Bidding and Drilling Under Uncertainty: An Empirical Analysis of Contingent Payment Auctions*

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Abstract

Auctions are often used to sell assets whose future cash flows require the winner to make post-auction investments. When a winner’s payment is contingent on the asset’s cash flows, auction design can influence both bidding and incentives to exert effort after the auction. This paper proposes a model of contingent payment auctions that explicitly links auction design to post-auction economic activity, in the context of Permian Basin oil auctions. The estimated model is used to demonstrate that auction design can materially impact both revenue and post-auction drilling activity, as well as mitigate or amplify the effects of oil price shocks.

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1 Introduction

Auctions are frequently used to sell assets whose future cash flows depend on the winner engaging in post-auction investment. A common feature of auction design in these settings is that the winner’s final payment is contingent on these cash flows, and therefore, the outcome of such investment. This links an auction’s design to investment incentives, and consequently, a bidder’s value for winning the auction in the first place. Examples of such auctions abound: payment in timber auctions is often based on the amount and type of wood harvested, final prices in highway procurement contracts depend on cost overrun clauses, and oil lease auctions involve an upfront cash bid along with a royalty payment that depends on the revenue from any recovered oil. Despite the fact that these very settings have been the basis for much of the seminal work in the empirical auction literature, the connection between auction design and bidder behavior at, and following, auction has been largely unexplored by this literature. Our paper studies the empirics of such contingent payment auctions with endogenous post-auction investment in the context of onshore oil auctions. We propose an empirical model of bidding and drilling, establish how joint variation in bids and drilling behavior informs model primitives, estimate the model on a new data set that matches auctions and drilling activity in the Permian Basin, and use the estimated model to demonstrate that auction design can materially impact both seller revenue and real economic activity, as well as mitigate or amplify the effects of oil price shocks.

Governments frequently use auctions to sell the rights to explore for oil or natural gas on government-owned land, and the predominant mechanism for such auctions involves explicit contingent payments. In a typical auction, the winner is the bidder who offers the greatest upfront cash payment (a “bonus”), and the winner has a pre-specified time to drill and begin production, if she so chooses. If the winner begins production, the winner must also pay a pre-specified fraction of the associated drilling revenues (a “royalty payment”). Auctions typically follow this fixed-royalty-variable-bonus format, but changing this format, for instance to one in which firms bid royalty rates, will influence not just the extent of competition at the bidding stage but also the incentives for the winner to drill as the price of oil fluctuates during the term of the lease.
Understanding the connection between auction design, bidding, and post-auction investment is crucial for many state and national governments that earn a large portion of their revenues either directly, based on auction outcomes, or indirectly, say in the form of taxes, from oil and gas activity. For instance, in this paper we study New Mexico, which attributes approximately 10% of its revenues to rents and royalties from mineral rights. The proportion is much larger when considering all revenue sources from oil and gas, including taxes and income from federal revenue sharing: in 2013, oil and gas revenue was the source of over 30% of its general fund (which pays for everything but roads). Furthermore, local economies, not just government coffers, can be greatly affected by changes in drilling activity. A large number of cities and towns across the U.S. have seen their populations swell and economies boom when oil and gas prices are high, only to see them deflate when these prices fall. Understanding the relationship between auction design and post-auction investment is essential for understanding the degree to which volatility in drilling activity, due to fluctuations in oil and gas prices, can be mitigated or exacerbated through auction design itself.

We study the bidding and post-auction drilling decisions in auctions used by the state of New Mexico to sell exploration leases on state-owned lands in the Permian Basin, one of the largest oil fields in the world. The state uses the standard fixed-royalty-variable-bonus auction format described above. From this point on we will refer to this format as a bonus auction, and be explicit about the value of the fixed royalty rate when needed. For our analysis we create a new data set that links bidding in these auctions with winners’ ex-post drilling decisions. We then build a rich model of a contingent payment auction in this setting, explicitly incorporating the ex-post drilling decision. In our model, the auction winner solves an optimal stopping problem.

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1See [http://www.emnrd.state.nm.us/ECMD/documents/2014_NMTRI_Oil_and_Gas_Study.pdf](http://www.emnrd.state.nm.us/ECMD/documents/2014_NMTRI_Oil_and_Gas_Study.pdf) for more information. The numbers are similar for other states like Wyoming (see [http://ballotpedia.org/Wyoming_state_budget_and_fiances](http://ballotpedia.org/Wyoming_state_budget_and_fiances) and [http://taxfoundation.org/article/federal-mineral-royalty-disbursements-states-and-effects-sequestration](http://taxfoundation.org/article/federal-mineral-royalty-disbursements-states-and-effects-sequestration)). An extreme example is Alaska, for which nearly 50% of state revenues were due to oil and gas production ([http://www.tax.alaska.gov/programs/programs/reports/AnnualReport.aspx?Year=2017#program40170](http://www.tax.alaska.gov/programs/programs/reports/AnnualReport.aspx?Year=2017#program40170)). Other, even non-OPEC member countries are also heavily reliant on revenues from the oil and gas sector. For example, it is responsible for roughly 40% of Mexico’s revenues ([Source: Baker Institute at Rice University](https://www.bakerinstitute.org/energy/exploitation/2013-2014-mexico-oil-tax-guide)).

2In a separate document, the New Mexico state legislature highlights the sensitivity of the revenue from oil and gas to fluctuations in the oil price. See [https://www.nmlegis.gov/Entity/LFC/Documents/Finance_Facts/finance\%20facts\%20oil\%20and\%20gas\%20revenue.pdf](https://www.nmlegis.gov/Entity/LFC/Documents/Finance_Facts/finance%20facts%20oil%20and%20gas%20revenue.pdf).
of whether and when to drill before the lease expires. Bidders view the auction as selling the rights for this option. Their values at auction depend on their (i) expectations of the quantity of oil, (ii) costs of drilling, (iii) beliefs about future oil prices, and (iv) residual claim on any oil revenue they earn if they decide to drill. As the format of the contingent payment auction determines whether, given the cost of drilling and the quantity of oil present, the winner decides to pay the cost of drilling in the face of oil price uncertainty, the bidder’s value for the lease and her post-auction investment decision are directly linked to the auction design itself.

As we explicitly endogenize values and incorporate a post-auction drilling stage, we must confront the identification of a number of parameters that do not appear in previous papers. In particular, we need to separately identify the distributions of drilling costs and quantities, both of which contribute to a bidder’s value of winning the auction for any given mechanism and expectation of future oil prices. Identification is complicated by our choice to model quantities as common across bidders. That is, we show that it is possible to nonparametrically identify our joint model of bidding and drilling if bidders have private quantities. To do this, we show that there is a one-to-one mapping between costs and drilling time, conditional on a price path, implying that the distribution of drilling times is informative of the distribution of costs. In parallel, standard arguments as in Guerre et al. (2000) show that the value from the optimal stopping problem is identified from bidding data in an affiliated private value setting. The structure of the model then connects these two elements and lets us identify quantities and cost separately and nonparametrically. The intuition from the private quantities setup highlights the role of the parametric assumptions in the common quantities model that we take to the data. In a common value setting, the nonparametric identification of values does not have an analogue (although the identification of per-unit costs still does), and we thus have to leverage parametric assumptions for identification as well as to aid in estimation. We then provide a tractable estimation procedure that exploits the structure of the optimal stopping rule. We find that the estimates from the structural model are in line with the real-world counterparts, which are not used for estimation.

Oil and gas auctions are an important driver of many states’ revenues and overall economic
activity. As such, governments are interested in how alternative mechanisms would impact sales and drilling (e.g. Congressional Budget Office (2016)), and some have even experimented with different designs. In contingent payment auctions, a bid can be viewed as a security whose value is determined by the future cash flow of the asset sold. Theory provides a range of alternative security design auctions (e.g. DeMarzo et al. (2005), hereafter DKS). We use our estimated model to simulate counterfactual economies where different, commonly discussed security designs are used to lease these tracts. There are two primary analyses in which we are interested. First, we analyze how outcomes in our sample would have changed had alternative securities been used. We find that, in terms of total seller revenues, a revenue-optimal bonus auction, in which the royalty rate is chosen to maximize seller revenue, outperforms other securities, including auctions where royalty rates are bid (an equity auction), or those where bidders submit cash bids and commit to paying the state the minimum of the bid and the oil revenues collected (a debt auction). The average expected revenue difference between optimal and the original bonus is about $10,400 per auction, which is close to 7% of the average auction revenue New Mexico earned in the auctions in our sample. While it is possible to alter the royalty rate to increase revenues, it is not possible to change the royalty rate in a way that increases both revenues and drilling rates. In fact, the higher royalty rate associated with the revenue-optimal bonus auction yields a 23% reduction in the probability of drilling a well.

Our second analysis focuses on the relationship between auction design, economic outcomes, and price shocks. Specifically, we use the estimated model to simulate how pre- and post-auction price shocks filter through a chosen auction design to influence bidding and drilling behavior. This is a valuable exercise since it sheds light on the ability of auction design to provide insurance against negative price shocks, as well as capture part of a windfall from positive price shocks. Here we find that the same revenue-optimal bonus auction is more sensitive to price shocks than baseline bonus bidding; however, for a broad range of oil prices and shocks it still outperforms

3For example, the state of Louisiana allows bidders to submit both bonus and royalty rates. See http://www.dnr.louisiana.gov/assets/OMR/Lease_Bid_Form_3-6-18.pdf. In some circumstances Alaska requires profit sharing with the winning bidder. See http://www.legis.state.ak.us/basis/aac.asp#11.82.933. While most of the offshore oil auctions held by the U.S. Department of the Interior use the standard bonus auction format, for a brief period in the 1970s firms bid royalty rates on profits (Hendricks & Porter (2014)).
other auction designs. Associated with somewhat lower frequency of well drilling relative to the historically used 1/6 royalty, it still generates appreciably higher revenues for the seller, except when there are especially negative post-auction price shocks.

We explore at length the forces that lead to these results. As discussed above, more competitive bidding can depress ex-post incentives to drill. We also identify another force against equity and debt auctions unique to common values involving an interaction between the winner’s curse and moral hazard. In these formats, the winner of the auction bids away the largest claims to the project, usually based on an especially optimistic signal (adjusted conditional on winning) of the true quantity. The winner is locked into her proposed split of the surplus from drilling even if the true quantity is realized to be significantly lower, which adversely impacts drilling incentives.

Related Literature

Our paper makes a number of contributions to the literature. The empirical auction literature has almost universally abstracted away from the interaction of post-auction investment and contingent payment contract design on bidder behavior. This is despite the fact that many auction environments that have been analyzed in the literature feature contingent payment clauses and post-auction investment, including, as described above, timber auctions and highway procurement.\(^4\) Athey & Levin (2001) (timber) and Bajari et al. (2014) (highway procurement) provide evidence of forward looking bidder behavior in the presence of contingent payment auctions. Our paper complements their results by estimating a structural model of firm behavior in a different setting that allows us to explore counterfactual mechanisms.\(^5\) Lewis & Bajari (2011) is the most closely related paper in the literature. They study scoring auctions used in highway procurement in which bidders submit cash bids and the length of time that they will take to complete the

\(^4\)See, for example, Athey et al. (2011), Haile (2001), Paarsch (1997), or Roberts & Sweeting (2013) for timber auctions, Krasnokutskaya & Seim (2011), Li & Zheng (2009), Jofre-Benet & Pesendorfer (2003) and Bhattacharya et al. (2014) are examples of papers studying highway procurement. Interestingly, many of these papers carefully study entry into auctions, which can be thought of as pre-auction investment.

\(^5\)Bajari et al. (2014) estimate a structural model of bidding in procurement auctions when post-auction adjustments to a bidder’s award are possible. However, in their paper the adjustments are considered fixed and known to all bidders in advance, and so the scope for alternative mechanisms to exploit variations in bidders’ beliefs over the likelihood of such adjustments is limited.
project. The winner is paid its bid and receives a bonus if it finishes early, and is penalized if not. In their model there is no post-auction uncertainty in the time it will take to complete a project, whereas this is an important feature in our setting as the winner faces price uncertainty over the course of the lease that affects whether and when to drill. Post-auction dynamic decision making is a key focus of ours as we are interested in the ability of different auction designs to either provide a form of insurance against a sharp reduction in drilling activity due to negative oil price shocks, or capture a portion of windfall profits attributable to a spike in oil prices.

The oil and gas sector is a critically important part of many regions’ economies, and correspondingly a number of papers look at aspects of oil and gas exploration, ranging from the leasing to the drilling stage. At the leasing stage, there has been much work focused on bidding in Outer Continental Shelf auctions (e.g. Hendricks & Porter (1988), Hendricks et al. (2003) or Haile et al. (2010)). These papers abstract from the relationship between endogenous post-auction outcomes and bidder strategy. Kellogg (2014) estimates the responsiveness of drilling decisions to the price of oil and finds that firms respond in a manner consistent with optimal investment theory. Our paper can be thought of as linking these two literatures, as we model both bidding and drilling decisions in onshore oil auctions.

Our paper features a model of contingent payment auctions with endogenous post-auction investment in which bidders have common values. To our knowledge, the theory literature on contingent payment auctions has yet to consider the case of common values when bidders make post-auction investment decisions. Our results show that common values can have important implications for security design. Auctions that link a bid directly to the size of the bidder’s residual claim, for example when bidders bid royalty rates, can curtail investment, and therefore lower seller revenues, in the presence of negative post-auction shocks. We show that this is empirically relevant in the case of the oil auctions we study, since we predict that revenues

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6 Another recent paper focused on oil auctions in New Mexico is Kong (2017a). We discuss this paper in greater detail in Section 2.


