Underbidding for Oil and Gas Tracts

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Common values auction models, where bidder decisions depend on noisy signals of common values, provide predictions about Bayesian Nash equilibrium (BNE) outcomes. In settings where these common values can be estimated, these predictions can be tested. We propose a series of tests, robust to assumptions about the signal structure, to determine whether the observed data could have been generated by a Bayesian Nash equilibrium. In the setting of oil and gas lease auctions in New Mexico, we find evidence that participation decisions are correlated and that participants systematically underbid in light of ex post outcomes.
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Oil and gas production in the state of New Mexico generates a tremendous amount of revenue. Home to one of the most productive oil basins in the US, New Mexico received $4.1 billion in oil and gas tax revenue in the fiscal year 2022.[1] Rights to drill on state lands are auctioned off each month by the New Mexico State Land Office (NMSLO), but the prices paid in these auctions are difficult to reconcile with the massive value provided to leaseholders. Although only one in eight leases is drilled, we find that the average profit from obtaining a lease, including undrilled tracts, exceeds five times the price paid at the lease sale. Such a dramatic difference between price paid and value is cause to suspect collusive behavior on the part of bidders in these sales. This paper examines features of the New Mexico oil and gas lease sales that would facilitate collusion and proposes a series of novel statistical tests for investigating collusion in common value markets.

Methods to detect collusion in first-price auctions (e.g., Porter and Zona (1993, 1999); Bajari and Ye (2003); Chassang and Ortner (2019); Chassang et al. (2022); Kawai et al. (2023); Kawai and Nakabayashi (2022)) focus on detecting bidding anomalies inconsistent with BNE bidding. These methods provide antitrust authorities with a set of statistical screening devices which are aimed at settings

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[1]Reported by the New Mexico Taxation and Revenue Department: https://www.tax.newmexico.gov/all-nm-taxes/oil-natural-gas-mineral-extraction-taxes/

where collusive bid patterns are not sufficiently sophisticated to disguise their intentions. We complement the existing methods by incorporating ex post returns to construct direct tests for BNE bidding. Information on ex post returns is available in many auction settings. Ex post returns are naturally available in oil and gas lease sales as lease values are measurable using publicly available production records, but can also be used more broadly in settings in which resale or secondary markets can be used to assess object value.

We consider the sale of oil and gas leases in first-price, sealed bid auctions by the NMSLO over a twenty-two-year period from 1994 to 2015. For each auction we observe each bid submitted, along with the identity of the bidder, as well as a land survey description of the tract. By connecting publicly available data on oil and gas production to geographic descriptions of leased tracts, we construct estimates of the profit generated by each lease. Examining the winners across the sample period, we find that the bidding market is highly concentrated, with the largest four bidders holding a market share of more than 50%. Since lease sales are held in person each month, these dominant bidders had ample experience with each other and many opportunities to interact.

First, we show that bidder participation decisions are correlated across bidder pairs, conditional on ex post tract value. We use a bivariate probit model to control for ex post value and bidder-sale fixed effects, rejecting the null hypothesis of zero correlation at the 5% significance level for 25 of 55 bidder pairs. Since the conditional independence of bid distributions is an implication of the common values auction with independent conditional signal distributions, we reject the null hypothesis that the observed bids were generated by this BNE. We relax the assumption of independent signal distributions for our subsequent tests.

Second, we utilize the return data to test for the existence of profitable strategic deviations. For strategies to constitute an equilibrium they must maximize ex ante expected payoffs regardless of the information available to bidders at the time of the auction. We propose an underbidding test based on the Nash equilibrium condition that unilateral deviations cannot be profitable. Our test builds on the bid-scaling (winner's curse) test proposed in Hendricks et al. (1987) and is robust to the information structure available to bidders. We find that under our preferred interest rate estimate auction participants substantially underbid relative to the maximally profitable unilateral deviation. We find that, holding rival bids constant, bidders can double their expected payoffs by tripling their bids, which is a violation of BNE bidding.

Finally, we test for the existence of profitable uniform upward deviations as considered in Feldman et al. (2016) and Bergemann et al. (2017). Winning bids in a first-price auction are bounded away from zero; if rival bids are too low, upward deviation strategies will be profitable because the value of winning outweighs the cost of raising one's own bid. Bergemann et al. (2017) show that the lowest distribution of bids that can sustain a BNE corresponds to a particular "worst-case" equilibrium where the information structure is such that it minimizes auctioneer revenue subject to the uniform upward deviation constraint. We formulate a statistical test based on the non-profitability of uniform upward deviations using data on the distribution of ex post values and winning bids. We find that within this class of deviations, where bidders raise the minimum bid submitted across all auctions, under our preferred interest rate estimate net deviation gains are between 230% and 530% of equilibrium payoffs.

While the test results we obtain are suggestive of the presence of collusion, it is important to note that none of the tests we propose *prove* its existence. Section VII discusses practical steps the auctioneer can take when facing bidders who seem likely to conspire to rig their bids.

Related literature

Our paper contributes primarily to the literature on statistical cartel detection in first-price auctions, see Porter (2005) for a survey. Porter and Zona (1993, 1999) find evidence that cartel bids are statistically different from non-cartel firms. Bajari and Ye (2003) devise an exchangeability test, which stipulates that under competition a bidder's own private information should be the only determinant of bids, while the identities of rival firms should not matter. Schurter (2017) and Chassang and Ortner (2019) propose tests for collusion using exogenous variations in reserve price levels. Kawai and Nakabayashi (2022) examine multi-round bidding and devise a test for correlation between the initial and subsequent bid. Kawai et al. (2023) propose a regression discontinuity approach by comparing marginal winning and marginal losing bids using bidders' incumbency or backlog status. Chassang et al. (2022) propose estimators for assessing the proportion of observed bidding histories that can be classified as competitive. They find evidence of missing mass in the bid distribution around marginal losing and winning bids in procurement auction in Japan. We applied this test but did not find evidence of missing mass close to losing bids in our data set.

Tests for collusion have also been applied for other auction settings. Conley and Decarolis (2016) propose tests to examine coordination in average-price auctions. Kaplan et al. (2016) provide tests for partial cartels in English auctions. Internal workings of cartels have been studied by Pesendorfer (2000) and Asker (2010). Caoui (2022) estimates damages from bid rigging.

Incentives to collude are studied more broadly in the face of antitrust authorities in Harrington (2005) and measured in the context of mergers in Miller et al. (2021) and Igami and Sugaya (2021). These papers exploit predictions obtained by the theory of repeated games (Green and Porter (1984); Rotemberg and Saloner (1986)).

Our paper also contributes to the literature on oil and gas lease auctions, see Porter (1995) for a survey on offshore auctions. Hendricks et al. (2003) test for winner's curse effects and confirm that bidders bid rationally in offshore sales. Kellogg (2014a) studies the effect of price expectations on the decision to drill onshore. Kong (2020, 2021), Bhattacharya et al. (2022) and Ordin (2019) study the same NMSLO data as we do. Kong (2020, 2021) studies the relationship between first-price and English auctions. Bhattacharya et al. (2022) endogenize the drilling decision and study the optimal royalty rate design in contingent payment auctions. Ordin (2019) studies the role of tax policies in oil and gas lease sales. Hodgson (2019) studies information externalities in UK offshore drilling decisions. Kong et al. (2022) study a two-dimensional bidding system in Louisiana where bidders submit a bonus bid and a royalty rate.

The paper is organized as follows: Section I describes our framework. We describe the auction model and discuss the assumptions. Section II devises statistical testing procedures aimed at detecting collusion. Section III describes the market and highlights features that may facilitate collusion. Section IV argues that bidders coordinate their bidding strategies. Section V shows that under our preferred interest rate estimate bidders underbid. Bids are too low to maximize ex ante bidder profit. Section VI examines the uniform upward deviation incentive and shows that under our preferred interest rate estimate bidders could profitably deviate by raising their minimum bids. Section VII concludes.

I. Framework

Our framework is the pure common values mineral rights model as described in Bergemann et al. (2017), which contains the classic mineral rights model proposed in Wilson (1977) as a special case.

