When the Seller Can't Commit: Bidder Response and Revenue Implications in Oil and Gas Lease Auctions

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Abstract

We study a US policy that set a reserve price for federal oil and gas lease auctions but then had a secondary sale at a lower price if no bids met the reserve price. Potential bidders responded by not bidding in spite of valuations exceeding the reserve price. Using a structural model, we find that the Inflation Reduction Act's elimination of these secondary lease sales would increase expected lease sales revenue by only $311 per parcel, relative to an average reserve price of $5,727, while decreasing the probability of sale by 2.9%. Accounting for rental and royalty revenue lost due to decreased sales implies that eliminating these secondary lease sales decreased total expected revenue by more than $10,000 per parcel on average.

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1 Introduction

In many economic settings where a principal sets policy and agents respond, a key requirement for policy efficacy is that the principal can credibly commit to the policy. When commitment is not credible, agents respond rationally, potentially eroding the policy's efficacy. For example, a monopolist who cannot commit to maintain high prices will find consumers strategically delaying purchases (Gul et al. 1986). An employer negotiating rates for piece-rate incentive schemes must be able to commit to not later "ratchet" down rates; failure to do so leads to reduced effort by the employee (Laffont and Tirole 1988). A venture capitalist who cannot commit to continued funding will receive reduced effort from entrepreneurs (Tirole 1999). While a rich theoretical literature examines how commitment failures can fundamentally alter economic outcomes, measuring these effects empirically has proven challenging, as it requires both observing agents' strategic responses and a tractable way to analyze counterfactual outcomes under commitment.

We examine commitment failure in the context of auctions, where a seller sets a reserve price and potential buyers choose both whether and how much to bid. While auction theory typically assumes the seller can commit to withdraw an item if no bids meet the reserve price, such commitment is often infeasible in practice: Procurement handbooks often specify that agents should negotiate directly with suppliers in the event of no bids meeting the reserve price.[1] In real estate auctions, the absence of bids can lead sellers to directly negotiate with potential buyers or relist the property at a lower reserve price (Selvanayagam 2024). When auctioning off assets from failing banks, the FDIC has employed a second auction with a lower reserve price if an asset is not sold in the initial auction (Skreta 2015). In all of these settings, anticipation of post-auction sales can lead potential bidders to strategically withhold their bids, undermining the reserve price's effectiveness and reducing revenues. However, analyzing the impact of commitment failure is challenging: Both the likelihood that potentially bidders strategically withhold bidding and the probability that the principal commits to the reserve price depends on their beliefs about each others' unobservable strategies, and these beliefs are rarely observable.

To overcome these challenges, we focus on a setting where the principal's commitment failure is explicitly held fixed by government policy, allowing us to focus on identifying how bidders respond to principal commitment failure. Specifically, we study U.S. federal oil and gas leases administered by the Bureau of Land Management (BLM). Prior to 2022, if no bids met the publicly-announced reserve price R, the BLM made the lease available through a secondary sale process known as "noncompetitive leasing", where the lease was

[1] See for example City of St. Petersburg (2024), City of Richmond (2024), and State of Louisiana (2024).

then made available for sale at a (usually) lower publicly-announced fixed price P. This is an ideal setting to study commitment failure as post-auction outcomes are observable in administrative data and the rules governing both auctions and noncompetitive lease sales were fixed by policy.

Secondary sales through noncompetitive leasing was a significant channel for federal oil and gas lease allocation: From 2003 to 2019, the BLM awarded 27,535 noncompetitive leases, comprising 27% of all federal onshore oil and gas leases (U.S. Government Accountability Office 2020a). Policy analysts argued that this system was reducing government revenues by disincentivizing competitive bidding. As a results, the Inflation Reduction Act of 2022 (IRA) eliminated noncompetitive leasing for oil and gas. However, the BLM continues to use noncompetitive leasing for other federal resources including solar and geothermal leases (Bureau of Land Management 2021, 2022a), making it important to understand this particular setting for current federal policy.[2]

We develop a theoretical framework showing how noncompetitive leasing affects bidding behavior and auction outcomes. In a static private-value auction setting without a post-auction stage, a bidder i will be willing to bid if her valuation ν_i exceeds the reserve price: $\nu_i \geq R$. However, in a dynamic setting with the possibility of a noncompetitive sale, a bidder whose valuation exceeds R may choose not to bid. Instead, she may wait for the possibility of acquiring the lease in the secondary sale at the lower, noncompetitive price P. We show that in this setting, a bidder will only be willing to bid if her valuation ν_i exceeds some screening value H that is strictly greater than R. The screening value H is a function of R, P, the distribution of valuations F, and the number of potential bidders N. A bidder with a valuation between P and H will prefer to not bid but wait for the option of submitting a noncompetetitive lease offer; a bidder with a valuation less than P will prefer not to participate, as illustrated in Figure 1.

Eliminating noncompetitive leasing (and committing to no sale in the event of no bid) has an ambiguous effect on seller revenue. In cases where there is a high probability the two highest valuations are above H, eliminating noncompetitive leasing will have almost no effect on revenues because competitive bids are likely to still be received. For cases where the highest valuation is likely between R and H, eliminating noncompetitive leasing will increase revenue as the highest valuation bidder would be willing to pay R but chooses to instead pay P. In cases where the highest valuation is likely less than R, eliminating noncompetitive leasing will decrease revenue as it eliminates sales in cases where a buyer would be willing

[2]Analyzing the impact of eliminating noncompetitive leasing using a pre-post analysis is challenging both because the Biden administration paused federal oil and gas lease auctions in 2021 and because the IRA included a number of other oil and gas reforms, including increasing both the rental and royalty rates and eliminating free anonymous nomination of potential lease parcels (Bureau of Land Management 2022b).

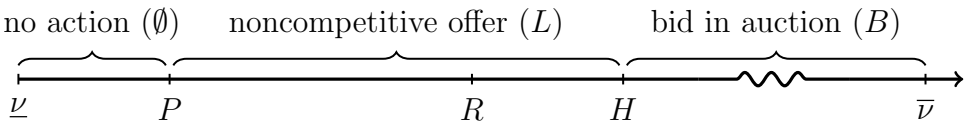


FIGURE 1: Diagram showing potential bidder i's preferred action as a function of her valuation ν_i, where P is the price of the lease if sold noncompetitively, R is the reserve price, and H is the screening value. If $\nu_i > H$, i will strictly prefer to bid in the auction (B). If $P < \nu_i < H$, i will strictly prefer to not bid and will wait for the opportunity to submit a noncompetitive offer (L). If $\nu_i < P$, i will strictly prefer to do nothing ($\emptyset$).

to pay P but not pay R.

We evaluate the counterfactual impact of removing non-competitive leasing using data on BLM lease auctions from four states which capture a wide range of expected productivity. About 44% of the parcels in our data are from Montana and the Dakotas, with 8% specifically from counties within the Bakken formation, a highly productive oil basin. The remaining 56% of parcels come from Nevada, a state with a large amount of federal land but very low oil and gas productivity. Because reserve price R and noncompetitive price P are set as functions of acreage but not expected oil and gas productivity, variation in R and P relative to expected productivity helps to jointly identify the screening value H and the distribution of valuations over a wide range of expected oil and gas productivities.

We use a structural auction approach to estimate the distribution of bidder valuations. One important feature of our setting is that BLM leases used an ascending auction format which admits multiple equilibria in bidding and therefore would normally require partial identification techniques such as moment inequalities (Haile and Tamer 2003). However, following the insights of Bresnahan and Reiss (1991), we show that with mild assumptions on the equilibrium, leasing outcomes are unique if we focus on the three discrete outcomes of whether the lease is sold via auction, sold via noncompetitive leasing, or not sold at all—even though equilibrium bids themselves are not unique. This approach allows us to estimate model primitives using maximum likelihood. We estimate our model assuming either gamma or lognormal distribution of valuations and find similar results for each.

Our empirical analysis yields four main findings. First, we show that the screening value H typically exceeds the reserve price R by a factor of 2-10, with the ratio larger for parcels with lower expected productivity. Second, we find that eliminating noncompetitive leasing would have modest effects on expected auction revenues: for most parcels, expected revenues would increase by less than \$500, which is less than 10% of the average reserve price in our data. Third, because eliminating noncompetitive leasing will reduce number of parcels sold, these small auction revenue increases would be swamped by a decrease in post-auction revenues from rental payments and royalties. Fourth, we find that revenues are much less

responsive to reserve price changes when the auction includes second-stage noncompetitive leasing, suggesting that seller commitment failure significantly constrains the effectiveness of reserve prices as a policy tool.

Our paper provides some of the first empirical evidence on how principal commitment failure affects economic outcomes. Within auctions, the theoretical literature on commitment failure begins with McAfee and Vincent (1997), followed by important contributions from Glowicka and Beck (2006); Menezes and Ryan (2005); Grant et al. (2006); Vartiainen (2013); Jun and Wolfstetter (2015); Skreta (2015) and Liu et al. (2019). Outside of auctions, theoretical work examining commitment failure includes studies of ratcheting in incentive contracts (Freixas et al. 1985; Laffont and Tirole 1988), bailouts (Schaffer 1989), monopolistic pricing (Gul et al. 1986), and other contracting (Crawford 1985; Green and Laffont 1987; Dewatripont 1989; Dewatripont and Maskin 1995; Crémer 1989). However, the empirical literature examining the impact of principal commitment failure is much more limited. The only other paper we are aware of is a recent working paper Liu et al. (2024), who examine seller commitment failure in an auction setting where items not sold are then re-listed for later auction at a lower reserve price.

Our paper also contributes to the growing literature on oil and gas auctions, including Bhattacharya et al. (2022), Hendricks et al. (2003), Kong et al. (2022), and Kong (2020). While much of this literature focuses on high-value leases where a sale is almost certain, our analysis includes leases with both high and low expected value, allowing us to examine how auction design affects outcomes across the full range of asset values.

Finally, our results inform ongoing policy debates about federal land management and energy production. The Inflation Reduction Act made significant changes to oil and gas policy—not only eliminating noncompetitive leasing, but also adding fees for lease nominations and increasing the royalty and rental rates. While concerns that noncompetitive leasing was eroding revenue was a major reason for federal investigations (U.S. Government Accountability Office 2020a) and legislative efforts (*Competes Act* 2021), our analysis finds that its elimination may have reduced rather than increased government revenues due to lost revenue from lease future development–rental and royalties. Moreover, as the BLM continues to use noncompetitive leasing for other resources like solar and geothermal rights, understanding its effects remains important for federal policy. Our results complement those of Bhattacharya et al. (2022) who also explore the consequences of auction design when there is potential post-sale development revenue. Our results are also important in understanding evolving policy on federal lands which are important as the US Federal Government is the largest owner of mineral rights in the United States and contributes 10% of total US natural gas production and 25% of total US crude oil production IER (2022). Other papers that

have examined the impact of government land policy on the energy industry include Lewis (2019), Fitzgerald (2010), Kong (2020), Brehm and Lewis (2021), and Leonard and Parker (2021).

The remainder of the paper is organized as follows. In section 2, we write a simple model to show how offering leases noncompetively erodes willingness to bid and affects government revenue. In section 3, we discuss additional institutional detail on BLM oil and gas lease auctions, and in section 4 we discuss our data. In section 5, we show descriptives of our data, including evidence of how parcel heterogeneity is tied to eventual lease allocation outcomes. Section 6 discusses our structural estimation methodology, with parameter estimates in section 7. In section 8, we examine policy counterfactuals. Section 9 concludes.

2 Theory

In this section, we show that when a principal cannot credibly commit to withholding an asset after a failed auction, potential bidders will submit bids only if their valuation exceeds a screening threshold H that strictly exceeds the reserve price R. We discuss the determinants of H and how this commitment failure affects expected revenue. We specifically focus on the case of noncompetitive leasing where the seller makes the lease available via a lotteryat a noncompetitive price P if no bid is received that meets or exceeds the reserve price R. We assume a second-price auction format, although the results can be generalized to other auction settings.

Players are indexed by i and there are N potential buyers. The reserve price R, noncompetitive price P, and number of potential buyers N are common knowledge. We assume that $P < R$. Every player $i = 1, \ldots, N$ randomly receives a valuation ν_i from a distribution F with a non-negative, possibly infinite support $[\underline{\nu}, \overline{\nu}]$ such that $0 \leq \underline{\nu} \leq P < R \leq \overline{\nu}$. Valuations are independently and identically distributed.

Once they receive their valuations, players can choose to place a bid in the auction or not. Bids must be at or above the reserve R. Because valuations are private knowledge, the number of potential competitors who are bidding in the auction and competing in the lottery is not known to potential buyers. Therefore, both auction and lottery entry are endogenously determined by the realization of valuations and expectations of other's valuations.

Bids are simultaneous and can be any real number weakly greater than the reserve price. The highest bidder pays the maximum of the reserve price and the second-highest bid. If no player bids and the auction fails, then players may offer to buy the lease noncompetitively. In the event of multiple buyers willing to buy the lease noncompetitively, the seller holds a lottery and randomly selects a winner from the set of noncompetitive offers. The winner of

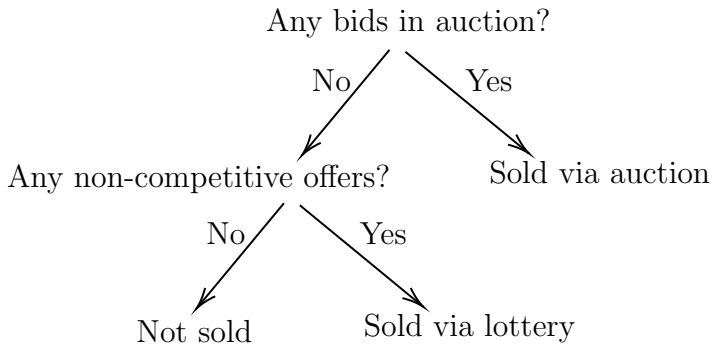


FIGURE 2: Diagram showing the decision tree of the principal as a function of player choices.

the lottery pays the noncompetitive price $P < R$. If no bid is received, then the parcel is not sold. This timing is illustrated in Figure 2.

As it is a weakly dominant strategy to bid one's own valuation in a second price auction, we assume that players do so here—conditional on submitting bids. We formalize this set of actions $a_i \in \{B, L, \emptyset\}$, where B refers to bidding in the auction (and bidding one's valuation ν), L refers to refraining from bidding in the auction and waiting to submit a noncompetitive offer in the lottery mechanism (in the event that no one else bids in the auction), and $\emptyset$ refers to doing nothing.

2.1 Characterizing payoffs

If player i has a valuation at or above the reserve price ($\nu_i \geq R$) and bids her valuation ($a_i = B$), her payoff depends on the reserve price and whether her bid exceeds the highest bid among all other players that bid, as given in equation 1:[3]

$$\pi_B(\nu_i|\nu_i \geq R) =$$
$$E\left[(\nu_i - \max\{R, \max_{j\neq i}\{\nu_j \cdot 1(a_j = B)\}\}) \cdot 1(\nu_i \geq \max_{j\neq i}\{\nu_j \cdot 1(a_j = B)\})\right] \quad (1)$$

If a player chooses to not bid but instead wait for the opportunity to submit a noncompetitive offer ($a_i = L$), her payoff depends on the noncompetitive price P, the probability that no one else submits a bid, and the expected number of other players who choose $a_j = L$. We use $p(\cdot)$ to represent the probabilty of an event. The payoff to choosing $a_i = L$ is given

[3]If $\nu_i < R$, player i will not be willing to submit a bid as her valuation is less than the reserve price. Therefore, for $\nu_i < R$, we need only consider actions $a_i \in \{L, \emptyset\}$.

in expression 2:

$$\pi_L(\nu_i) = (\nu_i - P) \sum_{k=0}^{N-1} \left[\frac{p\left(\max_{j \neq i}\{1(a_j = B)\} = 0,\ \sum_{j \neq i} 1(a_j = L) = k\right)}{k+1} \right] \tag{2}$$

Finally, the payoff to doing nothing ($a_i = \emptyset$) is zero.

2.2 Characterizing the equilibrium screening value

We focus on characterizing the symmetric Nash equilibrium, which involves a screening value H. Each player i bids her valuation ν_i in the auction ($a_i = B$) if $\nu_i \geq H$, waits to submit a noncompetitive offer in the event of no one else bidding ($a_i = L$) if $\nu_i \in [P, H)$, and does nothing ($a_i = \emptyset$) if $\nu_i < P$. To do this, we assume all players other than i use this strategy, and then characterize the value of H such player i's best response to is to also use this strategy.

