Comparing Open Outcry and Online Auctions: Evidence from North Dakota Mineral Auctions*

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Abstract

I study a switch from in person open outcry English auctions to online eBay-style ascending English auctions for mineral rights in a private values framework with unobserved heterogeneity. Using a natural experiment which alternated auction format for 5 years, I find that leases sold in online auctions yield higher revenues than similar parcels sold in in person auctions. What explains this revenue difference? I estimate a structural model of bidder values and then use it to perform counterfactual policy experiments which show that the revenue premium of online auctions can be explained by higher participation relative to the participation of in person auctions.

Replication code for this paper can be found at `https://github.com/ekarsten/persp-research-econ_Spr20/tree/master/FinalPaper/ReplicationCode` for any readers interested in the computational methods. Replication Data from Bloomberg and DrillingInfo is proprietary, however any researcher who acquires it can easily replicate all figures in the paper using the above-linked code.

*This paper is based on (but not identical to) my MA thesis.

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1 Introduction

Auctions are an essential tool employed by governments when allocating natural resources. Sellers face a choice among a wide array of auction formats, and their choice of format can have large effects on the outcome of the auction. Traditionally, the literature has studied choices between canonical auction formats such as comparing first price sealed bid auctions with second price or ascending English auctions. With the rise of new technologies, in particular online bidding, sellers face further choices in not only what auction format to use, but whether to hold that auction in person or online. There is a lack of empirical evidence on how a switch from in person to online auctions would affect bidder behavior and auction revenue. I show, contrary to conventional wisdom and economic theory, that the choice of whether to hold auctions online or in person, holding fixed auction format, has substantial revenue implications.

I use data from North Dakota mineral auctions that allows me to measure the revenue effects of auction setting as well as to calibrate a structural model which helps explain why the revenue difference might exist. For context, as of the year 2020, the state of North Dakota funds 13.9% of the cost of each student's public school education with revenue from the the trust lands. [1] Many other states do the same, so these state governments have an interest in auctioning their resources in a way that will bring in the most revenue for the state. From 2012 to 2016, the state of North Dakota ran a natural experiment where they alternated between holding online and open outcry auctions. The alternating format combined with controls for the quantity of oil and the prevailing market prices allow me to identify reduced form differences between the auction formats. Online auctions bring in between 20% and 160% higher bonus payments[2] per acre than an in-person auction for a similar lease.

The reduced form analysis prompts an important question: why is there such a large difference in auction outcomes between online and in-person auctions? To answer this question, I calibrate a structural model of auction behavior in the online auctions to recover the distributions of private values and unobserved tract heterogeneity using an endogenous model of bidder entry.[3] Using the calibrated structural model, I run counterfactual policy experiments to show that a decrease by about 4 participants considering bidding on the typical tract can explain the differences in revenue between the two auction settings. These

1. `https://www.land.nd.gov/trusts-funds`

2. The wide range of these estimates is attributable to different strategies for making "similar lease" comparisons. These choices are discussed in more detail in section 4.

3. Full details of the model and a discussion of the modeling assumptions is found in section 2.

policy experiments involve reducing bidder interest in all parcels until the revenue gap disappears. At this point, I verify my structural model with an outside moment to make a case for a reduced interest explanation as opposed to a collusive one.

I draw my model of bidder behavior in auctions from the existing literature on auction theory. A summary of of auction theory results can be found in Krishna (2009) or Milgrom (2004) based on work first derived in Milgrom and Weber (1982). For identification of my structural model, I draw heavily on the work of Hernández, Quint, and Turansick (2020). Their paper proves conditions under which second price auctions with private values and unobserved heterogeneity can be identified from data on the number of participants in the auction and the transaction price. Their paper is novel in that it is the only one which is able to identify auctions with unobserved heterogeneity without assuming that some non-winning bidders bid up to their value or that the seller observes the unobserved quality of the object being sold and sets reserve price accordingly. They use semi-parametric identification methods developed in Gallant and Nychka (1987). I will also rely on some of some of the partial identification ideas presented in Haile and Tamer (2003), in particular the assumption that in an English auction all bidders may not necessarily bid up to their valuation, but the bidder with the second highest valuation will.

I contribute to an extensive existing literature that makes comparisons between first price and second price auctions using models with unobserved heterogeneity and endogenous entry. The seminal revenue equivalence result, first proved in Vickrey (1961), shows that, under certain conditions, first and second price auctions should bring in equivalent revenues. There has however been an extensive empirical literature which has shown this result not to be the case in many real-world auctions which diverge from Vickrey's model of bidder valuation and behavior. Athey, Levin, and Seira (2011) estimate a structural model with unobserved heterogeneity, private values, and endogenous entry of first price sealed bid timber auctions and use it to make comparisons with ascending English auctions. They find that the sealed bid first price auctions can give higher revenues than their open outcry counterparts in settings with even a small amount of collusion. Kong (2020) explores a mineral auction setting where first price auctions give higher revenues than their open outcry counterparts. She shows that uncertainty about number of entrants combined with bidder risk aversion explains this difference. Identification in first price auctions has been well-established in papers like Guerre, Perrigne, and Vuong (2000).

My contribution lies at the intersection of the prior literature comparing first and second price auctions and a literature empirically examining eBay-style online auctions. Hasker and Sickles (2010) summarize the state of this literature. They highlight the fundamental challenge that it is hard to reconcile the bidding strategies observed on the platform with a theoretical description of the auction. The key difference is that in a traditional English auction, once there are no bidders who wish to raise the price, the auction ends. In an eBay-style auction however, the auction ends at a fixed time, so bidders may play more complex strategies where they wait before raising the bid. A key work in this literature is Bajari and Hortaçsu (2003). They estimate a structural model of eBay auctions and use it to estimate the magnitude of the winner's curse in common value auctions. Additionally, they prove a theorem that with common values, there is a symmetric Nash equilibrium of not bidding until the last minute in order to prevent others from being able to respond to the bid. In addition to the eBay literature, there are papers which explore the effects of other characteristics of auction format on outcomes. For example, Lacetera et al. (2016) show the revenue effects of different auctioneers in an ascending auction.

A relevant related literature models mineral auctions with common values. Hendricks, Pinkse, and Porter (2003) study bidding in first price offshore mineral auctions. They find that bidder behavior is consistent with expected bid shading derived in theory. Hong and Shum (2004) study English auctions with common values and are able to parametrically identify of bidder values based on the sequence of bids. While their identification result is useful, it is computationally burdensome and it makes strong assumptions about what the sequence of bids reveals about the value updating behavior of auction participants. Compiani, Haile, and Sant'Anna (2020) prove nonparametric partial identification results in first price auctions with common values, unobserved heterogeneity, and endogenous entry. Regrettably, their approach cannot be applied to data from English auctions. In fact, Athey and Haile (2002) proves that the Compiani et. al. model cannot be identified using bid data from second price auctions. A full discussion of why I do not make a common values assumption can be found in Section 2.

Another relevant literature discusses empirical tests for collusion in auctions. A discussion with the North Dakota director of minerals management from the time of the switch revealed that part of the switch in auction format was motivated by fears of collusion between bidders in the in person auctions. The economic literature on collusion has shown that it is very hard to prove or disprove collusion. Hendricks and Porter (1989) show that tests for collusion have to be tailored to detecting particular collusive mechanisms. Porter and Zona (1993) is able to detect collusive behavior conditional on knowing the identities of those in the cartel. Athey, Levin, and Seira (2011) are unable to prove collusion, but use their structural model to test for the effects of collusive cartels of various sizes. Hendricks, Porter, and Tan (2008) explore collusion in offshore mineral auctions with common values and show that the winner's curse can make bidding rings unstable. I am unable to make a definitive claim about collusion, but I am able to suggest bounds on the size of the bidding cartel should collusion have occurred in the open outcry auctions.

The paper proceeds as follows: Section 2 derives a theoretical model for bidding behavior in the online and open outcry auctions. It shows that I can recover the distribution of bidder values from the observed bid data in the online auctions. Section 3 describes the empirical setting's institutions and the available data. Section 4 provides reduced form estimates of the effects of the change in auction format on auction outcomes for North Dakota mineral auctions. Section 5 calibrates a structural model of bidder values in these auctions. It then uses the calibrated structural model to perform counterfactual policy experiments with different numbers of bidders entering the auction. Section 6 concludes.

2 Theoretical Model

I will first set out some preliminary assumptions about the setting which hold across all auction formats. I use notation similar to that of Hernández, Quint, and Turansick (2020) due to the similarity of my model to theirs. For simplicity of notation, I will refer to their paper by HQT from here on in.

Assumption 1 (Private Values and Unobserved Heterogeneity)**.** *The value of tract t is different across each bidder i and is multiplicatively decomposed as follows:*

$$\ln\left(V_{it}\right) = \psi\left(Z_t\right) + \theta_t + \varepsilon_{it}.$$

It is comprised of:

- *A deterministic part, $\psi(Z_t)$, where Z_t is a vector of observable characteristics of the parcel being auctioned and ψ is a function, not necessarily linear in the components of Z_t, which maps observable characteristics into a valuation.*
- *A component of heterogeneity, θ_t, observed by the bidders, but not by the econometrician. This is an iid draw of a random variable with cumulative density function F_θ, and probability density function f_θ.*

- *A private value, ε_{it}, observed by only bidder i. This is an iid draw from a distribution with cumulative density F_ε and probability density f_ε.*

Assumption 2. *The densities f_θ and f_ε are continuous and real analytic.*

This assumption is required for identification using the results from HQT. Their identification proof relies on this assumption because it allows them to prove properties of these densities by proving those properties on their power series expansions. The probability density of any common family of continuous distributions (Normal, Poisson, Weibull, etc.) satisfies this assumption, so it is a less restrictive assumption than the parametric or semi-parametric form that is used to approximate the true distribution. I maintain two further assumptions about bidding behavior from Haile and Tamer (2003).

