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Bid Takers or Market Makers? The Effect of Auctioneers on Auction Outcome†

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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 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. (*JEL* D44, D82, L62)

Auctions are central features of many important markets and have attracted a large body of academic research. This literature has mostly focused on the effects of different auction structures, comparing common designs such as English, Dutch, first-price sealed-bid and second-price auctions, to assess their effects on revenue and efficiency. It is well established that 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]

In contrast to this body of work on auction structure, much less is known about how the *process* of running an auction within a given auction may affect outcomes.

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[1] Overviews of auction theory can be found in Bulow and Roberts (1989), Klemperer (2004), and Milgrom (2004).

For example, the basic features of a common English auction include ascending price bids with the highest bidder being the winner. Models such as "button" English auctions in Milgrom and Weber (1982) naturally focus on these central features and abstract from issues related to the auction process. Yet, as Milgrom and Weber themselves highlight, auctions are complex environments, and many aspects of how an English auction is conducted can vary, such as the level of the opening bid and patterns and pace of price adjustments. It is an open empirical question whether process issues matter significantly for auction outcomes.

It is, however, generally challenging to study this question, because the processes used in real-world auctions are hard to quantify and observe. We take a novel approach to explore this issue by focusing on whether auctioneers systematically vary in the outcomes they achieve in English auctions. Billions of dollars worth of goods are transacted each year through live auctions (National Auctioneers Association 2009), with human auctioneers calling prices. Real-world auctioneers control a lot of features of the auction process and employ a variety of special tactics developed to enhance bidding. Our question of interest is whether these human auctioneers appear to be simply neutral "bid takers," or if instead they actively help to shape market outcomes in ways that are not yet captured in most auction analyses.

We use rich data on used car transactions at a leading used car wholesale auction house to explore whether the specific auctioneers conducting auctions have a systematic impact on outcomes. The data include over 850,000 cars auctioned by 60 auctioneers between 2007 and 2013 at the largest location of the auction house. Wholesale used car auctions are a particularly well suited market to study auctioneer effects. More than 10 million used cars are traded in the United States at wholesale auctions each year (Manheim Consulting 2011), totaling over \$80 billion in sales (National Auto Auction Association 2009). The structure is that of an ascending auction (English-style) with a live auctioneer and no predetermined time limits. Cassady (1967) argues that this is the format in which the auctioneer has the most potential to influence the sale. Because both buyers and sellers are professionals trading in high-value goods, all participants have strong incentives and an understanding of auctions. Our approach provides a strong test of the importance of the auction process because we identify only the *variation* across professional auctioneers in their ability to achieve outcomes. As such, our ability to detect process effects requires not only that the tactics employed by auctioneers matter for auction outcomes, but also that these tactics and abilities vary across auctioneers.[2]

Our primary measure of performance is each auctioneer's conversion rate, defined as the fraction of auctions that end in a sale.[3] The sellers of cars in these auctions set reservation prices that are binding often enough that a car going through the auction has on average about a 50 percent chance of selling. The auction house and its

[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 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.

auctioneers make it clear that the primary goal for an auctioneer is to maximize the probability of a car selling. We examine whether the probability that a given auction will result in a sale is affected by the particular auctioneer for that car. We also consider secondary performance metrics such as price (conditional on sale), high bid (not conditional on sale), and speed of sale.

Cars are not randomly assigned to auctioneers in these wholesale auctions, and this introduces 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. However, each of the auctioneers in our sample auctioned a very large number of cars and faced substantial variation in their sample of cars. Our primary identification strategy exploits that fact by focusing on a subset of cars that are allocated to lanes with less selection and by controlling for a rich set of observable factors at our disposal, including day, seller, and car-type effects in the regressions.

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 percent increase over an average conversion rate of 0.53). For the secondary outcome measures, 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). 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.

These effect sizes suggest that auctioneers can have meaningful economic impacts on auction outcomes. For example, 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. These performance enhancements in conversion rates due to higher ability auctioneers are comparable to those found in studies that estimate the effects of changes in auction design, information structure, and broader macroeconomic factors on similar outcomes (Hortaçsu et al. 2013, Tadelis and Zettelmeyer 2015). Applying the intuition of Coey, Larsen, and Sweeney (2014), we also estimate that changing from a poor performing to a high performing auctioneer increases revenue by more than the expected impact of adding 2.55 bidders to the auction. Furthermore, relying on the results of Bulow and Klemperer (1996), these improvements exceed the benefit of choosing an optimal reserve price.

These findings hold up to a wide range of robustness tests, including an alternative identification strategy, the use of an empirical Bayes shrinkage correction, and tests for persistence over time. The estimated auctioneer effects are, moreover, correlated with subjective evaluations of auctioneers made by the auction house and are predictive of which auctioneers left during a period of downsizing. These results, and the features of the market setting where we establish them, indicate 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.

Having documented that auctioneers vary systematically in their effects on auction outcomes, a natural next step is to explore the sources of these differences.

Identifying the potential mechanisms of auctioneer effects is challenging, but we are able to make some progress using both evidence from auction data as well as a short survey of auctioneers. We find little support for mechanisms that involve auctioneers generating different amounts of information about either car quality or participant reservation values during the auctions. Instead, most of our evidence points in a more psychological direction, with auctioneers differing in their ability to generate bidder excitement and urgency. In particular, it appears that the most successful auctioneers tend to be those who can best manipulate the pace of their auctions, with faster paced auctions resulting in better conversion rates. This is especially striking because the market that we study is well functioning and competitive, stakes are large, and participants are experienced professionals.

In providing evidence 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 2006; Podwol and Schneider 2011; and 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, Malhotra, and Murnighan 2005; and Cooper and Fang 2008), endowment effects (Heyman, Orhun, and Ariely 2004; Dodonova and Khoroshilov 2009), utility of winning (Cooper and Fang 2008), regret or fear of losing (Cramton et al. 2012; Filiz-Ozbay and Ozbay 2007); uniqueness of being first (Ku, Malhotra, and Murnighan 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). The 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 Murnighan (2005) also studied how time pressure can affect bidding, and Malhotra (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 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 designs. 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, McAdams and Schwarz 2007) and econometric approaches (Haile and Tamer 2003) to account for the richness of real auction environments.

Finally, we also contribute to the literature that has explored the impact of single individuals on organizational outcomes in several contexts (e.g., in chief executive officers and bosses, judges, teachers, scientists, and political leaders).[4] The evidence

[4] See, for example, Abrams, Bertrand, and Mullainathan (2012); Azoulay, Graff Zivin, and Wang (2010); Bertrand and Schoar (2003); Chetty et al. (2011); Galasso and Schankerman (2015); Hanushek (2011); Jones and Olken (2005); Lazear, Shaw, and Stanton (2012); and Malmendier and Tate (2009).

here is from a context where we would not expect to see meaningful individual heterogeneity; in particular, the competitive 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 differences in other contexts, it is striking that we find statistically and economically significant auctioneer effects. Moreover, as highlighted above, the heterogeneities that we document are useful not simply because they demonstrate that productivity differences exist, but also because they provide a framework and new source of variation for future work investigating auction markets and behavior.

The rest of the paper proceeds as follows. Section I describes the data and offers detail on the institutional context. The empirical strategy and our main results are reported and discussed in Section II. Section III provides a discussion of the economic significance of our estimates. Section IV is dedicated to exploring the mechanisms behind the heterogeneity across auctioneers. Finally, Section V offers concluding remarks.