For player i with valuation ν_i, we can write the payoff of $a_i = B$ as:

$$\begin{aligned} \pi_B(\nu_i | \nu_i > R, R, H, N) = \big(\nu_i - E(\nu_{(-i)} | H \leq \nu_{(-i)} < \nu_i)\big) \cdot p(H \leq \nu_{(-i)} < \nu_i) + \\ (\nu_i - R) \cdot p(\nu_{(-i)} < H) \end{aligned} \tag{3}$$

where $\nu_{(-i)}$ refers to the highest value drawn among all players excluding player i. Similarly, we can write the expected payoff of $a_i = L$ as:

$$\pi_L(\nu_i | P, H, N) = (\nu_i - P) \cdot p(\nu_{(-i)} < H) \cdot W(P, H, N) \tag{4}$$

where $W(P, H, N)$ is the probability player i wins the lottery conditional on no one bidding in the auction, and is defined in equation 5 (with full derivation in appendix A).

$$W(P, H, N) \equiv \frac{1 - p(\nu_j \leq P | \nu_j \leq H)^N}{N[1 - p(\nu_j \leq P | \nu_j \leq H)]} \tag{5}$$

Therefore, the equilibrium screening value H – the minimum valuation for which each player is willing to bid in the auction – is implicitly defined as a function of P, R, and N, and is the minimum valuation for which each bidder at least weakly prefers bidding in the auction rather than waiting for the possibility of the noncompetitive option or doing nothing, as shown in equation 6 below.

$$H = \min_H \left\{ H \in \text{support}(\nu_i) \quad \middle| \quad \pi_B(H | R, H, N) \geq \pi_L(H | P, H, N) \right\} \tag{6}$$

It is easy to see that because $P < R$, H is strictly greater than R. To see this, suppose that $H = R$. By the definition of H, a bidder with valuation $\nu_i = R$ would receive a weakly larger payoff from bidding in the auction than waiting for the noncompetitive option. However, this is a contradiction because $\nu_i = R$ leads to a zero payoff from bidding in the auction (equation 3) but a positive payoff from waiting for the possibility of noncompetitive leasing (equation 4).

2.3 Revenue implications and extensions

Given a reserve price R, how does the introduction of a noncompetitive option at price P affect expected auction revenues? In Figure 3, we graph the change in revenue that would result from going from a static auction setting with reserve price R to adding in noncompetitive leasing at a price $P \leq R$. These simulations use a setting where valuations are i.i.d. draws from a lognormal distribution with location and scale parameters 0 and 1. We do the exercise with four different possible numbers of potential buyers: $N = 2, 3, 5, 10$. Over most of the subplots, we find that adding in the noncompetitive option leads to a decrease in expected revenues. However, when the reserve price is set high relative to most of the valuations, adding a noncompetitive option increases expected revenues. In these cases, the seller has set a reserve price above the static revenue-maximizing reserve price. The addition of the noncompetitive option significantly increases the probability of sale and, therefore, expected revenues.

3 BLM Auctions

To examine the impact of seller commitment failure, we study auctions for oil and gas leases administered by the Bureau of Land Management (BLM). The BLM is responsible for all onshore oil and gas leasing on federal land in the U.S. The BLM is one of the largest managers and lessors of oil and gas worldwide, overseeing about 700 million acres of federally-owned subsurface mineral rights and administering 26.6 million acres of active oil and gas leases (U.S. Department of the Interior 2021). Since the 1980s, the BLM has typically used an ascending auction mechanism with a publicly announced reserve price R to allocate oil and gas leases.[4] In addition, from the 1980s up to 2022, the BLM also used what was known as noncompetitive leasing: Buyers interested in obtaining a lease without bidding in the auction could submit a noncompetitive lease application, and the application could be

[4]Prior to the 1980s, the BLM used a lottery system to allocate most leases, but used an auction of the leases with the highest expected productivity. See Brehm and Lewis (2021) for a discussion of how the lottery system led to allocative inefficiencies in the secondary market.

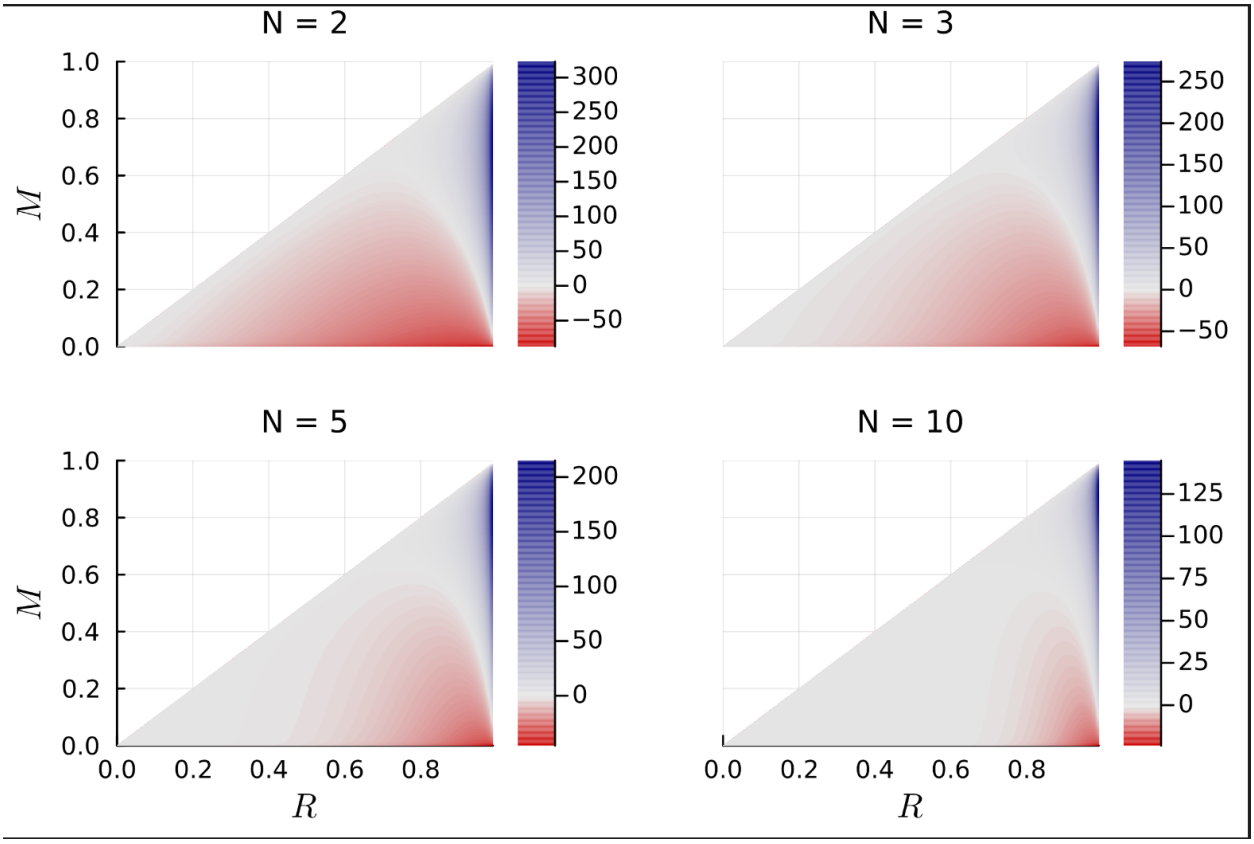


FIGURE 3: The percent change in revenue resulting from adding a noncompetitive price of P given a reserve price R. Each figure assumes $lognormal(0, 1)$ distribution of values. The four panels show results for the case of 2, 3, 5, and 10 potential bidders, respectively.

submitted as early as the day of the auction. If no bid was received in the auction, the lease would be sold to a noncompetitive lease applicant at a publicly announced price P, with the allocation determined by lottery if there was more than one applicant. In the case that no noncompetitive lease offer was immediately received, the BLM kept the lease open for noncompetitive leasing for a period of two years, after which it was taken off the market.[5]

Auctions were held separately for each of the regional BLM offices, where each regional BLM office has jurisdiction over federal land in one or more adjoining states. For the four states we examine in our study, the Montana BLM office administered lease auctions for federal land in Montana, North Dakota, and South Dakota while the Nevada BLM office administered lease auctions for federal land in Nevada. Starting in the mid 2010s, auctions were held on the EnergyNet.com platform.[6] Lease auction events were held approximately

[5]Bidders interested in leasing land taken off the market would then need to submit a nomination form to the BLM to renominate that land for oil and gas leasing.

[6]Before adopting EnergyNet.com as an auction platform, BLM used an in-person oral ascending auction format.

once per quarter for each BLM jurisdiction. Anyone interested in placing a bid for a parcel offered in a given lease auction event had to be a registered bidder on EnergyNet.com and register to participate in that particular auction event, but there was no upfront entry fee. Upon registration, the participant was free to bid in any of the leases offered within that auction event.

The BLM auction format was similar to eBay and other online ascending auction formats. A fixed time period was set for each parcel to be auctioned off.[7] Bids and prices were set on a per-acre basis. The bidding space began with a minimum at \$2/acre (which set the reserve price) and increased with an increment of \$1/acre. Thus, if one participant placed an initial bid of \$2/acre, the next bidder had to submit an integer per-acre bid of at least \$3/acre. The highest bid at the time that the auction ended was the winner. The EnergyNet platform did not accept bids below the reserve price. In addition to allowing for standard bid updating, the platform also included a proxy bidding feature, where a participant could input a reported maximum willingness to pay and the platform would automatically submit bids in behalf of the bidder up to the maximum reported willingness to pay.[8] For both standard bids and bids placed through the autobidding feature, players could always increase their bids, but they could neither withdraw nor lower their bids once placed.

While the bidding was in terms of dollars per acre for the bonus payment, the final payment included a number of additional fees: The winning bidder was required to pay the first year's rental on the lease (\$1.5/acre), an administrative fee (\$175), and an 1.5% commission to EnergyNet.com for administering the auction. In cases of non-integer acreage, the acreage measure was rounded up to the next highest integer for the purpose of calculating bids and fees. Therefore, given the size of the lease in acres A and the per-acre bid of B^A, the total nominal bid B^T was equal to:

$$B^T(B^A, A) = 1.015 \cdot [(B^A + 1.5) \cdot \lceil A \rceil + 175]. \tag{7}$$

As \$2/acre was the minimum per-acre bid, we define the nominal reserve price as $R(A) = B^T(2, A)$.

If a bidder wished to obtain the lease noncompetitively, the bidder would submit a noncompetitive application to the BLM. The noncompetitive application consisted of the

[7] Within our data, time allowed for bidding was either 1 hour, 2 hours, or 24 hours, with 2 hours being the most common.

[8] For example, if the current high bid was \$3/acre and some bidder entered that he was willing to bid up to \$10/acre, EnergyNet.com would update his bid to be \$4/acre, and potentially increasing it up to a maximum of \$10/acre if other higher bids were submitted. In early years, the platform allowed a bidder to opt in or out of the autobidding feature. However, now the platform uses only autobidding and encourages participants to submit their maximum willingness to pay.

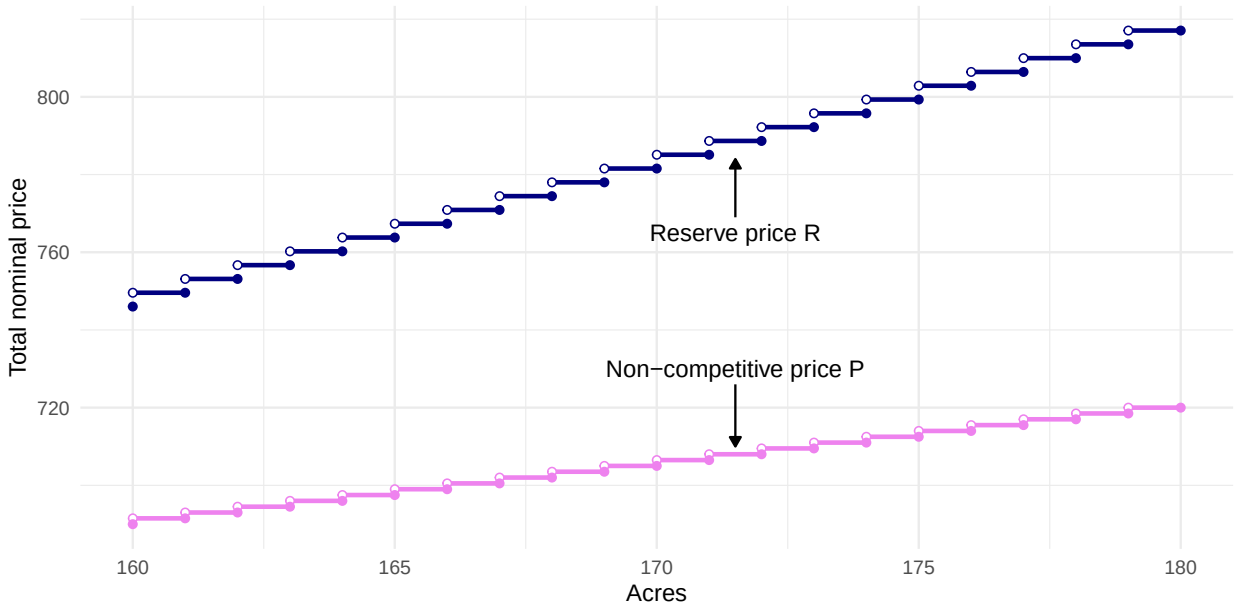


FIGURE 4: Schedule of nominal reserve price (darker line) and nominal noncompetitive price (lighter line) as a function of parcel acreage for parcels with between 160 and 180 acres.

first month's rental plus an administrative fee equal to \$450. Therefore, we define the nominal noncompetitive price as:

$$P(A) = 1.5 \cdot \lceil A \rceil + 450 \tag{8}$$

Figure 4 graphs reserve price $R(A)$ and noncompetitive price $P(A)$ relative to acreage A for leases with area between 160 and 180 acres, and shows that the gap between reserve price and noncompetitive price is increasing in acreage.

4 Data

We use four main sources of data. First, our auction data comes from EnergyNet.com, and we use EnergyNet data on bids and parcel characteristics from EnergyNet for all BLM lease auctions for Nevada, Montana, and North and South Dakota that were administered prior to January 2021. These data give information on acreage, parcel location, whether the parcel was sold via auction, winning bid, bidder ID numbers, the start and end times of the auction, and a time-stamp history of bids. Figure 5 shows an example of the bidding data for one parcel in Montana. There we see that bidder 10 submitted the initial bid at the reserve price of \$2/acre at 8:08 am, followed by a bid of \$3/acre by bidder 31 at 8:59 am, and so on, with

Bidder	Placed	Amount
Bidder #5	**9/22/2020 9:05:56 AM**	**$9**
Bidder #10	9/22/2020 9:05:02 AM	$8
Bidder #5	9/22/2020 9:04:34 AM	$7
Bidder #10	9/22/2020 9:00:21 AM	$6
Bidder #31	9/22/2020 8:59:29 AM	$5
Bidder #10	9/22/2020 9:00:13 AM	$4
Bidder #31	9/22/2020 8:59:26 AM	$3
Bidder #10	9/22/2020 8:08:09 AM	$2

FIGURE 5: Example of time-stamp bid data. Parcel 70228, from September 2022 Montana BLM auction.

the winning bid of $9/acre placed by bidder 5, four seconds before the auction ended at 9:06 am.[9]

From the EnergyNet data, we observe 22 total auction events, with the first held in December 2016 and the last held in September 2020. We limit our sample to this period because this is the period for which BLM auctions were held on the EnergyNet.com platform but before significant policy changes governing oil and gas leasing in the Biden administration.[10] Each of these auction events included auctions for multiple parcels, with the number of parcels offered in each auction event ranging from 8 to 305, with an average of about 94 parcels, for a total of 2,060 parcels offered for lease via auction. A full summary table giving information on each of these 22 auction events is given in Appendix table 6, including date, BLM office, parcel count, and number of registered bidders.[11]

Our second main source of data is the LR2000, a BLM database which tracks adminis-

[9]Evidence of the autobidding feature can be seen from the time stamps. In Figure 5, bidder 31's bid of $5 has a time stamp of 8:59:29 which comes before bidder 10's bid of $4, implying that bidder 31 submitting a willingness to pay of at least $5 but that it did not become the high bid until 9:00:13 when bidder 10 submitted a bid.

[10]While the Inflation Reduction Act (IRA) led to significant policy changes, early Biden policy enacted right after inauguration in January 2021 also significantly changed leasing policy, and in particular led to a pause in oil and gas lease auctions (Olmem and Lau 2021).

[11]The number of registered bidders comes from EnergyNet.com, the BLM website, and a FOIA request to the Montana BLM office.

trative actions on federal oil and gas leases. Crucially, the LR2000 contains information on whether a given parcel was sold competitively (via auction), noncompetitively (via lottery), or not at all. For noncompetitive lease sales, the LR2000 distinguishes between what are known as day-after sales (which come from cases where noncompetitive lease applications were placed the same day as the auction and awarded the day after in the event of no auction bidding) and the remaining other noncompetitive sales, which are called two-year sales (as leases were made available for noncompetitive sale for the two year period after the auction).

We use machine and hand matching to match parcels in the EnergyNet data with observations in the BLM LR2000. For 108 parcels in the EnergyNet data, we are either unable to credibly find the corresponding match within LR2000 or are unable to credibly code the lease allocation outcome of the parcel, and so we drop those observations. We also drop an additional 181 parcels which have areas less than 160 acres, which is often the minimum drilling unit size for a conventional natural gas well. This leaves a sample of 1,771 parcels.

