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

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**Abstract**

A large body of research has explored the importance of auction design and information structure on auction outcomes. Much less work has looked at the importance of auction process. We analyze more than 800,000 wholesale used car auctions, and explore the importance of auction process by testing for systematic differences in outcomes by auctioneer. Auctioneers may differ in how they conduct their auctions, varying for example in patterns of starting prices, price adjustments, or other techniques. Exploiting arguably random variation in the assignment of cars to auctioneers, we find large and significant differences in outcomes (probability of sale, price, and speed) across auctioneers. The performance heterogeneities that we find are stable across time and correlate with subjective evaluations of auctioneers provided by the auction house. Additional analyses and also survey evidence help to shed light on possible mechanisms that allow an auctioneer to stand out among his/her peers.

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## 1. Introduction

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

Although a large literature has explored the importance of auction structure on outcomes, much less work has focused on the process of running an auction (conditional on the auction design). As some auction theorists have noted (Klemperer, 2002; Milgrom, 2004), many auctions involve human participants who may be misinformed or boundedly rational in some way. In these settings, the details associated with how an auction is run may significantly influence outcomes.

An example of how auction process may vary from one auction to the next is the leeway that a live auctioneer has in how an auction is run. Despite the importance of ascending-bid auctions, there has been very little research exploring the impact of auctioneers within this auction design. Milgrom and Weber's (1982) work modeled English auctions assuming that prices rise continuously from a low level and that all participants hold down a button and can be observed dropping out of the auction at some point when the price rises too high. Within that structure, there is no role for an auctioneer and the focus naturally becomes on the information structure (e.g., private signals) of the bidders in the auction. But as Milgrom and Weber themselves highlight, many real-world ascending-bid auctions involve human auctioneers who are typically experienced professionals. These auctioneers can influence the process of an auction by choosing opening bid amounts, changing the pace of price adjustment, and deciding when to stop the bidding. In addition, many auctioneers (especially in the U.S.) interact with bidders and call out bids in a fast-paced, rhythmic chant, attempting to create a sense of urgency and excitement among bidders.

In this paper, we explore the importance of auction process by studying whether auctioneers can have a nontrivial, systematic impact on auction outcomes. We investigate this question in the context of wholesale, used-car auctions. This market is well suited to studying the role of auctioneers for several reasons. First, these are large markets – more than 10 million used cars are traded in the U.S. at wholesale auctions each year (Manheim, 2011), totaling over $80 billion in sales (NAAA, 2009). Second, because

[1] Overview of auction theory and the related literature are, among others, in Bulow and Roberts, 1989; Klemperer, 2004; Menezes and Monteiro, 2004; and Milgrom, 2004.

both buyers and sellers are professionals and because these cars are high-value goods, we expect all participants to have strong incentives. Third, as we will argue below, the institutional features and data available allow us to capture the causal impact of individual auctioneers on prices, the probability of sale, and other performance measures. Finally, the structure of these auctions is an ascending auction (English-style) with a live auctioneer and no pre-determined time limit, which Cassady (1967) argued is the format in which the auctioneer has the most potential to influence the sale.

Our data include over 800,000 cars auctioned by 60 auctioneers between 2007 and 2013 at the largest location of a leading operator of used-car auctions in the U.S. The primary measure of auctioneer performance that we analyze is each auctioneer's conversion rate (the fraction of cars that end in a sale). The auction company and its auctioneers make it clear that the primary role of the auctioneer in this context is to maximize the probability of each car selling. We also study two secondary performance metrics: residual price (the difference between sale price and market value) and speed of sale.

An obvious threat to the identification of auctioneer heterogeneity is that cars may not be randomly assigned to auctioneers. We discuss identification assumptions in detail below and argue that after controlling for important features of the auction (auction day, seller of the car, car type, etc.), the assignment of auctioneers to cars is quasi-random. We also provide additional tests including the exploitation of shift changes as a way to identify the causal impact of auctioneers on outcomes.

We find significant dispersion in auctioneers' fixed effects in each of the three performance measures. In our preferred specification, a one-standard deviation increase in auctioneer performance corresponds to an increase in the probability of sale by 2.3 percentage points (the average sales probability is 53%), an increase in residual sales price by $41.8 (the average sales price is $15,141), and an increase in speed of sale by 6.1 seconds (off of an average of 103 seconds). We apply an Empirical Bayes shrinkage correction to account for the fact that each auctioneer's effect is noisily measured and find that the estimated effects in general change very little, suggesting that the heterogeneity we find is not merely due to natural sampling variation. The performance enhancements in conversion rates due to higher-ability auctioneers (e.g. from the $10^{th}$ to the $90^{th}$ percentile) are generally comparable in magnitude to the effect of providing additional information as in Tadelis and Zettelmeyer (2011).

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

These results suggest that the way an auction is run can have a nontrivial impact on outcomes. Although documenting the differences in outcomes by auctioneer is by itself interesting, a natural and intriguing question is what the mechanism is that allows certain auctioneers to outperform others. We explore and test various hypotheses regarding the mechanism behind the heterogeneity that we find. In particular, we are interested in trying to distinguish between a differential ability of auctioneers to convey information to bidders to make rational decisions, and a differential ability to generate behavioral responses irrespective of the informational content. Rational explanations include the possibility that auctioneers are differentially informed about the features of a car or that some auctioneers deliberately keep the bidding open longer on each car in order to generate more bids (particularly bids from low-valuation bidders) and hence increase the amount of information available to auction participants. Behavioral explanations include the ability of auctioneers to generate excitement and convince potential bidders to participate and bid higher.

These mechanisms are difficult to disentangle, because they are largely observationally equivalent and not mutually exclusive. We present results from a survey we conducted in which auctioneers were asked to rank and comment on the importance of various traits and tools which a good auctioneer would possess. The responses (along with many conversations with practitioners) provide evidence against the idea that some auctioneers provide expert information about a car or that they are primarily trying to persuade sellers to lower their reservation values. The survey results do support the mechanism that some auctioneers are better at creating excitement and competitive arousal among buyers and that this sense of urgency leads to more sales. These survey results are consistent with our finding that auctioneers selling more cars also sell cars at higher prices and perform their auctions more quickly.

In spite of the historical prevalence of auctioneers and their prominence in live auctions still today, auctioneers have received little attention. To our knowledge, the only two studies examining auctioneers are Capizzani (2008), who presented experimental evidence regarding the presence of a live auctioneer, and Cassady (1967), who provided a detailed qualitative description of auctions and auctioneers.[2] In showing that auctioneer heterogeneity resides at least in part on 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 et al. 2007, Podwol and Schneider 2011, Malmendier and Szeidl 2008). In the literature, auction fever—also referred to as competitive arousal or

[2] Note that much of the literature uses the term "auctioneer" to refer to the auction house or platform (Hossain et al., 2013), or, in some cases, the seller. In this paper we reserve the term auctioneer strictly for referring to the person calling out bids at a live auction, and the term seller strictly for referring to the owner of the car who brings it to the auction house.

bidding frenzy—encompasses many behaviors, such as rivalry or spite (Morgan, Steiglitz, and Reis 2003; Ku et al. 2005, Cooper and Fang 2008); endowment effects (Heyman, Orhun, and Ariely 2004; (Dodonova and Khoroshilov, 2009); utility of winning (Cooper and Fang 2008); uniqueness of being first (Ku et al. 2005); and irrational limited attention (Lee and Malmandier 2011). Documenting the relevance of behavioral factors in auctions is particularly relevant in our context where actors are informed professionals, as in Goldreich (2004). Ku et al. (2005) also studied how time pressure can affect bidding, and Malhorta (2010) found, in a field experiment, that the combination of rivalry effects and time pressure is particularly strong in leading to additional bidding.

