Bailouts and the Preservation of Competition

The Case of the Federal Timber Contract Payment Modification Act

James W. Roberts* Andrew Sweeting†

July 27, 2015

Abstract

We estimate the value of competition in United States Forest Service (USFS) timber auctions, in the context of the Reagan administration's bailout of firms that faced substantial losses on existing contracts. We use a model with endogenous entry by asymmetric firms, allowing survivors to respond to the exit of bailed-out firms by entering more auctions and for these marginal entrants to have lower values than firms that would choose to enter in any event, a selective entry effect. Observed asymmetries and selective entry contribute to us finding that the bailout may have increased USFS revenues in subsequent auctions quite substantially.

JEL CODES: D44, H81, L20, L73

Keywords: Bailouts, Auctions, Entry, Selection, Timber

*Department of Economics, Duke University and NBER. Contact: j.roberts@duke.edu.

†Department of Economics, University of Maryland and NBER. Contact: sweeting@econ.umd.edu.

We are extremely grateful to Susan Athey, Jonathan Levin and Enrique Seira and Doug MacDonald of the Timber Data Company for sharing their data with us and to Coleman Doggett and the staff of the Forest History Society for their additional insight on the timber industry. We appreciate useful feedback from John Asker, Phil Haile, Ali Hortaçsu, Jakub Kastl, Tong Li, Brian McManus, Rob Porter, Katja Seim and numerous seminar and conference participants. Excellent research assistance was provided by Christoph Bauner, Yair Taylor and Huihui Wang. The research was supported by NSF grant SES-1260876. Any errors are our own.

1 Introduction

Government bailouts for financially-troubled industrial firms have been justified by policymakers on the grounds that they want to preserve employment, protect strategically impoirtant assets and maintain competition that might be weakened if the troubled firms were liquidated. Arguments that bailouts will prevent surviving competitors from exercising significantly greater market power were used during the rescue of defense contractor Lockheed in 1971, the first major industrial bailout in the U.S., as well as in subsequent bailouts, such as those of the automobile manufacturer Chrysler, and the airlines Pan-Am and Eastern.[1] Surprisingly, given the controversy surrounding most bailouts, and economists' natural interest in how market structure affects outcomes, there is almost no research trying to quantify the value of preserving competition in these settings (as discussed below, Wollmann (2014) is an exception).

In this article, we study this type of justification in the context of the Reagan administration's 1984 bailout of timber companies that faced bankruptcy following a slump in lumber prices. In this case it was argued that the bailout would maintain competition in future auctions where the government sells contracts to harvest timber on public lands. We focus on United States Forest Service (USFS) timber auctions in California, one of the three states (together with Oregon and Washington), that were most affected by the bailout. While many hundreds of sawmills (mills) and logging companies (loggers) purchase timber nationally, the bailout had potentially important effects for USFS revenues because, for a given tract, the potential bidders are, in practice, limited to the small number of firms active in nearby forests. A feature of how the bailout was implemented allows us to identify insolvent firms that would have been particularly likely to exit without assistance, and we estimate a model to quantify how much USFS revenues in subsequent auctions would have changed if these insolvent firms had exited.

As well as providing one of the first empirical evaluations of some of the effects of an industrial bailout, a central contribution of our paper comes from our use of an empirical model of competition in auctions where bidders are asymmetric (mills and loggers), and

[1] Lockheed: Secretary of the Treasury, John Connally, noted that "You can't have a corporate organization of [Lockheed's] type go under without seriously and adversely affecting future competition among suppliers to the defense establishment" (Senate, 92nd Congress 1st Session (1971)). See also Markusen (1997) and Newhouse (1982). Chrysler: Rep. John LaFalce (D-NY) said "I think we should consider...the preservation of competition within the automobile industry" (House of Representatives, 96th Congress 1st Session (1979)). Pan-Am and Eastern: the House Aviation subcommittee hearings included "extensive discussion of actions the government" could take to "preserve competition" in the industry. It was decided that the government needed the existing carriers to survive so they could remain "competitors to preserve the benefits of deregulation." (House of Representatives, 96th Congress 1st Session (1979)). See also Borenstein (1992) and Mathiesen (1995). Prior to Lockheed's 1971 bailout, assistance to private firms in the US was associated with wars and economic emergencies (Ritholtz (2009)).

entry is both endogenous and potentially *selective.* Endogeneity of entry arises when firms face costs of participating in an auction that are large enough to discourage at least some potential entrants from participating. As entry decisions are strategic substitutes, when some potential bidders are eliminated, as in our counterfactuals, the remaining firms will be more likely to enter, reducing any losses to the seller. By selective entry, we mean that these new (marginal) entrants may tend to have lower values for the timber being sold, and so be less valuable to the seller, than inframarginal entrants, who would want to enter auctions whether or not they faced competition from the bailed-out firms. As we discuss below, the degree of selection can have important effects on the value of additional potential bidders in an auction setting.

We model auctions with endogenous and selective entry by considering a two-stage auction game in an independent private values (IPV) environment. In the first-stage potential bidders receive noisy, private signals about their values for the object being sold, before taking simultaneous decisions about whether to enter the auction, which involves incurring a common entry cost. In the second-stage, entrants learn their true values and submit bids in a second-price auction.[2] In equilibrium, a firm will enter when it receives a high enough signal and the degree of selection, i.e., the extent to which inframarginal entrants tend to have higher values than non-entrants, will depend on the precision of the signals. In this way, our model can capture, as polar cases, two models that have been widely used in the theoretical literature and which also assume a common entry cost: the Samuelson (1985) (S) model, where each potential entrant knows its value before deciding whether to enter, so selection is perfect, and the Levin and Smith (1994) (LS) model, where each potential entrant only knows the distribution from which its value is drawn.

We view our model as a reasonable representation of the way that timber auctions actually work. A firm wishing to submit a bid conducts a survey ('cruise') of the tract in order to evaluate how much the timber on the tract is worth to the firm. A cruise, which can involve sending a team to the forest for several days, implies a non-trivial cost to participating in the auction, and we think of the entry cost in our model as being primarily the cost of acquiring information. Consistent with the IPV assumption, valuations may differ across firms, as firms may have heterogenous capacities to process different types of timber and in the contracts that they have to sell cut or processed timber to customers. However, even before they conduct a cruise, firms are likely to have some information about their private values through their knowledge of local forests and their own contracts and capabilities, as

[2] As discussed in detail below, our data comes from open-outcry auctions. We estimate the model assuming that the outcome of an open-outcry auction involves the entrant with the highest value winning the auction at a price equal to the value of the second-highest bidder.

well as the information on the tract published by the USFS when announcing the auction.[3]

We estimate our model using a sample of USFS auctions held in California from 1982 to 1989. Our estimates imply moderately selective entry into auctions, consistent with firms having some private information on their values but also collecting valuable additional information by performing cruises. Estimated entry costs are high enough that many firms that believe they have low values, in particular logging companies, choose not to enter, and they are broadly consistent with estimates of how much cruises actually cost.

In our counterfactuals, we remove the firms that were identified as being insolvent at the time of the bailout, but which we see as active in our data, as potential entrants from a set of auctions that were held after the bailout took place.[4] We predict that without these firms, USFS revenues would have fallen by an average of just over 11%. This can be seen as a fairly large effect as, for the average auction, we are only reducing the number of potential bidders from nine to seven, and in many settings, IO economists believe that three or four firms are sufficient to generate quite competitive outcomes, at least in the absence of collusive behavior.[5] It is also large relative to how much we predict that the USFS could have increased its revenues, without the bailout, by using an optimal reserve price (2.2%).

This large effect reflects three features of our model, the data and our estimates. First, most of the insolvent firms were mills, and our estimates show that mills have, on average, much higher values than logging companies, making them more valuable to the USFS. Second, in common with other studies of timber, we find that, within bidder type, values for tracts are heterogenous, so that adding an additional competitor can increase the expected first- or second-highest order-statistics of values significantly. This result holds even though we allow for cross-type asymmetries and cross-auction unobserved heterogeneity in values. Finally, selective entry plays an important role, as firms that enter auctions when the insolvent firms are removed, tend to have relatively low values and so cannot offset the drop in revenues very much. As discussed below, an LS-style common-entry cost model without no selection could predict that the USFS's revenues would increase when the number of potential entrants was reduced.

One should view our work as providing a partial analysis of the effects of the bailout,

[3]The information released by the USFS, unlike some state agencies, does not contain information about tree diameters, which is relevant information for mills that have machinery that can process particular sizes of tree.

[4]We only consider auctions where, once we remove the insolvent firms, there would still be two potential entrants. We are therefore ignoring auctions where the bailout prevented monopsony, and this will tend to give us smaller estimates of the value of preserving competition.

[5]For example, Bresnahan and Reiss (1991) find that two or three firms generate most of the effects of competition in a number of service industries. Mergers are also now rarely challenged unless the merger will reduce the number of significant competitors below four (Coate and Ulrick (2005)). Of course, these results refer to the number of actual competitors (entrants), not the number of potential entrants.

focusing on the revenue effect of changing the set of potential bidders in USFS auctions. We rely on several strong assumptions that could be relaxed in future work. In particular, we assume that value distributions, and other structural parameters, would be the same with and without the bailout. In reality, the bailout would have affected lumber prices and, therefore, the willingness of firms to pay for timber. As lumber prices are set in a much larger national market, quantifying the size of the effect on values would require estimates of the supply-elasticity of the rest of the domestic industry and imports, estimates of how much the bailout might have affected the exit decisions of solvent firms and a model of how expectations of future lumber prices would affect the bidding behavior of a mill or logger.[6] As a robustness check we show that it would have taken increases in surviving mill values of more than 10% to offset the effect of the removal of the insolvent firms on USFS revenues. We also do not try to account for the fact that, even if the insolvent firms had been liquidated without the bailout, the plant and equipment of the liquidated firms, might have been purchased by competitors or new entrants, although a long-run trend where the number of mills was falling suggests that de novo entry may have been unlikely.[7] The USFS could also have responded to firm exit by changes in strategy more radical than changing its reserve price, such as changing the number of auctions held, their location, or changing the amount of information provided to bidders. Finally, we do not try to quantify the effects of the bailout on other sellers of timber, including the federal Bureau of Land Management, state agencies and private landowners, or local economies, in many of which the timber industry may have accounted for a substantial share of employment.[8]

Our paper is related to several literatures. Industrial bailouts have received little attention in the academic literature, even though they are often justified by economic arguments such as the value of maintaining competition. Wollmann (2014) estimates a repeated two-stage entry model and uses it to predict how eliminating GM and Chrysler would have affected the commercial vehicle industry, taking into account that rival firms would likely have expanded their product portfolios. Wollmann's question is similar to ours, but as he assumes that unobserved product qualities and marginal cost shocks are unknown to firms

[6] In the early 1980s about one-third of the U.S. softwood harvest came from the Pacific coast (Adams, Hayes, and Daigneault (2006)), a share that subsequently declined as production transferred to the southern US.

[7] For example, the number of mills in California fell from 216 in 1968, to 142 in 1976 and 101 in 1982. Even with the bailout, the decline continued so that there were only 93 mills in 1988. There was an even more rapid decline in the 1990s when the courts prohibited logging in the habitats of the Northern Spotted Owl (Morgan, Keegan, Dillon, Chase, Fried, and Weber (2004)).

[8] Adams, Hayes, and Daigneault (2006) estimate that for the Pacific Southwest region, including California, national forests contributed 37.5% of the timber harvest in 1982, with 2.4% from other government forests, 52.3% from forests owned by industry and 7.8% from non-industrial private timberlands. A 25% share of USFS revenues was also distributed to state governments (U.S. GAO (1995)).

when they take entry decisions, his empirical approach effectively assumes no selection, like almost all of the entry literature in non-auction settings. In contrast, allowing for selection is central to our model.[9]

Bulow and Klemperer (1996) show that additional competition (i.e., an additional bidder) is more valuable to a seller than an optimal auction design, in an IPV setting with symmetric bidders and exogenous entry. In this case, the optimal design is simply a standard auction with an optimal reserve price. When bidder entry is endogenous, there are no similar general results, and the value of both additional potential bidders and different designs will depend on the way that entry is modeled. One standard approach, following LS, assumes that there is a common entry cost and that potential bidders have no private information about their values when they take their entry decisions. When bidders are symmetric, these assumptions lead to a mixed strategy symmetric equilibrium in the entry game, and when equilibrium entry probabilities are strictly less than one (and above zero), the model has the feature that expected revenues decline in the number of potential entrants.[10] When bidders are asymmetric, as we want to allow in our setting, the LS assumptions imply that at most one type should be mixing over entry in a type-symmetric equilibrium. Given how we define the set of potential entrants, this assumption would be inconsistent with our data as we observe partial entry by both mills and loggers in many auctions.[11] These results can change when one allows either for potential bidders to have some information on their values (selection), as we do in this paper, or one allows for potential bidders to draw idiosyncratic entry costs (e.g.,

[9]To be precise, Wollmann's approach assumes that products that only enter when GM and Chrysler are eliminated do not have systematically lower unobserved quality or higher costs than those that enter when GM and Chrysler are competitors. Standard entry models, such as the Berry (1992) model for airline markets, allow for firms to receive unobserved shocks to their payoffs prior to taking entry decisions, but they assume that these shocks do not affect the profits of other firms, so they should be interpreted as affecting sunk or fixed costs, rather than product quality or marginal costs. Similarly, dynamic entry models (e.g. Ericson and Pakes (1995)) assume that potential entrants are symmetric apart from i.i.d. shocks to their entry costs. In our model, signals are correlated with a bidder's value and the selected value of an entering bidder should affect other bidders' payoffs. In Roberts and Sweeting (2012) we estimate a model of entry into airline markets that allows for selection on entry costs and product qualities.

[10]A precise statement of Levin and Smith's (1994) result is that when the seller sets an optimal reserve price, expected revenues will increase in the number of (symmetric) potential bidders up to a number n^*, the highest number such that all bidders will choose to enter for sure, before declining monotonically above n^* (the corollary to their Proposition 9). This reflects the lack of the coordination in the entry process when potential entrants make simultaneous, independent entry decisions. In particular, as the number of potential entrants rises, the probability that a given player enter falls, and the probability that no bidders or a very small number of bidders enter rises, which reduces the seller's revenues even if the expected number of entrants increases.

[11]In estimating an LS model using data very similar to ours, Athey, Levin, and Seira (2011) assume that all potential mill entrants enter, so that only loggers mix. In an LS model with two asymmetric types, removing potential bidders of a high-value type that enters for sure would tend to hurt the seller even if the lower-value type mixes over entry.