Third, we use data from Enverus to construct measures of approximate expected productivity for the parcel. In particular, we draw a 10km radius from the approximate lease boundaries outward, and compute previous oil and gas production from that area. We then multiply the oil and gas production by the average oil and gas prices over the past 12 months. This serves as a proxy for expected productivity of the parcel. Finally, we use time series data on monthly oil prices (WTI-Cushing) and natural gas prices (Henry Hub) from the Energy Information Agency, as well as the consumer price index CPIAUCSL from the St Louis Federal Reserve FRED database.

5 Data Descriptives

Of the 1,771 parcels in our sample, we find that 23% are sold competitively, 11% are sold noncompetitively in day-after sales, 4% are sold noncompetitively sometime in the following two years, and 62% are not sold at all within the two year window. Table 1 shows the tabulation of outcomes by state. As North and South Dakota have relatively little federal ownership, the vast majority of our observations are from Montana (42% of parcels) or Nevada (56% of parcels). Relative to parcels in Nevada, parcels in Montana are both more likely to be sold by auction and to be sold noncompetitively. Parcels in the Dakotas are very likely to be sold via auction. Figure 6 shows maps of the centroids of these parcels, using colors to depict the sales outcome.

Table 2 gives summary statistics for parcels in our database. The first row gives summary statistics for the nominal per-acre bonus bid for the 400 parcels that receive bids. Of those 400 parcels that receive bids, 160 parcels are sold at the reserve price. The second row gives

	MT	ND	NV	SD	Total
Competitive sale (auction)	250	19	119	12	400
Noncompetitive sale, day after	95	0	107	0	202
Noncompetitive sale, 2 year	57	0	17	0	74
Not sold	339	0	753	3	1,095
Total	741	19	996	15	1,771

TABLE 1: Parcel outcome counts by state.

	Mean	Min	Max	Count
Acres	1,303.8	160	2,560	1,771
Reserve price (total, real)	5,727.1	867	11,425.5	1,771
Noncompetitive price (total, real)	2,866.1	801.8	5,286.4	1,771
Value of nearby production (in millions $, real)	201.5	0	9,694.7	1,771
Number of registered participants	20.8	7	56	1,771
Highest bid (bonus only, per acre, nominal)	22.2	2	604	400
Highest bid (total, real)	19,310.2	882	242,389.3	400

TABLE 2: Summary statistics at the parcel level.

the total real price for those 400 parcels that receive bids, including total bonus, first month's rental, the application fee, and the EnergyNet commission. The third row shows significant variation in acreage, with the mean just over 1,280 acres (or two square miles). The fourth and fifth rows give the total reserve price and total noncompetitive price, respectively, with the reserve price always larger than the noncompetitive price and the difference increasing in acreage, as shown previously in Figure 4.

The sixth row of Table 2 gives the number of registered bidders for the auction event, with a minimum of 7 registered bidders for an auction event in Nevada and a maximum of 56 registered bidders for an auction event in Montana. (The full details of each auction event are given in Table 6 in the appendix.) The last row of table 2 gives a value of nearby production. We calculate this in two steps. First, we sum cumulative oil and gas production for all wells drilled between the lease boundary and a 10 kilometer buffer which appear in our drilling and production database.[12] Second, we multiply this physical quantity by the average oil and gas prices over the previous 12 months prior to the lease. This serves as our proxy for expected lease productivity.

Theory suggests that more valuable leases will be the most likely to be sold via auction, whereas the least valuable leases will be the most likely to not be sold at all. Medium-value leases are the most likely to be sold noncompetitively. In Figure 7, we graph the CDF of

[12]Enverus production data typically starts in the 1960s; our results will understate production if there is significant pre-1960 production.

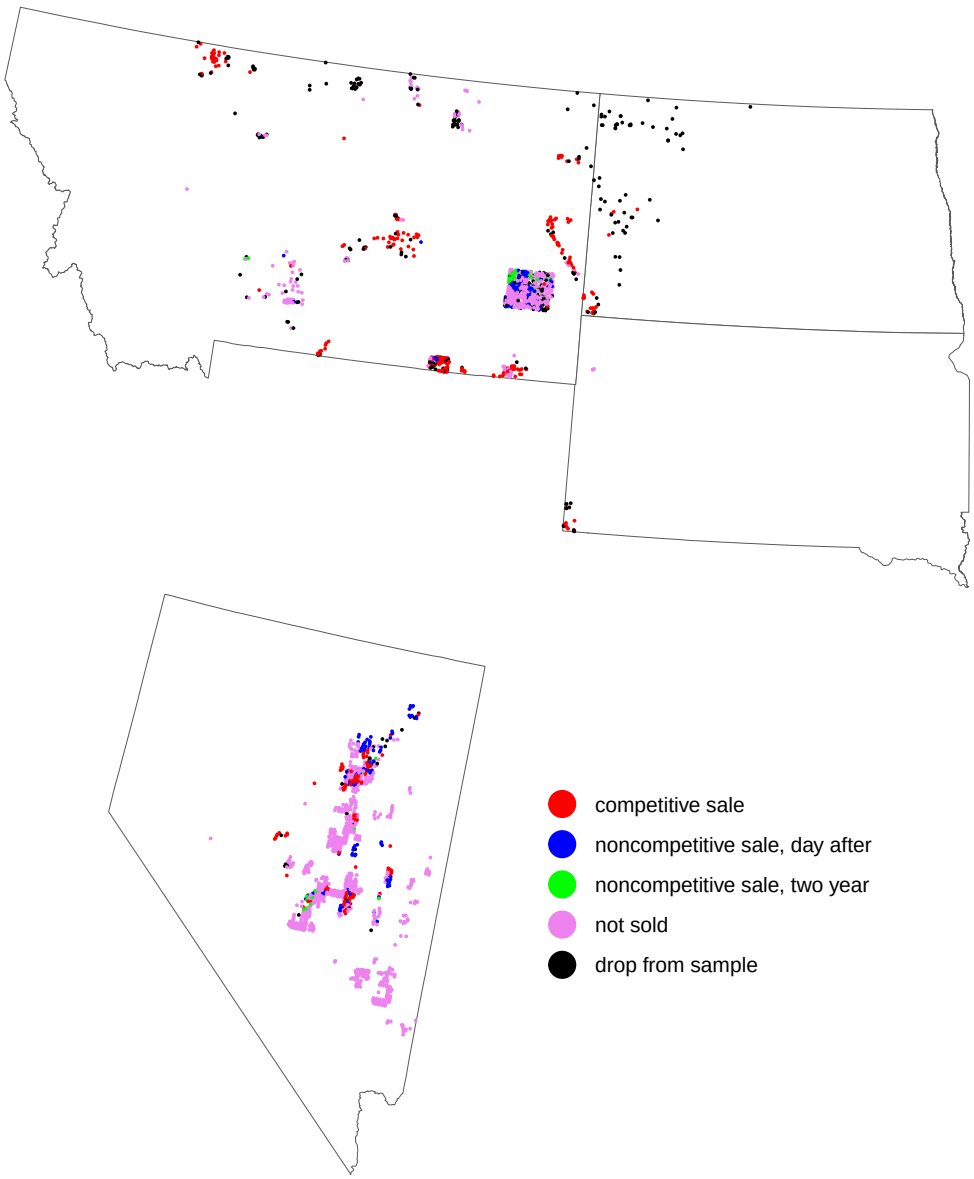


FIGURE 6: Parcel outcomes for parcels in Montana, North Dakota, and South Dakota (top panel) and Nevada (bottom panel), plotted at the parcel centroid.

our measure of expected production by outcome—whether the parcel was sold in auction, in day-after noncompetitive leasing, in two-year noncompetitive leasing, or not at all. We find that the value of nearby production for parcels sold competitively first-order stochastically dominates the value of nearby production for parcel sold noncompetitively in day-after sales. This, in turn, first-order stochastically dominates the value of nearby production for parcels not sold. We also find that the value of nearby production for leases not sold first order stocahstically dominates the value of nearby production for leases sold in two-year-after noncompetitive sales. This last ordering is surprising but seems to be driven by both the

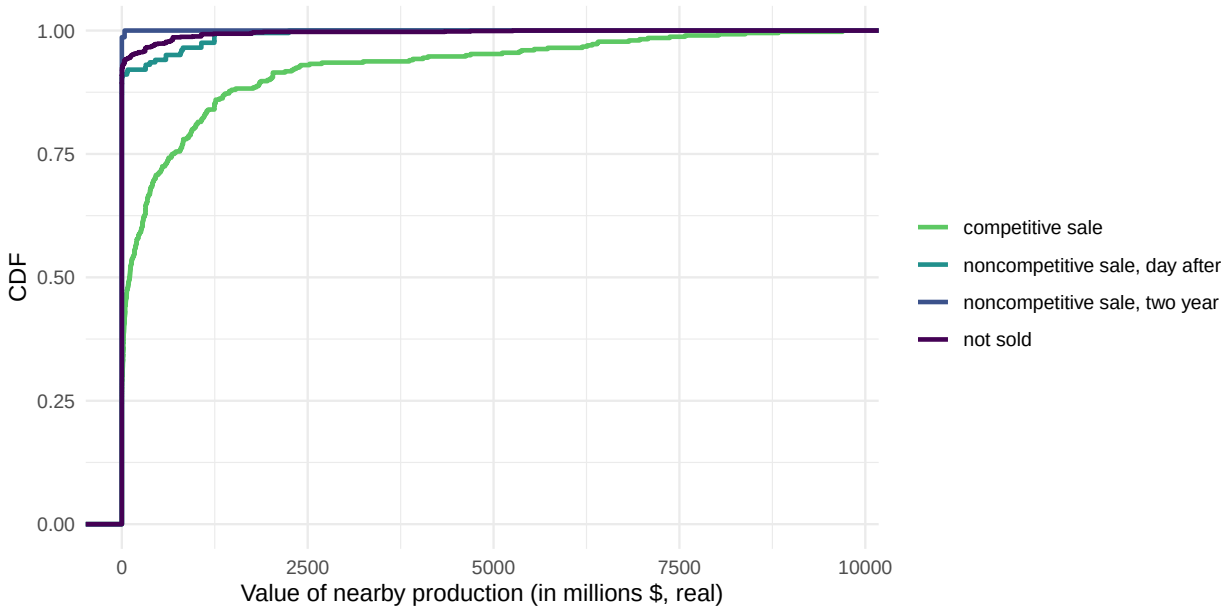


FIGURE 7: CDF of nearby production by auction outcome

small sample and the actions of a single player: only 74 parcels were sold noncompetitively in the two year period after the auction event, as shown in Table 1. Of these 74 parcels, 51 of them were Montana parcels originally offered in June 2017 and sold to a single buyer on November 30, 2017. Furthermore, when we pool the two types of noncompetitive leasing, we find that the distribution of expected productivity for leases sold noncompetitively first order stochastically dominates the distribution of expected productivity for leases not sold. Overall, our findings line up with theoretical predictions: Leases with low nearby production are the most likely to not be sold; leases with medium nearby production are the most likely to be sold noncompetitively, and leases with high nearby production are the most likely to be sold competitively.

Table 3 uses OLS regression to show some of the determinants of whether a lease is sold via auction or sold at all. The regression examines the probability that the lease is sold competitively (e.g., via auction) in columns 1-3 and the probability that the lease is sold at all, either competitively or noncompetitively in columns 4-6. Columns 1 and 3 show that higher acreage lots are less likely to be sold via auction and less likely to be sold at all. This reflects the fact that higher acreage leases tend to be those in areas with less pre-existing leasing and extraction. Therefore there is greater scope to offer larger leases. After controlling for the estimated value of nearby production within 10km of the lease (in row 2), the coefficient on log acres becomes small and statistically insignificant. The coefficient on the log of nearby value is positive and strongly significant, consistent with the idea that as

nearby production is likely to be a proxy for lease production, leases with higher production potential will be more likely to be sold via auction and sold in general. The third row is the log of the ratio of registered bidders to parcels offered within the auction event and is a proxy for the scarcity of leases relative to demand. We find in columns 3 and 6 that relative scarcity increases the probability of a competitive sale and any sale. We also find that that the interaction between our proxy for expected lease value and relative scarcity is statistically insignificant, implying that relative scarcity has a similar effect regardless of the productivity of the lease (regression results not shown).

	Dependent variable:					
	1(competitive sale)			1(comp. or day-after sale)		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(acres)	−0.114	−0.041	−0.050	−0.121	−0.056	−0.066
	(0.026)	(0.026)	(0.022)	(0.054)	(0.060)	(0.057)
Max{0, log(nearby value)}		0.031	0.028		0.027	0.024
		(0.005)	(0.006)		(0.006)	(0.007)
Log(total parcel count)			−0.105			−0.110
			(0.042)			(0.042)
Constant	1.013	0.346	0.950	1.172	0.589	1.218
	(0.174)	(0.191)	(0.340)	(0.404)	(0.475)	(0.484)
Observations	1,771	1,771	1,771	1,771	1,771	1,771
R^2	0.049	0.388	0.414	0.043	0.244	0.266
Adjusted R^2	0.049	0.387	0.413	0.042	0.243	0.265
Residual Std. Error	0.408	0.327	0.320	0.464	0.412	0.406

TABLE 3: Determinants of whether sold by auction (columns 1-3) or sold in either auction or in the day-after noncompetitive sale (columns 4-6). The first covariate is the log of the total acres. The second covariate is defined as the log of the nearby value of production within 10km of the lease when the log of that value is above 0, and 0 otherwise (including cases where nearby value is zero). The third covariate is the log of the ratio of number of registered bidders to total parcels offered within the auction event. Standard errors are clustered at the auction event level.

6 Econometric Model

6.1 Modelling Assumptions

We estimate a model of auction bidding and noncompetitive lease sales with the goal of understanding the impact of counterfactual auction designs on expected revenues and the probability of sales. Key data inputs include the endogenous lease sale outcome – whether sold by auction, sold via noncompetitive leasing, or not sold at all – as well as parcel observables including acreage and expected lease productivity. The key model primitives are the parameters of the distribution of bidder valuations, including how the distribution of valuations changes with observables. Importantly, the estimation accounts for how bidders may refrain from bidding if they believe the payoff to waiting for the possibility of winning the lease noncompetitively exceeds the payoff from bidding.

Implementing a structural model of auctions within our setting requires a number of assumptions. First, because our research is fundamentally interested in examining the impact of removing the noncompetitive option, we must identify the screening value H as well as the distribution of values both above and below it. Because we do not observe bids (and therefore values) below H, identifying this portion of the distribution requires relying on the functional form of parametric distributions. In our estimation, we focus on the gamma distribution as our main specification and also show results for the lognormal distribution. Our specifications for both distribution families allows the log expected value of the lease to be linear in observable parcel covariates, as discussed below in section 6.2.

Second, we must take a stand on the determinants of N – the number of potential bidders. Unfortunately, none of the direct measures of N in our data are adequate measures of potential bidders within our setting. For example, the number of bidders that submit bids is an inadequate measure because it is an endogenous outcome variable – and is equal to zero when no bids are submitted. A second potential measure is number of registered bidders N_t for each auction event. However, this in of itself is flawed because the number of registered bidders tends to increase when more parcels are made available and when the expected productivity of parcels offered increases. Indirect measures of N, such as the number of bidders who have submitted bids on nearby parcels in past auctions for nearby parcels as in Hendricks et al. (2003) and Bhattacharya et al. (2022) is also potentially flawed in our setting, especially for parcels with low expected productivity where nearby parcels are also unlikely to have received bids. We therefore use the following approach: First, we define the number of potential bidders N to be the maximum number of registered bidders ever observed in our data, calculated separately for each BLM office: We therefore set $N = 17$ for parcels offered in Nevada and $N = 56$ for parcels offered in Montana and

the Dakotas. We also include robustness results using values of N ranging from 5 to 50, and find that our counterfactual results revenue and sales are qualitatively unchanged. This implies that incorrect assumptions about the true number of potential buyers are not a source of significant bias in our estimation. Second, by assuming that each potential bidder has a valuation drawn from a parametric distribution with positive support, valuations may be any positive value including above H or below P. Therefore, our approach implicitly includes uncertainty in both the number of auction bidders and noncompetitive offers, similar to the approach Kong (2020) takes to model uncertainty in number of bidders.

A third assumption we make is the nature of signals and valuations. Throughout this paper, we assume that bidders have independent private valuations (IPV). IPV valuations have been used in a number of analyses of oil and gas lease auctions, including Kong (2020) and Kong et al. (2022). An alternate paradigm is common value auction, which has been used in analyzing oil and gas auctions by Hendricks et al. (2003) and Bhattacharya et al. (2022). Empirically distinguishing between common value and private value auctions is challenging unless one has exogenous variation in number of potential bidders N (Laffont and Vuong 1996) or if one observes multiple sealed-envelope bids as well as post-auction investment outcomes such as well drilling (Hendricks et al. 2003). The intuition for the latter is that conditional on winning bid amount, a larger gap between winning bid and second highest bid should be negative correlated with post-auction investment. Unfortunately, this is impossible to test in our setting because many parcels have no bids at all and ascending auction with eBay style bidding can only identify the valuation of the second highest bidder. In practice, oil and gas lease auctions typically will have both private and common value components because idiosyncratic costs and technologies contribute a private component and underlying resources contribute a common value component. In practice, each agent's true valuations likely include both private- and common-value components, and the extent to which each type matters depends on the setting: Private-value components are likely to be more important in both places with extensive oil and gas development as in Kong (2020) as well as in very low expected-productivity places with low probability of drilling.[13] We focus on IPV valuations because they are analytically tractable.