I. 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 United States, 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 that were received as trade-ins that the dealer did not want to sell on his or her own lot. 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 frequently present at the sale and decides whether or not to accept the high bid. 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 that operate at the auctions. If the final bid does not

[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.

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.[6]

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.[7] 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.[8] Section IV discusses the characteristics and tools of an auctioneer that are considered important.

The auctioneers at the location that 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. This compensation structure raises the important point that to the extent we observe auctioneer differences, it may stem from differential motivation to employ effective tactics that all auctioneers know rather than a differential ability to use or awareness of effective tactics.

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 percent 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. 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

[6] 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. Data on when bargaining occurred is unavailable.

[7] The National Auctioneers Association website (www.auctioneers.org) lists 29 schools.

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

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.[9] 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 who worked 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 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. Lastly, auctioneer identifiers let us detect the specific auctioneer who was on the block in a given lane for a given car.[10]

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 percent of cars sell.[11] 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 both sold and unsold cars (it is equal to sale price for sold cars). The average high bid is approximately \$15,500 for the cars in our sample. Lastly, on average, car auctions last one minute and 43 seconds.[12]

We consider four main performance measures for auctioneers: conversion rates (fraction of cars sold), the price conditional on selling, the highest bid for each car, and 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

[9] 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.

[10] 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.

[11] 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.

[12] 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 sell 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.

Table 1—Descriptive Statistics

	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
Observations	859,239	

Notes: This table presents summary statistics for the main sample described in the text. The total number of observations is 859,239. 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.

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.

We 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.[13] 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

[13] 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 role a good auctioneer can play in increasing conversion.

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.

II. Empirical Analysis

A. *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 variables about each auction in a regression setting. We argue that controlling for variables such as day effects, seller effects, and car-type effects addresses all main concerns about nonrandom aspects in the assignment of cars (and sellers) to auctioneers.

We estimate versions of the following regression model:

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

where 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 $\hat{\beta}_k$s 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:

$$(2) \qquad \hat{\beta}_{norm,k} = \begin{cases} \hat{\beta}_k - \dfrac{1}{M}\displaystyle\sum_{j=2}^{M} \hat{\beta}_j & for\ k = 2, \dots M \\ 0 - \dfrac{1}{M}\displaystyle\sum_{j=2}^{M} \hat{\beta}_j & for\ k = 1, \end{cases}$$

where $k = 1$ denotes the omitted auctioneer in equation (1).[14]

B. *Results*

We estimate equation (1) using four different outcomes of interest across eight specifications that incorporate increasing numbers of controls. Our primary outcome of interest is the probability of sale. We then move to discussing two different price metrics and the speed with which auctions are conducted. The estimated auctioneer effects across these specifications are summarized in Table 2.

Probability of Sale.—The first column in Table 2 provides the standard deviation of the auctioneer fixed effects for the eight specifications using probability of sale as the outcome of interest in a linear probability model. Specification 1 (raw values) suggests that the standard deviation in auctioneers' ability to sell cars is 0.051. Taken literally, this suggests that a one standard deviation improvement in auctioneer ability translates into a 5.1 percentage point higher probability of sale (off a base of 53 percent). Of course, the concern with these raw performance measures is that unobserved assignment of cars to auctioneers could be taking place. The additional rows in Table 2 report results for specifications including finer controls. Based on discussions with the auction house, a primary confounder is that auctioneers may be systematically assigned to sellers with differing levels of reservation values. Consistent with that selection process, we find that adding seller fixed effects reduces the standard deviation of auctioneer effects to 0.038.[15] We also find that adding time-of-day and auction-day fixed effects further reduces the standard deviation to 0.025. Once these controls are in the model, however, additional controls for lane effects and specific car characteristics change the estimates very little.

Figure 1 panel A shows the estimated normalized auctioneer effects across specifications by ranking auctioneers from lowest to highest sale-probability effects. This figure confirms the patterns from Table 2 that the variation drops as initial controls are added to the specifications but stabilizes across specifications from specification 3 onward. The figure also shows that the standard deviation in estimated auctioneer effects is not driven by a handful of outliers at the very top or bottom. One question about including these controls is whether the estimates of the auctioneer fixed effects are simply dampened, or if the ranking of the auctioneers is also significantly 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 0.94 suggests

[14] For some of our analyses we also make comparisons between auctioneers with high estimated effects and those with low estimated effects. Although our sample sizes are large enough to support precise estimation of the auctioneer effects, as a robustness check we also perform a Bayesian shrinkage procedure to help account for any remaining sampling variation that might inflate the differences between auctioneers at the ends of the estimated distribution of performance (Chandra et al. 2013, Jacob and Lefgren 2005, and Morris 1983). The details of the procedure are in the online Appendix.

[15] 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. Seller effects are well identified because there is substantial variation in exposure between sellers and auctioneers: on average, sellers had at least one car auctioned by 54 of the 60 auctioneers and the average auctioneer auctioned cars for 840 of the 1,087 large sellers.

Table 2—Standard Deviations of Estimated Auctioneer Effects with Varying Controls

	Probability of sale		Residual price		High bid		Time on block	
	SD	Coefficient of correlation with previous specification [*t*-stat]	SD	Coefficient of correlation with previous specification [*t*-stat]	SD	Coefficient of correlation with previous specification [*t*-stat]	SD	Coefficient of correlation with previous specification [*t*-stat]
1 Raw values	0.051		219.633		1,935.80		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]

Notes: This table displays the effect of a one standard deviation increase in auctioneer performance as measured by the probability of 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. Specification 2 includes seller fixed effects. Specifications 3 and higher add in the following controls, with 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.

that including seller fixed effects reduced the variation in auctioneer fixed effects, but did not greatly alter the rank order of the auctioneers.[16] Combining the results in Figure 1 and Table 2 reveals that the estimated effects are highly stable across specification 4 to specification 8 at both the aggregate and individual-auctioneer level. This stability of estimates provides some reassurance that the available controls are accounting for potential selection effects.[17]

As Figure 1 panel B shows, in our final specification (specification 8) after accounting for an exhaustive set of controls, we continue to estimate substantial

[16] We report Pearson correlation coefficients; rank-correlation coefficients (Spearman) are very similar.

[17] 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^2 values across these specifications. The R^2 values for the eight specifications are as follows (we omit these values from Table 2 given space constraints): 0.008, 0.074, 0.236, 0.240, 0.243, 0.252, 0.276, and 0.313. Although the largest increases in R^2 values occur between specifications 1 and 3, R^2 significantly increases from 0.240 in specification 4 to 0.313 in specification 8, while the level of auctioneer heterogeneity remains stable.