Moreno and Wooders (2011)).[12] We assume that entry costs are common across potential bidders as all timber companies have access to the same cruising technologies, while it also seems plausible that they should have some information on their values prior to performing a cruise.[13]

Many papers have empirically estimated auction models with endogenous entry, typically under the assumption that there is no selection.[14] Li and Zheng (2009) estimate an S-type of entry model with selection, and compare its fit to an LS model with heterogenous entry costs and an LS model with a common entry cost, finding that the last model fits their data on bidding for highway mowing contracts the best. Marmer, Shneyerov, and Xu (2013) and Gentry and Li (2014) consider the identification of models with imperfect selection based a generalization of the signal structure that we consider. We estimate a parametric model, using a method based on importance sampling (Ackerberg (2009)), which facilitates allowing for cross-auction unobserved heterogeneity in both bidder values, the degree of selection and entry costs.[15] In related work, Roberts and Sweeting (2013) and Bhattacharya, Roberts, and Sweeting (2014), we consider the value of alternative auction designs, such as a sequential bidding procedure and a two-stage entry rights approach, when entry is partially selective. In the current article, we use a partially selective model to find the value of additional potential bidders, and while we are motivated by the bailout that affected our data, one can also see the number of potential bidders as another margin that the seller could try to affect through its choice of sale strategy.

There is also a significant literature that has specifically studied timber auctions in several countries. We follow this literature in assuming that an IPV model is appropriate for the

[12]Samuelson (1985), Menezes and Monteiro (2000) and Li and Zheng (2009) show that in the S model, where potential bidders know their values when deciding whether to enter, the relationship between the number of potential bidders and expected revenues is distribution/parameter dependent. Li and Zheng (2009) identify the forces that determine how an increase in the number of potential bidders affects revenues in models with endogenous entry. In particular they show how a "competition" effect increases revenues through more aggressive bidding, while an "entry effect", where each firm may become less likely to enter when it faces more competition, will decrease revenues. In our setting, the relationship between the number of potential bidders and revenues will also depend on the asymmetry between bidder types and the degree of selection.

[13]See Sweeting and Bhattacharya (forthcoming) for more discussion comparing models with selection and models with variation in entry costs.

[14]See, for example, Athey, Levin, and Seira (2011) and Athey, Coey, and Levin (2013), who examine timber auctions using similar data, Bajari and Hortaçsu (2003), Palfrey and Pevnitskaya (2008), Krasnokutskaya and Seim (2011), Li and Zhang (2015), Bajari, Hong, and Ryan (2010) or Ertaç, Hortaçsu, and Roberts (2011).

[15]We have used this estimation approach in recent work on auctions (Roberts and Sweeting (2013) and Bhattacharya, Roberts, and Sweeting (2014)) and on modeling entry and competition in airline markets (Roberts and Sweeting (2012)). Other applications of the method include Hartmann (2006), Hartmann and Nair (2010) and Wang (2015) who use these methods to study consumer dynamic discrete choice problems and Bajari, Hong, and Ryan (2010) who use a related method to analyze entry into a complete information entry game with no selection.

auctions in our sample (e.g., Baldwin, Marshall, and Richard (1997), Brannman and Froeb (2000), Haile (2001) and Athey, Levin, and Seira (2011) (ALS hereafter)), and we allow for unobserved cross-auction heterogeneity in values which several papers (e.g., ALS, Li and Zheng (2009)) have shown to be important. Many papers in this literature estimate the seller's optimal reserve price (Mead, Schniepp, and Watson (1981), Mead, Schniepp, and Watson (1984), Paarsch (1997), Haile and Tamer (2003), Li and Perrigne (2003) and Aradillas-Lopez, Gandhi, and Quint (2013)). Our estimates indicate that the potential benefit to the seller of using an optimal reserve is quite small, and, in particular, much lower than the value of additional potential bidders, in the context of a model with selective entry.

The paper proceeds as follows. Section 2 describes the 1984 timber bailout in more detail. Section 3 presents our model of entry and competition in USFS timber auctions. Section 4 introduces the data. Section 5 describes our estimation method and discusses identification. Section 6 presents our structural estimates. Section 7 examines how much USFS revenues would have fallen if insolvent firms rescued by the bailout had exited the industry. Section 8 concludes. The Appendices contain details of our approach to dealing with the model's multiple equilibria and Monte Carlo studies of our estimation method.

2 USFS Auctions and The Federal Timber Contract Payment Modification Act of 1984

For over forty years, federal and state agencies have used auctions to sell contracts for harvesting timber on public land to private companies. Bidders in these auctions can be classified (e.g. ALS) as either mills or loggers, depending on whether they own processing facilities, with loggers reselling cut-timber to mills. When the USFS announces a sale, it provides its own estimate of the volume of each species of timber on the tract as well as estimated costs of removing and processing the timber, together with a reserve price. A firm must indicate it is willing to pay the reserve to participate in the auction. After the sale is announced, each bidder can perform its own private cruise of the tract to assess its value, and people in the industry have told us that firms will not bid without performing a cruise. These cruises can be informative about the tract's volume, species make-up and timber quality. The auction is held a few weeks after the sale is announced. The USFS uses both open-outcry and sealed-bid auctions, with the mix of formats varying over time. When we estimate our model we will use data on open-outcry auctions.

A feature of timber contracts prior to the bailout was that winning bidders only paid the seller when the timber was cut.[16] As contracts were also quite long in duration (many contracts in California lasted more than five years), this provided an incentive for firms to speculate by delaying the harvest when prices were expected to rise. Of course, this also meant that a winner would face large losses if lumber prices fell as, even if it returned the tract to the USFS, it would be liable for the difference between their bids and the winner's bid when the tract was re-auctioned.

Figure 1 shows the time series of quarterly prices (in 1983 $s per thousand board feet) for processed Douglas Fir, a common California lumber product (Sugar Pine and Hem Fir show similar patterns), from 1975 to the end of 1988, together with the average and 75th percentile of auction sale prices. We also show the average reserve price of USFS auctions in California for the period in which these are consistently reported in our data.

Both auction and lumber prices in California rose significantly in the late 1970s, a period that has been termed the "timber bubble" by Mattey (1990), who attributes this increase to a mix of speculative bidding and overly-optimistic USFS projections of construction demand for lumber.[17] Some evidence for speculation comes from the increasing difference between average sale prices and auction reserve prices, which, under the so-called "residual value" method, were based on the difference between the USFS's estimate of what the timber was worth at current prices and its estimates of harvesting costs.[18] Lumber prices fell dramatically in 1980 and 1981 when construction demand plunged as the Federal Reserve rapidly increased interest rates, in an attempt to reduce inflation (the average interest rate on a 30-year mortgage was 18.5% in November 1981[19] and housing starts in 1981 were 38% below their 1979 level[20]). Auction prices fell some months later than lumber prices, possibly because bidders, especially those without their own timberland, wanted to secure access to timber in case lumber prices recovered (Mattey (1990)).[21]

Mattey describes some firms faced losses of over $200/mbf on their existing federal contracts when prices fell, with industry-wide losses exceeding $2 billion (Wiegner (1984)). Con-

[16] In response to the crisis of the early 1980s, new contracts required winners to make both an initial downpayments and annual payments to the USFS (see https://www.law.cornell.edu/uscode/text/16/618, accessed July 21, 2015).

[17] Expectations about rising construction demand were coupled with expectations of falling softwood harvests in the Pacific Northwest due to its increased reliance on younger, smaller trees. U.S. GAO (1978), for example, placed weight on an Oregon State University study that predicted a six-fold increase in softwood prices between 1976 and 2000.

[18] See Baldwin, Marshall, and Richard (1997) for a detailed discussion of the method. The level of the reserve price was also constrained by a policy that 85% of auctions should result in a sale.

[19] http://www.freddiemac.com/pmms/pmms30.htm (accessed July 13, 2015)

[20] http://www.huduser.org/portal/periodicals/ushmc/summer12/USHMC_2q12_historical.pdf (accessed July 13, 2015)

[21] As James Geisinger, a representative for one firm, stated "there are basically two ways to go out of business in our industry. One is to have no timber to process, and the other is to have timber that may be too costly to process." (Mattey (1990), pg. 32)

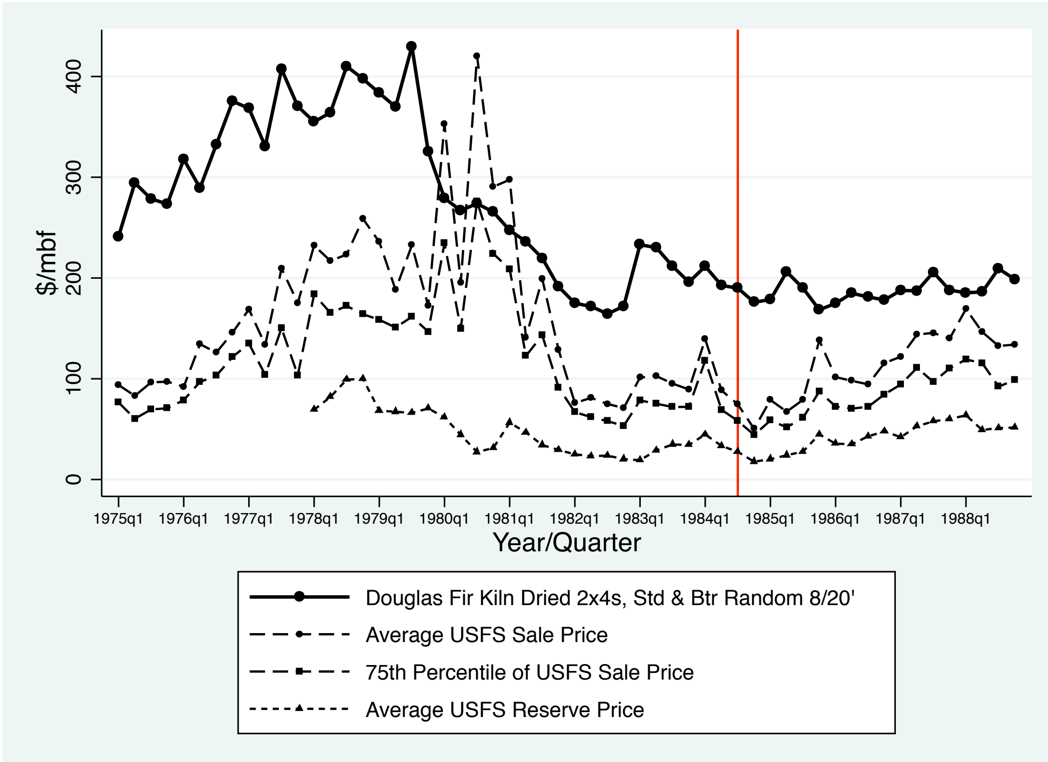

Figure 1: Prices of lumber products and USFS winning bids and reserve prices in California over time. Both are measured in $/mbf, in 1983 dollars. The vertical line is the quarter the Act was passed. The Douglas Fir prices come from Random Lengths Publishing Inc. The prices are quarterly averages of the prices, net f.o.b., received by surveyed mills in California. 2x4 indicates the type of lumber, Std & Btr is the wood grade, and 8/20' means that the shipments contained random lengths ranging from 8 to 20 feet. The USFS auctions that we use to construct the average sale price and the difference between sale price and reserve price exclude set-asides and salvage sales. Average reserve prices before 1978 are not shown due to a large number of missing values in our data.

sequently, the affected firms lobbied the government for relief from these contracts, which was attractive as, in bankruptcy, the government might "be lucky if it ended up collecting 25 cents on the dollar for defaulted contracts" (House of Representatives (1984)).

In 1983 the government moved to lengthen existing contracts (Federal Register 48 (1983)), but, when it appeared that this would not prevent troubled firms from shutting down (Reagan (1984)), Congress, with the support of the USFS, passed the Federal Timber Contract Payment Modification Act (HR 2838), which was signed into law on October 16th, 1984. The bill was sponsored by congressman from western states, including California, partly on the grounds that it would provide for "enhanced competition" (Senate (1984)) in future government auctions.[22]

[22]For example, Rep. Al Swift (D-WA) argued "Failure of these...companies will result in the increased

The Act allowed firms to buy out their existing contracts, returning tracts to the USFS at rates much lower than the prices in the original contracts (to avoid further depressing prices, the USFS spread out the sale of the returned tracts over a seven year period). Buyout rates were structured to give the most relief to firms in the most financial trouble. Firms with losses above their net book value could buy out at a rate of $10/mbf. Firms with losses between 50 and 100 percent of their net book value, could buy out at the maximum of $10/mbf and 10 percent of the contract overbid (the original price less the USFS's estimate of the value of the remaining merchantable timber on the tract). Firms with smaller losses could buy out at the maximum of $10/mbf and a percentage of the overbid that varied with the volume being bought out.[23] In total, a mixture of local firms and large national timber companies, including Weyerhaeuser (1984 net book value of $3.3 billion) and the timber subsidiary of Burlington Northern ($4.4 billion) paid $172 million (1984 dollars) for relief from 1,625 USFS contracts covering 9.7 billion board feet of timber that were originally priced at $2.5 billion (U.S. GAO (1989)).[24] Some firms' financial positions were transformed dramatically by the bailout. For example, Bohemia Corp. paid only $2 million to lower losses of $138 million (144% of its net book value) to $63 million (firm-specific numbers are taken from Wiegner (1984)).

In data provided to us by Doug MacDonald of the Timber Data Company, which helped the government determine buyout rates, we observe the rate paid by each firm that bought out of contracts. We define the set of firms that likely faced insolvency which we will assume would have exited without the bailout in our counterfactuals as those that paid the minimum buyout rate of $10/mbf. The average buyout rate of the other firms in our auction data that participated in the bailout is $41.90/mbf.

Figure 2 gives a sense of the scale of the bailout by indicating which mills in northern California, where most of our auction data comes from, were owned by firms that participated in the bailout. Roughly half of all mills participated and we classify around half of these participants as facing insolvency. The figure also shows the location of post-bailout (i.e., those taking place after October 1984) auctions where at least one participant mill submitted a bid. These auctions account for over 83% of the post-bailout auctions in our data, and 51% of these auctions were actually won by an insolvent mill.[25]

---

concentration of the timber industry, which will lead to decreased competition on future contract bids" (House of Representatives (1984)).

[23]For the first 125 million bf, this percentage was 15%. The percent increased in 5 percentage point increments for every 25 million bf over that amount (Muraoka and Watson (1986)).

[24]Under the same legislation, firms also paid $11.9 million to buy out of 279 Bureau of Land Management contracts originally priced at $436 million (U.S. GAO (1989)).

[25]These are only a sample of the USFS auctions in this region of California during this time period since our sample excludes first price auctions and auctions with some extreme features (like very high or low acreage). We give details on how we form our data sample in Section 4.

