. The questions included on the survey were based on preliminary discussions with the auction house and after some limited data analysis for this project. As such, the survey is not particularly scientific, but we believe that it nonetheless provides a useful starting point for considerations of the mechanisms used by auctioneers to achieve success. The auctioneers were asked to rank the importance of a number of skills/topics in determining a particularly effective auctioneer on a scale from 0 (very unimportant) to 5 (very important). These rankings are reported in Figure 7. They were also asked to choose one statement among four options which best describes the most important role of an auctioneer when auctioning off dealer cars in the wholesale market. The resulting answers to that question are presented in Table 3. Finally, the survey included an open response box that asked auctioneers to think of auctioneers they found "especially effective" and to describe what made those auctioneers different from an average auctioneer.

One clear fact that emerges from these surveys, discussions with the auction house, and our own observations of the auction process is that auctioneer performance differences are not driven by an ability to convey relevant information about the cars being auctioned. As Table 3 shows, of the 33 auctioneers, only one thought that the most important role of auctioneers in this setting was to provide expert information about cars. The options "Providing information about cars not otherwise available to bidders" and "Highlighting positive features of the car" also received low rankings reported in Figure 7. The institutional structure of these auctions also makes the information-revelation mechanism highly unlikely. Auctioneers rarely, if ever, discuss the features of a car during the one to two minutes while the car is on the auction block. The bidders in these auctions are experienced used-car dealers who know a great deal about the retail market for the cars being sold. The auctioneers do not inspect the cars they auction and typically see them for the first time a few seconds before beginning the auction. Bidders, in contrast, can walk around the car, inspect it prior to the auction, and are physically closer to the car during the auction than the auctioneer. Thus, although theoretically relevant and empirically applicable to other contexts, direct information revelation is highly unlikely to be an important source of auctioneer heterogeneity in this setting.

The survey evidence also provides little support for the possibility that good auctioneers are more successful at persuading sellers to accept fair prices. Again only 1 of 33 auctioneers (Table 3) chose that option as the most important factor in determining auctioneer success. That mechanism also received relatively low rankings on the 5-point scale (Figure 7).

The other three mechanisms (3 – 6) are difficult to identify via a simple survey, as they all involve effects on buyer behavior. In Table 3 we see that auctioneers overwhelmingly (31/33) selected the option that "auctioneers create a sense of excitement, competition, and urgency among buyers that encourages more bidding" as the most important role of the auctioneer. That is consistent with the possibility that Mechanism 6 is important, but because there were no options in that part of the survey that addressed the other buyer-related mechanisms, it does not preclude the importance of mechanisms 3 or 4. Of the options for important skills/tactics included in the survey, those receiving the highest ranking (Figure 7) were "creating competitiveness between bidders," "spotting interested but reluctant bidders," "having an effective chant," and "increasing engagement and excitement by running a fast-paced auction." Most of these seem primarily consistent with mechanisms related to behavioral biases, though spotting interested but reluctant bidders could reasonably be related to either Mechanism 3 or Mechanism 4. Interestingly, calling out good starting prices, which might plausibly be a way to generate bids from those with low valuations (Mechanism 3) received low rankings.

In their open-ended comments to the question of what separates an effective auctioneer from an average auctioneer, several respondents highlight the importance of speed and creating a sense of urgency among bidders through means that appear to target behavioral factors. For example, one auctioneer stated, “The most effective auctioneer's [sic] that I have seen tend to use speed as tool which create's [sic] a sense of urgency in bidders, force's [sic] split second decisions and does not allow for bidders to doubt or second guess their bidding decisions.” Another auctioneer stated that a good auctioneer “knows when to slow down and give someone that extra second to think to make the sale or for some people speed up so they get caught up in the bidding and end up paying to [sic] much.”

### 4.3 Quantitative evidence on potential mechanisms

In this subsection we consider patterns in our data that potentially speak to the relevant sources of heterogeneity. Here we rely both on our primary dataset as well as a secondary dataset that we describe below. Many of the results we present below are correlational analyses with a limited number of observations and thus should be interpreted with care. However, we argue that they are still useful in providing suggestive evidence of the mechanisms at play.

#### 4.3.1 Secondary auto auction dataset

In addition to our primary dataset, we have access to auction outcomes for cars sold at three US auction house locations from January 2007 to March 2010 for a different auction company. As with our primary dataset, both dealer cars and fleet/lease cars are sold at these auction houses. Many of the fleet/lease cars are sold through simulcast auctions, in which the auction can view a live video feed and participate online, although the actual auction still takes place physically at the auction house and most bidders are physically present. Data from these simulcast auctions contains additional information not available in our main sample, such as the timing of bids, the opening price called by the auctioneer (referred to as the fish price), and the first price which a bidder was willing to pay (referred to as the start price). This information can be very useful for testing various mechanisms. However, the data has several major limitations. First, auctioneer identities are not necessarily accurately recorded beyond the first auctioneer in a given lane on a given day and hence we restrict to the first hour an auctioneer works for each lane and day. Second, the sample is much smaller; after limiting to the first hour for each auctioneer-by-lane-by-day combination and imposing similar sample restrictions to those in our primary dataset, we restrict to auctioneers selling more than 100 simulcast cars and 100 dealer cars (non-simulcast). This leaves us with 42,597 cars sold by 16 auctioneers in simulcast auctions and 56,323 cars sold by 24 auctioneers in dealer (non-simulcast) auctions. For these reasons, and because simulcast auctions are mostly fleet/lease car sales, this secondary dataset is not well suited for our primary analysis in Section 3, but may still be able to provide suggestive evidence of mechanism.

Appendix Table A1 displays descriptive statistics for our secondary dataset. The dataset consists of two samples: dealer cars, which contain the same three measures as our primary dataset (probability of sale, residual price, and time on block); and simulcast cars, which also contain additional auction-level information.[33] Fish price minus starting price is the gap between the price initially called out by the auctioneer (fish price) and the lower price (start price) at which bidders actually begin signaling a willingness to pay. Residual fish price is the fish price less the blue book value. Fishing time is the number of seconds from the calling out of the fish price and the arriving at the start price. Bidding time is the number of seconds between the start price and the final bid. Hammer time is the number of seconds between the final bid and the end of the sale (when the next car rolls in)—i.e. the time in which the auctioneer calls out, "going once… going twice…sold," pounds down the gavel or "hammer," and begins the sale of the next car. Bids, bid speed, and price speed are the total number of bids, bids per second, and the price increase (from the starting price to the final bid) per second. In the simulcast sample, 78% of cars sold, a fraction twice as high as in the dealers sample. Simulcast auctions also run over twice as fast as those in the dealer sample. While the two samples in the secondary dataset are mutually exclusive (no car is in both samples), 11 auctioneers sold more than 100 cars in both samples. In order to deal with any mechanical differences which may occur in these measures in auctions which end in a sale vs those which do not, we limit our analysis to cars which actually did sell when examining any variable other than the probability of sale, as is done above with time on block and residual price in our main dataset.

With these measures from our secondary dataset, we attempt to replicate our main results. We once again estimate Equation (1) under each of our specifications and find relatively stable heterogeneity across specifications for each measure once seller fixed effects are taken into account. This is shown in the standard deviations reported in Appendix Table A2. These results provides further evidence of the external validity of the findings of auctioneer heterogeneity in Section 3. In particular, one standard deviation of auctioneer performance in the probability of sale and time on block in the dealer sample is of similar magnitude to the measures in our primary dataset. For simulcast cars the standard deviation of auctioneer effects is larger for the probability of sale and smaller for time on the block than for dealer cars. However, as a fraction of the mean probability of sale or time on the block (from Table A1), the standard deviations of auctioneer effects are relatively similar for dealer and simulcast cars. Also, although not shown in Table A2, for each outcome we find strong correlations in rankings of auctioneer fixed effects across specifications, just as in Table 2 for the primary dataset.

[33] High bid is not available in this secondary dataset.

### 4.3.2 Results

We begin our analysis by recalling findings from Section 3 that offer relevant insights on mechanisms. The patterns of correlations between auctioneer effects in conversion rates and prices can shed light on the relevance of Mechanism 2 (persuading sellers to lower reservation values). If auctioneers differed primarily in their ability to encourage sellers to lower their reservation values, then auctioneers with high conversion rates should find their average sales price to be lower conditional on sale. As seen in panel A of Figure 4, however, conversion rates and prices are positively correlated. This finding is consistent with the survey evidence and suggests that it is unlikely that the primary mechanism consists of auctioneers convincing sellers to lower their reserve prices.

