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ESTIMATION OF A MODEL OF ENTRY AND BIDDING ON WILDCAT OIL LEASES

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Abstract

This paper studies federal auctions for oil and gas exploration rights on the Outer Continental Shelf (OCS) from 1954 to 1970. In particular, I estimate the entry cost of bidding in wildcat oil leases whose geological and seismic characteristics are not well known by the bidders prior to bidding. Using that estimate and endogenizing the entry I then run counterfactual simulations to measure the effect of potential competition on government's revenue and analyze the choice of an optimal royalty rate.

1. Introduction

This paper studies federal auctions for oil and gas exploration rights on the Outer Continental Shelf (OCS) from 1954 to 1970. In particular, I estimate the entry cost of bidding in wildcat oil leases whose geological and seismic characteristics are not well known by the bidders prior to bidding. Using that estimate and endogenizing the entry I then run counterfactual simulations to measure the effect of potential competition on government's revenue and analyze the choice of an optimal royalty rate.

OCS wildcat auctions have been studied extensively in the literature. Porter (1995) provides a good summary of the previous work. Hendricks et al. (2003) analyzes whether bidders' behavior is consistent with rational and equilibrium bidding. They find that bidders are aware of the "winner's curse" and their bidding is largely consistent with equilibrium. In this paper, I conduct an analysis to see how the government's auction revenue (the winning bid) changes with the potential competition when entry is endogenous, and also simulate its revenue under different royalty rates.

Another contribution of this paper is to the literature on structural estimations of auctions. Structural econometrics of auction models has been studied widely since the pioneering work of

Paarsch (1992). Early work on this subject, Donald and Paarsch (1993) and Laffont and Vuong (1995), analyze parametric models, and use maximum likelihood and moment based estimators. One problem with these estimators is that objective function to be maximized includes highly nonlinear bid function which brings a significant computational burden. Guerre et al. (2000), proposes a non-parametric estimator which does not require computing the bid function but only the first order condition. All these papers examine first price sealed bid auctions with independent private values. Li et al. (2000, 2002) extend the analysis to conditionally independent and affiliated private values respectively, and Hendricks et al. (2003) considers the structural estimation of a common value model. Recent works by Li and Zheng (2009) and Athey et al. (2008) add the interesting feature of entry to the estimation problem within a private value setting. Ignoring the selection (entry) aspect of auctions is likely to give poor estimates. This paper extends the analysis for models with entry in private value framework to common value environment with entry. To the best of my knowledge, estimation of entry cost and simulation under endogenous entry in a first price common value auction setting as in this paper has never been done before. The closest papers to this one are Bajari and Hortacsu (2003), and Hendricks et al. (2003). While Bajari and Hortacsu (2003) examine a second price auction, this paper considers a first price auction. Moreover, Hendricks et al. (2003) (HPP hereafter) consider a first price common value auction model with entry yet they do not estimate the entry parameters nor entry cost that are needed to carry out the analysis in this paper.

The theoretical model I use is a version of HPP with a simplified entry condition as in Levin and Smith (1994). In this equilibrium firms play symmetric mixed strategies to decide whether to enter. This simplification considerably facilitates the estimation of the model. Indeed, I can estimate bidding and entry stage parameters separately in a straightforward way. However, this simplification in entry process costs us losing the information asymmetry in the entry stage which implies the possible effect of winner's curse is not considered in the entry stage. Though, the data set used in this paper is old and the auction mechanism has also changed after 1982, the approach taken in this paper can be considered as an illustration for how to conduct the analysis to reach policy implications. Generalizations of the model, especially for the entry stage, are quite possible though estimation would be more complex.

Previous papers estimating entry cost use fully structural estimation. Instead I use a reduced form approach for the bidding stage since it suffices for the current analysis and structural computations are heavier in first price common value auctions. Having estimated the model I test the equilibrium empirically using the test proposed by HPP. I then estimate the entry cost and run counterfactual simulations letting the entry be endogenous.

Section 2 briefly describes the OCS auctions mechanism. Section 3 explains the theoretical model and assumptions. Section 4 shortly gives some important summary statistics. Since I use the same data in HPP, I do not repeat the details of the data. Sections 5 and 6 explain the estimation method and provide results. Counterfactual simulations are discussed in Section 7. Section 8 concludes.

2. OCS Auction Environment

HPP and Porter (1995) give a detailed description of the OCS auction mechanism. Prior to the sale of wildcat leases, firms hire a geophysical company to "shoot" the seismic survey of a roughly 50 block area (HPP). Each tract is typically a block of 5000 acres. Having received the data from the seismic survey, each firm interprets this information possibly in different ways. Thus, it turns out that firms show interest on different tracts. Depending on the result of the seismic survey, firms may conduct an in-depth evaluation of the promising tracts before bidding. This tract specific analysis provides more accurate information in return for additional cost. Other than these two surveys firms do not have any information resource such as prior drilling results in or around the tract. Hence firms are symmetric ex-ante. In contrast, they do posses asymmetric information in drainage leases where some neighboring firms have prior information from previous drilling around the tract. Hendricks and Porter (1988) analyze equilibrium in these auctions. Bulbul Toklu and Toklu (2010) estimate the structural parameters of that model.