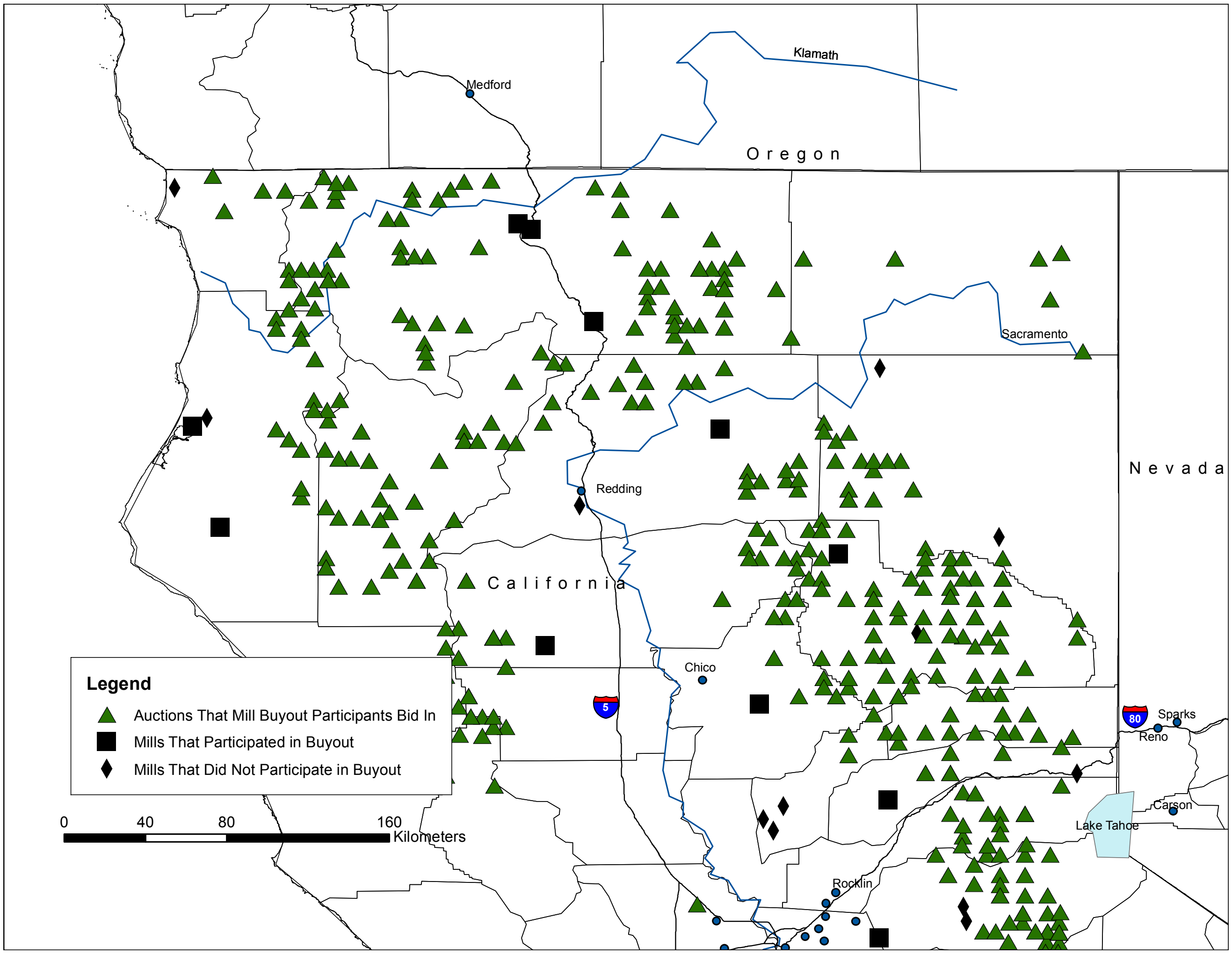

Figure 2: The figure shows the location of mills in Northern California (by participation in the buyout) and of all auctions held after October 1984 where at least one participating mill bid.

Of course, the effect of removing insolvent firms should depend on how many other firms might enter auctions in their place. A key feature of the data is that the firms typically only participate in auctions in quite limited geographic areas, so that the set of potential entrants is usually limited to firms that are active in the surrounding forests. This is illustrated in Figure 3 which shows the set of auctions entered by four specific mills that participated in the bailout. Given this pattern, and the mill and auction locations in Figure 2, the elimination of insolvent mills would clearly have reduced the number of mill potential entrants significantly in a substantial number of auctions. Fewer loggers bought out contracts, but as we show below, loggers tend to have much lower values for timber, so that the presence of loggers as potential bidders would have been largely unable to offset losses to the USFS had insolvent mills exited.

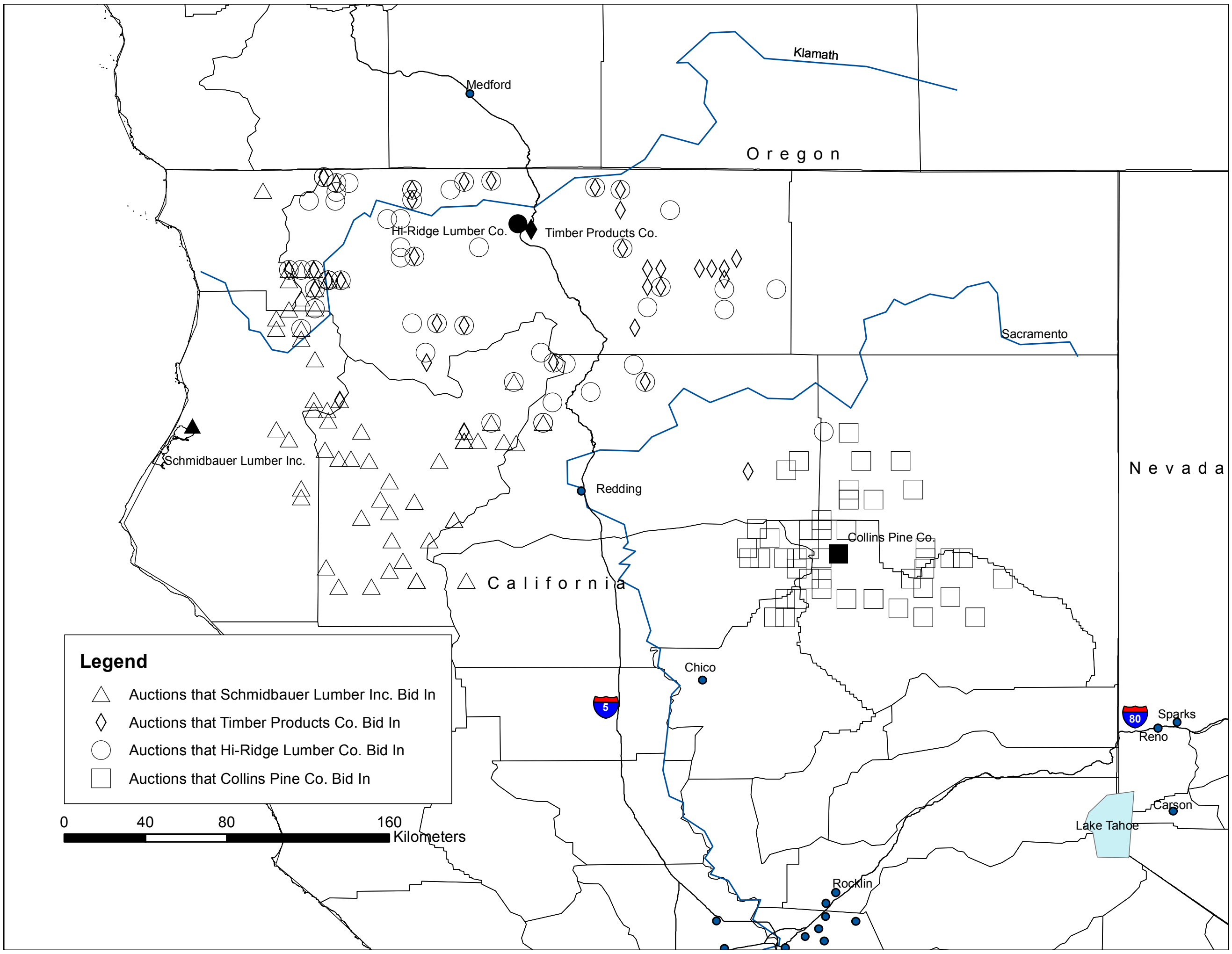

Figure 3: The figure shows the location of four specific mills that bought out of contracts and of auctions held after 1984 that these mills bid in.

3 Model

We now present the model that we estimate and use to assess the effects of removing insolvent firms from post-bailout auctions. As mentioned above, we focus on open-outcry auctions and follow the literature in assuming that an IPV model is appropriate.[26]

Consider an auction of timber tract a with $N_{\tau a}$ potential bidders (firms) of observable type τ with $\overline{\tau}$ types in total. In our setting $\overline{\tau} = 2$ and the types are mills and loggers. Type τ firm values V (in \$/mbf) are i.i.d. draws from a distribution $F^V_{\tau a}(V)$ (with associated pdf $f^V_{\tau a}(V)$), which is continuous on an interval $[0, \overline{V}]$. We set $\overline{V} = \$500$/mbf, which is significantly above the highest price observed in our data. The distribution can depend

[26] We use data from 1982-1989 when the ability of winners to resell their contracts, which can introduce a common value element, was limited (see Haile (2001) for an analysis of timber auctions with resale).

on the characteristics of the tract being sold, although the support is fixed. Both the $N_{\tau a}$s and the $f^V_{\tau a}(V)$s are common knowledge to all potential bidders. In practice, we will assume that the $f^V_{\tau a}(V)$s will be proportional to the pdfs of lognormal distributions with location parameters $\mu_{\tau a}$ and squared scale parameters σ^2_{Va} on the $[0, \overline{V}]$ interval, and, as a labeling convention, that $\mu_{1a} > \mu_{2a}$.

Firms play a two stage game. In the first stage, each firm independently decides whether to enter the auction, which requires incurring an entry cost K_a. Participation in open-outcry auctions is costly partly because bidders need to attend the auction, but in our context we think of most of the cost as coming from the cost of performing a cruise of tract, and, consistent with industry practice, we assume that firms cannot bid without incurring K_a. Prior to taking an entry decision, each firm i receives an independent, private information signal s_i about its value, where $s_i = v_i z_i$, $z_i = e^{\varepsilon_i}$, $\varepsilon_i \sim N(0, \sigma^2_{\varepsilon a})$. A firm who pays the entry cost finds out its true value v_i, since at this point the firm will have performed its own cruise. It is possible that a bidder's realized value is below the USFS's announced reserve price, R_a. For reasons connected with equilibrium selection, the parameters σ^2_{Va}, $\sigma^2_{\varepsilon a}$ and K_a are assumed to be common across the types.

In the second-stage, entrants with values above R_a submit bids in a second price auction. If any bids are submitted the object is sold to the highest bidder at a price equal to the maximum of the second highest bid and the reserve price. Although the auction format is modeled as second price sealed-bid, equilibrium strategies would be the same in an English button auction as we assume that bidders have independent private values. In Section 5 we will explain how we apply our model to data from an open-outcry auction. We assume non-collusive bidder behavior in the second-stage because, although there has been some evidence of bidder collusion in open-outcry timber auctions, ALS find strong evidence of competitive bidding in a similar sample of open-outcry auctions in California. Of course, collusion might have been sustained if the insolvent firms had exited the industry, and, in this case, our predictions may substantially underestimate how much USFS revenues would have fallen without the bailout.

3.1 Equilibrium

We assume that players use strategies that form type-symmetric Bayesian Nash equilibria, where "type-symmetric" means that every player of the same type will use the same strategy. In the second stage, entrants know their values so it is a dominant strategy for each entrant to bid its value. In the first stage, players take entry decisions based on what they believe about their value given their signal. By Bayes Rule, the (posterior) conditional density $g_{\tau a}(v|s_i)$

that a player of type τ's value is v when its signal is s_i is

$$g_{\tau a}(v|s_i) = \frac{f^V_{\tau a}(v)\frac{1}{\sigma_{\varepsilon a}}\phi\left(\frac{\ln\left(\frac{s_i}{v}\right)}{\sigma_{\varepsilon a}}\right)}{\int_0^{\overline{V}} f^V_{\tau a}(x)\frac{1}{\sigma_{\varepsilon a}}\phi\left(\frac{\ln\left(\frac{s_i}{x}\right)}{\sigma_{\varepsilon a}}\right)dx} \tag{1}$$

where $\phi(\cdot)$ denotes the standard normal pdf.

The weights that a player places on its prior and its signal when updating its beliefs about its true value depend on the relative variances of the distribution of values and ε (signal noise), and this will also control the degree of selection. A natural measure of the relative variances is $\frac{\sigma^2_{\varepsilon a}}{\sigma^2_{Va}+\sigma^2_{\varepsilon a}}$, which we will denote α_a. If the value distribution were not truncated above, a player i's (posterior) conditional value distribution would be lognormal with location parameter $\alpha_a\mu_{\tau a} + (1-\alpha_a)ln(s_i)$ and squared scale parameter $\alpha_a\sigma^2_{V\tau a}$.

The optimal entry strategy is a type-specific threshold rule where a firm enters if and only if its signal is above a cutoff, $S'^{*}_{\tau a}$.[27] $S'^{*}_{\tau a}$ is implicitly defined by the zero-profit condition that the expected profit from entering the auction of a firm with the threshold signal will be equal to the entry cost:

$$\int_{R_a}^{\overline{V}}\left[\int_{R_a}^{v}(v-x)h_{\tau a}(x|S'^{*}_{\tau a}, S'^{*}_{-\tau a})dx\right]g_{\tau a}(v|s)dv - K_a = 0 \tag{2}$$

where $g_{\tau a}(v|s)$ is defined above, and $h_{\tau a}(x|S'^{*}_{\tau a}, S'^{*}_{-\tau a})$ is the pdf of the highest value of other entering firms (or the reserve price R_a if no value is higher than the reserve) in the auction. A pure strategy type-symmetric Bayesian Nash equilibrium exists because optimal entry thresholds for each type are continuous and decreasing in the threshold of the other type.