The patterns related to the speed of auctions in Section 3 also help to speak to the relative importance of mechanisms 3 and 6. The finding that faster auctioneers tend to perform better, as shown in Table 3 and in panels B and C of Figure 4, serves as suggestive evidence in favor of an excitement-creation story and against the idea that good auctioneers aid in revealing information from low-valuation buyers. If auctioneers achieve success by generating more bidding from low-valuation bidders, one would expect the process to take a little more time than auctions where the auctioneer elicits bids closer to the final price from the outset. In contrast, we observe that auctioneers who achieve better conversion rates tend to run faster auctions. Our discussions with auctioneers and the auction house, as well as the survey evidence, highlighted that the auctioneers believe that fast-paced auctions help to create a sense of excitement in bidders.[34] Our findings on speed appear consistent with other work that has shown that time pressure induced by looming auction end-times appears to increase the propensity for overbidding (Ku, Malhorta, and Murnigham 2005 and Malhorta, 2010).[35]

Table 4 displays the t-stats from regressions of auctioneer effects for probability of sale on auctioneer effects for other measures. The first three rows of column 1 report t-stats from the regression lines shown in Figure 4, i.e. those estimated with our primary dataset. Column 2 displays estimates from the same regression using the auctioneer effects for probability of sale from the dealers sample of the secondary dataset, and column 3 for the simulcast sample. The second and third rows of column two regress the 24

[34] An alternative explanation for why speed would be positively correlated with auctioneer price effects and probability-of-sale effects would be that buyers with time costs may prefer to remain in the lane of a fast auctioneer, meaning that a fast auctioneer may lead to more bidders being present simply because bidders would prefer to see more cars without having to move between lanes, and more bidders being present can in turn increase prices and conversion. Note, however, that this could imply that bidders have high costs of moving between lanes. No industry participants suggested this mechanism plays an important role.

[35] Haruvy and Leszczyc (2010) and Lucking-Reiley, Bryan, Prasad, and Reeves (2007) find that on eBay, where auction duration is between one and seven days, longer-lasting auctions generate more bidder participation. However, Einav, Kuchler, Levin, and Sundaresan (2013) exploit experimentation at the seller level to find that auction duration does not affect auction outcomes on eBay. Our results, on the other hand, suggest that in the short-lived sales that we examine, where the average auction duration is less than two minutes, speed can be an important factor.

conversion rate effects from the dealers sample on residual price and time on block effects for the dealers sample. As discussed above, we believe auctioneer effects for probability of sale are more likely to be well identified in dealer sales rather than fleet/lease sales. Therefore, the remaining rows in column 2 continue to use conversion rate effects measured from the dealers sample and regress these effects on the various measures from the simulcast sample (recall there are 11 auctioneers which appear in both samples). As can be seen, the conversion rate effects are positively correlated in the two samples (a t-stat of 1.75). Column 3 presents results from the same regressions but using the 16 simulcast-measured probability of sale effects on the left hand side. All auctioneer effects used to create the t-stats reported in Table 4 come from the fully specified version of Equation (1).

Although the number of auctioneers is much smaller in this secondary dataset, the patterns of correlations among our three main measures of auctioneer ability are generally consistent with those found in our much larger primary dataset: price and conversion effects are positively correlated, although not as strongly as in the primary dataset, with t-stats of 1.42, 1.62, 0.14, and 1.44 for the four regressions relating these two measures in columns 2 and 3 of Table 4. Together, these results are consistent with our main findings that Mechanism 2, directly persuading sellers to lower reserve prices, is unlikely to be a major driving force. Further evidence of this lies in the final row of Table 4, which demonstrates that conversion rate effects are negatively correlated with hammer time. Recall that hammer time is the number of seconds from the moment the final bid is received until the sale is completed and the next car is rolled into the auction lane. If a good auctioneer convinces sellers to accept lower prices, we would expect this to lead conversion rate effect to be associated with longer hammer times, but we find the opposite, with t-stats from these regressions of conversion rate effects on hammer time effects of -2.31 and -1.79 in columns 2 and 3.[36]

The results in columns 2 and 3 of Table 4 also provide some evidence on the importance of speed. The t-stats demonstrate that time-on-block and conversion rates are generally negative correlated, although much less so than in our primary dataset. However, the detailed bid history in our secondary dataset allows us to examine this hypothesis somewhat more deeply. The length of time which the auctioneer spends fishing for bids (fishing time) and the length of time spent during the rising of the bids (bidding time) are not strongly correlated with conversion rate effects, but the hammer time is. This is suggestive that auctioneers with higher conversion rates may be those who pound down the hammer quickly (i.e. move quickly through the well known, “Going once. Going twice. Sold!” phase of the auction sale) and move on to the next car, leaving little time for bidders to hesitate or back down from

[36] Recall that these regressions include either 24, 16, or 11 auctioneer effects. Note that the critical values for a two-sided t-test at the 95% level with N-2 degrees of freedom (for the estimated slope and constant), are 2.074, 2.145, and 2.262 respectively for N=24, 16, and 11.

their bids. This is consistent with idea that thought speed (Pronin and Wegner 2006) and urgency may play a role.

We explore whether good auctioneers differ in their use of the fish price either to generate mental anchors for bidders (falling into Mechanism 6) or to reveal information through lower-value bids (Mechanism 3). For this analysis we turn again to our secondary dataset. Appendix Table A2 shows that we do find some heterogeneity among auctioneers in the residual fish price that they call for otherwise identical cars, as well as the fish price minus the start price. However, these differences do not appear to translate to heterogeneity in conversion rates. Table 4 shows that the conversion rate effects are not significantly correlated with the fish price minus the start price or with the residual fish price.

Another measure related to Mechanism 3 is the total number of bids submitted. Table 4 demonstrates that auctioneers with higher conversion rate effects also tend to receive more bids (t-stats of 1.34 and 2.34). This is consistent with the idea of letting more information be revealed through lower-value bids. However, this measure of bids is unable to capture how informed other bidders are of the drop out points of competitors.[37] Also, the fact that the auctioneer's number of bids received is correlated with the auctioneer's conversion rate may be mechanically capturing the correlation between conversion rates and prices. Specifically, given that bid increments do not vary much (they are typically $100), the number of bids is approximately equal to the difference between the final bid and start price divided by the bid increment. This same criticism applies to the final two measures in columns 2 and 3 of Table 4, bid speed (bids per second) and price speed (the dollar amount of increase per second). These two measures are both strongly positively correlated with conversion rate effects, with t-stats above 2, which may be capturing the association between prices and conversion rates rather than speed and conversion rates.

Returning to our primary dataset, we also search for evidence as to whether some auctioneers are better at attracting certain types of bidders, aiding in the process of matching buyers to cars as in Mechanism 4. To examine this hypothesis, we calculate three measures for each buyer: 1) size, given by the total number of cars purchased by the buyer in our full sample; 2) propensity to pay above market value, given by the average residual price paid by the buyer; and 3) match propensity, given by the percent of the buyer's purchases which were of a given make.[38] We then estimate the fully specified version of Equation (1) using these measures as outcomes. If auctioneers differ in their propensity to recognize the types of cars buyers are looking for, that effect might be especially relevant for buyers who

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[37] The bid history in the simulcast data records each bid but does not record the identity of the bidders who are physically present on the auction house floor, which represents a large majority of bidders, and hence it is impossible to tell at which point a given floor bidder ceased to bid.

[38] We use this measure as an outcome in equation (1) as follows: if the make of car $i$ is Honda, and the winner of the car is buyer $j$, we replace $Y_{ik}$ with the percent of all cars purchased by buyer $j$ which were Hondas. It is important to note that we are only able to calculate these measures for the winning bidder for a given auction sale, not for other bidders.

buy large numbers of cars. As shown in column 1 of Table 4, the t-stat from a regression of auctioneer fixed effects for the probability of sale on auctioneer fixed effects for buyer size is 1.71, suggesting that good auctioneers may be marginally better at attracting high-volume buyers. This marginal significance disappears, however, if instead of the actual volume of cars purchased we rank buyers according to their volume purchased and replace the outcome in equation (1) with the relative ranking of buyers. In this case, the t-stat drops to -0.12. Similar regressions of auctioneer conversion rate effects on propensity to pay over market value or buyer match propensity do not yield significant t-stats (0.41 and -0.93, respectively). Overall, we do not find strong evidence of the auctioneer differences in ability to sell cars being explained by differential ability to match buyers to cars.

