Empirical Analysis of Scoring Auctions for Oil and Gas Leases

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Abstract

I study a scoring auctions implemented in Brazil to sell oil exploration rights. Differently from most sales of this kind, bidders had to submit a multi-dimensional bid that included a bonus and an exploratory program. A non-linear scoring rule determined the winner. I propose a method to estimate the underlying primitive distribution of tract values and exploration commitment costs. Estimating the distribution of those primitives allows the evaluation of counterfactual revenues in alternative bidding schemes. I find that a first price auction would imply a 9.7% higher revenue from the sales examined.

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1 Introduction

In most auction settings, bidders are required to submit a one-dimensional bid, a monetary payment to be made in exchange for the good being bought or sold. However, the auctioneer might have interests that go beyond the maximization of net transfers, *e.g.*, auxiliary services and quality specifications. In those instances it can be interesting to use a scoring auction, in which bidders are required to submit a multi-dimensional bid that incorporates other dimensions the auctioneer cares about besides net monetary transfers. A scoring rule then takes into account all dimensions bid and assigns scores to each submission. The bidder with the highest score wins the auction. Requiring auction participants to bid in other costly dimensions may however depress expected revenues that could be accrued in simpler mechanisms, like a first price auction. Moreover, one could think of alternative schemes in the standard auction framework to attain those other goals, such as minimum standards or mandates. Evaluating outcomes in those different scenarios is complicated by the delicate strategic interaction that arises when bidders are allowed to distinguish themselves along different dimensions. In this paper, I study scoring auctions used in Brazil to allocate exploration rights for oil tracts and develop a procedure that allows the assessment of counterfactual revenues in alternative bidding mechanisms.

In 1997, a law ended the state monopoly of oil and gas exploration in Brazil. Since then, oil and gas exploration tracts have been allocated through an auction procedure. Although there have been some changes in the auction rules throughout the years, the basic principles remained the same. For each tract, interested bidders had to submit a bid along several dimensions. Just one of them being the bonus, the typical monetary payment in first price sealed bid auctions. Other dimensions included an exploratory program (in points) and the local content of inputs used in exploration and development of oil fields. Each bid was then assigned a score using a known formula that mapped bid vectors into a scalar value.

I develop and apply a method to estimate the value of the tract for each bidder as well as the costs associated to bidding in different dimensions. This method can be seen as an extension to general scoring auctions of existing procedures to estimate private values in first price sealed bid auctions, such as Guerre et al. (2000) and Li et al. (2002). It has been argued[1] that the private values assumption performs poorly when dealing with mineral rights auctions. In this setting, firms typically have asymmetric information about the mineral potential of the lease being offered. In this case, the expected value of the lease upon winning the auction will be typically lower than the expected value conditional only on information available to the firm at the moment of bidding. Therefore, in this particular sense, winning the auction conveys "bad news;" this is the so called "winner's curse." In this paper, I focus on a set of auctions for which this effect should be diminished. Specifically, I use a subset of auctions for which there was plenty of public available data about the tracts for sale, decreasing the importance of informational asymmetries across bidders with respect to oil and gas deposits.

As a starting point, I assume a private cost of bidding in each non-monetary dimension and a private monetary tract value that excludes all costs associated with those extra dimensions. Those values and costs are then point identified from the bidder's first order condition and observed distribution of bids. Under the private values assumption, information held by other players matters as long as they influence the probability of winning the tract given a certain bid vector. This probability and its partial derivatives are the main elements to be estimated from data. Estimation is based on a sampling procedure that in principle requires a homogeneous set of auctions. The auctions in the data set are not homogeneous Tracts are located in different sedimentary basins and differ in observed quality. I deal with this issue in two ways; (1) by adapting the bid homogenization procedure presented in Haile et al. (2003) to this non-linear scoring rule bidding model and (2) by controlling nonparametrically for different reserve prices.

Estimating the distribution of values and associated costs of bidding in these extra dimensions is important because it allows us to evaluate counterfactual outcomes under alternative bidding schemes. For instance, it makes possible to assess the government revenue in an alter-

[1]See Hendricks et al. (2003).

native first price auction, as performed by the U.S. government in similar exploration tracts in the Outer Continental Shelf (OCS). It is intuitive that the auctioneer revenue should be higher if dimensions other than bonus didn't exist, as the scoring scheme diverts competition away from the bonus component. However, the knowledge of such magnitudes is crucial if we want to evaluate the implications of extra bidding dimensions, such as exploratory effort and local content. Specifically, I find that a first-price auction would imply a 9.7% higher revenue from the sales examined, an increase in government revenue of 10.3 million U.S. dollars. The purpose of including those extra dimensions is a controversial matter, but it has been argued that they were introduced to increase the knowledge of Brazilian sedimentary basins and to foster the development of a national industry of oil equipment. Given the regulator's preference for mechanisms that foster exploration, we consider a counterfactual scenario in which the auctioneer sets exploration mandates and firms compete only through price. Those counterfactual scenarios can shed light on the opportunity costs of such policies, especially on the revenue that is forgone because of them. An analysis of the potential benefits of those policies, both in terms of increased knowledge of new reserves and local manufacturing of heavy equipment, is out of the scope of this paper.

The initial theoretical literature in scoring auctions (Asker and Cantillon (2008) and Che (1993)) focused on quasi-linear scoring rules. The monetary component entered linearly in the players utility function and in the scoring rule. This assumption allowed the authors to reduce the dimensionality of the players' types into a single dimension, generating a simple characterization in terms of each player's pseudo-type. Hanazono et al. (2013) later allowed for this type of single-dimension characterization for non-linear scoring auctions.

Characterization in terms of pseudo-types is not possible here. In previous studies the bidding vector of a player was sufficient to determine his own score, which is not the case in the scoring rule used here. In the auctions studied here the scoring rule is interdependent, that is, the bid vectors of all players matter in the determination of a given player score.

There is no general characterization result available for non-linear scoring auctions with interdependent scoring rules. I do not provide a full characterization; instead I identify and estimate primitives from the model using conditions that must hold in any Bayes-Nash equilibrium. Estimated primitives are then used to determine expected revenues in different first-price sealed bid mechanisms.

This is not the first article to empirically study scoring auctions. Lewis and Bajari (2011) studies bidding behavior in procurement auctions for road works in California that had two dimensions: cost and completion time. However, the scoring rule used to allocate road repair jobs was linear in cost and completion time, which sets their problem in the well studied case of scoring auctions that can be characterized by pseudo-type. The method used by Lewis and Bajari (2011) to estimate bidder's costs does not apply to the auctions studied here given the shape of the scoring rule.

Nakabayashi (2013) and Nakabayashi and Hirose (2016) are more closely related to this article. They provide structural estimation of the distribution of auction primitives for non-linear scoring auctions, but with independent scoring rules. The interdependence of the scoring rule here provides its own challenges in terms of estimation.

There have been a few studies of these Brazilian oil tract sales. None of them deal explicitly with the multidimensional bidding. This literature focuses in identifying the presence of information asymmetries (Matoso and Rezende (2011),Perez (2011)). Perez (2011) presents a very good description of those auctions and bidding behavior of oil firms and provides arguments in favor of the private values benchmark for the onshore tracts studied here.

The rest of the article is organized as follows: Section 2 presents the data set and discusses the subset of auctions used in estimation, Section 3 presents the theoretical model, Section 4 presents the estimation procedure, Section 5 presents the results and Section 6 concludes.