With multiple types, there may be several type-symmetric equilibria, where different types of firms have different entry thresholds. The entry literature has considered various ways of dealing with multiplicity. The approach we take here is to assume that σ_{va}, $\sigma_{\varepsilon a}$ and K_a are the same across the types and to assume that firms play an equilibrium where $S'^{*}_{1a} < S'^{*}_{2a}$ (the type with higher mean values has the lower threshold). With two types of bidders, our parameter restrictions imply that there is always exactly one equilibrium of this type. Appendix A explains the restrictions in more detail.[28]

[27] A firm's expected profit from entering is increasing in its value, and because values and signals are independent across bidders and a firm's beliefs about its value is increasing in its signal, a firm's expected profit from entering is increasing in its signal. Therefore, if a firm expects the profit from entering to be greater (less) than the entry cost for some signal s, it will also do so for any signal $\widetilde{s}$ where $\widetilde{s} > s$ ($\widetilde{s} < s$). As it will be optimal to enter when the firm expects the profit from entering to be greater than the entry costs, the equilibrium entry strategy must involve a threshold rule for the signal, with entry if $s > S'^{*}_{\tau a}$.

[28] We choose this approach for several reasons. First, it is computationally simple to implement and it

It is computationally straightforward to solve for the equilibrium entry thresholds given our selection rule. Specifically, we use a standard non-linear equation solver (in MATLAB) to solve the zero profit conditions (Equation (2)) subject to the constraint that $S'^*_{1a} < S'^*_{2a}$. The integrals in Equation (2) are evaluated on a 10,000 point grid, which runs from 0.01 to $\overline{V}$.[29]

4 Data

We estimate our model using a sample of USFS open-outcry auctions from California (USFS Region 5), where many firms participated in the bailout.[30] From the set of all such auctions held between 1982 and 1989, we drop small business set-aside auctions, salvage sales and auctions where data on USFS estimated costs are missing. We also remove auctions with extremely low or high acreage (outside the range [100 acres, 10,000 acres]), volume (outside the range [5 hundred mbf, 300 hundred mbf]), USFS estimated sale values (outside the range [\$184/mbf, \$428/mbf]), maximum bids (outside the range [\$5/mbf, \$350/mbf]) and those with more than 20 potential bidders (which we define below). We keep auctions that fail to sell due to no bidder being willing to meet the reserve price. We are left with 887 auctions. Note that our sample period coincides with auction and lumber prices being quite stable after their large declines in 1980 and 1981.

Table 1 shows summary statistics for our sample. Bids are given in \$/mbf (1983 dollars). For each auction, we observe the names of firms that submit bids. For any auction, we define the set of potential entrants as the observed bidders plus any firm that submitted a bid in any auction for a tract within 50 km of the tract in question over the next month. As 98% of observed bidders also bid in another auction within 50 km in the next month, this approach should capture almost all of the firms that would have been perceived as potential entrants by the USFS or auction participants.[31] The median number of potential bidders in

ensures that our fully parametric model is point identified, which greatly simplifies the counterfactuals. Second, the parameter restrictions are fairly reasonable ex ante (for example, it is likely to cost mills and loggers similar amounts to survey a tract) and, when we make them, we are still able to fit the entry probabilities of both types and revenue outcomes quite well. Finally, in practice, it is clear from the data that mills are more likely to enter auctions, consistent with $S'^*_1 < S'^*_2$, and that they have significantly higher average values than loggers, as they bid more and win more often. When the difference in values is large enough, only one equilibrium, that has the form that we assume, will exist, so that imposing this assumption ex ante is unlikely to be restrictive. Indeed, at the parameters we estimate multiple equilibria are not supported in any of the auctions (based on drawing 10 simulated auctions for each of the auctions in our data).

[29] The tolerances for solving the non-linear equations are set equal to 1e-13. Bhattacharya, Roberts, and Sweeting (2014) extend the methodology to first-price auctions where it is also necessary to solve for equilibrium bid functions.

[30] The data was generously provided to us by Susan Athey, Jon Levin and Enrique Seira.

[31] An alternative approach would be to use geographic areas, such as counties. However, as Figure 3 shows,

an auction is eight (mean of 8.9), evenly split between mills and loggers.

The median number of firms that indicated that they were willing to pay at least the reserve price is four (mean of 3.9), although some other firms may have incurred the entry cost and found out that their values were low. We account for this possibility in estimation. More mills than loggers tend to indicate that they will meet the reserve price (medians of three and one respectively), and, on average, mills submit bids that are 20.3% higher than those of loggers. Loggers win only 15% of the auctions in our sample. As suggested by ALS, mills may have higher values due to cost differences or imperfect competition that loggers face in selling harvested timber.[32] Note that in 54.5% of auctions where we observe at least one logger participating, not all of the mill potential entrants participate. As mentioned in the Introduction, an LS-type model with common entry costs would predict that if any loggers (low-value type) enter, then all of the mills (high-value type) must enter. The fact that this is inconsistent with our data provides one rationale for estimating a model that allows for selection.

Further suggestive evidence comes from estimation of a two-step Heckman selection model (Heckman (1976)) using data on the highest bid submitted by each firm during an auction. With no selection, an entrant's value should be a random draw from the distribution of values in the population of potential bidders, whereas if there is selection, we would expect entrants to have higher values as $S_\tau'^*$ rises, for example when there are more potential entrants. The second step regression uses an entrant's highest bid, as a proxy for its value, as the dependent variable, with tract characteristics, year dummies and a dummy for whether the bidder is a mill or a logger as controls, together with the Inverse Mills Ratio from a first step probit regression of the entry decision of each potential entrant, with the same controls plus a flexible polynomial of the number of other potential mill and logger entrants.[33] The identifying exclusion restriction is that potential competition affects a bidder's decision to enter an auction, but has no direct effect on values.

The second step results appear in column (2) of Table 2, with column (1) showing the estimates when we do not include the Mills Ratio. The positive and significant coefficient on the Inverse Mills Ratio is consistent with bidders being a positively selected sample of potential entrants. In addition, comparing the coefficient on LOGGER across the columns illustrates that selection partially masks the difference between logger and mill values. This

while bidding activity is clustered, many bidders participate in auctions in multiple counties.

[32]The difference between mill and logger entry rates could also be explained by a difference in entry costs for a given auction, which we assume away. In our data, the fact that a logger is less likely to win conditional on participating in the auction (conditional probability 0.155 vs. 0.279 for mills) suggests that loggers do not have higher entry costs, and in practice all firms have access to the same cruising technology.

[33]In an open-outcry auction some bidders may drop out below their values and as entrants we are using the subset of firms that actually participated in the auction.

Variable	Mean	Std. Dev.	25^{th}-tile	50^{th}-tile	75^{th}-tile	N
POTENTIAL ENTRANTS	8.93	5.13	5	8	13	887
LOGGER	4.60	3.72	2	4	7	887
MILL	4.34	2.57	2	4	6	887
INSOLVENT LOGGER	0.42	0.58	0	0	1	887
INSOLVENT MILL	1.64	1.35	1	1	2	887
FIRMS WILLING TO MEET THE RESERVE PRICE	3.86	2.35	2	4	5	887
LOGGER	0.99	1.17	0	1	1	887
MILL	2.87	1.85	1	3	4	887
INSOLVENT LOGGER	0.24	0.45	0	0	0	887
INSOLVENT MILL	1.18	1.04	0	1	2	887
WINNING BID ($/mbf)	86.01	62.12	38.74	69.36	119.11	847
BID ($/mbf)	74.96	57.68	30.46	58.46	105.01	3,426
LOGGER	65.16	52.65	26.49	49.93	90.93	876
MILL	78.36	58.94	32.84	61.67	110.91	2,550
INSOLVENT LOGGER	59.44	40.71	27.80	50.08	83.00	210
INSOLVENT MILL	77.26	58.55	31.02	60.99	108.87	1,050
AUCTION RESULTS IN SALE	0.95	0.21	1	1	1	887
LOGGER WINS	0.15	0.36	0	0	0	887
MILL WINS	0.80	0.40	1	1	1	887
INSOLVENT LOGGER WINS	0.08	0.27	0	0	0	887
INSOLVENT MILL WINS	0.42	0.49	0	0	1	887
RESERVE ($/mbf)	37.47	29.51	16.81	27.77	48.98	887
SELL VALUE ($/mbf)	295.52	47.86	260.67	292.87	325.40	887
LOG COSTS ($/mbf)	118.57	29.19	99.57	113.84	133.77	887
MFCT COSTS ($/mbf)	136.88	14.02	127.33	136.14	145.73	887
SPECIES HHI	0.54	0.22	0.35	0.50	0.71	887
DENSITY (hundred mbf/acre)	0.21	0.21	0.07	0.15	0.27	887
VOLUME (hundred mbf)	76.26	43.97	43.60	70.01	103.40	887
HOUSING STARTS	1620.80	261.75	1586	1632	1784	887

Table 1: Summary statistics for our sample of California ascending auctions from 1982-1989. All monetary figures in 1983 dollars. INSOLVENT refers to a firm that bought out contracts at the minimum $10/mbf rate. SPECIES HHI is the Herfindahl index for wood species concentration on the tract. SELL VALUE, LOG COSTS and MFCT COSTS are USFS estimates of the value of the tract and the logging and manufacturing costs of the tract, respectively. In addition to the USFS data, we add data on (seasonally adjusted, one-month-lagged) monthly housing starts, HOUSING STARTS, for each tract's county.

	(1)	(2)
CONSTANT	-5.475***	-5.792***
	(0.849)	(0.852)
LOGGER	-0.090***	-0.203***
	(0.026)	(0.04)
SCALE SALE	0.003	-0.017
	(0.054)	(0.054)
SPECIES HHI	0.025	0.064
	(0.056)	(0.057)
DENSITY	0.016	0.013
	(0.063)	(0.063)
VOLUME	0.0003	0.0002
	(0.0003)	(0.0003)
HOUSING STARTS	0.0002**	0.0002*
	(0.00008)	(0.00008)
log SALE VALUE	2.750***	2.775***
	(0.081)	(0.081)
log LOG COSTS	-1.052***	-1.093***
	(0.066)	(0.067)
log MFCT COSTS	-0.262*	-0.181
	(0.147)	(0.148)
$\widehat{\lambda}$		0.159***
		(0.044)
R^2	0.4297	0.4319
N	3,426	3,426

Table 2: Evidence of Selection. In both columns the dependent variable is log of the bid per mbf and year dummies are included. Column (2) shows the second step results for a two-step selection model, where the first step specification is a probit for entry where we include a flexible polynomial in the number of (other) potential mill and logger entrants. $\widehat{\lambda}$ is the coefficient on the Inverse Mills Ratio.

is to be expected as most mills enter, but loggers may only enter when they expect their values to be high enough to compete with mills.

The focus of our counterfactuals is on the value of additional potential bidders to the USFS. To provide an initial assessment, we regress the log of auction revenues (using only auctions that end in a sale) on auction characteristics (specifically SPECIES HHI, DENSITY, VOLUME, HOUSING STARTS, log SALE VALUE, log LOG COSTS, log MFCT COSTS and year fixed effects) and a count of the number of potential entrants. The coefficient on the count indicates that an additional potential entrant raises revenues by 3.3% (std. error 0.3%).[34] When we include separate measures of the number of mill and logger potential entrants, and also interact them, we find a larger, positive effect of additional mill potential entrants, and a smaller, positive effect of additional loggers, which also declines when there are more mills. This pattern is consistent with loggers having lower values and the fact that loggers only tend to win when they do not face competition from mills: in 74 of the 136 times that a logger wins an auction, there are no more than two potential mill entrants.

Using the additional data from the Timber Data Company on buyout rates, we can also compare the bidding behavior of insolvent and non-insolvent firms. There are two reasons for looking at this: first, our model assumes that insolvent mills (loggers) draw their values from the same distribution as non-insolvent mills (loggers), and one might be concerned that insolvent firms are systematically different to firms that did not get themselves into such financial difficulty; and, second, anticipation or implementation of the bailout may have directly impacted bidding behavior of these firms.[35] The regressions in Table 3 examine whether there is any evidence of this by relating a firm's bids and success in winning auctions to its buyout rate. All regressions include auction fixed effects, thereby removing the effects of cross-auction heterogeneity, so that identification comes from a within-auction comparison of firms with different degrees of financial distress, and we allow the effects to vary with whether the auction took place in the pre- or post-October 1984 period. Standard errors are clustered at the auction level. There is no indication that the level of financial distress systematically affected the level of bids, and while there is weak evidence that firms that bought out but which did not face insolvency were less likely to win an auction before the bailout (specification (3)), this effect disappears when we remove two specific firms, Sierra Pacific and Schmidbauer.

[34]The full results are available on request.

[35]Allowing for more than two types in the structural model would complicate how we deal with multiple equilibria.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	log(Bid/mbf)	log(Bid/mbf)	Win	Win	Win	Win
CONSTANT	4.018***	3.876***	0.254***	0.269***	0.126***	0.130***
	(0.027)	(0.036)	(0.021)	(0.021)	(0.020)	(0.018)
BUY OUT RATE = \$10/mbf	0.100	-0.067	0.012	-0.009	0.175*	0.109
	(0.092)	(0.221)	(0.063)	(0.075)	(0.098)	(0.088)
BUY OUT RATE > \$10/mbf	-0.037	-0.417	-0.130**	-0.105	0.174	0.161
	(0.098)	(0.526)	(0.063)	(0.070)	(0.210)	(0.212)
BUY OUT RATE = \$10/mbf × POST BAILOUT	0.002	-0.040	0.156	0.012	-0.123	-0.085
	(0.101)	(0.292)	(0.076)	(0.091)	(0.161)	(0.155)
BUY OUT RATE > \$10/mbf × POST BAILOUT	0.035	-0.018	0.109	0.042	-0.161	-0.155
	(0.107)	(0.829)	(0.075)	(0.021)	(0.213)	(0.215)
R^2	0.6549	0.7641	0.2392	0.3199	0.6658	0.6796
N	2,550	876	2,550	2,094	876	863
Set of Firms	Mills	Loggers	Mills	Mills	Loggers	Loggers

Table 3: OLS regressions in which the dependent variables are given in the top row of the table. POST BAILOUT is a dummy for the auction occurring after October 1984. Columns (4) and (6) exclude outlier firms. These are Sierra Pacific and Schmidbauer in column (4) and Sierra Timber Products in column (6). The row entitled “Set of Firms” indicates whether mills or loggers are included. All regressions include auction fixed effects and standard errors are clustered at the auction level.

5 Estimation

To take the model to data, we need to specify how the parameters of the model may vary across auctions, as a function of observed auction characteristics and unobserved heterogeneity. Both types of heterogeneity are likely to be important as the tracts we use differ in observed characteristics, such as sale value, size and wood type (see Table 1), and they also come from different forests so they are likely to differ in other characteristics as well. Both observed and unobserved heterogeneity may affect entry costs and the degree of selection, as well as mean values.