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

Our paper, finally, contributes to the literature on how specific individuals affect organizational outcomes: examples include CEOs and bosses (Bertrand and Schoar, 2003; Lazear, Shaw and Stanton, 2012; Malmendier and Tate, 2009), judges (Abrams, Bertrand and Mullainathan, 2013), political leaders (Jones and Olken, 2005), school teachers (Chetty et al., 2010; Hanushek, 2011), and scientists (Azoulay, Graff Zivin and Wang, 2010). Our evidence is from a context where the effects of individual heterogeneity, because of institutional features and as predicted by theory, should be minimal; it is, therefore, particularly striking (and economically relevant) that we find substantial auctioneer differences.

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

## 2. Institutional Details and Data

The company for which we have data specializes in providing auction services for the wholesale used car market. This company has many auction facilities around the U.S., where each facility holds an auction typically once or twice per week. Bidders at these auctions are licensed used-car dealers who typically plan to sell the cars they purchase on their personal used-car lots. The cars being sold come from two basic sources: “dealer” sellers and “fleet/lease” sellers. The dealer sales are cars being sold by retail car dealers and are primarily cars which were received as trade-ins that the dealer did not want to sell on his or her own lot. 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. 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. The highest bidder receives the car as long as the auction price exceeds the seller's secret reserve price. The high bidder can personally take it back to his or her used-car lot or arrange delivery through independent agencies which operate at the auctions.

Wholesale used car auctions are conducted by professional auctioneers. Most of them have some formal auctioneer training from one of many auctioneer schools located nationwide, the existence of which is by itself suggestive that auctioneer skills and training may matter.[3] 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.[4] Section 4 discusses the characteristics and tools of an auctioneer that are considered important.

The auctioneers at the locations we study here work as independent contractors and receive a fixed daily wage for each auction day they work. The auction house periodically uses small bonus incentives tied to targets like the fraction of cars sold on 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.

On the auction day the auctioneers are assigned to specific lanes. There are separate lanes for dealer sales and for fleet/lease sales. Many of the fleet/lease lanes are dominated by large corporate sellers and it is easily possible for a particular fleet/lease seller to command an entire lane on some auction days. Because the fleet/lease sellers bring large volumes of cars to the auction, they are typically given preferential treatment by the auction house. Of particular relevance for our study, the fleet/lease sellers can either bring their own auctioneer, or often use the same auctioneer that is provided by the company week after week. In contrast, dealers tend to sell cars in smaller volumes. 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 show up with 3 cars and be given run numbers 31-33 in lane 15. On average, 200-300 cars are auctioned off in each lane in a given day. The median seller in a lane on a given day represents only 6.4% of cars being auctioned in that lane on that day.

[3] The National Auctioneers Association website (www.auctioneers.org) lists 29 schools, and additional schools are listed elsewhere.
[4] For example, the World Auto Auctioneer Championship has been held annually since 1989.

While the method for assigning dealer cars to lanes produces a large amount of random variation in what cars an auctioneer will end up auctioning, it is definitely 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.[5] 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. For reasons provided above, we drop fleet/lease cars and focus on cars being sold by dealers in these auctions.[6] We take several additional steps to clean the data before running analyses. We drop a small number of observations with missing data or nonsensical values. We exclude observations having outlier values on our key variables (e.g. cars that sold for less than $100 or for more than $75,000). We then restrict the sample to auctions conducted on two specific days of the week (there are occasionally small specialty auctions conducted on other days of the week). We eliminate rerun auctions.[7] Lastly, we reduce the sample to the 60 auctioneers who auctioned off at least 5,000 cars during our sample period. This limits the sample of auctioneers to those that worked "full time" for at least a year or two during our sample period. Within these remaining 60 auctioneers, the median auctioneer performed just over 13,000 auctions during our sample period while the busiest auctioneer performed approximately 30,000 auctions.

Our final dataset contains information on 859,239 cars. For each car we observe the make, model, body style, age, and odometer mileage as well as an identifier for the seller of the car. We also observe the day and time of day of the auction, whether the car sold, the sales price, the amount of time spent auctioning off the car, and the lane in which the car was sold. Auctioneer identifiers let us detect the specific auctioneer who was on the block in a given lane for a car.[8]

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. About 53% of cars sell;[9] in the cases when the car does not sell, the

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

[6] Because the fleet/lease companies bring their own auctioneer or often have the same company-provided auctioneer every week, we have very limited variation in auctioneer assignment within a seller for fleet/lease cars.

[7] 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.

[8] At some auctions, there is also a "ringman" who is a company employee 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.

[9] 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

owner may take it back to his or her dealership or to a competing auction house and attempt to sell it there or may choose to auction the car again at an upcoming auction. The average sale price for sold cars is slightly above $15,000, and on average car auctions last 1 minute and 43 seconds.[10]

We consider three main performance measures for auctioneers: a) conversion rates (fraction of cars that sold); b) the price of cars conditional on selling, and c) the time that each car is on the block. In addition to their immediate economic rationale, conversion rates and price are important to the auction company because it earns commission fees based on a car selling. It is also seen as important to retain sellers, particularly large ones, to ensure volume at the auctions and, as such, selling cars at somewhat higher prices is a positive outcome. 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 specifically discussed these three 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. 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 once again 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 and speed.

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the highest bid is more than their reservation price. We unfortunately do not have any consistent data for the reservation prices set by sellers.

[10] 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 it is common for a car to take a very long (or short) time to sell for factors outside of the control of the auctioneer. For example, waiting for the seller, getting the information coded into the computer, or waiting for the next car to be driven into the lane can cause an auction to last much longer than normal.

# 3. Empirical analysis

### 3.1 Empirical strategy

One measure of auctioneer heterogeneity would be to simply calculate the average conversion rate, price of sale, and speed 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. Given 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 variable bias and not differential auctioneer ability. Therefore, our main analyses of auctioneer heterogeneity are based on the estimation of versions of the following regression model that allow us to control for various factors that may not be randomly assigned to auctioneers:

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

$Y_{ik}$ is one of our main outcome variables: an indicator for whether the car sold, the residual sales price, or time on the block (seconds). Individual cars are indexed by $i$ and auctioneers by $k$ .The vector $X_i$, includes, depending on the specification, fixed effects for various car $i$ characteristics, sellers, auction day, lane number, etc.). The estimates of interest are the $\hat{\beta}_k$'s, the auctioneer effects.

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

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

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

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

Our interest is in understanding whether there is substantial heterogeneity in these normalized auctioneer effects. Statistically our question of interest is whether the $\beta$ coefficients are jointly different from zero, which can be addressed through standard metrics such as *F*-tests. It is, however, also very useful to be able to talk about the economic magnitude of our findings by focusing on metrics such as the spread between auctioneers with high effects versus those with low effects. A challenge here is that even if there is no meaningful underlying heterogeneity in auctioneer ability, we would still expect random sampling variation to generate some degree of dispersion between our estimates of the best auctioneer and the worst auctioneer. This would especially be an issue if our effects were being estimated off of a smaller sample size. We therefore also perform analyses using a Bayesian Shrinkage procedure which corrects for sampling variation and has been used in many other settings such as evaluating differences in teacher quality.[11] Specifically, we calculate:

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

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

### 3.2 Heterogeneity in auctioneer performance

We begin by estimating the model in Equation (1) using probability of sale as the outcome of interest. We estimate 8 different specifications, where each specification adds additional controls. The first specification includes no controls (just the auctioneer fixed effects). Once again, we are interested in the variation in auctioneer fixed effects. The first column in Table 2 provides the standard deviation of the auctioneer fixed effects for the various specifications using probability of sale as the outcome of interest. Specification 1 (raw values) suggests that the standard deviation in auctioneers ability to sell cars is .051. Taken literally, this suggests that a one standard deviation improvement in auctioneer ability translates into a 5.1 percentage point higher probabiliy of sale (off a base of 53%). The solid line in Figure 1 graphically presents these raw auctioneer effects by ranking the 60 auctioneers from worst to best and plotting their associated fixed effect. There is a remarkable amount of variation across auctioneers with the two highest-performing auctioneers being able to sell cars at more than a 10 percentage point higher rate than average.