2 Brazilian oil tract auctions

Until the mid-nineties all oil exploration and production in Brazil was carried out by Petrobras, the state oil company, which had a legal monopoly over those activities. Petrobras had almost vertical control over the oil related industry. It was the sole responsible for exploratory drilling, production, transportation, refining and distribution of oil and gas. In 1997 a federal law ended the state monopoly and created the National Petroleum Agency (ANP) responsible for regulating the oil and gas industry. All mineral rights (offshore and onshore) remained State property and ANP was responsible for organizing auctions to allocate new exploration rights. Meanwhile, concession over sites being explored or developed by Petrobras were renewed in 1998 under the new law. All results from exploratory drills and seismic studies done by Petrobras during the monopoly period were transferred to ANP. The agency provided this information to all bidders participating in the subsequent oil and gas tract auctions.

Exploration rights were allocated through an auction mechanism in 10 different sales, one every year from 1999 to 2008.[2] In each sale, exploration tracts were offered in different sedimentary basins. Some of the auction rules changed over time, but in general firms were required to submit a closed sealed bid in 3 dimensions:

- b - A bonus, which was an upfront payment in the local currency (R$).
- e - An exploratory effort commitment. For each bid, a minimum exploratory program was required. This was a detailed plan of exploration, including exploratory drills and seismic studies. The bidder was contractually committed to this plan of exploration in case she won the tract. For each planned job (drilling exploratory well, 2D seismic, etc.) a certain number of exploration points was assigned by a known to all rule.[3] The sum of all exploration points for a bidder in a given tract constituted her exploration

[2] There were only two sales after 2008, both in 2013.

[3] For example, in the set of auctions I use in this paper, 1 exploratory well was worth $1,000$ points, while $1km$ of 2D seismic was worth 10 points.

effort commitment, e, for that bid.

- l - Local content (in %) of inputs. Bidders needed to submit a minimum local content for the inputs they would use. They had to bid separately a local content for the inputs they would use during exploration and development of oil and gas fields. Certification of the local content was done through a known methodology adapted from the National Development Bank (BNDES) that used a similar procedure in subsidized loans.

Each bid vector was then assigned a score given by a weighted sum of the ratios between the bid specific component and the maximum among all bidders for that specific component. More precisely,

$$S_i(\mathbf{b}, \mathbf{e}, \mathbf{l}) = \rho_b \frac{b_i}{\max_j b_j} + \rho_e \frac{e_i}{\max_j e_j} + \rho_l \frac{l_i}{\max_j l_j}, \tag{1}$$

where $\rho_b + \rho_e + \rho_l = 1$. The most peculiar aspect of this scoring rule is that bidder i score is determined not only by his own bid, as in previously studied scoring auctions, but is a nontrivial function of other players' bids. The weights used in the scoring rule, $\{\rho_i\}_{i=b,e,l}$, were defined by the auctioneer and were known to bidders months in advance of the auction date.

The weighting scheme used in different sales is summarized in Table 1. It is noticeable how the non-monetary dimensions gained importance throughout the years, especially the exploratory effort dimension. The exact reason for those changes is controversial. The general view that changes in the 5th sale had a strong political component, as those changes coincide with the beginning of a new Federal administration from a previous opposition party.

There were constraints to bidding possibilities in some of those dimensions. More specifically, there was always a reserve value for the bonus and "local content" was subject to minimum and maximum constraints. The reserve value for the bonus varied considerably for each tract and reflected seismic and exploratory wells information about the potential of the deposits known to the auctioneer. The minimum and maximum constraints for the local content were fixed for most of the sales, with some variation according to tract location (onshore, deep water or shallow water).

Table 2 presents a small summary of all sales. It presents the number of tracts offered in each sale, the number of tracts that were effectively sold as well the number of tracts offered onshore and offshore. The second to last column refers to the mean number of bidders conditional on the tract being sold. After the forth sale, there were several changes in the way the government auctioned those areas. Tracts were significantly reduced in size and the number of tracts offered increased sharply. Those are just some of the many changes introduced then, the most significant from the point of view of this paper was the introduction of the exploratory effort component. In the first four sales, a minimum exploratory effort was set by the auctioneer and was not bid upon. In the counter-factual analysis, it will be possible to evaluate this decision from the revenue point of view. This is because I will be able to evaluate the expected auction revenue under arbitrary pre-determined exploratory effort mandates.

2.1 Mature basins

The oil tract sales described above were probably too vast and varied to be studied under a single framework. In what follows I focus in a set of those auctions held for mature basins in the last 3 sales (2005 to 2008). I follow the taxonomy used by ANP and call "mature basin", a sedimentary basin that was already undergoing heavy exploration and development at the time of sale.

There are a few reasons for focusing on this data set at this moment. The most important one is that the private values assumption is reasonable in the context of those sales. Generalizing our treatment to the general affiliated values assumption would introduce another layer of complexity in an already cumbersome problem. By restricting to this sample and to the private values assumption, it is possible to center the analysis on the scoring mechanism, which is the focus of this paper.

There is a literature that argues against the private values assumption to model mineral rights auctions.[4] The idea is that the mineral deposit in a given exploration tract is unknown and firms will probably differ in their assessments of the value of those deposits. This information asymmetry creates the winner's curse: winning a tract is informative to the winner, which was most likely too optimistic regarding her assessment of tract value. If this is true, the distribution of values I estimate has a very different economic interpretation.

In the sales studied here, each bidder was given extensive data from seismic studies and exploratory wells. This geological data was formed by the state oil company accumulated knowledge during its monopoly period and from results of exploration activity by other firms that eventually became public. In this sense, private costs of operation, production and exploration arise as determinant factors in the bidding competition. It is not assumed under the private value hypothesis that oil exploration is not a risky business, just that firms do not differ considerably on their assessments of mineral deposits.

In fact some studies support this point of view. Although arguing in favor of the common values benchmark for most sales, Perez (2011) recognizes that for basins where there is extensive exploratory information, such as the Potiguar basin used here, most of the differences across bids should come from differences in exploration and operational costs and not differences in the assessment of potential reserve value. Brasil and Postali (2010) also argue in favor of differences in exploration know-how across companies, especially across Petrobras and its competitors, which argues in favor of important cost differences between firms.

Another reason for focusing on those mature sales is that the structural estimation approach used here requires a relatively homogeneous set of auctions. In estimation it is required to bin auctions in relatively homogeneous groups and estimate the distribution of values and costs separately for each of those bins. It would be possible to extend the estimation for different bins other than the mature basins used here, but this would not increase the precision or change any of the results presented here.

One caveat of restricting the analysis to these mature basins is that the local content

[4] See Hendricks et al. (2003) and Milgrom and Weber (1982) for a more general discussion and Matoso and Rezende (2011) for an evaluation of the private value hypothesis using the Brazilian oil tract sales.

dimension was not interesting in strategic terms in those auctions. In fact, virtually all bidders were bidding either at the maximum allowed for local content or very close to it as shown in Table 4. In those mature basin sales, more than 96% of bids were binding at the maximum of the local content component and those that were not binding were close to the maximum allowed.

By the shape of the scoring rule, if all bidders bid at the maximum allowed for l and it's indeed optimal for any specific bidder to do so, the last term in equation (1) is just a constant added to every bidder score. This will impair separate identification of local content bidding costs and other model primitives. The model and identification strategy developed here must take into account this fact. I will only be able to identify a private value for the tract that embeds the cost of bidding at the maximum of the local content dimension. On the other hand, it also simplifies the analysis by reducing the bid dimensionality and allowing for a more parsimonious representation of payoffs. However, I will not be able to study how firms differ in this specific cost, without making assumptions on the dependence of those costs and tract specific values. In the analysis that follows, for notational convenience, I will omit the local content component.