Each firm knows who conducts a seismic survey but does not know who is bidding on a tract. Tracts are sold simultaneously in a first-price sealed bid auction. The announced reserve price for tracts in the sample is $15 per acre. The government could and did reject bids above the reservation price but the rejection rate is less than 10% on wildcat tracts and usually occurred on marginal tracts (HPP). The winning firm has 5 years to explore the tract. If no wells are drilled during the lease term, government owns back the tract and may re-offer it later. If oil or gas is discovered and production occurs, the lease is automatically renewed. Producing firms pay a fixed fraction of their revenues from extraction called the *royalty rate* to the government. The royalty rate is 1/6 in the sample.

3. Theoretical Model

Theoretical assumptions of the model are similar to those in HPP. I will focus on the bidding behavior of the Big 12 firms. As HPP points out, there are hundreds of smaller firms bidding infrequently and they are probably not perceived as serious competitors by the major bidders since those smaller firms are less experienced and informed than the major bidders. Hence it is less likely to expect smaller firms behave according to the symmetric Bayesian Nash Equilibrium. For each tract t, N_t represents the number of potential bidders, who have conducted a seismic survey in an area containing tract t. If a firm finds tract t profitable enough, it then goes for a tract specific survey for tract t. Firms investing in tract specific survey are called active bidders. The number of active bidders is n_t. Firms still interested in tract t after the tract specific survey bid an amount above the reservation price, r_t and become actual bidders. In wildcat auctions the reservation price is argued to be too low in the literature. Li et al. (2000) assumes that the reservation price is non-binding. I will also follow that assumption in this paper. Hence, I needn't differentiate the terms "active bidder" and "actual bidder".

The value of tract t, V_t , is common but unknown to bidders. Potential bidders receive the symmetric seismic information, Z_t, and given this information they decide to become active or not. A bidder is called "enters" or "participates" auction t if it has decided to be an active bidder on tract t. I will focus on the symmetric Bayesian Nash Equilibrium where firms play symmetric mixed strategies for entry decisions as in Levin and Smith (1994). Though this is a stronger assumption than that in HPP, it significantly facilitates the estimation as well as the inference. Those who have decided to "enter" receive tract specific signals. As HPP points out, tract specific signals are more informative than seismic information. So I follow HPP assuming that firms only consider tract specific information in the bidding stage. Let S_{it} denote the private signal of bidder i from tract specific survey for tract t. I assume (V_t , Z_t, S_{1t} ,…, S_{nt}) are affiliated and the last n components are exchangeable with respect to bidder indices. Moreover, signals Z_t, S_{1t} ,…, S_{nt} for tract t are assumed to be independent for each tract conditional on the common value of tract. In other words, V_t is the only source of the affiliation among signals. I will use the vector S_t = (S_{1t} ,…, S_{nt}) to denote the collection of tract specific signals for tract t.

3.1 Bidding Stage

Each firm i only observes its private signal, S_{it}, but not those of others, S_{-it}. N_t, the number of potential bidders, is observable by all bidders but the entry decision of rivals is not. Let $p_k(s,z)$ denote the probability that a bidder has k active rivals given that the bidder has signal s and seismic information z. Because Z_t is symmetric among bidders and is the only available information prior to entry, Z_t turns out to be the only variable that affects entry; thus, the probability can be written $p_k(z)$[1]. I will suppress the variable z and use the shorthand notation p_k. This simplification alleviates the computational burden. Back to the model, let $Y_{it} = \max_{i \neq j} S_{jt}$ be the maximum signal among bidder i's rivals. I can then write the cdf of Y_{it} when bidder i decides to enter and has at least one rival as,

$$H_{Y_{it}|S_{it}}(y|s) = \sum_{k=1}^{N_t} \frac{p_k}{1-p_0} F_{Y_{it}|S_{it}}(y|S_{it} = s, n = k+1)$$

where, $F_{Y_{it}|S_{it}}(y|S_{it} = s, n = k+1)$ is the cdf of Y_{it} when i has exactly k rivals.

Also let $w_{it}(s,y) = E[V_t|S_{it} = s, Y_{it} = y, n \geq 2]$ be bidder i's expected value from tract t when its signal is s and the maximum of his rivals' signal is y. When bidder has no active rival, his expected value is $w_{it}(s) = E[V_t|S_{it} = s, n = 1]$. As Milgrom and Weber (1982) points out, affiliation makes $w_{it}(s,y)$ and $w_{it}(s)$ increasing functions. I will follow HPP deriving the optimal bidding strategy of a bidder who has a signal s. When each rival of bidder i adopts the increasing and differentiable bidding strategy $\beta(s)$ with inverse $\eta(b)$, bidder i chooses $b \geq r$ to maximize

$$\Pi_{it}(b,s) = (1-p_0) \int_{\underline{s}}^{\eta(b)} (w(s,y) - b) h_{Y_{it}|S_{it}}(y|s) dy + p_0(w(s) - b)$$

The first order condition for a maximum is

$$(1-p_0)\left[\left(w_{it}\left(s,\eta(b)\right) - b\right) h_{Y_{it}|S_{it}}(\eta(b)|s)\eta'(b) - H_{Y_{it}|S_{it}}(\eta(b)|s)\right] - p_0 = 0$$

Bidder i's best response b= $\beta(s)$ should also satisfy FOC above. Substituting it above gives:

$$(1-p_0)\left[\left(w_{it}(s,s) - \beta(s)\right)\frac{h_{Y_{it}|S_{it}}(s|s)}{\beta'(s)} - H_{Y_{it}|S_{it}}(s|s)\right] - p_0 = 0 \qquad (1)$$

[1] Note that bidders receive asymmetric signals in HPP and thus they keep the probability in its general form $p_k(s,z)$.