Assumption 3. *Bidders do not bid more than they are willing to pay.*

Assumption 4. *Bidders do not allow an opponent to win at a price they are willing to beat.*

In both the online and in person ascending English auctions, the private values assumption means that a bidder will not change their valuation after observing other bids in the auction. It is a well-known result that bidders should drop out of the auction at their value $\exp\left(\psi(Z_t) + \theta_t + \varepsilon_{it}\right)$. Thus, the transaction price will be $\exp\left(\psi(Z_t) + \theta_t + \varepsilon_{it}^{(2)}\right)$ where $\varepsilon_i^{(2)}$ is the second order statistic of the draws from the private value distribution. Observing transaction price alone is not sufficient to identify the distributions of the unobserved heterogeneity (f_θ) and the private valuations (f_ε).

The first identification issue is that in online auctions the observed number of bidders is not the same as the number of bidders who "drew" from the value distribution and considered bidding on the parcel. This motivates the need for an entry model. The model essentially has bidders arrive in sequence having drawn a value. They then place a bid informed by their value so long as the current high bid doesn't exceed their value. I describe this model in detail in the structural estimation section, it is the same one used in HQT. In order to identify the distribution of how many bidders will arrive at each auction, I need that distribution to have positive probability on a bounded support, observations of the number of bidders entering each auction, and an entry model which translates actual number of bidders into a distribution of how many might be observed placing bids. HQT Theorem 3 non-parametrically identifies the distribution of bidders considering each auction from this data.

The second identification issue is that I need to separately identify f_θ and f_ε. The HQT identification strategy here relies on the fact that more bidders will shift the order statistic which is drawn from private values f_ε without shifting the draw from the unobserved heterogeneity f_θ. In order to do this, HQT requires a participation shifter. For this, I follow Compiani, Haile, and Sant'Anna (2020) and use number of adjacent leases as a participation shifter. This participation shifter means that different auctions will draw from different distributions of the number of bidders, allowing the separate identification. HQT Theorem 4 provides the necessary non-parametric identification conditional on the entry model, based on observation of the transaction price and participation shifter.

3 Empirical Stetting

3.1 Institutional Background

Mineral rights are the right to drill for oil and gas under the surface of a particular tract of land. They are generally granted as 5 year leases which expire if a producing well has not been drilled. North Dakota Trust Lands manages much of the public land owned by the state of North Dakota. The mandate of the Surface and Mineral Management division is "obtaining fair market returns or royalties for use of these resources [surface and mineral acres]." [4]

North Dakota sits on top of the Bakken shale formation, the site of much of the hydraulic fracturing boom that took place between 2005 and 2015. Auctions are held on a quarterly basis for mineral rights controlled by North Dakota Trust Lands. Prior to the auction, there is a nomination process where firms, typically those planning to bid in the auction, nominate tracts of land to be auctioned.

Prior to August 2012, the state allocated all of their state-owned mineral rights by way of in person English auctions. Between August 2012 and August 2016, the state alternated between holding in person and online auctions on a platform called EnergyNet. Since August 2016, all auctions have been conducted online. For context, figure 1 presents an example map of parcels in the different auction formats to show the spatial distribution of parcels that were auctioned each way. Figure 2 shows the timing of online and in person auctions.

4. `https://www.land.nd.gov/surface-minerals-management`

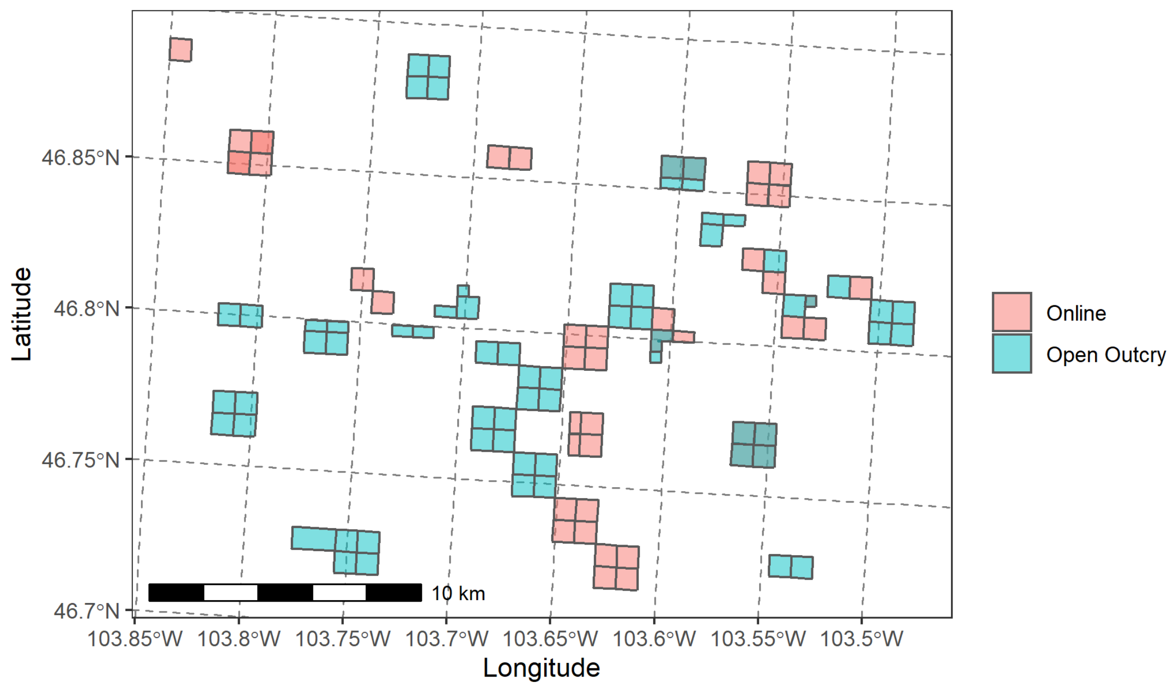

Figure 1: Example leases colored by whether they were auctioned in an online auction or an open outcry one. Note that some leases are auctioned multiple times (for example once in 2012, then the lease expires in 2017 and they get re-auctioned, sometimes in a different auction format).

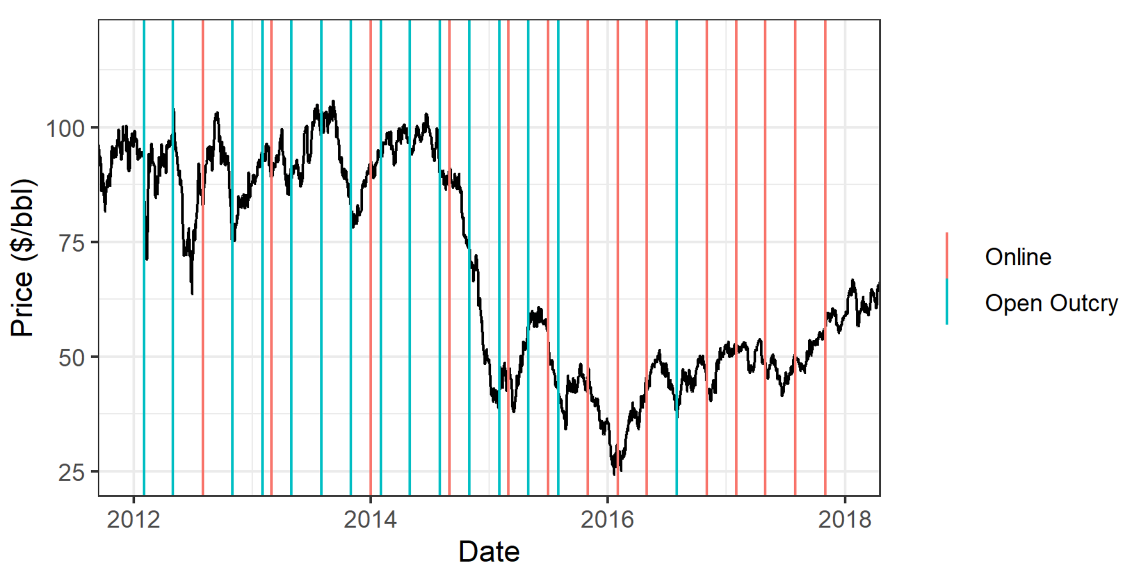

Figure 2: Prices over time with vertical lines indicating the timing of the auctions

The online auctions follow a format similar to eBay auctions. Bidders can see the description of a tract being offered and have several days from the opening of the auction until the auction closes to submit a bid. The participant with the highest bid when the auction closes pays that bid in exchange for a lease. Participants can submit bids in one of two ways.

1. They can enter an amount to bid.
2. They can enter a maximum bid into a proxy bidding algorithm which will increase their bid by the bidding increment, $1, until the highest bid is higher than their maximum bid or they hold the highest bid.

The sequence of bids is common knowledge to all bidders, but the identity of each bidder is hidden from the other bidders.