A seller has one tract for sale. Bidders $i = 1, \dots, N$ are risk-neutral and bid for the tract. The tract has a common value v contained in a compact interval $V = [\underline{v}, \overline{v}] \subset \mathbb{R}$. The value v is drawn from the cumulative distribution function (cdf) G with support V. The value distribution is common knowledge among bidders. Bidder i additionally receives private information about the value beyond knowing the prior distribution. This information comes from a signal $x_i \in [\underline{x}, \overline{x}] \subset \mathbb{R}$ that is correlated with the value v. We denote $\mathbf{X} = (X_1, \dots, X_N)$ the random variables and $\mathbf{x} = (x_1, \dots, x_N)$ the realizations. The joint distribution of signals and ex post tract value is $F(\mathbf{x}, v)$. The seller announces a minimum bid, or reserve price, $r \in \mathbb{R}_+$.

Denote the set of high bidders with $W(\mathbf{b}) = \{i \quad | b_i \geq b_j, \text{ for all } j = 1, .., N \text{ and } b_i \geq r\}$, where $\mathbf{b} = (b_1, \dots, b_N) \in B^N = [0, \overline{v}]^N$ denotes the vector of bids. Let the probability that bidder i receives the good be $q_i(\mathbf{b}) = 1/|W(\mathbf{b})|$ if bidder i is among the high bidders, and $= 0$ otherwise.

A bidding strategy for player i is a mapping $\beta_i : [\underline{x}, \overline{x}] \longrightarrow B$ from signals to bids. Let Σ_i denote the set of strategies for bidder i and let $\beta \in \mathbf{\Sigma} = \times_{i=1}^N \Sigma_i$ denote a strategy profile.

Bidder i's ex ante payoff from the first-price auction is given by

$$U_i(\beta) = \int_{v \in V} \int_{\mathbf{x} \in [\underline{x}, \overline{x}]^N} [v - \beta_i(x_i)]\, q_i(\beta(\mathbf{x}))\, F(d\mathbf{x}, dv). \tag{1}$$

The profile β is a Bayesian Nash Equilibrium (BNE) if and only if $U_i(\beta) \geq$

$U_i(\beta_i^{'}, \beta_{-i})$ for all $\beta_i^{'} \in \Sigma_i$.

Discussion of the assumptions.

Wilson (1977) and most of the subsequent empirical literature on common value auctions require stronger assumptions than stated above. Wilson assumes that the signal X_i is iid with continuous conditional cdf $F(.|v)$. The joint distribution of signals and ex post tract value is then $F(\mathbf{x}, v) = \prod_i F(x_i|v)G(v)$.[2]

Our data do not include information on bidders' signals. Proposition 4 in Laffont and Vuong (1996) establishes that the signal distribution $F(.|v)$ cannot be identified from bid data and ex post values alone. For example, monotone rescaling of signals results in observationally equivalent signal distributions. See also Somaini (2020) for identification results with interdependent signals. While signals cannot be identified directly, we can infer their statistical properties by analyzing bids, which are observed and are a strict monotone function of signals. If signals are independently distributed, bids must also be independent.

Prior empirical work on common value auctions typically adopts the Wilson BNE and imposes additional assumptions on the information structure to guarantee identification from observables. Bhattacharya et al. (2022) assume bidders receive noisy signals about oil quantities, while Hendricks et al. (2003) assume the signals are unbiased estimates of the ex post return conditional on winning.

We will test the null hypothesis that bids satisfy the conditional independence assumption in Section IV. A rejection of these tests could indicate bidder coordination prior to the auction or suggest that the iid signal assumption of Wilson's model is violated (e.g., if signals are correlated with factors other than the ex post return). With this caveat in mind, our main statistical analysis will be based on the weaker set of assumptions described above, which are robust to alternative information structures.

To summarize, our statistical analysis departs from the prior literature by using a weaker set of assumptions that is robust to all information structures, including the one proposed by Wilson. Our approach is robust to the specification of the signals and details of the Bayesian Nash equilibrium.

II. Testable Implications

This section describes testable implications of BNE bidding. We will formulate suitable statistical tests of these implications using the publicly available data on oil and gas lease sales from the New Mexico State Land Office (NMSLO).

[2]Based on the iid signal assumption Wilson (1977) and Milgrom and Weber (1982) characterize the symmetric BNE. Let $Y_i = \max_{j \neq i} X_j$ and $F_{Y_i|X_i}(.|.)$ be the conditional distribution of Y_i given X_i. Let $u(x_i) = E[v|X_i = x_i, Y_i = x_i]$ be the expected value conditional on the own signal being x_i and the high rival signal being at most x_i. The equilibrium strategy satisfies the first-order differential equation $b'(x) = [u(x) - b(x)] \cdot \frac{f_{Y_i|X_i}(x|x)}{F_{Y_i|X_i}(x|x)}$ with boundary condition $b(\underline{x}) = u(\underline{x})$. The solution is

$$\beta_i(x_i) = u(x_i) - \int_{\underline{x}}^{x_i} L(y|x_i)du(y) \quad \text{where} \quad L(y|x_i) = \exp[-\int_y^{x_i} \frac{f(x|x)}{F(x|x)} dx]. \tag{2}$$

The sealed-bid first-price auction has bidders submitting sealed bids and awards the item to the high bidder at his bid price. The identities of potential bidders are publicly known before every auction. On the day of the auction, the sealed bids are publicly revealed, and the high bidder wins. We let $\mathbf{b}^t$ denote the vector $(b_1^t, ..., b_N^t)$ and adopt the convention that $b_i^t = 0$ when potential bidder i refrained from bidding for lot t. We denote with z^t any information that is publicly available at time t, such as the oil and gas spot (and future) prices, that may affect bidders' signals $\mathbf{x}^t$ and thus bids $\mathbf{b}^t$. The variable v^t denotes the ex post return, which we calculate from the publicly observed drilling and production data.

We make the following assumption on the data generating process (DGP).

Assumption 1. *The observed data are* $(\mathbf{b}^t, v^t, z^t)_{t=1}^T$ *where* $(\mathbf{b}^t, v^t)$ are *identically and independently distributed conditional on exogenous covariates* $z^t \in Z$.

The assumption is commonly imposed in market games, see Tamer (2003).

We shall focus on three central implications of the mineral rights model, each requiring a decreasing amount of structure. First, we consider the classic Wilson model in which the submitted bids are independently distributed conditional on ex post returns and publicly available information at the time of the auction. Second, we relax the independence assumption and examine the null hypothesis that bidding strategies maximize ex ante expected returns, that is, that no bidder can systematically deviate from the equilibrium and receive strictly larger expected profits. Third, we examine winning bids and ex post returns data only, and consider the null hypothesis that bidders cannot find it attractive to uniformly bid upward. The last two properties hold regardless of bidders' information and the Bayesian Nash equilibrium. We shall describe these hypotheses in turn.

A. Independence

The data include detailed information on ex post drilling outcomes which allow us to calculate ex post returns for bidders, which we use as a control variable. Evidence of correlation in bids conditional on ex post returns is indicative of preplay communication, which would be a violation of the Bayesian Nash equilibrium condition in Wilson's mineral rights model.

Implication 1. *Consider the assumption of Wilson (1977). The bids (signals)* B_i *and* B_j *are independently distributed for all* $i, j \in N$ *conditional on the ex post value realization* v.

The null hypothesis of conditional independence is

$$H_0^{B|X} : B_i \perp B_j | v \text{ for all } i, j \in N, \tag{3}$$

with the alternative its negation. The null can be tested for individual bidders or for bidder pairs. A violation of the null hypothesis suggests that the data were not generated from the BNE in the Wilson model. This result could indicate that the data were not generated from a BNE (e.g. because of collusion among a subset of bidders) or that the data were generated by a BNE in a game with a different information structure (e.g. if value signals are truly correlated even after conditioning on ex post values).

B. Best Response Test

Next, we relax the assumption on the information structure and go beyond the Wilson model. A simple yet powerful test examines the BNE condition ex ante using equation (1).

Bidder i's payoff realization from an auction is given by

$$U_i(b, v) = [v - b_i]\, q_i(b_i, b_{-i}). \tag{4}$$

Consider a unilateral deviation $\phi : B \longrightarrow B$ which results in the modified payoff realization

$$U_i(b, v|\phi) = [v - \phi(b_i)]\, q_i(\phi(b_i), b_{-i}). \tag{5}$$

The BNE condition requires that a unilateral deviation cannot be profitable on average. Consider the ex ante payoff under the deviation strategy:

$$U_i(\beta|\phi) = \int_{v\in V} \int_{\mathbf{x}\in[\underline{x},\overline{x}]^N} [v - \phi\left(\beta_i(x_i)\right)]\, q_i(\phi\left(\beta_i(x_i)\right), \beta_{-\mathbf{i}}(\mathbf{x}_{-i}))\, F(d\mathbf{x}, dv). \tag{6}$$

This leads us to the following implication of BNE bidding.