Taking all of this evidence together, and combining it with the evidence from our surveys and observations of auctioneers, a few patterns begin to emerge. First, auctioneer effects are not driven by an ability to reveal information about cars and also are likely not primarily a result of convincing sellers to change their patterns of reservation prices. We do not have conclusive evidence on the different mechanisms related to changing patterns of bids. The qualitative results of the survey, however, point to some role for auctioneers influencing bidder behavior through tactics that create excitement among bidders, and we find quantitative evidence consistent with this hypothesis, both in our larger primary dataset and in our smaller secondary dataset. Further, in terms of specific mechanisms, both auctioneer surveys and patterns in the data suggest that the use of speed and time pressure to generate excitement and urgency may be an important component of how auctioneers affect auction outcomes.

## 5. Discussion and conclusion

The evidence presented in this paper shows that in well-functioning, high-stakes auctions, the specific manner in which the auction is run can have an important impact on outcomes. Using a large dataset from the wholesale used-car market, we find that auctioneers differ systematically in their ability to sell cars, as well as in the prices they get and the speed in which they do it; these differences are economically relevant.

Our results of a significant role of the auction process, and in particular of the “human” component in auctions, speak to the role that computerized online auctions may have in coordinating economic activity. There would seem to be strong efficiencies to computerized auctions, as they avoid the costs of employing professional auctioneers and auction-house staff and in online formats can avoid the often substantial transaction costs of bringing bidders and goods together in the same place. Yet recent work has documented that the popularity of online auctions may be fading (Einav, Farronato, Levin, and Sundaresan, 2012). Our findings suggest that human auctioneers have tactics that may improve auction revenue and, as such, might help to explain why computerized online auctions do not yet dominate the marketplace. Further studies into the behaviors of auctioneers could provide important insights that can be used to improve the performance of computerized auction mechanisms and more generally may be useful for quantifying the potential revenue losses from conducting naïve computerized auction processes.

Additional work is also needed to tightly pin down the mechanisms through which auctioneers affect outcomes, or the sources of auctioneer abilities. The evidence presented here is consistent with the presence of non-information-based (or behavioral) factors, in particular those creating urgency among bidders. However, we have also highlighted several information-based factors which could be at play, We hope that future research including controlled laboratory experiments can help shed light on the exact mechanisms involved.

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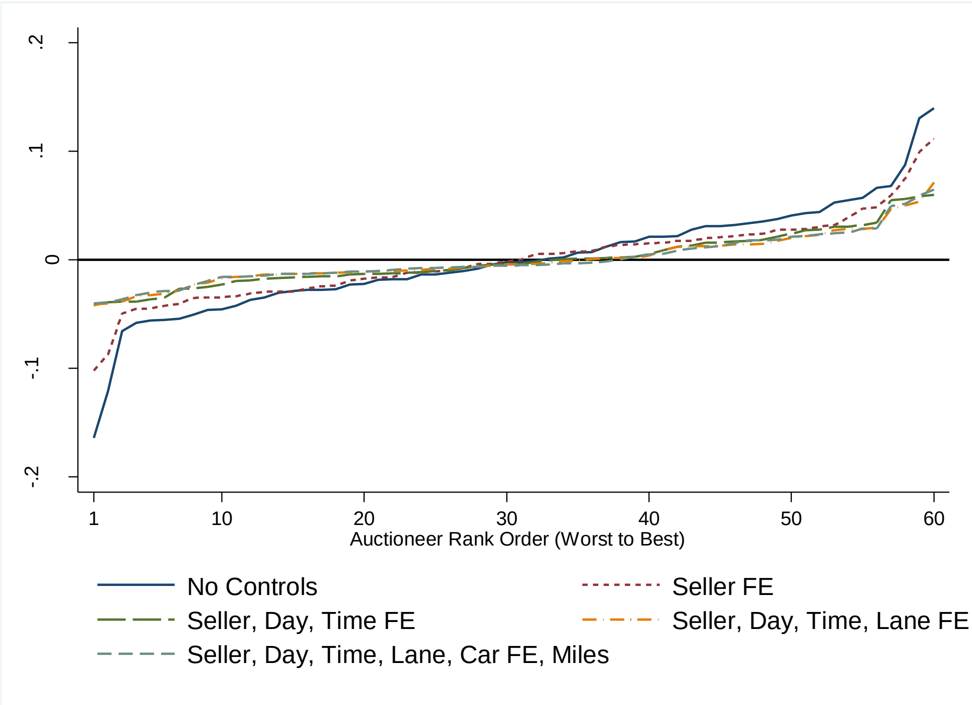
**Figure 1 - Auctioneer Differences in Probability of Sale.** Panel A plots the normalized fixed effects for each of the 60 auctioneers in our data. The fixed effects are obtained from a regression model with no controls, and then adding seller fixed effects, auction day and time of day, lane fixed effects, and car type fixed effects (see Equation (1) above), and normalized following the procedure described in Equation (2). Panel B plots the fully specified model's fixed effects (Specification 8 in Table 2) along with 95% confidence intervals.

**A: Comparison between specifications**




**B: Fully specified estimates with confidence intervals**

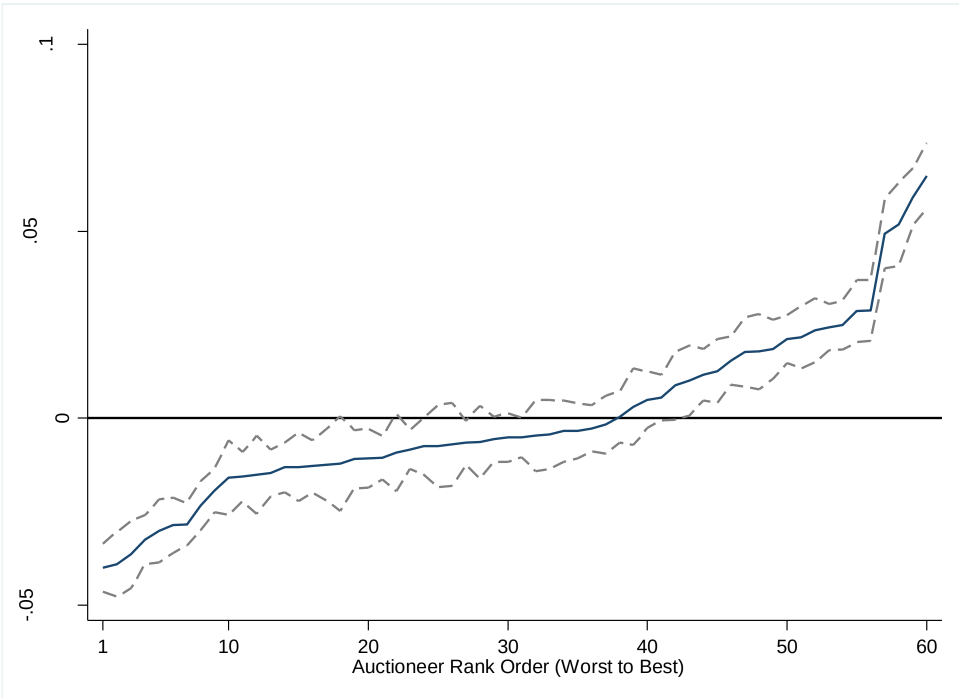


**Figure 2 – Comparison between Identification Strategies.** The panels below provide scatterplots that show the correlation in fixed effects for auctioneers based on probability of sale (Panel A), residual price (Panel B), high bid (Panel C) and time on the block (Panel D) between our two different identification strategies: the analysis within seller, auction day and time of day, lane, and car types fixed effects (Specification 8 in Table 2), and the identification based on shifts within a lane (lane*day) (Specification 9). Fitted lines are reported as well as the t-statistics from univariate linear regressions between the auctioneer effect estimates from the two identification approaches.