8 DKS address the issue of moral hazard associated with post-auction investment in relation to bidder reimbursement for the private values setting. They also consider the common values setting without the investment stage but do mention that incentives to exert effort could be depressed in such a model. Board (2007) and Cong (2014) incorporate post-auction investment in a contingent payment framework, but consider only private values.
and drilling activity would have been substantially lower had New Mexico used equity and debt auctions.

There is a long literature on identification of auction models. The classic identification results established in Guerre et al. (2000) or Athey & Haile (2002), have been extended to deal with issues like unobserved item heterogeneity or bidders’ endogenous entry decisions. To our knowledge, our results are the first on identification of contingent payment auctions, which is significant given their frequent use. As described above, we utilize information about ex-post actions for identification of primitives at the bidding stage. In ongoing work (Bhattacharya et al. 2018) studying identification of the benchmark DKS model, we have found that ex-post actions are indeed often—but not always—necessary for identification of the primitives.

Section 2 discusses the institutional framework and the data. Section 3 introduces the empirical model, discusses the link between auction design and economic outcomes, and provides empirical support for important modeling assumptions. Section 4 discusses identification and estimation. Section 5 evaluates how counterfactual security choices would have impacted bidding and drilling activity in our sample, and also how price shocks are filtered through these designs so as to impact economic activity. Section 6 concludes. The Appendices provide details on the nonparametric identification argument for a private values model, study the robustness of our counterfactual results to alternate specifications of the model, and provide additional details about our data and computation.

2 Empirical Setting and Data

We analyze auctions held by the New Mexico State Land Office (NMSLO), which is charged with managing 9 million acres of surface and 13 million acres of subsurface estate for the beneficiaries of the state land trust (e.g., schools and hospitals), amounting to about 1/6 of the land in New Mexico. As part of its responsibilities, the NMSLO sells leases that grant the right to drill for oil

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9For example, see Li et al. (2002), Krasnokutskaya (2011), or Hu et al. (2013) for unobserved heterogeneity and Gentry & Li (2014) for endogenous entry.

10For certain securities (like debt and call options), we show that observed variation at the time of bidding allows for nonparametric identification of the distribution of ex-post values in second-price auctions.
on the subsurface estate it manages. We focus on leases in the Permian Basin, which stretches from west Texas to southeastern New Mexico. The Permian Basin is the largest petroleum-producing basin in the U.S. and currently produces over 3 million barrels of oil per day, on par with the total production of Iran, the third largest producer in OPEC.11

The NMSLO sells leases via bonus auctions. In the bonus auction a winner’s payment consists of two components. First, all bidders submit cash bonus bids. The bidder who submits the highest bonus bid wins the auction and pays the seller this bid immediately following the auction. The second component involves royalty payments. Prior to the auction the NMSLO informs bidders of the lease’s royalty rate, which is the amount the winner must pay in the event it finds and produces “paying quantities” of oil or gas.12 The standard royalty payments are either 1/8 or 1/6 of the revenues from the oil. The leases grant the winner a five year period during which it has the right, but not the obligation, to drill.13

We combine data from several sources. From the NMSLO, we use auction sheets that detail the auction date, bids, bidder names, and the geographic location for every lease auction held between years 1994 and 2012 inclusively. The NMSLO uses both open outcry and sealed-bid auctions. For open outcry auctions we only observe the winning bidder and bid. For sealed-bid auctions we observe all bids and the bidders who submitted them. Below we will restrict our sample to sealed-bid auctions, but before doing so we create a measure of the set of potential bidders for each auction, which we denote by $N$. For every tract, we follow the literature (e.g. Roberts & Sweeting (2016) or Athey et al. (2011)) and set $N$ equal to the number of unique bidders in the neighborhood of 2 km that participated in some auction within 2.5 years from the tract’s sale date.14 We also use data from Drillinginfo, an industry data vendor, to determine

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11For comparison sake, the Ghawar oil field in Saudi Arabia, the world’s largest, can produce 5.8 million barrels per day.
12“Paying quantities” mean that production is sufficiently large to repay operating expenses of a well with a reasonable profit.
13Kong (2017a,b) also uses data from the NMSLO and studies the relationship between the two auction formats that the NMSLO uses: open outcry and sealed-bid auctions. We focus only on the sealed-bid auctions, as knowledge of the entire set of bids is important for our approach. As discussed below, we complement this dataset with post-auction activity since, unlike Kong’s papers, our emphasis is on the relationship between the auction and this drilling activity. Kong (2017b) contains more details about the history of the NMSLO.
14The one exception to this rule is that we always classify the firm Yates Petroleum as being a potential bidder since it competes in the vast majority of auctions.
whether and when drilling occurs on each lease. For every well that is drilled, Drillinginfo provides us with the well’s spud date and latitude and longitude.\footnote{Drillinginfo provides output data for a subset of the wells, but at times the data is missing, and production is measured irregularly. For this reason we will not use the data in estimation, but we will reference the data when evaluating our model’s out-of-sample fit, and also when defining “oil-rich” areas, which we discuss below.} We then use GIS software to merge wells to leases using the location of the well and the geographic boundary descriptions contained in the lease data. Lastly, we use daily data on WTI crude oil prices from FRED at the St. Louis Federal Reserve.

We limit the sample in three ways. While the primary reason for exploration in the Permian Basin during our sample period is oil, wells in our dataset produce gas as well. In an effort to simplify the model below, we only use tracts that are expected to be “oil-rich,” as proxied
by proximity to oil-rich wells based on production data from Drillinginfo. Second, to improve the homogeneity of our sample, we use only wildcat-type tracts, leaving out development leases corresponding to especially well-known territories. Finally, we limit the sample to include only sealed-bid auctions, as our approach requires information on the correlation of bids within auctions. Further details on sample selection are in Appendix C.1. We are left with 914 auctions.

Figure 1 shows a map of the auctions and subsequent drilling activity in our data. The green shapes are leases, and the drilling rig icons indicate which leases were drilled. Leases are spread throughout New Mexico’s portion of the Permian Basin, and drilling is not concentrated in any one subregion of the data. Moreover, if the data are disaggregated by year, there is no evidence of clustering of leasing or drilling activity by sale date.

Table 1 provides summary statistics for our sample. The average number of potential bidders in an auction is 3.87, and the average number of submitted bids is 2.25. The average winning bid is about $62,000, although the distribution of winning bids is fairly disperse, with a standard deviation and interquartile range comparable to the mean. There is also sizable within-auction...
variation in bids, as the median of the ratio of the winning bid to the second highest bid is 1.91.

Drilling is a fairly rare event, and when drilling occurs it happens with some delay. Only about 9.3% of leases are drilled, and the mean delay is about 3.6 years. More than 50% of wells are drilled over 4.4 years into the lease. About 86% of leases carry a royalty rate of 1/6, while the remainder have a royalty rate equal to 1/8. Most tracts tend to be half a square mile, or 320 acres, in area. Finally, while we do not report these statistics in the table, the average well produces oil for 85 months with a median of 69.

Figure 2 shows oil price, bidding and drilling dynamics over the course of the sample. There is a great deal of variation in the price of oil during our sample period. In the late 1990s it hovered at prices below $20/barrel (bbl), only to later rise to well over $100/bbl by 2007. After that the price of oil fell precipitously, only to see another spike after 2010. The auctions in our sample are spread throughout these fluctuations in the price of oil. As the figure shows, the winning bid in our auctions closely tracks the price of oil, as does the frequency of drilling. Note that our sample of auctions stops at the end of 2012, but the leases sold in these auctions may be drilled after 2012, which is why the distribution of drilling activity extends beyond the distribution of sales. In Section 3.4 we more fully explore the relationship between the price of oil and both bidding and drilling behavior in our data. Before doing so, in the next section we posit a model that theoretically relates fluctuations in the price oil, auction design, bidding, and drilling decisions.

3 Model

In this section, we present a model of bidding in oil lease auctions in which the bidders take into account the drilling decision that happens after the auction.

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A lease’s royalty rate depends on whether the lease is categorized as “discovery” (1/6) or “exploratory” (1/8). In conversations with a staff member of the NMSLO whose job it is to recommend certain leases be called discovery or exploratory, we have been told that the decision is largely arbitrary. Wells tended to be classified as discovery in the beginning of the sample, when oil prices were low, and exploratory later on, when prices were higher. While the collinearity in oil prices and royalty rates prevents us from being able to exploit variation in royalty rates to identify or test our model, we show in Section 4 that we can identify our model without variation in observed royalty rates.
Figure 2: Oil price and (a) winning bid and (b) number of auctions let and number of leases sold.

3.1 Setup

A set of $N \geq 2$ bidders compete for tracts in a first-price sealed-bid auction. There is a quantity $q$ of oil that can be extracted from the ground which is common to all bidders. Each bidder gets a signal $q\xi_i$ for the quantity that she can extract, with $E[\xi_i] = 1$ so that the expectation of the signal is $q$. Each bidder submits a cash bid $b_i$ for the right to drill on the particular tract of land. The bidder who submits the highest bid wins the right to drill on the land for a period of $T$ years. Drilling is costly, and it also requires the winner to pay a royalty rate $\phi$ to the seller, based on the revenue from the oil. Thus, the model consists of two stages—bidding, followed by drilling—and we discuss the stages in reverse chronological order.

3.1.1 An Optimal Stopping Model of Drilling Decisions

We assume that upon the conclusion of the auction, the winner learns the true quantity $q$ of oil in the ground. The winner must immediately spend an amount $X$, which represents the costs associated with owning a lease even in the absence of drilling, such as administrative burden and yearly rental payments to the NMSLO.\(^\text{17}\) She then learns her cost of extraction $c_i$, which is drawn from some distribution with cdf $H(\cdot; q)$. Based on this cost of extraction, the bidder

\(^{17}\text{We abstract from modeling these rental payments directly as they are on the order of$\$1 per acre per year, and thus are small relative to the bonus bids and royalty payments.}\)
chooses when to drill (and spend $c_i$), extract, and sell the oil. For simplicity, we assume that all three of these actions occur simultaneously.\footnote{Anderson et al. (2018) suggests that once a well operator has started drilling from a well, they do not stop production in response to fluctuations in prices, which is consistent with a one-time decision to drill a well.} Thus, if these actions occur at time $t$, then the contemporaneous payoff to bidder $i$ is

$$
(1 - \phi) \cdot P_t \cdot q - c_i,
$$

where $P_t$ is the price of oil at time $t$.

The choice of time $t$ to drill is an optimal stopping problem. The winner must choose a stopping time $\tau$, bounded by $T$, to maximize the expected discounted value of (1), i.e.,

$$
V(q, c) \equiv \max_{\tau \leq T} \mathbb{E}_{P_\tau} \left[ e^{-r\tau} ((1 - \phi) P_\tau q - c)^+ \right],
$$

where the expectation is taken over $P_\tau$ given that the price process starts at $P_0$.\footnote{The notation $x^+ \equiv \max\{x, 0\}$ incorporates the possibility that the owner never drills and thus earns zero from the drilling stage.} Note that $\tau$ is not a single number but rather a stopping time—a stochastic function that is adapted to the price process $P_t$ so that the decision of whether to stop by time $t$ cannot depend on $P_s$ for $s > t$.

### 3.1.2 The Bidding Stage

The drilling problem from (2) microfound bidder values. Let

$$
v(q) \equiv \mathbb{E}_{c \sim H(\cdot, q)} V(q, c)
$$

denote the value from the bidding stage if the true quantity of oil is $q$ (after paying $X$, which we make explicit below). This quantity feeds into the signals of values at the time of bidding since (i) bidders are uncertain about the true quantity as well as their idiosyncratic costs at the time of bidding, and (ii) bidders face the standard “winners’ curse” concern that the signal conditional on winning is an overestimate of the true quantity. In particular, bidders will choose their bid
$b(\tilde{q}_i)$ as a function of their signal $\tilde{q}_i = q\xi_i$ by maximizing

$$
\mathbb{E}_q \left[ (v(q) - X - b) \cdot \Pr \left( \max_{j \neq i} \beta(\tilde{q}_j) < b \right) \bigg| \tilde{q}_i = q\xi_i, \max_{j \neq i} \tilde{q}_j \leq \tilde{q}_i \right],
$$

where the expectation encapsulates that the beliefs over $q$ are conditional on both the signal as well as winning the contest. In equilibrium, each bidder bids as if her signal were marginal (i.e., coincides with the second-highest signal). Bidders who expect profits less than $X$ do not bid.

### 3.2 Further Assumptions and Properties of the Model

 Throughout the paper, we will make the following assumption on the price process.

**Assumption 1** Consider the optimal stopping problem

$$
\max_{\tau \leq T} \left\{ \mathbb{E}_{P_0} \left[ e^{-r\tau} (P_\tau - z)^+ \right] \right\}.
$$

The stopping rule associated with (4) has the form

$$
\tau = \min\{t \geq 0 : P_t \geq P_{t,T}^*(z)\},
$$

for some function $P_{t,T}^*(z)$ that is strictly increasing in $z$ for all $t \leq T$.

This assumption has a natural economic interpretation: if the cost of stopping is larger, then the minimum price needed to stop at any particular point is larger. This assumption is useful in estimation since, after renormalization, (2) can be transformed to (4). Since the stopping time (i.e., drilling delays) are observed, Assumption 1 provides a path towards identifying properties of the cost distribution from the post-auction drilling decision.