***Implication** 2. In any BNE under any information structure and for any bidder i, the function ϕ that maximizes the ex ante expected payoff in equation (6) must be the identity mapping.*

This property can be used to detect any deviation from BNE bidding. Our goal is to detect whether bidders systematically underbid. We follow Hendricks et al. (1987) in considering linear deviations, that is, deviation strategies that multiply all bids by a scalar $\alpha > 0$ such that $\phi(b) = \alpha \cdot b$. See also Chassang et al. (2022) who propose tests for competition under scalar deviations of this type. They estimate an upper bound on the probability that bidders' beliefs are consistent with competition in any informational environment. In our setting bounds on bidders' beliefs about tract values can be estimated from the data, enabling us to test the existence of profitable deviations directly.

Letting $\alpha^* = \arg\max_\alpha U_i(\beta, \alpha)$, Implication 2 of BNE bidding leads to the following null hypothesis:

$$H_0 : \alpha^* = 1. \tag{7}$$

Originally, this type of best response test was aimed at testing for the presence of the winner's curse (systematic overbidding, or $\alpha^* < 1$). We expand this test to check optimality of bidding more generally.

C. Uniform Upward Deviation

Our third test of BNE bidding focuses on the profitability of uniform upward deviations. These deviations can be examined empirically solely based on information from winning bids, and represent a special case of deviations described under Implication 2. Importantly, no information on losing bids is required for this test.

A uniform upward deviation to b is defined as a deviation $\widetilde{\beta}_i$ from strategy β_i where submitted bids are equal to $\widetilde{\beta}_i(x) = \max\{b, \beta_i(x)\}$ for any $x \in [\underline{x}, \overline{x}]$. The profitability of such a deviation is assessed by comparing the increase in payoff from winning additional auctions with the higher bid to the decrease in payoff from paying the higher bid in auctions that would have been won in equilibrium. This class of deviations has been studied before by Feldman et al. (2016), who use it to establish a lower bound on winning bids in correlated equilibria of private-value auctions, and Bergemann et al. (2017), who use the constraints imposed on the distribution of winning bids to derive a tight lower bound on expected revenue that is robust to the information structure. We use the observed distribution of winning bids and valuations to test the hypothesis that uniform upward deviations are not profitable.

Examining uniform upward deviations proves a valuable tool for empirical analysis, as it solely relies on realized ex post returns data and prices paid. It does not require information on losing bids, which may not be readily accessible. Unlike the class of scalar deviations considered in the previous section, this class of uniform upward deviations incorporates the value of winning auctions in which the bidder did not originally participate. Consequently, this test has the power to detect deviations from competitive bidding in cases where other tests that rely only on scalar deviations would not. Prior empirical work specifies the information distribution of bidders or the details of the Bayesian equilibrium or information on the bidding histories. Our approach departs from the prior literature and is robust to the specification of the information structure, signals, and other details of the Bayesian equilibrium. We test whether observed returns and prices paid lead to profitable uniform upward deviations.

Let $H_i(b|v)$ denote the probability that bidder i wins with a winning bid less than or equal to b when the value is v. Note that this probability is well defined for any information structure and equilibrium strategies. For the sake of notational simplicity, we omit the explicit dependence on the information structure and equilibrium strategies. Consequently, $H(b|v) = \sum_{i=1}^{N} H_i(b|v)$ denotes the total probability that the winning bid is less than or equal to b when the value is v. In a BNE, a bidder receives the ex ante expected rent

$$\int_{\underline{v}}^{\overline{v}} \int_0^{\overline{b}} [v-p] H_i(dp|v) G(dv). \tag{8}$$

Suppose bidder i uniformly deviates up to b. For auctions where the winning bid is greater than or equal to b, outcomes and therefore payoffs are unchanged. For auctions where the winning bid is less than b, the deviator now wins the auction and receives a payoff of $v - b$. The ex ante expected payoff to the deviator is therefore given by:

$$\int_{\underline{v}}^{\overline{v}} [v-b]H(b|v)G(dv) + \int_{\underline{v}}^{\overline{v}} \int_{b}^{\overline{b}} [v-p]H_i(dp|v)G(dv). \tag{9}$$

The attractiveness of the upward deviation depends on whether the gains outweigh the losses incurred from deviating:

$$\int_{\underline{v}}^{\overline{v}} [v-b]H(b|v)G(dv) - \int_{\underline{v}}^{\overline{v}} \int_{0}^{b} [v-p]H_i(dp|v)G(dv) \leq 0. \tag{10}$$

Let $S \subseteq \{1, \ldots, N\}$ denote a subset of bidders. By summing equation (10) across bidders in S, we obtain

$$|S| \int_{\underline{v}}^{\overline{v}} [v-b]H(b|v)G(dv) - \int_{\underline{v}}^{\overline{v}} \int_{0}^{b} [v-p] \sum_{i \in S} H_i(dp|v)G(dv) \leq 0. \tag{11}$$

Implication 3. *In any BNE under any information structure, inequality (11) holds for all b and all $S \subseteq \{1, \ldots, N\}$.*

We refer to Bergemann et al. (2017) Lemma 1 for a rigorous proof argument. Under the null of competitive bidding, we assume that the observed bids are generated by a profile of BNE bidding strategies that adhere to the uniform upward deviation constraint. The null hypothesis necessitates that the expected net deviation payoff is non-positive. We test Implication 3 using the null hypothesis:

$$H_0 : \frac{|S| \int_{\underline{v}}^{\overline{v}} [v-b]H(b|v)G(dv) - \int_{\underline{v}}^{\overline{v}} \int_{0}^{b} [v-p] \sum_{i \in S} H_i(dp|v)G(dv)}{\int_{\underline{v}}^{\overline{v}} \int_{0}^{\overline{b}} [v-p] \sum_{i \in S} H_i(dp|v)G(dv)} \leq 0, \tag{12}$$

which normalizes deviation gains by the ex ante expected rent for bidders in S.

The test for uniform upward deviation incentives is robust to details of the Bayesian game being played and the information available to bidders. The incentive constraint remains valid if bidders are asymmetrically informed, completely uninformed, or completely informed about the tract values. The bound also applies when there is unobserved auction heterogeneity, that is, when bidders publicly observe a part of the common value that is not recorded in the data. The bound is also robust to risk aversion – if bidders were risk averse, we would expect more aggressive bidding, pushing bids even higher.

Next, we shall describe the market and data.

III. Data

We study oil and gas lease sales held monthly by the New Mexico State Land Office (NMSLO) on the third Tuesday of each month between 1994 until 2015. The data, available at Martin et al. (2025), include lease sale information (NMSLO (2022a); Bhattacharya et al. (2022)), post sale drilling information (NMSLO (2022b); SNM (2022)) and oil and gas prices (EIA (2023a,b,c,d); BLS (2022); Bloomberg (2022)).[3] Every month the NMSLO distributes a list of leases which are sold at auction next month. Bidders can nominate an area for auction. Leases typically cover a land area of 320 acres.

Lease Sale Procedure

It is a legal requirement that the NMSLO awards leases by one of two types of auction formats[4]: (i) sealed-bid first-price auction and (ii) open-outcry English auction. For most of the sample period both formats were used in each monthly sale.[5] The assignment of auction format is mostly random, although conversations with the leading auctioneer during the sample period suggest that, in the case of split tracts (a tract larger than 320 acres that is split into two separate lots for the sale), the first price auction is used for the larger of the two halves or for the part closest to an existing lease owned by the bidder that nominated the tract. The monthly lease sale proceeds in two stages: First, the sealed bids for the first set of leases are unsealed and announced publicly. Every lease is awarded to the high bidder. Second, the set of English auction leases are awarded in sequence by means of an open outcry auction where all eligible bidders are present in the room. Every month the same set of bidders interact. We do not include auctions taking place after 2015 in our sample as the post-award production record is incomplete.