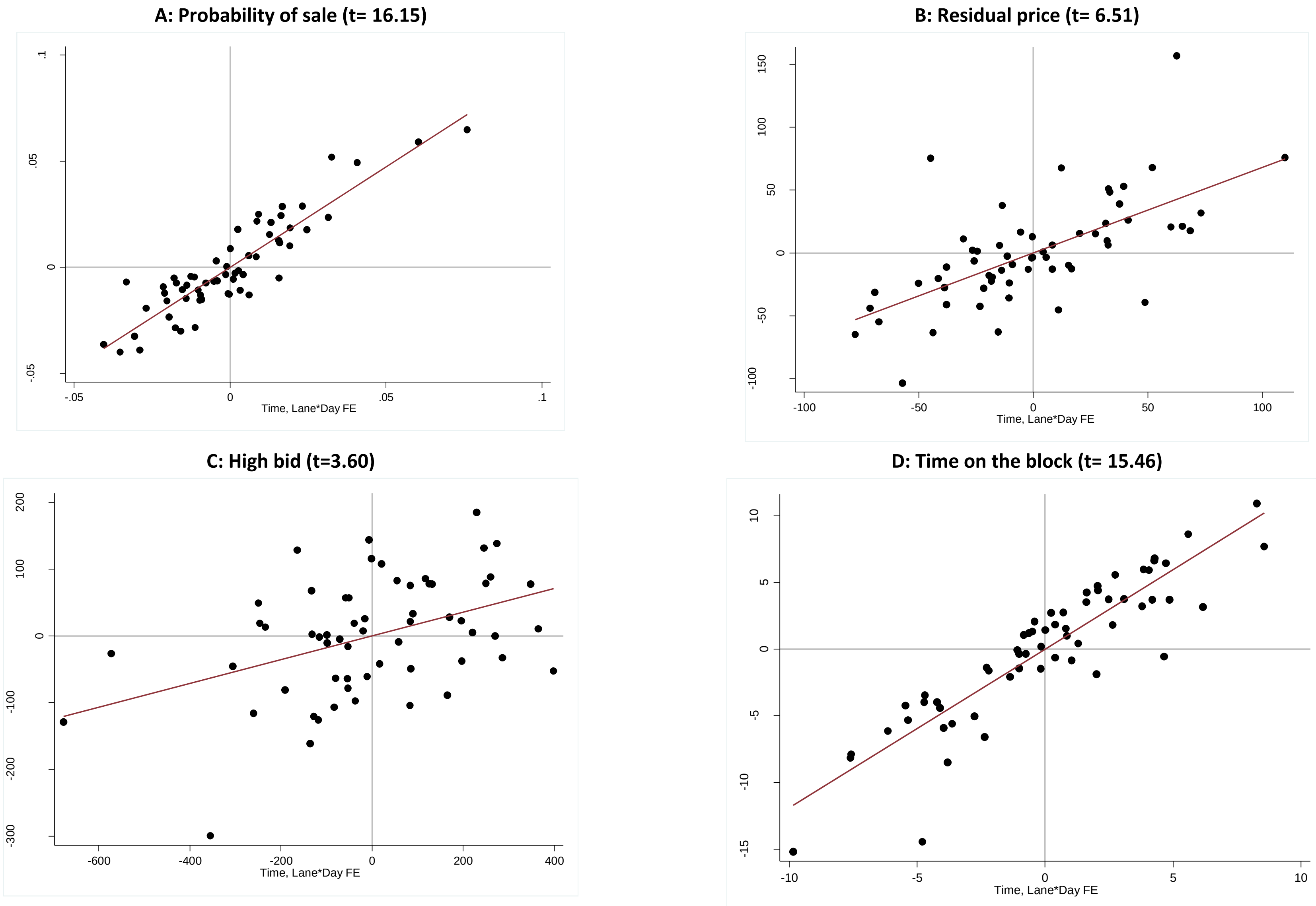


**Figure 3 - Correlation of Fixed Effects between 2007-09 and 2010-13.** Using the identification within seller, auction day and time of day, lane, and car types, we estimated auctioneer fixed effects separately using data for 2007-09 and then 2010-13. The panels below provide scatterplots that show the correlation in fixed effects between 2007-09 and 2010-13 for probability of sale (Panel A), residual price of sale (Panel B), high bid (Panel C) and time on the block (Panel D). Fitted lines are reported as well as the t-statistics from univariate linear regressions between the outcomes in the two years for each measure. The analysis here is limited to the 49 auctioneers with at least 2,000 observations in each of the two time periods.

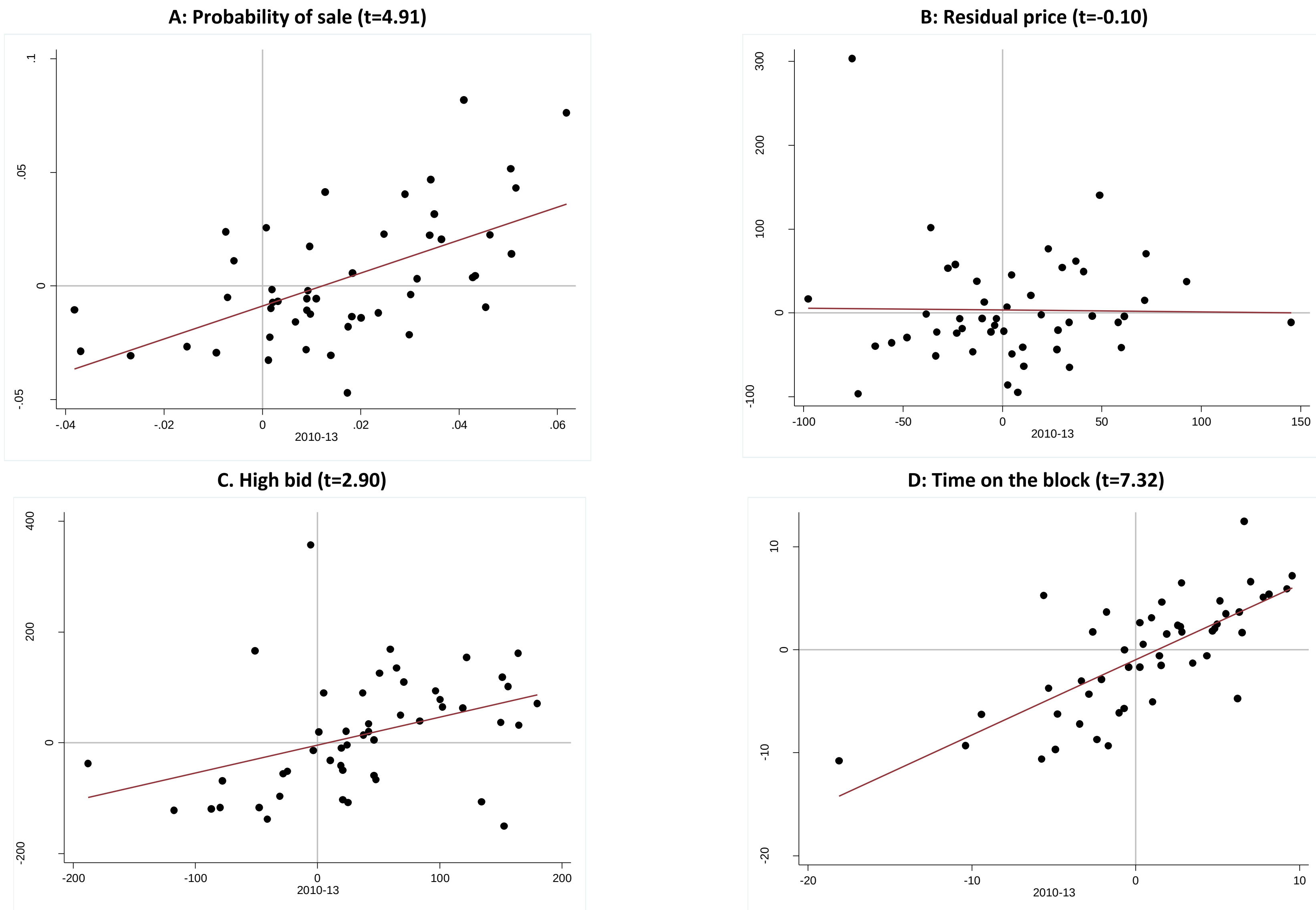
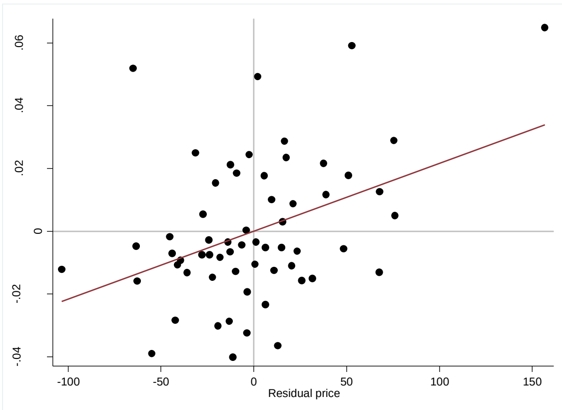
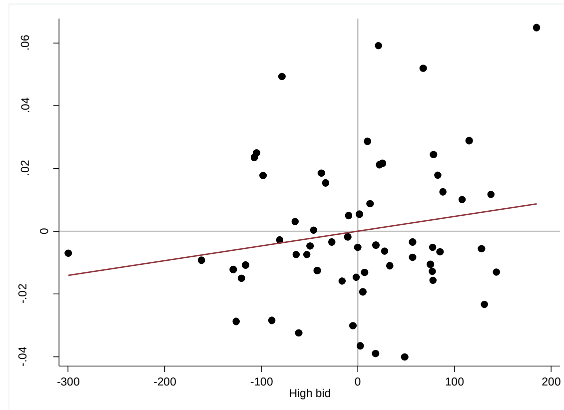


**Figure 4 - Correlation between Performance Measures.** The panels below provide scatterplots that show the correlation in fixed effects for auctioneers based on probability of sale, residual price, high bid and time on the block for sold cars. All fixed effects come from the fully specified model estimates within seller, auction day and time of day, lane, and car types. Fitted lines are reported as well as the t-statistic from univariate regressions between the outcomes for each measure.