Fourth, while our theory in section 2 focuses on a second-price sealed bid auction, our auction setting is an ascending auction, which can exhibit multiple equilibria in bids (Haile and Tamer 2003). However, in eBay-style ascending auctions where the platform allows for an autobid feature, Bajari and Hortacsu (2003) show that one equilibrium is for all bidders

[13]One reason why firms buy low expected-productivity leases is that oil and gas operators can report lease holdings and undeveloped subsurface reserves on balance sheets, increasing the attractiveness of the firm to investors and potential lenders. See DeSantis (2018) on this phenomenon in oil and gas leasing and Healy and Palepu (2001) for a general discussion of asset quality misreporting.

to wait until the end of the pre-set auction period to bid so that other bidders cannot update beliefs from information in one's bid. Bajari and Hortacsu (2003) show that if bidders wait until nearly the end to bid, the resulting strategy will be to use the autobid feature to bid as if in a sealed bid second-price auction. We find evidence of similar bid timing in our setting: Of the 400 auctions that received a bid, 25%, 37%, and 54% had high bids placed within the last five seconds, one minute, and five minutes of the auction. Figure 8 plots the cdf of the time of bidding. The lightest line is the cdf of the time at which the last bid was placed, the medium colored line is the cdf of the time at which the highest bid was placed, and the darkest line is the cdf of the time at which the first bid was placed. Therefore, our bidding patterns appear to be consistent with the second price sealed-bid auction with noncompetitive option discussed in section 2. Furthermore, to deal with the potential of multiple equilibria in the case where players do not follow the Bajari and Hortacsu (2003) last-minute bidding strategy, our estimation procedure discussed below uses data only on whether the bid was sold by auction, lottery, or not at all – and not on the actual bids themselves. This approach, following the insights of Bresnahan and Reiss (1991), allows for potential multiple equilibria in bidding strategies while only imposing the weak equilibrium restriction assumption that the screening value H in our setting is identical to that of a second price sealed-bid auction.

Finally, we make the simplifying assumption that the bid space is continuous rather than in \$1/acre increments as discussed in section 3. Imposing a discrete bid space is challenging to implement. One approach that allows for a discrete bid space is the set-identification approach of Haile and Tamer (2003); however, their approach does not allow for identification of valuations below the screening value. Another approach is to directly model a discrete bid space and compute Nash equilibrium bid strategies. Unfortunately, we have found that such an approach is computationally infeasible with significant convergence problems.[14] One paper that does account for discrete bid intervals is Hickman et al. (2017), but they focus on a setting where the next highest bid can be any real number conditional on being at least a discrete increment above the previous highest bid – as opposed to being a bid within a specific discrete bid space.

[14]Specifically, a discrete bid space in a second-price sealed bid auctions requires solving for an infinite number of indifference conditions – e.g., for what valuation ν_i a bidder i is indifferent between bidding b and $b + \Delta$, where Δ is the bid increment and b and $b + \Delta$ are both in the discrete bid space. It also requires assuming an extra initial condition because whether a bidder is indifferent between bidding b and $b + \Delta$ will also depend on the indifference condition for $b - \Delta$ vs. b as well as the indifference condition for $b + \Delta$ vs. $b + 2\Delta$.

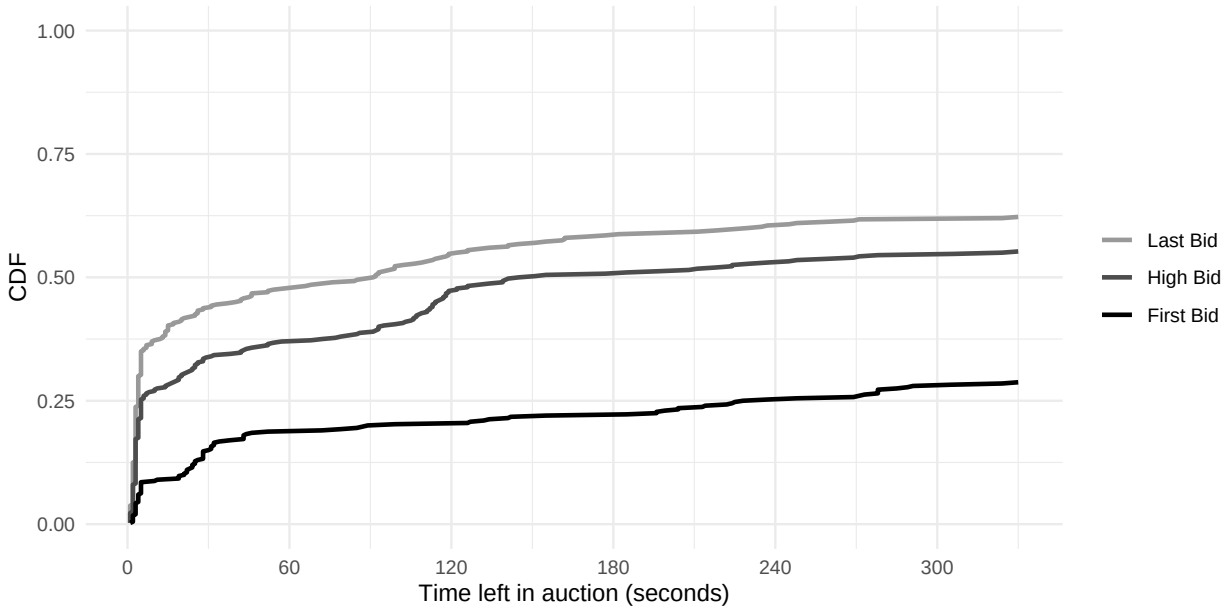


FIGURE 8: CDF of bidding times, where x-axis is time of bid relative to the end of the auction. The lightest line is the cdf of the time at which the last bid was placed, the medium colored line is the cdf of the time at which the highest bid was placed, and the darkest line is the cdf of the time at which the first bid was placed. Graph focuses on the subset of the data where time left is approximately 5 minutes or less.

6.2 Model Estimation

The dataset for this model estimation consists of observations for each lease parcel j that is auctioned within auction event t. The endogenous outcome variable in our setting is lease sale outcome $Y_{jt} \in \{B, L, \emptyset\}$, where B means parcel j was sold via auction, L means the parcel was sold in a day-after noncompetitive lease sale (lottery), and $\emptyset$ means that the parcel was not immediately sold. We pool two-year noncompetitive lease sales cases with no-sale cases because, as discussed above, two-year after sales are a small fraction of sales and are largely driven the large purchase decision of a single buyer in Montana. Doing so allows us to abstract away from the dynamic decision of when to submit a noncompetitive offer in the two-year after sales period. Following the descriptive results in table 3, we denote Z_{jt} to be the same vector of observable lease characteristics as in our OLS regressions in Table 3. The reserve price R_{jt} and the noncompetitive price P_{jt}, are observed and are functions of acreage (see equations 7 and 8 above). The number of potential bidders for parcel j in auction event t is denoted as N_{jt}. We denote $X_{jt} = \{Z_{jt}, R_{jt}, P_{jt}, N_{jt}\}$ to be all data for observation j save the endogenous outcome Y_{jt} and we denote $D_{jt} = \{Y_{jt}, X_{jt}\}$ to be the vector of all data for observation j.

We use two specifications for the distribution of valuation $F(\nu_{ijt})$: The gamma as our

main specification, and the lognormal as a robustness check. For both distributions, the parameters of the distribution depend on the vector Z_{jt} and a vector of parameters θ which includes a vector β and scale parameter σ:

1. Gamma: We parameterize with shape parameter $\alpha = \exp(Z_{jt}\beta)$ and with a constant scale parameter σ_G.

2. Lognormal: We parameterize as F as having (log) location parameter $\mu = Z_{jt}\beta$ and with a constant (log) scale parameter σ_{LN}.

Both of these functional forms ensure that $\log E(\nu_{ijt}|Z_{jt})$ is linear in Z_{jt}.

We assume independent private valuations, where each bidder i within the set N_t draws valuation ν_{ijt} from the distribution $F(\nu_{ijt}|Z_{jt};\theta)$ and where θ is the vector of unknown parameters. We also assume that in the case of multiple parcels offered within auction event t, bidder valuations are not correlated across parcels and that bidding behavior is independent across parcels.

This allows us to write the likelihood of observing each outcome Y_{jt} as:

$$p(Y_{jt}|X_{jt},\theta) = \begin{cases} 1 - [F(H(X_{jt};\theta)|Z_{jt};\theta)]^{N_t} & \text{if } Y_{jt} = A \\ [F(H(X_{jt};\theta)|Z_{jt};\theta)]^{N_t} - [F(P_{jt}|Z_{jt};\theta)]^{N_{j,t}} & \text{if } Y_{jt} = L \\ [F(P_{jt}|Z_{jt};\theta)]^{N_t} & \text{if } Y_{jt} = \emptyset \end{cases} \tag{9}$$

and the log likelihood of the data as

$$LL\left(\theta\middle|\left\{D_j\right\}_{j=1}^{J}\right) = \sum_{j=1}^{J} \log p(Y_{jt}|X_{jt};\theta). \tag{10}$$

7 Model Estimates

We estimate the model separately for each BLM office. In Table 4, we present the results for Montana (including the Dakotas), with column 1 giving the gamma specification and column 2 giving the lognormal specification. Both specifications give very similar log likelihood values, with a very slightly better fit for the lognormal distribution. Results for Nevada are in columns 3 and 4, with the gamma distribution in column 3 and the lognormal distribution in column 4. Again, both models give very similar log likelihood. While parameter estimates for the β terms differ, the predicted index $Z_{it}\hat{\beta}$ from the gamma specifications are highly correlated to the predicted index from the lognormal distribution, with Spearman correlation coefficients of 0.999 for both Montana and Nevada. See Appendix Figure 16 for a scatter plot of index values.

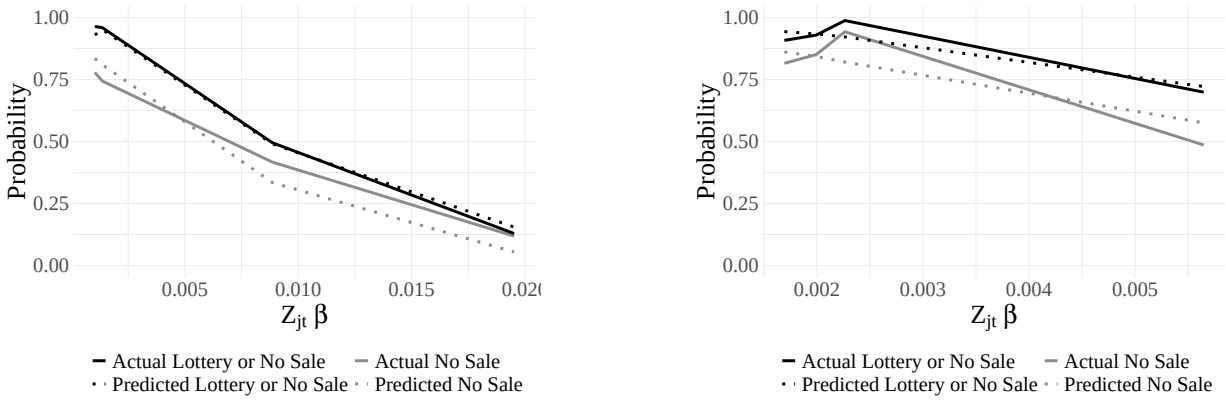
	Montana/Dakotas		Nevada	
	Gamma	Lognormal	Gamma	Lognormal
	(1)	(2)	(3)	(4)
β: Intercept	-8.82	-18.71	-2.44	-6.14
	(0.65)	(2.92)	(1.02)	(4.01)
β: Log(acres)	0.38	0.84	0.066	0.34
	(0.089)	(0.2)	(0.13)	(0.5)
β: Max{0, log(nearby value)}	0.13	0.28	0.047	0.19
	(0.0065)	(0.044)	(0.0076)	(0.039)
β: Log(total parcel count)	-0.045	-0.21	-0.83	-3.3
	(0.054)	(0.13)	(0.095)	(0.56)
σ	3.82	1.72	7.04	2.24
	(0.41)	(0.16)	(0.49)	(0.12)
Log Likelihood	-488.67	-485.62	-628.46	-627.08
Total potential bidders	56	56	17	17
Total parcels	775	775	996	996

TABLE 4: Model parameter estimates. Montana and Dakotas are in columns 1 and 2; Nevada is in columns 3 and 4. Baseline results using Gamma specification are in columns 1 and 3; alternative specification using lognormal is in columns 2 and 4.

Our parameter estimates in Table 4 illustrate how observable lease characteristics affect valuations. For example, the β coefficient for $\max\{0, \log(\text{nearby value})\}$ is positive and statistically significant, reflecting the fact that higher productivity of nearby parcels shifts potential bidder valuations to the right. The coefficient on log(total parcel count) is negative and is statistically significant for Nevada, reflecting the idea that more parcels on offer decreases competition for any given parcel, consistent with the idea that bidders have limited budgets for lease purchases. Most interestingly, we find positive coefficients on log acreage, with the coefficient being positive for Montana. This contrasts with our OLS analysis in Table 3 where we find larger acreage is correlated with both lower probability of auction sale as well as increased probability of no sale. Using this structural model allows us to disentangle the role of acreage in determining prices R and P from its role in shifting valuations.

	Montana/Dakotas				Nevada			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β: Intercept	-6.3	-7.05	-7.77	-8.71	-1.21	-1.91	-2.61	-3.52
	(0.62)	(0.64)	(0.64)	(0.65)	(1.02)	(1.02)	(1.02)	(1.02)
β: Log(acres)	0.35	0.37	0.38	0.38	0.058	0.064	0.067	0.069
	(0.082)	(0.085)	(0.087)	(0.089)	(0.13)	(0.13)	(0.13)	(0.13)
β: Max{0, log(nearby value)}	0.13	0.13	0.13	0.13	0.047	0.047	0.047	0.047
	(0.0063)	(0.0064)	(0.0064)	(0.0064)	(0.0076)	(0.0076)	(0.0076)	(0.0076)
β: Log(total parcel count)	-0.04	-0.042	-0.044	-0.045	-0.83	-0.83	-0.83	-0.83
	(0.052)	(0.053)	(0.053)	(0.054)	(0.095)	(0.095)	(0.095)	(0.095)
σ_G	3.96	3.86	3.83	3.82	7.32	7.12	7.03	6.97
	(0.41)	(0.41)	(0.41)	(0.41)	(0.5)	(0.49)	(0.48)	(0.48)
Log Likelihood	-487.98	-488.24	-488.47	-488.65	-628.36	-628.43	-628.47	-628.49
Total potential bidders	5	10	20	50	5	10	20	50
Total parcels	775	775	775	775	996	996	996	996

TABLE 5: Model parameter estimates — robustness to number of potential bidders. Montana and Dakotas are in columns 1 through 4, ; Nevada is in columns 5 through 8. All estimates assume a gamma distribution. Number of potential bidders ranges from 5 (columns 1 and 5) to 50 (columns 4 and 8).



(a) Montana/Dakotas

(b) Nevada

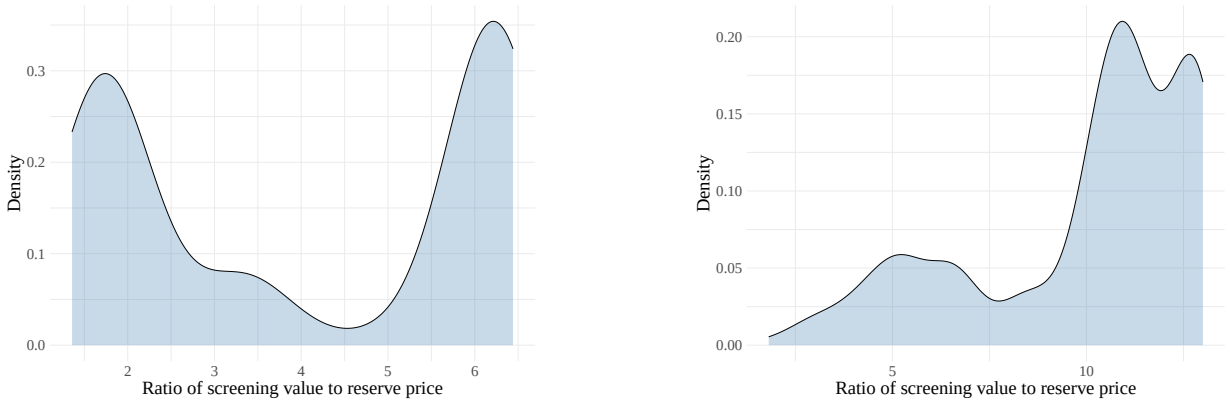
FIGURE 9: Model fit.