Of course, Assumption 1 is a non-primitive assumption, but it holds when placing the following, very natural (primitive) assumption on the price process $P_t$.

\footnote{See Section 25.2 of Peskir & Shiryaev (2006).}
Assumption 2 \( P_t \) follows a geometric Brownian motion, i.e., \( dP_t/P_t = \mu_p \, dt + \sigma_p \, dB_t \).

While we will be imposing Assumption 2 in some of the identification argument and the entire estimation procedure, we do not expect it to be the weakest condition under which our arguments will apply.\(^{21}\)

The value of holding the lease has natural comparative statics. Note that \( V(q,c) \) is strictly increasing in \( q \) and strictly decreasing in \( \phi \) and \( c \). Under Assumption 2, the value is strictly increasing in \( P_0 \). Furthermore, note that under Assumption 2, we can write

\[
\mathbb{E}_{P_0'} \left[ e^{-rT} \left( (1 - \phi)P_T q - c \right)^+ \right] = \frac{P_0'}{P_0} \cdot \mathbb{E}_{P_0} \left[ e^{-rT} \left( (1 - \phi)P_T q - c \cdot \frac{P_0'}{P_0} \right)^+ \right],
\]

so the stopping problem associated with a price \( P_0' > P_0 \) is isomorphic to one starting at \( P_0 \) but with a lower cost. Thus, the expected drilling delay is nonincreasing in \( P_0 \). Similar arguments show that the expected delay is nonincreasing in \( q \) and nondecreasing in \( \phi \). Thus, the effect of the royalty rate \( \phi \) on seller revenues is ambiguous: while a higher \( \phi \) gives the seller a greater share of the revenues if drilling occurs, it also lowers bids and delays drilling.

Finally, we impose a number of technical conditions on the quantity and cost distributions in the problem.

Assumption 3 The densities of \( q \) and \( \xi \) are positive on compact support and \( \mathbb{E}[\xi] = 1 \). The distribution of \( c \) as a function of \( q \) is such that \( \mathbb{E}_{c \sim H(\cdot;q)} V(q,c) \) is increasing in \( q \). Bids are increasing and continuously differentiable in \( q_\xi \).

Assumption 3 ensures that costs rise slowly enough as a function of quantities \( q \) so that the expected value from holding a lease still increases in \( q \). If per-unit extraction costs are stochastically decreasing with quantities, then it is easy to check that this assumption is satisfied,\(^{22}\) as would be the case, for instance, in a model where the fixed and marginal costs of drilling are drawn from distributions that are independent of quantity. This monotonicity assumption also

\(^{21}\)It is also the case that under Assumption 2, \( P_{t,T}(z) \) is decreasing in \( t \) for all \( T \), but this fact—which arises from the option value of keeping the stock declining in time—will not be directly used in the identification argument in Section 4.

\(^{22}\)Simply factor out \( q \) from the maximand in (2) to verify this statement.
implies that bidders who obtain higher signals of \( q \) are also more optimistic about the value of obtaining the rights to drill. The second part of Assumption 3 is a technical one, and it could be derived from more primitive assumptions. For instance, Assumption 5 (see the appendix) together with a restriction that the distribution of \( c \) is independent of \( q \xi \) would imply that the bidding equilibrium is differentiable in \( q \xi \). Alternatively, we could impose appropriate smoothness conditions on how the distribution of \( c \) changes with \( q \), although we do not pursue that avenue here.

### 3.3 Link Between Auction Design, Values, and Investment

Our model endogenizes bidder values, \( v(q) \), which is in contrast to much of the literature that treats these values as model primitives.\(^{23}\) Specifically, as (2) and (3) make clear, in our model a bidder’s value is a function of their expectation of drilling cost, their expectation of future oil prices, the quantity of oil present, and the mechanism itself, which can be seen in (2)'s dependence on the fixed royalty rate \( \phi \). Thus, if an alternative mechanism were chosen, the incentive to drill would change, and consequently, so would bidder values. While the seller could choose different values for \( \phi \), and setting \( \phi = 0 \) corresponds to an all cash auction, a wider range of securities are available. Two alternatives that the theory literature (e.g. DKS) points to are equity and debt auctions. In an equity auction bidders bid royalty rates, and the bidder who submits the highest royalty rate wins and is committed to pay that royalty rate following production. In this case

\[
V(q, c)^{Equity} \equiv \max_{\tau \leq T} \mathbb{E}_P \left[ e^{-r \tau} \left( (1 - \phi^{Equity}) P_T q - c \right)^+ \right], \tag{5}
\]

where the only difference from (2) is that the royalty rate is endogenously determined by the auction winner, hence the superscript on \( \phi \). In a debt auction a firm bids an amount \( d \) and commits to paying the seller the minimum of \( d \) and the oil revenues collected. The firm that submits the highest \( d \) wins. Since drilling is not mandatory, the firm will only drill in the case

\(^{23}\)A notable exception is Lewis & Bajari (2011), who provide an empirical analysis of highway procurement auctions with delay costs. Athey & Ellison (2011) provide a theoretical analysis of internet search auctions that explicitly stresses the connection between values and auction design.
that revenues exceed \( c + d \). Therefore, in a debt auction

\[
V(q, c)^{Debt} \equiv \max_{\tau \leq T} \mathbb{E}_{P_0} \left[ e^{-r\tau} (P_{\tau} q - c - d)^+ \right].
\]  

(6)

The implication of our model is that auction design itself affects, through its impact on bidder values and investment incentives, real economic activity. To illustrate, consider an auction with realizations for costs in quantities in line with the estimates presented in Section 4.3.\(^{24}\) The seller’s choice of security affects the winner’s drilling decision, which is embodied in her optimal stopping trajectory. This is demonstrated in Figure 3, which overlays the winner’s optimal stopping trajectories for a variety of security designs on a five-year sample of the realized price of oil in our data. The thin solid trajectory (second from the bottom) corresponds to the standard auction design used in New Mexico. In this case the winner would choose to drill near the middle of 2004, when the price of oil crosses the optimal stopping curve. If the royalty rate is increased

\(^{24}\)Specifically, quantities are distributed exponentially with mean 60,000, costs are distributed log-normally with mean parameter 14.4 and standard deviation parameter 0.64, realized \( q = 42,000 \) bbl, \( P_0 = 41.60 \), \( N = 4 \), \( X = 4,970 \), \( \mu_p = 0.0355 \), and \( \sigma_p = 0.3038 \), and a winner for whom realized \( c = \) $1 million and \( \xi = 1 \).
from 1/6 to 0.26, the bidder lays claim to a smaller share of any revenue earned so that drilling is less likely, and in this case is delayed by a few months (the thick solid trajectory). If the seller used an all cash auction, the winner is the full residual claimant on any revenues earned, and this accelerates drilling (the long-short-long dashed trajectory at the bottom). In each of these cases with different $\phi$s, the winner’s optimal stopping trajectory is independent of her cash bid. However, if the seller uses an equity or debt auction, her stopping path will be directly affected by her winning bid. In the debt auction, the winner pledges to pay the seller at least $1,113.60K, and this leads her to delay drilling until halfway through 2005 (the dotted trajectory). In the equity auction the winner commits to a royalty rate of 56%, and so investment is even less likely. It is not until the lease nearly expires that the winner of the equity auction decides to drill (the dashed trajectory at the top). In this illustration of the various auction formats, while investment clearly depends on which security is used, drilling always happened. Thus the effect of auction design on real economic activity is witnessed through accelerated, or delayed, drilling. However, were the realized price path different, drilling may not have occurred at all for some security designs, and so auction design could impact not just delays, but total production. In our empirical analysis below we find that auction design affects delays and total production.

It is also important to point out that due to the varying drilling incentives created by alternate auction designs, the same bidder has different values of winning the auction depending on security design. When $\phi$ changes from 0, to 1/6, to 0.30, the winner’s value decreases from $133.1K, $86.2K, to $55.4K. Her value falls to $34.3K with debt, and $21.9K with equity.

Before turning to the identification and estimation of our model, we now discuss some of the modeling choices we have made and why they are reasonable for the setting we consider.

### 3.4 Discussion of Modeling Choices

In this section we discuss and provide evidence for a number of the assumptions we make in our model of bidding and drilling decisions. In the model bidding and drilling are responsive

---

25This is the value of the royalty rate that we find would maximize sample-wide revenues among all bonus auction formats.
26Of course her cash bid varies with $\phi$. 

to oil prices. Columns (1)-(5) of Table 2 explore these relationships in our data. Column (1) shows estimates of a regression of an auction’s entry rate on the price of oil at the time of the auction, the number of potential bidders, the size of the tract, year fixed effects, and the tract’s geographic location. There is a statistically significant effect of an increase in the current price of oil on the number of participating bidders, although the magnitude is not that large, as a $10 increase in the price of oil leads to an increase in the entry rate of 1.7 pp. Bids are much more responsive to the price of oil. As column (2) shows, using the same controls from column (1), a $10 increase in the price of oil increases the winning bid by 7.7%.

The next three columns of Table 2 illustrate the sensitivity of drilling decisions to the price of oil. Column (3) shows estimates from a linear probability model of whether a tract was drilled as function of the same covariates used in columns (1) and (2). A $10 increase in the price of oil at the time of sale increases the probability that a tract is drilled by 2.1 pp, which is a quantitatively large effect compared to the overall drilling probability of 9.3%. Column (4) explores how the timing of drilling responds to the initial oil price. We estimate a Tobit model with right truncation at the lease’s expiration date, and find that a $10 increase in the price of oil speeds up drilling by about 83 days. Conditional on drilling, the expected effect is somewhat muted. In column (5) we explore within-lease drilling dynamics. Specifically, we regress whether a tract was drilled in a particular month on the price of oil at the time of auction, the current price of oil, the time since the auction was held, and the interaction between the current price of oil and the time since the auction was held. We also control for the size of the tract, its geographic location and year fixed effects. We find that a higher current price of oil increases the probability of drilling, and that drilling is more likely to occur as the lease approaches expiration. For example, the estimates imply that the instantaneous probability of drilling at the mean current price of oil is twice as high when there is one year left on the lease.

The entry rate is the ratio of the number of actual to potential bidders.

Specifically, we include fixed effects for the lease’s Township and Range, which are standard geographical units set forth by the Public Land Survey System. Townships run east to west from a designated parallel, and Ranges run north to south from a designated principal meridian. Townships and Ranges are each roughly six miles wide.

For the range of prices in our data the marginal effect of a $10 increase in the current oil price on expected drilling time is one to two weeks.
as compared to when there are three years left. We also find that the sensitivity to the price of oil increases as the end of the lease nears. For example, the impact of an increase in the price of oil of $50 to $60 on the instantaneous drilling probability is 1.94 times as large when there is one year left on the lease as compared to when there are three years left. Taken together, the results in Table 2 illustrate basic patterns in the data that are consistent with the model’s predictions of how bidding and drilling decisions respond to prices and the length of time left on a lease.

Throughout the empirical analysis in the paper, we assume that quantities are common to all bidders and thus focus on a common values framework. While this is arguably the standard approach in modeling oil auctions (e.g., Hendricks & Porter (1988) and Hendricks et al. (2003), albeit in offshore oil auctions), it is important to note that some work models oil auctions using a private values framework,\textsuperscript{30} including Kong (2017a), who also analyzes New Mexico oil auctions. Beyond choosing the paradigm that is more typical in the literature, there is some evidence in the data that supports common values in our setting. Columns (6)-(8) of Table 2 show the results of regressions of whether or not a well is drilled on leases that received at least two bids, as a function of the winner’s bid, various measures of the competitors’ bids, and controls for the number of potential bidders, the price at auction, lease acreage, as well as year and geography fixed effects. Each column shows that the winner is more likely to drill when the losers bid more aggressively, as proxied for by the second highest bid, the average of the other bids submitted at auction, or the ratio of the second highest bid to the winner’s bid. As would be predicted by a model with common values, the winner is more likely to drill when her competitor is more optimistic about the future profitability of the lease.

Our model makes a number of assumptions about drilling. First, it assumes that bidders drill a well and sell all production immediately at the current price of oil. This stark assumption is made for theoretical and computational simplicity. However, for the wells in our sample for which we have production data, about 60% of the total production occurs in the first two years, and so while the assumption that all revenue is earned at the time of production is strong, we do

\textsuperscript{30}Li et al. (2000) introduce a “conditionally independent private information” framework that nests affiliated private values and pure common values. They provide identification results for the model (leveraging parametric restrictions for pure common values), and their estimates lie closer to the affiliated private values paradigm.
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<td>$I[\text{Drill}]$</td>
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Table 2: The sensitivity of firms’ decisions to the price of oil. Every column except (5) gives ordinary least squares estimates of the dependent variable in the last row of the table on the controls shown in the table, as well as the lease’s acreage. Column (5) shows estimates of the Tobit model described in the text. Time Since Auction is the number of months since the auction was held. All regressions are run at the lease level except for column (5) which is at the lease-month level. Columns (1)-(4) use all leases in our sample. Column (5) uses only leases on which drilling occurred. Columns (6)-(8) use only auctions in which at least two bids were submitted. Robust standard errors in parentheses. The standard errors in column (5) are clustered at the lease level. Estimates in column (5) are multiplied by 100,000 for readability. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. 
not view it as completely unreasonable for this setting. Second, the model assumes that only one well is drilled per lease, which is in line with the majority of leases (61%) of our sample.\footnote{For this we count wells drilled within one week of each other as the same well.} Third, we assume that the decision to drill is driven by the solution to an optimal stopping problem. Herrnstadt et al. (2017) make the point that drilling near the end of a lease may be primarily due to desire to hold onto a lease. In our data, however, wells that are drilled near the end of the lease (after the median delay) only tend to produce about 15% less oil than those drilled earlier in the lease, and this difference is not statistically significant. This provides some evidence against the argument that end-of-lease drilling may be conducted even if expected quantities are low purely to preserve the option value of drilling beyond the initial lease term.