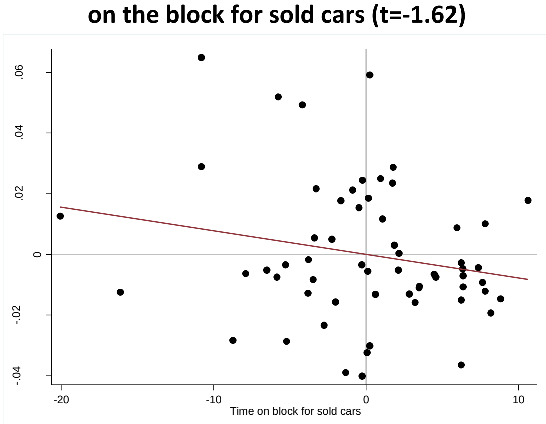
**A: Probability of sale and residual price (t=3.29)**



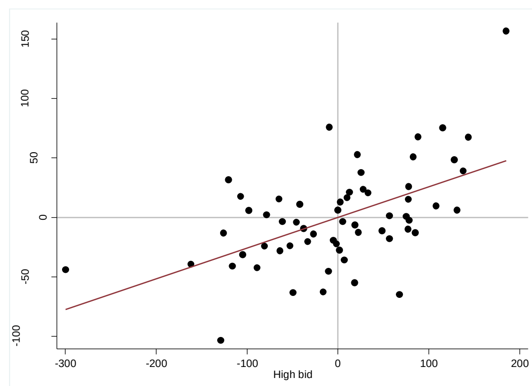

**B Probability of sale and high bid (t=1.40)**



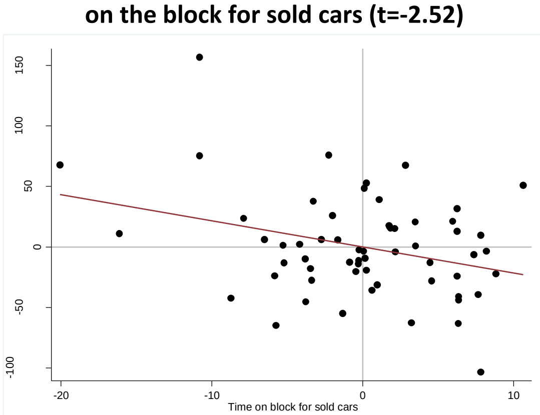

**C: Probability of sale and time on the block for sold cars (t=-1.62)**




**D: Residual price and high bid (t=4.93)**




**E: Residual price and time on the block for sold cars (t=-2.52)**




**F: High bid and time on the block for sold cars (t=-1.98)**

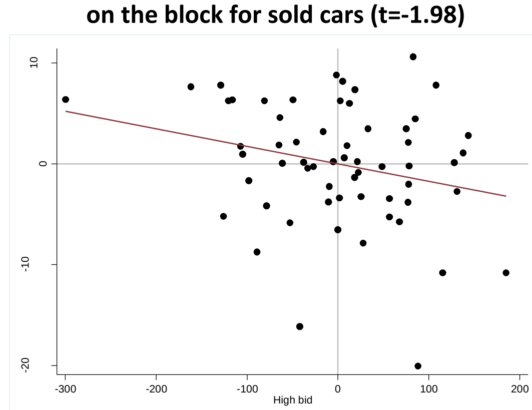


**Figure 5 – Correlation of Performance Measures with Subjective Evaluations.** The panels below provide scatterplots that show the correlation in fixed effects for 41 auctioneers between the company's subjective evaluations (on a 0 to 1 scale) and probability of sale, residual price, high bid and time on the block for sold cars. All fixed effects come from the fully specified model within seller, auction day and time of day, lane, and car types. Fitted lines are reported as well as the t-statistic from univariate regressions between the subjective evaluation and each performance measure.

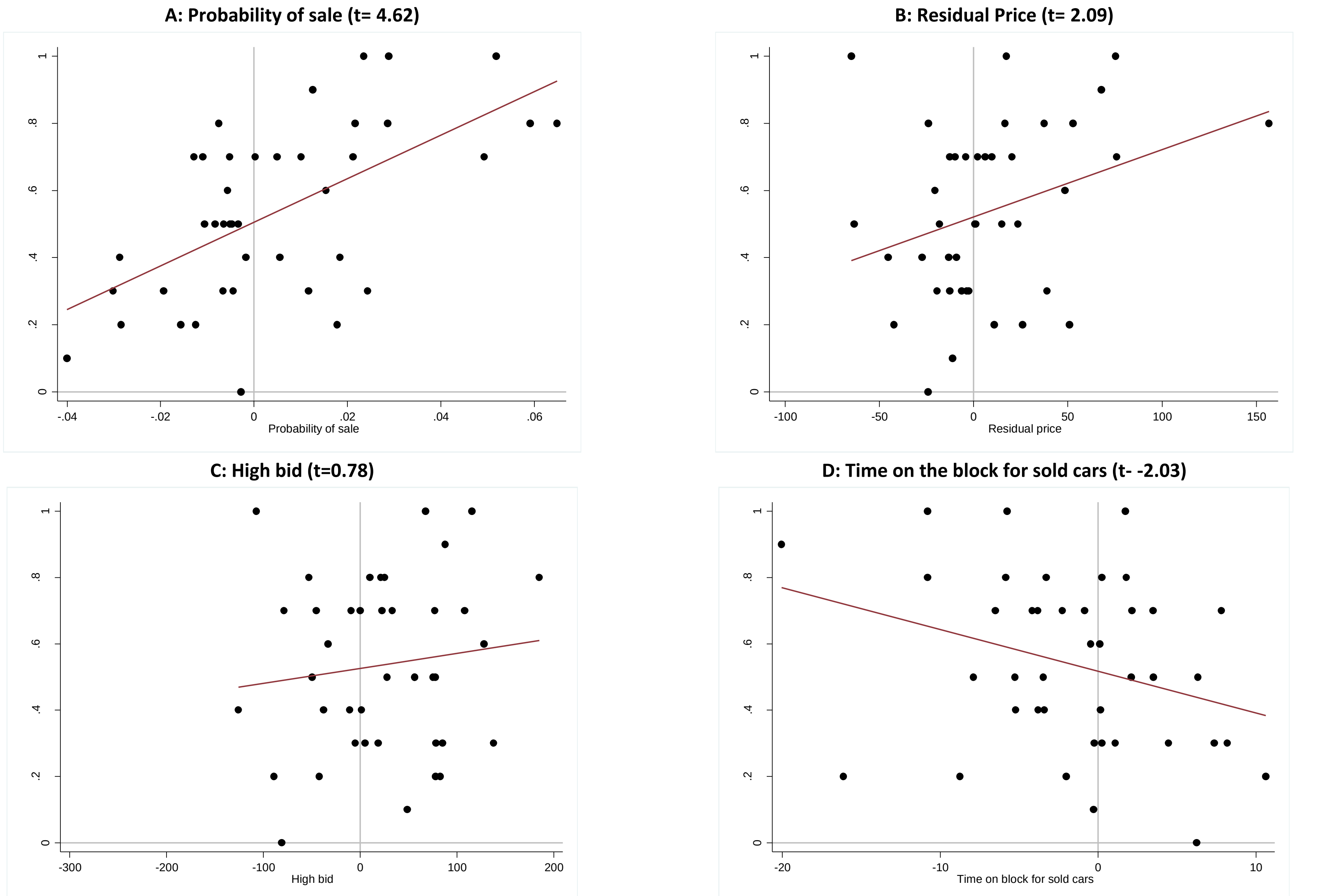


**Figure 6 – Performance rankings for auctioneers still at the company in 2012 and auctioneers who left the company by 2012.** The estimated auctioneer fixed effects are obtained from the fully specified regression model with seller fixed effects, auction day and time of day, lane fixed effects, and car type fixed effects, distinguishing between auctioneers who were still at the company by the end of 2012 (Stayers, *N*=41; black filled in dots) and those who left by between the end of 2008 and 2012 (goers, *N*=18, red empty dots).