3.2 Data

Estimation requires three kinds of data: auction results, price data, and market research data suggestive of tract quality. Auction results come from the State of North Dakota's land trust website. [5] The sequence of bids in the online auctions comes from the platform EnergyNet, which is responsible for conducting the online auctions. [6] The State of North Dakota provided auction notices showing which parcels were nominated for each auction and which firm nominated them. Table 1 provides summary statistics of some of the relevant characteristics of the auctions to provide the reader with the necessary context to imagine the magnitudes of the estimates later in the paper. One relevant note regarding this table is that it appears that open outcry auctions bring in more revenue, this isn't a particularly meaningful comparison though because it isn't comparing the differences in revenue between auctions for similar parcels with similar market oil prices.

Daily spot prices for the Clearbrook pricing center (used to price the Bakken shale formation) come from S&P Platts. These data cover May 2012 through December 2019. As we see from figure 2, there is extensive variation in the auction prices over the period being studied.

Additional descriptive data covering 1951 to 2020 comes from DrillingInfo, which provides the lease location, the production decisions that the lessee made, and the quantity of oil they

5. https://www.land.nd.gov/Minerals/AuctionHistory
6. https://www.energynet.com/page/Government_Sales_Results_Previous

Variable	Open Outcry	Online
Revenue ($/Acre)	736.89 (2202.32)	190.38 (1208.66)
Log Revenue	3.61 (2.66)	2.76 (1.99)
Number of Bidders		2.98 (1.69)
Tract Size (Acres)	84.74 (47.06)	89.46 (49.05)
Adjacent Leases	1.82 (2.3)	0.86 (1.84)

Table 1: Summary Statistics: Mean (SD) of several variables in the dataset.

extracted on a monthly basis. I use these data to construct a picture of what a particular firm might expect a new tract to produce based on results from similar nearby tracts that were reporting production at the time of bidding. In the appendix, figure 8 shows variation in space and time of mean oil extracted and figure 9 shows the same thing for gas.

4 Reduced Form Results

As we see from figure 2, the alternating structure of the online and open outcry auctions at a wide variety of price levels gives us a controlled environment for precisely estimating the effect of the change in auction structure on auction outcomes. This section uses the natural experiment of the alternating policy change to estimate some of the effects of switching to online auctions. Additionally, this section will explore the validity of the private values modeling assumption.

4.1 Auction Outcomes

The first and most interesting outcome is revenue. The state of North Dakota wants to select the auction format which maximizes the revenue they get from each parcel of land they auction off. As discussed in the institutions section, it is part of their mission to obtain fair market prices for the use of their resources. In order to test the revenue differences between the two auction formats, I run several different regression specifications. The overall goal of these is to control for differences in price and differences in quantity of oil and gas that can be extracted. The dominant part of the firm's profit function is the revenue they can get from selling the oil they extract, so this is an important thing to control for. I begin with the conservative approach of adding year interacted with location fixed effects, it essentially estimates the effect of online auctions as differences between parcels auctioned in the same

6 mile grid in the same year that were auctioned using different formats. The estimate for this specification is found in model (1) of table 2.

	Dependent variable:				
	Log(Winning Bid) in \$/acre				
	(1)	(2)	(3)	(4)	(5)
Online	0.976***	0.406***	0.222**	0.195*	0.425***
	(0.109)	(0.106)	(0.103)	(0.105)	(0.103)
Year * Location FE	Yes				
Price (3 periods) + Quantity		Yes	Yes		
Spline Price + Quantity				Yes	Yes
Lease Provision			Yes		Yes
Observations	5,316	5,316	4,047	5,316	4,047
R^2	0.927	0.253	0.288	0.351	0.338
Adjusted R^2	0.916	0.252	0.286	0.350	0.336
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 2: Regressing winning bid on online auction controlling for year and location as proxies for price and mineral quality

Models (2) - (5) in the same table control directly for mineral quantity and price. For price, the models use the mean price in the last three months (after a log transformation). For quantity, they use the mean of the peak amount of each oil and gas for wells that were drilled in the same 6 mile grid (range by township) in the three years leading up to the auction taking place[7]. I interpret this as a good proxy for the sort of market research that bidders might be doing. Note that both quantity and price change over time and quantity changes over space as well. Additional models perform a spline regression on each price and quantity (accounting for the possibility that responses are not log-linear). Finally, I include controls for lease provisions in some of our models. These provisions include the royalty rate that must be paid for oil extracted as well as conditions about whether drillers can use the surface land or whether there are possible protected paleontological artifacts that might be encountered while extracting the oil.

The results from these regressions are reported in table 2. There is some variation in the coefficient for the effect of online auctions, but after transforming the log linear coefficient

7. Results in this paper are not sensitive to look-back windows in the range of 6 months to a few years. More years results in less missing or imputed data, but also less variation over time. Losing variation over time in quantity is not a concern because one wouldn't expect the geology's true quality to vary too much over time.

a reader should take away that online auctions yield between 20% and 160% more revenue per acre than open outcry auctions for similar parcels. An important point of discussion is the wide range of these coefficients. The regression with only fixed effects doesn't control for lease provisions and only controls for prices at the year level. This means that the controls for variation in the market conditions are not necessarily as precise as they are in the other models, and the estimate should be taken with a grain of salt. It does however better control for unobservable spatial and temporal heterogeneity that is not captured in the other regressions, so its coefficient remains an important point of comparison. The other four models estimate an effect in the range of a 20% to 50% increase in revenue which is still a substantial difference worth exploring further.

5 Structural Estimation

The reduced form section prompts questions about why there is such a large difference in the competitiveness of the online and open outcry auctions. In order to shed light on some of these questions, I will estimate a structural model of the distributions of bidder valuations from the online auctions. This will allow me to run counterfactual policy experiments where I simulate what would have happened in the open outcry auctions had they been held on the online platform under different conditions for entry. The goal of this is to tease out the magnitude of reduction in bidder participation which might replicate the revenue difference between the online auctions and the open outcry ones. A structural model has the advantage that I am comparing apples to apples by simulating what would have happened in an open outcry auction had it been held online instead. The reduced form alternative is a comparison to a similar but not identical parcel from an online auction.

The apples-to-apples nature of this comparison relies on some modeling assumptions. I am assuming that valuations for the online auctions and the open outcry auctions are drawn from the same distribution. Given the temporal overlap of these auctions and the ex-ante possibility that a parcel could be nominated for either auction time, this appears to be a reasonable assumption. I am also assuming that bidders in online auctions do not engage in any collusive or uncompetitive behavior which would mask my ability to correctly recover value distributions. Finally, I am assuming the form of an entry model to back out how number of bidders drawing from the value distribution corresponds to the number of bidders observed bidding in the auction. Recall that some bidders might consider a parcel, but never bid because by the time they arrive at the auction, they see that the current high bid exceeds their valuation. I will use the same entry model as was used to describe eBay auctions in HQT. This model features the property that not all bidders who draw valuations will be observed placing bids. The specifics of this model are described in step 2 of the following estimation process. My entry model is reduced form in the way that parcel quality influences entry probability, but it makes specific parametric assumptions about the distribution of bidders considering the auction (Poisson) and about the process by which bidders increment their bid throughout the auction.

5.1 Estimation Process

I will estimate the densities f_θ and f_ε from the online auction data using the method from HQT described in the identification section. There are three steps to the estimation procedure. The first step is to run the regression of the second highest bid in each auction (which must be equal to the second highest bidder's valuation) on the observable predictors of auction value

$$\ln\left(B_{it}^{(2)}\right) = \beta Z_t + T_{it}.$$

We define in this equation T_{it} to be the transaction residual whose distribution we wish to decompose into a θ component of unobserved heterogeneity and an ε component of private value.

The second step in the estimation process is to estimate the entry model. We define our entry process as occurring in two parts. First bidders arrive at the auction according to some Poisson process with parameter λ. As they arrive in sequence at the auction, they draw a private value from f_ε. If their private value is higher than the current high bid, they place some bid randomly on the interval between the high bid and their value. If the private value is lower than the current high bid, that bidder doesn't enter the auction. At the end of the auction, bidders bid up to their value. This entry model means that the firms observed placing bids are only a subset of those which drew values from f_ε and considered bidding in the auction. Thus it is necessary to estimate $P\left(N_{obs} = k \mid N = n\right)$. I do this by simulating a million entries processes for each n from 1 to 100.

Having worked out how many observed bidders to expect conditional on the number of bidders who drew a value for the auction, we need to estimate the parameterization of the Poisson distribution. One identifying assumption is that there is some participation shifter, an instrument that makes some auctions have more participants without changing the bid residuals of the auctions. I will follow Compiani, Haile, and Sant'Anna (2020) and use number of firms with preexisting adjacent leases as a participation shifter. I will call this shifter X which is a random variable taking one of the three values in $\{0, 1, 2+\}$. We then estimate the Poisson parameter λ_x for each of these values of the shifter using MLE on the following

$$\arg\max_{\lambda_x} \sum_{m=1}^{M_x} \ln \left(\sum_{n=2}^{\infty} \frac{1}{1 - e^{-\lambda_x} - \lambda_x e^{-\lambda_x}} \frac{\lambda_x^n e^{-\lambda_x}}{n!} P\left(N_{obs} = n_m \mid N = n\right) \right)$$

where we have truncated realizations of 0 or 1 bidders out of the Poisson distribution. Figure 3 has kernel density estimates which visually suggest that the truncated Poisson distribution fits our data quite well.