Although it is straightforward to extend the model to incorporate bidder asymmetries, we assume that bidders are symmetric. While many of the bidders in the data are likely very similar, one bidder, Yates Petroleum stands out from the rest. It participates in nearly 95% of the auctions. This is why we model the firm as always being a potential entrant, as discussed in Section 2.

Finally, in this model, the source of the option value of waiting to drill stems exclusively from price shocks. The evidence above suggests that bidders are sensitive to the price of oil in a manner consistent with this model. In Appendix B, we present some correlational evidence that firms also tend to drill soon after their neighbors\'s drill. We have abstracted from the impact that neighbors have on a firm’s drilling decision in our baseline model since that would necessitate developing a much more complex game for the post-auction stage, and is beyond the scope for the current paper. However, we are interested in the robustness of our empirical analysis below to the possible impact that neighbors have on the decision to drill. Therefore, in Appendix B we extend the baseline model to incorporate neighbors’ drilling decisions in a more reduced-form way. Despite the model’s simplicity, it still allows a lease-holder’s option value to stem from the ability to wait for information generated by neighbors’ drilling decisions, and in Appendix B.2 we illustrate that our main findings are robust to this modeling extension.
4 Identification and Estimation

In this section we discuss identification and estimation of the model presented in Section 3. Even though we will place parametric restrictions on our model, in Section 4.1 we provide intuition for the variation in the data that helps to identify model primitives by appealing to a formal identification result in an affiliated private values setting. In Section 4.2 we discuss our specific parameterization of the model, our estimation procedure, and three alternative specifications that we use to illustrate robustness. In Section 4.3 we present and discuss model estimates. For readability sake, we keep the material in this entire section brief, and relegate formal propositions, proofs, estimation details, and specifics of alternative model specifications to appendices that we reference throughout.

4.1 Identification

The primitives of the model are the distribution of the true quantity of oil $q$, the distribution of signal noise $\xi$, the distribution of drilling costs $c$, which can depend on $q$, and the cost $X$. The observables are bids and drilling times (if a tract is drilled), and the entire path of the price of oil at all times. Since we adopt a common values framework, we will take a parametric stance on identification of the model that we outlined in Section 3. However, to provide the intuition for what features of the data are informative of primitives of the model, we discuss the intuition for nonparametric identification of an affiliated private values version of the model. We provide the formal identification results in Appendix A, and in the following discussion we reference the appropriate lemmas and propositions in the appendix.

Suppose that, unlike in the model in Section 3, bidders have affiliated private quantities. That is, instead of $q\xi_i$ representing bidder $i$’s signal of the true quantity $q$, it is an exact measure of how much oil bidder $i$ can extract. We will show that this model’s primitives are nonparametrically identified. After doing so, we will discuss which aspects of the model remain nonparametrically identified, and which do not, once bidders have common values.

32We assume that the price process—and thus the beliefs over the price process—are observed directly in the data.
The identification argument proceeds in three steps. First, consider the post-auction investment stage. The time at which drilling commences is based on a comparison of per-unit revenues and per-unit costs $c/q\xi$. Specifically, the winner solves

$$
\arg\max_{\tau \leq T} \left\{ \mathbb{E}_{P_0} \left[ e^{-r\tau} \left( P_\tau - \frac{1}{1-\phi} \cdot \frac{c}{q\xi} \right)^+ \right] \right\},
$$

which is simply the optimal stopping problem from (2) with $q$ replaced by $q\xi$ and $(1-\phi) \cdot q\xi$ factored out. The solution to the optimal stopping problem in (7) defines the one-to-one map between the effective costs $c/q\xi$ and the stopping time $\tau$. Inverting this map, one can recover the unit costs given the value of $\tau$, which shows that the distribution of unit costs is identified from the distribution of delays in the data. This result is formalized in Lemma 1 of Appendix A.2. Note also that the value of maximum in (7), which represents per-unit profits, is identified as well.

The second step is to separate costs from quantities. The key observation is that the private values framework will allow us to identify total values—i.e., total profits from the optimal stopping problem—directly from the bids (Guerre et al. 2000, Li et al. 2002). This is done in Lemma 2 of Appendix A.2. In our model, a bidder’s total value is

$$
v_i = (1-\phi) \cdot q\xi_i \cdot \mathbb{E}_c \left\{ \max_{\tau \leq T} \left\{ \mathbb{E}_{P_0} \left[ e^{-r\tau} \left( P_\tau - \frac{c}{(1-\phi)q\xi_i} \right)^+ \right] \left\{z^{(\ast)} \right\} \right\} \right\} - X,
$$

where the term labeled ($\ast$) corresponds to per-unit profits identified at the first step. Given these values and the ($\ast$) term at multiple levels of $P_0$, it is straightforward to solve for $q\xi_i$ and $X$. See the proof of Proposition 1 in Appendix A.2. The final step of the procedure invokes the result of Kotlarski (1967) to identify the distributions of $\xi$ and $q$.

Discussing identification in the private values model is informative since it highlights the role of parametric assumptions in the common values model. The critical issue in the common values setting is that ex-ante bidder valuations cannot be factored in a way similar to (8), where the valuation is a function of a term identified from the drilling stage and a term that depends only
on the quantity of oil. Although drilling delays are still informative of the distribution of per-unit costs \( c/q \) in a common values setting, this information cannot be used directly for identification of the model’s primitives in the same way that (7) is used in the private values environment.\(^{33}\) Additionally, the valuations themselves are not identified from the bids, since there is no analogue of the Li et al. (2002) inversion in this setting. We now introduce the parametric assumptions we impose in order to help address these two problems and identify the model’s fundamentals, and also how we estimate these parameters.

### 4.2 Estimation

Our estimation approach is applied under a common values paradigm and leverages parametric assumptions. We use a method of simulated moments approach to estimation that proceeds in three steps. First, we estimate the parameters of the price process. This price process can give us the optimal drilling path for any quantity \( q \) and cost \( c \). Second, for each set of candidate parameters for cost and quantity distributions, we can simulate bidding and drilling decisions of the agents. Third, we then match a set of model-implied moments to the data. Further details of the estimation procedure are in Appendix C.2.

#### 4.2.1 Estimating the Price Process

We impose Assumption 2 on the price process, so that

\[
P_t = P_0 \cdot \exp \left( \left( \mu_p - \frac{\sigma_p^2}{2} \right) t + \sigma_p B_t \right).
\]  

\(^{33}\)However, it is still useful to be able to recover the distribution of \( c/q \) conditional on a bid, since this allows us to compute the expected per-unit profits conditional on winning for a bidder who submits the bid \( b_i \). Note that once we have a particular unit cost \( c/q \), the unit profits are simply given by \( \max_x E_{P_0} [P_x - c/(q(1 - \phi))] \), which can be computed with knowledge of the price process. The distribution of \( c/q \) conditional on a bid (i.e., a signal) and conditional on winning is identified from the data as argued above. Thus, the expected per-unit profits, with the expectation taken over the distribution of \( c/q \), are still identified.
We observe the price process in discrete intervals \( \Delta = 1/12 \) (corresponding to one month). Taking logs of (9) gives

\[
\log(P_{t+\Delta}) - \log(P_t) = \left( \mu_p - \frac{\sigma_p^2}{2} \right) \Delta + \sigma_p \sqrt{\Delta} \epsilon_t, \tag{10}
\]

where \( \epsilon_t \) is the Brownian innovation, and thus distributed standard normal and i.i.d. across time. We estimate (10) via an ordinary least squares regression.

### 4.2.2 Computing Optimal Stopping Trajectories

The next step involves computing the drilling rule \( P^*_t(c) \) as a function of \( c \) and (implicitly) \( q \). There is no known analytical solution for this trajectory (when \( T < \infty \)), so we use a well-established numerical procedure, often used in the pricing of American options, to approximate it.\(^{34}\) In particular, we approximate the Brownian motion by a sequence of Bernoulli variables: the innovation over a period of \( \delta \) can take on either a value of \( \sqrt{\delta} \) or \( -\sqrt{\delta} \). We find an approximation \( w(t, z) \) associated with the value function in problem (4). Given the Bernoulli random walk, this approximation satisfies

\[
w(t, z) = \max \left\{ g(t, z), \frac{1}{2} \left[ w(t + \delta, z + \sqrt{\delta}), w(t + \delta, z - \sqrt{\delta}) \right] \right\}, \tag{11}
\]

where

\[
g(t, z) = e^{-rt} \left[ (1 - \phi) \cdot \exp \left( (\mu_p - \frac{\sigma_p^2}{2}) t \right) z - c \right]
\]

is the payoff from drilling. The boundary condition is that \( w(T, z) = \max \{ 0, g(T, z) \} \), i.e., the bidder will drill at the expiry date if and only if it is instantaneously profitable to do so. We can solve (11) by iterating from \( t = T \) backwards to \( t = 0 \) in step size \( \delta \). Doing so immediately

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\(^{34}\)Chapter 6 of Kwok (2008) discusses the relevant numerical methods in detail. Fundamentally, the approximation of a Brownian motion by a discrete random walk follows from Donsker’s theorem, which is a functional version of the standard Central Limit Theorem.
defines the stopping region as

\[ S_{\text{opt}} = \left\{ (t, p) : w(t, z) = g(t, z) \text{ and } z = \frac{1}{\sigma_p} (\log p - (\mu_p - \sigma_p^2/2)t) \right\}, \]

i.e., the set of times and prices where the first component of the right-hand side of (11) is larger. This gives us an approximation for the threshold \( P_{t,T}^*(c) \). Note that this step does not depend on any candidate parameters other than \( \mu_p \) and \( \sigma_p \), which are estimated in the previous step.

### 4.2.3 Parameterization

We now place parametric assumptions on the primitives of the model as follows. An auction that happens \( t \) months since the beginning of the sample period has primitives

\[
q \sim \text{Exp}(\lambda_q),
\]

\[
\xi_i \sim \text{Weibull}(\lambda_{\xi,0}, \lambda_{\xi,1}), \text{ and } c \sim (1 - p) \cdot \log - \mathcal{N} \left( \mu_0 + \alpha \log(q) + \beta_1 t + \beta_2 t^2, \sigma_c \right) + p \cdot \infty.
\]

We say the common component of quantities \( q \) is distributed exponentially with mean parameter \( \lambda_q \). The idiosyncratic shocks \( \xi_i \) have a Weibull distribution with scale and shape parameters \( \lambda_{\xi,0} \) and \( \lambda_{\xi,1} \) chosen so that \( \mathbb{E} \xi_i = 1 \) for normalization. Finally, we let \( \log c \) be \( \infty \) with probability \( p \) (corresponding to an especially large cost to capture the many other reasons outside of our model that we might not see drilling) and, with probability \( 1 - p \), distributed normally with mean parameter \( \mu_c = \mu_0 + \alpha \log(q) + \beta_1 t + \beta_2 t^2 \) and scale parameter \( \sigma_c \).

To test the robustness of our results, we explore alternative parameterizations of our structural model in Appendix B. In one model we allow the mean of \( q \) to depend on the number of potential bidders \( N \) as a reduced-form way of capturing differences across tracts that are observable to bidders but unobservable to the econometrician. In another model, we let the means of both costs and quantities differ across leases intended for horizontal and vertical oil wells. We also consider a model in which bidders learn from their neighbors’ drilling decisions. These models and their associated counterfactual results are in Appendix B.
Table 3: Parameter estimates. Standard errors, in parentheses, are based on 50 bootstrap iterations.

<table>
<thead>
<tr>
<th>$\lambda_q$ (K bbl)</th>
<th>Std. Dev. of $\xi$</th>
<th>$\mu_0$</th>
<th>$\alpha$</th>
<th>$\beta_1$</th>
<th>$\beta_2 \times 10^4$</th>
<th>$\sigma_c$</th>
<th>$p$</th>
<th>$X($)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>67.2 (0.9)</td>
<td>1.29 (0.02)</td>
<td>7.103 (0.018)</td>
<td>0.731 (0.001)</td>
<td>0.0059 (0.0001)</td>
<td>-0.016 (0.003)</td>
<td>0.717 (0.009)</td>
<td>0.248 (0.008)</td>
<td>3,868 (628)</td>
</tr>
</tbody>
</table>

4.2.4 Method of Simulated Moments

Given a candidate set of parameters, auction-specific $N$ and $P_0$ observed in the data, and the value function computed in the previous step, we take draws of the agents’ signals and map them into bids. Further, we take draws of the winner’s cost and determine the drilling delay using the observed path of the price of oil. For every auction in the sample, we do this many times and match averages of simulated bids and drilling moments to the data. We match the winner’s bid, the second-largest bid, the auction-average bid, and the number of bidders as bidding moments. On the drilling side, we use the indicator for drilling incidence as well as the indicator multiplied by the price at auction, the length of the delay, and the indicator for immediate drilling. To ensure all these variables are well-defined, we set delay to 5 years for tracts that are not drilled. We do not attempt to match realized production figures because, as discussed in footnote 15, the production data is missing for some wells and a number of them have yet to finish producing.