The lease duration is five years, during which time the winning bidder can drill a well. If oil or gas is found, then the lease can be extended until all minerals have been extracted. Any revenues arising from the well are subject to various revenue taxes and royalty payments at a rate depending on the type of lease. Additionally, leaseholders are charged a negligible rental rate, typically \$0.50 or \$1.00 per acre. The winning bidder pays corporate taxes on profits, which is a proportional deduction and thus neutral to the bidding calculus. The winning bidder pays the bid bonus immediately after the auction and receives the net return on future and uncertain minerals extracted.[6]

Choice of annual interest rate. In selecting our interest rate, we recognize

[3] Data from NMSLO have been studied in the prior literature. Kong (2020, 2021) studies the relationship between first-price and English auctions. Bhattacharya et al. (2022) study the effect of post auction drilling decisions on the optimal auction design in terms of the royalty rate.

[4] The legal setting is described in New Mexico Statues, Chapter 19, Article 10, Section 19-10-17: https://law.justia.com/codes/new-mexico/2019/chapter-19/article-10/section-19-10-17/

[5] During the summer of 2016 the auctions moved online. Starting in 2019 most of the sales were conducted in first-price format only.

[6] If during future production it is found that the well can be used to extract minerals for multiple leases, then bidders are by law required to enter a pooling agreement. While the share of leases with pooling agreements is relatively small in our data (less than four percent), it forces bidders to engage and cooperate with each other on those leases.

that oil and gas leases function as option contracts, granting the lessee the right to drill without obligation. Pindyck (1991) shows that for spanned real options, where oil futures and option markets incur minimal transaction costs, the market value of the option can be determined using the Black Scholes model based on the risk-free rate, bypassing the firm's internal interest rate. If spanning does not hold, dynamic programming techniques are used to determine the option value based on the firm's interest rate instead of the risk-free rate.

Following Décaire et al. (2020) and Bhattacharya et al. (2022) we use a firm-level interest rate for our calculations. Décaire (2024) estimates that the cost of capital for US gas exploration firms is 7.8% during our sample period. Studies by Froot et al. (1993); Berk et al. (2004); Gilje and Taillard (2016) indicate that project-specific risks, systematic risks and differences between private and public lead to annual interest rates being set above the cost of capital. Décaire (2024) also provides a formal method to elicit the firm-year level hurdle interest rate for 70,026 onshore gas wells drilled in the US between 1983 and 2010, showing that projects located in ex ante riskier areas command an interest rate premium. His method forecasts future production and gas prices, estimating the annual interest rate as the lowest expected internal rate of return across all the firm's projects within a year. His analysis indicates that the average hurdle rate is above the firm's cost of capital of 7.8%, but the difference is not statistically significant.

Décaire et al. (2020) adopt a 10% interest rate when studying a real option exercise for US gas wells, with sensitivity analysis conducted using annual discount rates of 7.5% and 12.5%. We follow recent studies on oil and gas exploration decisions, including Kellogg (2014a); Hodgson (2019); Herrnstadt et al. (2024), by adopting a 10% interest rate as our baseline. Additionally, we consider a 15% interest rate as a robustness check, acknowledging the possibility of higher hurdle rates used by firms in our dataset.

Our data contain detailed information on ex post drilling outcomes and production until May 2023 which enables us to calculate the future return following the prior literature. After the auction, the winner of the tract obtains the tract lease and the subsequent oil and gas extraction is publicly observed. Bhattacharya et al. (2022) and Hendricks et al. (2003) construct the value measure using the realized value of minerals extracted from ex post drilling activity. We follow this definition of the common value and construct our value estimates by matching publicly available production data to leases. We obtain a list of all oil and gas wells in New Mexico from the New Mexico Oil Conservation Division (OCD) describing the location of each well. We then match these well locations to the geographic descriptions of leased tracts provided by the NMSLO in the letting announcements. For each lease we aggregate the monthly oil and gas production of each well (collected from monthly production reports submitted to the OCD) and weigh them with deflated crude oil and gas prices. To account for production delays, we discount all returns to the date of the auction using a ten percent annual interest rate. We account for the royalty rate, which varies by the type of lease, and deduct a revenue tax of 7.1%[7]. Our final gross revenue measure equals the realization of the discounted ex post value of the oil field net of royalties and taxes. Our gross revenue measure is a lower bound on revenues, as it is based on observed production and does not include potential future production beyond 2023.[8] We define the common value v as the net return, which equals the gross revenue measure minus the well cost.

Well costs are measured following the formula described in Kellogg (2014a,b), which is based on drilling rig rental costs predicted by oil future prices. Kellogg studies oil extraction in the Texas region of the Permian Basin, while most of the wells we study fall in the New Mexico region of the Permian Basin. Kellogg notes a significant positive correlation between 18-month-ahead oil prices and rig dayrates. He regresses daily drilling rig rental rates on 18-month-ahead oil prices and obtains an R-squared of 0.64. This regression is used to predict the daily rig rental rate, which is then multiplied by the expected number of drilling days to get the expected rental cost, which is in turn multiplied by three to produce total expected drilling costs.[9]

We update Kellogg's previous estimate of 19.2 days to drill a well by incorporating two significant changes. First, we use a more conservative average of 34 days, calculated from a sample of 332 New Mexico drilling cost records from publicly available reports on pooling agreements[10]. Second, we take into account well cost heterogeneity by calculating separate day rate estimates based on the observed annual well cost depth quintile. This approach enables us to factor in variations in well costs associated with different well depths. Our revised Kellogg formula accounts for variation in well costs based on the observed well depth and is about 75% higher than Kellogg's.

Our well cost estimates do not account for heterogeneity in well costs across bidders or potential challenges bidders may encounter in accessing capital. While cost differences may exist across bidders, we follow Hendricks et al. (2003) and Bhat-

[7]According to Chapter 2 of the "Decision-Makers Field Guide (2002)," (available online at https://geoinfo.nmt.edu/publications/guides/decisionmakers/2002/dmfg2002_complete.pdf) there are six taxes imposed directly on oil and gas extraction and processing: (i) severance tax which amounts to 1.875% during the first 5-7 years of production and then increases to 3.75%; (ii) conservation tax of about 0.19%; (iii) emergency school tax of 3.15% for oil and 4% for gas minus drilling credit which is given some times; (iv) ad valorem production tax of about 0.39%; (v) natural gas processors tax of 0.45% and (vi) ad valorem equipment tax of 0.07%. Totaling these taxes amounts to about 7.1%. The rate of 7.1% is also reported as tax revenues obtained in the year 2000 on the value of oil and gas reported by the Taxation and Revenue Department, see Figure 5 in Decision-Makers Field Guide (2002). Following Ordin (2019) we observe that corporate profit taxes do not affect the bidding calculus as the tax rate applies proportionally.

[8]An alternative measure of gross revenues uses the oil and gas future prices at the time of the auction as weights to discounted quantities instead of the realization of the oil and gas prices at the time when production takes place. The resulting gross revenue measure is very similar in magnitude but on average slightly larger than the measure obtained using the realized prices.

[9]The scaling factor of three emerged from conversations with industry members who estimated that rig rental costs constitute on average one third of total drilling costs.

[10]Under pooling agreements, parties are legally obligated to submit an Authorization for Expenditure (AFE) to New Mexico's Oil Conservation Division, providing details on the anticipated cost of a proposed well. By parsing AFEs filed between 2000 and 2014, SNM (2023), we extracted information on reported well depth, the number of days drilled and the total well cost.

tacharya et al. (2022) in assuming that these differences are small in magnitude or not known at the time of the auction. However, our counterfactual exercises explore scenarios where well costs become prohibitively costly for all but a small subset of bidders. In these exercises, we artificially reduce the number of potential competitors from thirteen bidders to seven and four. This artificial scenario allows us to analyze the impact of such constraints on the bidding process.

Descriptive Summary Statistics

Table 1—Summary Statistics for Awarded Tracts

	All	First-Price	English
Number of Auctions	9,717	4,535	5,182
Gross Revenue (minus royalty and tax payment)	464.1	521.9	413.6
	(2,745)	(3,127)	(2,360)
Well Cost	180.5	183.4	178.1
	(700.0)	(747.0)	(656.2)
Net Revenue v	283.6	338.5	235.5
	(2,197)	(2,507)	(1,885)
Winning Bid	52.82	58.68	47.70
	(113.5)	(138.8)	(85.0)
Reserve Price	4.71	4.53	4.87
	(4.398)	(4.302)	(4.474)
Fraction Drilled	0.125	0.119	0.131
	(0.331)	(0.323)	(0.337)
Well Cost of Drilled Tracts	1,443	1,543	1,363
	(1,448)	(1,613)	(1,297)
Fraction Productive When Drilled	0.885	0.902	0.872
	(0.319)	(0.298)	(0.334)
Disc Revenue of Productive Tracts	4,180	4,860	3,620
	(7,236)	(8,373)	(6,099)

Note: The data consist of all awarded auctions between 1994 and 2015. Dollar figures are measured in thousand of 2000 US dollars. Standard deviations are in parentheses.