Let M_{it} be the highest bid submitted by bidder i's rival or the reserve price in the absence of a rival bid. Because of the monotonicity of β and η, the cdf and pdf of M_{it} conditional on the bid variable, B_{it}, can be expressed as follows:

$$G_{M_{it}|B_{it}}(m|b) = [1 - p_0]H_{Y_{it}|S_{it}}\big(\eta(b)\big|\eta(m)\big) + p_0$$

$$g_{M_{it}|B_{it}}(m|b) = \frac{[1 - p_0]h_{Y_{it}|S_{it}}\big(\eta(b)\big|\eta(m)\big)}{\beta'(\eta(m))}$$

Substituting these in equation (1) gives,

$$w_{it}\big(\eta(b), \eta(b)\big) = b + \frac{G_{M_{it}|B_{it}}(b|b)}{g_{M_{it}|B_{it}}(b|b)} = \xi(b, G) \tag{2}$$

In the private value setting Guerre et al (2000) use the equation above to identify and estimate the value distribution non-parametrically. HPP uses it testing jointly for affiliation, symmetry, and equilibrium bidding. I will also follow their way to test the model using that equation.

3.2 Entry Stage

In the entry stage where firms have information Z_t from seismic survey, each bidder decides whether or not to go for a tract specific survey and receive more precise signal, S_{it}. Those who have decided to make a tract specific survey are called "entered" bidders. I model the entry behavior as in Levin and Smith (1994) where bidders follow symmetric mixed strategies. In this setup the entry probability and thus the number of entering bidders are endogenous and determined according to the following zero profit condition,

$$K_t(Z_t, N_t) = \int \Pi_{it}(\beta(s), s) f_s(s) ds \tag{3}$$

where K_t is the entry cost which contains the cost for tract specific survey as well as the time and effort spent for bid preparation, and the opportunity cost of bidding. The right hand side of the equation is the ex-ante expected profit a bidder gets from entering the auction and bidding optimally in the second (bidding) stage.

In a mixed strategy equilibrium expected profits from both entering and not entering should be the same. Also, bidders make their participation (entry) decisions independently given Z_t. So participation decisions of firms can be viewed as independent Bernoulli random variables conditional on Z_t with identical probability of entry for all bidders[2]. This entry setup assumes that firms are ex-ante identical in terms of information. Because potential bidders only have seismic information, this means seismic information is not subject to interpretation among firms, which also implies winner curse is not an issue in the entry stage. This may be a strong assumption yet it simplifies the estimation of the entry parameters. Moreover, one can think that the symmetric entry probability is unrelated to the value of the tract. However, as will be clear later, entry cost for tract t depends on the value, V_t; therefore, entry probability is also dependent upon the value, V_t, through the zero-profit condition.

4. The Data

The sample consists of sales of wildcat tracts off the coasts of Texas and Louisiana held during the period 1954-1970 inclusive. For all the tracts that has received at least one bid we know the date of sale, location, acreage, the identity of participating bidders and the amounts they bid, whether any wells were drilled, and production of oil and natural gas through 1991. HPP calculated the ex-post value of tracts by subtracting discounted drilling costs and royalty payments from discounted revenues. They converted production flows into revenues using the real wellhead prices at the date of the sale, and discounted them to the auction date at a 5% per annum rate. They used the survey from the American Petroleum Institute to compute discounted drilling costs for each tract using the same discount rate. Also royalty payments are computed by taking 1/6 of the discounted revenues. Tracts not drilled are given a value of zero[3].

HPP also constructs a measure for the number of potential bidders on each tract in the following way. They define a neighborhood for each tract and count the number of Big 12 firms that bid on the tract or in its neighborhood. The rationale they provide is that if a Big 12 firm is interested in the area it will probably bid on at least one tract. Recall that the analysis is conducted only for the Big 12 firms since other fringe firms are less experienced and thus likely to deviate from the equilibrium behavior.

[2] There may also be other asymmetric pure-strategy equilibria of the game. One evidence consistent with this symmetric equilibrium is that participation rates of Big 12 firms are close to each other varying mostly from 0.3 to 0.5 and the set of actual bidders changes from auction to auction indicating that firms may use the same entry probability to make their entry decisions.

[3] Though having a measure for the tract value is very unique and also useful for the econometric analysis, HPP indicates that this is subject to measurement error due to sources such as firms' expectations about the future prices of oil, using a specific discount rate, and truncated production histories in 1991.

TABLE 1					
Summary of Wildcat Sales: sold, drilled, big twelve, more than 2 potential bidders, 1954-1970					
	Total # of Tracts	Hits	Mean Rev	Mean Net Rev	Mean Hibid
Summary Statistics	837	402	58.94	13.89	8.00

* Dollar figures are in millions of 1982 dollars

Moreover, in the estimation I only used the drilled tracts for which more than 2 potential bidders exist. The zero value assigned to tracts that are not drilled may not represent the actual tract value, and firms may diverge from competitive behavior when there is no potential rival. **Table 1** provides the summary statistics for the sample used in estimation. In this set of tracts, average ex-post profit is around $13.89 million and the average winning bid is $8 million. Fraction of tracts drilled in the whole sample is around 75%, and the fraction of productive tracts among drilled tracts is around 50% respectively.