Table 3 presents a summary of the available information for those auctions. The bonus bid for those mature basin tracts was substantially lower than the offshore tracts auctioned in previous sales, but still substantial. The average bonus bid for those three sales was a little above R$570,000, or US$250,000. In Table 3 it is also reported the frequency in which a bidder won the tract while submitting the highest bonus and/or the highest effort. In sales 9 and 10 it was not unusual for a bidder to win the tract while not submitting the highest bid on both effort and bonus components. This was the case for 28% and 26% of auctions in sales 9 and 10, respectively. This conveys the importance of multidimensional competition in this auction setting. A fact worth noting is the already mentioned knowledge firms had about those tracts. Many tracts had even some exploratory drilling already done in site, the results of which were available beforehand to all participants. Some even had exploratory wells that found oil (#wells (hits) variable),[5] even though less common this was not rare.[6]

3 Model

I start by assuming there is a fixed set of bidders. Each bidder has private value/costs given by $\nu_{it} = (\omega_{it}, \beta_{it}) \sim H_{it}$, where i denotes the bidder and t the auction in question. I make the assumption that ν_{it} is independent across t and i. The component ω_{it} represents the value of tract t to bidder i in the case i has no ex-ante commitment in exploratory effort. Following the discussion of the previous section, ω_{it} will embed the maximum allowed local content.[7] This will become clearer later, but for now one can think of ω_{it} as being the private value held by a bidder in a first price sealed bid auction. In turn, β_{it} represent the marginal costs associated with exploratory effort. The assumptions so far set this problem in the well studied independent private values (IPV) benchmark. The value of tract t to bidder i upon committing to an exploratory effort e_{it} is

$$\pi_{it}(\omega_{it}, e_{it}) = \omega_{it} - \beta_{it} e_{it}. \tag{2}$$

If bidder i decides to participate in the auction for tract t, she must submit a multidimensional bid (b_{it}, e_{it}), in which b_{it} is the bonus, the upfront payment in local currency, and e_{it} is a commitment in exploratory effort (in points). Note that the dependence between ω_{it} and β_{it} is not restricted *a priori*. The IPV assumption implies ν_{it} is independent across i,

[5] Data on exploratory wells is made available by ANP through their data management department. This data set includes among other things, the location of each exploratory well drilled in Brazil and a brief description of the results. Report on drilling activity is mandatory and after the report is made the specifics of the result remain confidential for a given period of time. However, the brief description of the results is publicly available. This is the information I use to compute the number of *hits* in a given tract. I consider a hit any report of the presence of oil and gas, even if reported as *not commercial*.

[6] It may seem counter intuitive that exploratory tracts would already have wells with proven reserves. From the data is not possible to determine the size of those reserves. Given the logic of the tract leasing system in Brazil, those wells were probably not profitable enough at the time they were drilled so they remained undeveloped.

[7] More specifically, 85% of local content in the development phase and 80% of local content for exploration phase.

which does not restrict the dependence between ω_{it} and β_{it}. This is important because ω_{it} should include private costs of field development and production that may be correlated to exploration commitment costs, β_{it}.

The bonus payment is typically subject to minimum requirements. I call r_t the minimum bonus or the reserve price. Therefore, $(b_{it}, e_{it}) \in [r_t, \infty) \times [0, \infty)$ for all bidders who decide to submit a bid for tract t. Naturally, by (2), if $\omega_{it} < r_t$ a potential bidder would choose not to submit a bid. Moreover, as there are no bid formulation costs, it is always optimal to submit a bid if $\omega_{it} \geq r_t$.

One important aspect of those auctions is that bidders had to make their decisions without ex-ante knowledge of the number of bidders that would actually participate,[8] a fact I take seriously in the analysis that follows. The auctioneer assigns a score to each bidder i using the scoring rule in (1) and the tract t is assigned to the bidder with the highest score. The winner must then pay the bonus bid and is legally bound to the exploration bid, which must be performed in the following years.

3.1 Equilibrium

We consider Bayes-Nash equilibria of the participation and bidding game. In every such equilibrium, i chooses to submit a bid if and only if

$$\omega_{it} \geq r_t. \tag{3}$$

Bidder i is interested in the set of opponents who actually submit a bid. Let $\eta_i \in \mathcal{I}_i$ denote this set, where $\mathcal{I}_i$ is the set of all subsets of $I \backslash i$. The probability that i faces the set

[8] At the moment of the auction, the auctioneer and all participants were in a closed room. The auctioneer would call bidders to move forward all bids for tracts in a given region. Bidders would then line up and submit to the auctioneer their bids for all tracts in that area in sealed envelopes. The auctioneer would then move to the next area, until all areas were offered. It was not possible to infer how many bidders were interested in a specific tract given the size of the queue that was formed. This is in contrast to some of the previous sales, in which bidding submission was specific to each offered tract. There is anecdotal evidence that bidders would bring to the auction a few envelopes for each tract they were interested in. The choice of which envelope to submit would depend on the size of the queue of interested participants.

of opponents η_i is given by:

$$p(\eta_i|r_t) = \Pr\left(\left(\bigcap_{j\in\eta_i}\{\omega_{jt}\geq r_t\}\right)\bigcap\left(\bigcap_{j\notin\eta_i}\{\omega_{jt}< r_t\}\right)\right). \tag{4}$$

Conditional on satisfying (3), let ($b_{it}(\nu_{it})$,$e_{it}(\nu_{it})$) denote the Bayes-Nash equilibrium strategy for bidder i. Conditional on facing a given set η of opponent players, bidder i cares about the types of other players and their equilibrium strategies only up to the point that this affects his probability of winning. We can write the probability that i achieves the highest score among all bidders in η after submitting a bid (b, e) as:

$$G^{it}(b,e|\eta) = \Pr\left(S_i(b,e,b_{-it}(\nu_{-it}),e_{-it}(\nu_{-it}))\geq S_j(b,e,b_{-it}(\nu_{-it}),e_{-it}(\nu_{-it}))\,\forall j\in\eta|\eta\right), \tag{5}$$

where $b_{-it}(\nu_{-it}), e_{-it}(\nu_{-it})$ represent the Bayes-Nash equilibrium strategies for all opponents of i in η. Bidders do not observe the set η of opponents that will actually participate before submitting their bid vectors. They only know the reservation price r_t, which will be used to compute the relevant probability of winning the auction. Using (5) and (4), we have that the probability a bid (b, e) will be the winning bid conditional on a reserve value r_t is:

$$G^{it}(b,e|r_t) = \sum_{\eta\in\mathcal{I}_i} p(\eta_i|r_t)G^{it}(b,e|\eta).$$

We are now ready to study the bid formulation problem. Given participation and equilibrium bidding strategies for players $I\backslash i$, the problem of bidder i, once satisfying (3), can be written as

$$\max_{b\geq r_t, e\geq 0} G^{it}(b,e|r_t)\left(\omega_{it}-\beta_{it}e-b\right). \tag{6}$$

For the rest of this section, we assume that $G^{it}(b,e|r_t)$ is differentiable in $(b,e)\,\forall r_t$. If the choice of bidder i is interior, then it must satisfy the necessary first order condition for an optimum.