The third and final step in the estimation process is to recover the distributions of values. Following HQT Theorem 5, we know that the pdf of the transaction price residual conditional a Poisson entry model is

$$f_T(t) = \frac{\lambda^2 e^{-\lambda}}{1 - e^{-\lambda} - \lambda e^{-\lambda}} \int_{-\infty}^{\infty} f_\theta(t - s)(1 - F_\varepsilon(s)) f_\varepsilon(s) e^{\lambda F_\varepsilon(s)} ds$$

the final step is to define a quasi-parametric approximation to each f_θ and f_ε and then we perform MLE on the above likelihood of each observed transaction price using the fitted λ based on the participation shifter. The quasi-parametric approximations come from Gallant and Nychka (1987) and are defined as:

$$f_Z(z) = \left(\sum_{k=0}^{K} \beta_{Z,k} H_k \left(\frac{z - \mu_Z}{\sigma_Z} \right) \right)^2 \varphi \left(\frac{z - \mu_Z}{\sigma_Z} \right)$$

where $H_0(x) = 1$, $H_1(x) = x$, $H_k(x) = \frac{1}{\sqrt{k}} \left(x H_{k-1}(x) - \sqrt{k-1} H_{k-2}(x) \right)$ are the probabalist's Hermite polynomials. For this to be a valid density, we need the condition that $\sum_{k=1}^{K} \beta_{Z,k}^2 = 1$. Additionally, we cannot separately identify two means, so we normalize the mean of the distribution of unobserved heterogeneity to zero. Thus the space over which we are performing MLE is $(\mu_\varepsilon, \sigma_\varepsilon, \sigma_\theta, \vec{\beta}_\varepsilon, \vec{\beta}_\theta)$ to semi-parametrically identify the two distributions of interest.

5.2 Estimation Results

The first step is to control for observable tract heterogeneity. I run two versions of two different specifications. The first includes the controls from reduced form model 1 (year * township * range fixed effects). The second includes the controls from reduced form model 5 (log price, quantity, parcel characteristics and provisions, royalty rate). Additionally, for each of these models, I do a version where I control for the number of bidders and a version where I do not in the first stage estimation.

	Dependent variable:				
	Number of Bidders	Log Bonus			
	(1)	(2)	(3)	(4)	(5)
1 Adj. Firm	0.245*	0.097	0.045	0.403***	0.149
	(0.147)	(0.071)	(0.055)	(0.148)	(0.098)
2+ Adj. Firms	1.535***	0.153*	0.064	1.231***	0.344***
	(0.139)	(0.083)	(0.065)	(0.148)	(0.103)
Year * Location FE		Yes	Yes		
Spline Price + Quantity				Yes	Yes
Number of Bidders FE			Yes		Yes
Observations	815	815	815	794	794
R^2	0.132	0.907	0.946	0.270	0.692
Adjusted R^2	0.130	0.884	0.932	0.256	0.683
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 3: Regressions testing whether number of firms with adjacent leases affects log bonus other than by increasing the number of bidders.

In the second step, I calibrate the entry model for each value of our participation shifter. I begin by testing whether our instrument for shifting participation is relevant and meets the exclusion restriction. From table 3, it is clear in the first regression that our participation shifter does indeed shift participation. This is even more evident and quite compellingly shown in figure 3. In table 3, we also test whether adding controls for number of bidders eliminates the reduced form effect that our participation shifter has on the log bonus residual. It appears that the effect is greatly diminished in magnitude, but it doesn't go away entirely. This could be attributed to the fact that 2+ adjacent firms is collapsing a few categories into one and more granular categories would make this significance disappear. Due to limited numbers of observations for the higher categories, I am unable to use a more granular instrument. Thus adjacent lessees appears to be a strong, but not entirely exogenous instrument for bidder entry.

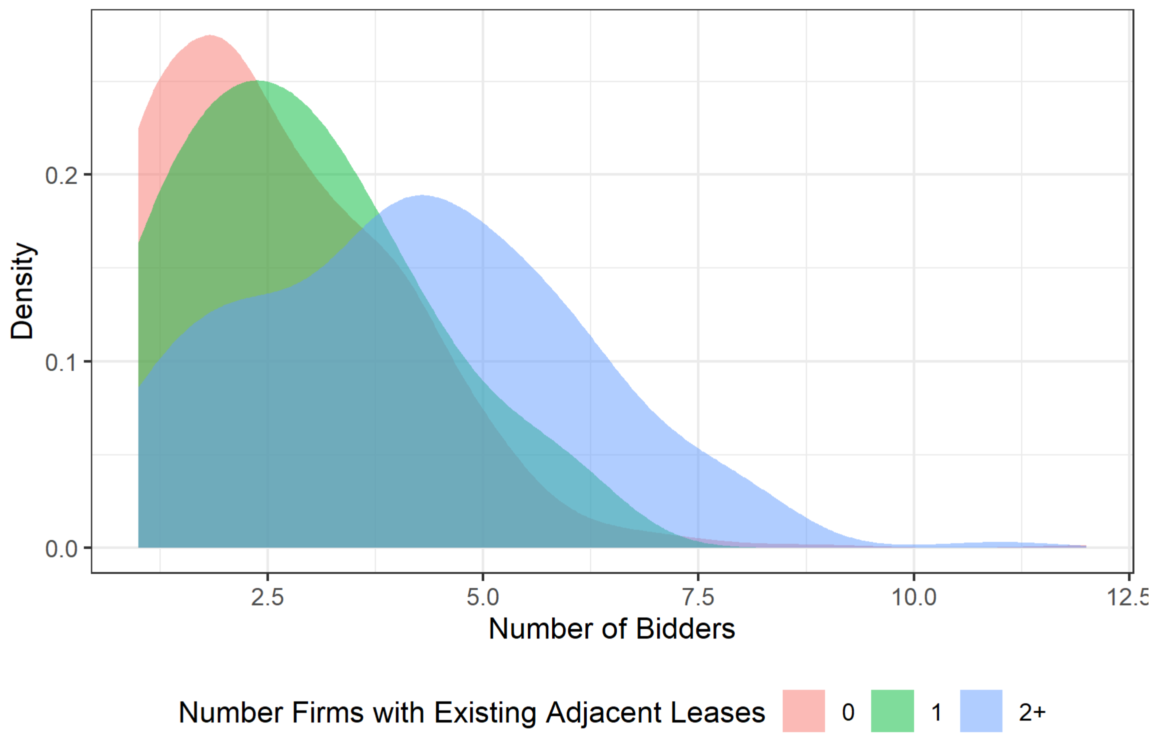

Figure 3: Distributions of bidder entry by number of firms with adjacent preexisting leases to the lease up for auction.

	0 Adj. Leases	1 Adj. Leases	2+ Adj. Leases
λ	4.66 (0.2)	5.01 (0.35)	9.23 (0.52)
Observations	362	122	159
-2 Log Likelihood	1136.08	381.05	619.66

Table 4: Entry Model Estimates

Having provided some justification for the instrument, I use MLE to estimate λ for each value of the participation shifter. We see in table 4 that each estimate of λ for each value of the instrument is distinct with fairly tight standard errors.

Now we take the estimates from the entry model and fit a normal model of each f_θ and f_ε. While the identification result allows for a more general semi-parametric form, a normal-normal model captures the salient residual decomposition of interest. The results from this estimation are presented in table 5. Impressively across the three different models we see consistency in the relative magnitudes of the estimates. Not a lot should be read into the estimates of the means, the fact that they are negative makes sense because the winning bids generally come from the right tail of the distribution. From the standard errors we see that consistently the variance on ε, the individual values, is generally larger than the variance on

	Mod1 w/ N	Mod5 w/ N	Mod1 no N	Mod5 no N
μ_ε	-1.75 (0.13)	-3.36 (0.27)	-3.51 (1.35)	-3.57 (0.55)
σ_ε	2.84 (0.18)	5.48 (0.35)	6.01 (2.28)	6.04 (0.86)
σ_θ	1.71 (0.11)	3.29 (0.22)	3.97 (1.51)	3.86 (0.56)
Observations	643	623	643	623
-2 Log Likelihood	1086.45	1064.26	1385.32	1297.98

Table 5: Value Model Estimates

the unobserved heterogeneity θ.

5.3 Counterfactual Comparisons

Recall that the structural model allows me to test how reductions in bidder participation could affect the auction results in the open outcry auctions. Quantifying this participation reduction could suggest competing stories about what accounts for the revenue difference. The first competing story is that it is costly to participate in an in person auction because it involves hiring a local representative or transporting an employee to the site of the auction. Online auctions do not have these entry costs. The second story is that in person auctions might have colluding parties. A collusive cartel would only have to outbid those not in the cartel and thus auction results would have the appearance of fewer auction participants. While I do not have the data to distinguish between these two explanations, I am able to provide bounds on these explanations. I can show the reduction in average number of bidders which explains the difference in auction revenue. This can be interpreted as either the number of participants who didn't attend because of higher costs, or it can be interpreted as the size of the members of the collusive bidding ring considering the typical auction.

The policy experiment I perform is scaling the entry parameters λ by some scale factor. This simulates reduced participation across all auction groups by participation shifter. It retains the feature that "better" parcels according to the exogenous participation shifter will still attract more bids. I then draw a number of bidders N for each open outcry auction and simulate draws from f_θ and f_ε. This allows me to compute the winning bid, number of bidders considering the parcel, number of bidders bidding on the parcel, surplus of winning bidder, and proportion of auctions with only one bidder observed. As λ shrinks, fewer bidders bid in the typical auction and therefore surplus is higher and the average winning bid is lower.