The concern with these raw performance measures is that unobserved assignment of cars to auctioneers could be taking place. Based on discussions with the auction house, a primary confounder with the raw data is if certain auctioneers are systematically assigned to sellers that have lower or higher reservation values than other sellers. To control for this concern, we include seller fixed effects in the second specification.[12] Figure 1 illustrates how including these controls significantly reduces the amount of variation across auctioneers. Table 2 indicates that the standard deviation of auctioneer fixed effects is reduced from .051 to .038 when seller fixed effects are included. One question about including these controls is whether the auctioneer fixed effects are simply dampened, or if the ranking of the auctioneers is also signficantly changed. The second column in Table 2 provides the coefficient of correlation between specification 2 (and the other specifications) and the previous specification and also t-stats in

[11] See Morris (1983) and Jacob and Lefgren (2005) for a detailed explanation. See also Chandra et al. (2013) for a recent application of Bayesian Shrinkage techniques to the study of (organizational) productivity differences.

[12] We include a dummy variable for each of 1087 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.

brackets. The correlation coefficient of .94 suggests that including seller fixed effects reduced the variation in auctioneer fixed effects, but did not greatly alter the rank order of the auctioneers.

Likely due to macroeconomic factors, the probability of sale in our data changes substantially throughout the sample period. Once again, this can bias the dispersion of auctioneer fixed effects if some auctioneers worked more in certain periods during our sample than others. In Specification 3, we include time controls—both auction day (day*month*year) effects and time of day (hour-by-hour) effects. Once again, Figure 1 and Table 2 indicate that these controls reduce the amount of variation in the auctioneer fixed effects. Specification 4 includes fixed effects for the 55 lanes that operated at some point during our sample. This produces a slight decrease in the standard deviation of auctioneer fixed effects. We continue to find that the rank ordering of auctioneers is very similar from one specification to the next.

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

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

We now turn to the other two performance metrics for auctioneers. The first is residual price which is the price that was obtained by the auctioneer for a sold car minus the wholesale blue book value which is calculated by the auction house using a proprietary formula. We "residualize" the price with this wholesale value as a way to absorb additional unobserved heterogeneity that may exist about the car that is hard to control. The second performance metric is the amount of time the auctioneer takes to run the auction (in seconds).

The results for these two performance metrics are presented in the second and third set of columns in Table 2. The standard deviation in raw values across auctioneers is very large ($219) and is reduced to

$55.84 after including seller fixed effects. This suggests that some nonrandom sorting of cars to auctioneers is taking place in this environment. The standard deviation for the residual price effects stabilize after Specification 4 at about $40.[13] The time on the block effects are fairly stable - especially after controlling for seller fixed effects. The effect size suggests that a one standard deviation increase in auctioneer speed is associated with running an auction in 6 seconds less time (off a base of 103 seconds). The stability in these findings are an indication of speed being an individual characteristic or style which does not depend heavily on the car being auctioned off, the seller, or other environmental contingencies.

Sampling variation can explain 20-25% of the variation in the residual price effects. Specifically, the standard deviation for Specification 8 with Bayesian Shrinkage applied is $31.99 (compared to $41.78 without the shrinkage). The time effects are not very affected by sampling variation with a standard deviation of 5.87 once shrinkage is applied (compared to 6.07 without the shrinkage). Thus, with the exception of residual price (which was estimated to have a fairly small amount of variation in fixed effects to begin with), sampling variation appears to have very minor effects on our outcomes of interest.

### 3.3 Identifying auctioneer effects off of shift changes

In this section, we propose a second way to causally identify estimates of auctioneer ability that uses natural variation associated with work shift changes. We then compare these new auctioneer estimates with the estimates from the previous section.

On a typical auction date, two auctioneers will be assigned to work each lane. These two auctioneers will take turns auctioning off cars in that lane. Auctioneers may switch at any time, but we observe that auctioneer typically switch roughly every 30 or 60 minutes in what appear to be somewhat 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 stint.

We can exploit the variation in auctioneers that occurs within a lane on a given day by including lane*day fixed effects when estimating auctioneer ability.[14] By looking within a lane on a given day, we are able to control for additional unobserved factors that may exist (number of buyers at the auction located near a given lane, unobserved characteristics about the cars/sellers assigned to that lane, etc.) when estimating auctioneer fixed effects.

We once again estimate the model in Equation (1) while controlling for seller, time of day, and 13,687 lane*day fixed effects. Figure 2 provides scatter plots of the estimates from Specification 8 in the

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

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

previous section and the estimates using the lane*day fixed effects for each of our three performance metrics. The estimates that we find are strongly correlated across identification strategies: probability of sale (t-stat = 18.9), residual price (t-stat = 6.51), and time on the block (t-stat = 15.46). Finding similar auctioneer estimates when looking within a lane*day lends credibility to the estimates that we found in the previous section.

**3.4 Stability of heterogeneity over time**

If these estimated effects reflect persistent differences in auctioneer abilities, then we would expect them to be fairly stable over time; an auctioneer who performed better in the first half of our sample (2007-2009) should also perform better 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) and time fixed effects (t-stat = 7.32) between the two sample periods. We do not find persistence in the residual price fixed effects across the two periods (t-stat = -0.10). This is consistent with other findings that we produce which suggest that the price effects we estimate are not as strong or well-identified as the effects on probability of sale and speed. The persistence of the probability of sale and speed effects, however, suggests that we are tapping into something about auctioneers that is stable and robust across time.

**3.5 Correlation between performance measures**

As discussed earlier, the primary objective of auctioneers as seen by the auction house is to maximize the probability of selling a car. However, it is informative to consider how auctioneers who excel in selling a large fraction of their cars perform in the other two metrics (residual price and speed).[15] It is possible that the individual auctioneers who have the best performance for the probability of sale achieve this at the cost of one of the other metrics. For example, perhaps it is auctioneers who go really slow and take a lot of time to do the auction that are able to acheive better conversion rates.

A concern with correlating the time-on-the-block effects with other outcomes is that there may be a mechanical bias. The average time on the block for cars that sell is approximately 11 seconds longer than the time on the block when the car does not sell. This may be in part due to the extra recording time that is required when a sale occurs. Thus, if an auctioneer is able to obtain a higher probability of sale than another auctioneer, he/she may mechanically have a longer time on the block as well. In order to avoid this bias, we produce and use time on the block fixed effects for each auctioneer based only on cars that sold rather than all cars. Thus, we are able to obtain a measure of how fast an auctioneer typically

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

performs auctions that is uncorrelated with the conversion rate of the auctioneer. Appendix Figure 1 illustrates that the time-on-the-block fixed effects using sold cars only are highly correlated with the time-on-the-block fixed effects when using all auctions (t-stat = 22.00). From this point on, we will always use the time-on-the-block fixed effects from sold cars in order to avoid bias when doing correlations.