The first order conditions for b and e are given respectively by:

$$G_b^{it}(b_{it}, e_{it}|r_t)\left(\omega_{it} - \beta_{it}e_{it} - b_{it}\right) = G^{it}(b_{it}, e_{it}|r_t), \tag{7}$$

$$G_e^{it}(b_{it}, e_{it}|r_t)\left(\omega_{it} - \beta_{it}e_{it} - b_{it}\right) = \beta_{it}G^{it}(b_{it}, e_{it}|r_t). \tag{8}$$

Substituting (7) in (8) we have:

$$G_e^{it}(b_{it}, e_{it}|r_t)\frac{G^{it}(b_{it}, e_{it}|r_t)}{G_b^{it}(b_{it}, e_{it}|r_t)} = \beta_{it}G^{it}(b_{it}, e_{it}|r_t),$$

which gives us

$$\beta_{it} = \frac{G_e^{it}(b_{it}, e_{it}|r_t)}{G_b^{it}(b_{it}, e_{it}|r_t)}. \tag{9}$$

Finally, substituting the expressions for β_{it} above in (7) hands the expression for ω_{it}, (10):

$$\omega_{it} = b_{it} + \frac{G^{it}(b_{it}, e_{it}|r_t)}{G_b^{it}(b_{it}, e_{it}|r_t)} + \frac{G_e^{it}(b_{it}, e_{it}|r_t)}{G_b^{it}(b_{it}, e_{it}|r_t)}e_{it}, \tag{10}$$

where the subscripts denotes the appropriate partial derivatives. We note that $G^{it}(b, e|r)$ is in principle identified from the data and hence, the first order conditions above identify values and costs parameters for firms that submit a bid in the interior of their possibility set. Equation (10) is of special interest, since it is the natural extension of the first order condition that identifies the private value in first-price sealed bid actions. This equation can be re-written as

$$\omega_{it} - \beta_{it}e_{it} = b_{it} + \frac{G^{it}(b_{it}, e_{it}|r_t)}{G_b^{it}(b_{it}, e_{it}|r_t)}, \tag{11}$$

which is the analog to the first order conditions in Guerre et al. (2000). The value of a tract, after considering commitment costs, is equal to the firm's bonus payment plus a mark-down term, the same way as in a first-price sealed bid auction.

3.2 Bid homogenization

As I discussed above, the scoring auction model estimated here still awaits for a full characterization. When presenting the first order conditions, I was intentionally agnostic about the structure that a full characterization of the model might impose to $G^{it}(b, e|r)$, the probability i wins auction t, conditional on a given play by i. Estimating this function nonparametrically will typically be data demanding and observed auction heterogeneity will severely hinder the estimation by the need of nonparametrically controlling for many observables.

In this subsection, I derive a homogenization result in the spirit of Haile et al. (2003). The bid homogenization is a way to allow the binning of auctions with different observed characteristics when estimating the distribution of values as if they came from the same underlying data generating process. I let H_i^0 denote the latent joint distribution of homogenized private values and costs. The homogenization step rests on the assumption that observed auction characteristics shift the underlying values in a similar fashion for all players.

Assumption 1. *For any auction t, there exist positive α_t and γ_t, such that:*

$$(\omega_{it}, \beta_{it}) = (\alpha_t \omega_{it}^0, \gamma_t \beta_{it}^0) \; \forall i, \tag{12}$$

where $\nu_{it}^0 = (\omega_{it}^0, \beta_{it}^0) \sim H_i^0$.

Assumption 1 restricts the role of auction heterogeneity. I only allow for auction heterogeneity that shifts the distribution of private values and costs multiplicatively.

Initially I also assume that $r_t = \alpha_t r_0$, that is, the reserve price follows the same homogenization rule as the private value ω_{it}. This assumption will be relaxed when estimating the model. It is kept here for simplicity and because it will inform how one should control for differences in the reserve price when comparing homogenized auctions.

Obviously, I do not observe values; only bids are observed. Therefore I need a way to translate the shifts in the distribution of values to shifts in equilibrium play. Proposition 2 below show how shifts in the underlying distribution of values are linked to equilibrium bidding.

Let $\{(b_i^0(\nu_{it}^0), e_i^0(\nu_{it}^0))\}_{i\in I}$ be a vector of Bayes-Nash equilibrium strategies of the homogenized auction, *i.e.*, the auction with primitives distribution given by H_i^0.

Proposition 2. *The vector*

$$\left\{\alpha_t b_i^0(\omega_{it}/\alpha_t, \beta_{it}/\gamma_t), \frac{\alpha_t}{\gamma_t} e_i^0(\omega_{it}/\alpha_t, \beta_{it}/\gamma_t)\right\}_{i\in I} \tag{13}$$

is a Bayes-Nash equilibrium of auction t.

Proof. First, we note that since the reservation price is also scaled by α_t, the participation rule (3) will imply exactly the same participation in auction t as in the homogenized auction. Second, if all other players play according to the prescription in (13), then

$$G^{i0}(b, e) = G^{it}\left(\alpha_t b, \frac{\alpha_t}{\gamma_t} e\right). \tag{14}$$

This is immediate from the definition of the scoring rule in (1) and follows from the fact that each of the fractions in the scoring rule will be unaltered by the change in scale and by the unaltered participation decisions just discussed. We note now that if $(b^\star, e^\star)$ is the chosen strategy when i's private value and costs are $(\omega_{it}^0, \beta_{it}^0)$, then

$$G^{i0}(b^\star, e^\star)\left(\omega_{it}^0 - \beta_{it}^0 e^\star - b^\star\right) \geq G^{i0}(b, e)\left(\omega_{it}^0 - \beta_{it}^0 e - b\right)\ \forall (b, e, l).$$

Multiplying both sides by α_t and using (14), we have that

$$\begin{aligned} G^{it}\left(\alpha_t b^\star, \frac{\alpha_t}{\gamma_t} e^\star\right)&\left(\alpha_t \omega_{it}^0 - \gamma_t \beta_{it}^0 \frac{\alpha_t}{\gamma_t} e^\star - \alpha_t b^\star\right) \\ &\geq G^{it}\left(\alpha_t b, \frac{\alpha_t}{\gamma_t} e\right)\left(\alpha_t \omega_{it}^0 - \gamma_t \beta_{it}^0 \frac{\alpha_t}{\gamma_t} e - \alpha_t b\right)\ \forall (b, e, l). \end{aligned}$$

Noticing that $\alpha_t \omega_{it}^0 = \omega_{it}$ and $\gamma_t \beta_{it}^0 = \beta_{it}$, establishes the result. $\square$

4 Estimation

In this section, I propose an estimator for the individual cost of bidding in the exploratory effort dimension, β_{it}, and for the value of the tract ω_{it}. The core of the estimation procedure recovers the objects in the right hand side of equations (9) and (10) by a sampling procedure. This sampling procedure is based on the assumption that the distribution of bidder's primitives is the same in all auctions, *i.e.*, that auctions are homogeneous. In practice there is considerable auction heterogeneity: tracts differ in size, sedimentary basin location and amount of exploratory work already executed. These differences will shift the distribution of bidders private information and thus change bidding behavior. I control for observable auction heterogeneity in a homogenization first step. I propose a procedure that leverages on the result of Proposition 2, which establishes how shifts in the distribution of auction primitives translates into shifts in bid components. After the homogenization procedure, all bids are as if drawn from the same homogenized underlying distribution. By Proposition 2, this procedure is valid as long as Assumption 1 holds.

The auctions studied here were also subject to different reserve values, or minimum bonus. This is auction heterogeneity of a different nature than described above. Reserve values can not only proxy for characteristics associated with tract desirability,[9] but also change the set of bidders willing to participate in the auction. Therefore when recovering the distribution of private values, I nonparametrically control for differences in reserve values.

I first describe the bid homogenization procedure and then the core of the estimation.

4.1 Homogenized bids

I start by imposing some additional structure in the primitive shifters α_t and γ_t. In particular, I assume that:

$$\alpha_t = e^{x_t'\alpha} \text{ and } \gamma_t = e^{x_t'\gamma},$$

[9]See Roberts (2013) for a treatment of unobserved heterogeneity in auctions and reserve prices.

where x_t is a $m \times 1$ vector of observables for auction t and α and ω are $m \times 1$ vectors of parameters. Using Proposition 2,

$$\log b_{it} = x_t'\alpha + \log b_{it}^0, \tag{15}$$

where b_{it}^0 is the homogenized bonus. Additionally,

$$\log e_{it} - x_t'\alpha = -x_t'\gamma + \log e_{it}^0, \tag{16}$$

where e_{it}^0 is the homogenized exploratory effort.