For counterfactual policy experiments, I use Model 5 without controls for N. The four models are quite consistent (as is seen in table 5), and model 1 is based on section * township * year fixed effects which haven't been estimated for all of the tracts in the open outcry auctions. Model 5 without N doesn't introduce bias into the value calculations that would come from the fixed effects for N.

Results from these simulations are reported in table 6. The actual row on the table represents the actual open outcry auctions. Each of the simulation rows should be interpreted as the counterfactual outcome should the parcel in that auction have been auctioned in an online format instead. These simulations do not include any parcels that were auctioned in online auctions, but they do use the value distributions that were recovered using the online auction data.

Experiment	Avg Log Price	Avg N	Avg N Obs	Avg Surplus	Prop w/ 1 Bid
Actual	2.06 (0.1)				0.43 (0.01)
Sim. 0.25	1.36 (0.07)	2.11 (0.04)	1.72 (0.03)	3.28 (0.1)	0.5 (0.01)
Sim. 0.3	1.63 (0.06)	2.38 (0.03)	1.88 (0.02)	3.46 (0.08)	0.43 (0.01)
Sim. 0.4	2.19 (0.08)	2.97 (0.04)	2.18 (0.02)	3.6 (0.11)	0.32 (0.01)
Sim. 0.5	2.71 (0.08)	3.58 (0.05)	2.46 (0.03)	3.66 (0.1)	0.24 (0.01)
Sim. 0.75	3.84 (0.11)	5.21 (0.07)	3.1 (0.04)	3.49 (0.08)	0.13 (0.01)
Sim. 1	4.76 (0.11)	6.85 (0.09)	3.63 (0.04)	3.25 (0.06)	0.07 (0.01)

Table 6: Policy experiments where we scale entry parameters of poisson process (by the factor listed in the table) to simulate higher entry costs in the open outcry auctions during the overlap period (2016 and later). The standard errors are boostrapped from multiple iterations of the simulation based on different random samples with replacement of the open outcry leases going into the simulation.

Notice in the policy simulation that the experiment which replicates the actual average log bid (scaling entry parameters by between 0.3 and 0.4) also dramatically increases the proportion of auctions with only a single bidder participating. This parameter's estimate is within a margin of error of the same parameter estimated from our data and not used as a moment in calibrating the simulation. This is verification that the structural model is a good description of what is going on in the auction. in particular, this outside moment lends a lot of credence to the reduced bidder interest story due to higher costs of entry in the open outcry auctions. While we cannot observe the full distribution of number of bidders in the open outcry auctions, the fact that we are able to match one of the moments of that distribution is highly suggestive that reductions in bidder participation account for the revenue difference.

One interesting outcome of this policy simulation is how large of a decrease in number of bidders is necessary to replicate the actual revenue residuals from the open outcry auctions.

We see that the decrease necessary is by about 4 participants considering bidding in the typical auction. It suggests that in open outcry auctions only two to three bidders are interested in most tracts. This could be a result of the process of bidding in open outcry auctions. Large firms hire land-men to represent them and to bid on their behalf. These representatives have to be sent out with instructions for which parcels to bid on meaning that most parcels will not garner a lot of interest even if they are valuable. Alternatively, the difference could be the result of some collusion. A collection of firms colluding would look similar to there being many fewer bidders because essentially the firms in the bidding cartel who have agreed to take the parcel only need to outbid firms not in the cartel. While there is no direct evidence of collusion and I do not intend to make that accusation in this paper, the collusion story is not inconsistent with the data we observe.

Another parameter of interest that our experiment uncovers is the increase in average surplus associated with fewer bidders participating in each auction. The average surplus increases as I reduce bidder interest and then decreases when bidder interest gets very small. This is because as interest gets quite small, there begins to be a higher number of auctions where nobody bids. On the other hand there is the competing effect that as there are fewer bidders, but still multiple bidders with some interest in the parcel, the typical difference between the highest bid and the second highest bid will be larger. We see that the experiment which does a good job of replicating the actual average log bid has a surplus about .2 log points higher than the simulation as if the auctions had been held online. This means that the typical winning bidder in an open outcry auction had about a 20% higher surplus than a bidder in an online auction. From table 6, I compute the change in average surplus as $\exp(3.6) - \exp(3.25) \approx \$10$ per acre. The typical lease has 80 acres and the typical participant wins about 3 parcels. Thus we back out an entry cost barrier difference of $2,400. This is a plausible estimate of the cost of entering an in-person auction relative to an online one, providing yet another simulated moment which suggests the strength of my structural model.

An additional policy experiment we might wish to perform is to look at the average bidder surplus as a function of bidder participation to see what level of our policy experiment participation multiplier might maximize bidder surplus. This experiment is summarized in figure 4. We see unsurprisingly that for the high quality parcels for which we calibrated a Poisson entry parameter of 9.23, average surplus is maximized when participation is very low, this is because for these parcels if there is only one bidder interested, they will almost certainly have a high enough value to bid on it, so surplus only decreases as more bidders consider the parcel and begin bidding up its value. On the other hand, for the more "typical" parcels, surplus is optimized at a shifter of about .4. This actually corresponds to what our

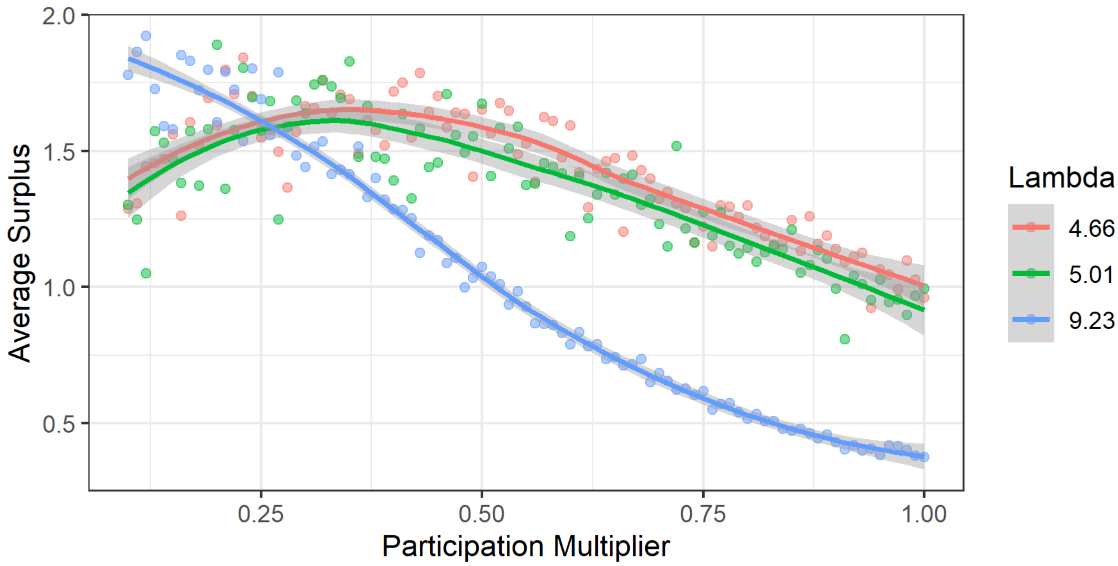

Figure 4: Average Bidder surplus for each lease type as a function of changing auction interest through costs associated with entry.

prior experiment recovered as being equivalent to the in person auction, suggesting that in person auctions were essentially optimal in that they optimized surplus for participating bidders but were naturally bad for the state of North Dakota as has been show with prior revenue results in this paper.

6 Conclusion

I have performed both a reduced form and a structural analysis of the effects of North Dakota's switch from open outcry to online auctions. I found in the reduced form section that online auctions bring in between 20% and 160% more revenue than open outcry auctions. I also provided empirical justification for modeling onshore oil and gas auction settings with private values. I found in the structural model that variation in bidder's private values makes up more of the variation in value than variation in unobservable quality of the well. I also found that the revenue difference in the open outcry auctions could be explained by entry costs that result in about four fewer bidders considering bidding on the typical parcel, and verified this model with an outside moment, the proportion of auctions of each type with only one bidder.

This paper is not without its limitations. The estimation of distributions f_θ and f_ε is currently constrained to the normal parametric form. Future work could implement semi-parametric estimation. Another limitation is that I am only able to use the proportion of auctions with 1 bidder to verify the reduced bidder interest explanation. A more robust analysis would be able to observe the full distribution of bidders in open outcry auctions, but this data is unavailable. The final limitation is that I am unable to distinguish between collusion and higher entry costs. I know that four fewer bidders consider the typical parcel, but I do not know whether this is because there are four bidders in a cartel or because there are four bidders who didn't want to pay for a flight to Bismark, ND.

Future work might follow from further exploration of the rich bidding data available on EnergyNet for online mineral auctions. This paper is the first to use such data, and there are likely useful applications of such data across other research questions in energy economics. Additionally, I see future work looking into the effects of auction format on production outcomes to model whether firms operate assets differently depending on the surplus associated with acquiring those assets (and not their intrinsic value).

For the field empirical auction research, a key takeaway is that economists should consider subtleties of auction setting when making comparisons across auctions. For example, the literature that compares first and second price auctions attributes the difference to a change in the auction format, but sometimes these format changes are associated with changes in auction setting (such as a move from submitting a sealed bid by mail to bidding in person), and my research shows that such seemingly small changes in auction setting can in fact be material.