4.3 Parameter Estimates

The parameter estimates are reported in Table 3. As some of the parameters are difficult to interpret on their own, we explain their implications in the context we study. The standard deviation of the noise $\xi$ is estimated to be 1.29, which corresponds to a within-auction correlation of signals of about 0.23 and a correlation of 0.48 between $q$ and a draw of $q\xi_i$.

We estimate that the average hypothetical well is expected to produce about 67,200 barrels of oil. However, we predict that wells which are drilled are expected to produce 104,500 barrels,

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35We set bids of potential entrants who do not enter to zero when computing these moments.

36We use weights equal to the sample-wide standard deviations of the selected outcomes in the data, but we modify them slightly so that the weight on the moments related to the winning bid and the drilling delay are equal to the sum of the weights on the other moments related to the bids.
which is fairly close to the average of 96,100 barrels produced by all the wells in our sample for which we have production data (note that our estimation procedure did not try to match these production data). Of course, incomplete production for wells drilled near the end of the sample would suggest that production quantities in the data are themselves underestimates of true quantities.\footnote{We have experimented with extrapolating quantities for wells that are still producing and have found that the gap closes, but only somewhat since most wells in our data do not produce for especially long.}

The estimates imply that the probability of an “infinite-costs-well” is 0.25. This is indicative of the probability that one of any number of reasons that firms decide not to drill, and which are beyond the scope of the model, occurs. The model predicts an average cost of $4.4 million for wells that are drilled. This is comparable to estimates, which we did not try to match in estimation, from the U.S. Energy Information Administration (EIA) during our sample period.\footnote{See, for example, \url{https://www.eia.gov/dnav/ng/hist/e_ertwo_xwn_nus_mdwa.htm} or \url{https://www.eia.gov/analysis/studies/drilling/pdf/upstream.pdf}.}

We also predict that the cost to drill a well doubles roughly every two years during our sample period, which is also in line with EIA estimates of trends in historical drilling costs.\footnote{Only recently, after our sample of auctions are held, have drilling costs begun to decline.}

Finally, the winner’s payment of $X$ is estimated to be $3,868. This estimate includes any costs associated with owning the lease that are independent of drilling, such as filing paperwork associated with transferring ownership, or land rents paid to the NMSLO. As a point of comparison, if the cost only included land rents, which are about $1 per acre per year, we would expect $X$ to be equal to $1,600.

We end our discussion of parameter estimates by noting that the model fits other moments in the data fairly well. Our estimates imply a mean winning bid of $60,920 compared to a winning bid of $62,200 in the data. Our model slightly over predicts the average winning bid, $27,400 compared to $24,800 in the data (setting bids of potential entrants who do not enter to zero). The model does a fairly good job of predicting the probability that a well is drilled. Our model predicts the probability to be 0.101 compared to 0.093 in the data. The model also does a good job of predicting the distribution of delays in the data (which we did not try to match in estimation), as shown in Figure 4, with the main discrepancy that the model slightly under
The model over predicts the entry rate to be 0.74.

5 The Real Impact of Auction Design

In this section we use our estimated model to perform two primary analyses. In Section 5.1 we analyze the counterfactual question of what would have been the effects if New Mexico had employed a different auction design during our sample time period. In Section 5.2 we explore the interaction between the price of oil, auction design, seller revenues, and drilling activity more generally. Both analyses are informative about the economic mechanisms driving the interaction between price uncertainty, auction design, seller revenue, and real economic activity, as well as a number of practical policy questions faced by all agencies that sell mineral leases.

Before we discuss these analyses, it is important to note that existing theoretical results do not give sharp predictions about what we should expect to find. Absent an endogenous post-auction investment by the winner, which in our case is the decision of whether and when to
drill, results from DKS suggest that equity auctions generate higher revenue than debt and cash auctions, although the comparison with bonus auctions is unclear. Adding in the endogenous drilling decision introduces moral hazard and makes the comparison between the mechanisms unclear, as discussed, for instance, in Cong (2014). Additionally, our model features common values. To our knowledge, there is no existing theory or empirical work that evaluates contingent payment mechanisms with endogenous post-auction investment in a common values framework. For this reason we will spend some time discussing the basic economic fundamentals of common value contingent payment auctions and endogenous post-auction investment that drive our counterfactual results.

5.1 Alternative Auction Designs in the Permian Basin

How would revenue and drilling activity have changed if New Mexico had employed alternative auction designs during our sample period? In this section we answer this question by using our estimated model to simulate counterfactual outcomes under the following five auction designs: (a) bonus auction with a royalty equal to the 1/6th rate that is chosen by the NMSLO (“baseline”), (b) a royalty-rate auction in which firms bid \( \phi \) (“equity”), (c) an auction in which firms bid the face value of debt and commit to paying the seller the minimum of the bid and the oil revenues collected (“debt”), (d) a pure cash auction in which there is no payment after the auction (“cash”), and (e) a bonus auction where a royalty rate \( \phi^* \) is chosen by the seller so that if this auction were used over the course of the sample, the seller’s revenues would be maximized among all bonus auction formats (“revenue-optimal bonus”). In determining the revenue-optimal bonus royalty rate, there are two opposing forces of increasing \( \phi \): the seller claims a larger portion of revenues, but the probability of drilling decreases, as do bonus bids. We determine that \( \phi^* = 0.26 \) by searching over a rich grid of possible royalty rates for the value of \( \phi \) rate that maximizes simulated sample-wide revenues. To compute the counterfactual outcomes, for each mechanism we consider, we use the estimated parameters and auction observables to simulate 1,000 runs of auctions and drilling decisions for each auction in our data, and then average these simulations across the entire sample of auctions. Appendix B illustrates the robustness of the
Table 4: Sample-wide simulations of bidding, revenues, and measures of economic activity by security type

<table>
<thead>
<tr>
<th></th>
<th>Winning Bid</th>
<th>Revenue ($K): Royalty</th>
<th>Probability of Drilling</th>
<th>Delay (days)</th>
<th>Total Oil Production (bbl)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline Bonus</td>
<td>$60.9K</td>
<td>94.6</td>
<td>155.5</td>
<td>0.103</td>
<td>1,324</td>
</tr>
<tr>
<td>Equity</td>
<td>29.3%</td>
<td>92.4</td>
<td>92.4</td>
<td>0.0660</td>
<td>1,471</td>
</tr>
<tr>
<td>Debt</td>
<td>$2.3M</td>
<td>79.0</td>
<td>79.0</td>
<td>0.0659</td>
<td>1,577</td>
</tr>
<tr>
<td>Cash</td>
<td>$99.8K</td>
<td>0</td>
<td>99.8</td>
<td>0.143</td>
<td>1,267</td>
</tr>
<tr>
<td>Rev.-Opt. Bonus (φ* = 0.26)</td>
<td>$41.9K</td>
<td>124.0</td>
<td>165.9</td>
<td>0.079</td>
<td>1,359</td>
</tr>
</tbody>
</table>

Table 4 shows results for revenues across the sample period. We estimate total revenues of about $155,500 for the baseline bonus bidding auction with φ = 1/6. Approximately 39% of this revenue comes from bids while the remaining amount is generated through post-auction royalty payments. The revenue-optimal bonus scheme yields lower bonus payments, as one would expect, but increases total revenues by about $10,400. Most of the revenues generated by the revenue-optimal bonus auction stem from royalties, with the winner’s bid contributing only about 25%. If New Mexico were to have used equity auctions, then the revenue per auction (which comes entirely from royalties) would drop to $92,400 per auction, about 40% lower than the revenues from bonus bidding. Debt auctions decrease revenue even further, to $79,000 per auction. Interestingly, pure cash auctions (i.e., with a royalty rate of 0) do better than both debt and equity, with an average of $99,800 per auction. Thus, including the moral hazard element of drilling overturns the ranking of debt or equity versus cash from DKS.40

Of course a government agency holding these auctions may not simply care about maximizing revenue, but also about the level of economic activity generated by the auctions. The last three columns of Table 4 summarize the average drilling rates, delays, and extracted quantities for these securities. These metrics are also helpful in understanding why (among standard securities) a bonus bidding scheme appears best when both revenue and drilling are considered, and why bonus formats outperform equity and debt. When moving from the baseline auction to equity,

40The results in Appendix B show that cash may not produce greater revenues than equity auctions in some alternative specifications of the model. However, cash always produces a higher probability of drilling, and the baseline bonus format always yields greater revenue and economic activity than do either the equity or debt auction.
drilling probabilities *decrease* from 10.3% to 6.6% and drilling delays increase by about 5 months. This can be traced back to the fact that the mean winning royalty rate in the equity auction is 29.3%, which is almost twice as much as the baseline royalty rate; the stronger competition in the bidding stage sufficiently depresses incentives to drill so that the net effect is a decrease in revenue. The drilling probability for debt auctions is much lower than in the baseline auction. However, while the drilling probabilities in the equity and debt auctions are very similar, the debt auction yields higher total production. That is because with a winning bid of $2.3 million, drilling is not profitable unless quantities are large enough that they can cover the face value of this debt plus the cost of drilling.\(^{41}\) Of course, cash preserves the strongest incentives to drill, and indeed the drilling decision is privately efficient for the winner and socially efficient as well (for a planner with the same discount rate). Finally, the revenue-optimal royalty rate decreases drilling rates slightly, but compensates for this by generating considerably larger royalty revenues when drilling occurs.

Thus, there is strong evidence in the data that the moral hazard element of post-auction economic activity is substantial. However, the interaction between this moral hazard element and bidding behavior at auction is subtle. It depends on the common value framework we consider, a topic not yet explored in the literature. For example, compare the baseline auction with the equity auction. The economic forces driving lower drilling and lower revenue in the equity auction are more nuanced than a simple comparison between the pre-determined \(\phi = 1/6\) in the baseline auction, and the endogenously determined \(\phi = 0.293\) in the average equity auction. Indeed, focusing solely on the average of the winning royalty rate masks two important forces affecting outcomes in an equity auction.

First, the winner’s bid in the equity auction, and thus the promised royalty rate, is correlated with \(q\) since it depends on \(q\xi_i\). Bidders submit higher royalty rate bids for leases with higher quantities of oil. However, even though the winner may have committed herself to a high royalty rate, the large \(q\) makes her more likely to drill. That is, the correlation between \(q\) and the winner’s bid is a force towards increasing the revenues of an equity auction. A similar effect

\(^{41}\)The winner (unlike in equity) is then the residual claimant on all profits from drilling beyond this face value; thus, debt incentivizes drilling higher-quantity wells relative to equity.
exists for debt, but no such force exists for bonus or cash auctions as the bonus or cash bid, which depend on $q \xi$, is sunk at the drilling stage, and thus does not affect investment decisions.

A second force to highlight is an analogue of the “winner’s curse” on post-auction economic activity for securities like equity and debt. This force is generated by the fact that a bid is also affected by the signal’s noise $\xi$. Consider the equity auction: while the average bid is about 29.3%, conditional on drilling it is actually appreciably lower at 24.9%. This happens because in a contingent payment auction in a common values framework, bidders are locked into bids based on their signal. Indeed, an agent with an especially high signal, even after updating beliefs about $q$ conditional on own victory, may still overestimate the underlying true quantity of oil when it is time to submit her bid. In a standard bonus auction (or a pure cash auction), this simply causes her to bid a large cash bonus, but it has no impact on post-auction drilling incentives. However, in equity and debt auctions, a high bid due to a high $\xi$ erodes her incentive to subsequently drill for oil.

An implication of these observations is that, conditional on the true quantity of oil, a seller’s revenue is nonmonotonic in the winner’s signal. Figure 5 plots the bids, probability of drilling, and seller’s revenue in both an equity and debt auction where the realized $q$ equals 67,200 barrels, i.e. the estimated mean of $q$. The costs are set to the level implied by the model estimates for year 2014, with the mean parameter of 15.9 and the standard deviation parameter of 0.717. The number of potential bidders is set to 4, and the oil price at the auction to $P_0 = $50. The average is computed over 10,000 random realizations of price paths starting from $P_0$.

The probability of drilling decreases with the signal as the realized quantity is the same but the winner commits to a higher bid due to higher $\xi$s. The revenue curve then illustrates that these two countervailing forces generate a nonmonotonicity in revenue. The nonmonotonicity is not present in a common values bonus auction, since the probability of drilling, and therefore also royalty revenue, is independent of the signal. It is also not present in a private values bonus auction, in which the probability of drilling and revenue would increase in the signal since it is the quantity the winner would produce.\(^{42}\)

\(^{42}\)Note that it could be present in a private value equity auction as well, but in a private value auction the winner would never want to adjust her bid given information revealed at the auction. Indeed, the profit of a
Figure 5: Probability of drilling, revenue, and bids for equity (a, b) and debt (c, d) as functions of signals.