5. Estimation

In this section I describe the parametric assumptions I make for the econometric analysis and explain the estimation methodology. Because I assume the reserve price is non-binding, the number of active bidders is observed. Hence, I can estimate the model in two stages. In principle, to do the structural estimation one can assume a signal distribution and using the monotone bid function one can derive the bid distribution to construct the likelihood function. In a first price common value auction there are two basic problems with this approach. First, the bid function is highly nonlinear and does not have a closed form solution except for a few cases. So deriving the bid distribution is not trivial. Second, as Donald and Paarsch (1993) point out, the support of the bid distribution depends upon the parameters to be estimated which rules out the standard application of the asymptotic theory. To overcome this problem Bajari & Hortacsu (2003) use Bayesian estimation in a second price common value auction.

In order to model endogenous entry one needs to know two entry variables: Entry cost and entry probability. Both of them can be estimated using the zero profit condition. In fact, one does not even need to do structural modeling for the bidding stage for this purpose. The idea is that since the bid function is monotone one can change the conditioning signal variable with the observed bid variable. Thus, one does not have to estimate the latent signal distribution, which allows the use of a reduced form approach for the bidding stage. I use maximum likelihood (ML) and simulated maximum likelihood (SML) estimations for bidding and entry stages, respectively. For the entry stage, because seismic signal Z_t is an unobserved covariate in the likelihood function, I integrate it out, but the likelihood function does not have closed form. So I simulate the likelihood function.

5.1 Estimation of Bidding Parameters

Recall that I assume that tract specific signals, S_{it}, are affiliated for a given tract t but independent conditional on tract value, V_t. Because a bid is an increasing function of the signal, $b_{it} = \beta(S_{it})$, bids are also affiliated but independent conditional on V_t. I assume bids admit a lognormal distribution conditional on V_t as follows

$$G_{b_{it}|V_t,N_t,n_t}(b|V,N,n) = lognorm(\mu(V_t,N_t,n_t),\sigma(V_t,N_t,n_t))$$

where, $\mu(V_t,N_t,n_t) = \beta_1 + \beta_2 V_t + \beta_3 N_t + \beta_4 n_t$ and $\sigma(V_t,N_t,n_t) = \beta_5 + \beta_6 N_t + \beta_7 n_t$ are the parameters of the lognormal distribution, and n_t is the number of bids submitted to tract t. Because I assume a nonbinding reserve price, n_t is also the number of active bidders in auction t. Note that active bidders do not observe the number of entering rivals and thus n_t. However, I include n_t as a covariate of the bid distribution since a bid is a function of the entry probability which together with N_t determine the expected number of entering bidders. Moreover, coefficients of n_t are also critical in understanding the winner's curse and competition effects. Recall that in a common value auction setting an increase in the number of rivals having asymmetric information triggers two counteracting effects. Bidders may increase their bids due to competition effect; or considering that the winner will be the most optimistic bidder ex-post, they may reduce their bids. The net effect comes out from the interaction of these two effects. Furthermore, letting $g_{b_{it}|V_t,N_t,n_t}(.|.)$ denote the pdf of $G_{b_{it}|V_t,N_t,n_t}(.|.)$, the likelihood function for auction t conditional on V_t, N_t , and n_t is

$$L_t(\sigma_t,\mu_t|V_t,N_t,n_t) = \prod_{i=1}^{n_t} g_{b_{it}|V_t,N_t,n_t}(b_{it}|V_t,N_t,n_t)$$

Then ML estimates of the bidding stage parameters can obtained as

$$(\widehat{\beta_1}, \dots, \widehat{\beta_7}) = \max_{\beta_1,\dots,\beta_7} \left\{ log \sum_{t=1}^{T} L_t(\sigma_t, \mu_t | V_t, N_t, n_t) \right\}$$

Note that one can solve equation (1) to obtain the bid function explicitly. Though it is not practical in this setup, one can then use the inverse bid function to obtain pseudo values for signal realizations. Signal distribution is non-parametrically identified and estimation of it can be done as in Guerre et el. (2000). However, to estimate the entry cost and simulate endogenous entry this is not necessary, so we do not have to deal with the computational difficulties involved therein.

5.2 Estimation of Entry Parameters

Before making their entry decisions firms observe the symmetric seismic signal, Z_t, and use the mixed strategy entry probability which equates the entry cost $K_t(Z_t, N_t)$ with the ex-ante expected profit $\int \Pi_{it}(\beta(s), s) f_s(s) ds$. In this analysis entry cost is presumed to be known by firms yet unobserved to the econometrician. So, one first needs to estimate the entry cost $K_t(Z_t, N_t)$ in order to simulate the endogenous entry. Because Z_t is the only information available to firms prior to entry, firms' entry decisions will be affiliated but independent conditional on Z_t. Since V_t is sufficient for Z_t , I will assume that entry decisions are independent conditional on tract value,V_t, and are distributed with Bernoulli process conditional on V_t with the entry probability

$$p_{n_t} = p(V_t, N_t, n_t) = \frac{\exp(\alpha_1 + \alpha_2 V_t + \alpha_3 N_t + \alpha_4 n_t)}{1 + \exp(\alpha_1 + \alpha_2 V_t + \alpha_3 N_t + \alpha_4 n_t)}$$

.