Our estimation approach is based on Ackerberg (2009)'s method of simulated maximum likelihood with importance sampling. This method involves solving a large number of games with different parameters once, calculating the likelihoods of the observed data for each of these games, and then re-weighting these likelihoods during the estimation of the distributions for the structural parameters. This method is attractive when it is believed that the parameters of the model are heterogeneous across auctions and it would be computationally prohibitive to re-solve the model (possibly many times in order to integrate out over the heterogeneity) each time one of the parameters changes.

To apply the method, we assume that the parameters are distributed across auctions according to the following distributions, where X_a is a vector of observed auction characteristics and $TRN(\mu, \sigma^2, a, b)$ is a truncated normal distribution with parameters μ and σ^2, and lower and upper truncation points a and b.

$$\text{Location Parameter of Logger Value Distribution: } \mu_{a,\text{logger}} \sim TRN(X_a\beta_1, \omega^2_{\mu,\text{logger}}, 2, 6)$$
$$\text{Difference in Mill/Logger Location Parameters: } \mu_{a,\text{mill}} - \mu_{a,\text{logger}} \sim TRN(X_a\beta_3, \omega^2_{\mu,\text{diff}}, 0, 1.5)$$
$$\text{Scale Parameter of Mill and Logger Value Distributions: } \sigma_{Va} \sim TRN(X_a\beta_2, \omega^2_{\sigma_V}, 0.01, 2.01)$$
$$\alpha\text{: } \alpha_a \sim TRN(\beta_4, \omega^2_{\alpha}, 0, 1)$$
$$\text{Entry Costs: } K_a \sim TRN(X_a\beta_5, \omega^2_K, 0, 20)$$

The set of parameters to be estimated are $\Gamma = \{\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \omega^2_{\mu,\text{logger}}, \omega^2_{\mu,\text{diff}}, \omega^2_{\sigma_V}, \omega^2_{\alpha}, \omega^2_K\}$, and a particular draw of the parameters $\{\mu_{a,\text{logger}}, \mu_{a,\text{mill}}, \sigma_{Va}, \alpha_a, K_a\}$ is denoted θ_a. Note that the supports of the structural parameters are not functions of the parameters, which is a requirement for our method to work, and we choose them to be wide enough to include all reasonable values of the parameters. For example, the support of K, [\$0, \$20]/mbf, includes very large realizations of entry costs, both relative to the average winning bid (\$86.01/mbf, see Table 1) and plausible estimates of cruise costs (see Section 6).

These specifications reflect our assumptions that σ_v, α and K are the same across bidder-types within an auction, although they can vary across auctions. One could allow for the cross-auction heterogeneity for the different parameters to be correlated, but when we have tried to allow for completely flexible correlation structures, we have not found consistently significant correlations across specifications and the estimation time increases significantly.[36]

Denoting the outcome for an observed auction by y_a, the log-likelihood function for a sample of A auctions is

$$\sum_{a=1}^{A} \log \left(\int L_a(y_a|\theta)\phi(\theta|X_a, \Gamma)d\theta \right) \tag{3}$$

where $L_a(y_a|\theta)$ is the likelihood of the outcome y in auction a given structural parameters θ, $\phi(\theta|X_a, \Gamma)$ is the pdf of the parameter draw θ given Γ, our distributional assumptions, the unique equilibrium strategies implied by our equilibrium selection rule and auction characteristics, including the number of potential entrants, the reserve price and observed characteristics X_a.

Unfortunately, the integral in (3) is multi-dimensional and cannot be calculated exactly. A natural simulation estimator would be

$$\int L_a(y_a|\theta)\phi(\theta|X_a, \Gamma)d\theta \approx \frac{1}{S}\sum_{s=1}^{S} L_a(y_a|\theta_s) \tag{4}$$

where θ_s is one of S draws from $\phi(\theta|X_a, \Gamma)$. The problem is that this would require us to make new draws of θ_s and re-solve the model S times for each auction in our data each time one of the parameters in Γ changes. Instead, we follow Ackerberg by recognizing that

$$\int L_a(y_a|\theta)\phi(\theta|X_a, \Gamma)d\theta = \int L_a(y_a|\theta)\frac{\phi(\theta|X_a, \Gamma)}{g(\theta|X_a)}g(\theta|X_a)d\theta \tag{5}$$

where $g(\theta|X_a)$ is the importance sampling density whose support does not depend on Γ, which is true in our case because the truncation points are not functions of the parameters. This can be simulated using

$$\frac{1}{S}\sum_{s} L_a(y_a|\theta_s)\frac{\phi(\theta_s|X_a, \Gamma)}{g(\theta_s|X_a)} \tag{6}$$

where θ_s is a draw from $g(\theta|X_a)$. Critically, this means that we can calculate $L_a(y_a|\theta_s)$ for a given set of S draws once, and during estimation of Γ simply change the weights $\frac{\phi(\theta_s|X_a,\Gamma)}{g(\theta_s|X_a)}$, rather than re-solving the game.

This simulation estimator will only be accurate if a large number of θ_s draws are in

[36] Li and Zheng (2009) estimate a Samuelson model, i.e., one with perfect selection, and one type of bidder allowing for a common shock to affect the distribution of values and the distribution of entry costs.

the range where $\phi(\theta_s|X_a,\Gamma)$ is relatively high, and, as is well known, simulated maximum likelihood estimators are only consistent when the number of simulations grows fast enough relative to the sample size. We therefore proceed in two stages. First, we estimate Γ using $S = 2,500$ where $g(\cdot)$ is a multivariate uniform distribution. Second, we use these estimates $\widehat{\Gamma}$ to repeat the estimation using a new importance sampling density $g(\theta|X_a) = \phi(\theta_s|X_a,\widehat{\Gamma})$ with $S = 500$ draws per auction. The supports of the structural parameters are the same for $\phi(\cdot)$ and both stages of $g(\cdot)$. Appendix B provides Monte Carlo evidence that the estimation procedure works well even for smaller values of S.

To apply the estimator, we also need to define the likelihood function $L_a(y_a|\theta)$ based on the data we observe about the auction's outcome, which includes the number of potential entrants of each type, the winning bidder and the highest bids announced during the open-outcry auction by the set of firms that indicated that they were willing to meet the reserve price. A problem that arises when handling data from open-outcry auctions is that a bidder's highest announced bid may be below its value, and it is not obvious which mechanism leads to the bids that are announced (Haile and Tamer (2003)).

In our baseline specification we therefore make the following assumptions that we view as conservative interpretations of the information that is in the data: (i) the second highest observed bid (assuming one is observed above the reserve price) is equal to the value of the second-highest bidder[37]; (ii) the winning bidder has a value greater than the second highest bid; (iii) both the winner and the second highest bidder entered and incurred K_a; (iv) other firms that indicated that they would meet the reserve price or announced bids entered and incurred K_a and had values between the reserve price and the second highest bid; and, (v) all other potential entrants may have entered (incurring K_a) and found out that they had values less than the reserve, or they did not enter (did not incur K_a). If a firm wins at the reserve price we assume that the winner's value is above the reserve price. Based on these assumptions, the likelihood of an observed outcome where a type 1 (mill) bidder wins the auction, a type 2 (logger) bidder submits the second highest bid of b_{2a}, and $n_{\tau a}-1$ other firms of type τ participate (i.e., indicated they would pay the reserve or placed bids) out of $N_{\tau a}$ potential entrants would be proportional[38] to the following, where $S'^{*}_{\tau a}$ are the equilibrium

[37]Alternative assumptions could be made. For example, we might assume that the second highest bidder has a value equal to the winning bid, or that the second highest bidder's value is some explicit function of his bid and the winning bid. In practice, 96% of second highest bids are within 1% of the high bid, so that any of these alternative assumptions give similar results. We have computed some estimates using the winning bid as the second highest value and the coefficient estimates are indeed similar.

[38]This ignores the binomial coefficients, which do not depend on parameters.

entry thresholds:

$$
\begin{aligned}
L_a(y|\theta) \propto f_2(b_{2a}|\theta) * \Pr(enter_2|v_2 = b_{2a}, S^{*\prime}_{2a}, \theta) \times &\left(\int\limits_{b_{2a}}^{\overline{V}} f_1(v|\theta) \Pr(enter_1|v_1 = v, S^{*\prime}_{1a}, \theta) dv \right) \\
\times &\left(\int\limits_{R_a}^{b_{2a}} f_1(v|\theta) \Pr(enter_1|v_1 = v, S^{*\prime}_{1a}, \theta) dv \right)^{(n_{1a}-1)} \\
\times &\left(\int\limits_{R_a}^{b_{2a}} f_2(v|\theta) \Pr(enter_2|v_2 = v, S^{*\prime}_{2a}, \theta) dv \right)^{(n_{2a}-1)} \\
\times &\left(1 - \int_{R_a}^{\overline{V}} f_1(v|\theta) \Pr(enter_1|v_1 = v, S^{*\prime}_{1a}, \theta) dv \right)^{(N_{1a}-n_{1a})} \\
\times &\left(1 - \int_{R_a}^{\overline{V}} f_2(v|\theta) \Pr(enter_2|v_2 = v, S^{*\prime}_{2a}, \theta) dv \right)^{(N_{2a}-n_{2a})}
\end{aligned}
\tag{7}
$$

reflecting the contributions to the likelihood of the second highest bidder, the winning bidder, the other firms that attended the auction and those that do not attend, respectively.[39]

5.1 Identification

Our fully parametric model is point-identified under our assumption on equilibrium selection. However, as usual, it is natural to ask under what conditions our model would be identified non-parametrically.

Gentry and Li (2014) show non-parametric identification of an "affiliated-signal" partially selective entry model for standard auctions, including the case where there is unobservable cross-auction heterogeneity that affects both entry costs and the distribution of values. The essence of their results is that the joint distribution of values and signals and entry costs are either partially or point identified when there are observed exogenous variables that affect equilibrium entry thresholds. These variables could include the number of potential entrants (N), reserve prices or some variable that affects the entry costs that bidders have to pay. In our setting, as reserve prices reflect the USFS's estimates of the value of the timber (which we control for in estimation) and we do not observe variables affecting entry costs, we rely on variation in the number of potential entrants. Fortunately, in our data there is considerable

[39]If an entrant wins at the reserve price, then the likelihood is calculated assuming that winning bidder's value is above the reserve.

variation (the 10th and 90th percentiles of $N_m + N_l$ are 2 and 16).[40] They also note that there will be additional sources of identification when potential entrants can be classified into different observed types, as we can do in our setting, under the assumption that only one type-symmetric equilibrium would be played across auctions with the same primitives. As we explained in Section 3, this is an assumption that we impose when estimating our model.[41]

Although their identification proofs are constructive, Gentry and Li note (p. 332) that more parametric estimation approaches are likely to be preferred in practice, especially when controlling for observable variation across auctions. We also introduce parametric unobserved heterogeneity across auctions in the degree of selection (α), as well as entry costs and values, so that we can use the computationally convenient importance sampling estimator.[42] This also allows us to better fit the considerable heterogeneity that exists in both entry and winning bids across auctions with similar characteristics in our data. While we do not explore identification in this expanded model here, we refer interested readers to Bhattacharya, Roberts, and Sweeting (2014) where we use the scaled sensitivity parameter approach of Gentzkow and Shapiro (2013) to investigate which moments identify the parameters in the context of a selective entry model for low-bid procurement auctions with ex-ante symmetric bidders. There we find that heterogeneity in the number of observed entrants is especially important in determining the estimated value of ω_α.

6 Results

Table 4 presents the parameter estimates for our structural model. We allow the USFS estimate of sale value and its estimate of logging costs to affect mill and logger values and entry costs since these are consistently the most significant variables in regressions of reserve prices or winning bids on observables and in the specifications in Table 2. We also control for species concentration since our discussions with industry experts lead us to believe that this matters to firms. The right-hand columns show the mean and median values of the structural parameters when we take 10 simulated draws of the parameters for each auction. For the rest of the paper, we refer to these as the "mean" and "median" values of the parameters. A "representative" auction means an auction with the mean parameters, 4 potential bidders

[40]As Gentry and Li show, limited variation, caused, for example, by the discreteness of the number of potential entrants, may result in only partial identification. As they also note, as the degree of variation increases these bounds should become tighter.

[41]Of course, our selection assumption does something slightly stronger by imposing that a particular equilibrium, where mills have the lower entry threshold, is played.

[42]We note that in our estimation, we assume that unobserved heterogeneity in entry costs and values is uncorrelated. As noted in Section 5, we have tried to allow for more flexible correlation structures without finding consistently significant results.

of each type (median values) and a reserve price of \$27.77/mbf, the average observed in our data. All standard errors are based on a nonparametric bootstrap with 100 repetitions.

The coefficients show that tracts with greater sale values and lower costs are more valuable, as one would expect. There is significant unobserved heterogeneity in values (the standard deviation of μ_{logger}) and in the difference between mill and logger mean values (the standard deviation of $\mu_{\text{mill}} - \mu_{\text{logger}}$) across auctions.

Based on the mean value of the parameters, the mean values of mill and logger potential entrants are \$61.95/mbf and \$42.45/mbf respectively. Figure 4 shows the value distributions for potential entrants of both types for these parameters. Our estimates also indicate a moderate degree of selection, and partly for this reason this difference in values is greater than the difference in the average bids of mills and loggers (Table 1) or the differences found by ALS when estimating a non-selective entry model using sealed-bid data (see their Figure 2). For the representative auction, we can compare the difference in values between a marginal bidder who observes signal $S'^{*}_{\tau a}$, and the average (inframarginal) entrant. The average mill entrant's value is \$68.13/mbf and the average marginal mill bidder's value is \$45.22/mbf. The fact that the average potential mill entrant's value is higher than the average marginal mill's value reflects the fact that most mills enter. The comparable numbers for average entrant and marginal loggers are \$59.80/mbf and \$48.13/mbf, respectively. The differences between marginal and inframarginal bidders is indicative of the degree of selection in the entry process.[43]

The mean entry cost is \$2.05/mbf, or \$4.49/mbf in 2010 dollars.[44] One forester we spoke with estimated current cruising costs of approximately \$6.50/mbf in 2010 dollars, which is at least broadly consistent with our estimates, and it is also sensible that our estimate is less than the forester's estimate if firms in our data are able to use any information they learn on a cruise when deciding whether to enter other auctions.

Our estimated model is able to match the main moments in the data quite well. For example, on average 0.99 loggers participate in each auction, while our model predicts 1.07 loggers will enter and have values greater than the reserve. For mills these numbers are 2,87 and 2.44 respectively. In the event of sale, average prices are \$85.76/mbf, compared to a prediction of \$86.39/mbf.

[43]Marginal loggers tend to have higher values than marginal mills because in an auction with asymmetric bidder types the weaker type (loggers) expect to face stronger rivals than stronger types (mills) do and so they need to have higher expected values to justify entry.