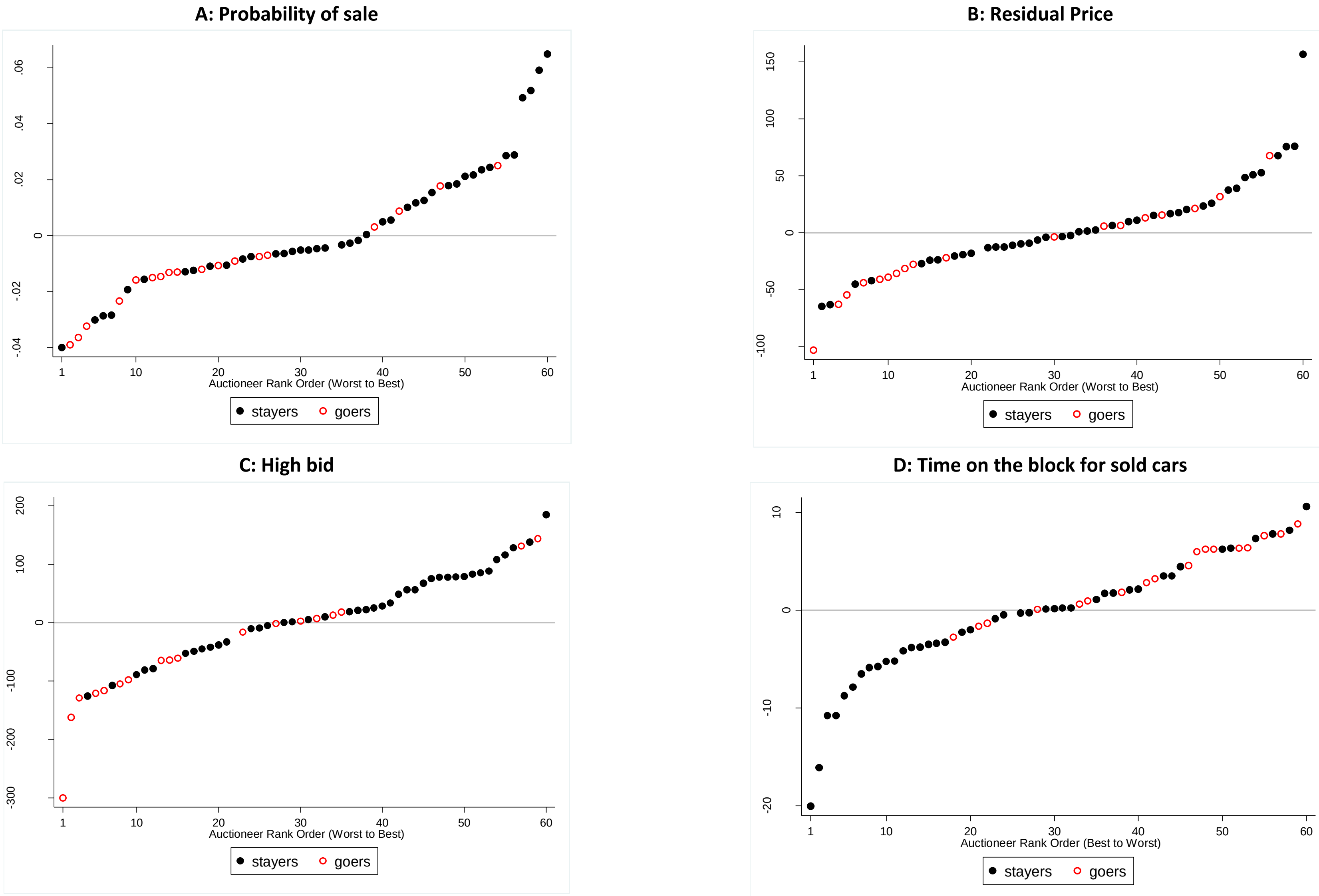


**Figure 7 - Survey results.** This figure reports the average ratings received by various proposed answers to a question asking auctioneers to rate the importance of tactics for determining a "highly effective" auctioneer (from 0-lowest to 5-highest).

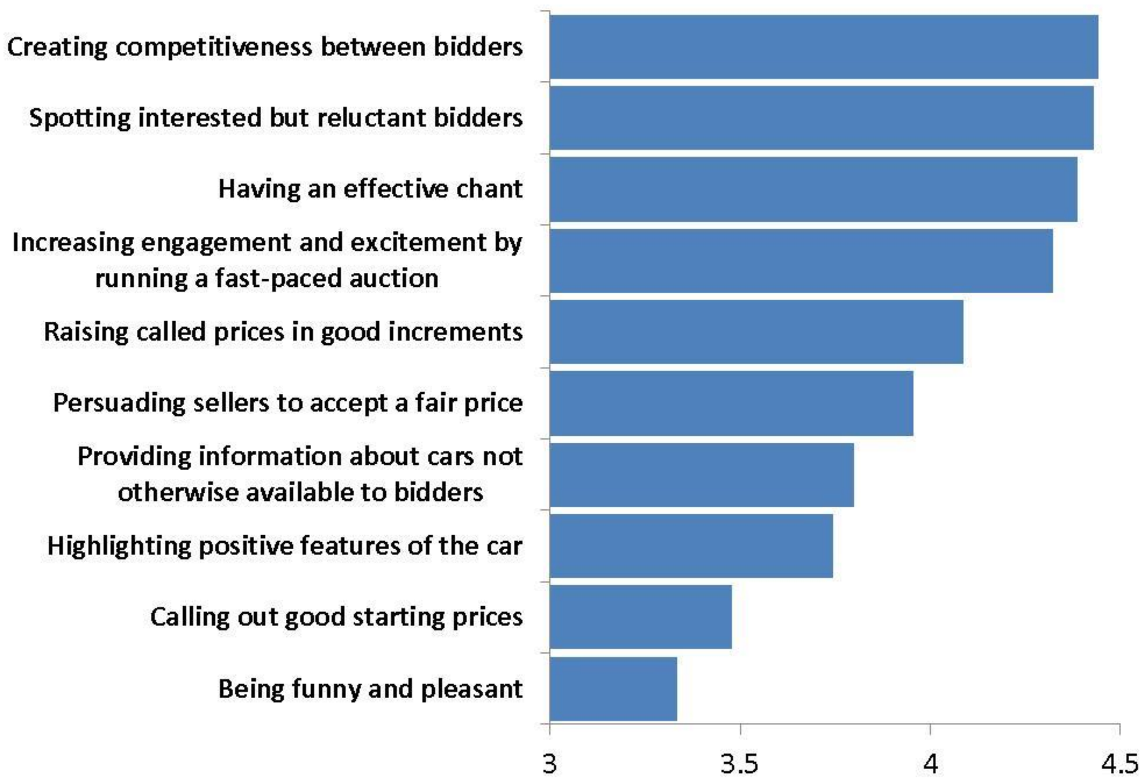


**Table 1: Descriptive statistics.** This table presents summary statistics for the main sample described in the text. The total number of observations is 859,240. Due to data limitations and errors in the auction house's data recording, the number of observations with valid time-on-block measures is 777,960.

| | Mean | Standard Deviation |
|---|---|---|
| Share of cars sold | 0.53 | |
| Sale price | $15,141 | $9,568 |
| Residual price | $377 | $1,669 |
| High bid | $15,652 | $9,861 |
| Time on the block (sec) | 103.18 | 74.03 |
| Age (years) | 4.43 | 3.28 |
| Miles | 56,237 | 33,731 |
| Number of observations | 859,240 | |

**Table 2: Standard deviations of estimated auctioneer effects with varying controls.** This table displays the effect of a one-standard-deviation increase in auctioneer performance as measured by the probability the car sold, residual price, high bid and the time on the block. Each cell of the table comes from a separate regression on auctioneer fixed effects and varying degrees of controls as specified. In addition to the standard deviation, the second column for each outcome measure reports the coefficient of correlation between two consecutive specifications, and, in brackets, the t-statistic on the coefficient estimate from a linear regression of the estimated auctioneer effects from each specification on a constant and the auctioneer effects from the subsequent specification. Specification 1 includes no controls, 2 includes seller fixed effects, and specifications 3 and higher add in the following controls, which each specification also including all controls from specifications preceding it: 3) time of day and auction day fixed effects, 4) lane fixed effects, 5) make fixed effects, 6) make*age fixed effects and fifth-order polynomial in mileage, 7) make*model*age fixed effects, 8) make*model*age*body fixed effects.