Then for a given tract t, the probability that observed n_t bidders enter the auction is,

$$L_t(\alpha_1, \alpha_2, \alpha_3, \alpha_4 | V_t, N_t, n_t) = p(V_t, N_t, n_t)^{n_t} (1 - p(V_t, N_t, n_t))^{N_t - n_t}$$

Entry parameters can then be estimated as follows[4]

$$(\widehat{\alpha_1}, \widehat{\alpha_2}, \widehat{\alpha_3}, \widehat{\alpha_4}) = \max_{\alpha_1,\alpha_2,\alpha_3,\alpha_4} \left\{ log \sum_{t=1}^{T} L_t(\alpha_{11}, \alpha_{12}, \alpha_{13} | V_t, N_t, n_t) \right\}$$

[4] In the earlier stages of this study I assumed that seismic signal Z_t is normally distributed with a mean, V_t ,and variance $a_1 + a_2 V_t$. I then estimated the entry stage parameters as well as the distribution of Z_t by simulated maximum likelihood. Though this approach is more appropriate for this paper, bidders consistently overestimate the expected value of each tract which yields higher entry costs. So I have decided to follow the simpler way where I used V_t as a proxy for Z_t and entry decisions distributed independently conditional on V_t.

Finally, I estimate the entry cost using the zero-profit condition. Note that condition (3) contains the unknown signal distribution parameters as follows

$$K_t = \int_{\underline{s}}^{\bar{s}} \Big\{ \Big[p_0\big(E(V_t|S=s)-\beta(s)\big) + \sum_{k=1}^{N_t-1} p_k \int_{\underline{s}}^{s} \big(E(V_t|S=s, Y=y, n_t=k+1) - \beta(s)\big) f_{(y|s)}(y|s, n_t=k+1)dy \Big] f_s(s)ds \Big\}$$

where, I suppressed the bidder indices since bidders are symmetric. Moreover, because tract specific signals, S_t, are more informative (sufficient) than seismic signal, Z_t does not appear as an additional conditioning variable when S_t is available. To estimate K_t, I simply use the monotonicity of the bid function and rewrite the above identity in terms of bids. To do this first notice the following

$$G_{b_{it}|V_t,N_t,n_t}(B \le b|V,N,n) = Prob(\beta(s) \le b|V,N,n) = F_{s_{it}|V_t,N_t,n_t}(\beta^{-1}(b)|V,N,n)$$

Then we also have,

$$g_{b_{it}|V_t,N_t,n_t}(b|V,N,n) = \frac{f_{s_{it}|V_t,N_t,n_t}(s|V,N,n)}{\beta'(s)} \text{ where } b=\beta(s) \text{ and } db=\beta'(s)ds.$$

Moreover, since p_k is not updated with the signal S_t, it remains the same in the equation.

Plugging these back into K_t's equation gives,

$$K_t = \int_{\underline{b}}^{\bar{b}} \Big\{ \Big[p_0(E(V_t|B=b)-b) + \sum_{k=1}^{N_t-1} p_k \int_{\underline{b}}^{b} (E(V_t|B=b, M=m, n_t=k+1) - b) g_{(m|s)}(m|b, n_t=k+1)dm \Big] g(b)db \Big\}$$

6. Estimation Results

Table 2 and **3** summarize the estimation results for entry and bidding stages. Among the entry parameters, coefficients of N_t and n_t are significant. Because higher entry probability raises the expected number of active bidders, n_t has a positive significant coefficient explaining most of the variation in entry probability.

TABLE 2: Estimation of the entry process

		p	
Variables	Coefficient	Estimate	s.e
Cost C	α_1	-0.19109	0.12685
Value V	α_2	-0.03591	0.06288
Number of Potential Bidders N	*α_3	-0.32024	0.01777
Number of Bidders n	*α_4	0.66540	0.02063

* Significant at 95%

TABLE 3: Estimation of the bid distribution

	mean			variance		
Variables	coefficient	estimate	s.e	coefficient	estimate	s.e
Cost C	*β_1	1.61493	0.08108	*β_5	1.03705	0.05775
Value V	*β_2	0.00020	0.00005	β_6	0.00005	0.00005
					-	
Number of Potential Bidders N	*β_3	0.02286	0.01119	β_7	0.00227	0.00798
Number of Bidders n	*β_4	0.25482	0.01251	*β_8	0.04612	0.00947

* Significant at 95%

Regarding the bidding estimates, except for the coefficients of N_t and V_t in the scale parameter, all parameters are significant. The mean of equilibrium bids increases with tract value V_t as expected. One interesting point is that coefficients of n_t have positive signs implying that expected competition among bidders overcomes the winner's curse effect and makes bidder bid more aggressively. In my model, because seismic signal Z_t is symmetric among bidders, there is no winner's curse effect for the entry stage. In general, a bid is a function of number of potential firms, entry probability, and the private tract specific signal. One way to analyze the winner's curse effect is to increase the probability of entry while keeping all other variables constant, and observe the change in bids. Since bidding stage is not structural in my model, I cannot totally observe this separate effect but the total change in equilibrium bid function. Positive coefficients of n_t indicates that this effect is dominated by the expected competition among bidders and bids are raised accordingly in equilibrium. Nevertheless, this does not mean that winner's curse is totally dampened by competition. HPP shows that winner's curse exists and firms correct their bids in equilibrium taking it into account. In a structural model where firms have asymmetric seismic signals, the effect of winner's curse in the entry stage can also be quantified.

To see the fit of the model I simulate entries and then bids using the calibrated model. Figures 1 and 2 show the actual bid dispersion and the simulated bid dispersion respectively. The model seems to provide a moderate approximation to the actual outcome.