The takeaway from this section is that the NMSLO’s current bonus auction format dominates both the equity and debt auction alternatives. The bonus format generates greater revenue and spurs more economic activity than either of these options. However, determining whether the NMSLO chose the “best” possible fixed royalty rate for the bonus auction is a more complicated question because it depends on how it trades off greater revenue versus more drilling. If the agency prefers to generate as much revenue as is possible, clearly increasing the royalty rate bidder, conditional on \( q \) and on winning, is increasing in the signal in a private values auction. The profit of a bidder conditional on winning and conditional on \( q \) is necessarily decreasing in a common values equity auction because of this pre-commitment to higher royalty rates.
from the current amount is advisable. However, this comes at the cost of reduced drilling. The bonus format with a royalty rate equal to zero (i.e. the cash auction) is the design to use if the agency cares most about spurring production. The agency’s preferences likely lie somewhere in between these two extremes, and we can check whether the current status quo format helps them to balance these different objectives. The preceding analysis shows that it can. If instead we had found that the royalty rate associated with the revenue-optimal bonus auction was below the royalty rate that the NMSLO actually uses, our advice would have been to reduce the current royalty rate since both revenue and production would have risen. In fact, one could argue that our results show that the agency is potentially doing a nice job of balancing these somewhat dueling agendas, since we predict that the increase in revenues from switching to a revenue-optimal bonus auction is 6.6%, and the increase in production from switching to a cash auction is 31.6%. We avoid taking too strong a stand on whether they are in fact setting the appropriate royalty rate since we do not know the relative weights they place on drilling versus revenue, and computing the social value of an increase of 6.6% of revenue to be spent on the provision of public goods, or the general economic spillovers that could be attributable to an increase in production of 31.6% are beyond the scope of this paper.

5.2 The Impact of Auction Design on Revenues and Drilling with Uncertainty

In this section we explore the sensitivities of bidding and drilling behavior to the price of oil, and how these are governed by auction design. Local governments may be especially concerned with these sensitivities since certain securities might be more successful at shielding their budgets and the local economy from oil price shocks. However, since a lease lasts for a long period of time, there are a number of different types of price shocks a government may be concerned with. We focus on two cases here: (i) shocks to the price of oil before bidding and (ii) shocks to the oil price at the very start of the lease but after bidding occurs so that the winner is locked into her bid. Aside from these price shocks, committing to a mechanism also requires gauging the response of bidding and drilling outcomes to changes in the number of potential bidders. The impact of
auction design over our sample period aggregates the sensitivities of different designs to these pre-auction and post-auction price shocks as well as to differing numbers of competitors. While the types of analyses in this section could be performed using any parameterization of our bidding and drilling model, we find the analyses here particularly insightful as the parameterization we use is based on estimates from actual bidding and drilling behavior. It also helps inform the results from Section 5.1.

5.2.1 Pre-Auction Price Shocks

We begin by exploring the sensitivity to the price of oil at the time of auction in Figure 6. In particular, for a given number of potential bidders \(N = 4\) we vary \(P_0\) and compute (a) expected revenues and (b) the probability that drilling occurs before the lease expires. Quantities in this exercise are integrated out, and the distribution of costs is set to have the parameters implied by the model estimates for year 2004. To integrate out possible future price paths, we take the average over 10,000 randomly drawn price trajectories originating at \(P_0\).

First consider panel (a). We see that the seller’s expected revenue is maximized for all values of \(P_0\) by using the revenue-optimal bonus auction. The baseline auction that sets \(\phi = 1/6\) does well, but leaves substantial revenues on the table at high values of \(P_0\). Equity, debt, and cash show weaker results, performing at comparable levels for low and mid-range prices. For high values of \(P_0\), equity and debt auctions do worse than cash. The intuition is that when prices are high, while both cash and equity auctions induce more competitive bidding, the increased competition in the bidding stage depresses drilling incentives in an equity auction, whereas they are not affected in a cash auction as the winning bidder is the full residual claimant of all future oil revenues.

The sensitivity of economic activity to shocks to \(P_0\) is highlighted in Panel (b) of Figure 6. As one would expect, cash gives the strongest incentives to drill for any initial price. Clearly drilling activity is less impacted by shocks to \(P_0\) in a bonus mechanism than when either an equity or debt auction is used. Indeed, drilling activity in debt and equity is almost unresponsive to the price of oil at the time of the auction.
5.2.2 Post-Auction Price Shocks

There may also be substantial shocks to prices following auction. To address the abilities of different mechanisms to insulate against this type of price shock, we conduct an experiment in which firms bid when $P_0 = 50$, but then allow prices to move to $P'_0$ immediately after bidding. This shock is unanticipated at bidding. Figure 7 shows average revenues for many auctions simulated with these shocks as a function of $P'_0$ for different mechanisms.

Comparing the revenue-optimal bonus and baseline auctions, we see that the revenue-optimal bonus still outperforms the baseline for all but very negative price shocks. For these bonus auctions, the total revenue for a shock to $P'_0$ equals the bonus bid at $P_0 = 50$ plus the royalty revenue when $P_0 = P'_0$ shown in Figure 6. When considering pre-auction price shocks (Figure 6), the revenue-optimal bonus auction outperforms the baseline auction even at low prices since both the bonus and royalty revenue for each auction type drop when $P_0 = 50$ moves to, say, $P_0 = 30$. When this shock happens after bidding (Figure 7), the baseline auction still has a relatively high bonus since the bidders expect to give up less of the surplus. Furthermore, drilling in the baseline auction is approximately equally sensitive to price shocks so that on net the baseline auction dominates. Total revenue from equity and debt is even more sensitive to ex-post price shocks than it is in the revenue-optimal bonus auction. Indeed, for these auction types it is
even more sensitive to ex-post price shocks than to ex-ante price shocks. Once again, ex-post price shocks do not lock in winners of equity and debt auctions to bidding away large fractions of the revenues, and they are thus more likely to drill when prices jump. On net, equity yields the highest total revenue for especially high price shocks. On the other hand, when prices drop, auctions that distort investment decisions less, such as bonus or cash auctions, will perform better.

5.2.3 Auction Design over the Price Cycle

The previous two subsections discussed the impact of security design on the resiliency of bidding and drilling to pre-auction and post-auction price shocks. However, a seller typically commits to one auction design over a long period of time, and thus there can be numerous pre- and post-auction price shocks facing the many auctions held by a seller. In this section we analyze how various security designs affect bidding and drilling over a price cycle. Of course there are an infinite number of price paths we could consider, and so to illustrate our results, we use the price path observed during our sample.

Figure 8 overlays the price of oil against (a) the cumulative revenues and (b) number of wells drilled under the different auction designs we consider.\footnote{For bonus bidding, the bonus is added to cumulative revenue at the time of the auction. Royalty revenues} While the terminal points of the five
Figure 8: Cumulative (a) revenue and (b) wells drilled for auctions in the sample, for bonus bidding, equity, debt, cash, and optimal bonus.

series in (a) show the order from before—equity and cash give about 2/3 the cumulative revenue from bonus bidding, while optimal bonus improves on the default bonus—the correlation with price fluctuations is also informative. The difference between the five mechanisms is persistent from the start of the sample, but cumulative revenues rise more sharply during oil price shocks when using optimal bonus than the other mechanisms. This is especially prominent during the large spike in oil prices in 2008. Consistent with the results in Table 4, panel (b) shows that this acceleration in cumulative revenues is due to both the “extensive margin” of drilling more wells as well as the “intensive margin” of earning more royalties per well drilled relative to equity and debt. Panel (b) also shows that the revenue-optimal bonus yields lower drilling than the baseline at any given time.

5.2.4 Auction Design vs. Increasing N in Contingent Payment Auctions

We end this section with a discussion of the effect of competition in a contingent payment setting with post-auction investment, which is another issue a designer must consider. While the theory literature has focused on the importance of attracting bidders relative to auction design (e.g., Bulow & Klemperer (1996)), our real-world parameters suggest that changing the auction format are added at the time of drilling.
has an even larger impact. We will also point out the negative effect that increasing $N$ has on the performance of equity and debt auctions.\(^4^4\)

Consider Figure 9, which is the same as Figure 6 except that $N = 8$ as opposed to 4. Note that this is a large change in $N$ in our context. In bonus and cash auctions, increasing $N$ leads to higher revenue because the winning bonus bid is greater when $N = 8$ than when $N = 4$, and drilling decisions are unaffected by $N$ since they do not depend on the bonus bid at auction.\(^4^5\) In equity and debt auctions the opposite holds due to the relationship between the winning bid and the winner’s moral hazard post auction. The primary takeaway from the comparison between these figures, however, is that the impact of changing security design on revenue and drilling is generally much larger than the impact of even dramatic increases in $N$.\(^4^6\)

\(^4^4\)This observation complements the proof-of-principle provided in Cong (2014) by suggesting that parameters under which revenues from an equity auction decrease with $N$ are reasonable in a realistic empirical setting.

\(^4^5\)The winning bonus bid is greater for two reasons. First, as $N$ increases, unless bidders have very low signals, the bid they submit increases. Second, since there are more bidders, there is an increased chance of a high realization of $\xi$ which will determine the winning bid.

\(^4^6\)Of course the other obvious takeaway from this comparison is that even if a seller is constrained to using a particular security design, the decision of when to hold an auction, that is at what value of $P_0$, is also very important for revenue and drilling decisions. We leave the exploration of the impact of auction timing to future work and also refer to Cong (2017) for a theoretical analysis.
6 Conclusion

In many auction environments, sellers use contingent payment auction formats that make the winning bidder’s final payment to the seller a function of the future cash flows of the auctioned asset. Moreover, those cash flows are also often affected by post-auction investment decisions made by the winning bidder. Therefore, the auction design employed by the seller will endogenously affect bidder values for winning an auction, and thus impact both seller revenue and real economic activity in the form of bidder investment.

Despite the common use of contingent payment auction designs in settings where winners make important post-auction investment decisions, including some of the most frequently analyzed environments in the empirical auctions literature, we find it striking that there is virtually no empirical work studying the connection between auction design and bidder behavior not only at, but more importantly following, auction. This is unfortunate, as these are some of the best examples available of where auction design can impact real economic outcomes, and not just the division of surplus between sellers and buyers.

Our paper aims to fill this gap in the empirical literature. To do so, we studied a classic example of contingent payment auctions with post-auction investment: oil auctions. Using a new dataset that links bidding and drilling decisions in onshore oil auctions in the Permian Basin, we estimated a model in which bidder values are endogenous functions of the quantity of oil, the costs of drilling, and, of course, the auction design itself. The benefit of estimating such a model is that it allowed us to make counterfactual statements about an important policy question facing many government entities that sell the rights to drill for oil on government-owned land: what auction design should be used?

The answer to this question of course depends on the seller’s objective function. By incorporating both bidding and drilling decisions into our model, we can evaluate the impact of auction design on both outcomes, something that cannot be done by the literature which ignores post-auction investment. While we of course do not know the particular weights the NMSLO places on these two outcomes, our findings offer some support for their decision to use a bonus auction format, since it generated both more revenue and more production than equity or debt auctions.
While the NMSLO could have generated more revenue if it had used a higher royalty rate, this would have come at the cost of less drilling activity and lower overall production. The increased revenue is of course important for New Mexico, which attributes approximately 10% of its total revenues to rents and royalties from mineral rights. But the decline in real economic activity would probably also generate negative spillover effects for related industries. In fact, one applied topic that we hope to pursue in future work is the measurement of such spillovers and improving our understanding of the impact of auction design on local economies more broadly.

Indeed, we hope our work will inspire others to pursue more questions related to contingent payment auction settings, as there are a plethora of interesting examples to study. As Skrzypacz (2013) notes in his survey of auctions with contingent payments, the benchmark model of DKS can be enriched on many dimensions, and the current paper suggests that these dimensions may be empirically quite important. There are many other avenues that we believe are especially promising for empirics, and two of particular note are risk aversion and informal contingent payment contracts. A risk averse seller may value lower variance in the real economic activity generated by the auctions they hold, and a model like the one we use in this paper could be easily enriched to allow for this type of seller preferences. Additionally, as DKS point out, there are many real-world cases where the seller cannot commit to a particular security design and must compare a variety of securities that cannot be ordered unambiguously. Empirical work must overcome the challenges of identification of a richer set of primitives than in standard auctions, and our approach of utilizing some information from ex-post outcomes may be applicable.
References


Appendix

The following appendices contain further details on the identification of an affiliated private values version of our model, the robustness of our results to alternative model specifications, and sample formation and computation.

A Identification of an Affiliated Private Values Model

In this appendix, we present a model in which quantities follow an affiliated private values paradigm. The goal is to formalize the arguments given in Section 4.1 to show that the primitives of this model can be nonparametrically identified from data on bids and the timing of drilling.

A.1 Setup of an Affiliated Private Values Model

The affiliated private values framework follows the same setup as the model in Section 3; however, we interpret the signal $q \xi_i$ as the true quantity of oil a bidder can extract. This value is a combination of an auction-specific common component $q$ and an idiosyncratic term $\xi_i$ that could be due to differences in technology across bidders in terms of the quantity of oil they can extract. As before, the model consists of bidding followed by drilling. The drilling stage is the same as in Section 3.1, with the difference that $q$ is replaced by the bidder-specific quantity $q \xi_i$.

The bidding problem does change due to the move from common to private values. As before, the bidding problem from (2) (with $q$ replaced by $q \xi_i$) microfound the values for the bidders, but—given that the bid itself is cash rather than a more complex security—the problem is otherwise standard. In particular, define $v_i \equiv \mathbb{E}_i V(q \xi_i, c)$, and let $f(\cdot|v_i)$ denote the pdf of the highest value of $i$‘s opponents if $i$‘s value is $v_i$, and $F(\cdot|v_i)$ be the associated cdf. Then, a symmetric, continuously differentiable, monotone bidding strategy $b(\cdot)$ would solve

$$v = \arg \max_z \left[ (v - X - b(z))F(z|v) \right],$$
which implies that bidders follow the strategy

\[ b'(v) = (v - X - b(v)) \cdot \frac{f(v|v)}{F(v|v)}. \] (13)

The boundary condition is that \( b(X) = 0 \); note that any bidder with \( v_i < X \) would expect negative profits from entering and would thus not bid (or bid \( b = 0 \)).