Note: For each plot, the x-axis gives the estimates index value $Z_{it}\hat{\beta}$ in quantiles while the y-axis gives average outcomes by quantile. We graph both the actual probability of no sale and no sale plus lottery sale (solid lines) as well as the model predicted probability of no sale and no sale plus lottery sale (dotted lines). The left graph shows results for Montana plus Dakotas while the right shows results for Nevada.

Figure 9 plots model fit using the gamma specification. There, we compute quantiles of our estimated index variable $Z_{it}\hat{\beta}$. Then, for each quantile of the index $Z_{it}\hat{\beta}$, we plot both both the average within-quantile actual probability of no sale and no sale plus lottery sale as well as the average within-quantile model predicted probability of no sale and no sale plus lottery sale. The solid lines give the average probabilities from the data; the dashed lines give the average probabilities as predicted by the model. The gap between the darker and lighter lines gives the predicted probability of a lottery sale. The model fit is generally quite good. However, our model predicts relatively constant probability of lottery sale as a function of the index. In contrast, our data shows that as the index variable increases, Montana exhibits a decreased probability of lottery sale while Nevada exhibits an increased probability of lottery sales. In addition, Nevada exhibits a slight increase in probability of no sale for intermediate increases in the index variable.

Table 5 gives robustness results where we vary the assumed number of potential bidders, ranging from 5 to 50. We find that varying number of potential bidders has almost zero effect on log likelihood and very little effect on estimated β for covariates. The major effect of increasing the assumed number of potential bidders is a decrease in the intercept term, reflecting the idea that if one is to rationalize the patterns of sales we see in the data, more bidders requires a lower average valuation. In our counterfactual section, we find that revenue and sales probability counterfactuals are robust to variation in assumed number of potential bidders.

How large is the implied screening value? In Figure 10, we plot the density of the ratio



(a) Montana/Dakotas (b) Nevada

FIGURE 10: Density plots of ratio of screening value to reserve price

Note: For each plot, the x-axis gives the ratio of screening value to reserve price while the y-axis gives density. The left graph shows results for Montana plus Dakotas while the right shows results for Nevada.

of the screening value to the reserve price. The left panel shows that for Montana, the distribution is bimodal with many parcels having a screening value to reserve price ratio less than two, and many others with a ratio greater than five. In Nevada where expected lease productivity is lower, almost all parcels have screening value to reserve price ratio exceeding five, and many have a ratio exceeding 10. In Appendix Figure 17, we plot a scatter plot comparing the screening value-reserve price ratio for the lognormal and the gamma specifications, and find highly correlated values, with screening values from the gamma distribution often but not always somewhat larger than those from the lognormal specification.

In general, assuming different number of bidders in model estimation leads to different screening values. We find that estimating the model with a smaller number of bidders implies slightly higher screening values (see Appendix Figure 19 for density plots). This fact is driven by two countervailing factors. First, holding distribution of valuations fixed, a smaller number of potential bidders will have higher screening values because decreasing the number of potential bidders decreases the likelihood that at least one bidder's valuation exceeds any given value. Second, our parameter estimates in Table 5 show that decreasing the assumed number of potential bidders shifts the estimated distribution of valuations to the left. This decreases the probability that at least one bidder's valuation exceeds any given value, which decreases the implied screening value. We find in the next section that these two countervailing effects largely cancel out, leading to nearly identical revenue and sales probability counterfactuals regardless of the assumed number of bidders.

8 Policy Counterfactuals

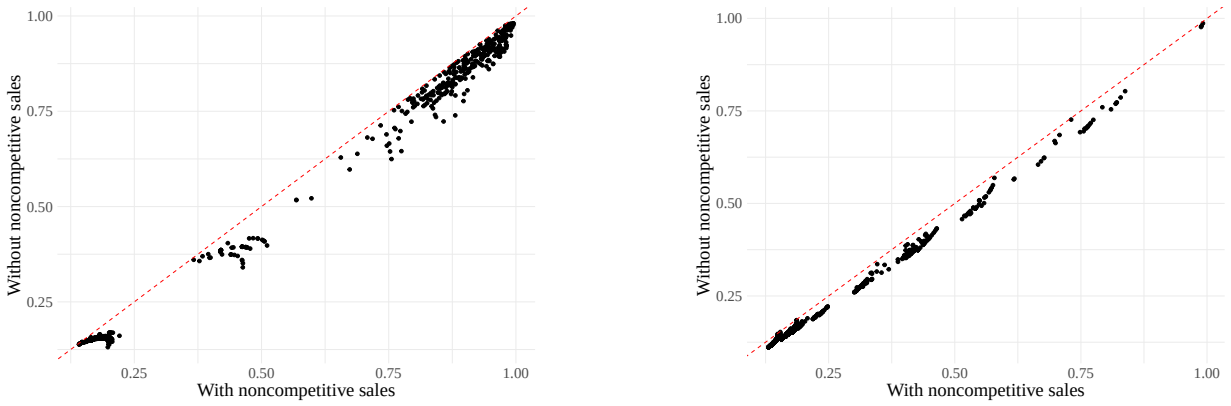
The major concern of policy makers was that the secondary sales process through noncompetitive leasing was decreasing revenues by disincentivizing agents from bidding, thereby reducing revenues. Policy makers were much less focused on the impact of noncompetitive leasing on whether parcels were leased (U.S. Government Accountability Office 2020a; *Competes Act* 2021). In this section, we explore counterfactuals of alternative auction designs, including the impact of eliminating noncompetitive leasing and the impact of raising reserve prices. We focus both on the probability that leases are sold as well as expected revenues from lease sales, where our revenue counterfactuals assume a second price auction. In the last part of this section, we also examine the impact of eliminating noncompetitive leasing on later lease development revenue from rentals and royalties.

8.1 Impact of eliminating noncompetitive lease sales

Figure 11 is a scatter plot comparing the probability that a lease is sold under both the noncompetitive lease system (x-axis) and the probability that a lease is sold when the noncompetitive leasing system is eliminated (y-axis). The figure shows that eliminating noncompetitive leasing decreases probability of lease sale, with the largest decreases in probability of sale coming from those with intermediate probabilities of lease sale. Appendix Figure 20 shows that the change in probability of lease is typically less than 5%, with Montana having a few parcels for which probability of lease sale decreases by 10% or more. On average, our model estimates predict that eliminating noncompetitive leasing reduces probability of a lease sale by 3.4% for Montana and the Dakotas and 2.5% for Nevada.

Figure 12 graphs the expected revenue implied by lease sales both with the noncompetitive lease system (x-axis) and when noncompetitive leasing is eliminated (y-axis). The graph shows that expected revenue increases are quite small, with the largest increases coming from those that have intermediate expected revenues. Appendix Figure 21 shows that the increase in expected revenues from eliminating noncompetitive leasing is larger in Nevada – with a mean revenue increase of $456 than it is in Montana – with a mean revenue increase of $126. For almost all parcels, expected revenue increases from eliminating noncompetitive leasing are less than $1,000, which is much less than the average reserve price of $5,727 .

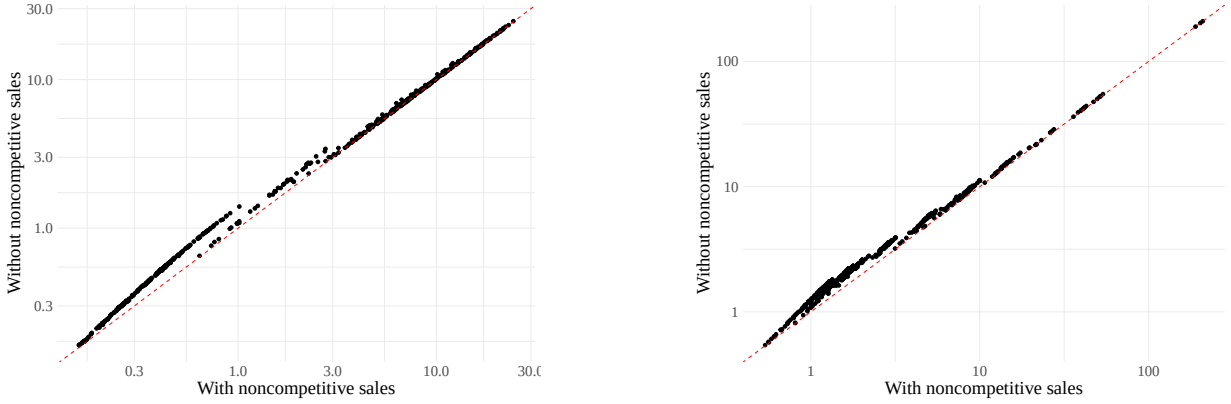
Our counterfactual results about the impact of eliminating noncompetitive leasing on lease sale probability and expected revenue are quite robust to our model estimation assumptions about the number of potential bidders N. For example, if in Nevada we estimate the model assuming only 5 potential bidders, eliminating noncompetitive leasing decreases the probability of a lease sale by 2.4% and increases expected lease sale revenues by $472. In



(a) Montana/Dakotas (b) Nevada

FIGURE 11: Scatter plot comparing probability of lease sale with and without noncompetitive leasing

Note: For each plot, the x-axis gives the probability of lease sale in the presence of noncompetitive leasing while the y-axis gives the probability of lease sale without noncompetitive lease sales. The left graph shows results for Montana plus Dakotas while the right shows results for Nevada.

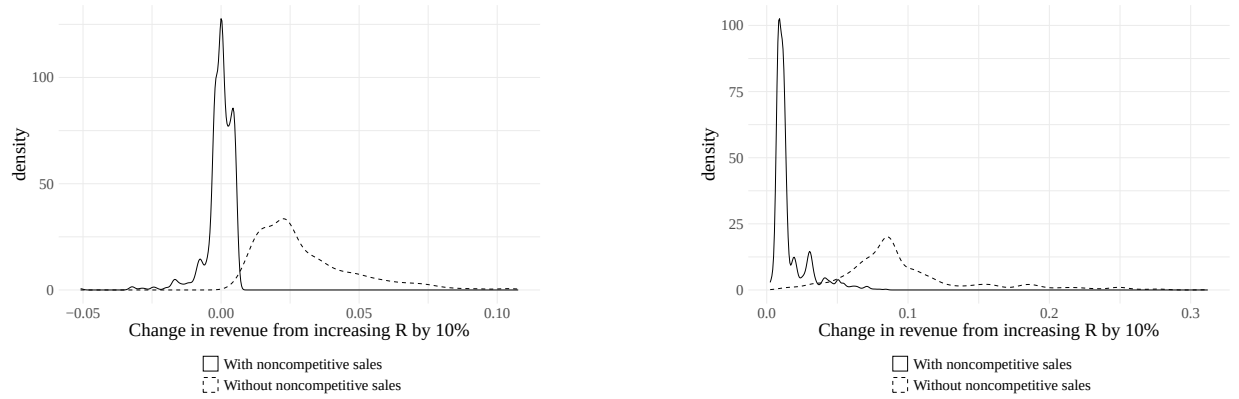


(a) Montana/Dakotas (b) Nevada

FIGURE 12: Scatter plot comparing expected lease sale revenue, in thousands of dollars with and without noncompetitive leasing.

Note: For each plot, the x-axis gives the expected lease sale revenue (in thousands of dollars) in the presence of noncompetitive leasing while the y-axis gives the expected lease sale revenue (in thousands of dollars) without noncompetitive lease sales. Both axes use a log10 transformation. The left graph shows results for Montana plus Dakotas while the right shows results for Nevada.

contrast, assuming 50 potential bidders in Nevada implies that eliminating noncompetitive leasing decreases the probability of a lease sale by 2.6% and increases expected lease sale revenues by $452. Appendix figures 20 and 23 plot the density of the impact of eliminating noncompetitive leasing on the probability of lease sale and expected lease sale revenues respectively, and show that the densities are remarkably similar regardless of estimation assumptions about the number of potential bidders.



(a) Montana/Dakotas (b) Nevada

FIGURE 13: Density of change in expected revenue, in thousands of dollars, from increasing reserve price 10%.

Note: For each plot, the x-axis gives change in expected revenue, from increasing reserve price by 10%, both with and without noncompetitive leasing. The y-axis plots density. The left graph shows results for Montana plus Dakotas while the right shows results for Nevada.

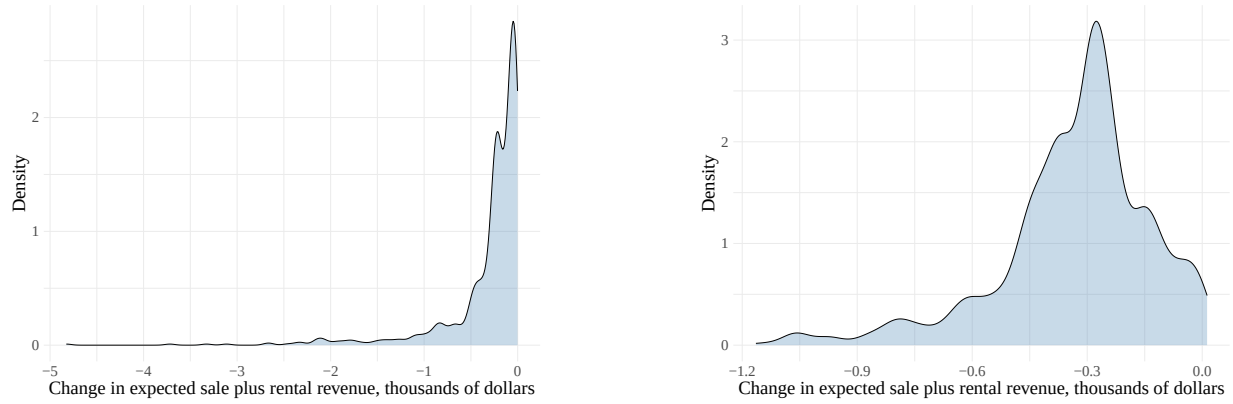
8.2 Impact of reserve price adjustments

How much would changing the reserve price affect lease sale revenue? Much of the focus in auction literature is on determining the extent to which reserve prices are set optmimally. However, calculations of revenue impacts of changing the reserve price can be biased if one does not account for the commitment failure of the seller. For this setting, we focus specifically on the revenue impact of raising the reserve price R from its set level up by 10%, exploring the revenue impacts in settings both with and without noncompetitive leasing at government-set prices P.

Figure 13 plots the density of change in expected revenue from increasing the reserve price by 10%, both with the noncompetitive lease program and without it. The figure shows that increasing the reserve price by 10% has a larger increase in revenue when there is no noncompetitive leasing. With noncompetitive leasing, increases in reserve price have a much smaller impact on revenue, and in some cases actually lead to a decrease in expected revenue.

8.3 Accounting for rental and royalty revenue

Our focus in section 8.1 is on the impact of eliminating noncompetitive lease sales on revenues from the initial sale. However, additional government revenue comes from additional annual rental and royalty payments: Rental payments are annual per-acre fees paid prior to the lease becoming productive, and nominal rental rates were \$1.50/acre for the first 5 years of the lease and \$2/acre for the remaining 5 years of the lease. Royalty payments are a fraction



(a) Montana/Dakotas (b) Nevada

FIGURE 14: Density of change in expected revenue from lease sales and rental revenue only, in thousands of dollars, from eliminating noncompetitive leasing.

Note: For each plot, the x-axis gives change in expected revenue from lease sale and subsequent rental revenue, from eliminating noncompetitive leasing. The y-axis plots density. The left graph shows results for Montana plus Dakotas while the right shows results for Nevada.

of revenues from production paid to the government and were equal to 12.5%. In practice, royalty payments comprise the vast majority of oil and gas lease revenue to the federal government (Tracey 2020). Eliminating noncompetitive leasing will reduce both rental and royalty payments because eliminating noncompetitive leasing decreases the probability of a lease sale.

Rental revenue: In computing the loss in rental revenue, we assume that the lessee would keep the lease for a full 10 years, implying 9 additional years of rental payments beyond the initial sale. Therefore, the predicted impact of eliminating noncompetitive leasing is the change in probability of leasing multiplied by the net present value of rental payments for the remaining 9 years, assuming an annual discount rate of 3%.

Figure 14 graphs the impact of removing noncompetitive leasing on lease sale revenue plus expected rental revenue. The impact on rental revenue is negative, and while small, almost completely dominates the increase in revenue from lease sale revenue itself. As a result, the impact of eliminating noncompetitive leasing will decrease sale plus rental revenue by an average of $326 per parcel. Figure 14 graphs the predicted distribution of impacted sales for Montana and the Dakotas in the left panel and for Nevada in the right panel.

Royalty revenue: The impact of eliminating noncompetitive lease sales on revenue is even more negative when accounting for royalty revenues. However, computing the loss in expected royalties is more challenging because it requires modeling future drilling and

production. Most BLM leases are typically not drilled until the final year of the ten-year lease (U.S. Government Accountability Office 2020b) (see also Herrnstadt et al. (2024). Our lease sale dates range from 2016 to 2020, so we would expect early leases to commence drilling in 2026 to 2030, with production data being reported shortly thereafter. Predicting future production and royalties from these leases is therefore a somewhat speculative activity, so we use a conservative prediction algorithm designed to give a likely lower bound on actual future royalties.