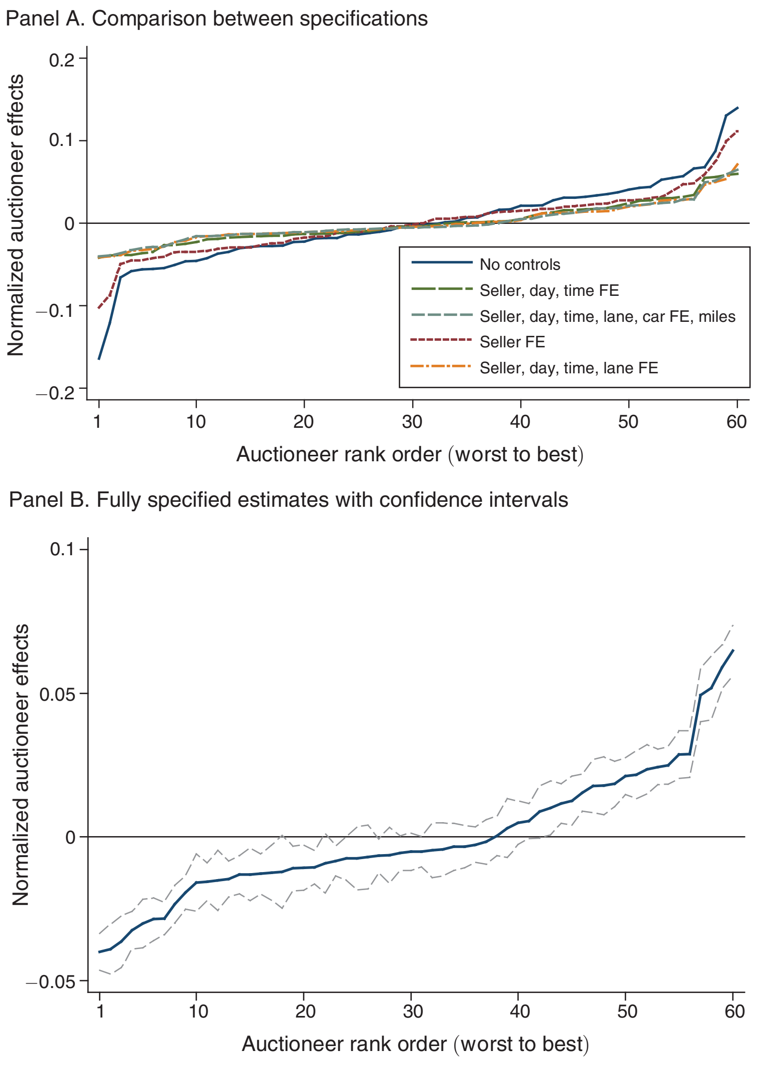

Figure 1. Auctioneer Differences in Probability of Sale

Notes: Panel A plots the normalized fixed effects for each of the 60 auctioneers in our data. The fixed effects are obtained by running 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)), 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 percent confidence intervals.

variation in estimated auctioneer effects.[18] A one standard deviation improvement in auctioneer ability results in a 2.3 percentage point increase in the probability of

[18] Although the dichotomous nature of the sold outcome would usually point toward a logit or probit specification, the large number of fixed effects we use in our analysis tends to lead to non-convergence in the logit or probit. In order to check that our reliance on the linear probability model is not problematic, we employed a two-step procedure. In the first step, we regressed the sold dummy on all of our controls in specification 8 *except* for the auctioneer effects. We obtained the predicted values from this regression. We then ran a logit regression of sold on the auctioneer dummies and the predicted probability of sale from step one. The estimated auctioneer effects from this two-step procedure are very highly correlated (0.95 correlation) with those we get in our specification 8.

selling a car (off a base of 53 percent), and cars assigned to auctioneers at the top and botttom of the distribution would show around a 10 percentage point gap in sales probability. Figure 1 panel B shows the 95 percent confidence intervals around each of the auctioneer effect estimates and shows that for 43 of the 60 auctioneers, the confidence intervals on the normalized effect exclude 0.[19] An F-test of the joint hypothesis that all of the estimated auctioneer coefficients are zero is rejected with p-value < 0.001, suggesting that the estimated dispersion in auctioneer effects is unlikely to be random.

Price Metrics.—Although the auction house's primary metric of interest is sale probability, the sellers of cars at auctions obviously also care about the price those cars achieve. We examine two price metrics as secondary performance measures. 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 results for these metrics are presented in the second and third 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 ($1,936). 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 stabilizing to approximately $88.[20] As we saw for the primary probability-of-sale metric, the rank order of auctioneer effects is generally quite stable from specification 4 onward. Again, an F-test of the joint hypothesis that all of the estimated auctioneer effects are zero has p-value < 0.001 for both of these metrics.

Speed.—As a final secondary measure of performance, we analyze the amount of time that an auctioneer takes to run an auction. Table 2 reports the effects for time-on-block, measured as the length of time in seconds a car was on the block regardless of whether or not it sold. Across every specification that includes controls, we estimate that a one standard deviation increase in auctioneer ability on the time-on-block dimensions is associated with a reduction of between 5 and 6 seconds in auction length (off a base of 103 seconds). These results are highly stable across specifications in terms of both the standard deviation of effects and the rank ordering of auctioneer effects. An F-test of the hypothesis that all estimated effects are zero has a p-value < 0.001. The stability in these findings is an indication of speed being

[19] The confidence intervals in Figure 1 panel B are symmetric confidence intervals formed using robust standard errors. We have also run the analysis while clustering the standard errors at auctioneer level. Clustering *lowers* the standard errors of our auctioneer coefficients. We are reporting the more conservative unclustered standard errors in this version of the paper.

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

an individual characteristic or style that does not depend heavily on the car being auctioned off, the seller, or other environmental contingencies.

An interesting question regarding speed effects is whether these simply are a mechanical reflection of the probability-of-sale effects reported above. The average time on the block for cars that sell is approximately 11 seconds longer than the time on the block for unsold cars. 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. We analyze this issue by estimating auctioneer effects on time-on-block for sold and unsold cars separately. Online Appendix Figure A.1 illustrates that the time-on-block fixed effects using only cars that sold are highly correlated with the time-on-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.1, panel B). This suggests that time-on-block likely reflects systematic differences across auctioneers in the overall pace at which they conduct their auctions.

Correlation across Metrics.—As we seek to better understand whether auction process has systematic impacts on the outcome of auctions, it is important to consider how these different performance metrics correlate. The variation in auctioneer effects we identified above suggests that process (e.g., auctioneer differences) matters, but does that point to auctioneers who have more effective tactics than others overall or to auctioneers who vary in which performance metrics they impact effectively? Understanding these correlations can be important for gaining insight into the possible mechanisms by which auctioneers affect auction outcomes, an issue to which we return in further detail in Section IV.

Although the statistical power to identify these correlations is somewhat limited, we generally find that auctioneers estimated to be more effective on one dimension are more effective on other dimensions as well. Using specification 8 from Section IIB, panels A–F of Figure 2 provide all the pair-wise 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 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.[21] Specifically, auctioneers that run auctions faster (and thus have a *small* time-on-block fixed effect) sell more cars ($t = -1.62$) and obtain higher residual prices ($t = -2.52$) and high bids ($t = -1.98$).[22] This supports the statement made by the auction house's general manager that "sales price and speed are generally the parents of conversion rate." Because these effects tend to correlate with each other, it makes sense to talk about "auctioneer quality" as a one-dimensional construct, and we will at times use that language in the remainder of the paper.

[21] To avoid the potential mechanical bias between time-on-block and sales probability mentioned above, for this analysis, and all other analyses reporting correlations with time-on-block, we use estimates of effects of time-on-block for sold cars only.

[22] 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.