Figure 1

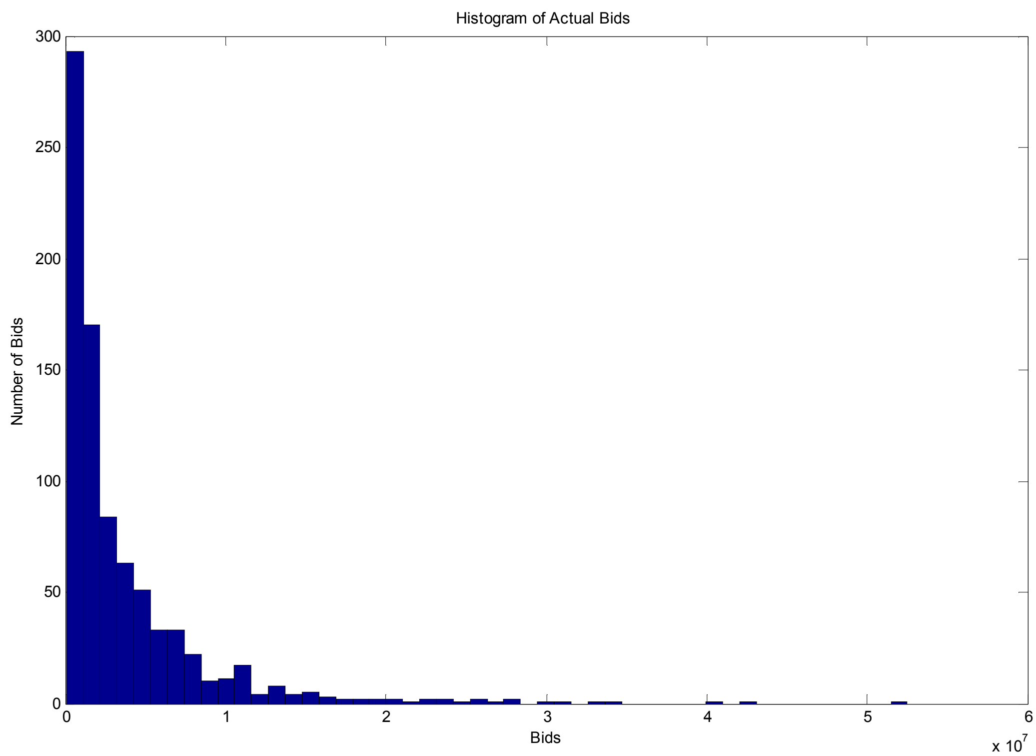
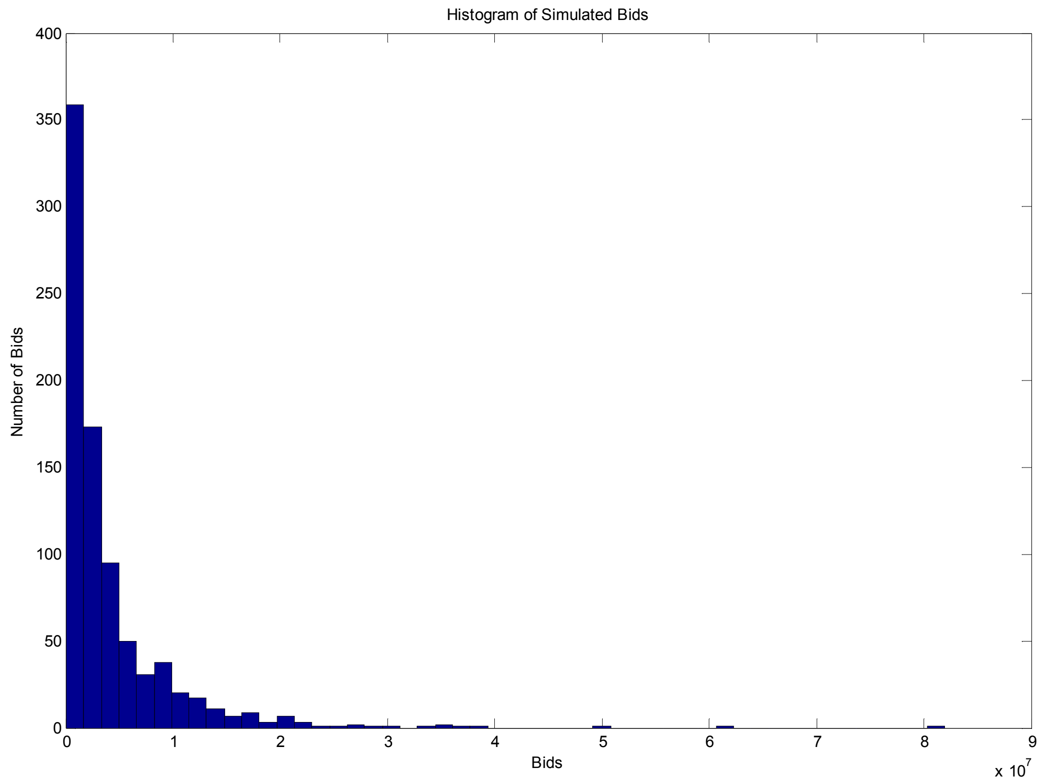


Figure 2



One other aspect I need to check is the consistency of the model with the equilibrium. So far all estimations were carried out in reduced form and I have not imposed any equilibrium condition. So, one needs to make sure that estimates satisfy the equilibrium. To test this empirically I will use the transformed first order condition as in HPP. This is indeed a joint test for all modeling assumptions as well as equilibrium. We would expect the difference between $w_{it}\big(\eta(b),\eta(b)\big)$ and $b+\frac{G_{M_{it}|B_{it}}(b|b)}{g_{M_{it}|B_{it}}(b|b)}$ to be zero for each bid observation.