Using Specification 8 from Section 3.2, Panel A of Figure 4 shows the correlation between probability-of-sale fixed effects and residual-price fixed effects, Panel B shows the correlation between probability-of-sale fixed effects and speed, and Panel C shows the correlation between residual-price fixed effects and speed. Auctioneers with the highest fixed effects for probability of sale also have higher than average fixed effects for prices obtained (t-stat = 3.29) and are marginally faster at selling cars as well (t-stat = -1.62).[16] We also find that auctioneers who acheive high prices for cars are faster than average (t-stat = -2.52). Although the statistical power to identify these correlations is somewhat limited, we find no evidence that auctioneers who are doing well on their main objective function (maximizing probability of sale) are doing so at a cost to secondary objectives. If anything, we find that auctioneers who are better in one dimension are better in the other dimensions as well. This supports the statement made by the auction house's general manager that "sales price and speed are generally the parents of conversion rate" and is something that we will come back to when discussing potential mechanisms for these effects in the next section.

### 3.6 Comparing the estimates with subjective measures of auctioneer performance

As another check on the validity of the estimated auctioneer effects, we compare our "objective" estimates of auctioneer ability with "subjective" evaluations of auctioneer ability produced internally by the auction company. Based on our request, the auction company produced evaluations for the 41 full time auctioneers working in the Fall of 2012. The evaluations they produced were based on a multidimensional subjective assessment by a 3-person senior auctioneer panel. 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 5 we correlate the company's subjective rankings with our estimated fixed effects (once again using the full model, Specification 8). Panel A, B, and C provide correlations between the subjective evaluations and fixed effects for probability of sale, residual price, and speed, respectively. We find significant correlations between their measure of who the best auctioneers are and our measure of auctioneers who have a high probability of sale (t-stat = 4.62), who obtain high prices (t-stat = 2.09), and who conduct fast auctions (t-stat = -2.03). The correlations that we

[16] A larger time-on-the-block fixed effect represents an auctioneer who takes more seconds to sell a car on average. Thus, a negative sign on the correlation between time-on-the-block and probability of sale suggests that auctioneers who sell more cars are faster than average.

find, especially with the probability-of-sale metric, are remarkably strong and lend additional credibility to the idea that we are identifying true differences in auctioneer ability.

### 3.7 Predicting job termination decisions

Due to the recession that took place during our sample period, the company significantly downsized the number of full-time auctioneers between the start and end of our sample. Specifically, there are 59 full time auctioneers at the start of our sample. Of these 59 auctioneers, 18 were no longer working for the company by 2013 (and one new auctioneer was hired). This downsizing provides us with an additional test for the validity and relevance of our measure of heterogeneity in auctioneer ability. We are interested in analyzing whether the auctioneers who stayed in the sample ("stayers") were better than the auctioneers let go during the downsizing and exited the sample ("goers").[17]

Figure 6 displays the auctioneer effects from the fully specified model (Specification 8) for each performance measure. The auctioneers who left the company before 2012 are highlighted in red. Note that many of the worst-performing auctioneers in each dimension (the left tail of auctioneers in panels A and B and the right tail of auctioneers in panel C) left the firm during the downsizing. In contrast, the large majority of the best-performing auctioneers (the right tail in panels A and B and the left tail in panel C) were retained by the firm. Regressions of the auctioneer fixed effects on a dummy for whether the auctioneer was a stayer or not suggest that these results are statistically significant at conventional levels (probability of sale, t-stat = 2.53; residual price, t-stat = 2.15; time on the block for sold cars, t-stat = -3.16). Again, the fact that our ability measures significantly predict who exited the sample during a downturn provides evidence in favor of our metric representing true ability.

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

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

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

for each car sold, this translates to an increase in revenue to the auction company of $24,600.[18] Similar calculations can be done for the value of auctioneers who systematically obtain higher prices and/or go faster. However, it is harder to translate these values into company profit since fees received are not based directly on these measures.

Another way to benchmark the results is to compare our estimated effects with the results from related studies that estimate the effects of certain changes in auction design and information structure on similar outcomes. In particular, Tadelis and Zettelmeyer (2011) estimate the impact of randomly providing additional information in a wholesale car auction. They find that additional information translates into a 6.3 percentage point increase in probability of sale and a $236 increase in average price. These effects are slightly bigger than the 5.6 percentage point and $96 that we estimate to be the difference in average probability of sale and price obtained by an auctioneer at the 10th and at the 90th percentile.

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

The analyses in the previous section provide robust evidence that, even in a well-functioning auction market, individual auctioneers can significantly impact key market outcomes. This suggests that auctioneer skills are a real phenomenon. Uncovering this fact is important in and of itself; however, it also begs the questions of what the mechanisms are through which this effect might operate. Below we discuss several possible answers. 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 which define an effective auctioneer. Finally, we discuss further the empirical results from Section 3 that can also provide evidence of certain mechanisms over others.

### 4.1 Potential mechanisms

#### *4.1.1 Rational bidding explanations*

Several potential mechanisms are consistent with rational bidding behavior:

1. It may be that the variation we observe in the probability of achieving a sale comes not from a differential ability to increase the distribution of bids but rather from a differential ability to persuade sellers to accept lower prices.

[18] These calculations are extremely rough and ignore many other potentially important factors. For example, if the probability of sale increases, it could cause more sellers to bring their cars to this market suggesting that the value of the auctioneer is even higher. It is also possible that an auctioneer that is able to sell more cars is causing lower sales for the other auctioneers. Thus, the overall value of the 90th percentile auctioneer to the auction company is smaller than we estimate.

2. An auctioneer who is able to provide more information about the quality or value of the product for sale can increase revenues. For example, auctioneers might differ in their knowledge about the quality of particular cars or in their ability to convey that to the bidders.
3. An additional information-revelation mechanism, broadly consistent with models of rational and sophisticated bidder behavior, is that some auctioneers may be better at inducing patterns of bids which reveal more information about the distribution of bidder valuations. In Milgrom and Weber's (1982) classic model of English auctions with affiliated values, all potential bidders reveal something about their valuation as the auction is conducted because 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 one would predict from classic theory. If some auctioneers are particularly good, however, at getting those with lower private signals about the market value of the car to initially bid, they could increase the information revealed and hence raise overall prices. It could be, for example, that some auctioneers are particularly good at choosing the starting prices or bid increments they call in a way that induces a greater number of initial bids from those with low valuations. Or, perhaps, some auctioneers are better at identifying low-valuation bidders and recognizing their bids early before focusing on the bids by those who will eventually win the auction.[19]

Of the three mechanisms listed above, the second one can for the most part be ruled out, because auctioneers rarely if ever discuss the features of a car during the one to two minutes while the car is on the auction block. The bidders in this auction 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 see them for the first time a few seconds before beginning the auction. Bidders can walk around the car, inspect it prior to the auction and are physically closer to the car during the auction than the auctioneer. In our discussions with auctioneers, the auctioneers never suggest that they are better informed about the quality of particular cars than the bidders at the auction. Thus, although theoretically relevant, this characterization of auctioneer heterogeneity is unlikely to apply in this setting.

[19] 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), a writer and former auto auctioneer, who placed in the top ten at the World Auto Auctioneers Championship (and who is also an experienced buyer, former auction house owner, and seller both on the dealer side and fleet/lease side of the auto auction business) explained several of the hand signals which would be confusing to a lay observer:

*4.1.2 Behavioral explanations*

An alternative interpretation for the observed auctioneer effects could be that some auctioneers are better at exploiting irrationalities in bidding behavior. 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". Anecdotally, auctioneers report that their chant can be used to increase excitement and that they employ various techniques to increase the feeling of competition between bidders.[20] Buyers with limited attention may be attracted to certain cars, or fixate on certain information, due to factors influencing salience but not directly related to car value. Thus auctioneers may have different abilities to manipulate the pace or cadence of auctions in a way that sways emotions, affects salience, or influences the ability of buyers to think about what other buyers might be thinking. Or it may be the case that some auctioneers are better than others at recognizing and encouraging the participation of reluctant but potentially high-value bidders. Speed is also frequently discussed as an important differentiating factor between a mediocre and a great auctioneer. The fast-paced chant allows an auctioneer to perform an auction quickly this can potentially cause bidders to bid more than they would if the auction was taken at a very slow pace.