| | | **Probability of sale** | | **Residual price** | | **High bid** | | **Time on block** | |
|---|---|---|---|---|---|---|---|---|---|
| | | **Standard deviation** | **Coefficient of correlation with previous specification [t-stat]** | **Standard deviation** | **Coefficient of correlation with previous specification [t-stat]** | **Standard deviation** | **Coefficient of correlation with previous specification [t-stat]** | **Standard deviation** | **Coefficient of correlation with previous specification [t-stat]** |
| 1 | **Raw values** | 0.051 | | 219.633 | | 1935.80 | | 7.48 | |
| 2 | **Seller FEs** | 0.038 | 0.94 [21.46] | 55.842 | 0.67 [6.89] | 981.64 | 0.93 [19.66] | 5.77 | 0.95 [24.31] |
| 3 | **Seller, time of day, auction day FEs** | 0.025 | 0.73 [8.19] | 52.559 | 0.61 [5.88] | 678.92 | 0.90 [15.99] | 5.75 | 0.81 [10.74] |
| 4 | **Seller, time of day, auction day, lane FEs** | 0.023 | 0.97 [31.44] | 40.274 | 0.86 [13.14] | 333.02 | 0.88 [13.92] | 5.00 | 0.98 [36.59] |
| 5 | **Seller, time of day, auction day, lane, make FEs** | 0.023 | 0.99 [106.33] | 40.963 | 0.99 [49.65] | 350.87 | 0.96 [27.18] | 5.26 | 0.99 [79.07] |
| 6 | **Seller, time of day, auction day, lane, make*age FEs, miles** | 0.024 | 0.99 [122.8] | 41.864 | 0.98 [42.74] | 163.51 | 0.77 [9.09] | 5.23 | 0.99 [510.73] |
| 7 | **Seller, time of day, auction day, lane, make*model*age FEs, miles** | 0.023 | 0.99 [123.26] | 41.619 | 0.99 [52.11] | 95.18 | 0.86 [12.62] | 5.23 | 0.99 [289.38] |
| 8 | **Seller, time of day, auction day, lane, make*model*age*body FEs, miles** | 0.023 | 0.99 [139.15] | 41.776 | 0.98 [38.39] | 87.94 | 0.97 [29.83] | 5.23 | 0.99 [231.28] |

**Table 3: Survey results from role-of-auctioneer question**

| Question: *"If you had to pick one of the statements below, which one do you think best describes the most important role of auctioneers at [company's] auctions?"* | | |
|---|---|---|
| | Option | Number of respondents choosing option |
| 1 | Auctioneers create a sense of excitement, competition, and urgency among buyers that encourages more bidding | 31 |
| 2 | Auctioneers provide expert information about cars on the block that bidders do not know themselves | 1 |
| 3 | Auctioneers persuade sellers to accept the fair market price | 1 |
| 4 | Buyers know what a car is worth and will bid accordingly. Therefore, auctioneers do not have a large impact on auction outcomes | 0 |

**Table 4: Correlations between auctioneer measures.** This table displays t-stats from a regression of the auctioneer fixed effects for the probability of sale on the auctioneer fixed effects for other measures. Column 1 uses fixed effects measured from our primary dataset. Column 2 relates the auctioneer effects for probability of trade from the secondary dataset dealers sample with effects from the dealers and simulcast samples. Column 3 relates the auctioneer effects for probability of trade from the secondary dataset simulcast sample with effects from the dealers and simulcast samples. There are 60 auctioneers in the primary dataset, 24 in the secondary dealers sample, 16 in the secondary simulcast sample, and 11 who are in both the dealers and simulcast samples of the secondary dataset.

| **Primary dataset** | **(1) Prob sale t-stat** | **Secondary dataset: Dealers sample** | **(2) Prob sale t-stat, Dealers** | **(3) Prob sale t-stat, Simulcast** |
|---|---|---|---|---|
| High bid | 1.40 | Probability of sale | --- | 0.95 |
| Residual price | 3.29 | Residual price | 1.42 | 1.62 |
| Time on block | -1.62 | Time on block | 0.61 | -0.71 |
| | | **Secondary dataset: Simulcast sample** | | |
| Buyer size | 1.71 | | | |
| Buyer avg residual price | 0.41 | Probability of sale | 1.75 | --- |
| Buyer match propensity | 0.93 | Residual price | 0.14 | 1.44 |
| Rank of buyer size | -0.12 | Time on block | -0.90 | -0.24 |
| | | Fishing time | -0.39 | -0.32 |
| | | Bidding time | 0.04 | 0.66 |
| | | Hammer time | -2.31 | -1.79 |
| | | Fish price minus start price | 0.66 | 0.63 |
| | | Residual fish price | -0.96 | -0.08 |
| | | Bids | 1.34 | 2.34 |
| | | Bid speed | 2.27 | 2.74 |
| | | Price speed | 2.82 | 2.63 |

## Appendix

**Figure A.1: Distribution of auctioneer shift length on a lane and given day**

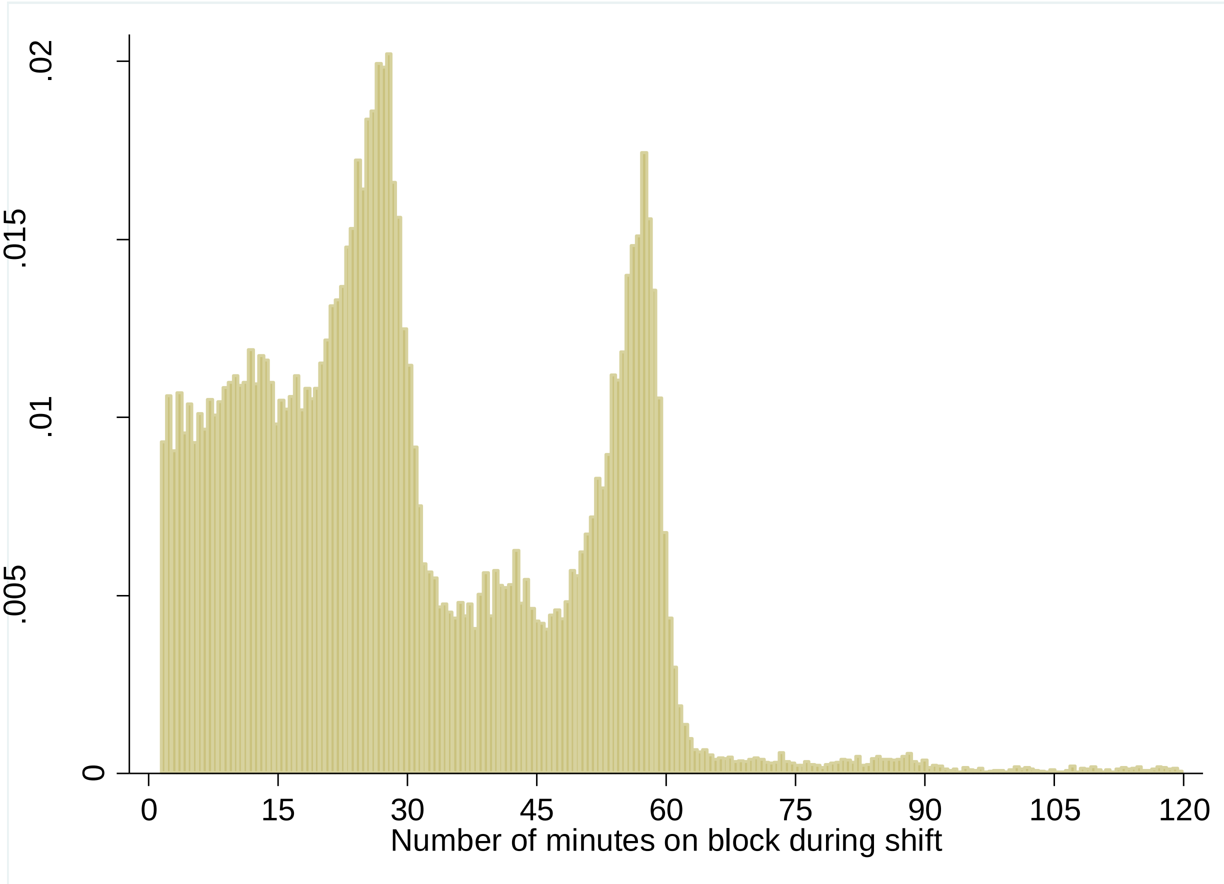
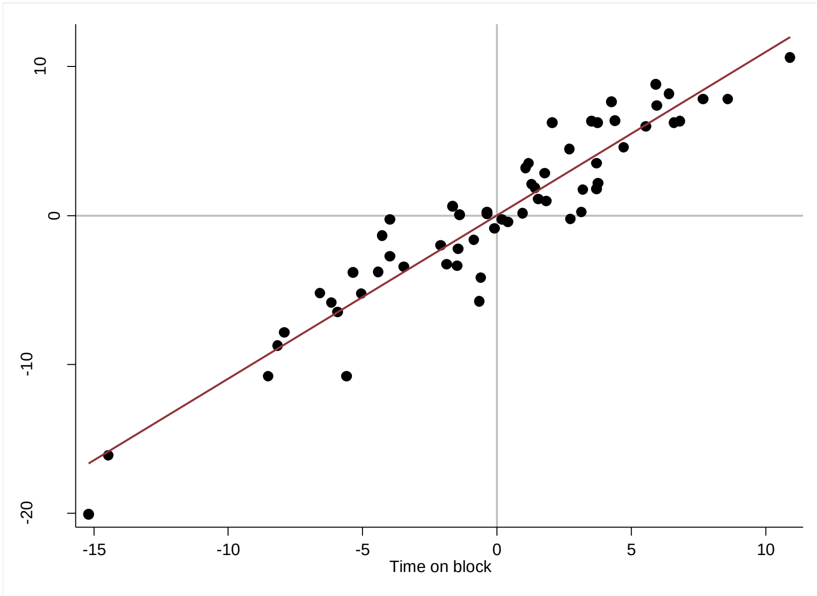