This suggests a two step procedure to estimate α, γ and the homogenized bonus and effort. First, I estimate (15) by OLS. The residual of this regression will gives the desired homogenized bonus. In a second step, we can use $\hat{\alpha}$ to estimate γ in equation (16). This last step also gives homogenized values of exploration effort as residuals.

The vector of regressors x_t contains potentially relevant observables about the tracts. These include variables summarized in Table 3 and additional dummy controls for sales and sedimentary basin. The sales (year) dummy should also control for fixed differences in expectations about the price of oil in each date. The results from the bonus equation (15) estimation is presented in Table 5. In turn the results from the effort equation (16) are shown Table 6.

The area of a given tract seems to have no predictive power on the bonus component of bids, which is hardly unexpected. The area of a tract would be an informative variable only if there was absolutely no other information available about the tracts. The number of wells drilled have a significant impact on the bonus component of the bid. One extra well drilled corresponds to an average increase of approximately 11.56% on the bonus bid. The coefficient on wells that hit hydrocarbonates gives the additional average change in the bonus component from a hit well compared to a dry well. This coefficient was found to be not significantly different from zero, which is not surprising if one takes into account the very small number of such occurrences. One must keep in mind that the tracts being offered in those sales are exploratory tracts. Therefore it is natural that there are only a few reports of oil and gas discoveries available.

I find a significant negative effect of having a neighbor tract sold in a previous sale on the exploration effort component of the bid. I interpret this as reflecting lower costs from being in an area with established oil exploration, with more local suppliers and better infra-structure, which translates in our model into lower costs of exploration commitment.

Figure 1 shows the homogenized bids that result from the estimation of equations (15) and (16). Each point shows the values of the homogenized exploration and bonus components for a given bidder. The positive correlation in bid components is expected as bidders equate the optimal bid in both margins.

4.2 Estimation of values and costs

The last subsection showed how to recover for each bid (b_{it}, e_{it}) the so-called homogenized bid (b^0_{it}, e^0_{it}). In this subsection I describe how to recover from each homogenized bid, the homogenized value ω^0_{it} and costs β^0_{it}. It is possible then to use Assumption 1 back to recover estimates for ω_{it} and β_{it}.

The main element needed to estimate ω^0_{it} and the cost of bidding in the exploratory effort dimension β^0_{it} through equations (9) and (10) is the function $G^{i0}(b, e|r)$ and its partial derivatives. This function gives the probability bidder i wins the homogenized auction with a given minimum bonus r after submitting a vector of bids (b, e). I estimate this object by a kernel regression that resembles conditional CDF estimation.

Under the hypotheses of the homogenization procedure, it is as if all bid vectors in each auction are realizations of the same underlying random variables. Since we know the scoring procedure that allocates a set of bids to a given score, we can easily compute for each realized auction whether a bid vector (b, e) wins or not against the homogenized bids from auction t. Define $Y^0(b, e)$ as the Bernoulli random variable that equals 1 if bid (b, e) wins the homogenized auction auction and $y_t^0(b,e)$ as its realization:

$$y_t^0(b,e) = \begin{cases} 1 & \text{if bid } (b,e) \text{ wins against } (b_t^0, e_t^0), \\ 0 & \text{otherwise,} \end{cases}$$

where (b_t^0, e_t^0) represents the already homogenized bids in auction t.

The kernel regression used is based on the following equality:

$$\mathbb{E}\left[Y^0(b,e)|r\right] = G^{i0}(b,e|r). \tag{17}$$

If all auctions had the same reserve bonus, it would be possible to use the unweighted average of $y_t^0(b,e)$ as an estimator for the left hand side of equation (17). In principle, the reserve bonus could affect participation in those auctions, changing expected level of competition, which would impact bidders optimal strategies. More specifically, the reservation bonus affects the underlying distribution of (b_t^0, e_t^0) and therefore needs controlling. One alternative is to only use auctions with the same reserve bonus when averaging over $y_t^0(b,e)$. This implies splitting the sample into different estimation bins for every observed level of the reserve bonus.[10] In the case of the present study the reserve bonus varies continuously in the data, which makes this approach infeasible. Instead, I estimate $G^{i0}(b,e|r)$ by kernel regression using the reserve bonus as nonparametric control.

I use the knowledge of the scoring rule to propose a smoother estimator for $G^{i0}(b,e|r)$. Instead of averaging over a binary variable, $y_t^0(b,e)$, I use a continuous measure as the dependent variable. This is explained in more detail next.

Let $Q^0(b,e)$ be the random variable giving the difference between the score attained by bid (b,e) and the maximum opponent score:

[10]This is exactly the case in Reguant (2014), which bins auctions based on week days when sampling bids for estimation.

$$Q^0(b,e) = \tilde{S}^{i0}(b,e) - \max_{j \neq i} \tilde{S}^{j0}(b,e),$$

where $\tilde{S}^{i0}(b,e)$ represents the random score[11] a bidder i would obtain in the homogenized auction by bidding (b,e) and $\tilde{S}^{j0}(b,e), \quad j \neq i$, represents the random opposing scores given that bidder i bids (b,e). Now let q_t^0 be the sample analog of Q^0, that is,

$$q_t^0(b,e) = S_t^{i0}(b,e) - \max_{j \neq i} S_t^{j0}(b,e),$$

where $S_t^{i0}(b,e)$ represents the score bid (b,e) obtains against the realization of opponents bids (b_t^0, e_t^0) and $S_t^{j0}(b,e)$ is the score opposing bidder j obtains against bid (b,e) and the rest of opposing bids.

By definition, $Y^0(b,e) = 1\{Q^0(b,e,l) \geq 0\}$ and $y_t^0(b,e) = 1\{q_t^0(b,e) > 0\}$. Ties have zero probability as the distribution of equilibrium play is continuous and in fact are not observed in the data. The estimator for the probability that (b,e) wins auction t is then given by:

$$\hat{G}(b,e|r) = \frac{\sum_{t=1}^{T_n} \Phi\left(\frac{q_t^0(b,e)}{h_0}\right) K\left(\frac{r_t - r}{h}\right)}{\sum_{t=1}^{T_n} K\left(\frac{r_t - r}{h}\right)},$$

where $\Phi(\cdot)$ denotes the Normal CDF; $K(\cdot)$ is a two-sided kernel; h and h_0 are bandwidths that approach zero at the appropriate rate.[12] Naturally, when $h_0 \to 0$, the fraction $q_t^0(b,e)/h_0$ diverges to ∞ in case $q_t^0(b,e) \geq 0$ $(y_t^0(b,e) = 1)$ or to $-\infty$, in case $q_t^0(b,e) < 0$. Therefore this estimator converges to the non-smooth estimator discussed above.

The bandwidths h_0 and h were chosen according to the rule of thumb. In particular, I set $h = c_h \times \sigma_r \times (T_n)^{-1/5}$ and $h_0 = c_{h_0} \times \sigma_q \times (T_n)^{-2/5}$, where σ_r and σ_q are the standard

[11] Remember that the score of a given bidder is a nontrivial function of the vector of bids of all players. Therefore, even conditional on her own bid, a bidder's score is still not known by her when the bid is decided.