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Appendix A: Additional Reduced Form

6.1 Reduced Form Competitiveness

	Dependent variable:				
	Win at Minimum Bid				
	(1)	(2)	(3)	(4)	(5)
Online	−0.219***	−0.134***	−0.108***	−0.078***	−0.097***
	(0.029)	(0.018)	(0.020)	(0.019)	(0.021)
Year * Location FE	Yes				
Price (3 periods) + Quantity		Yes	Yes		
Spline Price + Quantity				Yes	Yes
Lease Provision			Yes		Yes
Observations	5,316	5,316	4,047	5,316	4,047
R^2	0.800	0.170	0.219	0.200	0.237
Adjusted R^2	0.768	0.169	0.218	0.198	0.235
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 7: Linear probability regressions on indicator for winning parcel at minimum bid.

Another indicator of auction competitiveness is whether an auction is won at the minimum bid. North Dakota does not set reserve prices, so the minimum bids in these auctions are all \$1 or \$2. This means that a tract of 640 acres (allowing the drilling of 8 lateral wells) could be sold with bidders paying something like \$640 plus some small additional auction fees for the right to drill. Parcels sold at these prices are not necessarily of high mineral quality, but it is implausible to think that these uncompetitive bids represent the true valuation of any of the bidders in the auction given that a lease is a real option to have the exclusive drilling rights for the following 5 years. I run linear probability regressions on probability of winning an auction at the minimum bid against the same coefficient specifications as I did for revenue. Results are reported in table 7. We see the same discrepancy between the fixed effects model and the other four, but we are able to conclude that online auctions have roughly 10% to 20% fewer parcels transacting at the minimum bid. This is a remarkably large change and suggestive of auction dynamics being much more competitive in the online auctions.

Tracts which receive no bids are an important indicator of uncompetitive auctions. I observe only 3 such auctions in the entire dataset, indicating that this rarely occurs. This is not a large enough sample to make comparison between the online and in person auctions.

We should expect to see that most parcels get bid on by somebody given the absence of reserve prices and the option value of holding a lease.

	Dependent variable:				
	Winner is the Nominator				
	(1)	(2)	(3)	(4)	(5)
Online	-0.107^{*}	-0.186^{***}	-0.193^{***}	-0.213^{***}	-0.226^{***}
	(0.055)	(0.023)	(0.025)	(0.025)	(0.025)
Year * Location FE	Yes				
Price (3 periods) + Quantity		Yes	Yes		
Spline Price + Quantity				Yes	Yes
Lease Provision			Yes		Yes
Observations	4,047	4,047	4,047	4,047	4,047
R^2	0.675	0.068	0.095	0.102	0.118
Adjusted R^2	0.621	0.067	0.093	0.100	0.115
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 8: Linear probability regressions on indicator for the same bidder nominating and winning a parcel

A final reduced form indicator of auction competitiveness is whether the firm that nominates a tract is the same as the firm that wins the tract at auction. While it is possible that the firm that nominates a tract should be more likely to win it (because they have some private value that is higher like being closer to their pipeline network) we should not expect a change in auction framework to do anything to the probability that the winner is the nominator. That said, we do see a change which can have either of two interpretations. The first is that in online auctions, other bidders can't see which bidder is the nominator. The nominator might have a high private value and therefore place high bids. If another bidder makes a common values interpretation of the high bidder's bid, then they may update to believe it is more valuable and incorrectly interpret a private shock as a common shock. I reject a common values modeling of these auctions, and turn to the explanation of either collusive behavior or fewer bidders in the open outcry auctions. It is reasonable to expect that nominating a parcel might be a signalling mechanism that other bidders should not bid on this. It could also be that there are few enough bidders that only the nominee is seriously considering the parcel. The output from these regressions (with the same sets of controls as in the prior two tables), is found in table 8. I take away the conclusion that between 10% and 20% fewer parcels are sold to the nominator in online auctions as compared to open outcry ones.

6.2 Common Values Tests

While common values is the traditional way of modeling resource extraction, it may not be a good model in North Dakota mineral auctions. The signals bidders receive are generally just market research in the form of observing the output of nearby wells, geological surveys, and imputing what the output of a new well nearby might be. Therefore, we might expect that variation in valuations after controlling for this information might be dominated by private values. There are large firms and small firms. There are firms that have existing truck or pipeline collection networks in particular areas. These differences constitute private values, and bidders in these auctions might know not to correct valuation based on bids that are more revealing of private values than of common values.

In order to test this, I will follow Athey and Haile (2002)'s Theorem 9 for a test of common values in an ascending auction. The intuition of this test is that in an auction with more bidders and common values, the bids near the top of the value distribution will be lower in expectation when there are more bidders in the auction because they will have had more prior bids that correct their valuation downwards. On the other hand, with a private values assumption, bidders near the top of the distribution will not correct their bids downwards because other bidder's valuations don't influence their own valuation. Formally the test we are performing is as follows. Letting $n \geq 3$ be the number of bidders in the auction, we have the private values null hypothesis that

$$LHS = E[B^{n-2:n-1)}] = \frac{2}{n}E[B^{(n-2:n)}] + \frac{n-2}{n}E[B^{(n-1:n)}] = RHS$$

where $B^{(i:j)}$ is the i^{th} highest bid in an auction with j bidders. The common values alternative would give the relation

$$E[B^{n-2:n-1)}] > \frac{2}{n}E[B^{(n-2:n)}] + \frac{n-2}{n}E[B^{(n-1:n)}]$$

We can estimate these expectations using bid data. Because the third highest bid, $B^{(n-2:n)}$, may not reach the full valuation of the third highest bidder because of the format of our auction,[8] we know that we are slightly underestimating the right hand side of the above equation. Therefore, if we find that the left hand side is not greater than we have strong

8. This is because the bidding strategies employed in our auction mean that the third highest bidder may put in a max bid lower than their value, walk away from their computer, see that the current high bid exceeds their value and never place a high bid that actually reflects their value in the auction.

evidence of private values in spite of the bias in the measurement on the right hand side. I will note that this test assumes symmetric bidding strategies.

n	LHS	RHS	Difference	p	LHS_{obs}	RHS_{obs}
3	-0.09 (0.68)	-0.83 (0.93)	0.73	1.00	208	145
4	0.05 (0.58)	-0.26 (0.59)	0.31	1.00	145	137
5	0.08 (0.51)	0 (0.62)	0.09	1.00	137	72
6	0.22 (0.62)	-0.02 (0.43)	0.24	1.00	72	38
7	0.16 (0.43)	-0.06 (0.37)	0.22	1.00	38	13
8	0.08 (0.31)	-0.03 (0.87)	0.11	0.83	13	8

Table 9: Athey and Levin test for common values in Acending Auctions, Reduced form model 1 Controls for parcel value

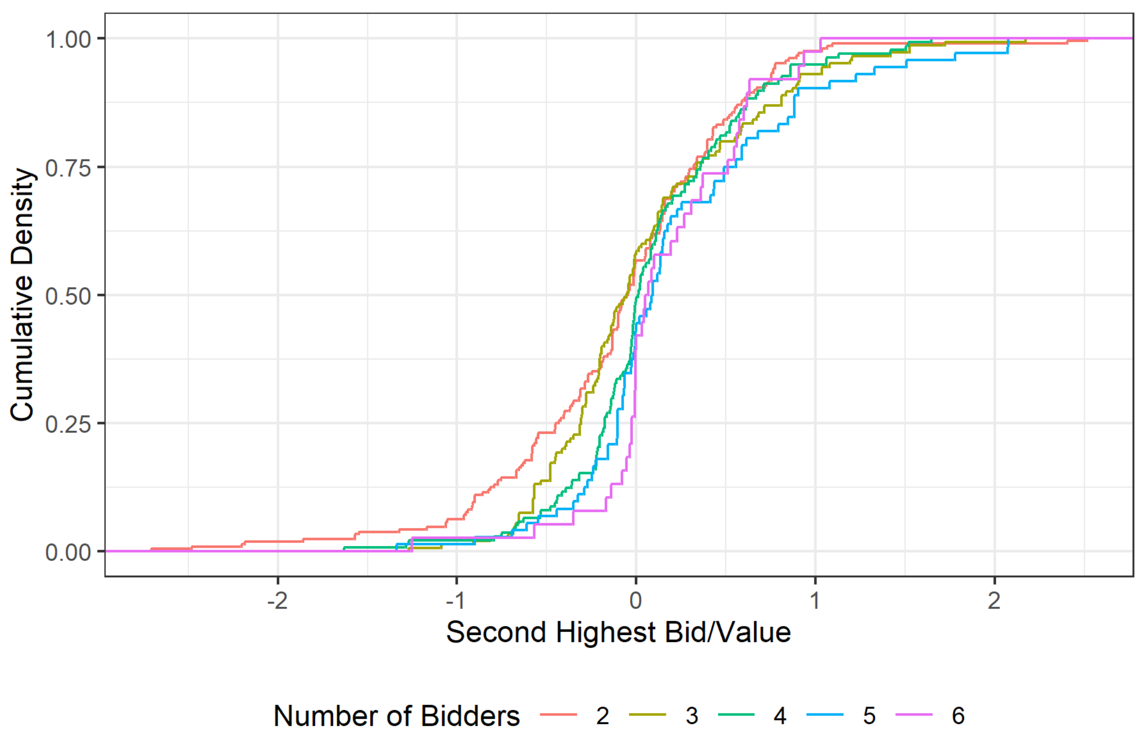

Figure 5: Distribution of second highest bid residual from model 1 according to number of bidders in the auction.