Table 1 shows that 4,535 sales were held using first-price auctions while 5,182 using an English auction format. Table 1 considers only pre-2016 sales as the initial drilling decision can occur at the end of the lease term, as shown in Bhattacharya et al. (2022). All dollar magnitudes are deflated using 2000 dollars.

Strikingly, the bonus bid is very small relative to tract value. The bonus bid equals \$53,000 on average, which amounts to 19 percent of the average tract value. In comparison, the offshore lease sale literature has shown bids being much closer to the value of the tract. Hendricks et al. (1987) report winning bids in offshore sales equal 76 percent of tract value for wildcat sales and 49 percent for drainage sales.

A second surprising element is that only about 12.5 percent of awarded tracts are drilled.[11] Of the wells drilled, 89 percent are productive (i.e. the well produced oil or gas), which is high compared to the 45 percent for offshore tracts found

[11] The drilling rate estimate is almost identical to the onshore drilling rate reported in the prior literature, see Bhattacharya et al. (2022).

by Porter (1995). However, the onshore drilling rate is low compared to the 78 percent offshore rate. We hypothesize that the low drilling rate is a result of lease hoarding, which appears common for onshore leases.[12] We shall provide further evidence on the number of undrilled leases hoarded by individual bidders below.

Interestingly, the auctioneer's revenues are higher for first-price auctions than for English auctions, both in terms of royalty payments and bonus bids, see also Kong (2020). For split tracts, in which both auction formats were used and the assignment (according to conversations with the lead auctioneer) is essentially random, the first-price auction generates 33% higher cash bonus bid and a 11% higher royalty return per acre. We can reject the null of identical bonus bids across the two formats at the one percent significance level. Yet, the null of identical royalty returns cannot be rejected. During the year 2019 the NMSLO began awarding leases exclusively in the more favorable first-price format.

The revenue ranking is surprising in the light of the classic theoretical work on symmetric BNE bidding equilibria in standard auction formats. Milgrom and Weber (1982) derive that English auctions generate more revenues than first-price auctions on average. One explanation for the revenue superiority of the first-price auction format is that some coordination or collusion arises in English auctions. Avery (1998) shows that bidders may use initial jump bids to signal their intention to rivals, which gives rise to multiple equilibria in English auctions, some of which may have drastically reduced revenues. Indeed, we observe jump bidding in English auctions conducted online, where the timestamp of each bid is recorded.[13]

Suspiciously low English auction bids arise also in split tract sales, where bidders should arguably have the same value estimate for both halves. There are 335 occasions where a bidder failed to win the English auction although the bidder submitted a bid in the first-price auction that was (substantially) higher in per-acre terms than the selling price in the English auction. On 194 of these occasions, the bidder failed to win both the first-price auction and the English auction. On average the bidder's losing first-price auction bid was 120 percentage points higher than the final English auction price. While these bid patterns seem odd, they can in fact arise as a BNE when bidders have beliefs that they will be outbid in the English auction. Since BNE bidding in English auctions may resemble coordination or collusion, our subsequent analysis focuses on first-price auction sales.

Factors Facilitating Collusion

[12] Accoding to a Wilderness Society's article from December 15, 2015, hoarding is common in the oil and gas industry. For instance, suspension of federal leases has affected 3.25 million acres in April 2015. See https://www.wilderness.org/articles/blog/land-hoarders-oil-and-gas-companies-are-stockpiling-your-public-lands.

[13] The NMSLO online English format is similiar to eBay sales where the current standing winning price is revealed to rival bidders and not the submitted bid. In the online English lease sale in January 2019, Slash Exploration LP started the bidding with a bid substantially above the reserve, and two attempts by rival bidders during the next sixteen hours to outbid Slash Exploration failed, resulting in Slash Exploration winning the lease.

There are several factors in the lease sale market that may facilitate coordination or collusion. We think of collusion as an implicit or explicit arrangement to limit competition among market participants and to increase profits.

Table 2—Bidding Returns for Top Bidders

Bidder	No of Bids	No of Wins	Return v on average	Bid b across auctions	ROI won
YATES PETROLEUM CORP	5,810	4087	210.46	30.67	1225
DANIEL E GONZALES	828	592	571.12	65.57	589
DOUG J SCHUTZ	784	548	235.56	68.78	20
THE BLANCO COMP.	617	103	413.48	14.39	6240
SLASH EXPLORATION LP	403	95	22.96	10.94	352
CHASE OIL CORPORATION	320	227	102.17	43.83	534
FEATHERSTONE DEV. C.	284	121	305.30	27.58	572
MARBOB ENERGY CORP	278	130	726.32	78.40	698
BAR CANE INC	220	129	391.74	60.95	461
FRINGE	N/A	3640	342.98	76.02	601

Note: The data consist of all awarded auctions between 1994 and 2015. Dollar figures are measured in thousand 2000 US dollars.

The market we study is concentrated, with three firms winning half of all leases sold at auction. In such a setting, a small set of firms coordinating their actions can have a big impact on market price. Table 2 reports summary statistics for bidders who won more than 50 leases between 1994 and 2015 and together account for two thirds of all bids submitted and 62% of auction awards. The table also includes a "fringe" bidder accounting for all remaining bids. We report dollar measures on average across all auctions won by the bidder. Yates Petroleum Corp has a market share of about 42% in the number of leases with more than 1,000 active (undrilled) leases (320,000 acres) held during any calendar year between 2000 and 2015. It was acquired by EOG Resources in 2016 for $2.5 billion. Yates Petroleum operated beyond the New Mexico region and held about 1.5 million acres in at least seven US states at the time of acquisition. The next largest bidders are Daniel E Gonzales and Doug J Schutz, both of whom have a 6% market share each, which amounts to more than 500 leases. These two bidders held on average more than 130 active (undrilled) leases during the period 2000 to 2015.

The rate of return from winning an auction (ROI), measured by the profits (the tract value minus the bonus bid) divided by the bonus bid and finally multiplied by 100, is substantial. It equals more than 881 percentage points on average across all bidders and auctions. The high percentage arises as the lease acquisition cost is very low relative to the return. We shall examine the null that the bonus bid is too low to be consistent with competitive bidding in Sections V and VI.

Leases are homogeneous products that can be resold in the future. Competition is only in terms of price, so a cartel need only coordinate in the price dimension to collude. Sales occur regularly at monthly intervals, with bidders gathering in person for each sale. Consequently, bidders know the identity of other potential bidders before they bid. Bidders may have formed relationships with each other at prior sales or as a result of pooling agreements they are required by law to enter into when a well spans multiple leases. Bidders participating in the NMSLO's auctions have faced allegations of illicit conduct in other states.[14] Multiple leases are awarded at each sale date, allowing bidders to divide the market without using side payments. Additionally, leases can be resold at subsequent periods, underlining the common value property and providing a mechanism for bidders to implement a suitable market division. The frequency of sales makes it costly for firms to deviate from any agreement. To summarize, the market exhibits characteristics that facilitate collusion. It is a concentrated market, a homogeneous product is sold, multiple leases are sold at every sale date, and sales occur at regular monthly intervals.

Next, we shall conduct statistical tests to examine whether we can reject the null of competitive bidding.

IV. Conditional Independence Test

Competitive behavior requires that bidders submit their bids independently of each other conditional on the information available to them. Bidding strategies cannot be coordinated or correlated; a player's strategy should be a function of their signal only. Coordination among competing bidders or information sharing is not legal at auctions. In contrast, when bidders coordinate or communicate prior to the auction, then we may expect bids to be correlated beyond the information available to bidders individually. This section considers tests aimed at distinguishing these two hypotheses based on the assumptions of Wilson (1977).

It could be argued that such patterns of coordination could also arise due to exogenous variations over time. For example, bidder pairs may be more active in certain seasons, or respond in the same way to variation in oil prices or any other exogenous shock. For example, a pattern of bid rotation would emerge when bidders are less likely to bid if a sizable number of leases have been won in the preceding sale.

We exploit the timing of individual auctions to account for these alternative explanations. Our data have multiple auctions taking place on the same date. A sale occurs once a month, and all auctions within a sale have an identical bid submission deadline. In total our data have 259 sales dates between 1994 and 2015 with an average 18 first price auctions taking place per sale.