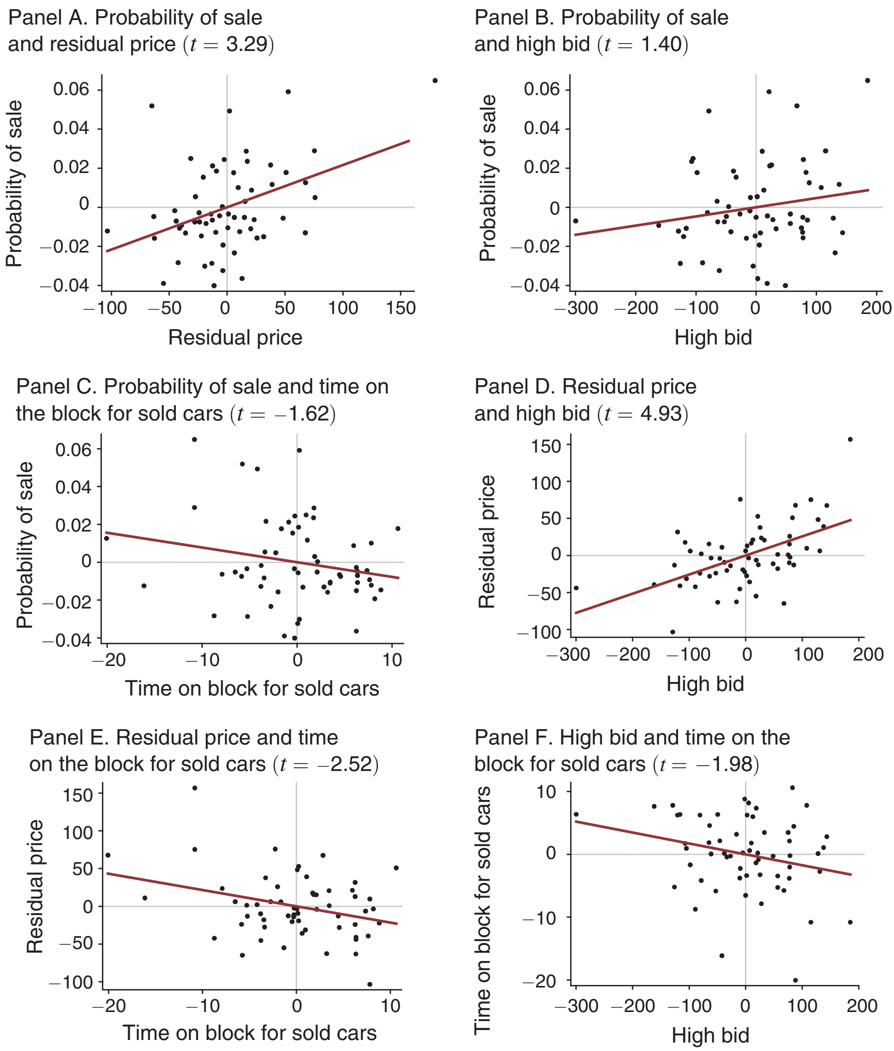

FIGURE 2. CORRELATION BETWEEN PERFORMANCE MEASURES

Notes: The panels 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.

C. *Robustness*

The findings in Section IIB reveal substantial variation in auction outcomes generated by the auctioneer who is assigned to a particular car. Those results rely on our identifying assumption that once we have controlled for seller fixed effects and other auction and car-type effects that there is no remaining selection on unobservables affecting the estimated auctioneer effects. In this section, we report a number of different robustness check exercises that further support the interpration of our results as valid estimates of auctioneer effects.

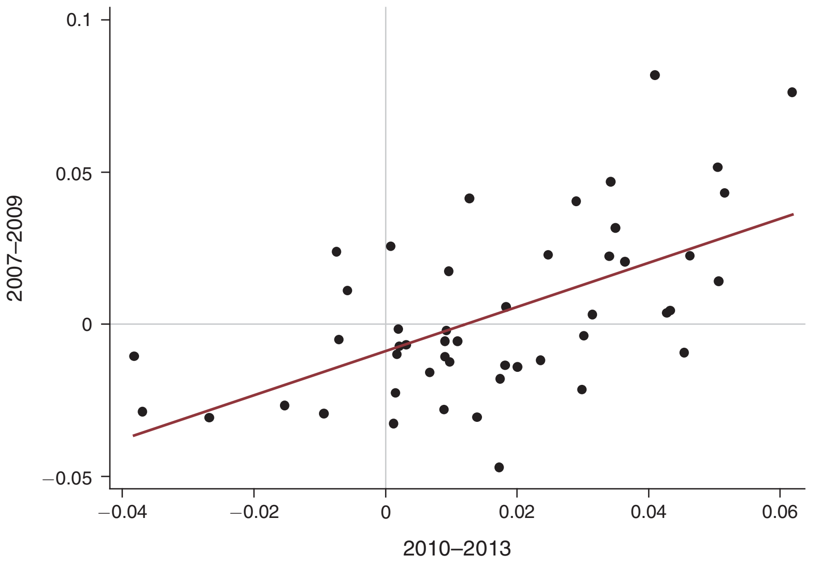

Figure 3. Correlation of Fixed Effects between 2007–2009 and 2010–2013

Notes: Using the identification within seller, auction day and time of day, lane, and car types, we estimated auctioneer fixed effects separately using data for 2007–2009 and then 2010–2013. The figure provides a scatterplot that shows the correlation in fixed effects between 2007–2009 and 2010–2013 for probability of sale. The fitted line is reported as well as the t-statistics from univariate linear regressions between the outcomes in the two years for each measure ($t = 4.91$). The analysis is limited to the 49 auctioneers with at least 2,000 observations in each of the two time periods.

Persistence 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 both the first and second half of our sample period. We find a strong, positive correlation with probability of sale (t-stat $= 4.91$) between the two sample periods. Online Appendix Figure A.2 shows the correlations across time for the other performance metrics. There also is a positive correlation across time for the time-on-block fixed effects (t-stat $= 7.32$) and 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.

Comparison with Auction-House Evaluations.—Another test for the validity of our estimates is to look for whether they correlate with assessments of auctioneer quality made by the auction house. We run two different checks for correlation between our estimated auctioneer effects and auction-house metrics. We focus on our estimates for the primary performance outcome of probability of sale and note that results are generally similar for the other performance metrics.

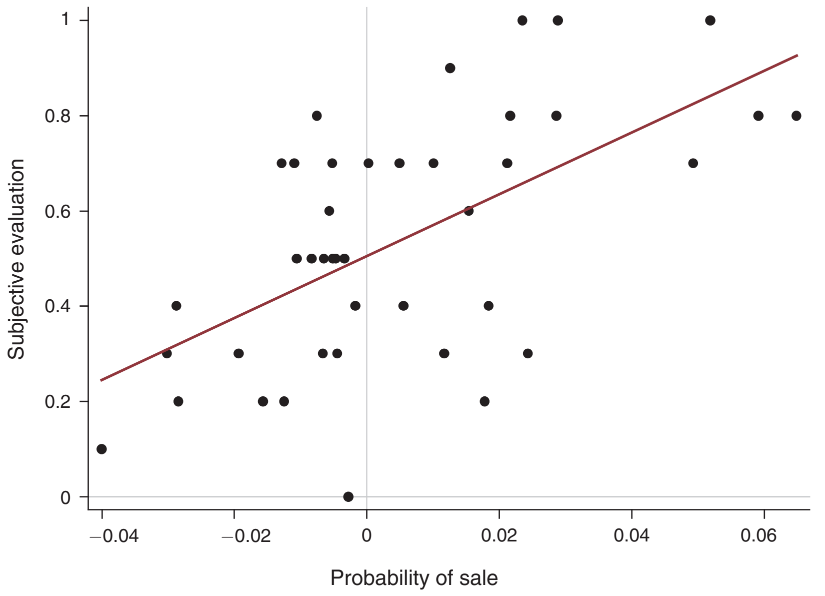

Figure 4. Correlation of Probability-of-Sale Performance with Subjective Evaluations

Notes: The figure provides a scatterplot that shows the correlation in fixed effects for 41 auctioneers between the company's subjective evaluations (on a 0 to 1 scale) and probability of sale. All fixed effects come from the fully specified model within seller, auction day and time of day, lane, and car types. A fitted line is reported as well as the t-statistic from a univariate regression of the subjective evaluation on estimated (normalized) probability of sale ($t = 4.62$).