Describing his experience as an auto auctioneer, award-winning auctioneer 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. Even an open hand instead of a pointed finger conveyed a sense of openness, a belonging, a mutual goodwill that would get a far more experienced man to trust me. It was power and beauty and it lead to over 500 successful auctions in 2 years" (Lang 2010). Similarly, award-winning auctioneer B.J. Lewis commented, "You've got to make them believe they need to bid where you want them to bid" (Reynolds, 2003).

## 4.2 Survey evidence

Identifying and separating these mechanisms has important implications for understanding bidder behavior in auctions, the role of information revelation, as well as for improving the design of auctions to maximize revenues. The challenge in identifying these mechanisms, however, is that they have observationally similar predictions and, also, are not mutually exclusive. Our first approach to trying to understand the mechanism better is through a survey.

The auction house conducted a short anonymous survey with 33 of their auctioneers to explore the mechanism for how an auctioneer becomes better than average. The survey asked participants to choose

[20] Several older papers in the linguistics literature focus on the chant of the auctioneer. See Kuiper and Tillis (1985) and Fitzpatrick (1940).

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 results of this question are shown in Table 3, which demonstrates that 93% (31/33) chose the option “auctioneers create a sense of excitement, competition and urgency among buyers that encourages bidding,” whereas statements about auctioneers persuading sellers to accept fair market prices and auctioneers providing expert information about cars received one vote each.

Figure 7 shows the results of the average rankings auctioneers gave on a scale from 0 (very unimportant) to 5 (very important) to a range of different potential skills/topics in determining a particularly effective auctioneer. Although the survey is not overly scientific, the tactics auctioneers rank as more relevant appear to generally point toward mechanisms related to generating bidder excitement. Creating competitiveness, spotting reluctant bidders, having an effective chant, and increasing engagement and excitement by running fast-paced auctions are the highest ranked items. Interestingly, calling out good starting prices, which might plausibly be a mechanism for generating bids from those with low valuations, received very low rankings. We also find evidence against the ideas that auctioneers provide useful information about cars or generate their effects primarily through adjusting seller reservation prices, as these ranked very low in the survey.

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

**4.3 Quantitative evidence distinguishing among mechanisms**

The survey evidence is very useful in identifying potential mechanisms and ruling out other mechanisms. We can also look to the data to try to understand mechanisms as well. For example, if auctioneers differed primarily in their ability to encourage sellers to lower their reservation values, auctioneers with high conversion rates should find their average sale price to be lower conditional on sale. We find, however, that conversion rates and prices are positively correlated, as seen in panel A of Figure 4. This finding, in conjunction with the survey evidence, suggests that it is unlikely that the primary mechanism consists of auctioneers convincing sellers to lower their reserve prices.

Second, the finding that faster auctioneers tend to perform better, as shown in Table 3 and in panels B and C of Figure 4, serves as suggestive evidence in favor of the behavioral, excitement-creation story and against the idea that good auctioneers aid in revealing information from low-valuation buyers. Specifically, in auctions which generate 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, 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.

## 5. Discussion and conclusion

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

Our results speak to the role that computerized online auctions may have in coordinating economic activity. There would seem to be strong efficiencies to computerized auctions, as they avoid the costs of employing professional auctioneers and auction-house staff and in online formats can avoid the often substantial transaction costs of bringing bidders and goods together in the same place. Yet recent work has documented that the popularity of online auctions may be fading (Einav et al., 2012). Our findings suggest that human auctioneers have tactics that improve the efficiency of auctions and as such may help to explain why computerized online auctions do not yet dominate the marketplace. Further study into the behaviors of human 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 efficiency losses from conducting naïve computerized auction process.

Additional work is needed to tightly pin down the mechanisms through which auctioneers affect outcomes. While the evidence presented here is consistent with behavioral factors—in particular, those which create urgency among bidders—we hope that future research including controlled laboratory experiments can help shed light on the exact mechanisms involved.

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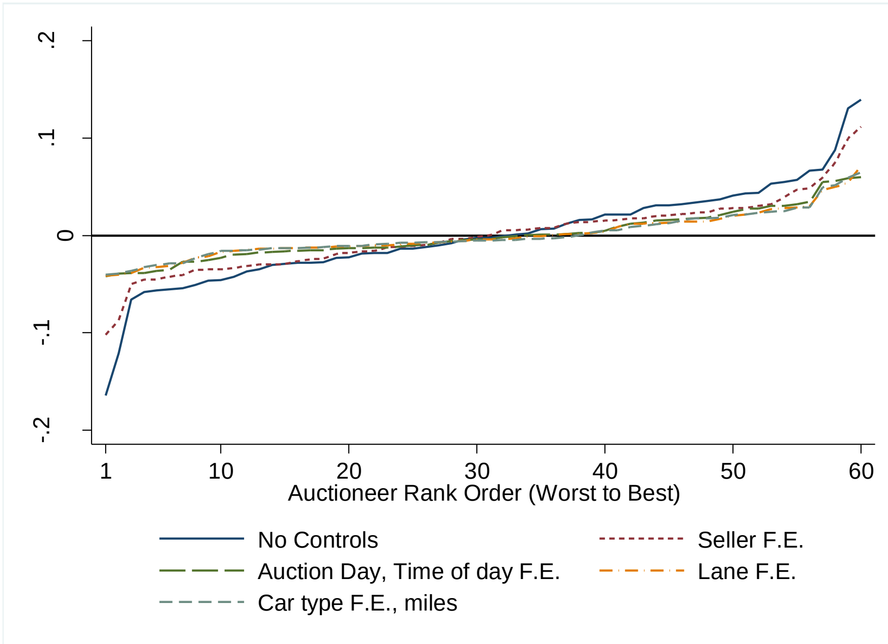
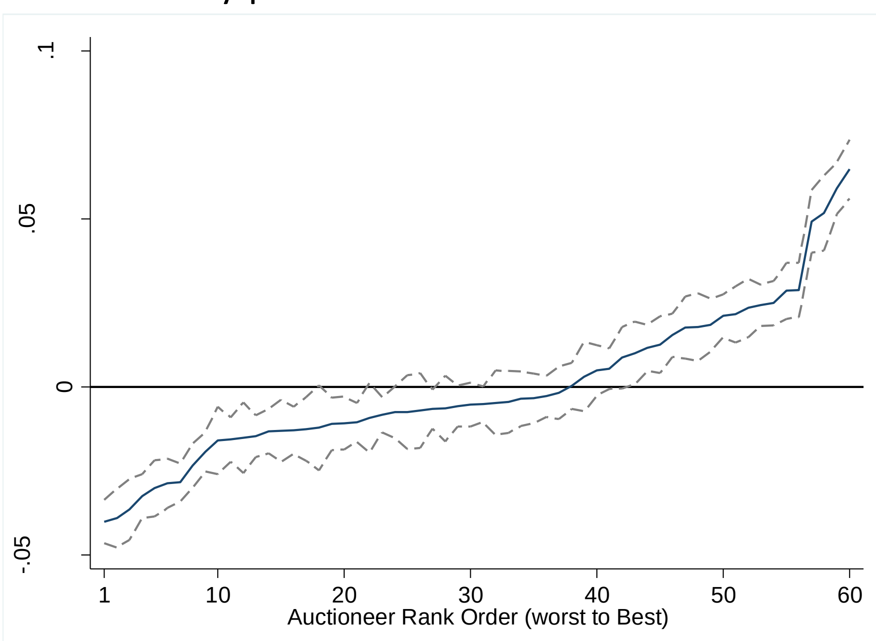
## Figure 1 - Auctioneer Differences in Probability of Sale

Panel A plots the normalized fixed effects for each of the 60 auctioneers in our data. The fixed effects are obtained from a regression model with no controls, and then adding seller fixed effects, auction day and time of day, lane fixed effects, and car type fixed effects (see equation (1) above). Panel B plots the fully specified model's fixed effects along with 95% confidence intervals.