Wilson's mineral rights model assumes the signal x_i is drawn independently from a conditional cdf $F(x_i|v, z)$, where v denotes the common value of the oil

[14] On March 15, 2012, the US Department of Justice filed a law suit alleging bid-rigging in Colorado, see https://www.justice.gov/atr/case/us-v-sg-interests-i-ltd-et-al. Reuters reported on June 25, 2012, that email exchanges between Chesapeake Energy Corp and a competitor apparently intended to avoid bidding against each other in Michigan, see https://www.reuters.com/article/us-chesapeake-land-deals-idUSBRE85O0EI20120625. On March 1, 2015, the US Department of Justice indicted the CEO of Chesapeake Energy Corp for bid rigging in Oklahoma, see https://www.bloomberg.com/news/articles/2016-03-01/chesapeake-co-founder-mcclendon-indicted-over-lease-bid-rigging.

field and z are auction date variables. We do not observe the signal realizations $\mathbf{x}$ but do observe the bids $\mathbf{b}$ and the ex post outcome v and control for z using auction date fixed effects. In Wilson's BNE a bid is a strict monotone function of a bidder's signal, $b_i = b(x_i)$. Since signals are drawn independently from $F(x_i|v,z)$, and bids are a function of one signal only, bids will be distributed independently after conditioning on ex post returns. These assumptions lead to the following null hypothesis for competitive bidding:

$$H_0^{B|X} : b_i \perp b_j | v, z \text{ for all } i, j \in N, \tag{13}$$

with the alternative hypothesis:

$$H_1^{B|X} : b_i \not\perp b_j | v, z \text{ for some } i, j \in N. \tag{14}$$

As most bids in our data are equal to zero (the convention we adopt to represent that a bid was not submitted), our test statistic aggregates bids into the binary bid submission variable $s_i = \{1 \text{ if } b_i > 0; \ = 0 \text{ otherwise } \}$.

We test the null, $s_i \perp s_j | v, z$ for any pair $i, j \in N$ with a parametric bivariate probit framework. The biprobit controls for bidder-specific date effects and ex post return values (linear and quadratic). The correlation coefficient in the biprobit measures the bidder-pair correlation not accounted for by ex post return and date fixed effects z^t.

Wilson additionally assumes that the conditional cdf F is identical for all bidders. Asymmetries in the distribution of bids could arise if, e.g., the variance in the signals differs across bidders. We are not concerned with testing for the presence of such asymmetries; here we only assume that bids are independently (not necessarily identically) distributed.

Table 3—Biprobit Correlation Coefficients

Pairs	H_0 of Zero Correlation rejected at			Sign of Correlation Coefficient	
	10%	5%	1%	Positive	Negative
55	26	25	14	40	15

Note: Test results are reported for the null of a zero correlation coefficient in the bivariate probit for bidder pairs. The data consist of all pairs in which both bidders are active on sales involving at least 200 auctions occuring before 2015. Explanatory variables include ex post return, ex post return squared and bidder specific sale-date fixed effects.

Table 3 indicates that a quarter to one half of bidder pairs have correlation coefficients that are significantly different from zero, depending on which significance level is considered. The majority of coefficients are positive. Consequently, we can reject the null of independence in the mineral rights model. The evidence suggests that if the game played by bidders is the same as in the mineral rights model, bid submission decisions are coordinated. This coordination arises among a quarter to one half of bidder pairs mentioned in Table 2.

The evidence so far has been inconsistent with competitive bidding in the mineral rights model, but could be produced by a different information structure. In the presence of unobserved heterogeneity – characteristics of the tract that are (i) informative of its value, (ii) observed by bidders, and (iii) not recorded in the data – some bidder pairs would exhibit correlation in participation decisions driven by the unobserved heterogeneity. Because unobserved heterogeneity affects the value signal in the same direction (either positively or negatively) for all bidders, any correlation induced by it should be positive, see Krasnokutskaya (2011). To examine whether the correlation we observe could be explained by unobserved heterogeneity, we examine the distribution of participation correlation coefficients across bidder pairs.

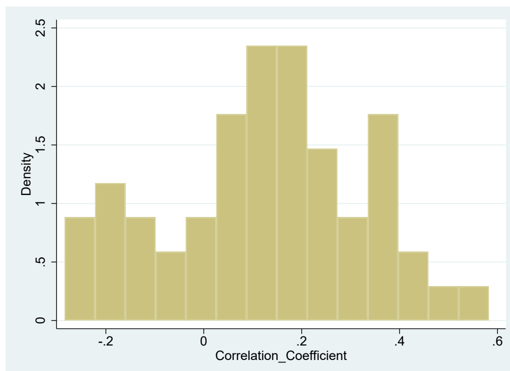


Figure 1. Histogram of Biprobit Correlation Coefficient Estimates

Figure 1 plots the histogram of correlation coefficient estimates. Some bidder pairs appear to refrain from bidding against each other, while the majority of bidder pairs complement each other in bid submission. There are both sizable negative and positive correlation coefficients, with surprisingly little mass at zero. The histogram differs from that of a normal distribution in that it has a hump at -0.2 and another hump at 0.15. Such a bimodal distribution is inconsistent with the strictly positive correlation that would arise under unobserved heterogeneity.

The empirical evidence considered so far cannot be reconciled with competitive bidding under the mineral rights model. Having rejected the null of independent bid distributions, we are left with two possibilities. First, the bidding strategies that generated the data could be coordinated rather than competitive, e.g. some bidders refrain from bidding or submit "phony" bids. Alternatively, the correlation in bids could be explained by the underlying information structure mediating ex post returns and bids, or by inclusion of a prior stage in which bidders make auction participation decisions. If signals are positively correlated across some pairs and negatively correlated across others, the observed patterns of positive and negative bid correlation could arise in a competitive equilibrium. The next two sections consider statistical tests of bidding in the common values BNE that are robust to the underlying information structure.

V. Underbidding

This section examines whether bidders systematically under- or overbid.

If bidders coordinate in order to suppress bid payments, then such behavior will be detectable by finding the existence of a profitable deviation in the bidder's choice problem. Since we observe all bids, as well as the ex post return, we can measure the observed average payoff and use it to test the null that a systematic deviation cannot be profitable.

We develop a test procedure that is applicable regardless of the underlying information structure. We examine deviations from observed bidding in which all bids of a bidder are multiplied by a positive scalar, holding rival bids fixed. Of course, richer deviation strategies can be permitted and the test augmented. Nevertheless, in our case, even a scalar deviation results in a substantial profit increase.

Recall the null hypothesis

(15)

$$H_0 : \alpha^* \equiv \arg\max_{\alpha} \int_{v \in V} \int_{\mathbf{x} \in [\underline{x}, \overline{x}]^N} [v - \alpha \cdot \beta_i(x_i)]\, q_i(\alpha \cdot \beta_i(x_i), \beta_{-\mathbf{i}}(\mathbf{x}_{-i}))\; F(d\mathbf{x}, dv) = 1.$$

Let $S \subseteq \{1, \ldots, N\}$ denote a subset of bidders. By summing across bidders in S, and estimating the expectation using the sample average, we compute the following test statistic:

$$\widehat{\alpha}^* = \arg\max_{\alpha} \frac{1}{|S|} \sum_{i \in S} \frac{1}{|\mathcal{T}_i|} \sum_{t \in \mathcal{T}_i} \left[v^t - \alpha \cdot b_i^t\right] q_i(\alpha \cdot b_i^t, b_{-i}^t)). \tag{16}$$

In this equation, the objective function computes the average payoff realization when bid b_i^t in all auctions is multiplied with the scalar parameter α, and $\mathcal{T}_i$ represents the set of auctions in which bidder i participated.

A slope estimate $\widehat{\alpha}^* < 1$ suggests the potential presence of the winner's curse or risk aversion, see Matthews (1983) and Maskin and Riley (1984). On the other hand, $\widehat{\alpha}^* > 1$ suggests that bidder i underbid. Hendricks et al. (1987) propose a precursor bid scaling test and (weakly) reject the winner's curse in offshore sales. Kong (2020) develops an alternative approach that does not rely on ex post returns and finds evidence of risk aversion. Chassang et al. (2022) propose bid scaling tests designed for scenarios in which the econometrician may not observe values.