### A.2 Identification of an Affiliated Private Values

We assume the price process \( P_t \) is observable, as it will be directly identified with any data on oil prices over time. The following lemma shows that we can identify per-unit costs.

**Lemma 1** Suppose we see a tract owner drill at time \( 0 < t^* \leq T \). If the price process \( P_t \) is observed, then under Assumption 1, the corresponding value of \( c/q \xi \) is identified. If drilling is immediate (\( t^* = 0 \)), then we recover an upper bound on \( c/q \xi \). If drilling never occurs, we recover a lower bound.

**Proof.** Factoring out \((1 - \phi) \cdot q \xi \) from (2), we see that the optimal stopping time also solves

\[
\arg\max_{\tau \leq T} \left\{ \mathbb{E}_{P_0} \left[ e^{-r\tau} \left( P_\tau - \frac{c}{(1 - \phi)q \xi} \right)^+ \right] \right\}.
\]

Given the process \( P_t \), the optimal boundary \( P^*_t (c/[(1 - \phi) \cdot q \xi]) \) can be determined by solving the optimal stopping problem directly. Given continuity of the price path, we know that if drilling happens at time \( t^* \), it must be that \( P_{t^*} = P^*_{t^*,T} (c/[(1 - \phi) \cdot q \xi]) \). Since the latter function is strictly monotone in its argument, we can invert \( P^*_{t^*,T}(\cdot) \) and identify \( c/q \xi \).

If drilling occurs immediately, then we only have partial identification: we can bound

\[
P_0 \geq P^*_{0,T} \left( \frac{c}{(1 - \phi) \cdot q \xi} \right),
\]

which by monotonicity of \( P^*_{0,T}(\cdot) \) provides an upper bound on \( c/q \xi \). If drilling never occurs, then
we know that it must be that

\[ P_t < P_{t,T}^* \left( \frac{c}{(1 - \phi) \cdot q\xi} \right) \]

for all \( t \leq T \). Each of these inequalities translates to a lower bound \( c_t \), i.e., \( c/q\xi \geq c_t \). Thus, for auctions in which the winner never drills, we obtain a lower bound given by \( \min_t c_t \). ■

Lemma 1 demonstrates that the time until drilling, the post-auction outcome that we observe, is sufficient to recover one specific component of the distribution of post-auction values. We can identify per-unit drilling costs since the price process we observe is a per-unit price, and the relevant margin for the bidder is unit-by-unit. However, this specific quantity we can recover conflates two objects: the cost of extraction (learned after the auction) and the quantity that can be extracted (known at the time of the auction). To separate these two quantities, we can use the fact that the bids convey information about the expected payoffs to the bidders, and these expected payoffs can be recovered.

**Lemma 2** Given Assumption 3, the distribution of values \( v_i = \mathbb{E}_c V(q\xi, c) - X \) is identified.

**Proof.** This follows directly from the inversion of Li et al. (2002), as the value associated with bid \( b_i \) is given by

\[ v_i = b_i + \frac{G(b_i|b_i)}{g(b_i|b_i)}, \]

where \( g(\cdot|b_i) \) is the pdf of the maximum of \( b_- \), given \( b_i \) and \( G(\cdot|b_i) \) is the associated cdf, both of which are directly identified in the data. Assumption 3 ensures that the values have a continuous density. ■

In the identification argument in Proposition 1, we leverage the fact that this value is a *total* value instead of a per-unit one. To complete the proof, we impose the following assumptions on the price process.

**Assumption 4** We make two assumptions related to the price process.

(a) For each quantity \( q\xi \), there exists a \( P_0 \) such that a bidder with quantity \( q\xi \) will bid and with probability 1 will either (i) drill with some delay, or (ii) not drill.
(b) For any quantity \( q_\xi \), \( P_0 \) as in (a), and cost \( c \), there exists a price path \( P_t, 0 \leq t \leq T \), starting at \( P_0 \) (and in the support of the process) such that if a bidder with quantity equal to \( q_\xi \) wins the auction, learns a cost \( c \), and faces a price path \( P_t \), then she will drill at some time \( t^* \leq T \).

By ensuring there is an initial price where no winner—regardless of how low a cost draw she receives—drills immediately, part (a) of Assumption 4 ensures that delays are sufficient to identify drilling costs near the left tail of the distribution. Note that this assumption is unfortunately not simply a restriction on primitives, as it is an equilibrium outcome that depends on the price process as well as the optimal stopping behavior.\(^{47}\) Part (b) of Assumption 4 lets us identify the right tail of the distribution of costs, but it is much less restrictive: since the optimal drilling threshold is increasing in cost, we can consider sample paths of the price that all start at \( P_0 \) but reach successively higher levels. This assumption will be satisfied under natural price processes that have full support over all continuous sample paths, such as the geometric Brownian motion condition in Assumption 2.

We conclude with one technical assumption standard in the identification of models with affiliated values or unobserved heterogeneity, which lets us use correlation in the bid distribution within-auction to disentangle idiosyncratic values from the common component (Kotlarski 1967, Li et al. 2002, Krasnokutskaya 2011).

**Assumption 5** The distributions \( \log q \) and \( \log \xi \) have non-vanishing characteristic functions.

We can now state our main identification result for the private values version of the model in Section 3.

**Proposition 1** Under Assumptions 1, 3, 4, and 5, the distributions of \( q, \xi, \) and \( c \) (as a function of \( q_\xi \)) are nonparameterically identified, as is \( X \).

**Proof.** Fix a number of players, a time horizon, and a quantile \( \alpha \) of the distribution of quantities \( q_\xi \). Find a price \( P_0 \) such that the bidder in the \( \alpha \)-quantile bids and does not drill immediately \(^{47}\)Without this assumption, the left tail of the cost distribution is not identified.
(per Assumption 4(a)), and restrict to auctions where this bidder wins. Fix a price path $P_t$ starting from $P_0$; we know that there exists a $c(P_t)$ such that all agents with costs less than $c(P_t)$ will drill at a point in $(0, T)$ when facing this path. Thus, by Lemma 1, the distribution of drilling times conditional on this path identifies unit costs on $[0, c(P_t)/q\xi]$. (Note for clarity that the values of $c(P_t)$ and $q\xi$ are not separately known at this step.) Assumption 4(b) states that for any value $\bar{c}$, there exists a price path $\bar{P}_t$ such that $c(\bar{P}_t) \geq \bar{c}$. Thus, we can loop over all possible price paths $P_t$ and identify the entire distribution of unit costs as this quantile of the quantity distribution—although, once again, the specific quantity $q\xi$ has not been identified yet.

Lemma 2 shows that the left-hand side of

$$v_i = (1 - \phi) \cdot q\xi_i \cdot \mathbb{E}_c \left[ \max_{\tau \leq T} \left\{ \mathbb{E}_{P_0} \left[ e^{-r\tau} \left( P_\tau - \frac{c}{(1 - \phi)q\xi_i} \right)^+ \right] \right\} \right] - X. \tag{14}$$

is identified. Note that the term marked ($*$) depends only on the distribution of unit costs $c/q\xi$ and thus is identified. We can repeat this procedure for a different initial value $P_0'$ and identify all components of the equation

$$v'_i = (1 - \phi) \cdot q\xi_i \cdot \mathbb{E}_c \left[ \max_{\tau \leq T} \left\{ \mathbb{E}_{P_0'} \left[ e^{-r\tau} \left( P_\tau - \frac{c}{(1 - \phi)q\xi_i} \right)^+ \right] \right\} \right] - X \tag{15}$$

except for $q\xi_i$ and $X$. Now, since ($*$) and ($**$) are strictly different from each other (because values are increasing in initial price), (14) and (15) are two linearly independent equations that can be solved for $q\xi_i$ and $X$. This identifies $X$ and the value of $q\xi_i$ at the $\alpha$ quantile. Repeating for all $\alpha$ identifies the entire distribution of $q\xi$.

The distributions of $q$ and $\xi$ are then identified separately following the argument in Li et al. (2002), under Assumption 5. ■

Essentially, Lemma 1 shows that unit costs—and, given the structure of the optimization problem, unit profits—are identified. Lemma 2 shows that total values are identified. The difference is due to two sources: quantities and the cost $X$. Exogenous variation in the price of
oil at the time of bidding shifts value at the time of bidding without shifting \( X \).\(^{48}\) This variation allows us to identify the fundamental component of value in this situation (i.e., quantities) and \( X \) separately. Thus, this argument requires both a post-auction outcome as well as variation at the time of the auction.

We make two further comments about the identification argument. First, note that Proposition 1 used variation at the time of the auction that kept \( X \) constant—but it only required this variation to keep \( X \) fixed conditional on \( q \xi \). Thus, the model has the empirical content to recover variation in \( X \) across \( q \xi \), or to use the condition that \( X \) is independent of \( q \xi \) as a source of over-identifying restrictions. Estimating \( X(q \xi) \) could be of economic interest in other settings, as the theory of auctions with contingent payments does suggest that such a dependence introduces adverse selection issues and could reverse the main results of DKS (see, for instance, Che & Kim (2010)). Second, it is in practice difficult to find sufficient variation in observed price paths \( P_t \) to satisfy Assumption 4 empirically. In most situations, we would expect researchers to place parametric assumptions on estimation when recovering the full distribution of costs. However, it is also interesting to note that relaxing Assumption 4 still identifies the distribution of costs on part of the support: the left and right tails are not identified nonparametrically. Yet, such variation is sufficient to place bounds on (\( \ast \)) and (\( \ast \ast \)) from (14) and (15), and thus (14) and (15) together place bounds on \( X \).

\section*{B Robustness to Alternative Specifications of Structural Model}

In this appendix, we consider the robustness of our findings to alternative specifications of the structural model.

\(^{48}\)In the specific formulation of the model, they do not shift costs either, but that is not the crux of the identification argument. We can check that we could estimate a \( P_0 \)-specific cost distribution, with two caveats. First, we would need to impose a non-primitive condition that there exist \( P_0 \) and \( P'_0 \) such that (\( \ast \)) and (\( \ast \ast \)) in (14) and (15) are different. Second, it is a much stronger assumption that drilling with nontrivial delay will always occur for any \( P_0 \)—and thus in practice would only obtain partial identification nonparametrically. But, noting that fixing \( P_0 \) is not the crucial part of the procedure lends credence to the empirical content of a parametric specification where the cost distribution could depend on \( P_0 \), which could be relevant in other settings.
B.1 Alternative Models

We consider three alternative specifications of our baseline model presented in Section 4.3. The first two involve different parameterizations of the model, while the third involves a substantive change to the mechanics of that model.

**Unobserved Heterogeneity.** One concern is that tracts are unobservably heterogeneous in the quantity of oil bidders expect to recover. A simple method to control for this type of unobserved heterogeneity is to let the quantity of oil in an auction depend on the number of potential bidders in that auction, as more bidding in a general area, which directly affects our calculation of $N$, might be associated with higher overall expected quantities. We thus use the baseline parameterization in (12) but let quantities be parameterized as exponential with mean $\lambda_q + \alpha_q^N \cdot N$, where $\alpha_N$ is a new parameter to be estimated.

Table 5 presents parameter estimates for this model. We estimate that auctions with one additional bidder are associated with a increase in the (perceived) quantity of oil of about 3,500 bbl. While the standard deviation of $\xi$ is estimated to be slightly lower, which we would expect if accounting for unobserved heterogeneity reduces the bid dispersion that is attributed to idiosyncratic signals $\xi_i$, the fact that the estimate is fairly similar to that in the baseline model suggests that there may not be a lot of unobserved heterogeneity across our auctions. Indeed, we show below that our counterfactual results are very similar for both this model and the baseline model. The other estimates are very similar to those in the baseline model.

**Vertical and Horizontal Drilling.** Towards the end of our data horizontal well drilling became much more prevalent in the Permian Basin. Prior to 2008 nearly every well drilled...
was a vertical well. The differences in drilling technology lead to both differences in costs and in quantities; indeed, production from horizontal wells is significantly larger than production from vertical ones. To account for such differences, we estimate a model in which we include a “horizontal” dummy for tracts in which we expect there to be horizontal drilling, if there is drilling at all. For tracts in which drilling is observed, this dummy is set to 1 if the first well drilled is horizontal. For tracts in which we do not observe drilling, we set this dummy to 1 if the tract was sold on or after 2005. We choose 2005 because based on the average delay, wells drilled on all tracts sold after 2005 are likely to be horizontal. We thus change the parameterization from (12) to

\[
q \sim \text{Exp} \left( \lambda_q^V \cdot 1[\text{Vertical}] + \lambda_q^H \cdot 1[\text{Horizontal}] \right),
\]

\[
c \sim (1 - p) \cdot \log \mathcal{N} \left( \mu_0^V \cdot 1[\text{Vertical}] + \mu_0^H \cdot 1[\text{Horizontal}] + \alpha \log(q) + \beta_1 t + \beta_2 t^2, \sigma_c \right) + p \cdot \infty,
\]

with the parameterization of \( \xi_i \) unchanged. In estimating this model, we add the interaction of the horizontal dummy with bids and drilling rates as additional moments that help identify the differences between horizontal and vertical wells.