The first auction-house metric is a subjective evaluation of auctioneer ability. At our request, the auction company produced evaluations for the 41 full-time auctioneers working in the fall of 2012 (prior to their 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). In Figure 4, we correlate the company's subjective rankings with our estimated fixed effects for probability of sale (once again using the full model from specification 8 in Table 2). Correlations with other performance metrics (speed and price) can be found in online Appendix Figure A.3. The company's subjective rankings are strongly correlated with our measure of auctioneers who have a high probability of sale (t-stat $= 4.62$). This lends additional credibility to the idea that we are identifying true economically relevant differences in auctioneer ability.

We 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 full-time auctioneers over our sample period. Of the 59 auctioneers at the start of our sample, 18 were no longer working for the company by 2013 (and one new auctioneer was hired).[23] Figure 5 displays the ordered auctioneer fixed effects from the fully specified model (specification 8) for

[23] We do not have direct information 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.

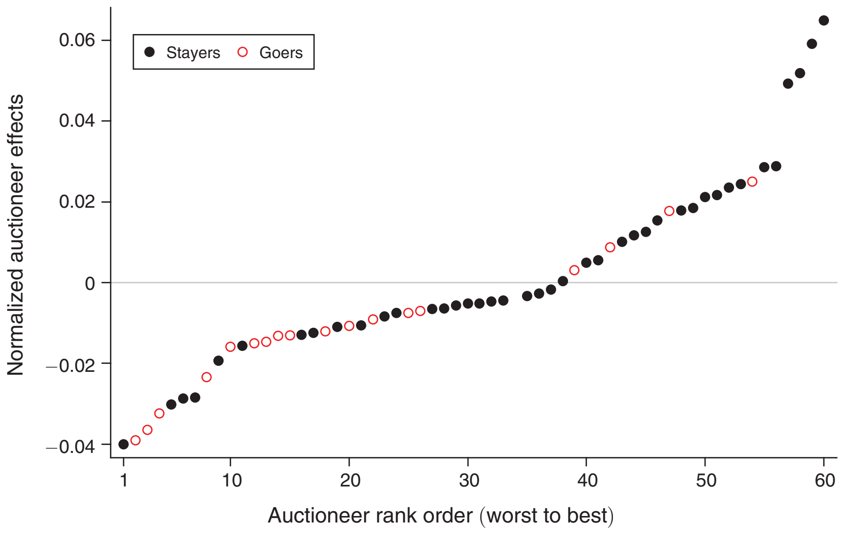

Figure 5. Performance Rankings for Auctioneers Still at the Company in 2012 and Auctioneers Who Left the Company by 2012

Notes: 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, $N = 41$; filled in dots) and those who left between the end of 2008 and 2012 (goers, $N = 18$, empty dots).

probability of sale (online Appendix Figure A.4 shows results for the other performance metrics). The auctioneers who left the company before 2012 are those represented with open-circle dots. Many of the worst-performing auctioneers left the firm during the downsizing. In contrast, the large majority of the best performing auctioneers based on our estimates were retained. Regressions of the auctioneer fixed effects 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 $= 2.53$). Again, the fact that our ability measures predict who exited the sample during a downturn provides evidence in favor of our metrics representing true ability.

Alternative Identification: Shift Changes.—Finally, we experimented with an additional method to help overcome selection and causally identify estimates of auctioneer ability. 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 (online Appendix Figure A.5).

We can exploit the variation in auctioneers that occurs within a lane on a given day by including lane $\times$ day fixed effects when estimating auctioneer ability.[24] This

[24] 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

specification allows us 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. The estimates of auctioneer ability that we obtain with this approach strongly correlate with those from specificiation 8 in our main analysis: the *t*-stats on a regression of these alternative estimates on the original estimates for probability of sale, residual price, high bid, and time on the block are 16.15, 6.51, 3.60, and 15.46, respectively (see online Appendix Figure A.6). Consistent with our earlier discussions, the effects for probability of sale and time on the block appear highly robust, while those for the price metrics are somewhat less so.

D. *Competition across Auctioneers*

Our estimation up to this point has shown that auctioneers vary substantially in the effects that they generate in auctions, and that because effects are correlated across performance metrics it is reasonable to talk about auctioneer quality. However, our evidence does not reveal whether highly effective auctioneers are better in terms of absolute effects, or instead they achieve their outcomes at the expense of lower performing auctioneers. In either case, our evidence suggests that auctioneer tactics can affect auctions in important ways that are unexplained by current auction theory. However, understanding whether auctioneer differentials reflect competition between auctioneers across lanes in the auction house or independent performance differences is important for both practical business applications (e.g., implications for the auction house) and for future work exploring how the auction process matters.

This question is very difficult to address given the variation in our data. As argued above, for our main results we rely on a large amount of idiosyncratic variation in the assignment of cars to auctioneers, which works because each auctioneer auctions thousands of vehicles from hundreds of different sellers on different days. Testing for competition across lanes, however, requires variation in the mix of auctioneers and specifically variation in the quality of the auctioneers auctioning at any point in time. The ideal variation for us would have each auctioneer auctioning cars at times with a mix of other auctioneers who are strong and others who are weak. Such variation would allow us to assess whether good auctioneers excel primarily when paired with many poor auctioneers and vice versa.

Unfortunately, there is fairly limited variation in the quality mix of auctioneers. To see this, first let the term "average auctioneer quality" within a given time frame refer to the value obtained by averaging the normalized auctioneer fixed effect for probability of sale for each auctioneer averaged over the cars auctioned within that time period. Across the 536 days in our sample, the auction day with the highest average auctioneer quality was a day when the average (normalized) auctioneer fixed effect for probability of sale was 0.013, and the day with the lowest average auctioneer quality had a value of −0.006. The standard deviation in average auctioneer quality across days after controlling for year fixed effects is only 0.002.

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.

We find similarly little variation in average auctioneer quality across hours, with a standard deviation, after controlling for day fixed effects, of only 0.004. Only once we consider very narrow time windows do we start to detect meaningful variation in average auctioneer quality. If we look at average normalized auctioneer effects for probability of sale for auctioneers auctioning cars in two-minute windows, the standard deviation after controlling for day fixed effects is 0.01. It is not entirely clear that exploiting this short-term variation in the quality mix of auctioneers provides a very powerful test of cross-lane competition effects. Nonetheless, we exploit this variation to the extent that we can in order to get at least suggestive evidence of whether our main results appear to come more from independent auctioneer effects or instead from cross-lane competitive spillovers.