**A: Comparison between specifications**

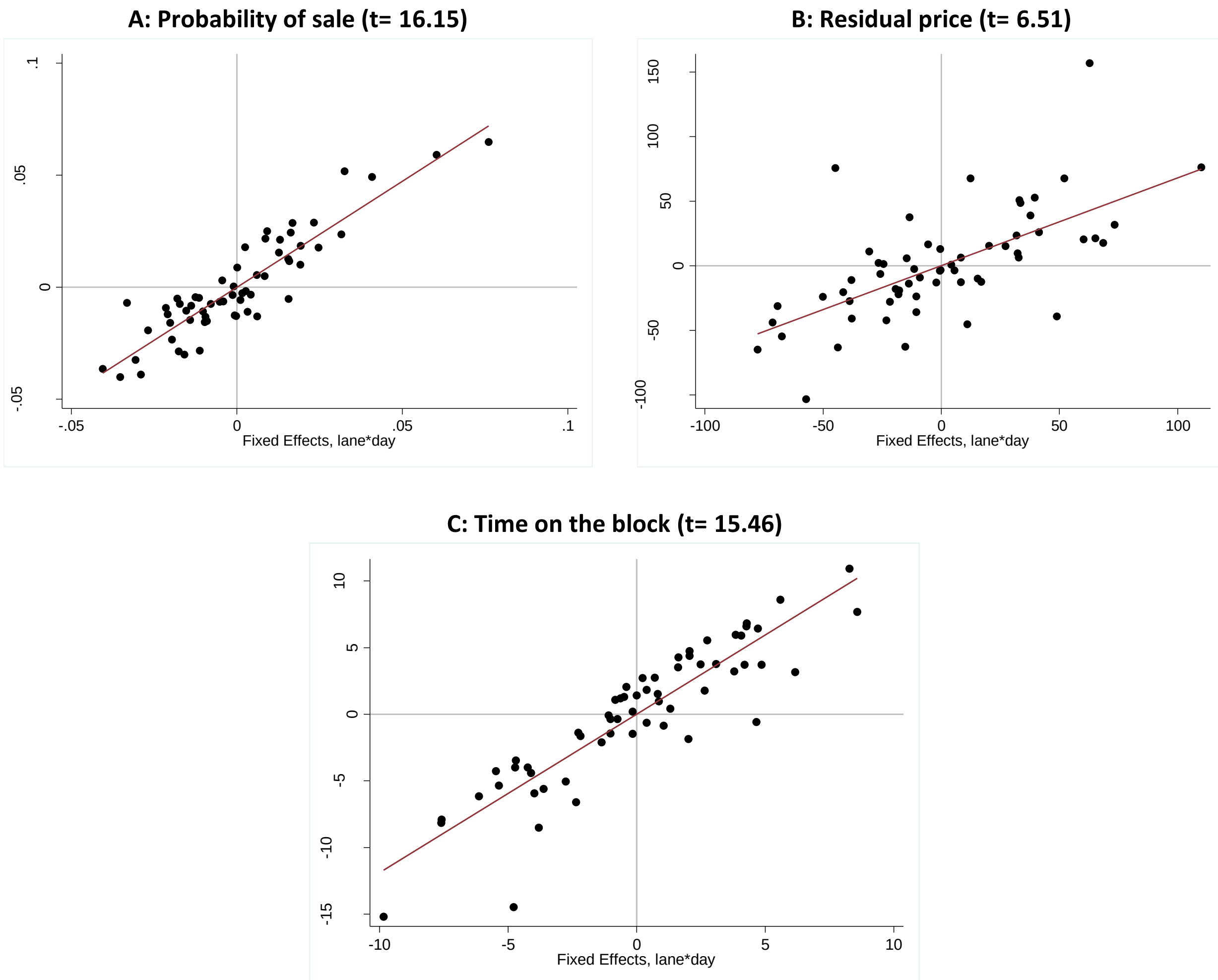



**B: Fully specified estimates with confidence intervals**



## Figure 2 – Comparison between Identification Strategies

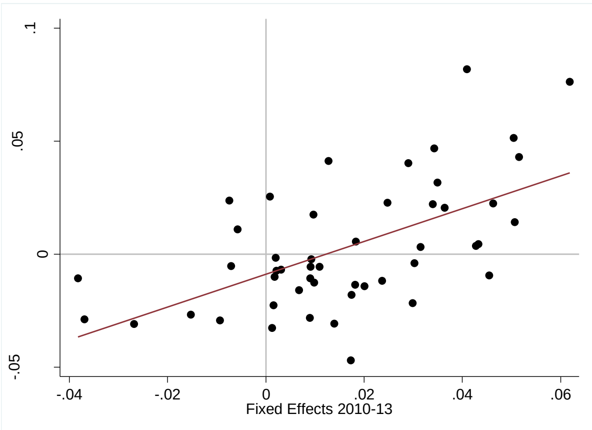
The panels below provide scatterplots that show the correlation in fixed effects for auctioneers based on probability of sale (Panel A), probability, residual price (Panel B) and time on the block (Panel C), between our two different identification strategies: the analysis within seller, auction day and time of day, lane, and car types ("car types"), and the identification based on shifts within a lane (lane*day) (see Section CCC). Fitted lines are reported as well as the t-statistics from univariate linear regressions between the auctioneer effect estimates from the two identification approaches.



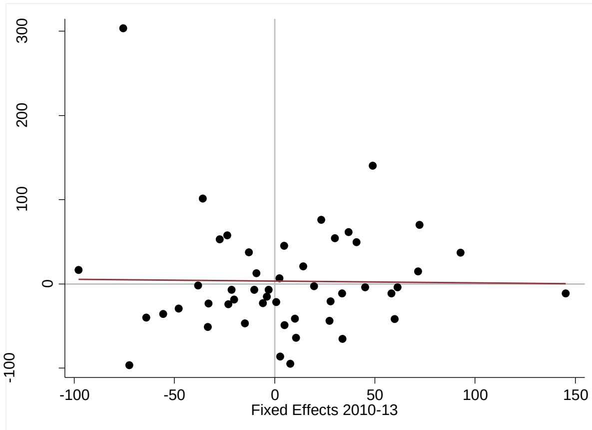
## Figure 3 - Correlation of Fixed Effects between 2007-09 and 2010-13