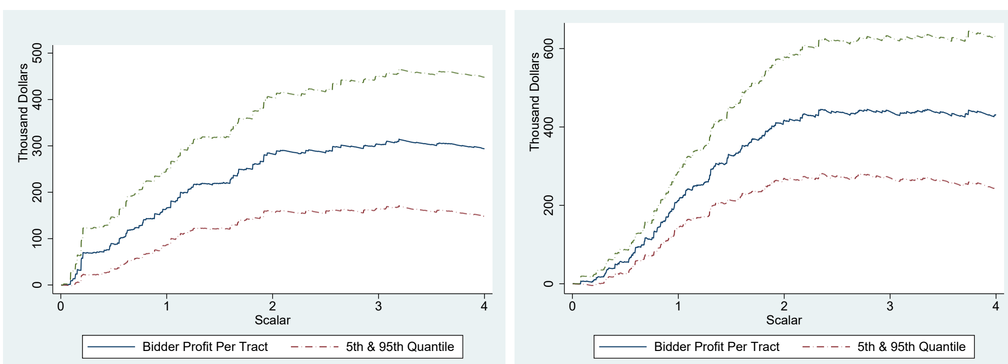
We obtain the sampling distribution for the test statistic using a block bootstrap to account for correlation due to the exogenous variables z^t by resampling blocks of auctions where an individual block consists of a six-month sequence of auctions. Kunsch (1989) shows the approach is consistent when the exogenous variable z^t is stationary.

TABLE 4—BEST RESPONSE TEST: OPTIMAL BID SCALAR $\hat{\alpha}^*$

	Overall	Bidder	
		Top-5	Non-Top-5
Bid Scalar Estimate $\hat{\alpha}^*$	3.26	3.19	2.78
5th and 95th Quantile	[2.19,3.79]	[2.04,3.19]	[2.15,3.82]

Note: The confidence region is estimated using 2000 bootstrap samples by resampling from the set of all auctions using the block bootstrap.

Table 4 reports the scalar estimate overall and for two subgroups of bidders: the five bidders in Table 2 who submit the most bids and all other bidders. Bidders in all groups substantially underbid. That is, holding rival bids constant, an individual bidder would optimize their expected payoff across auctions by increasing their own bid by a factor of three. Clearly, we can reject the null of BNE bidding in first-price auctions using our baseline interest rate estimate, suggesting that bidders coordinate to keep prices substantially below market value. Note that the test does not establish that tripling bids would result in BNE bidding as rival bids were held constant when computing α^*; if one bidder were to triple her bid, a profitable deviation may still exist for rivals.



Top Five Bidders. Non-Top Five Bidders.

FIGURE 2. SIMULATED PROFIT VARYING THE BID SCALAR α

Figure 2 plots the estimated per-auction profit function varying the bid scalar α. The left panel considers the top five, while the right panel considers all other bidders. The figures report 5th and 95th profit quantiles across bootstrap samples.

In both cases profits are increasing at $\alpha = 1$, with the simulated optimal profit about twice as large as the observed profit.

Empirical auction work typically imposes assumptions on the information structure available to bidders and the details of the BNE. A key advantage of the underbidding test is that these details do not have to be specified. The test is robust to informational assumptions and the details of the BNE because it utilizes observable ex post oil extraction returns and bid data. Ex post returns are readily available in our setting and are available more broadly in settings where the lots can be resold or there is an active secondary market for the good.

While the evidence of underbidding under our baseline interest rate estimate rejects the hypothesis of BNE bidding, it does require knowledge of losing bids. The next section provides a test that solely requires knowledge of winning bids.

VI. Uniform Upward Deviation

This section examines whether a uniform upward deviation is profitable. This test is applicable regardless of the underlying information structure available to bidders and regardless of the BNE played. While the test does not provide a comprehensive examination of rationality, it addresses a crucial concern when facing potentially colluding bidders. Are the observed winning bids too low to be in equilibrium?

The uniform upward deviation constraint, which leads to a tight lower bound on revenues in first-price auctions as shown in Bergemann et al. (2017), is attractive for empirical purposes. It requires minimal data, solely requiring knowledge of winning bids and ex post values. It does not involve knowledge of losing bids, the underlying information structure, or the equilibrium bid strategies.

The uniform upward deviations test is operationalized based on realizations of ex post returns and winning bids. Replacing expectations in equation (12) with their sample analogues yields

$$\begin{aligned}(17)\qquad &\left\{\frac{|S|\sum_{t=1}^{T}[v^t - b\cdot a^t]\cdot 1(b\cdot a^t \geq p^t)}{\sum_{i\in S}\sum_{t=1}^{T}[v^t-p^t]\cdot 1(p_i^t = p^t)}\right.\\ &\left. -\frac{\sum_{i\in S}\sum_{t=1}^{T}[v^t-p^t]\cdot 1(p_i^t=p^t)\cdot 1(b\cdot a^t\geq p^t)}{\sum_{i\in S}\sum_{t=1}^{T}[v^t-p^t]\cdot 1(p_i^t=p^t)}\right\}\leq 0,\end{aligned}$$

where v^t is the observed value, p^t the winning price, p_i^t the winning price when bidder i won the auction, and a^t the acreage of the tract. We specify deviation bids as linear in acreage, with $b \in B = \left\{\left(\frac{p^t}{a^t}\right)\right\}_{t=1}^{T}$.

As a test statistic, we examine the maximal deviation gains normalized by profits,

$$D_T^S = \max_{b \in B} \left\{ \frac{|S| \sum_{t=1}^T [v^t - b \cdot a^t] \cdot 1(b \cdot a^t \geq p^t)}{\sum_{i \in S} \sum_{t=1}^T [v^t - p^t] \cdot 1(p_i^t = p^t)} - \frac{\sum_{i \in S} \sum_{t=1}^T [v^t - p^t] \cdot 1(p_i^t = p^t) \cdot 1(b \cdot a^t \geq p^t)}{\sum_{i \in S} \sum_{t=1}^T [v^t - p^t] \cdot 1(p_i^t = p^t)} \right\}. \tag{18}$$

We consider the null hypothesis

$$D_T^S \leq 0. \tag{19}$$

To obtain the sampling distribution for the test statistic, we use a block bootstrap method to account for correlation arising from the exogenous variables z^t by resampling auction blocks consisting of six-months of sales. The use of the block bootstrap enables us to obtain a consistent measure of the sampling distribution for D_T^S when the exogenous variables z^t are stationary, as shown in Kunsch (1989). We use 2000 bootstrap samples for the calculations.

Table 5 presents the results of the test. The column labeled "All, when $|\hat{S}|$ equals 13" considers the set of all potential bidders, whose cardinality we estimate as the maximum number of bidders across all auctions, which is a consistent and superefficient estimator. While this is a commonly used approach in the empirical auction literature, we examine the robustness of the results to alternative definitions. The column labeled "All, when $|\hat{S}|$ equals 7" artificially reduces the set of potential bidders to seven. We also include a specification where the potential number of bidders is artificially reduced from thirteen to four.

The column labeled "Top Five" considers the five bidders in Table 2 who submit the most bids. To ensure the active participation of these bidders, we select the sub-period from February 2007 until October 2013, during which all five bidders regularly submitted bids, participating in 78% of the sales.[15] Additionally, we examine a specification where the potential number of top five bidders is artificially reduced to three.

The column labeled "Top Three" pertains to the sub-period from February 2007 until May 2015, during which three out of the "Top Five" bidders consistently submitted bids.[16]

According to Table 5, the optimal upward deviation gain equals 5.29 times the realized profit. It quintuples profit for "Top Five" bidders, quadruples profit for "Top Three" bidders and triples profit for all bidders "when $|\hat{S}|$ equals 7". We can reject the null hypothesis that the deviation is not profitable at the 1% confidence level for all groups of bidders. Therefore, under our preferred interest

[15] Doug J Schutz and Slash Exploration LP commenced bidding in February 2007. The Blanco Company stopped bidding in April 2013.

[16] These three bidders are Yates Petroleum Corp, Doug J Schutz and Slash Exploration LP.