To exploit the variation in auctioneer ability in small time windows, we analyze how an auctioneer being active (i.e., auctioning cars) in a given time frame affects the overall sales probability in that period and compare that effect to the direct effect that we estimated earlier. We first calculate, for each two-minute window in the data, the fraction of cars sold (over all cars auctioned in that time frame). This serves as the dependent variable for our analysis. The key independent variables of interest are measures of the share of cars auctioned (sold or unsold) in that time window for each of the 60 auctioneers. We then regress the fraction sold for each two-minute window on the auctioneer shares as well as a range of additional controls.[25] We normalize the estimated coefficient on the shares of cars per auctioneer with the same procedure as for the main auctioneer effects in the previous analyses. We refer to these normalized coefficients as an auctioneer's net effect on the probability of sale. If the main effects estimated previously reflect independent auctioneer effects, then the normalized net estimates from this two-minute window analysis should be similar to the main effects. That is, if there are no offsetting effects on other auctioneers, an auctioneer who typically raises sale probability by 0.05 and auctions 10 percent of the cars in a two-minute window should raise the overall sale fraction in the window by 0.005 and should have an estimated effect by share of cars sold of 0.05. However, if most of the effects come from cross-lane competition, an auctioneer will have a much lower net effect on the overall sales rate than they do for their own cars.

We find that auctioneers' estimated net effects are very similar to the direct effects estimated in the main analysis. Figure 6 shows a scatter plot of the net estimates from this two-minute window analysis against the direct auctioneer effects estimated in the preferred specification 8 in our main analysis. The two effects are highly correlated, and the linear best-fit line is close to the 45-degree line. With the caveat that we have limited variation to exploit, these results are at least suggestive that the main effects stem from auctioneers having independent effects on cars. This analysis shows no evidence that good auctioneers achieve their higher outcomes at the expense of the lower performing auctioneers. We present related evidence consistent with these findings in Section IV, where we explore whether a given auctioneer appears to be affecting bidding for a fixed set of bidders (i.e., affecting bidders

[25] Additional controls include day and time-of-day fixed effects, seller fixed effects for offering any car in the window, and indicators for the lanes active with at least one car run in the window.

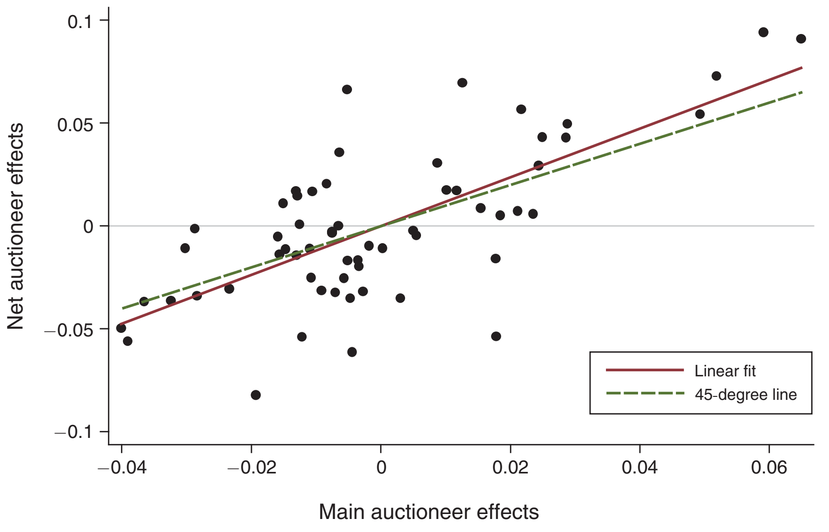

Figure 6. Correlation of Main Probability-of-Sale Performance with Net Auctioneer Effect on Sales

Notes: The values on the x-axis are the normalized estimated auctioneer effects for probability of sale as from specification 8 of the regression model in (1). The values on the y-axis are the normalized estimated coefficients from a regression of the fraction of cars sold in two-minute time windows on each auctioneer's share of auctioned (sold or unsold) in that window for each of the 60 auctioneers, plus a range of controls as described in Section IID ($t = 7.71$).

on the intensive margin) or attracting bidders who would not otherwise be in that auctioneer's lane (i.e., affecting bidders on the extensive margin).

III. Benchmarking the Economic Significance of Auctioneers

Having established that heterogeneities exist among auctioneers, we now present several approaches to evaluating the economic importance of these process effects on auctions.

First, we can consider the effects of having access to high-quality auctioneers on the expected revenue for both sellers and the auction house. Our estimates from Section IIB reveal that moving from the tenth to ninetieth percentile in auctioneer ability raises the probability a car will sell, holding all else equal by 0.056. Moving from a low-end to high-end auctioneer in this way would increase the expected revenue per car for a seller by \$848.[26] For the auction house, this 5.6 percentage point increase in the probability of sale translates roughly to the auctioneer selling 112 more cars per year (auctioneers perform on average approximately 2,000 auctions per year). Given that our analysis in Section IID suggests small or no competitive spillovers to other auctioneers, the auction house obtains substantially more revenue

[26] We estimate an increase of 0.056 in the probability of sale from tenth to ninetieth percentile of auctioneer ability and multiplying that by the average sale price of \$15,141 yields the estimate of \$848 higher expected revenue. Here we use the term "expected revenue" to refer to the expected payment received by the seller from the high bidder.

from high-performing auctioneers; assuming an average fee to the auction house of \$200 for each car sold, an extra 112 cars sold per year implies an extra \$22,400 in auction-house revenue per year. This increase corresponds to an improvement in just one auctioneer's performance. Using the same line of reasoning, if all auctioneers who perform below the median were to improve their performance to the median level, auction house revenue would increase by \$137,530 annually, and if all auctioneers performing below the ninetieth percentile were to move to the ninetieth percentile level, revenues would increase by \$691,727 annually.

Another way to benchmark the results is to compare our estimated effects with results from related studies in the same industry that estimate the effects of certain changes in auction design and information structure on similar outcomes. Tadelis and Zettelmeyer (2015), for example, estimate that providing additional quality information about cars in similar wholesale auctions increases the probability of sale by 6.3 percentage points. That effect is quite similar to the differences we observe between auctioneers at the tenth and ninetieth percentile of estimated effects (5.6 percentage points). The estimated impact of auctioneer differences on sale prices at auctions are also comparable to the results reported in Hortaçsu et al. (2013) for how automaker financial distress impacts car resale values. Hortaçsu et al. find that a 1,000-point increase in the credit default swaps spread for an auto manufacturer is associated with a drop in average prices for that manufacturer's used cars at auctions of \$68, which is an effect size that lies between our residual price effect estimates for a standard deviation change (\$42; see Table 2) and the ninetieth percentile to tenth percentile differences in auctioneer ability (\$96; see online Appendix Figure A.4).