The basic idea of our algorithm is that future drilling and the lifetime production (expected ultimate recovery, or, EUR) of any future wells on the BLM leases in our sample will resemble recent drilling and production over the period 2022–24. Therefore, we do an exercise where we predict EUR for wells beginning production for 2022–24 as a function of EUR for wells beginning production in 2021 and earlier. Our analysis accounts for previous drilling both in the vicinity of a lease – capturing depletion effects – as well as other wells within the local neighborhood – capturing the fact that hydrocarbon resource endowments are spatially correlated. To account for the possibility that some leases will not have drilling and production by end of lease, we include within our prediction model locations where there was no new production between 2022and 2024, and code the dependent-variable EUR for those locations as zero. Then, to predict future production, we use as independent variables EUR for all producing wells observed in our data, and use the model estimates to predict EUR for future possible drilling. Finally, we take the model predictions of future EUR from the leases in our sample and use decline curve analysis to predict the present discounted production and therefore royalties. We operationalize this concept with the following steps, and we provide further details in appendix E.

1. We assume that only leases in Montana and North Dakota have a non-zero probability of positive production. We assume zero production for Nevada given its very low number of productive wells. We also assume zero production for the small number of sample parcels in South Dakota: these are located in the far southwestern corner of the state, are not within a core oil and gas production area.

2. We first examine how predicted production from wells with production starting 2022 and beyond depends on observed production from wells beginning production in 2021 and before, with our earliest observable production data from Enverus beginning in the 1960s. We then use this to predict future production beyond the time period of our data. We focus on using as dependent variable the most recent 3 years of new production data as the median lease in our sample starts in mid-2018, implying drilling in mid-2028, which is just over three years beyond the last date we observe

first-production in the data (late 2024).

(a) We use Enverus-estimated ultimate recovery (EUR) of both oil and gas at the well level.

(b) We use as our unit of observation the Public Land Survey Section (PLSS) square mile section. We create four variables of aggregated EUR at the section level: Total gas EUR and total oil EUR for wells beginning production in 2021 and before, and total gas EUR and total oil EUR for wells beginning production between 2022 and October 2024, the latest date we observe production in our data.

(c) We estimate the Poisson regression specification for each resource type $j \in \{\text{oil}, \text{gas}\}$, where i indexes PLSS sections:

$$\begin{aligned}\log E[\text{total EUR}_{ij,2022-24}] = \beta_{0j} + \beta_{1j} \log(1 + \kappa_j \cdot [\text{total EUR}_{ij,1960s-2021}]) \\ + \beta_{2j} \sum_{i' \neq i} \log(1 + \kappa_j \cdot [\text{total EUR}_{i'j,1960s-2021}]) w_{ii'}(d_{ii'}) \quad (11)\end{aligned}$$

Here, κ_j is an unknown parameter and $w_{ii'}$ are Gaussian kernel weights based on $d_{ii'}$, the distance between PLSS sections i and i'. Both κ_j and the Gaussian kernel bandwidth are estimated along with the β parameters through maximum likelihood.

3. Given zero observed production on our leases to date, we focus on predicting future production for wells that may be drilled beyond the date range observed in our data (e.g., in November 2024 and beyond). To do this, we use parameter estimates from equation (11) to construct predicted future EUR as a function of total $\text{EUR}_{2022-24}$ plus total $\text{EUR}_{1960s-2021}$ instead of just total $\text{EUR}_{1960s-2021}$. This mechanically increases the value of covariates in (11), so we then scale predicted values for future EUR such that the mean of the predicted values is equal to the mean of predicted values using our estimation of equation 11 (where only EUR from wells beginning production in 2021 are included in the dependent variables).

4. We use data on EUR, first 6 months of production, and first 12 months of production to estimate the monthly decline rate assuming exponential decline.

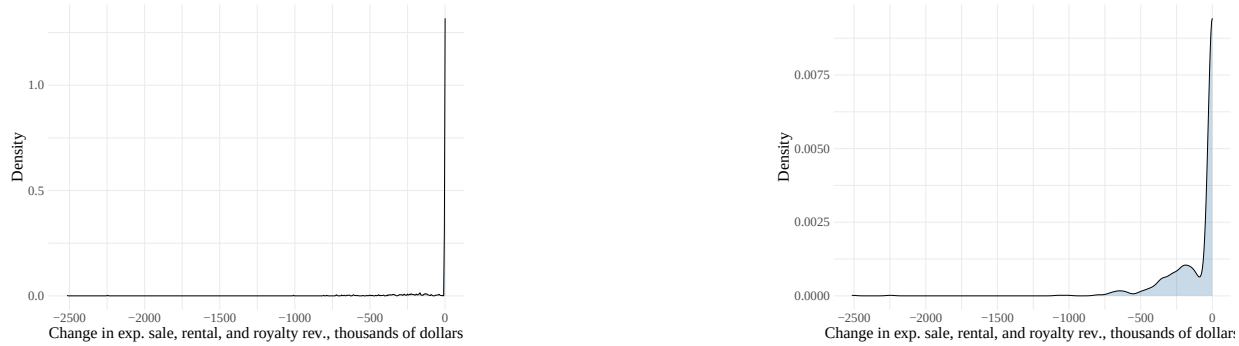
5. We compute the present discounted production (PDP) for both oil and gas production using predicted EUR from step 3, estimated decline rate from step 4, and the monthly discount rate of 0.25%, equivalent to an annual discount rate of 3%.

6. We multiply the oil PDP and the gas PDP by the real price of oil and gas respectively at the time of lease auction to compute the expected present discounted value (EPDV) of production.

7. To compute predicted lease level production, we assume that only for leases where there has been production within 2 km is there a positive probability of drilling and production before the end of the BLM lease. This, along with the assumption that only leases in North Dakota and Wyoming will have production, implies that only 9% of leases in our sample will a non-zero probability of future production. For cases where only a single PLSS section spans a lease, expected production is the EPDV computed in the previous step. For cases in which a lease intersects multiple PLSS sections, assume production comes from the PLSS section with the lowest predicted EPDV. We assume that drilling and production happens in the final year of the lease. To compute expected royalty revenue, we multiply EPDV by 12.5%. To compute the loss in royalty revenue from eliminating noncompetitive leasing, we multiply the expected royalty revenue by the change in probability of lease sale (see Figure 11).

Our goal is to construct a reasonable lower bound on expected future royalties, so the above steps include several conservative assumptions. For example, the predictive exercise in equation 11 uses all sections and not only those that have had production, eliminating the selection bias that happens when one predicts production for future leases only using data on existing wells. We also assume no drilling and production unless the BLM lease is within Montana or North Dakota and is located within 2 km of existing production. We use the lowest predicted value of production if the lease spans multiple sections, which also implies that multi-section leases have production on only one section.

Using this estimate, we predict that eliminating noncompetitive lease sales would decrease expected lease sale, rental, and royalty revenue by an average of $29K per parcel. In other words, the impact of eliminating noncompetitive leasing leads to a dramatic decrease in government revenue largely due to lost royalty payments, in spite of the fact that we conservatively assume that only leases within North Dakota and Montana within 2 km of existing production will have production. The left panel of figure 15 shows the distribution of the change in sale, rental, and royalty revenues for Montana and the Dakotas. This graph shows that the overall large average loss in revenues from eliminating noncompetitive parcels is driven by the long left tail of locations with large future production, but losses are much larger for those parcels predicted to have a positive likelihood of production: Conditional on being a parcel with positive predicted probability of production in the event of being leased—e.g., those in Montana and North Dakota within 2 km of existing production—the



(a) Montana/Dakotas: 2km

(b) Montana/Dakotas: 5km

FIGURE 15: Density of change in expected revenue from lease sales, rental, and royalty, from eliminating noncompetitive lease sales.

Note: For each plot, the x-axis gives change in expected revenue from lease sale and subsequent rental revenue, from eliminating noncompetitive leasing. The y-axis plots density. Both the left and right panels show results for Montana plus Dakotas only, where in the left we assume future production and royalties can only happen if parcel is within 2km of existing production at the time of sale, and in the right we assume future production and royalties can only happen if parcel is within 5km of existing production at the time of sale.

expected per-parcel revenue loss is equal to $321K.

The right panel of Figure 15 shows the distribution of expected change in revenue from sale, rental, and royalty revenues if we are less conservative and assume that for Montana and North Dakota, leased parcels only result in drilling, production and royalties if within 5 km (rather than 2 km) of an existing lease. Here, the expected loss in revenues increases from $29K to $43K per parcel. Conditional on being a parcel with positive predicted probability of production in the event of being leased—e.g., those in Montana and North Dakota within 5 km of existing production—the expected per-parcel revenue loss is equal to $287K.

Overall, our attempts to measure predicted royalty losses are likely conservative, and we view our estimates as likely understating the royalty losses resulting from eliminating noncompetitive lease sales. However, given the challenge of predicting future production in this setting, we take our estimates as representative of the magnitude of royalty losses, not precise point estimates. Overall, our results suggests an average revenue loss of at least $10K per parcel offered via auction—an even smaller, more conservative number than our estimated $29K per parcel, and we note that as our predictions make conservative assumptions, potential revenue losses could be much higher.

9 Conclusion

A seller in an auction faces a commitment problem in setting a reserve price, and the seller faces a tradeoff between expected revenue conditional on a sale and probability of a sale. This tradeoff is similar to that of a monopolist who in setting prices faces a tradeoff between higher revenues per sale and number of sales. When a monopolist model is extended to a dynamic setting (e.g., Gul et al. (1986)), the consumer has the incentive to wait to buy in order to reach a lower price, and that incentive erodes the monopolist's ability to charge the profit-maximizing price from a static model. Similarly in auctions, the fact that the consumer can withhold bidding and the fact that seller has an incentive to still try to sell the asset in the event of no initial bids means that buyers are incentivized to withhold bids which thereby erodes the efficacy of setting a reserve price.

We examine the incentive to withhold bidding within the setting of US federal onshore oil and gas leases where the government had a policy that in the event of no bids meeting the reserve price, the lease would then be made available noncompetitively, meaning that it would be made available in a lottery at a price lower than the reserve price. Using data on bidding and lease allocation outcomes, we estimate a structural model where the primitives are the parameters of the bidder valuations. We show that removing the noncompetitive lease sales option would lead to small decreases in probability of lease sales and small increases in lease sale revenues, but that there are significant revenue losses once we account for lost rental payments and royalties. We also show that the inability to commit to no sale in the event of no bid implies that revenue is much less responsive to changes in reserve price than if the seller can commit.

Our results are novel in that they are among the first to empirically examine the impact of principal commitment failure in a mechanism design setting. To our knowledge, the only other paper to examine this question is Liu et al. (2024) who examine an auction setting where unsold items are then re-auctioned at a lower reserve price. Both that paper and ours rely on identifying the impact of commitment failure in auctions with pre-specified policies that mandate commitment failure. Future research is needed that quantifies the impact of commitment failure in more complicated settings, including those where the principal's commitment failure is endogenously determined by beliefs about bidder actions, as well as the impact of commitment failure in settings other than auctions.

Our results are relevant to understanding the impact of US energy policy in general and the Inflation Reduction Act specifically. Our research shows that the IRA elimination of non-competitive leasing decreased both overall leasing and government revenue overall, contrary to the expectations of policy makers at the time. Further research is needed to examine other

facets of changing US oil and gas policy. For example, the IRA not only eliminated non-competitive leasing but also implemented a new fee to nominate parcels for leasing and also increased the reserve price. Furthermore, the transition in US presidential administrations has led to flip-flopping policy statements and increased policy uncertainty. Further research is needed to quantify the impacts of evolving US energy policy on production, government revenues, and greenhouse gas emissions.

References

Bajari, Patrick and Ali Hortacsu, "The Winner's Curse, Reserve Prices, and Endogenous Entry: Empirical Insights from eBay," *The RAND Journal of Economics*, 2003, *34* (2), 329–355.

Bhattacharya, Vivek, Andrey Ordin, and James W. Roberts, "Bidding and Drilling under Uncertainty: An Empirical Analysis of Contingent Payment Auctions," *Journal of Political Economy*, 2022, *130* (5), 1319–1363.

Brehm, Paul and Eric Lewis, "Information asymmetry, trade, and drilling: evidence from an oil lease lottery," *RAND Journal of Economics*, 2021, *52* (3), 496–514.

Bresnahan, Timothy F. and Peter C. Reiss, "Empirical models of discrete games," *Journal of Econometrics*, 1991, *48* (1), 57–81.

Bureau of Land Management, "Bureau of Land Management in Arizona to Competitively Offer Solar Energy Zone Leases," available at `BureauofLandManagementinArizonatoCompetitivelyOfferSolarEnergyZoneLeases` November 2021.

_ , "Geothermal Lease Sale," available at `https:///www.blm.gov/sites/default/files/docs/2022-07/NV_Geot_20220715_Sale_Notice.pdf` August 2022.

_ , "IMPACTS OF THE INFLATION REDUCTION ACT OF 2022 (PUB. L. NO. 117-169) TO THE OIL AND NATURAL GAS LEASING PROGRAM," Available at `https://www.blm.gov/policy/im-2023-008` November 2022.

City of Richmond, "City of Richmond, California Municipal Code," `https://library.municode.com/ca/richmond/codes/code_of_ordinances?nodeId=ARTIIADGO_CH2.52COPUPR_ARTIGEPR_2.52.100SCPURUCO` 2024. Sec 2.52.310 (7). Accessed: 2024-09-06.

City of St. Petersburg, "City of St. Petersburg, Florida Municipal Code," `https://library.municode.com/fl/st._petersburg/codes/code_of_ordinances?nodeId=PTIISTPECO_CH2AD_ARTVPUCOET` 2024. Sec 2-191 (k). Accessed: 2024-09-06.
Competes Act

***Competes Act**, S. 2962, 117th Congress 2021. Introduced in the Senate but not passed.*

Crawford, Vincent P., *"Efficient and Durable Decision Rules: A Reformulation," Econometrica, 1985, 53, 817–835.*

Crémer, Jacques, *"Arm's Length Relationships," The Quarterly Journal of Economics, 1989, 110, 275–295.*

DeSantis, Mark K., *"Oil and Gas Companies Gain by Stockpiling America's Federal Land," Technical Report, Center for American Progress 2018.*

Dewatripont, Mathias, *"Renegotiation and Information Revelation over Time: The Case of Optimal Labor Contracts," The Quarterly Journal of Economics, 1989, 104, 589–619.*

_ **and Eric S. Maskin**, *"Credit and Efficiency in Centralized and Decentralized Economies," Review of Economic Studies, 1995, 62, 704–719.*

Fitzgerald, Timothy, *"Evaluating Split Estates in Oil and Gas Leasing," Land Economics, 2010, 86 (2), 294–312.*

Freixas, Xavier, Roger Gesnerie, and Jean Tirole, *"Planning under Incomplete Information and the Ratchet Effect," The Review of Economic Studies, 1985, 52 (2), 173–191.*

Glowicka, Ela and Jonathan Beck, *"A note on reserve price commitments in Vickrey auctions," 2006.* `https://mpra.ub.uni-muenchen.de/6669/`.