Table 6 presents estimates of this specification of the model. The estimates of this model support horizontal wells being both more productive and expensive to drill. According to these estimates, the median production from vertical wells that are drilled is 78.1K barrels of oil, compared to median production of 128.1K barrels from drilled horizontal wells. The median cost to drill a vertical well is $3.1 million, which is much lower than the $7.3 million required to drill a horizontal well.
Table 7: Regression of whether a winner drilled in month $t$ on the current price of oil and whether neighbors drilled in the previous year. Neighbors are defined by wells within 1 km, 2 km, or 5 km of the tract. Standard errors are clustered at the lease level. Coefficients for $P_t$, Time Since Sale, and $P_t \times$ Time Since Auction are multiplied by 100,000 for scaling. Coefficients for the indicator Did Neighbor Drill? are multiplied by 100. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

A Model of Learning from Neighbors. In the baseline model, the sole source of the option value of waiting comes from price shocks. While Table 2 shows evidence that drilling is sensitive to prices, it is possible that firms may wait to drill in order to learn about the underlying quantity by observing the production of nearby wells that are drilled.

We first investigate whether there is any evidence of such learning in our sample. Table 7 presents estimates from an adaption of the regression whose estimates were shown in Column (5) of Table 2. In particular, for every tract-month observation in the dataset, we construct a dummy for whether a “neighboring” tract is drilled in the past year. In constructing the set of neighboring wells, we use all wells drilled in the sample. Table 7 considers three definitions of neighbors: wells within 1 km, 2 km, or 5 km of the (centroid of the) tract. Columns (2)–(4) provide evidence that drilling often follows instances when neighbors—and especially close neighbors—drill. The magnitude of the effects of price and time since sale do not appreciably change.
In an effort to understand the impact of neighbors drilling, we propose a simple model of learning about the “state” of the tract and calibrate it to study the effect on the parameter estimates. We say that a tract can be either “good” or “bad.” At the start of the drilling phase, the winner learns the “base quantity” $q$ and has a prior $\pi_0$ that the tract is good. If the tract is good, then the true quantity of oil in the ground is $q \cdot \chi$ for some $\chi > 1$. If the tract is bad, then the true quantity of oil in the ground is simply $q$. In both cases, the cost is the cost $c$ that the winner learns at the start of the drilling process.

We consider a simple model in which drilling by neighbors is purely good news: in the case when the state is good, neighbors will drill with some Poisson rate $\eta$, and when the state is bad, they never drill. Then, if no news arrives, the winner gets increasingly pessimistic about the tract. In particular, her beliefs conditional on no news arriving evolve according to

$$\dot{\pi}_t = -\eta \cdot \pi_t \cdot (1 - \pi_t).$$

This pure good news model is a standard framework in the theoretical literature on learning and provides a simple benchmark for this empirical work. See Horner & Skrzypacz (2016) for a survey. The optimal stopping problem becomes

$$\max_{\tau \leq T} \mathbb{E}_{P_0} \left[ e^{-rT} ((1 - \phi)P_\tau \cdot q \cdot (\pi_\tau \chi + (1 - \pi_\tau)) - c)^+ \right],$$

where $\pi_t$ follows the differential equation (16) if there has not been drilling by neighbors and is simply equal to 1 if there has been drilling.

Instead of estimating the model directly, we calibrate the new parameters of the model. The arrival rate of neighbors’ information $\eta$, the prior $\pi_0$, and the ratio of the quality $\chi$ of the good state to the bad. We calibrate $\eta$ to the drilling rate of neighbors, conditional on drilling, on the entire population of tracts and set it to the reciprocal of 2.5 years. We calibrate $\pi_0$ to be the proportion of leases in the dataset in which at least one neighbor drilled, which is 0.2. To better understand these numbers, note that these parameters imply that for a lease in which no neighbor drills, the belief that the state is good drops from 0.2 to 0.07 after three years and
to 0.05 after four years. Finally, we let $\chi$ be the ratio of observed production in cases in which a neighbor drilled (and we have production data for the tract) and cases in which a neighbor did not drill (and we still have production data for the tract). We find this to be 1.5. We set $\lambda_q$ to be 61.1 K, since this implies that the mean quantity of oil in this model is equal to $\mathbb{E}Q = (1 - \pi_0)\lambda_q + \pi_0 \chi \lambda_q = 67.2$, the value of $\lambda_q$ in the baseline model. We have also estimated a version of the model where we still calibrate values of $\pi_0$, $\eta$, and $\chi$ based on the data but estimate all other parameters. The counterfactual simulations (presented in the next section) based on either approach are very similar to one another, and also to those produced by the baseline model.

B.2 Robustness of Counterfactual Results to Alternative Model Specifications

Table 8 presents counterfactual model simulations for five specifications. To make comparisons easy, the first panel in the table repeats the results for the baseline model that also appeared in Table 4. The next three panels in Table 8 present counterfactual simulation results for the three specifications discussed in Appendix B.1. The last panel in the table shows the counterfactual simulation results for the neighbors model when we shut down information shocks.

The table shows that the counterfactual results are, for the most part, both qualitatively and quantitatively similar across the different model specifications. For instance, the revenue-optimal bonus auction continues to produce the most revenue of all the specifications we consider, and the cash auction produces the highest probability of drilling. We continue to find that equity and debt auctions perform worse than the baseline bonus auction format: they each produce less revenue and a lower probability of drilling. Our result that, within a bonus auction format, it is not possible to produce both more revenue and a higher probability of drilling than in the baseline format with $\phi = 1/6$, still holds. The seller determined to use a bonus format continues to face a tradeoff of revenues and production. While we took a simple approach to modeling learning from neighbors, we do find that the introduction of this form of learning does not substantially
change our counterfactual results.\footnote{It is interesting to compare the fourth and fifth panels of Table 8. When information shocks are shut down in the neighbor model, drilling is delayed by about 6-8%. However, the overall probability of drilling very slightly increases. This is because the fraction of leases where information shocks were key to spurring drilling (that is they received a positive information shock for neighbors and would not have drilled without it) is smaller than the fraction of leases that would have been drilled if the belief of a high $q$ had remained constant, but did not because this belief decreased over time.}

The one change from the baseline model is that in the models with $q$ depending on $N$ and with a distinction between vertical and horizontal wells, we find that equity now produces more revenue than a cash auction, even though the cash auction continues to lead to higher drilling probabilities. This makes sense since in the model in which $q$ depends on $N$, while equity is hurt by an increased $N$ (see the discussion in Section 5.2), because $q$ increases in $N$ this can lead to especially large revenue payoffs in an equity auction, and in the model that allows for vertical wells to produce greater quantity, equity can generate especially high revenues due to a similar argument. Despite the slight advantage equity enjoys over a cash auction in two of the five models shown in Table 8, it still underperforms against the baseline and revenue-optimal bonus. Thus, the conclusion that the seller should use a bonus auction format is robust to all of these modeling specifications.

\section{Data and Computational Details}

In this appendix, we discuss the data construction and sample selection and then provide computational details.

\subsection{Data Construction and Sample Selection}

The dataset is constructed from two sources: (1) lease data including scans of bid sheets and geographic locations from the New Mexico State Land Office and (2) well production and spud data from DrillingInfo. Together, they cover every tract leased by the state of New Mexico between January 1994 and September 2015 plus every well that was drilled or began production between January 1990 and January 2016 anywhere in the state. From this starting point, we proceed in several steps.
<table>
<thead>
<tr>
<th>Model</th>
<th>Winning Bid</th>
<th>Revenue ($K):</th>
<th>Probability of Delay (days)</th>
<th>Total Oil Production (bbl)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baseline Model:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline Bonus</td>
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<td>155.5</td>
<td>0.103</td>
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<td>92.4</td>
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<td>79.0</td>
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<td>99.8</td>
<td>0.143</td>
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<tr>
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<td>165.9</td>
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<tr>
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<td>169.1</td>
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<td><strong>Neighbor Model, with Information Shocks:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline Bonus</td>
<td>$56.1K</td>
<td>89.7</td>
<td>145.8</td>
<td>0.097</td>
</tr>
<tr>
<td>Equity</td>
<td>36.3%</td>
<td>88.2</td>
<td>88.2</td>
<td>0.049</td>
</tr>
<tr>
<td>Debt</td>
<td>$2.4M</td>
<td>77.4</td>
<td>77.4</td>
<td>0.054</td>
</tr>
<tr>
<td>Cash</td>
<td>$93.8K</td>
<td>0</td>
<td>93.8</td>
<td>0.135</td>
</tr>
<tr>
<td>Rev.-Opt. Bonus ($\phi^* = 0.26$)</td>
<td>$39.3K</td>
<td>116.7</td>
<td>156.0</td>
<td>0.074</td>
</tr>
<tr>
<td><strong>Neighbor Model, with No Information Shocks:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline Bonus</td>
<td>$61.1K</td>
<td>87.8</td>
<td>148.9</td>
<td>0.100</td>
</tr>
<tr>
<td>Equity</td>
<td>36.6%</td>
<td>86.5</td>
<td>86.5</td>
<td>0.052</td>
</tr>
<tr>
<td>Debt</td>
<td>$2.3M</td>
<td>74.7</td>
<td>74.7</td>
<td>0.061</td>
</tr>
<tr>
<td>Cash</td>
<td>$102.6K</td>
<td>0</td>
<td>102.6</td>
<td>0.139</td>
</tr>
<tr>
<td>Rev.-Opt. Bonus ($\phi^* = 0.26$)</td>
<td>$42.8K</td>
<td>113.8</td>
<td>156.6</td>
<td>0.077</td>
</tr>
</tbody>
</table>

Table 8: Sample-wide simulations for alternative model specifications

First, we clean bidder names indicated in the bid sheets. For instance, for two bidders listed as “Yates Corp.” and “Yates Petroleum Corporation” we need to assign the same id. To that end, we use a software called OpenRefine, a powerful data cleaning tool, to suggest clusterings of names that are likely similar (based on abbreviations and misspelling). We evaluate these suggestions by hand and, from the original 835 unique names, we end up with 545 bidder identifiers. Based on these, we construct a measure of potential bidders for each auction. For every tract, we
compute the number of unique bidders in the neighborhood of 2 km that participated in some auction within 2.5 years from the tract’s sale date.

The next step is to identify oil-rich wells. DrillingInfo contains production data, in terms of oil and gas quantities, for a fairly large subset of the wells that were in fact drilled. For each well, we set oil revenue to be equal to the quantity of oil extracted times the mean spot oil price over the extraction period. An equivalent procedure is followed to set gas revenues. A well is denoted as oil-rich if the ratio of oil revenue to gas revenue (plus $1 to account for oil-only wells) is greater than 5. We do this for all wells in the dataset. For each tract, we then find the set of all wells drilled within 5 km of it. We classify a tract as one that is expected to be oil-rich if at least half the wells within a 5 km radius are oil-rich. If a tract does not have any wells drilled in its neighborhood, we drop that tract as well to adopt a conservative definition of oil-rich tracts. This procedure yields a median revenue ratio of oil to gas revenues of 11.9 in our final sample and 1.6 as the first quartile.

The rest of our approach consists of merging various data sources and removing misrecorded observations. First, we drop observations with misrecorded lease IDs in the NMSLO dataset. Then, we do the same for the geography files from DrillingInfo. We then intersect these two datasets and restrict the sample to the Permian Basin. We then drop observations where the number of bidders indicated in the GIS shapefiles does not coincide with the number of nonzero bids (< 4% of the sample).\(^50\) We finally restrict the sample to oil-rich tracts and open outcry auctions before 2012, as well as to exploratory and discovery leases.

C.2 Computational Details

The preliminary computation stage involves construction of optimal stopping paths and derivation of unit agent valuations. The latter are defined as valuations for agents with unit quantity expectations at time \(t = 0\) with initial price \(P_0 = 1\) and a range of drilling costs. The royalty rate is also set to 0. Note that the bidder valuations in our model given by (2) can be rewritten

\(^50\)For a handful of observations, multiple bidders within an auction were assigned the same id. When, as a consequence, the imputed number of potential bidders for such auctions is less than the number of actual bidders, the observations are dropped.
as

\[ V(\tilde{q}, c) = (1 - \phi)\tilde{q}P_0 \max_{\tau \leq T} \mathbb{E}_1 \exp(-r\tau) \left( P'_\tau - \frac{c}{(1 - \phi)\tilde{q}P_0} \right)^+ \] = (1 - \phi)\tilde{q}P_0 V(z) \tag{17} \]

where \( P'_\tau \) is the price process starting from 1 and \( z = c/(1 - \phi)\tilde{q}P_0 \). The aforementioned unit valuations here are \( V(z) \).

After estimating the price process parameters via a simple OLS, we follow the procedure outlined in Section 4.2.2. While it is described as a way to derive optimal stopping trajectories, one of its byproducts is, in fact, \( V(z) \). Indeed, we note that for a given level of costs \( c \), a quantity signal \( \tilde{q} \), and initial price \( P_0 \) one has

\[ V(z) = w(0, P_0) \tag{18} \]

The method of random walks is applied with 100,000 iterations over the time period of 5 years, so \( \delta = 0.00005 \). The values of \( V(z) \) are computed on a fine grid and interpolated linearly in between the grid points when needed.

Given these unit valuations, it is straightforward to solve (13) for any given set of model parameters. We use one of the Matlab’s basic routines, \texttt{ode113}. Finally, for simulations it is also required to intersect stopping paths corresponding to a given pair \((\tilde{q}, c)\) with the oil price trajectory. Since the stopping paths are derived at the preliminary stage, this is also a simple task.