A further useful benchmark for assessing auctioneer effects is also the revenue impact of increased competition from additional bidders participating. The number of bidders at a given auction sale is rarely observable in wholesale auto auction data; however, Coey, Larsen, and Sweeney (2014) demonstrated that, under quite general conditions (correlated private or common values), the effect on expected revenue from *removing* a random bidder from n-bidder ascending auctions, denoted $\Delta(n)$, is bounded above by the following:

$$\Delta(n) \leq \frac{2}{n}\left[E\left(B^{n-1:n}\right) - E\left(B^{n-2:n}\right)\right], \tag{3}$$

where $B^{m:n}$ is the mth order statistic of bids and where $n > 2$.[27] Under the assumption that expected revenue is concave in the number of bidders (i.e., the revenue increase from a move of n-1 to n bidders is larger than the revenue change from n to $n+1$ bidders), the effect of *adding* (rather than removing) a random bidder to

[27] $B^{m:n}$ is an order statistic of *drop-out* points of bidders, and thus in a private values button auction, $B^{n-1:n}$ corresponds to the final bid. The intuition behind (3) can be seen by noting that, in a correlated private values button auction with no public reserve price, if one bidder were removed at random from an n-bidder auction, with probability $(n\text{-}2)/n$, the removed bidder will not be one of the top two bidders, and revenue will be unchanged; with probability $2/n$, revenue will drop to the third-order statistic, $B^{n-2:n}$, and (3) holds with equality. A similar result holds for Haile and Tamer (2003) settings, with a weak inequality, and common values settings, with a strict inequality.

an n-bidder auction is also bounded above by the same expression.[28] We extend this intuition by observing that under the same assumptions, the effect of adding k random bidders to an n-bidder auction is weakly bounded above by

$$\frac{2k}{n}\Big[E\big(B^{n-1:n}\big) - E\big(B^{n-2:n}\big)\Big]. \tag{4}$$

Coey, Larsen, and Sweeney (2014), using similar auto auction data to ours, find that the upper bound in (3), averaged over all values of $n > 2$, is given by \$333. Therefore, applying (4), the effect on seller revenue of a move from the tenth to ninetieth percentile in an auctioneer's conversion rate is greater than the improvement from adding 2.55 more bidders. Based on personal experience observing many auto auction sales, we note that there are rarely more than ten bidders actively participating (or even paying attention to the auctioneer), and thus an increase of 2.55 more bidders is substantial. Genesove (1991) reports similar numbers of bidders from observation of auto auctions, and these facts do not seem to have changed drastically in the past 25 years.

Finally, in addition to the benchmarks above, it is interesting to ask how important a good auctioneer is relative to setting optimal reserve prices. Under quite general assumptions, Bulow and Klemperer (1996) demonstrated that the participation of one additional, random bidder (which is bounded above by \$333 as described above) increases seller revenue for a given car more than an optimal reserve price would.[29] This implies that the seller revenue effects that we find moving from the tenth percentile to the ninetieth percentile (\$848) are larger than the increase in expected seller revenue, which would be obtained by using the optimal reserve price.

IV. The Sources and Mechanisms of Auctioneer Heterogeneity

The analyses in Section II provide robust evidence that, even in a well functioning auction market, individual auctioneers can significantly impact key market outcomes. A natural next step is to explore the mechanisms that might explain why some auctioneers outperform others. 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 (some of which was already presented in Section II) that helps establish the potential relevance of the various mechanisms considered here.

[28] Coey, Larsen, and Sweeney (2014) provide sufficient conditions for revenue concavity to hold.

[29] The result of Bulow and Klemperer (1996) applies whether bidders' values are independent or correlated, and whether signals are private or affiliated. The result relies on bidders being symmetric and having decreasing marginal revenue functions (in the sense of Bulow and Roberts 1989).

A. *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]

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.[31] For example, some auctioneers may be particularly good at choosing the initial price 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

[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 that has more of an 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] For example, Quint (2014) provided a theoretical example in which the revelation of lower bids in a common value English auction environment could lead to revenue gains of up to seven percent. See also Vincent (1995).

bids early before focusing on the bids by those who will eventually win the auction.[32]

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" (Lang 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.** An auctioneer might facilitate bargaining between the high bidder and the seller if the final bid does not meet the seller's secret reserve price. This may be through a quick round of bargaining on the auction block or may occur through "bids off the wall," "bids from the vending machine," or "phantom bids" (see, Ashenfelter 1989, Vincent 1995), where the auctioneer acts as though the final bidder still faces a stream of competing bids, thus signaling to the final bidder that the reserve price has not yet been met.[33]

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, Malhotra, and Murnighan 2005; Ockenfels, Reiley, and Sadrieh 2006; Malmendier and Szeidl 2008; and 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,

[32] 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.

[33] 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, but we are told that such bargaining occurs rarely at the auction house from which our primary data arises, although it does occur frequently at some other auto auction houses (Larsen 2014).

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 these potential mechanisms using observational data. First, 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) 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 initially called 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.

Furthermore, the discussion of the mechanisms above focuses on how auctioneers might affect auction outcomes through the *intensive* margin, altering outcomes for a given set of bidders. However, several of these hypothesized mechanisms might also affect outcomes through the *extensive* margin, influencing additional bidders or more high-value bidders to participate. For example, an auctioneer generating excitement (Mechanism 6) or helping bidders match to cars they would prefer (Mechanism 4) might attract a higher number of bidders or a higher proportion of high-value bidders to that auctioneer's sales. Additionally, if some auctioneers run more efficient auctions (which, as highlighted above, could occur through a variety of mechanisms), more time-sensitive bidders might attend that auctioneer's sales, again affecting the extensive margin.

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 studying the behavior of auction participants (for example through experimental methods). In the next two subsections 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. We also present evidence on the question of whether these mechanisms appear to be affecting outcomes through the extensive or intensive margin.

B. *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 short time the car is on the 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

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

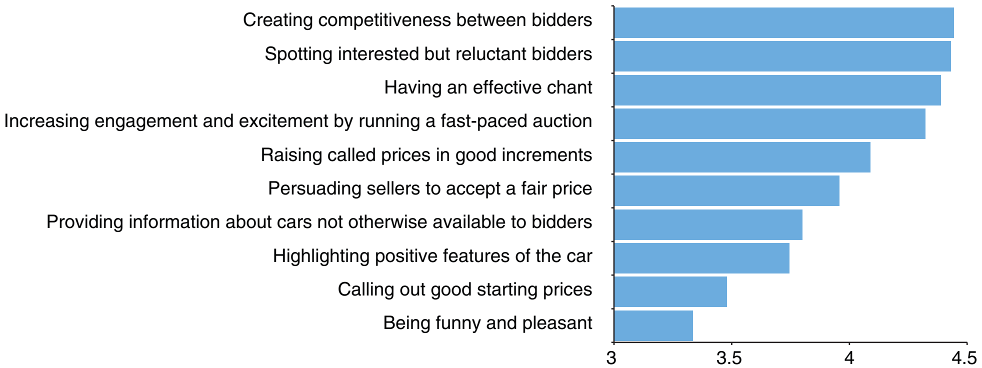

Figure 7. Survey Results

Note: 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).

determining auctioneer success. That mechanism also received relatively low rankings on the five-point scale (Figure 7).

The other four 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 3–5. 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) or to anchoring (one concept in Mechanism 6 not related to excitement), 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 auctioneers that I have seen tend to use speed as a tool, which creates a sense of urgency in bidders, forces 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 too much."[34]

C. *Quantitative Evidence on Potential Mechanisms*

In this subsection we consider patterns in our data that speak to the relevant sources of heterogeneity. We rely both on our primary dataset as well as a secondary auto-auction dataset described in the online Appendix (Section A.3) that contains information on fewer auctioneers (only 16) but records a variety of additional auction-level outcomes not contained in our primary dataset. Many of the results that we present below are correlational analyses with a limited number of observations, and thus should be interpreted with care. However, we argue that, taken together, they provide a consistent view of the mechanisms at play. We begin our analysis by recalling some findings from Section II 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 2, 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 II 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 4 and in panels C, E, and F of Figure 2, 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.