TABLE 5—TESTING UNIFORM UPWARD DEVIATION INCENTIVES: $H_0 : D_T^S \leq 0$

Set of Bidders when $\|\hat{S}\|$ equals		All 13	All 7	Top-Five 5	Top-Three 3
Baseline Estimates	D_T^S	5.29	2.55	4.24	3.61
		(1.15)	(0.58)	(1.00)	(1.51)
	10-% level	3.75	1.79	3.34	2.13
	5-% level	3.28	1.54	3.01	1.81
	1-% level	2.43	1.12	2.39	1.21
Robustness Checks					
(i) Using Prices of Futures Contracts	D_T^S	6.42	3.13	4.77	3.95
		(1.04)	(0.52)	(1.05)	(1.63)
	10-% level	5.03	2.47	3.84	2.54
	5-% level	4.52	2.22	3.60	2.18
	1-% level	3.56	1.71	2.92	1.49
(ii) Artificially setting $\|\hat{S}\| = 4$	D_T^S	1.18	1.18	2.21	2.18
($\|\hat{S}\| = 3$ in column "Top-Five" and		(0.30)	(0.30)	(0.60)	(1.05)
$\|\hat{S}\| = 2$ in column "Top-Three")	10-% level	0.80	0.80	1.66	1.20
	5-% level	0.67	0.67	1.47	0.99
	1-% level	0.41	0.41	1.09	0.59
(iii) Multiplying Well Costs by 2	D_T^S	3.59	1.74	2.98	2.17
		(2.80)	(1.69)	(0.87)	(1.22)
	10-% level	1.56	0.71	2.00	0.96
	5-% level	0.96	0.40	1.59	0.59
	1-% level	0.06	0.00	0.81	0.00
(iv) Real Interest Rate of 15%	D_T^S	2.97	1.34	3.58	2.85
		(1.20)	(0.61)	(1.00)	(1.35)
	10-% level	2.05	0.90	2.58	1.48
	5-% level	1.51	0.64	2.20	1.14
	1-% level	0.74	0.23	1.53	0.51

Note: Standard deviations are reported in parenthesis. The standard deviations of variables and the confidence levels of the null hypothesis are estimated using 2000 bootstrap samples by resampling using the block bootstrap.

rate estimate we reject the null of BNE bidding.

Robustness Checks

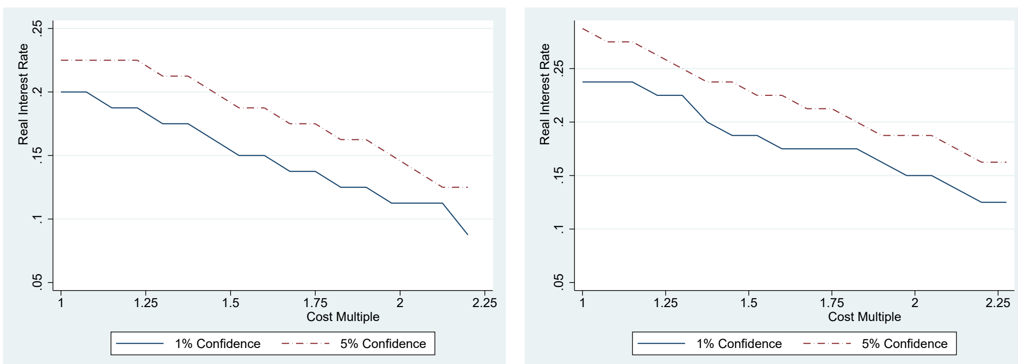
How robust is the test result? Table 5 reports robustness checks which relax one or more assumptions used to calculate the test statistic. We shall comment on the column "Top Five" bidders; the test results for "All" bidders "when $|\hat{S}|$ equals 7" and "Top Three" bidders are described in Table 5.

First, we examine the scenario where bidders did not form expectations about future prices correctly and instead evaluated future prices with the currently expected future price, see Hendricks et al. (1987). Specifically, we use 4-month-ahead oil and gas futures contracts traded on the New York Mercantile Exchange as an alternative measure of future prices. In this case, the test statistic increases to 4.77 for "Top Five" bidders, and we reject the null of no deviation gains at all confidence levels.

Second, we consider artificially reducing the potential number of bidders by replacing the consistent estimator $|\hat{S}| = \max_t N^t = 13$ with $|\hat{S}| = 4$. This implies the deviation benefit in equation (17) involves four bidders, while the cost include all bidders. For the "Top Five" bidders scenario we artificially replace the deviation benefit number with an even smaller number $|\hat{S}| = 3$. For "Top Five" bidders the test statistic D_T^S becomes 2.21. We reject the null of no deviation gains for "Top Five" bidders at all significance levels, meaning we can reject BNE bidding.

Third, we artificially double well cost estimates. This adjustment reduces the test statistic D_T^S for "Top Five" bidders to 2.98. We can reject the null of no deviation gains at all confidence levels for top "Top Five" bidders and at the 5 percent level for other groups.

Fourth, we artificially increase the real interest rate to 15%. This modification reduces the test statistic D_T^S for the "Top Five" bidders scenario to 3.58. We can reject the null of no deviation gains for "Top Five" bidders at all significance levels and therefore reject BNE bidding.



Realized Prices. Prices of Futures Contracts.

Figure 3. Interest Rate and Cost Multiples Needed to Satisfy Uniform Upward Deviation Incentives: Top Five Bidders

Finally, we illustrate graphically the joint levels of interest rates and cost multipliers required to justify the observed bids as the outcome of BNE play. Figure 3 displays the test results indicating the rejection region of the null that $D_T^S \leq 0$ for "Top Five" bidders. We use the block-bootstrap method with 2000 bootstrap samples to obtain the sampling distribution for the test statistics. Points situated to the south-west of the depicted line reject the null $D_T^S \leq 0$ at the reported significance level, while points located to the north-east cannot reject the null. The first figure shows that a real interest rate above 20% or a cost increase over 100% is needed to rationalize the data as the result of BNE bidding.[17] The second fig-

[17]This figure is based on realized prices and constructed using a discrete grid of well costs and interest

ure, which uses oil and gas future contracts as an alternative price measure, shows that the rejection regions expands outward, requiring even higher interest rates or cost multiples. Consequently, we conclude that significantly elevated interest rates or drilling costs are required to rationalize the observed bids as consistent with a BNE.

VII. Conclusion

This paper documents evidence of systematic underbidding in oil and gas lease sales in New Mexico. Features of this market are favorable towards bidder collusion. Leases cover small homogeneous units of land and are awarded at regular time intervals at in-person auctions. The buyer's side is highly concentrated, with half of all leases won by only four bidders who know each other well and interact regularly.

Using the ex post value of leased tracts, we test for the presence of non-competitive bidding in three ways. First, we test whether bidder participation decisions are uncorrelated conditional on ex post returns and find statistically significant evidence of both positive and negative pairwise correlation. Second, we test whether bidders maximize their expected profit (holding rival strategies constant) and find that under our preferred interest rate estimate bidders could approximately double their expected profit by more than tripling each submitted bid. Finally, we test whether bidders can increase payoffs by uniform upward deviations. We find that under our preferred interest rate estimate bidders could increase their expected profit by more than fourfold, which is inconsistent with BNE bidding.

There are several steps NMSLO can take, some of which it has already taken, to combat low auction revenues and to move toward the best-case outcome. First, the NMSLO could raise the reserve price, which has occurred in recent years. Using information from prior production outcomes of neighboring tracts, the reserve price could be raised much further to a level close to the predicted lease value. Second, information about lease values, from geological studies and historic production data on neighboring tracts can be made available to bidders along with the lease sale announcement, which would reduce informational asymmetries between bidders and encourage competition. Third, NMSLO has made changes in regulation that make it more difficult for firms to acquire leases and renew them without drilling for oil. This makes the practice of hoarding land to protect any information rent a bidding ring may have more expensive, as it necessitates the drilling of wells. Fourth, barriers to entry could be reduced by attracting new bidders, which was encouraged with the shift to online auctions in 2016. Fifth, the identities of bidders could be concealed, making it more difficult to detect deviations from the collusive agreement. NMSLO introduced this practice when it moved to online auctions. Sixth, packages of tracts can be offered at auctions

rates. At each point in this grid, we employ block bootstrap sampling of the test statistic to determine the rejection region.

instead of individual tracts and lease sales could take place at less frequent time intervals. Doing so would increase the benefits of deviation from a collusive agreement, making collusion more difficult to sustain. Taken together, these steps may limit the potential for collusion, which is a primary concern for the NMSLO if it is to meet its objective of "optimizing revenues while protecting [New Mexico's] heritage and [its] future."

While it is premature to fully assess the impact of these measures on oil and gas exploration, their influence is already reflected in auction revenues. When comparing the four-year period before and after 2016, auction revenues per acre nearly tripled.

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