[44]We could also assume that firms that did not participate did not incur K. The estimates under this assumption (available on request) are very similar except that there is slightly more selection and slightly higher entry costs. These changes are sensible as we are now assuming that fewer firms entered and that all that did so had values above the reserve price.

	β parameters				ω parameter		
Parameter	Constant	log SELL VALUE	log LOG COSTS	SPECIES HHI		Mean	Median
$\mu_{a,\text{logger}}$	-9.6936	3.3925	-1.2904	0.2675	0.3107	3.5824	3.5375
$\sim TRN(X_a\beta_1, \omega^2_{\mu,\text{logger}}, 2, 6)$	(1.3690)	(0.1911)	(0.1332)	(0.1386)	(0.0213)	(0.0423)	(0.0456)
$\mu_{a,\text{mill}} - \mu_{a,\text{logger}}$	3.6637	-0.4998	-0.0745	-0.1827	0.1255	0.3783	0.3755
$\sim TRN(X_a\beta_3, \omega^2_{\mu,\text{diff}}, 0, 1.5)$	(0.8890)	(0.1339)	(0.0919)	(0.1007)	(0.0163)	(0.0242)	(0.0249)
σ_{Va}	4.0546	-0.7379	0.1393	0.0895	0.0796	0.5763	0.5770
$\sim TRN(X_a\beta_2, \omega^2_{\sigma_V}, 0.01, 2.01)$	(0.7872)	(0.0994)	(0.1025)	(0.0813)	(0.0188)	(0.0273)	(0.0302)
α_a	0.7127	-	-	-	0.1837	0.6890	0.6992
$\sim TRN(\beta_4, \omega^2_{\alpha}, 0, 1)$	(0.0509)				(0.0446)	(0.0362)	(0.0381)
K_a	1.9622	-3.3006	3.5172	-1.1876	2.8354	2.0543	1.6750
$\sim TRN(X_a\beta_5, \omega^2_K, 0, 20)$	(13.2526)	(2.7167)	(2.4808)	(1.5721)	(0.6865)	(0.2817)	(0.3277)

Table 4: Simulated maximum likelihood with importance sampling estimates allowing for non-entrants to have paid the entry cost. The rightmost columns show the mean and median values of the structural parameters when we take 10 simulated draws of the parameter for each auction. Standard errors based on nonparametric bootstrap with 100 repetitions. $TRN(\mu, \sigma^2, a, b)$ is a truncated normal distribution with parameters μ and σ^2, and upper and lower truncation points a and b. Based on 887 auctions.

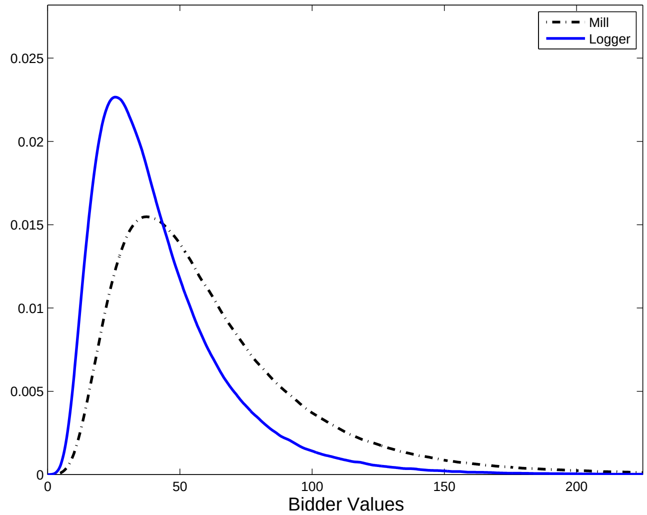

Figure 4: Comparing the value distributions for mills (dash-dot) and loggers (solid). Based on the mean value of the parameters from Table 4.

7 The Value of Preserving Competition in Auctions

We now use our estimated model to predict how the USFS's revenues in post-bailout auctions would have changed if the firms that faced insolvency before the bailout had not been potential entrants.

Our evaluation procedure involves the following steps. First, for each of the auctions in our data we draw 10 sets of auction-specific parameters, based on the estimates in Table 4. Second, for each of these auction-draw combinations, we solve our model both with all of the potential entrants observed in the data and with the insolvent firms removed, using (for now) the reserve price in the data. Third, for each of these cases, we simulate 5 million outcomes to calculate expected sale revenues in the event of sale and the probability of sale. Rather than assuming that the USFS receives no payoff when a tract is not sold, we follow Li and Zheng (2011), and Paarsch (1997), in one of his specifications, by assuming that the USFS receives an expected payoff equal to the observed reserve price, reflecting its ability to re-auction the tract in the future.[45] Fourth, we average across the draws for each auction to give us a predicted change in revenues for each of the 545 post-bailout auctions in our data. In reporting our results, however, we only aggregate across the 489 auctions where there are at least two remaining potential entrants when the insolvent firms are removed. As mentioned in the Introduction, revenues would fall more if we included the remaining auctions, but it is not clear that USFS would actually have tried to run auctions in these

[45] Aradillas-Lopez, Gandhi, and Quint (2013) use the USFS's estimate of sale value less its estimate of costs as the agency's payoff when a tract is unsold. This number is similar to the reserve price.

cases.

Set of Exiting Firms	Non-strategic Reserve Δ Revenues	% Change	Optimal Reserve Δ Revenues	% Change
Firms that Buy Out at $10/mbf	$43.52 m	11.11%	$35.40 m	9.07%
	($3.00 m)	(0.37%)	($2.69 m)	(0.37%)
All Firms that Buy Out	$73.48 m	19.56%	$64.07 m	17.06%
	($4.99 m)	(0.48%)	($4.32 m)	(0.44%)
Mills that Buy Out at $10/mbf	$40.83 m	10.46%	$33.19 m	8.50%
	($2.87 m)	(0.35%)	($2.60 m)	(0.36%)

Table 5: The table shows the change in USFS revenues in our sample of post-bailout auctions. For $ figures, m indicates millions. The columns with the "Non-strategic Reserve" header assume that once the firms exit the market, the USFS continues to set the reserve price observed in the data. The columns with the "Optimal Reserve" header assume that once the firms exit the market, the USFS sets an optimal reserve price. Bootstrapped standard errors are in parentheses. All numbers are based on auctions that, for each assumption about the firms that are no longer potential entrants, would still have had at least two potential entrants.

The 'non-strategic reserve' columns of the first row in Table 5 present the results. We predict that without the insolvent firms, USFS revenues would have fallen by a total of $43.52 million[46], or 11.1% of what expected revenues would be with the insolvent firms as potential entrants. As well as being economically significant, the prediction is also precise (standard error on the percentage change is 0.37%). The drop in revenues comes almost entirely from a drop in revenues from auctions that result in sales: the expected percentage of tracts that do not sell only increases from 4.1% to 5.7%. The second row of Table 5 shows that revenues fall by substantially more if all firms participating in the bailout are excluded as potential entrants (in this case the number of auctions we are using falls to 458 in order to maintain at least two remaining potential entrants).

The 'optimal reserve' columns show the predicted changes when we allow the USFS respond to the absence of the insolvent firms in the counterfactual by using an optimal reserve price (we continue to assume the observed non-optimal reserve when the insolvent firms are included).[47] The reductions in expected revenues when the insolvent firms are excluded only fall by about one-fifth, and remain large and statistically significant. The fact

[46]Recall that sealed-bid USFS auctions and auctions by other government agencies would also have been affected, so the total revenue effect on government auctions would be much larger.

[47]We assume that the USFS would set an optimal reserve with full knowledge of the parameters for a particular auction and the number of potential entrants. If the USFS was uncertain about some parameters, this would tend to reduce the value of setting an optimal reserve price. The optimal reserve is found by searching over a fine grid of reserve prices where we calculate expected revenues based on a fixed set of 5 million simulations for each auction.

that the a reserve price only increases revenues by a small amount, and by much less than the addition of potential bidders, is consistent with what happens in models with exogenous bidder entry. In that setting, Bulow and Klemperer (1996) show that an additional bidder is more valuable to the seller than an optimal reserve, or any alternative auction design.[48]

This result does not have to hold for additional *potential* bidders when entry is endogenous, because, as in the symmetric and common entry cost LS model, additional competition can actually lower the seller's revenues. However, because additional potential competition (at least from the insolvent firms, see discussion below) increases expected revenues significantly given our parameter estimates, it is once again more valuable than a reserve price that is a relatively blunt tool for the seller to try to extract information rents from bidders.[49] As an illustration, consider the representative auction where the non-strategic reserve is \$27.77/mbf. The use of a seller-optimal reserve, of \$55/mbf, only reduces the expected (combined) bidder profit from \$22.80/mbf to \$22.09/mbf (raising expected USFS revenues from \$70.20/mbf to \$70.83/mbf).[50] While this finding does not imply that no auction design would have offset the USFS's losses, and indeed the optimal design is not known for this partially selective entry model, it does provide an additional metric by which the revenue changes from the loss of competition should be seen as large, and it also suggests that when entry is endogenous and moderately selective the seller may be better-advised to try to encourage interest in the object being sold rather than trying to employ the most-widely discussed design tool in the literature.[51]

We now turn to the question of why the changes in revenues when the insolvent firms exit are so large. Our view that an 11% effect is large comes from the fact that, for the average post-bailout auction, we are only reducing the number of potential entrants from (approximately) nine to seven and that, as mentioned in the Introduction, in many homogeneous product industries one would expect five or six firms to lead to quite 'competitive' outcomes. There are three reasons why we find large revenue effects when the insolvent firms are removed.

The first reason is that most of the insolvent firms were mills, and that, on average,

[48]Bulow and Klemperer's results are derived under the additional assumptions that bidders are symmetric, always have higher values of winning the good being sold than the seller does of holding onto it, and that bidders' marginal revenue curves are always downward sloping. Under these assumptions, an auction with an optimal reserve is the optimal design.

[49]It is blunt, in part, because an increase in the reserve price tends to reduce entry which, in turn, tends to increase the information rents of the firms that do enter.

[50]A reserve price has a larger effect on seller revenues when there are fewer potential entrants, as in our counterfactuals.

[51]See Sweeting and Bhattacharya (forthcoming) for a comparison of the performance of several auction designs when entry is partially selective, including examples where a design change increases expected revenues by more than the addition of a potential bidder. Therefore while potential competition may typically be more valuable than adding a reserve price, the general Bulow and Klemperer result certainly does not hold.

we estimate that mills have much higher values than loggers, so that the removal of a mill has much more of an effect on revenues than the removal of an 'average' potential entrant, because mills tend to enter and win or set the auction price more often. Specifically, on average, 1.8 potential entrant mills are classified as insolvent, compared with 0.4 loggers. The importance of mills is illustrated in the final row of Table 5, which shows that revenues decline by almost as much as in the baseline case when we remove only affected mills as potential entrants. Recall that the very large difference in estimated mean values for mills and loggers - which is much larger than the difference in the average observed bids of entrants of each type - partly reflects the fact that our model allows for selective entry.

The second reason is that there is substantial heterogeneity of values within a type for a given auction, which implies that adding additional bidders (entrants) can increase the expected first- or second-highest order statistics of entrant values quite substantially. To illustrate the effects of variance, consider an auction with exogenous entry where six symmetric bidders draw their values from a lognormal distribution with location parameter 3.9607 and scale parameter 0.5763 (the mean estimated parameter values for mills), and a non-strategic reserve price (and value to the seller of holding onto the tract) of \$27.77/mbf (the median reserve price in the sample). When the number of bidders falls from six to five, expected USFS revenues decrease from \$79.66/mbf to \$73.57/mbf, or 7.6%. If the scale parameter is halved to 0.2882, the percentage decrease in revenues from losing a bidder is much smaller, 4.0%. Note that we find significant within-auction heterogeneity in values even though we explicitly allow for cross-auction heterogeneity in mean values. In this regard our results are consistent with ALS and Aradillas-Lopez, Gandhi, and Quint (2013), who also allow for cross-auction heterogeneity in timber auctions.

The final reason is that our estimated model implies that there is (moderate) selection in entry. In an LS model with a common entry cost, where there is no selection, expected revenues could increase with the removal of a potential entrant, and this is true even when values are heterogeneous. This is partly because the new entrants that are induced to enter when competition is reduced are just as likely to as valuable to the seller as the inframarginal entrants who would have entered in any event. This is not true when there is selection, because the marginal entrants are likely to have relatively low values, and, because the marginal entrants know this, the amount of new entry also tends to be small. To see this, we extend the previous example where the six initial firms are now potential entrants, $K = 2.0543$ and $\alpha = 0.6890$, their estimated mean values. The seller's expected revenue is \$76.55/mbf and the expected number of entrants is 4.38. When a potential entrant is removed, the expected number of entrants only falls from 4.38 to 3.96, as the entry probability of the remaining firms increases from 0.73 to 0.80. However, the expected value of a firm that only enters because the number of competitors has fallen is \$46.83/mbf, compared with an expected value of the average entrant when there are six potential entrants of \$70.00/mbf. Expected revenues fall to \$71.25/mbf (a decline of 6.9%).[52] If entry was more selective, then the revenue decrease might be larger. For example, if $\alpha = 0.1$, then reducing the number of potential entrants from six to five would lower revenues by 7.3%.

Our counterfactuals assume that the elimination of insolvent firms would not affect the values of the survivors. It is reasonable to assume that the elimination of one local competitor would not affect the value of a surviving mill as output (i.e., lumber) prices are determined in a much broader regional or national market. The value of a surviving logger might be expected to fall, suggesting our predictions are underestimates, if surviving mills are able to exercise greater monopsony power in the local market for cut-timber. On the other hand, the exit of insolvent mills throughout the western US, which could well have happened without the bailout, would almost certainly have affected equilibrium lumber prices, especially once construction activity recovered from its early 1980s low. Evaluation of this effect would require estimation of the elasticity of lumber imports, the supply-elasticity of the rest of the domestic industry and of how the bailout affected the exit decisions of solvent firms. This exercise is beyond the scope of this paper.[53] Instead, as a simple check on the sensitivity of our results, we re-calculate our predictions assuming that, when insolvent mills exit, surviving mill values increase by 2, 5 or 10%, with entry costs, selection and logger values held constant. More surviving mills enter auctions and, upon entry, submit higher bids. Table 9 in Appendix C shows the results. Expected USFS revenues still fall by more than 9% when mill values increase by 2%, and even when they increase by 10%, we predict that USFS revenues would decrease by 3.38% (s.e. 0.38%). Therefore surviving mill values would have had to increase by significantly more than 10% for USFS revenues not to have declined if the insolvent mills had exited.