We see in table 9 that the left hand side is insignificantly larger than the right hand side which is consistent with the known downwards bias in the right hand side and is suggestive of an absence of common values in this setting. I report p values for the significance of the difference between the left and right hand sides from a pooled t test of the two. The p values are all quite large to the point where I fail to reject the assumption of private values. Therefore, it seems that I am safe in proceeding in this setting with the assumption that after controlling for observable variance in mineral quality and price, the primary driver of differences in bids is private values and not signals of common values.

Figure 5 shows that after controlling for observable parcel characteristics we see no difference in the distribution of values conditional on number of bidders in the auction. The formal test only compares one moment of these distributions, but this figure allows the reader to visually verify that a range of other moments defining the distribution would be consistent with the theory that transaction price residuals are not particularly affected in this setting by the number of bidders in the auction. If anything, we see that auctions with fewer bidders tend to have higher values, a finding inconsistent with a common values model of the market. Equivalent figures using reduced form model 5 controls have similar results and are in the appendix: table 10 and figure 11.

6.3 Similarity of Open Outcry and Online Tracts

One key assumption in performing counterfactual policy experiments on the open outcry auctions (and the reduced form analysis) is that the underlying distribution of values (both in the unobserved heterogeneity of the tract and in the bidders' private values) is the same in the two auction formats. Because the auctions have different revenue outcomes, this might lead to firms nominating different tracts in online auctions than in open outcry auctions during the period when these two auctions alternated.

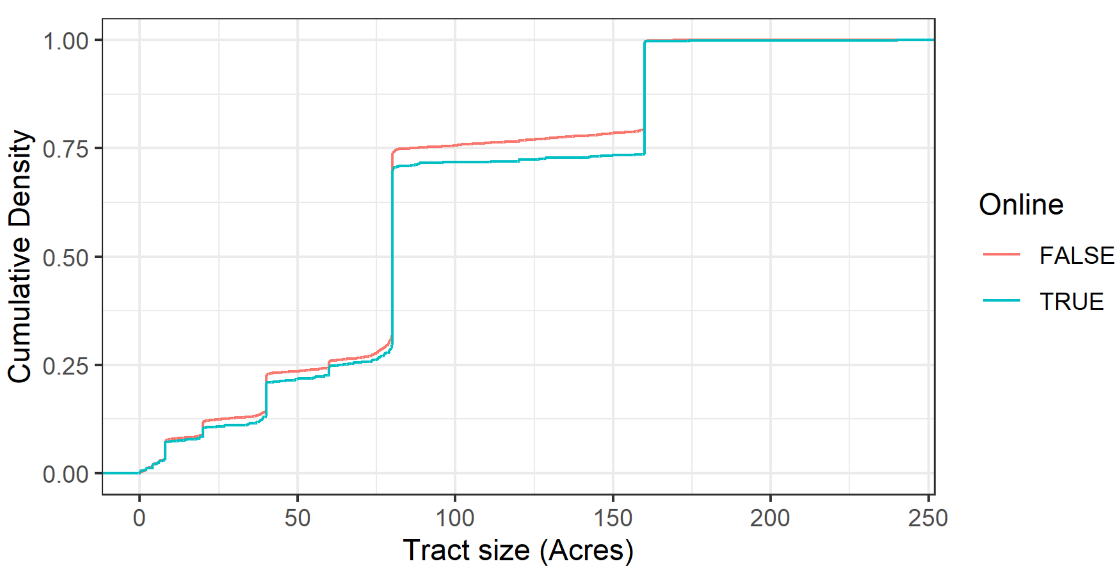

Figure 6: Distribution of sizes of parcels allocated to each auction

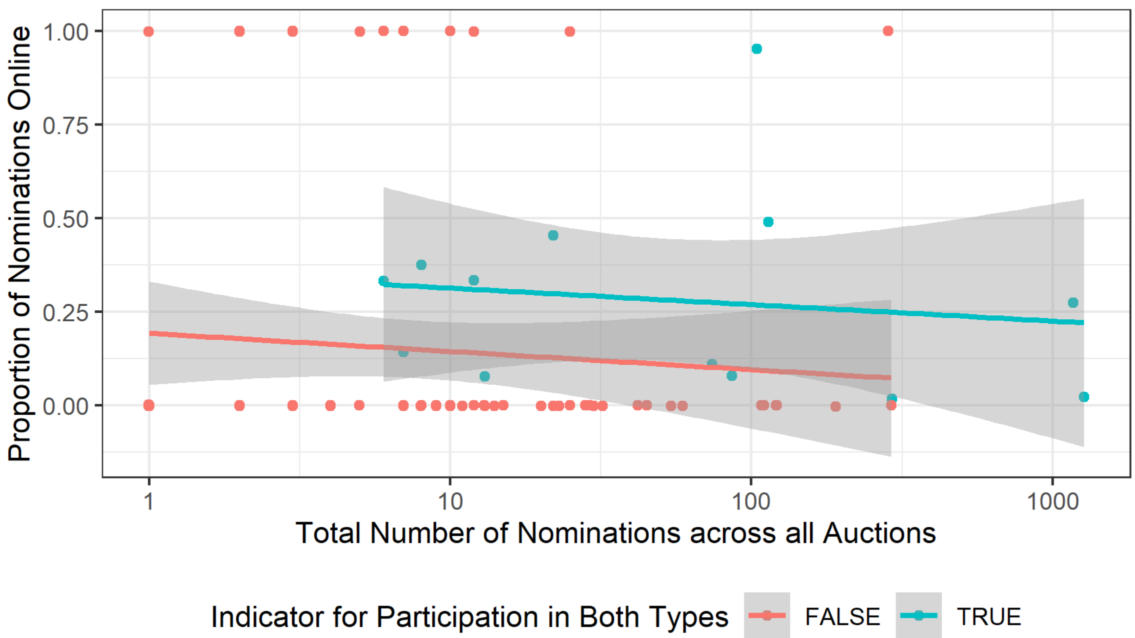

Figure 7: Nomination Patterns by Firm Size

Note that if online auctions yield higher prices, then the selection would be to put more valuable parcels in the open outcry auctions. This mechanism would work in the opposite direction of all the effects observed in this paper, so we could still safely interpret the measurements in this paper as lower bounds on the effect of the change in auction format.

There is empirical evidence suggestive of the idea that the parcels in these two auctions are not materially different from one another. Figure 6 shows the cumulative densities of the tract sizes in each open outcry and online auctions. They are fairly similar (although not identical). Figure 7 shows whether firm size affects whether a firm nominates more in online or open outcry auctions. The regressions in table 11 in the appendix show no significant relationship. Of all the township-range combinations which auction a parcel, 65% only use offline auctions, 8% only use online auctions, and the rest use a combination of both. There are no obvious patterns to the spatial distribution of these grids suggesting that certain formations are systematically selected into one auction format or another.

Appendix B: Additional Figures

Additional Figures Describing the Data

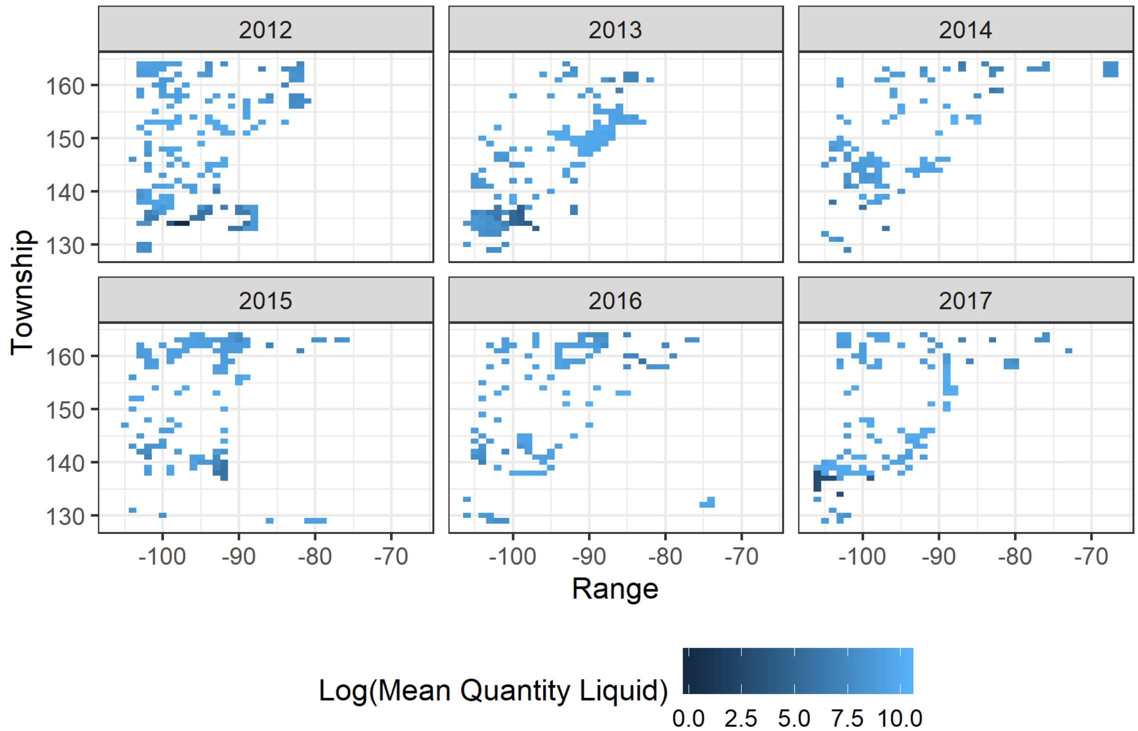

Figure 8: Average peak production month quantity of oil from wells in this township-range combination expected based on activity that occurred prior to the year of the auction. Grids colored in each year represent township range pairs that had an auction in that year.