**Figure A.2 - Correlation between time on the block and time on the block for sold cars and unsold cars**

**A: Time on the block and time on the block for sold cars (t=22.00)**




**B: Time on the block for sold cars and time on the block for unsold cars (t=10.66)**

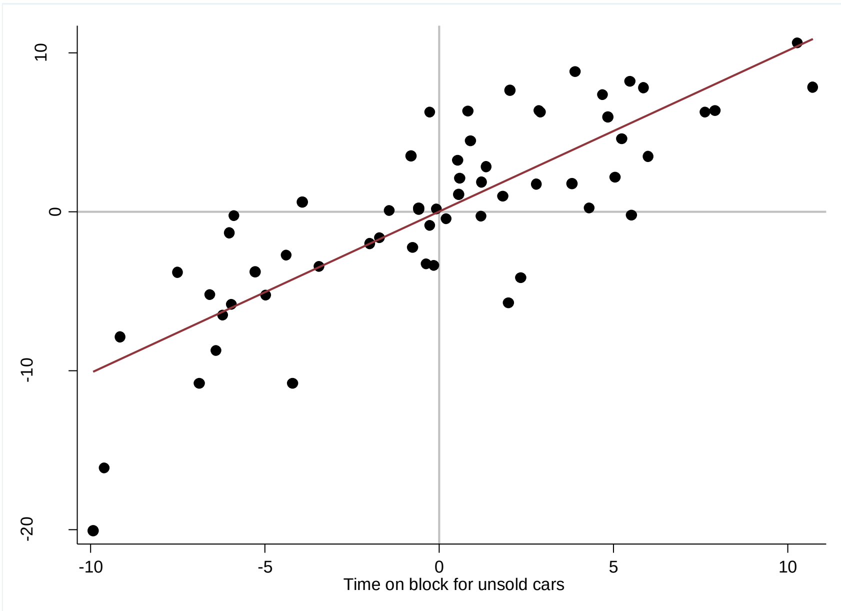


**Table A.1: Descriptive Statistics for Secondary Dataset** This table displays descriptive statistics for dealers and simulcast samples from the secondary dataset. Probability of sale, residual price, and time on block are as defined for the primary dataset and are the only variables observed in the dealers sample. Fish price minus starting price is the gap between the price initially called out by the auctioneer (fish price) and the lower price (start price) at which bidders actually began signaling a willingness to pay. Residual fish price is the fish price less the blue book value. Bids, bid speed, and price speed are the total number of bids, bids per second, and the price increase (from the starting price to the final bid) per second. Fishing time is the time from the calling out of the fish price and the arriving at the start price. Bidding time is the time between the start price and the final bid. Hammer time is the time between the final bid and the end of the sale. Sample sizes report the number of cars in each sample used in calculating the probability of sale measure. All other measures are reported using only cars which sold (20,738 in the dealers sample and 33,295 in the simulcast sample).

| | **Dealers sample** | | **Simulcast sample** | |
|---|---|---|---|---|
| Panel I. | **Mean** | **Standard deviation** | **Mean** | **Standard deviation** |
| Probability of sale | 0.37 | 0.48 | 0.78 | 0.41 |
| Residual price | -153.10 | 1754.11 | -293.25 | 1938.38 |
| Time on block | 70.74 | 36.15 | 33.73 | 13.46 |
| Fishing time | | | 8.66 | 7.70 |
| Bidding time | | | 18.14 | 11.36 |
| Hammer time | | | 6.92 | 4.92 |
| Fish price minus starting bid | | | 1448.36 | 1178.79 |
| Residual fish price | | | -72.72 | 1994.45 |
| Bids | | | 12.90 | 8.36 |
| Bid speed (bids per second) | | | 0.39 | 0.22 |
| Price speed ($ per second) | | | 37.07 | 28.97 |
| Sample size (number of auctioneers) | 56,323 (24) | | 42,597 (16) | |

**Table A.2: Standard deviations of estimated auctioneer effects with varying controls from secondary dataset.** This table displays the effect of a one-standard-deviation increase in auctioneer fixed effects from using various outcome measures from the dealers-only sample of 56,323 observations (24 auctioneers) and the simulcast sample of 42,597 observations (16 auctioneers), both from the secondary dataset. Each cell of the table comes from a separate regression on auctioneer fixed effects and varying degrees of controls as specified.

| | Dealers sample | | | Simulcast sample | | |
|---|---|---|---|---|---|---|
| Panel I. | Prob sale | Residual price | Time on block | Prob sale | Residual price | Time on block |
| 1 Raw values | 0.130 | 685.563 | 7.803 | 0.137 | 468.074 | 2.571 |
| 2 Seller FEs | 0.049 | 262.123 | 8.296 | 0.087 | 437.976 | 2.711 |
| 3 Seller, time of day, auction day FEs | 0.052 | 211.332 | 7.398 | 0.075 | 181.305 | 2.504 |
| 4 Seller, time of day, auction day, lane FEs | 0.046 | 287.234 | 6.362 | 0.076 | 205.598 | 2.245 |
| 5 Seller, time of day, auction day, lane, make FEs | 0.046 | 279.375 | 6.330 | 0.074 | 193.111 | 2.264 |
| 6 Seller, time of day, auction day, lane, make*age FEs, miles | 0.048 | 321.191 | 6.539 | 0.081 | 170.332 | 2.232 |
| 7 Seller, time of day, auction day, lane, make*model*age FEs, miles | 0.049 | 276.841 | 6.429 | 0.081 | 165.439 | 2.370 |
| 8 Seller, time of day, auction day, lane, make*model*age*body FEs, miles | 0.044 | 298.093 | 6.357 | 0.085 | 160.529 | 2.355 |

| Panel II. Simulcast sample | Fishing time | Bidding time | Hammer time | Fish minus start | Residual fish | Bids | Bids per second | $ per second |
|---|---|---|---|---|---|---|---|---|
| 1 Raw values | 1.809 | 1.665 | 0.712 | 336.551 | 352.578 | 1.659 | 0.057 | 6.082 |
| 2 Seller FEs | 1.514 | 1.294 | 0.720 | 194.060 | 514.388 | 1.264 | 0.043 | 4.633 |
| 3 Seller, time of day, auction day FEs | 1.263 | 1.434 | 0.741 | 170.206 | 215.531 | 1.218 | 0.037 | 4.102 |
| 4 Seller, time of day, auction day, lane FEs | 1.135 | 1.420 | 0.746 | 170.684 | 275.813 | 1.475 | 0.041 | 4.262 |
| 5 Seller, time of day, auction day, lane, make FEs | 1.137 | 1.428 | 0.747 | 170.925 | 268.624 | 1.469 | 0.041 | 4.266 |
| 6 Seller, time of day, auction day, lane, make*age FEs, miles | 1.108 | 1.469 | 0.777 | 161.039 | 259.774 | 1.483 | 0.041 | 4.231 |
| 7 Seller, time of day, auction day, lane, make*model*age FEs, miles | 1.101 | 1.645 | 0.779 | 154.207 | 274.367 | 1.599 | 0.042 | 4.300 |
| 8 Seller, time of day, auction day, lane, make*model*age*body FEs, miles | 1.200 | 1.890 | 0.876 | 156.058 | 260.946 | 1.839 | 0.045 | 5.154 |