It is also possible that the plant and equipment of many insolvent firms would have been purchased by either incumbents or new entrants. This possibility is also hard to assess without a better model or more complete data, although it is certainly plausible that more efficient equipment would have been purchased by surviving firms rather than being scrapped. In the case of purchase by rival local mills, however, the changes in competition that drive

[52]Note that in this example, reducing the heterogeneity in values would still reduce the size of the revenue change. For example, if the scale parameter is halved to 0.2882, the seller's expected revenues would fall by only 3.0% when the number of potential entrants falls from six to five, a smaller percentage change than when the scale parameter is 0.5763.

[53]Our discussions with people in the industry, for example at the publication Random Lengths, support the idea that it is unlikely lumber prices would have risen rapidly without the bailout. In fact in Congressional hearings on the draft bill, several speakers argued that if the contracts were enforced lumber prices would fall even further through a disorderly cutting of the timber (House of Representatives, 98th Congress 2nd Session (1984)).

our results would still tend to reduce USFS revenues.[54]

8 Conclusion

This article has estimated the value of additional competition in auctions with endogenous entry in the context of the Reagan administration's 1984 bailout of the timber industry. This intervention, which, like most bailouts, was controversial, aimed to prevent the closure of firms that faced heavy losses on earlier contracts USFS and other timber contracts, and it was partly motivated by a desire to preserve competition in future federal timber auctions. We have evaluated that claim, motivated by the fact that, when entry into an auction is endogenous, the direction of the effect of additional competition on revenues is theoretically ambiguous and, given the number of surviving firms, one might expect any revenue effects to be small.

Using a model where bidders can be asymmetric, there is unobserved heterogeneity across auctions and we can estimate the degree to which entry into auctions is selective, i.e., the extent to which potential bidders with higher values are more likely to enter, we predict that USFS revenues in post-bailout auctions would have been 11% lower if the firms in the greatest financial distress had exited the industry. This is a relatively large change in revenues given that the average auction in our sample has over nine potential entrants and, by our criterion, only two of them were saved by the bailout. This result reflects three features of our model and our estimates. First, mills, which were more likely to be insolvent, are estimated to have significantly higher average values than loggers, implying that the more relevant piece of information is that a much larger share of mills were insolvent. Second, we estimate that bidder values for a given tract are heterogeneous, so that adding an additional competitor can increase the expected first- or second-highest order-statistics of values quite substantially. Finally, the fact that we estimate auction entry to be moderately selective plays an important role, as while, without the bailout, additional surviving firms (including mills) may have entered the auction, these marginal entrants tend to have relatively low values so that their entry has only a small effect on expected USFS revenues. We also show that the USFS would have only been able to offset a small proportion of the revenue loss by using an optimal reserve price, the most widely considered design tool in the literature.

This research could be pushed in several directions. One direction concerns the ability of a seller, such as the USFS, to control the degree of selection through the information

[54] Of course, if a firm owns two mills one might want to model its value as being the maximum of two different draws from the value distribution as in Li and Zhang (2015). Alternatively, the buyer might have closed its existing plants, in which case assuming a single draw would still be appropriate.

that it releases to potential bidders before they have to decide whether to incur the costs of researching the product for sale. Variation in the information provided by different federal and state agencies might be used to identify this effect in the timber context. Increasing selection will always tend to improve efficiency as it will tend to raise the probability that the potential bidder with the highest value wins the object being sold, while economizing on the entry costs of those with lower values. However, for the seller, raising the degree of selection can reduce expected revenues, because it can increase the information rents of bidders with high values substantially (Sweeting and Bhattacharya (forthcoming)). However, to the extent that bidder rents encourage investment and potential interest in timber auctions there may be some potential long-run advantage for the USFS in making entry more informative. A second direction would involve a more thorough examination of the effects of the bailout, taking into account the equilibrium effects that the bailout had on lumber prices, imports, the potential purchase of the plant and equipment of insolvent firms by their solvent competitors and the exit decisions of those competitors, as well as the potential benefits to maintaining employment in the affected rural areas. This would be especially valuable as, especially during recessions and financial crises, there are often demands for governments to assist private firms.

References

Ackerberg, D. (2009): "A New Use of Importance Sampling to Reduce Computational Burden in Simulation Estimation," *Quantitative Marketing and Economics*, 7(4), 343–376.

Adams, D., R. W. Hayes, and A. Daigneault (2006): "Estimated Timber Harvest by U.S. Region and Ownership, 1950-2002," U.S. Department of Agriculture Report PNW-GTR-659.

Aradillas-Lopez, A., A. Gandhi, and D. Quint (2013): "Identification and Inference in Ascending Auctions with Correlated Private Values," *Econometrica*, 81(2), 489–534.

Athey, S., D. Coey, and J. Levin (2013): "Set-Asides and Subsides in Auctions," *AEJ Microeconomics*, 5(1), 1–27.

Athey, S., J. Levin, and E. Seira (2011): "Comparing Open and Sealed Bid Auctions: Theory and Evidence from Timber Auctions," *Quarterly Journal of Economics*, 126(1), 207–257.

Bajari, P., H. Hong, and S. Ryan (2010): "Identification and Estimation of a Discrete Game of Complete Information," *Econometrica*, 78(5), 1529–1568.

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

Baldwin, L. H., R. C. Marshall, and J.-F. Richard (1997): "Bidder Collusion at Forest Service Timber Sales," *Journal of Political Economy*, 105(4), 657–699.

Beresteanu, A., I. Molchanov, and F. Molinari (2009): "Sharp Identification Regions in Models with Convex Predictions: Games, Individual Choice, and Incomplete Data," *Cemmap Working Paper CWP 27/09*.

Berry, S. T. (1992): "Estimation of a Model of Entry in the Airline Industry," *Econometrica*, 60(4), 889–917.

Bhattacharya, V., J. Roberts, and A. Sweeting (2014): "Regulating Bidder Participation in Auctions," *RAND Journal of Economics*, 45(4), 675–704.

Borenstein, S. (1992): "The Evolution of U.S. Airline Competition," *Journal of Economic Perspectives*, 6(2), 45–73.

Brannman, L., and L. Froeb (2000): "Mergers, Cartels, Set-Asides, and Bidding Preferences in Asymmetric Oral Auctions," *Review of Economics and Statistics*, 82(2), 283–290.

Bresnahan, T., and P. Reiss (1991): "Entry and Competition in Concentrated Markets," *Journal of Political Economy*, 99(5), 977–1009.

Bulow, J., and P. Klemperer (1996): "Auctions Versus Negotiations," *American Economic Review*, 86(1), 180–194.

Ciliberto, F., and E. Tamer (2009): "Market Structure and Multiple Equilibria in Airline Markets," *Econometrica*, 77(6), 1791–1828.

Coate, M. B., and S. W. Ulrick (2005): "Transparency at the Federal Trade Commission: The Horizontal Merger Review Process 1996-2003," Discussion paper, Bureau of Economics Federal Trade Commission.

Ericson, R., and A. Pakes (1995): "Markov-Perfect Industry Dynamics: A Framework for Empirical Work," *Review of Economic Studies*, 62(1), 53–82.

Ertaç, S., A. Hortaçsu, and J. Roberts (2011): "Entry into Auctions: An Experimental Analysis," *International Journal of Industrial Organization*, 29(2), 168–178.

Federal Register 48 (1983): "Extension of Certain Timber Sale Contracts," to be codified at 36 C.F.R. pt. 223.

Gentry, M., and T. Li (2014): "Identification in Auctions with Selective Entry," *Econometrica*, 82(1), 315–344.

Gentzkow, M., and J. Shapiro (2013): "Measuring the Sensitivity of Parameter Estimates to Sample Statistics," *Working Paper*.

Haile, P. A. (2001): "Auctions with Resale Markets: An Application to U.S. Forest Service Timber Sales," *American Economic Review*, 91(3), 399–427.

Haile, P. A., and E. Tamer (2003): "Inference with an Incomplete Model of English Auctions," *Journal of Political Economy*, 111(1), 1–51.

Hartmann, W. (2006): "Intertemporal Effects of Consumption and Their Implications for Demand Elasticity Estimates," *Quantitative Marketing and Economics*, 4(4), 325–349.

Hartmann, W., and H. Nair (2010): "Retail Competition and the Dynamics of Demand for Tied Goods," *Marketing Science*, 29(2), 366–386.

Heckman, J. (1976): "The Common Structure of Statistical Models of Truncation, Sample Selection, and Limited Dependent Variables and a Simple Estimator for Such Models," *Annals of Economic and Social Measurement*, 5, 475–492.

House of Representatives (ed.) (1984): *Congressional Record 10545*.

House of Representatives, 96th Congress 1st Session (1979): "H. R. Report," No. 5805.

House of Representatives, 98th Congress 2nd Session (1984): "Federal Timber Contract Paymeny Modification Act: hearing before the Subcommittee on Forests, Family Farms and Energy of the Committee on Agriculture, House of Representatives, H.R. 5649," No. 5805.

Krasnokutskaya, E., and K. Seim (2011): "Bid Preference Programs and Participation in Highway Procurement Auctions," *American Economic Review*, 101(6), 2653–2686.

Levin, D., and J. L. Smith (1994): "Equilibrium in Auctions with Entry," *American Economic Review*, 84, 585–599.

Li, T., and I. Perrigne (2003): "Timber Sale Auctions with Random Reserve Prices," *Review of Economics and Statistics*, 85(1), 189–200.

Li, T., and B. Zhang (2015): "Affiliation and Entry in First-Price Auctions with Heterogeneous Bidders: An Analysis of Merger Effects," *American Economic Journal: Microeconomics*, 7(2), 188–214.

Li, T., and X. Zheng (2009): "Entry and Competition Effects in First-Price Auctions: Theory and Evidence from Procurement Auctions," *Review of Economic Studies*, 76, 1397–1429.

——— (2011): "Information Acquisition and/or Bid Preparation: A Structural Analysis of Entry and Bidding in Timber Sale Auctions," *Journal of Econometrics*, 168(1), 29–46.

Markusen, A. (1997): "The Economics of Defence Industry Mergers and Divestitures," *Economic Affairs*, 17(4), 28–32.

Marmer, V., A. Shneyerov, and P. Xu (2013): "What Model for Entry in First-Price Auctions? A Nonparametric Approach," *Journal of Econometricsour*, 176(1), 46–58.

Mathiesen, M. (1995): "Bankruptcy of Airlines: Causes, Complaints and Changes," *Journal of Air Law and Commerce*, 61, 1017–1050.

Mattey, J. P. (1990): *The Timber Bubble that Burst*. Oxford University Press.

Mead, W. J., M. Schniepp, and R. Watson (1981): "The Effectiveness of Competition and Appraisals in the Auction Markets for National Forest Timber in the Pacific Northwest," Washington, DC: U.S. Department of Agriculture, Forest Service.

——— (1984): "Competitive Bidding for U.S. Forest Service Timber in the Pacific Northwest 1963-83," Washington, DC: U.S. Department of Agriculture, Forest Service.

Menezes, F., and P. Monteiro (2000): "Auctions with Endogenous Participation," *Review of Economic Design*, 5, 71–89.

Moreno, D., and J. Wooders (2011): "Auctions with Heterogeneous Entry Costs," *RAND Journal of Economics*, 42(2), 313–336.

Morgan, T., C. Keegan, T. Dillon, A. Chase, J. Fried, and M. Weber (2004): "California's Forest Products Industry: A Descriptive Analysis," Discussion paper, United States Department of Agriculture USFS.

Muraoka, D. D., and R. B. Watson (1986): "Improving the Efficiency of Federal Timber Sale Procedures: An Update," *Natural Resources Journal*, 69(26).

Newhouse, J. (1982): *The Sporty Game*. Alfred A. Knopf.

Paarsch, H. J. (1997): "Deriving an Estimate of the Optimal Reserve Price: An Application to British Columbia Timber Sales," *Journal of Econometrics*, 78, 333–357.

Palfrey, T., and S. Pevnitskaya (2008): "Endogenous Entry and Self Selection in Private Value Auctions: An Experimental Study," *Journal of Economic Behavior and Organizations*, 66, 731–747.

Reagan, R. (1984): "Statement on Signing the Federal Timber Contract Payment Modification Act," Presidential Signing Statement.

Ritholtz, B. (2009): *Bailout Nation*. John Wiley & Sons.

Roberts, J., and A. Sweeting (2012): "The Potential Entry Defense in Airline Mergers," *Working Paper*.

——— (2013): "When Should Sellers Use Auctions?," *American Economic Review*, 103(5), 1830–1861.

Samuelson, W. F. (1985): "Competitive Bidding with Entry Costs," *Economic Letters*, 17, 53–57.

Senate (ed.) (1984): *Congressional Record 11887*.

Senate, 92nd Congress 1st Session (1971): "Hearings Before the Committee on Banking, Housing and Urban Affairs," Emergency Loan Guarantee Program.

Sweeting, A. (2009): "The Strategic Timing of Radio Commercials: An Empirical Analysis Using Multiple Equilibria," *RAND Journal of Economics*, 40(4), 710–742.

Sweeting, A., and V. Bhattacharya (forthcoming): "Selective Entry and Auction Design," *International Journal of Industrial Organization*.

U.S. GAO (1978): "Projected Timber Scarcities in the Pacific Northwest: A Critique of Eleven Studies," Report to Congress.

——— (1989): "Federal Timber Sales: Legislative and Administrative Assistance Provided to Timber Purchasers," Report to the Chairman, Subcommittee on National Parks and Public Lands, Committee on Interior and Insular Affairs, House of Representatives.

——— (1995): "Forest Service: Distribution of Timber Sales Receipts Fiscal Years 1992-94," Fact Sheet for Ranking Minority Member, Subcommittee on the Interior and Related Agencies.

Wang, E. (2015): "The Impact of Soda Taxes on Consumer Welfare: Implications of Storability and Taste Heterogeneity," *RAND Journal of Economics*, 46(2), 409–441.

Wiegner, K. (1984): "The Great Timber Bailout of 1984," *Forbes*, 134, 162–165.

Wollmann, T. (2014): "Trucks Without Bailouts: Equilibrium Product Characteristics for Commercial Vehicles," *Working Paper*.

A Multiple Equilibria and Equilibrium Selection (FOR ONLINE PUBLICATION)

Even when we restrict attention to type-symmetric equilibria, a game with more than one bidder type may have multiple equilibria where different types of firm have different thresholds. For example, in our empirical setting, some parameters would support both equilibria where the mills have a lower entry threshold ($S'^{*}_{\text{mill}} < S'^{*}_{\text{logger}}$), and equilibria where loggers have a lower threshold ($S'^{*}_{\text{mill}} > S'^{*}_{\text{logger}}$).