Additional Reduced Form Figures

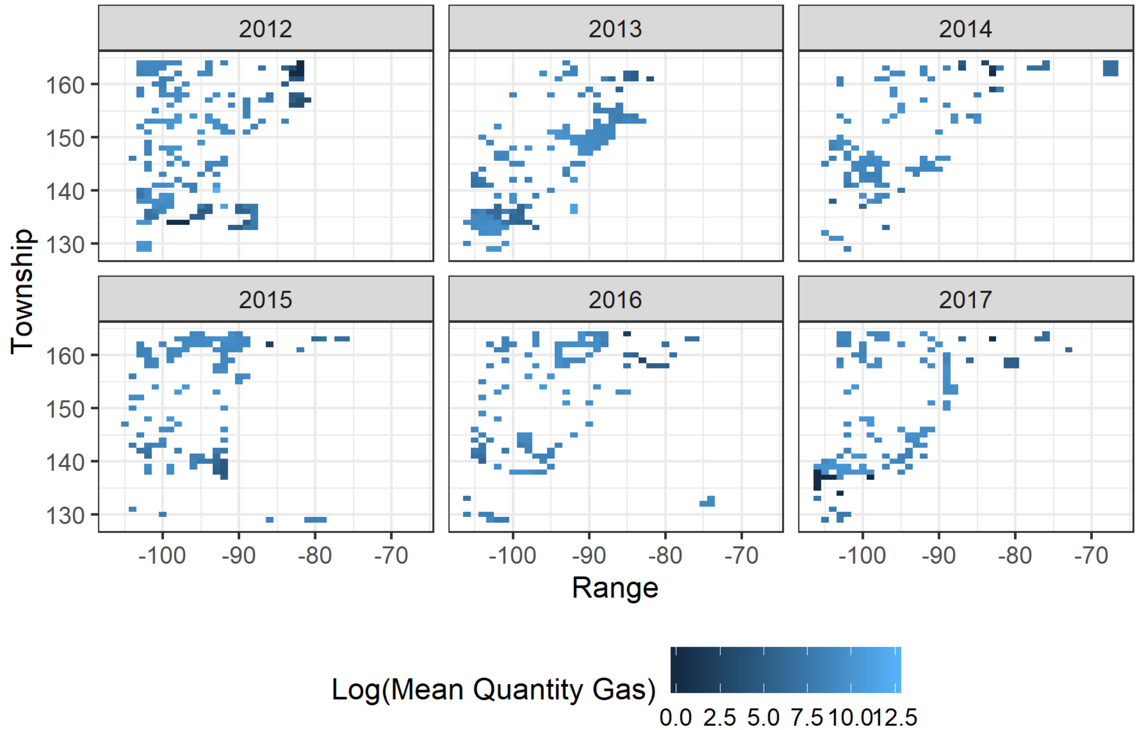

Figure 9: Average peak production month quantity of gas from wells in this township-range combination expected based on activity that occurred prior to the year of the auction. Grids colored in each year represent township range pairs that had an auction in that year.

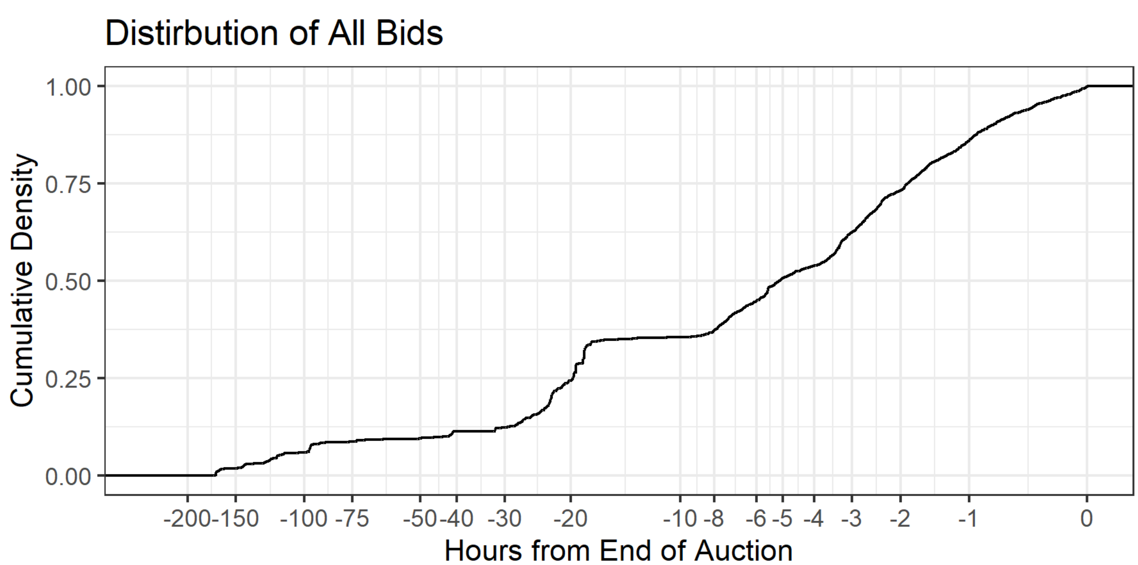

Figure 10: Distribution of Bid Timing for All Bids. Note that this figure uses a log transformed scale on the x axis.

n	LHS	RHS	Difference	p	LHS_{obs}	RHS_{obs}
3	-0.27 (1.78)	-0.32 (1.33)	0.05	0.99	208	145
4	0.55 (1.34)	0.73 (1.34)	-0.18	0.00	145	137
5	1.07 (1.37)	1.05 (1.17)	0.02	0.79	137	72
6	1.28 (1.17)	1.21 (1.29)	0.07	0.92	72	38
7	1.39 (1.33)	1.27 (1)	0.12	0.82	38	13
8	1.41 (0.92)	1.19 (0.77)	0.23	0.90	13	8

Table 10: Athey and Levin test for common values in Acending Auctions, Reduced form model 5 Controls for parcel value

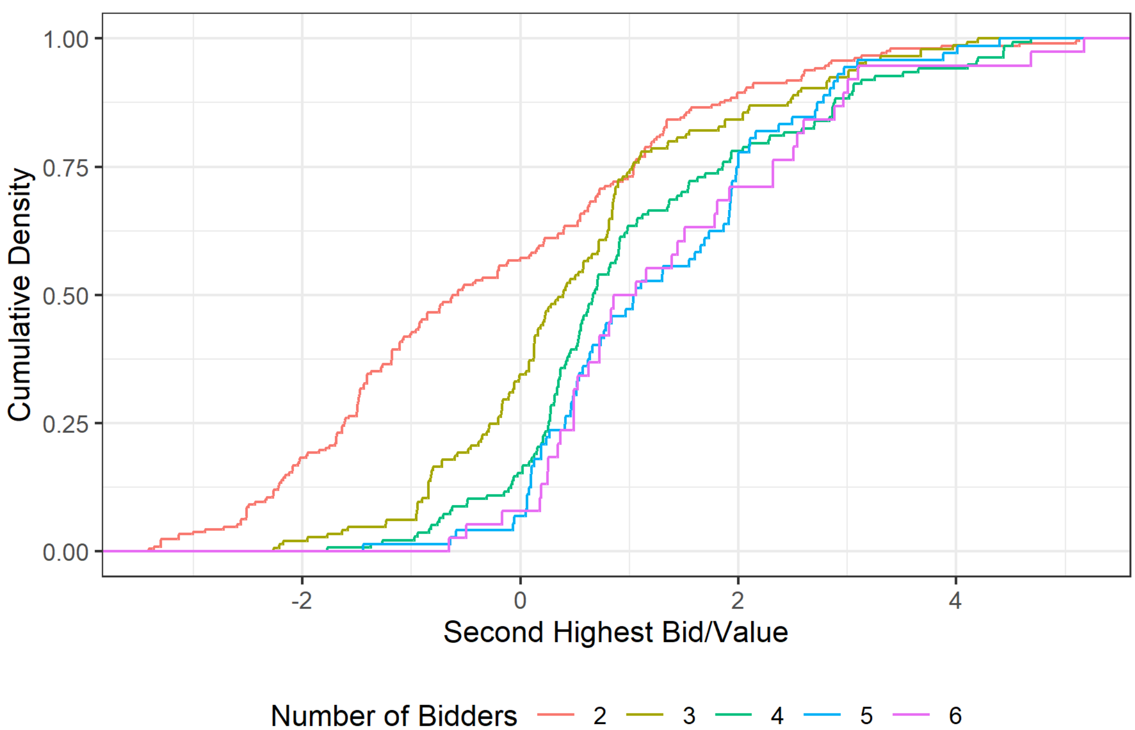

Figure 11: Distribution of second highest bid residual from model 5 according to number of bidders in the auction.

	Dependent variable:	
	Proportion of Nominations Online	
	(1)	(2)
Log(Total Nominations)	−0.006	−0.021
	(0.022)	(0.027)
Participate Both		0.164
		(0.248)
Interaction		0.002
		(0.061)
Intercept	0.181***	0.194***
	(0.063)	(0.068)
Observations	100	100
R^2	0.001	0.024
Adjusted R^2	−0.009	−0.007
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 11: Regressions testing whether larger firms (those who nominate more parcels) are more likely to nominate in online auctions