However, before estimating this statistic I need to impose some further parameterization regarding tract values. So far I have not said anything regarding the distribution of tract values, V_t. To compute $w_{it}\big(\eta(b),\eta(b)\big)$ I need to define a distribution for tract values. Because tracts are expected to be spatially correlated, I will utilize this in defining the distribution of V_t, $f_{V_t}(V)$. In the earlier stages of this study, I assumed a spatial AR process for tract values as follows:

$V = \rho WV + u$,where V is the Tx1 vector of tract values, W is the TxT spatial weight matrix, $u \sim N(0, \sigma^2 I)$ is the error term, and ρ and $\sigma^2$are the parameters to be estimated. Following the estimation way in Ord (1975) I got the estimates for ρ and σ^2. The problem with this is that the estimate for σ^2 is so large that expectations for tract values become unstable. Having encountered this problem I chose a simpler assumption for tract values. For each tract value ,V_t, I construct a neighborhood with a radius of 15 miles centered on V_t. Within this neighborhood I assume tract values are normally distributed, and estimate the mean and the variance of the corresponding distribution for each tract value. Of course, the distribution of tract values is affected by the choice of radius. I also experimented with different radii and chose this one since it makes on average 25 tracts to be contained in each neighborhood, and the mean and the variance estimates do not get extreme values.

Figure 3

$$w_{it}\big(\eta(b),\eta(b)\big) - \left(b + \frac{G_{M_{it}|B_{it}}(b|b)}{g_{M_{it}|B_{it}}(b|b)}\right)$$

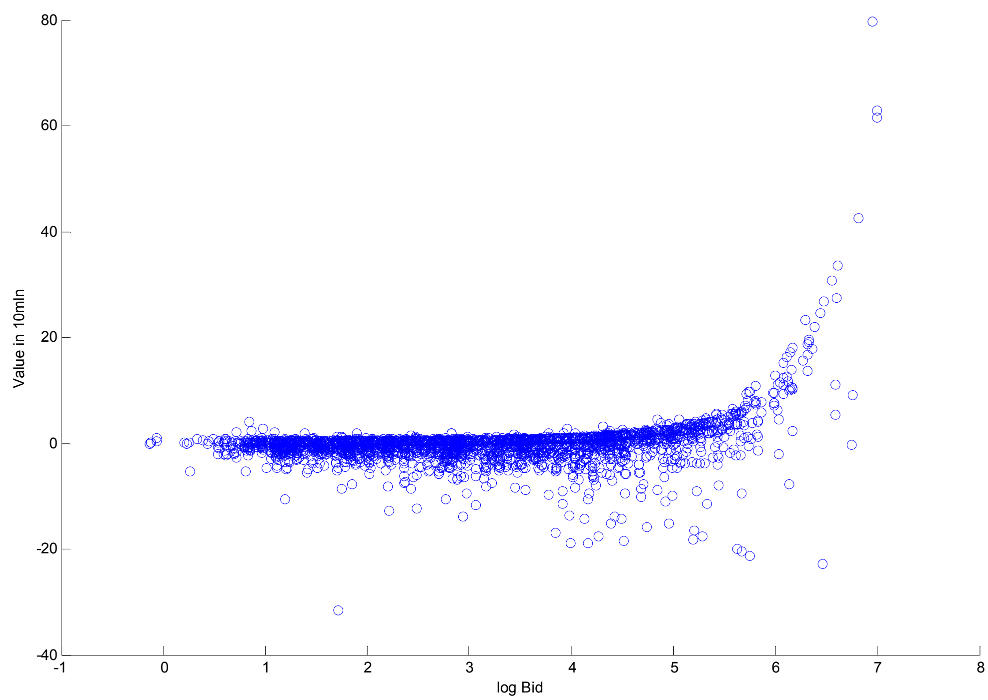


Figure 3 shows a plot of the aforementioned test statistic with respect to bid values. HPP finds that although this condition is satisfied by some bids, there are still bid values violating it. The results are similar here as well. Especially for larger bid values equilibrium behavior gets harder to be justified. Finding bootstrap confidence bands for all bids is quite time consuming since I do parametric estimation. Instead I choose a random sample from the data by block bootstrap and obtained the confidence bands for this sample. Results are given in Figure.

Figure 4 here

Next, I estimate the entry cost using the transformed zero profit condition. Entry cost changes with tract value and the number of potential bidders. So I choose a representative tract (tract # 786) whose properties are close to sample averages. Its value is around \$13.5 million and has 7 potential bidders. Entry cost for this tract is calculated as \$2.8 million with a standard error of 0.9. I calculated its standard error by varying the radius of its neighborhood from 1 mile to 30 miles. Expected tract value strongly affects the entry cost and changes with the neighborhood radius. Hence, obtaining standard errors in this fashion may be expected to be a plausible approximate.

7. Counterfactual Analysis

In this section I run counterfactual simulations using the calibrated model to find empirical answers to questions regarding potential competition and the royalty rate. First, I quantify the effect of potential competition on government's auction revenue (winning bid). Government can utilize this information to encourage or discourage potential competition. Then, I conduct an analysis for the royalty rate by simulations which will be explained in the last section.