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

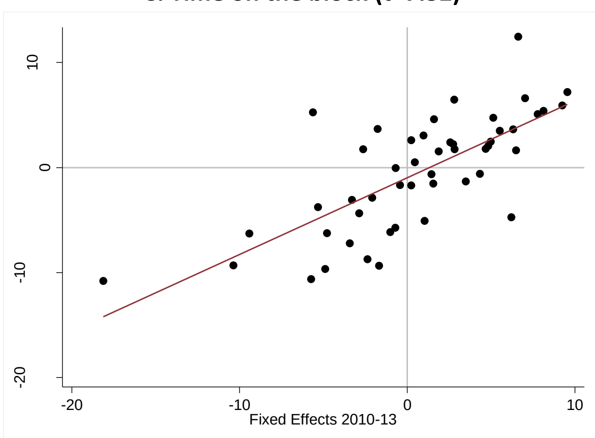
**A: Probability of sale (t=4.91)**




**B: Residual price (t=-0.10)**



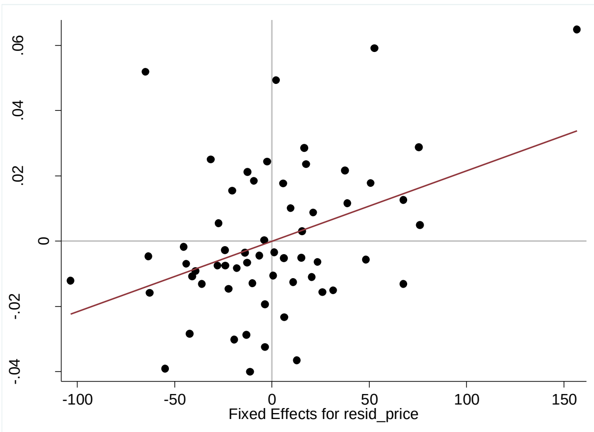

**C: Time on the block (t=7.32)**



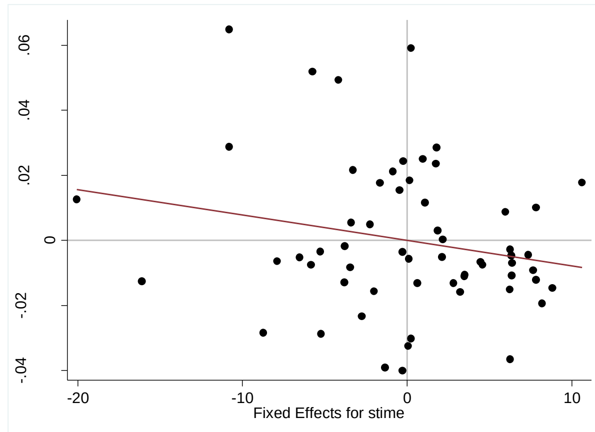
## Figure 4 - Correlation between Performance Measures

The panels below provide scatterplots that show the correlation in fixed effects for auctioneers based on probability of sale (sold) and price of sale (resid_price) (Panel A), probability of sale and time on the block *for sold cars* (stime) (Panel B), and residual price and time on the block for sold cars (Panel C). All fixed effects come from the fully specified model estimates within seller, auction day and time of day, lane, and car types. Fitted lines are reported as well as the t-statistic from univariate regressions between the outcomes for each measure.

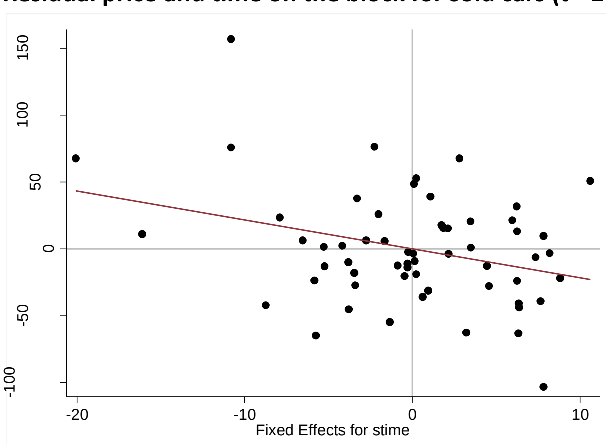
**A: Probability of sale and residual price (t=3.29)**




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



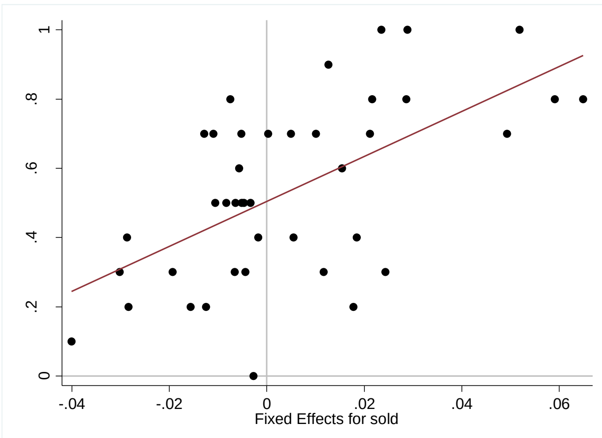

**C: Residual price and time on the block for sold cars (t=-2.52)**



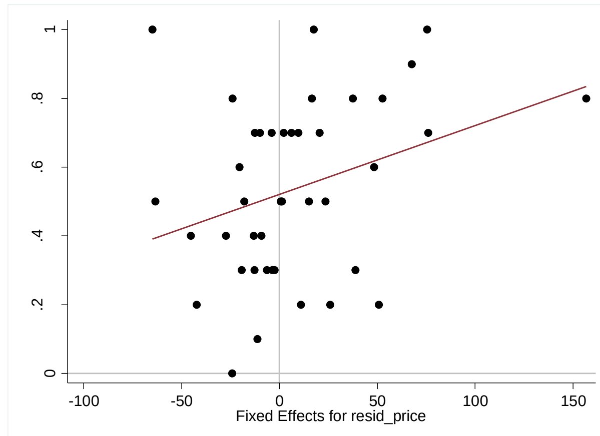
## Figure 5 – Correlation of Performance Measures with Subjective Evaluations

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

**A: Probability of sale (t= 4.62)**




**B: Residual Price (t= 2.09)**




**C: Time on the block for sold cars (t- -2.03)**

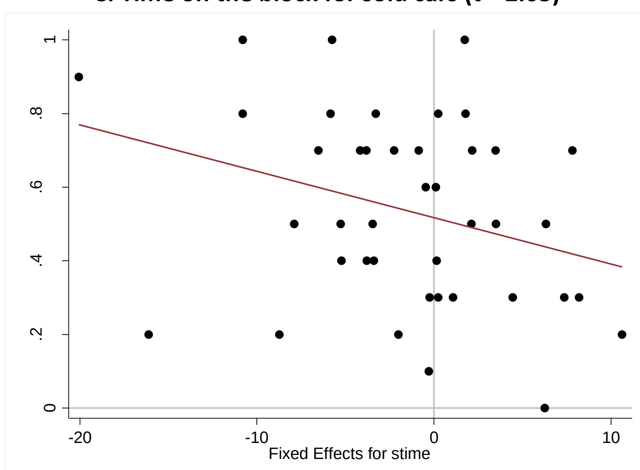
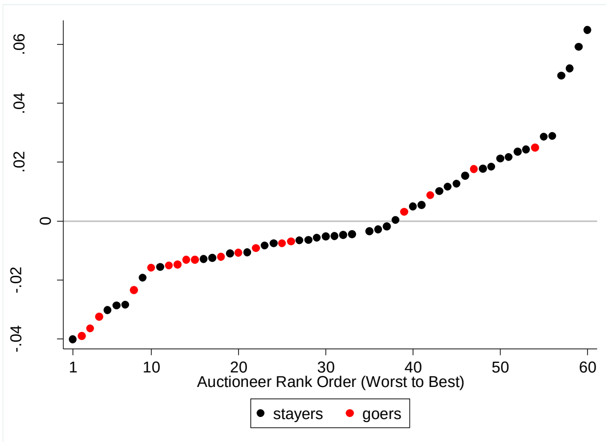