[12] In the application, I use the triweight kernel.

deviations of the reserve bonus, r_t, and $q_t^0(b,e)$ respectively. The bandwidths h and h_0 satisfy optimal smoothing conditions for conditional CDF estimation (see Li and Racine (2007) for a review of conditional CDF nonparametric estimation).[13]

The other objects of interest I need to estimate are the partial derivatives of $\hat{G}(b,e|r)$ with respect to bonus and exploratory effort $\hat{G}_b(b,e|r)$ and $\hat{G}_e(b,e|r)$. I estimate those using the partial derivatives of $\hat{G}(b,e|r)$:

$$\hat{G}_b(b,e|r) = \frac{\sum_{t=1}^{T_n} \frac{1}{h_0}\phi\left(\frac{q_t^0(b,e)}{h_0}\right)\frac{\partial q_t^0(b,e)}{\partial b}K\left(\frac{r_t-r}{h}\right)}{\sum_{t=1}^{T_n} K\left(\frac{r_t-r}{h}\right)},$$
$$\hat{G}_e(b,e|r) = \frac{\sum_{t=1}^{T_n} \frac{1}{h_0}\phi\left(\frac{q_t^0(b,e)}{h_0}\right)\frac{\partial q_t^0(b,e)}{\partial e}K\left(\frac{r_t-r}{h}\right)}{\sum_{t=1}^{T_n} K\left(\frac{r_t-r}{h}\right)},$$

where the function $\phi(\cdot)$ is the standard normal density.

I estimate the homogenized value of a tract ω_{it}^0 and the cost of bidding in the exploratory effort dimension β_{it}^0 using the empirical analogs of equations (9) and (10):

$$\hat{\beta}_{it}^0 = \frac{\hat{G}_e(b_{it}^0, e_{it}^0|r_t)}{\hat{G}_b(b_{it}^0, e_{it}^0|r_t)},$$
$$\hat{\omega}_{it}^0 = b_{it}^0 + \frac{\hat{G}(b_{it}^0, e_{it}^0|r_t)}{\hat{G}_b(b_{it}^0, e_{it}^0|r_t)} + \frac{\hat{G}_e(b_{it}^0, e_{it}^0|r_t)}{\hat{G}_b(b_{it}^0, e_{it}^0|r_t)}e_{it}^0.$$

Finally we can then use the results from the previous subsection to recover tract values, ω_{it}, and exploration effort costs, β_{it}:

$$\hat{\omega}_{it} = e^{x_t'\hat{\alpha}}\hat{\omega}_{it}^0,$$
$$\hat{\beta}_{it} = e^{x_t'\hat{\gamma}}\hat{\beta}_{it}^0.$$

[13]Constants were set at $c_{h_0} = 1$ and $c_h = 3$.

5 Results

Figures 2 and 3 show, respectively, the density of estimated tract values $\hat{\omega}_{it}$ and marginal costs of exploration commitment $\hat{\beta}_{it}$.

The density of estimated tract values in Figure 2 is shown in the log scale, given the non-negligible density of extreme values for $\hat{\omega}_{it}$. The estimated distribution of private values is extremely asymmetric, with mean R$8,210,000.00 and median R$401,830.00. Those values are de-homogenized, that is, they incorporate variability in lease values that is controlled for in the homogenization step. The rest of the variation can be understood in light of the fixed investment costs involved in oil exploration & development and firms' cost differentials. One should keep in mind that oil tracts auctioned in the sales studied here are in areas that already underwent extensive exploration, in which undiscovered oil deposits are not expected to be big. This magnifies the effects of those cost differentials.

Figure 3 shows the estimated density of the marginal cost of exploration commitment $\hat{\beta}_{it}$. The mean estimated marginal cost of bidding one extra exploration effort point is R$1,081.00 and the estimated distribution is also asymmetric. But how should one interpret those values? As discussed in section 2.1, the exploratory effort part of the bid was given in points. For each exploratory effort job, *e.g.*, wells, 2D seismic and 3D seismic there was a point correspondence. In the case of the sales studied here the point value of specific exploratory jobs was given by the correspondence in Table 7. For illustrative purposes, suppose that a firm submitted an exploration effort bid of $2,000$, this firm could either drill 2 exploratory wells or implement 200 km of 2D seismic and so forth. Since the firm has the option of which job it will actually implement, $1,000 \times \hat{\beta}$ can be seen as a lower bound on the actual cost of drilling a well.

There are other reasons to believe that the estimate $\hat{\beta}$ gives a lower bound on the actual exploration cost. The most obvious one is that it ignores the benefits to the firm of the exploratory drilling. It could be even optimal *ex-post* for a firm in the absence of the exploratory effort commitment to not drill at all.[14] However the benefit from drilling should always be

[14]See Hendricks and Porter (1996) for a treatment of exploratory drilling decisions.

positive. Another reason for considering $\hat{\beta}$ a lower bound is that the trade-off between the bonus and the exploratory effort component is also one between a payment today and a cost tomorrow. If a bidder wins a tract, it must pay the full amount of the bonus component on the spot, while the exploration effort is a commitment to jobs done in the future. This alone would be a reason for expecting the actual costs of exploration to be higher than those suggested by $\hat{\beta}$.

This could of course be aggravated in the presence of credit constraints. If firms have different opportunity costs of capital, they will trade-off the bonus payment today and future exploration at a different rate. This effect could shed light on the nature of the skewness in the distribution of $\hat{\beta}_{it}$.[15] Many firms might be willing to trade-off exploration effort for the bonus payment in a rate that does not correspond to actual exploration costs. Therefore, it must be stressed the interpretation of the β coefficient as a bid specific marginal cost of exploration commitment and not actual exploration costs faced by firms. Naturally, since the exploration effort has to be carried out at some point, it must be related to the actual cost of exploration. In this sense, the average $\hat{\beta}$ computed here translates into a lower bound to the average cost of drilling an exploratory well of R$1,081,000.00, or approximately US$500,000.00. This is in the ball park of the actual cost of drilling an exploratory well.

5.1 Counterfactual revenues in alternative bidding schemes

In this section I evaluate the cost for the Brazilian Oil National Agency (ANP) of having the scoring auction design in comparison to a traditional first price sealed bid auction, as carried by the U.S. Government in Outer Continental Shelf (OCS) tract sales.

I simulate counterfactual bids from a first price sealed bid mechanism in which each bidder's i private value at auction t is given by ω_{it}.[16] Note that ω_{it} was exactly defined as the

[15] In fact, for the same reason, this can also help explain the dispersion in $\hat{\omega}_{it}$.

[16] This simulation is actually carried out using the homogenized values, which naturally gives us a homogenized counterfactual revenue. Given the model homogenization assumption (Assumption 1), we can recover the true expected counterfactual revenue for any level of observed tract characteristics x_t through

$$\mathbb{E}\left[R_t\right] = \exp\left(\alpha' x_t\right) \mathbb{E}\left[R_0\right],$$

tract value in the absence of any exploration commitments. It is important to stress however that since I do not observe variation in local content bids, ω_{it} incorporates a mandate of local content equivalent to the maximum local content bid allowed.

Table 8 presents the counterfactual revenues under a first price sealed bid mechanism. The first two columns describe the expected counterfactual revenue at the mean of observables for the two mechanisms. The following two columns report the total expected revenues for each sale in the two mechanisms. Finally, the last two columns report the total amount forfeited in terms of revenue as a consequence of the scoring mechanism. Those estimates suggest that ANP could have had a total revenue 9.7% higher on the sales examined, or a total increase in government revenue of 10.3 million U.S. dollars.

This extra revenue would come at the expense of no exploration commitment at all. It was however the goal of the auctioneer to guarantee that some exploration was performed on those tracts. So I consider a different counterfactual first price sealed bid auction in which auctions have fixed exploration commitment levels. This was in fact the system in place in the first four ANP sales, so the results from this counterfactual analysis can be seen as the cost of switching from a mandate system to the scoring mechanism that incorporates exploration commitment as part of the bid. This is possible because besides the tract value ω_{it}, I also recover the exploration cost β_{it}. I then generate different distributions of values for various levels of exploration mandates. Note that the counterfactual private values under the first price auction with exploration mandate is given by:

$$\tilde{\omega}_{it}^{\bar{e}} = \omega_{it} - \beta_{it}\bar{e}$$

Following the same procedure as before, I am able to calculate expected counterfactual revenues for each exploration mandate $\bar{e}$. Figure 4 shows the revenue for different levels of exploration mandates. The solid line indicates the revenue for different exploration effort mandates. The dotted line marks the expected revenue under the scoring mechanism. A

where R_0 stands for the homogenized revenue and R_t for the "true" revenue.

first price auction with exploration mandate of a little less than 100 exploration points would would provide the same expected revenue as the scoring mechanism. The average exploration effort bid in those sales was on average many times higher than that, as shown in Table 3. In fact, the average exploration effort bid among winning bidders in the scoring mechanism was $1,060$ exploration points. This is indicative that the scoring mechanism, by allowing firms to bid exploration efforts, was effective in getting higher average exploration much cheaper than a mandate system would.