7.1 Quantifying the Effect of Potential Competition on Government's Revenue

This section describes how to quantify the effect of potential competition on winning bid which turns out to be the revenue for the government. In general, a change in the number of potential bidders affects bids in more than one way. Li and Zheng (2009) (LZ hereafter) coin the terminology "entry effect" and "competition effect" to analyze the total effect by a change in the number of potential bidders. They quantify these two effects using a structural model for private value procurement auctions. Later, De Silva et al. (2009) carry the analysis to a more general setting including common values. LZ defines the "competition effect" as the effect on bids caused by increasing the number of potential bidders one unit while keeping the equilibrium entry probability the same. In IPV setting, LZ shows that "competition effect" makes bidder more aggressive. For common value settings like the one in this paper; however, the effect is ambiguous since the winner's curse effect works in the opposite direction making bidders behave less aggressively (De Silva ,2009).

Moreover, LZ defines the "entry effect" as the effect of increasing the number of potential bidders on bids through the entry stage. In practice this amounts to subtracting the "competition effect" from the "total effect", which measures the total effect of increasing the number of potential bidders on bids allowing everything change according to model dynamics. LZ shows that "entry effect" is counteracting the "competition effect", and the "total effect" can make bidders behave less aggressively, an argument that cannot be implied by IPV models without entry. For the common value case the "entry effect" is again ambiguous due to winner's curse considerations and depends upon the model parameters.

To sum up, the total effect of potential competition is uncertain in a model with endogenous entry, and case specific analysis is required for inference. Using the calibrated model and endogenizing the entry, I run counterfactual simulations to quantify the total effect of potential competition on winning bid. I take the same representative tract for which I estimated the entry cost. Using the zero-profit condition and estimate for the entry cost, I find the symmetric equilibrium entry probability for this tract. Then I increase the number of potential bidders from 2 to 12 one by one, and for each number I find the corresponding entry probability again and simulate entries and bids. I record the change in winning bid as the total effect of potential competition on winning bid. Note that since my model is not structural for the bidding stage I cannot quantify the "entry" and "competition" effects separately. Figure 5 shows the change in average winning bid in response to potential competition.

Figure 5 here

It is clear that increasing number of potential firms triggers the competition effect more compared to winner's curse effect. Hence the winning bid consistently rises with the potential competition. This may give government an incentive to encourage potential competition among wildcat tracts. Recall that because entry stage rules out asymmetries we ignore the possible effect of winner's curse for the entry stage. This result makes more sense in environments where seismic signal is more precise, and thus informational asymmetries are negligible in the entry stage.

7.2 An Ex-Post Analysis for the Royalty Rate

One of the policy parameters that the government can manipulate in OCS auctions is the royalty rate. Though there are both theoretical and empirical results for the computation of the optimal reserve price, finding an optimal royalty rate has not been investigated much, to the best of my knowledge. The royalty rate is the fraction which is multiplied by the discounted revenues of producing firms to determine the amount producing firms have to pay. Reducing the royalty rate makes tracts more valuable for firms, thus spurring firms to enter and bid higher which means higher revenue for the government. On the other hand, the government can only get a smaller portion of this raised revenue as well. Clearly, there is a trade off for the government, and I use the calibrated model to conduct an ex-post analysis for the royalty rate. To do this, I use the same representative tract and change the royalty rate from 0 to 1, and report the optimal rate as the one that gives highest ex-post total revenue for the government. For each royalty level, firms' entry behavior is determined endogenously again. This analysis may not be used safely in determining policy since it relies on strong assumptions. As the royalty rate and thus the tract value changes, bidders' expectations should adjust accordingly so that if a firm wins the auction it should extract the same amount of oil, make the same revenue, and spend the same money. In other words this assumes production decisions of firms do not change once the firm wins the auction. This assumption is strong since marginal cost of producing is not constant during production. Especially when production is lowered at later stages, marginal cost gets higher which makes firm stop producing earlier. Increasing the royalty rate can result in earlier abandonment of the tract than what is observed for the initial royalty rate. Because production decisions are not controlled for in this analysis, royalty rates maximizing government's total surplus are likely to be overestimated.

Figure 6 here

Another issue is that optimal royalty rate changes with tract value in this analysis. For ex-ante more profitable tracts optimal royalty rates are higher under the aforementioned assumptions. Figure 6 shows the change in government's revenue, which is the sum of winning bid and royalty revenue, for the same representative tract. The maximizing royalty rate appears to be 2/5 which is much higher than the applied rate 1/6, and likely to be overestimated for the stated reason. To conclude, estimates given in this section may better be taken as an approximate upper bound for the optimal royalty rate due to upward bias. A better estimate can be obtained using a dynamic model where firms' production decisions are updated at any given time depending on the instantaneous expected revenue.

8. Conclusion

This paper analyzes the widely used OCS wildcat auction data set, and attempts to find answers to policy questions using a common value model with endogenous entry. Although a fully structural estimation would enable one to make a more detailed analysis, a reduced form approach for estimating bidding parameters suffices to estimate entry cost and deduce some policy implications without ignoring selection (entry) issue. Potential competition among bidders seems to dominate all other counteracting effects and make bidders bid aggressively which may give the government an incentive to encourage potential competition. Moreover, an ex-post analysis for the royalty rate shows that the government's choice of 1/6 royalty rate can be justified considering the upward bias in our estimate.

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