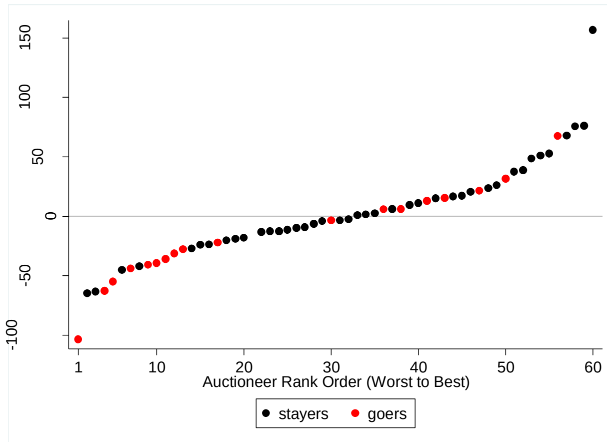
**Figure 6 – Performance rankings for auctioneers still at the company in 2012 and auctioneers who left the company by 2012**

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

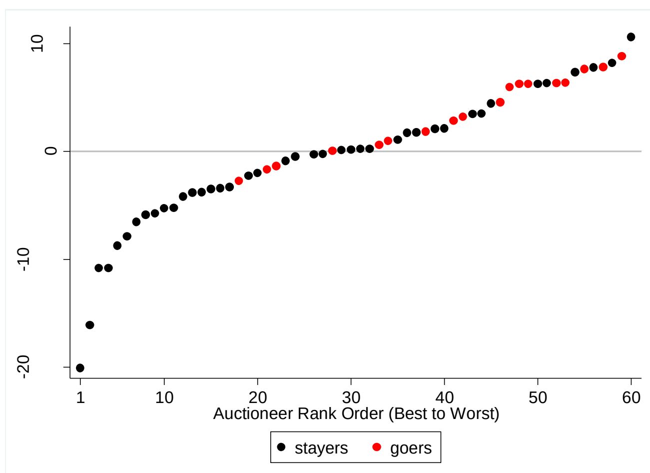
**A: Probability of sale**




**B: Residual Price**

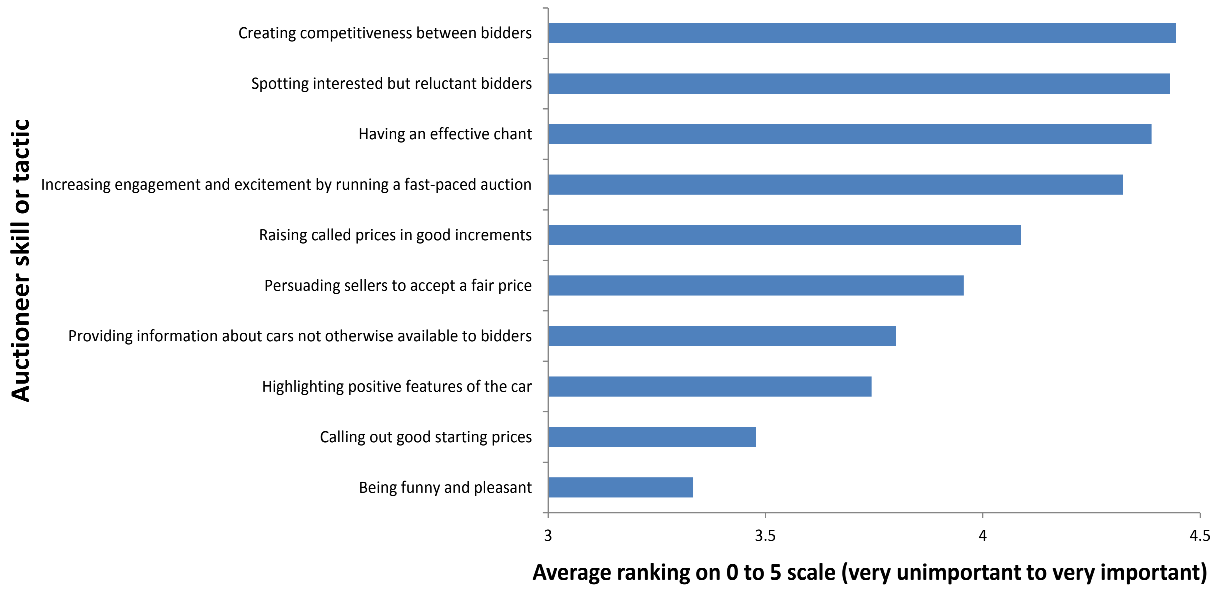



**C: Time on the block for sold cars**



## Figure 7 - Survey results

This figure reports the average ranking received by various proposed answers to a question asking auctioneers a rating of importance of tactics for determining a "highly effective" auctioneer (from 0-lowest to 5-highest agreement):



## Table 1: Descriptive statistics

| | Observations | Mean (Std. Deviation) |
|---|---|---|
| Share of cars sold | 859,240 | 0.53<br>(0.50) |
| Sale price ($) | 455,224 | 15,140.97<br>(9567.57) |
| Price - Expected Price ($) | 424,852 | 377.24<br>(1669.43) |
| Time on the block (s) | 777,960 | 103.18<br>(74.03) |
| Age (years) | 859,239 | 4.43<br>(3.28) |
| Miles | 859,240 | 56,236.51<br>(33,730.87) |

**Table 2: Standard deviations of estimated auctioneer effects with varying controls**

This table displays the effect of a one-standard-deviation increase in auctioneer performance as measured by the probability the car sold, residual price, 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 specification, 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.

| | | **Probability of sale** | | **Residual price** | | **Time on block** | |
|---|---|---|---|---|---|---|---|
| | | **Standard deviation** | **Coefficient of correlation with previous specification** | **Standard deviation** | **Coefficient of correlation with previous specification** | **Standard deviation** | **Coefficient of correlation with previous specification** |
| **1** | **Raw values** | 0.051 | | 219.633 | | 7.48 | |
| **2** | **Seller FEs** | 0.038 | 0.94 [21.46] | 55.842 | 0.67 [6.89] | 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] | 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] | 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] | 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] | 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] | 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] | 5.23 | 0.99 [231.28] |

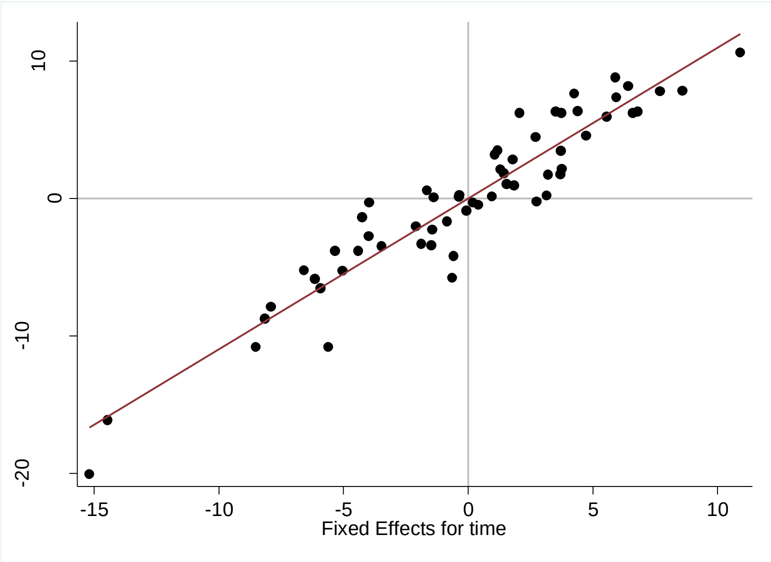
## Table 3: Survey results from role-of-auctioneer question

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

# Appendix

**Figure A.1 - Correlation between time on the block and time on the block for sold cars and unsold cars**

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




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