6 Conclusion

I study auctions held by the Brazilian government to allocate oil and gas exploration tracts. Different from similar auctions held elsewhere, firms competed for tracts in a multidimensional bidding system. Firms were asked to submit a bonus payment and an exploration program. A non-linear scoring rule translated the bid vector of all players into a score, which determined the winner. In this article, I estimate private values of bidders as well as the costs associated to bidding in some of those dimensions. I parametrize firms objective function and model bidding competition under the assumption of independent private values (IPV). I restrict the analysis to auctions in mature basins, in which the IPV assumption is reasonable. I then propose an estimator for bidder-tract specific private values as well as specific costs associated with exploration. Although the focus here is in a specific non-linear scoring rule, the method proposed can be easily applied to other scoring procedures.

Computation of those values and costs is important to understand the outcome of alternative policies. One important policy question regarding those auctions is how much revenue the Brazilian government forfeited to have this multi-dimensional bidding scheme. For instance, it makes possible to assess the government revenue if the sale mechanism were a first price auction, as in the U.S. Golf of Mexico (OCS) oil tract sales. I find that a first-price auction would imply 9.7% higher revenue from the sales examined, an increase in government revenue of 10.3 million U.S. dollars. However, it seems to have been the goal of the auctioneer to assure some exploration in those tracts. I then evaluate counterfactual scenarios in which the auctioneer uses a first price sealed bid mechanism with exogenously fixed exploration mandates. I argued that the scoring mechanism performs better than the mandate system in terms of the trade-off exploration vs. revenue.

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Table 1: ρ weights

Sales	**Bonus** (b)	**Exp. effort** (e)	**Local content** (l)	
			Exploration	**Development**
1 - 4	85%	0%	3%	12%
5 - 6	30%	30%	15%	25%
7 - 10	40%	40%	5%	15%

Notes: Weights used in equation (1) to evaluate multi-dimensional bids and assign winners.

Table 2: Overview of Oil Tract Sales

sale year	auctions	sold	onshore	offshore	# bidders (mean)	mean bonus (millions US$)
1999	27	12	4	23	1.75	13.14
2000	23	21	10	13	2.19	8.59
2001	53	34	10	43	1.68	5.92
2002	54	21	15	39	1.57	1.35
2003	909	101	254	654	1.05	0.09
2004	913	154	294	619	1.22	1.45
2005	1134	248	504	621	1.52	1.50
2006	284	38	96	185	2.21	5.91
2007	271	117	91	180	2.36	5.20
2008	130	54	130	0	1.70	0.50

Table 3: Mature Basin Sales Descriptive Statistics

Averages (std in parenthesis)	**Sale 7**	**Sale 9**	**Sale 10**
Active bidders	1.52	2.13	1.69
	(0.75)	(1.53)	(0.93)
Bonus (R$ 000)	336.76	790.33	903.60
	(939.93)	(1074.59)	(660.71)
Exploration effort	498.41	1010.05	1790.50
	(732.92)	(900.93)	(1149.71)
1^{st} bonus = winner	0.94	0.88	0.91
	(0.25)	(0.32)	(0.29)
1^{st} effort = winner	0.96	0.84	0.79
	(0.19)	(0.37)	(0.41)
1^{st} effort and bonus = winner	0.90	0.72	0.74
	(0.30)	(0.45)	(0.45)
km^2	31.33	26.51	28.73
	(6.41)	(6.30)	(4.19)
# wells	1.96	2.05	1.41
	(2.30)	(1.95)	(1.60)
# wells (hits)	0.26	0.09	0.09
	(0.73)	(0.37)	(0.29)
Neighbor offered = 1	0.92	0.88	0.76
	(0.28)	(0.32)	(0.43)
Neighbor sold = 1	0.85	0.88	0.76
	(0.36)	(0.32)	(0.43)
Sale 0 neighbor = 1	0.81	0.86	0.68
	(0.39)	(0.35)	(0.47)
# bidders	217	147	60
# auctions	143	43	34

Table 4: Bids binding at local content caps

Sale	#Bids	Max of exp	Max of dev
7	217	0.96	0.96
9	147	0.99	1.00
10	60	0.97	0.97
Maximum allowed local content bid			
Development phase:		85%	
Exploration phase:		80%	
Minimum allowed local content bid			
Development phase:		77%	
Exploration phase:		70%	

Notes: Top panel informs the fraction of bids at the maximum allowed local content levels for the exploration and development phases.

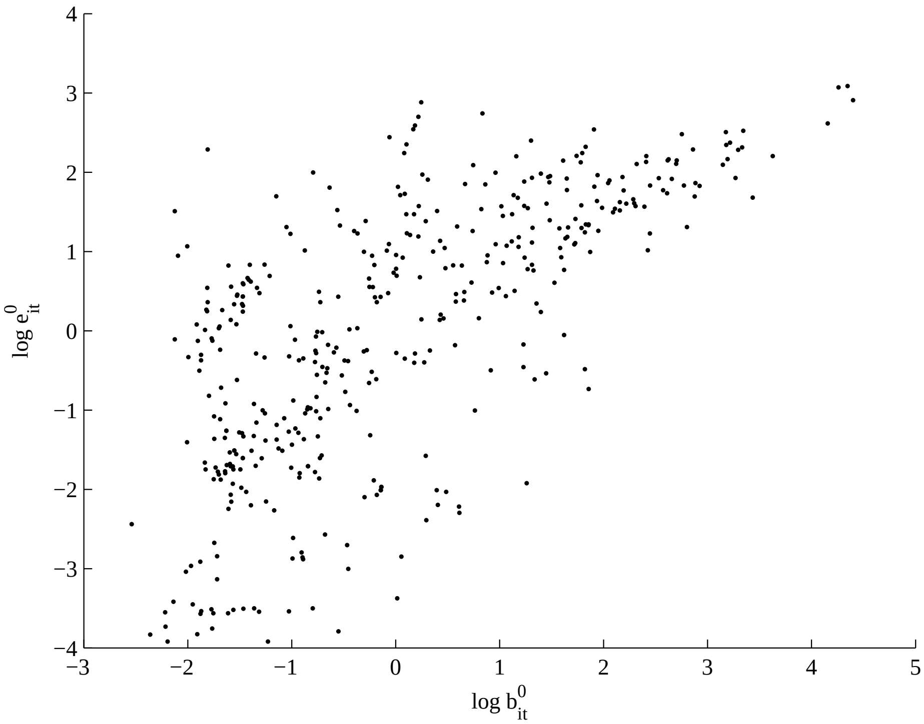
Table 5: Estimates for α by OLS (t in parenthesis)

	Estimate
$\log(km^2)$	-0.0727
	(0.20)
# wells	0.1156
	(2.36)
# wells (hits)	-0.0476
	(0.27)
Neighbor sold	-0.08
	(0.38)
Controls	
Basin	Yes
Sale	Yes
N	424

Table 6: Estimates for γ by OLS (t in parenthesis)