Grant, Simon, Atsushi Kajii, Flavio Menezes, and Mathew J. Ryan, *"Auctions with options to re-auction," International Journal of Economic Theory, 2006, 2, 17–39.*

Green, Jerry R. and Jean-Jacques Laffont, *"Posterior Implementability in a Two-Person Decision Problem," Econometrica, 1987, 55, 69–94.*

Gul, Faruk, Hugo Sonnenschein, and Robert Wilson, *"Foundations of Dynamic Monopoly and the Coase Conjecture," Journal of Economic Theory, 1986, 39, 155–190.*

Haile, Philip A. and Elie Tamer, *"Inference with an Incomplete Model of English Auctions," Journal of Political Economy, 2003, 111 (1).*

Healy, Paul M and Krishna G Palepu, *"Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature," Journal of Accounting and Economics, 2001, 31 (1), 405–440.*

Hendricks, Kenneth, Joris Pinkse, and Robert H. Porter, *"Empirical Implications of Equilibrium Bidding in First-Price, Symmetric, Common Value Auctions," The Review of Economic Studies, 2003, 70 (1), 115–145.*

Herrnstadt, Evan, Ryan Kellogg, and Eric Lewis, *"Drilling Deadlines and Oil and Gas Development," Econometrica, 2024, 92 (1), 29–60.*

Hickman, Brent R., Timothy P. Hubbard, and Harry J. Paarsch, *"Identification and Estimation of a Bidding Model for Electronic Auctions," Quantitative Economics, 2017, 8 (2), 505–551.*

IER, *"Oil and Natural Gas Production on Federal and Non-Federal Lands, 2016-2021.," Technical Report, Institute for Energy Research 2022.*

Jun, Byoung Heon and Elmar G. Wolfstetter, *"Auctions with imperfect commitment when the reserve may signal the cost to re-auction," International Journal of Industrial Organization, 2015, 40, 11–21.*

Kong, Yunmi, *"Not knowing the competition: evidence and implications for auction design," The RAND Journal of Economics, 2020, 51 (3), 840–867.*

_ , Isabelle Perrigne, and Quang Vuong, *"Multidimensional Auctions of Contracts: An Empirical Analysis," American Economic Review, 2022, 112 (5), 1703–1736.*

Laffont, Jean Jacques and Jean Tirole, *"The Dynamics of Incentive Contracts," Econometrica, 1988, 56 (5), 1153–1175.*

Laffont, Jean-Jacques and Quang Vuong, *"Structural Analysis of Auction Data," The American Economic Review: Papers and Proceedings, 1996, 86 (2), 414–420.*

Leonard, Bryan and Dominic P. Parker, *"Fragmented Ownership and Natural Resource Use: Evidence from the Bakken," Economic Journal, 2021, 131 (635), 1215–1249.*

Lewis, Eric, *"Patchwork Policies, Spillovers, and the Search for Oil and Gas," American Economic Journal: Economic Policy, 2019, 11 (1), 380–405.*

Liu, Hui, Yao Luo, and Ruli Xiao, *"Dynamic Bidding under Relisting and New Entry: Evidence from Judicial Sales," 2024. Working Paper.*

Liu, Quingmin, Konrad Mierendorff, Xianwen Shi, and Weijie Zhong, *"Auctions with Limited Commitment," American Economic Review, 2019, 109, 876–910.*

McAfee, R. Preston and Daniel Vincent, *"Sequentially Optimal Auctions," Games and Economic Behavior, 1997, 18, 246–276.*

Menezes, Flavio and Mathew J. Ryan, *"Reserve price commitments in auctions," Economics Letters, 2005, 87, 35–39.*

Olmem, Andrew and Philip K. Lau, *"Biden administration takes action on oil & gas permits but policy still evolving," Insights, Mayer Brown 2021.*

Schaffer, Mark E., *"The Credible-Commitment Problem in the Center-Enterprise Relationship," European Economic Journal of Comparative Economics, 1989, 13, 359–382.*

Selvanayagam, Ruban, *"What Happens if No One Bids on a House at Auction?,"* https://www.doi.gov/news/energy-revolution-unleashed-interior-shatters-previous-records-11-billion-2018-oil- *2024. Accessed: 2024-09-06.*

Skreta, Vasiliki, *"Optimal auction design under non-commitment," Journal of Economic Theory, 2015, 159, 854–890.*

State of Louisiana, *"Louisiana Revised Statues,"* https://casetext.com/statute/louisiana-revised-statutes/revised-statutes/title-33-municipalities-and-parishes/chapter-27-e-biodistrict-new-orleans-act/section-33903968-general-powers *2024. Sec 2.52.310 (7). Accessed: 2024-09-06.*

Tirole, Jean, *"Incomplete Contracts: Where Do We Stand?," Econometrica, 1999, 67 (4), 741–781.*

Tracey, Brandon S., *"Revenues and Disbursements from Oil and Natural Gas Production on Federal Lands," available at* https://crsreports.congress.gov/product/pdf/R/R46537. *September 2020.*

U.S. Department of the Interior, *"Report on the Federal Oil and Gas Leasing Program," Department of the Interior.* https://www.doi.gov/sites/doi.gov/files/report-on-the-federal-oil-and-gas-leasing-program-doi-eo-14008.pdf *November 2021.*

U.S. Government Accountability Office, *"Oil and Gas: Onshore Competitive and Noncompetitive Lease Revenues," available at* https://www.gao.gov/assets/gao-21-138-highlights.pdf. *November 2020.*

_ , *"Oil and Gas Permitting: Actions Needed to Improve BLM's Review Process and Data System," available at* https://www.gao.gov/assets/d20329.pdf. *March 2020.*

Vartiainen, Hannu, *"Auction Design without commitment," Journal of the European Economics Association, 2013, 11, 316–342.*

A Theory details

Derivation of $W(P,H,N)$: We focus on the case where $H \geq P$. We define $\tilde{F}(P,H) = F(P)/F(H)$, meaning the probability that a given valuation is less than P conditional on it being less than H. Then, we can simplify $W(P,H,N)$ as follows:

$$\begin{aligned}
W(P,S,N) =& \sum_{k=0}^{N-1} \frac{1}{k+1} \binom{N-1}{k} \tilde{F}^{N-1-k}(P,H) \left(1-\tilde{F}(P,H)\right)^k \\
=& \frac{1}{N} \sum_{k=0}^{N-1} \binom{N}{k+1} \tilde{F}^{N-1-k}(P,H) \left(1-\tilde{F}(P,H)\right)^k \\
=& \frac{1}{N\left(1-\tilde{F}(P,H)\right)} \sum_{k=1}^{N} \binom{N}{k} \tilde{F}^{N-k}(P,H) \left(1-\tilde{F}(P,H)\right)^k \\
=& \frac{1}{N\left(1-\tilde{F}(P,H)\right)} \left[\sum_{k=0}^{N} \binom{N}{k} \tilde{F}^{N-k}(P,H) \left(1-\tilde{F}(P,H)\right)^k - \tilde{F}^N(P,H)\right] \\
=& \frac{1-\tilde{F}^N(P,H)}{N(1-\tilde{F}(P,H))}
\end{aligned}$$

where the last step follows from the binomial theorem.

Existence and uniqueness of H: Using the rule of difference in powers, we can rewrite the previous equation as:

$$\begin{aligned}
W(P,H,N) =& \frac{1}{N} \frac{(1-\tilde{F}(P,H))(\tilde{F}^{N-1}(P,H) + \tilde{F}^{N-2}(P,H) + \ldots + 1)}{1-\tilde{F}(P,H)} \\
=& \frac{1}{N} \sum_{k=0}^{N-1} \tilde{F}^k(P,H) = \frac{1}{N} \sum_{k=0}^{N-1} \left(\frac{F(P)}{F(H)}\right)^k
\end{aligned}$$

Recall from the characterization of the equilibrium screening value, equations (3) - (6), the screening threshold can be found as the point where:

$$\pi_B(H|R,H,N) = \pi_L(H|P,H,N)$$

Substituting $\nu_i = H$, and assuming $F(\nu)$ is a continuous and differentiable function:

$$\begin{aligned}\pi_B(H|R,H,N) &= \big(H - E(\nu_{(-i)}|H \le \nu_{(-i)} < \nu_i)\big) \cdot p(H \le \nu_{(-i)} < H) + \\ &\quad (H-R) \cdot p(\nu_{(-i)} < H) \\ &= (H-R) \cdot p(\nu_{(-i)} < H) \\ \pi_L(H|P,H,N) &= (H-P) \cdot p(\nu_{(-i)} < H) \cdot W(P,H,N)\end{aligned}$$

Equating both equations, substituting the expression for $W(P,H,N)$, and simplifying, we find that the equilibrium screening value H is the solution to the following equation:

$$G(H,P,R) = \frac{H-R}{H-P} - \frac{1}{N}\sum_{k=0}^{N-1}\left(\frac{F(P)}{F(H)}\right)^k = 0$$

Again, focusing on the case $H \ge R \ge P$:

$$\begin{aligned}\lim_{H\to P} G(H,P,R) &= -\infty \\ \lim_{H\to R} G(H,P,R) &= -\frac{1}{N}\sum_{k=0}^{N-1}\left(\frac{F(P)}{F(R)}\right)^k < 0 \\ \lim_{H\to \infty} G(H,P,R) &= 1 - \frac{1}{N}\sum_{k=0}^{N-1} F^k(P) > 0\end{aligned}$$

The last inequality follows from the second term being an average of numbers strictly between 0 and 1. Since we assume $F(\nu)$ is a continuous and differentiable function, $G(H,P,R)$ is a continuous and differentiable function of H. Therefore, by the intermediate value theorem, there exists a value H such that $G(H,P,R) = 0$.

For uniqueness, it is simple to note that:

$$\frac{\partial G(H,P,R)}{\partial H} = \frac{R-P}{(H-P)^2} + \frac{1}{N}\sum_{k=0}^{N-1} k\left(\frac{F(P)}{F(H)}\right)^{k-1}\frac{f(H)}{F(H)},$$

where $f(H) = F'(H)$. Since $F(\nu)$ is a continuous and differentiable function, $f(H) > 0$ for all H. Therefore, $\frac{\partial G(H,P,R)}{\partial H} > 0$ for all H, meaning that $G(H,P,R)$ is a strictly increasing function of H. Therefore, there is a unique value of H that solves $G(H,P,R) = 0$. Further, $H > R$.

Expected revenue with noncompetitive option: The expected revenue comes from an expected auction revenue, and an expected noncompetitive revenue. The expected revenue from an auction is further divided into the expected payment by the second highest bidder if the second highest winner bids above R, and R in case the bidder with the second highest valuation does not bid:

$$E[Revenue] = \int_H^\infty y(1-F(y))dF^{n-1}(y) + nRF^{n-1}(H)(1-F(H)) + P(F^n(H) - F^n(P))$$

B Data and variable construction

Constructing measures of nearby production. We use the "flat" files from Enverus. Because we do not have lease shapefiles for all leases in our data, we first construct "outer bound" lease boundaries as follows: Each lease data file from EnergyNet has the PLSS section or sections that contain the lease. We then use the boundaries of the lease from PLSS shapefiles to construct an "outer bound" for the lease such that the outer bound is the boundary of the PLSS sections that contain the lease. Then, to construct measures of nearby production, we find all wells that lie within 10 km of the "outer bound" of the lease.

We then construct measures of cumulative oil and gas production for all wells that lie within the 10km buffer around the lease "outer bound". These cumulative measures use all production from Enverus monthly production files that happened prior to the month of the auction. To get a proxy of the value, we multiply these cumulative oil and gas production amounts by the average 12 month prices of crude oil and natural gas in the 12 months prior to the lease being offered.

C Additional descriptives

C.1 Auction event summary

Table 6 gives a table on information on each auction event, giving the date, BLM office (where the Montana office administers leases in Montana, North Dakota, and South Dakota), number of parcels offered, number of parcels that are in our sample, and number of registered bidders.

Date	Office	Parcels	In-sample	Reg. bidder count
12 2016	MT	88	44	15
3 2017	NV	67	67	10
6 2017	MT	156	127	19
9 2017	MT	15	7	19
3 2018	MT	109	74	15
12 2017	MT	204	177	26
12 2017	NV	208	208	13
3 2018	NV	40	40	9
6 2018	NV	166	163	17
9 2018	MT	30	21	22
12 2018	MT	23	14	31
3 2019	MT	305	261	49
7 2019	NV	200	194	16
7 2019	MT	34	10	56
9 2019	NV	28	23	9
9 2019	MT	13	6	56
10 2019	NV	141	138	11
12 2019	NV	156	154	7
12 2019	MT	20	16	23
3 2020	MT	8	5	19
9 2020	NV	11	9	9
9 2020	MT	38	13	36

TABLE 6: Table giving date, BLM office, parcel counts, count of parcels within sample, and number of registered bidders, for each auction event in our sample.

D Additional structural model and counterfactual results.

This section contains a number of additional results from the structural model estimation and counterfactuals:

1. Figure 16 are scatter plots of the index values $Z_{it}\hat{\beta}$, comparing the gamma and lognormal specifications for Montana and the Dakotas (left panel) and Nevada (right panel).

2. Figure 17 are scatter plots of the ratio of screening value to reserve price, comparing the gamma and lognormal specifications for Montana and the Dakotas (left panel) and Nevada (right panel).

3. Figure 18 are scatter plots of the the probability of a lease sale, comparing the gamma and lognormal specifications for Montana and the Dakotas (left panel) and Nevada (right panel).

4. Figure 19 are density plots of the ratio of the screening value and the reserve price implied from different assumptions about the number of potential bidders (from estimates in Table 5).

5. Figure 20 are density plots of the impact of eliminating noncompetitive leasing on the probability of lease sale.

6. Figure 21 are density plots of the impact of eliminating noncompetitive leasing on expected lease sale revenue, measured in thousands of dollars.

7. Figure 22 are density plots of the impact of eliminating noncompetitive leasing on the probability of lease sale implied from different assumptions about the number of potential bidders (from estimates in Table 5).

8. Figure 23 are density plots of the impact of eliminating noncompetitive leasing on expected lease sale revenue implied from different assumptions about the number of potential bidders (from estimates in Table 5).

E Predicting future production and royalties

Here, we discuss in more detail the steps used to predict the predicted production from leases and therefore royalties.

E.1 Poisson regression

We first report details on how we estimate the Poisson regression in equation 11. We use a generalized version of the Poisson likelihood that accounts for non-integer values of the dependent variable, leading to the following log likelihood function below. With a dependent variable y_i, independent variables x_i, and unknown parameter θ, the Poisson regression log likelihood function is:

$$\log L(\theta)|X,Y) = \sum_{i=1}^{m}(y_i\theta' x_i - \exp(\theta' x_i) - \log\Gamma(y_i+1) \tag{12}$$

Here, $\log\Gamma(y_i+1)$ is used instead of $\log(y_i!)$, providing an identical log likelihood if y_i consists of integers but also allowing for non-integer values of y_i.

The regression specification involves using Gaussian weights $w_{ii'}$ as a function of the distance $d_{ii'}$) between any two given PLSS sections i and i'. We define the weights $w_{ii'}$ as:

$$w_{ii'} = \frac{\phi(d_{ii'}/b)\cdot\mathbf{1}[d_{ii'}/b \le c]}{\sum_{j\neq i}\phi(d_{ij}/b)\cdot\mathbf{1}[d_{ij}/b \le c]} \tag{13}$$

where b is the Gaussian kernel bandwidth and c is the caliper, which we set to 2.5. Distance $d_{ii'}$ is measured in meters.

Given the nonlinearity of how the Gaussian bandwidth b and the parameter κ enter the likelihood, we estimate this in a nested procedure:

1. In an outer loop, we perform a grid search over $\log\kappa$, using values ranging from -9 to 2 in intervals of 0.5.

2. For each guess of $\log\kappa$, we perform a univariate search over the gaussian bandwidth parameter $b \in [500m, 100km]$ for the b that maximizes the log likelihood.

3. At each evaluation of b, we estimate β and calculate the log likelihood using Poisson regression.

4. We use quadratic interpolation to find the best fit of $\log\kappa$ and bandwidth b. We then use these values to re-estimate the Poisson model, finding the values of β_1, β_2, and β_3 that maximize log likelihood.

Add discussion of what the units of measurement are for EUR for oil and gas.

We then compute total EUR over all wells in the data (up to October 2024) and use these along with our estimated Poisson parameter results in Table 7 to predict future production. Because mechanically these will lead to higher predicted production than if we use only EUR from wells beginning production in 2021 or earlier, we compute both predicted production

	(1) Oil	(2) Gas
β_1	6.822	7.227
β_2	0.069	0.072
β_3	0.358	0.485
$\log \kappa$	6.58	3.12
bandwidth b	14,092	14,484
N	120,732	120,732
Log likelihood / N	-32149.2	-80985.9

TABLE 7: Poisson regression estimates of equation 11, with estimates for oil in column 1 and estimates for gas in column 2.

using pre-2021 EUR only as well as predicted production using all EUR, and scale our predicted production values down by the ratio of the two values. Specifically, we scale predicted oil production using a factor of 0.88 and scale predicted gas production using a factor of 0.85.

E.2 Decline estimation

We estimate decline rates using a method-of-moments calculation. We assume that wells follow exponential decline so that production in month t for well i is $q_{it} = q_{i0}\zeta^t$ with $\zeta \in (0,1)$ where q_{i0} is a well-specific initial production rate. Cumulative production over the first t months is then $Q_{it} \equiv \sum_{s=1}^{t} q_{is}$, which can be re-written as

$$Q_{it} = q_{i0} \sum_{s=1}^{t} \zeta^s = q_{i0} \left(\frac{\zeta}{1-\zeta} \right) (1 - \zeta^t).$$

We note that EUR is simply $Q_{i\infty} = q_{i0}\zeta/(1-\zeta)$. The well-specific IP rate can be eliminated by differencing the logarithm of production at any two periods:

$$\log(Q_{is}/Q_{it}) = \log \frac{\sum_{k=1}^{s} \zeta^k}{\sum_{k=1}^{t} \zeta^k} = \log \frac{1-\zeta^s}{1-\zeta^t}$$

For each well in the data, Enverus reports estimated EUR as well as the first 6 and 12 months of production, conditional on producing at least 6 and 12 months respectively. We use these numbers to infer the average decline rate of production in the data, estimating it separately for oil and gas production.