[34] As highlighted above, in conversations or open-ended survey comments, none of industry participants highlighted Mechanism 5 as important for an auctioneer's role.

Table 4—Correlations between Auctioneer Measures: *t*-Statistics

Regressors in univariate regressions	Outcome variable: Auctioneer fixed effects for probability of sale—primary dataset (1)	Outcome variable: Auctioneer fixed effects for probability of sale—secondary dataset (2)
Primary dataset		
Auctioneer fixed effects for buyer average residual price	0.41	
Auctioneer fixed effects for buyer match propensity	−0.93	
Auctioneer fixed effects for share of unique buyers per car sold	−0.28	
Secondary dataset		
Auctioneer fixed effects for fishing time		−0.32
Auctioneer fixed effects for bidding time		0.66
Auctioneer fixed effects for hammer time		−1.79
Auctioneer fixed effects for fish price minus start price		0.63
Auctioneer fixed effects for residual fish price		−0.08
Auctioneer fixed effects for bids		2.34
Auctioneer fixed effects for bid speed (bids per second)		2.74
Auctioneer fixed effects for price speed ($ per second)		2.63

Notes: 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 and column 2 uses fixed effects measured from our secondary dataset.

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. 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, Malhotra, and Murnighan 2005 and Malhotra 2010).[35]

We also examine the hypothesis of Mechanism 4 that some auctioneers may be better at attracting certain types of bidders, aiding in the process of matching buyers to cars. Using our primary dataset still, we calculate two measures for each buyer: (i) propensity to pay above market value, given by the average residual price paid by the buyer, and (ii) match propensity, given by the percent of the buyer's purchases which were of a given make.[36] We then estimate the fully specified version of equation (1) using these measures as outcomes. We find—see Table 4—that regressions of auctioneer conversion rate effects on auctioneer effects for the 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.

[35] Haruvy and Leszczyc (2010) and Lucking-Reiley et al. (2007) find that on eBay, where auction duration is between one and seven days, longer lasting auctions generate more bidder participation. However, Einav et al. (2016) 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 we examine, where the average duration is less than two minutes, speed can be an important factor.

[36] We use this latter 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 that 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.

Column 2 of Table 4 displays similar *t*-stats to those in column 1, where auctioneer effects are measured using our secondary dataset (described in more detail in online Appendix A.3). From this dataset, we obtain the following auction-level variables: fish price (the price initially called out by the auctioneer); start price (the price at which bidders actually begin signaling a willingness to pay); residual fish price (fish price less the blue book value); fishing time (seconds from calling out the fish price and arriving at the start price); bidding time (seconds between the start price and the final bid); hammer time (seconds between the final bid and the time when the sale is marked as complete—i.e., the time in which the auctioneer calls out, "going once … going twice … sold," pounds down the gavel or "hammer," and stops the sale); bids (total number of bids received); bid speed (total number of bids divided by time on block); and price speed (gap between final bid and start price, divided by time on block). We then compute auctioneer-level effects by again estimating equation (1) separately for each of these measures, as well as the probability of sale, as the outcome. The first three rows in column 2 of Table 4 provide further suggestive evidence on the importance of speed. The length of time that 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 are those who *end* the sale quickly and move on to the next car, leaving little time for bidders to hesitate or back down from their bids. This is consistent with the idea that thought speed (Pronin and Wegner 2006) and urgency may play a role. Because hammer time measures the length of time after the final bid has been placed and before a successful sale is declared, we suspect that this measure is more likely to be a characteristic of the auctioneer rather than a tool for influencing a specific auction. Results in online Appendix Table A.2 are also consistent with this hypothesis, demonstrating that hammer time effects are quite stable as additional observables are controlled for, as in the case of time-on-block effects in our primary dataset. The final two rows in column 2 of Table 4 also display findings consistent with speed playing a role: auctioneers who tend to have a faster pace of price adjustment—either measured by the number of bids arriving per second or the dollar increase (from start price to final price) per second—tend to also have higher conversion rates.

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). Online Appendix Table A.2 shows that some heterogeneity exists 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, as 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 positive 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.[38]

We return again to our larger, primary dataset to explore whether auctioneers appear to be affecting the extensive margin (attracting more bidders or more high-value bidders) rather than the intensive margin (influencing outcomes for a given set of bidders). First, we do not find evidence consistent with auctioneers attracting a different number of buyers. Although the number of bidders is unobserved, if auctioneers differ primarily in their ability to attract a larger number of bidders, we would expect better auctioneers to sell to a wider range of unique buyers. However, we find that there is very little variation across auctioneer in the share of unique buyers to whom cars are sold; the average number of unique buyers as a share of the total cars sold in a given day by an auctioneer ranges between 0.89 and 0.94 (mean $=$ 0.92, standard deviation $=$ 0.01). The last row in column 1 of Table 4 demonstrates that this measure does not correlate with auctioneer conversion rate effects (t-stat $= -0.28$). Second, we find evidence that auctioneers who perform better by our primary performance measures (such as conversion rate) also tend to have sales in which the winning bidder exhibits a higher residual price than that bidder does on average. We perform this check by using buyer-specific residual prices (average residual price of a given buyer minus overall residual price) instead of the overall residual price as our price outcome variable. We find that the auctioneer fixed effects estimates (and the correlation with the other fixed effects from the other outcome measures) are essentially unchanged, suggesting that the difference that we observe across auctioneers can be observed *within* the sales to individual buyers, and that auctioneer heterogeneity is unlikely to be driven by extensive margin effects of differential attraction of high-value or low-value buyers to different auctioneers.

Taking all of this evidence together, and combining it with the findings 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 and urgency among bidders, and we find quantitative evidence consistent with this hypothesis, both in our larger primary dataset and in our smaller secondary dataset.

[37] The bid history in the secondary data records each bid but does not record bidder identities, and hence it is impossible to identify in the data the point at which a given bidder ceased to bid.

[38] This same criticism is applied to bid speed and price speed; these two measures are both strongly positively correlated with conversion rate effects, with t-stats above two; and this fact may be capturing the association between prices and conversion rates rather than speed and conversion rates.

V. Discussion and Conclusion

The evidence presented in this paper shows that in well functioning, high-stakes English auctions, how 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, are consistent with the way in which some recent auction platforms are organized. The peer-to-peer auction platform Tophatter (www.tophatter.com), for example, organizes online auctions that are fast-paced, and where shoppers join each other live in "cartoon" auction rooms, with avatars including a virtual auctioneer. It appears as though this rapidly growing online platform is trying to replicate, in a virtual context, some aspects of in-person auctions, including the presence of an auctioneer. Consistent with our results, speed seems to be a key factor on this platform to generate excitement. The findings from our analysis can therefore provide some insights to the design of these kinds of platforms and applications, both in order to maximize the efficiencies of computerized, online auctions and to exploit features of the operating of human auctioneers that can be sources of advantages also on the web. Further studies into the behavior 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 fully identify the mechanisms through which auctioneers affect outcomes, or the sources of auctioneer abilities; this additional research would provide a more complete understanding of bidder behavior and the functioning of real-world auction markets. The evidence presented here is consistent with the presence of noninformation-based (or behavioral) factors, in particular those creating urgency among bidders. However, we have also highlighted several information-based factors that 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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