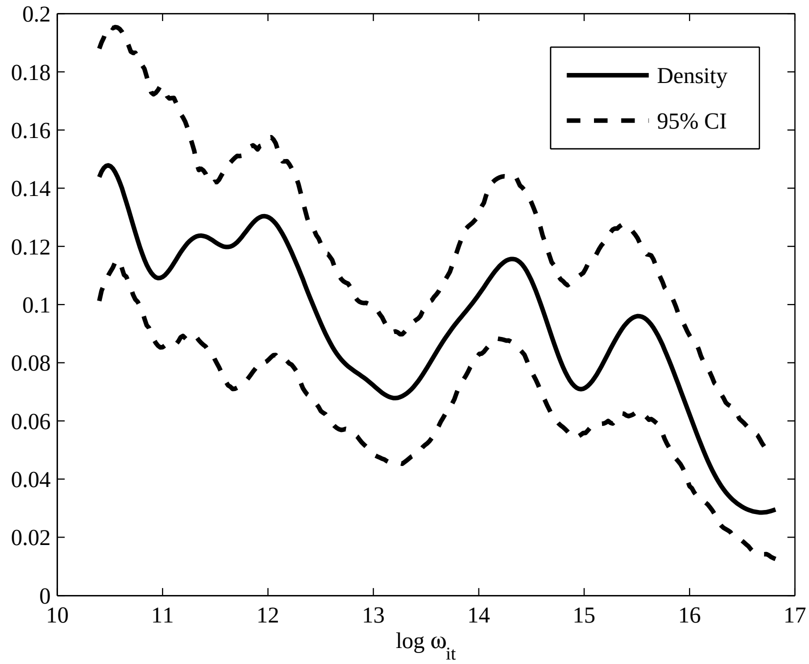
	Estimate
$\log(km^2)$	-0.3818
	(1.27)
# wells	0.0118
	(0.35)
# wells (hits)	0.1806
	(1.44)
Neighbor sold	-0.5525
	(3.34)
Controls	
Basin	Yes
Sale	Yes
N	424

Figure 1: Homogenized Bids



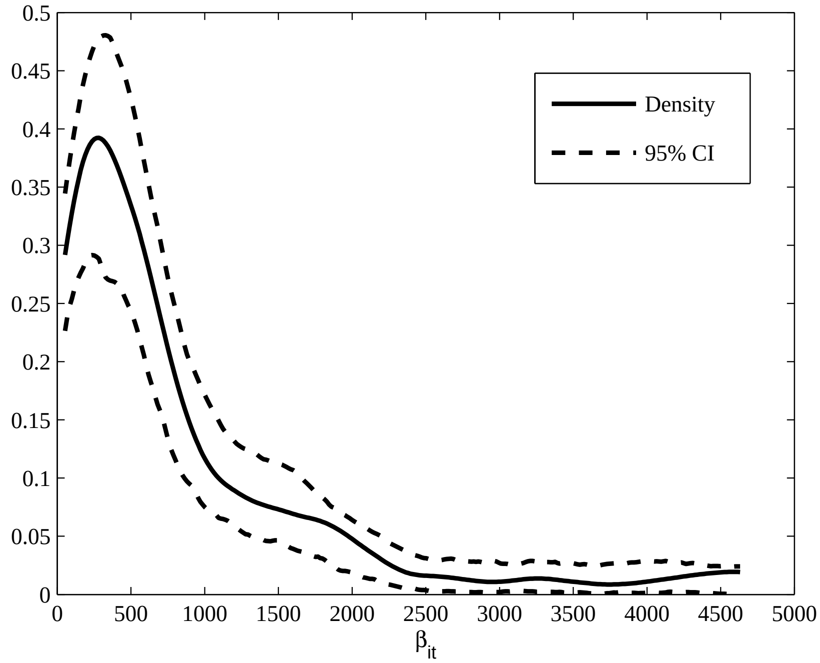
Notes: Homogenized bids are estimated residuals from the estimation of equations (15) and (16) and reported in Tables 5 and 6.

Figure 2: $\hat{\omega}_{it}$ density



Notes: Density estimated by kernel regression with bandwidth chosen by the rule of thumb. CI interval computed using 200 bootstrap samples. The distribution is normalized to the average of the observables, *i.e.*, in the figure above $\log \hat{\omega}_{it} = \bar{x}_t' \hat{\alpha} + \log \hat{\omega}_{it}^0$.

Figure 3: $\hat{\beta}_{it}$ density



Notes: Density estimated by kernel regression with bandwidth chosen by the rule of thumb. CI interval computed using 200 bootstrap samples. The distribution is normalized to the average of the observables, *i.e.*, in the figure above $\log \hat{\beta}_{it} = \bar{x}_t' \hat{\gamma} + \log \hat{\beta}_{it}^0$.

Table 7: Exploratory effort job correspondence

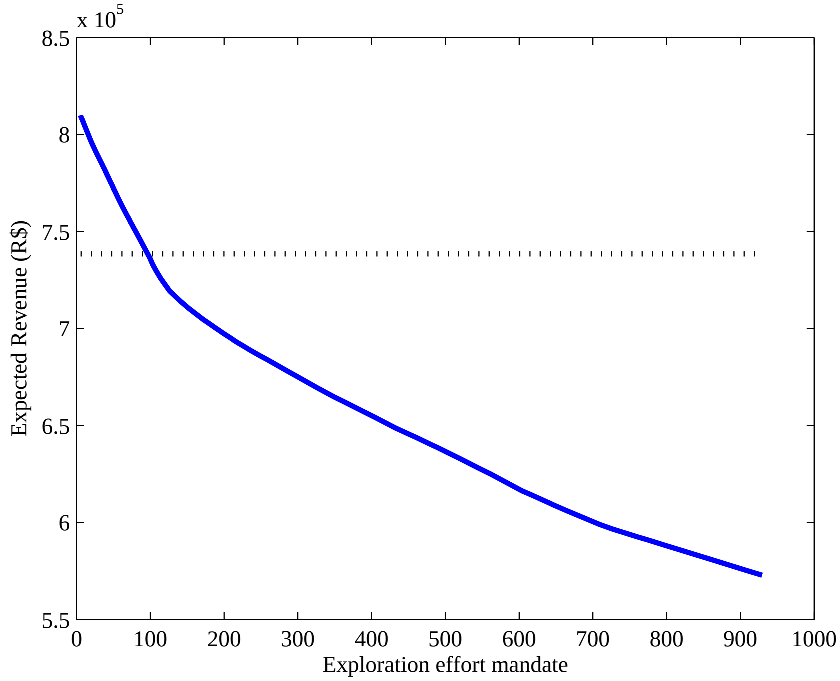
Exploration job	**Points**
Exploratory well	1,000
km 2D seismic	10
km^2 3D seismic	50

Table 8: Counterfactual revenue (in thousands)

	Expected Revenue at $\bar{x}_t$		Total Expected Revenue		Revenue forfeited	
	Score	**First price**	**Score**	**First price**	**R$**	**US$**
Sale 7	315	346	46,585	51,089	4,504	1,997
Sale 9	1,344	1,474	59,205	64,930	5,725	3,236
Sale 10	3,694	4,052	126,557	138,794	12,237	5,112

Notes: Columns marked as 'Score' refer to expected revenues under the scoring mechanism as implemented in those auctions. 'First price' refers to expected revenues under a pure first price auction mechanism with no *a priori* exploration commitments Counterfactual revenues in Brazilian Reais (R$) in all columns but the last.

Figure 4: Counterfactual revenue comparison: Mandates vs. scoring auction



Notes: The solid line shows the expected revenue from first price sealed auctions in which the exploration mandates are set *ex-ante*. The dotted line marks the expected revenue from the implemented scoring mechanism. All revenues are normalized to a tract at the average of characteristics, $\bar{x}$.