Letting w index wells, j index the product (oil or gas), and s, t index time periods, we define the following moment, which relates the change in cumulative production over two time periods to the decline rate ζ:

$$M_{wj}(s,t;\zeta) \equiv \left[\log \frac{Q_{wjs}}{Q_{wjt}} - \log \frac{1-\zeta^s}{1-\zeta^t} \right]^2.$$

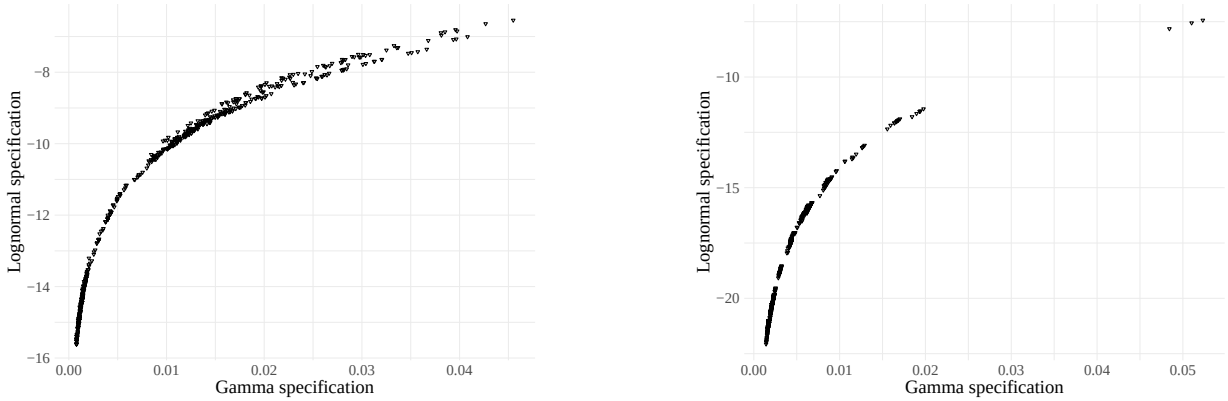
$[\alpha_1, \alpha_2, \alpha_3]$	(1) Oil	(2) Gas
$[1/3, 1/3, 1/3]$	0.9829	0.9885
$[1, 0, 0]$	0.9689	0.9925
$[0, 1, 0]$	0.9826	0.9886
$[0, 0, 1]$	0.9833	0.9884

TABLE 8: Estimates of ζ from equation 14 for various values of $\boldsymbol{\alpha} \equiv [\alpha_1, \alpha_2, \alpha_3]$. Estimates for oil in column 1 and estimates for gas in column 2.

Rather than perform GMM with three separate sample moments, we aggregate these into a single moment that allows us to choose a weighting that yields the highest decline rate ζ as this will provide the most conservative estimate for future production. Thus, our moment is

$$M_j(\boldsymbol{\alpha}) \equiv \sum_w \alpha_1 M_{wj}(6, 12; \zeta) + \alpha_2 M_{wj}(6, \infty; \zeta) + \alpha_3 M_{wj}(12, \infty; \zeta) \tag{14}$$

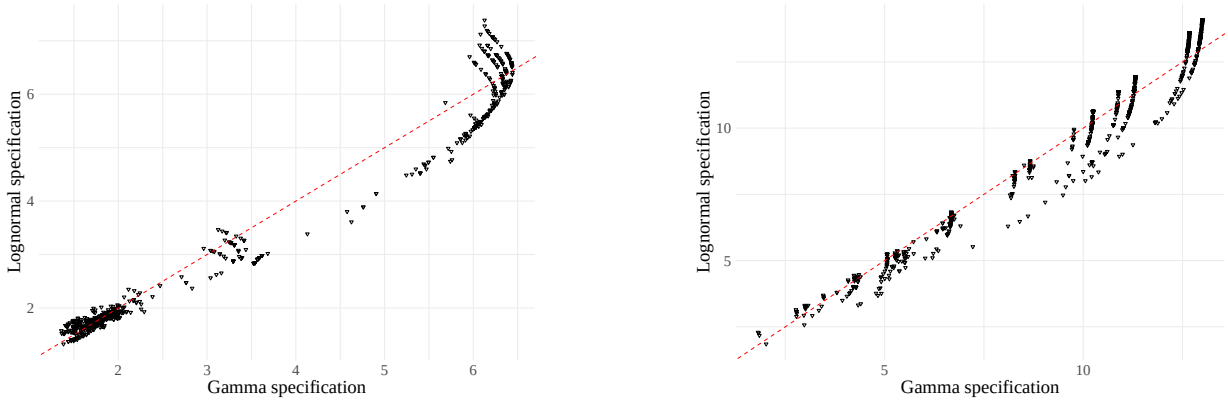
We then use a standard univariate optimization routine to minimize (14) to find best-fit values of ζ given weights $\boldsymbol{\alpha}$. Our results for various weight vectors $\boldsymbol{\alpha}$ are shown in Table 8. Our estimates yield $\zeta = 0.9833$ for oil and a values of ζ =0.9925 for gas, corresponding to values of $\boldsymbol{\alpha} = [0, 0, 1]$ and $[1, 0, 0]$ respectively.



(a) Montana/Dakotas (b) Nevada

FIGURE 16: Comparing indices $Z_{it}\hat{\beta}$ between gamma and lognormal specifications.

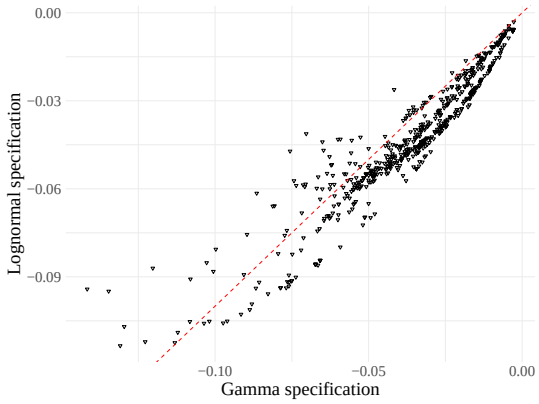
Note: For each plot, the x-axis gives the estimated index value $Z_{it}\hat{\beta}$ for the gamma specification while the y-axis gives the index for the lognormal specification. The left graph shows results for Montana plus Dakotas while the right shows results for Nevada.



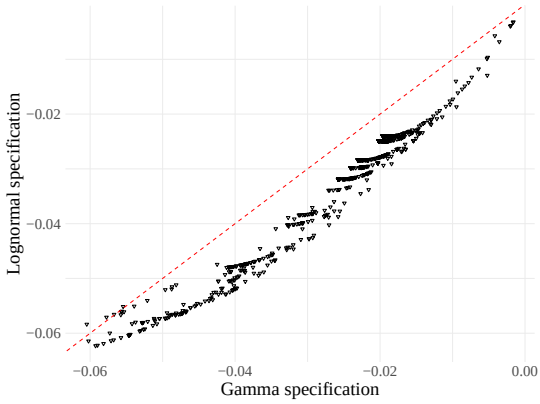
(a) Montana/Dakotas (b) Nevada

FIGURE 17: Comparing the screening value to reserve price ratio between gamma and lognormal specifications.

Note: For each plot, the x-axis gives the estimated ratio of screening value to reserve price for the gamma specification while the y-axis gives the estimated ratio of screening value to reserve price for the lognormal specification. The left graph shows results for Montana plus Dakotas while the right shows results for Nevada.



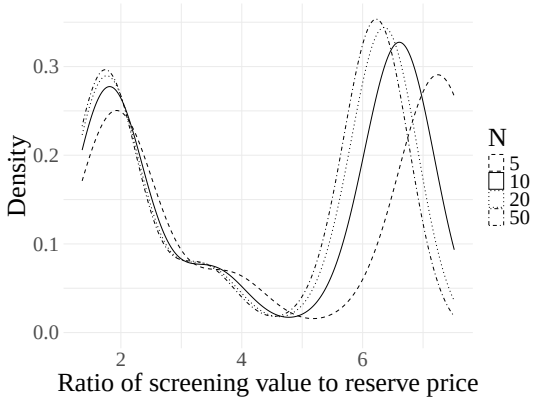
(a) Montana/Dakotas



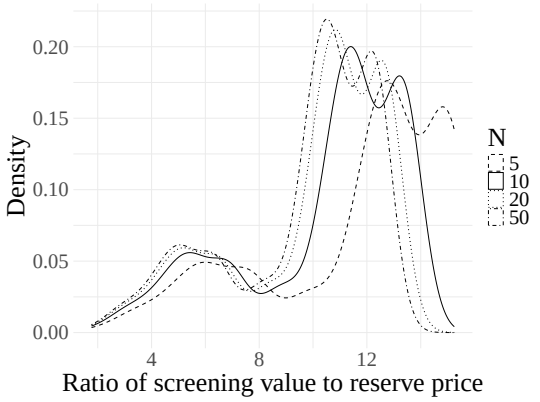
(b) Nevada

FIGURE 18: Comparing the impact of eliminating noncompetitive leasing on probability of lease sale between gamma and lognormal specifications.

Note: For each plot, the x-axis gives the estimated impact of eliminating noncompetitive leasing on probability of any lease sale for the gamma specification while the y-axis gives the estimated impact of eliminating noncompetitive leasing on probability of any lease sale for the lognormal specification. The left graph shows results for Montana plus Dakotas while the right shows results for Nevada.



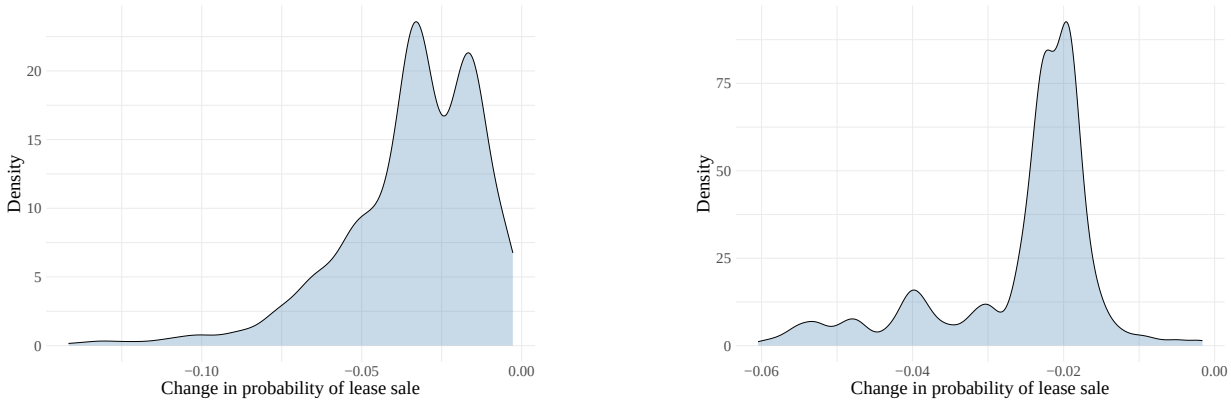
(a) Montana/Dakotas



(b) Nevada

FIGURE 19: Comparing the ratio of screening value to reserve price R under different assumptions of number potential bidders..

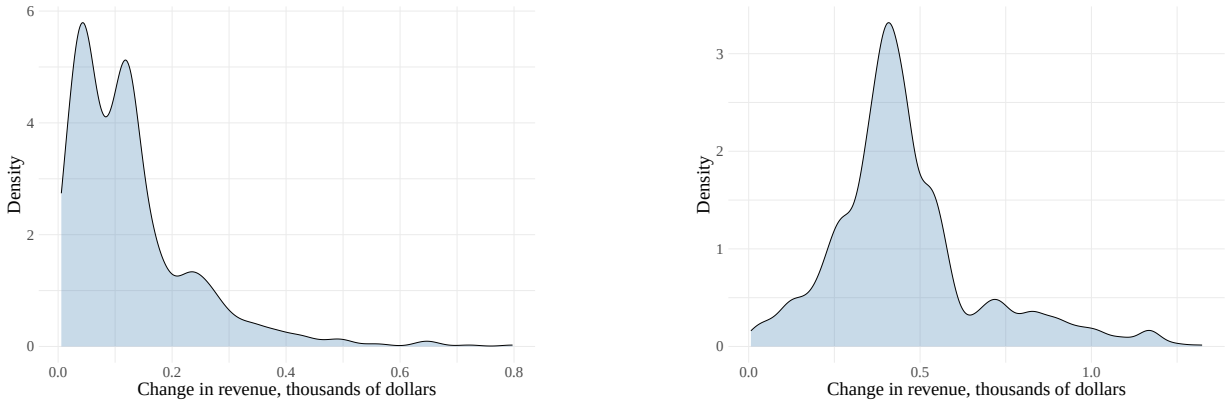
Note: For each plot, we plot the density of screening value to reserve price ratio under specifications for different values of number of potential bidders using the gamma distribution (see Table 3 for model parameter estimates). The results show that assuming a smaller number of potential bidders typically implies a higher screening value. The left graph shows results for Montana plus Dakotas while the right shows results for Nevada.



(a) Montana/Dakotas (b) Nevada

FIGURE 20: Density plots of impact of removing noncompetitive leasing on probability of lease sale

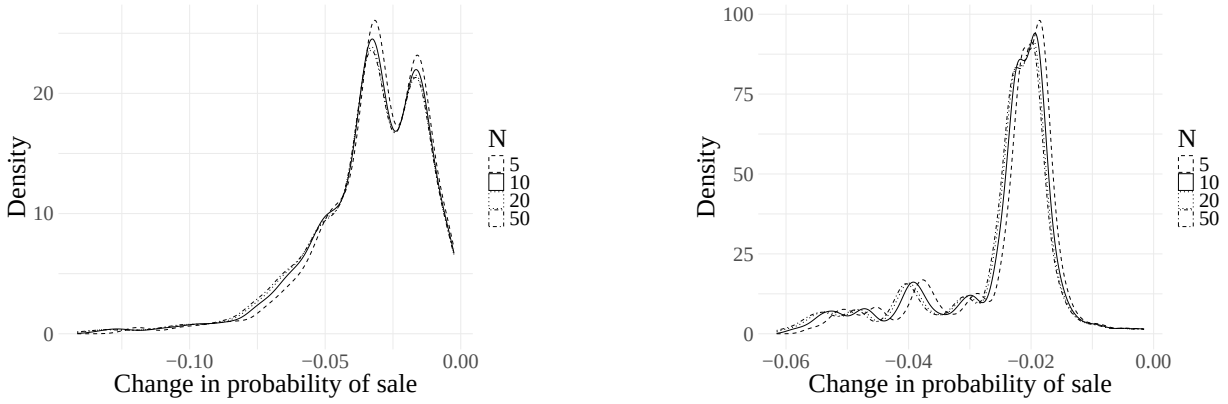
Note: For each plot, the x-axis gives the impact of removing noncompetitive leasing on probability of lease sale while the y-axis gives density. The left graph shows results for Montana plus Dakotas while the right shows results for Nevada.



(a) Montana/Dakotas (b) Nevada

FIGURE 21: Density plots of impact of removing noncompetitive leasing on lease sale revenue, thousands of dollars.

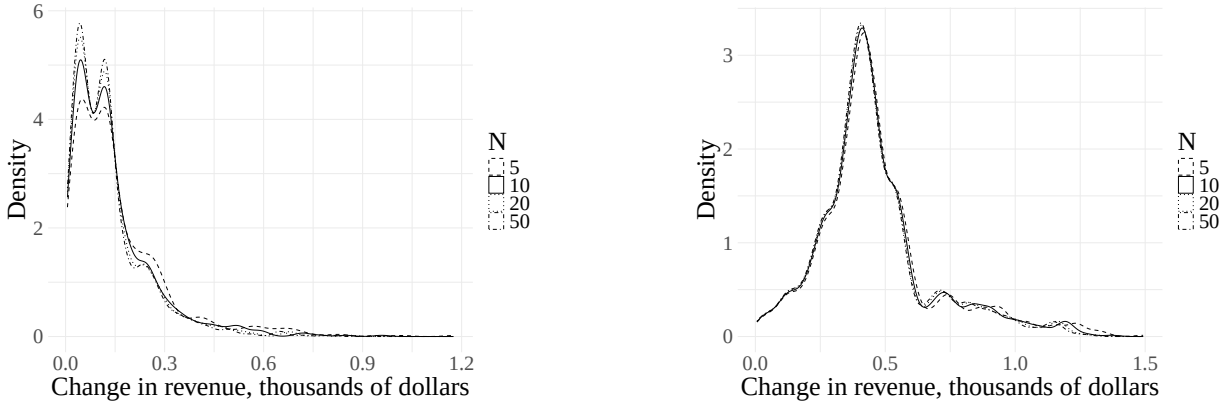
Note: For each plot, the x-axis gives the impact of removing noncompetitive leasing on lease sale revenue while the y-axis gives density. The left graph shows results for Montana plus Dakotas while the right shows results for Nevada.



(a) Montana/Dakotas (b) Nevada

FIGURE 22: Impact of removing noncompetitive leasing on probability of lease sale with different number of potential bidders.

Note: For each plot, the x-axis gives the impact of removing noncompetitive leasing on probability of lease sale while the y-axis gives density. The graph compares probabilities for number of potential bidders ranging from 5 to 50. The left graph shows results for Montana plus Dakotas while the right shows results for Nevada.



(a) Montana/Dakotas (b) Nevada

FIGURE 23: Impact of removing noncompetitive leasing on expected lease sale revenue with different number of potential bidders.

Note: For each plot, the x-axis gives the impact of removing noncompetitive leasing on expected lease sale revenue while the y-axis gives density. The graph compares probabilities for number of potential bidders ranging from 5 to 50. The left graph shows results for Montana plus Dakotas while the right shows results for Nevada.