This is illustrated in the first panel of Figure 5, which shows the reaction functions for the entry thresholds of both types of firm, when there are two firms of each type, $\sigma_V = 0.05, K = 4, \alpha = 0.1$ ($\sigma_\varepsilon = 0.0167$) and $\mu_1 = \mu_2 = 5$, so that the types are actually identical.[55] The reserve price R is set to 20. There are three equilibria (intersections of the reaction functions), one of which has the types using identical entry thresholds (45° line is dotted), and the others involving one of the types having the lower threshold (and so being more likely to enter). The fact that there are at most three equilibria follows from the inverse-S shapes of the reaction functions.

The second panel in Figure 5 shows the reaction functions when we set $\mu_1 = 5.025$ and $\mu_2 = 5$, holding the remaining parameters fixed. This change causes the reaction function of type 1 firms to shift down (for a given S'_2 they wish to enter for a lower signal) and the reaction function of the type 2 firms to shift outwards (for a given S'_1, type 2 firms are less willing to enter). There are still three equilibria, but because of these changes in the reaction functions, there is only one equilibrium where the stronger type 1 firms have the lower entry threshold so that they are certainly more likely to enter. When the difference between μ_1 and μ_2 is increased, there is only one equilibrium and it has this form, as illustrated in the third panel of Figure 5.

The result that with two types of bidders there is a unique equilibrium with $S'^{*}_1 < S'^{*}_2$ when $\mu_1 \geq \mu_2$ and σ_V, σ_ε and K are the same across types holds generally if the reaction functions have only one inflection point.[56] Under these assumptions it is also generally true that the game has a unique equilibrium, in which it will be the case that $S'^{*}_1 < S'^{*}_2$, if $\mu_1 - \mu_2$ is large enough.

The empirical literature on estimating discrete choice games provides several approaches

[55]In this diagram the reaction function represents what would be the symmetric equilibrium best response between the two firms of a particular type when both firms of the other type use a particular S'.

[56]In general, the exact shape of the reaction functions depends on the distributional assumptions made for the distributions of values and signal noise. Under our distributional assumptions, we have verified that the reaction functions have no more than one inflection point based on more than 40,000 auctions involving different draws of the parameters and different numbers of firms of each type.

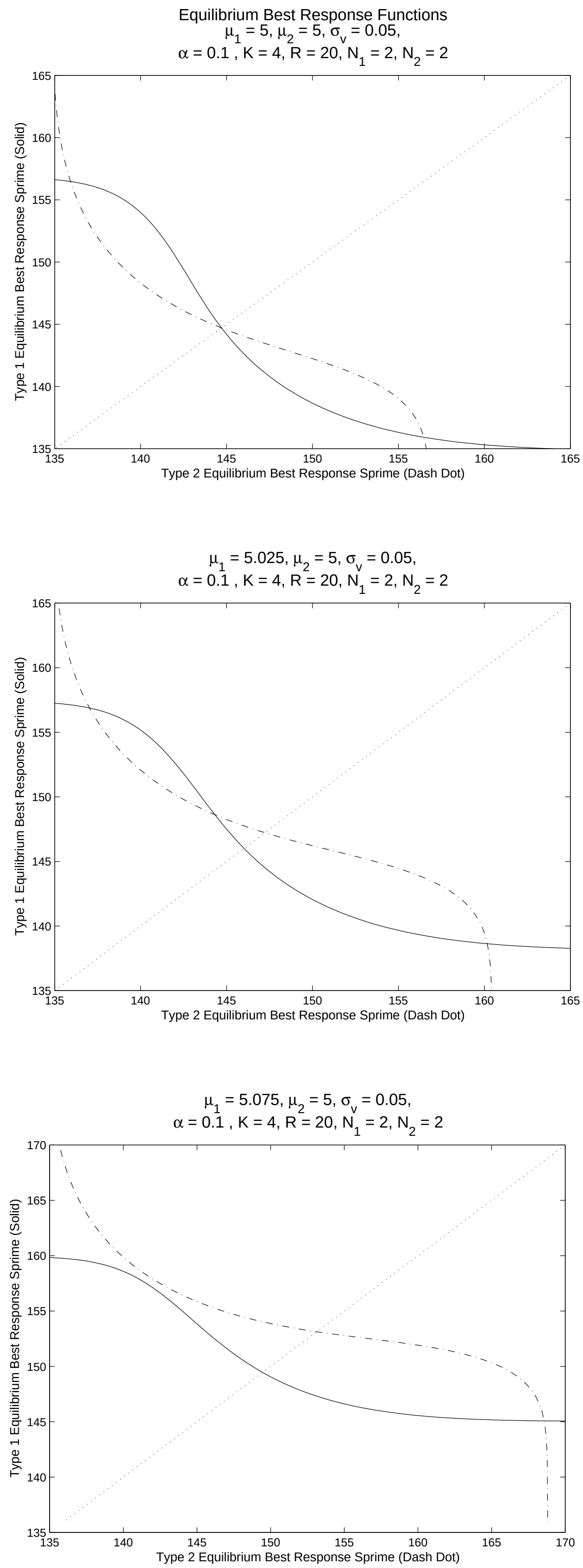

Figure 5: Reaction functions for symmetric and asymmetric bidders. In the top panel, the types are identical so that $\mu_1 = \mu_2 = 5$ and there are two firms of each type, $\sigma_V = 0.05, K = 4, \alpha = 0.1$ ($\sigma_\varepsilon = 0.0167$). In the next two panels firms are asymmetric in means only and the solid (dash dot) lines correspond to the type with the higher (lower) mean. In the middle (bottom) panel $\mu_1 = 5.025$ and $\mu_2 = 5$ ($\mu_1 = 5.075$ and $\mu_2 = 5$) and the remaining parameters are held fixed. The 45° line is dotted.

for estimating games with multiple equilibria including assuming that a particular equilibrium is played, estimating a statistical equilibrium selection rule that allows for different equilibria to be played in the data (Sweeting (2009) and Bajari, Hong, and Ryan (2010)) and partial identification tecnhiques that may only give bounds on the parameters (e.g. Ciliberto and Tamer (2009) and Beresteanu, Molchanov, and Molinari (2009)). In this paper we assume that the parameters σ_V, σ_ε and K are the same across types and that, if there are multiple equilibria, the equilibrium played will be the unique one where $S_1'^* < S_2'^*$. We view our focus on this type of equilibrium as very reasonable, given that it is clear in our data that mills (our type 1) tend to have significantly higher average values than loggers (our type 2), so that it is almost certain that only one equilibrium will exist (a presumption that we verify based on our parameter estimates).

B Monte Carlos (FOR ONLINE PUBLICATION)

This Appendix describes a set of Monte Carlo exercises where we investigate the performance of our Simulated Maximum Likelihood (SML) estimator, which uses Importance Sampling, to approximate the likelihood of the observed outcome for a particular auction (Ackerberg (2009)). This evidence is important because SML estimators may perform poorly when the number of simulation draws is too small. We also study the performance of our estimator under alternative definitions of the likelihood, which make different assumptions about the data available to the researcher.

Simulated Data

To generate data for the Monte Carlos, we allow the number of {mill, logger} potential entrants to take on values {3,3}, {5,5}, {8,8}, {6,2} and {2,6} with equal probability. For each auction a, there is one observed auction covariate x_a, which is drawn from a Uniform [0,1] distribution, and the vector X_a is equal to $[1\ x_a]$. We assume

$$\text{Location Parameter of Logger Value Distribution: } \mu_{a,\text{logger}} \sim N(X_a\beta_1, \omega^2_{\mu,\text{logger}})$$
$$\text{Difference in Mill/Logger Location Parameters: } \mu_{a,\text{mill}} - \mu_{a,\text{logger}} \sim TRN(X_a\beta_3, \omega^2_{\mu,\text{diff}}, 0, \infty)$$
$$\text{Scale Parameter of Mill and Logger Value Distributions: } \sigma_{Va} \sim TRN(X_a\beta_2, \omega^2_{\sigma_V}, 0.01, \infty)$$
$$\alpha\text{: } \alpha_a \sim TRN(X_a\beta_4, \omega^2_{\alpha}, 0, 1)$$
$$\text{Entry Costs: } K_a \sim TRN(X_a\beta_5, \omega^2_{K}, 0, \infty)$$

where $TRN(\mu, \sigma^2, a, b)$ is a truncated normal distribution with parameters μ and σ^2, and upper and lower truncation points a and b. The true values of the parameters are $\beta_1 =$

$[2.8; 1.5]$, $\beta_2 = [0.3; 0.2]$, $\beta_3 = [0.5; -0.1]$, $\beta_4 = [0.5; 0]$, $\beta_5 = [4; 4]$, $\omega_{\mu,\text{logger}} = 0.2$, $\omega_{\sigma_V} = 0.3$, $\omega_{\mu,\text{diff}} = 0.2$, $\omega_\alpha = 0.2$ and $\omega_K = 2$. The reserve price can take on values of 10, 30 or 50. We allow for R to be correlated with x, as one would expect if the seller sets a higher reserve price when he believes the tract has higher value. Specifically, for each auction, we take a draw u_a from a uniform $[0, 1]$ distribution and set

$$R_a = 10 \text{ if } \frac{x_a + u_a}{2} < 0.33$$
$$R_a = 30 \text{ if } 0.33 \leq \frac{x_a + u_a}{2} \leq 0.66$$
$$R_a = 50 \text{ otherwise.}$$

For each auction we find the unique equilibrium that satisfies the constraint that $S'^*_{\text{mill}} < S'^*_{\text{logger}}$, and generate data using the equilibrium strategies assuming that the auction operates as a second price sealed-bid auction, or, equivalently, an English button auction. The exercises described below all use the same 100 data sets of 1,000 auctions each.

Having constructed the data we estimate the parameters in three different Monte Carlo exercises, which differ in the importance sampling density used to draw the simulated parameters.

B.1 Monte Carlo Exercise 1: Importance Sampling Density is the True Distribution of the Parameters

In the first exercise we make the (generally infeasible) assumption that the researcher knows the true distribution of each of the parameters, which depends on the value of x_a for a particular auction. The number of simulation draws per auction is set equal to 250, and different draws are used for each auction. We compute the results for four different definitions of the likelihood (the same simulation draws are used in each case) that make different assumptions about the information available to the researcher, which will vary with the exact format of the auction (open-outcry vs. sealed-bid) and with the information that the seller collects about entry decisions. The alternative assumptions are:

1. the researcher observes the values (as bids) and identities of all firms that pay the entry cost and have values above the reserve, and he observes the entry decision of each potential entrant;

2. the researcher observes the values (as bids) and identities of all firms that pay the entry cost and have values above the reserve, and he knows that these firms entered, but for

other firms he does not know whether they paid the entry cost and found that their values were less than R, or they did not pay the entry cost;

3. the researcher observes the value and identity of the firm with the second highest value as the final price, the identity of the winning bidder (e.g. whether it is a mill or logger), the identity of all entering firms with values above the reserve price and he observes the entry decision of each potential entrant;

4. the researcher observes the value and identity of the firm with the second highest value as the final price, the identity of the winning bidder (e.g. whether it is a mill or logger), the identity of all entering firms with values above the reserve price, but for other firms he does not know whether they paid the entry cost and found that their values were less than R, or they did not pay the entry cost. This informational assumption forms the basis of the likelihood function shown in Equation (7).

Table 6 shows the mean value of each parameter and its standard deviation across the simulated datasets for each definition of the likelihood. With the true distribution as the importance sampling density and $S = 250$, all of the parameters are recovered accurately, including the standard deviation parameters. Several of the parameters appear to be recovered less precisely when less information is available to the researcher (likelihood definition 4), but the differences are never large.

B.2 Monte Carlo Exercise 2: Importance Sampling Density is a Uniform Distribution

When the true distributions are unknown, it is necessary to choose importance sampling densities that provide good coverage of the possible parameter space. In this exercise we draw parameters from independent uniform distributions where $\mu_{a,\text{logger}} \sim U[2,6]$, $\sigma_{Va} \sim U[0.01, 2.01]$, $\mu_{a,\text{mill}} - \mu_{a,\text{logger}} \sim U[0, 1.5]$, $\alpha_a \sim U[0,1]$, $K_a \sim U[0,20]$. In this case we set the number of simulation draws per auction equal to 1,000 to try to compensate for the fact that a relatively small proportion of the simulated draws are likely to be close to the parameters that really generate the data (in our empirical work we use 2,500 simulated draws per auction so that we get even better coverage). We use the four alternative definitions of the likelihood that we used for the first exercise.

Table 7 shows the mean value of each parameter and its standard deviation across the simulated datasets for each definition of the likelihood. The parameters which determine the means of each distribution are recovered accurately, but four out of the five standard

			Likelihood Definition			
Parameter	Variable	True Value	1	2	3	4
Logger	Constant	2.8	2.7793	2.7830	2.7918	2.7873
Location Parameter			(0.1094)	(0.1224)	(0.0893)	(0.0776)
	x_a	1.5	1.4954	1.4962	1.4945	1.4950
			(0.0999)	(0.1070)	(0.1211)	(0.1247)
	Std. Dev.	0.2	0.1904	0.1930	0.1849	0.1848
			(0.0182)	(0.0204)	(0.0320)	(0.0312)
Difference in Mill and Logger	Constant	0.3	0.3128	0.3025	0.3195	0.3139
Location Parameters			(0.0633)	(0.1477)	(0.1037)	(0.0551)
	x_a	0.2	0.1815	0.1897	0.1981	0.1925
			(0.0909)	(0.1045)	(0.1042)	(0.0942)
	Std. Dev.	0.2	0.1873	0.1888	0.1872	0.1820
			(0.0190)	(0.0278)	(0.0286)	(0.0277)
Value Distribution	Constant	0.5	0.5153	0.5190	0.5205	0.5307
Scale Parameter			(0.1311)	(0.1221)	(0.1003)	(0.0534)
	x_a	-0.1	-0.1007	-0.1022	-0.0895	-0.0795
			(0.1099)	(0.1065)	(0.0892)	(0.0759)
	Std. Dev.	0.3	0.2797	0.2749	0.2804	0.2771
			(0.0267)	(0.0268)	(0.0321)	(0.0280)
α (Degree of selection)	Constant	0.5	0.4979	0.4561	0.4809	0.5100
			(0.1358)	(0.2151)	(0.1716)	(0.0815)
	x_a	0.0	-0.0145	-0.0403	-0.0167	0.0068
			(0.1266)	(0.2003)	(0.1649)	(0.1337)
	Std. Dev.	0.2	0.1886	0.1853	0.1869	0.1891
			(0.0199)	(0.0300)	(0.0299)	(0.0407)
Entry Cost	Constant	4.0	4.0269	4.0115	4.0604	4.0743
			(0.5182)	(0.5386)	(0.7512)	(0.8108)
	K	4.0	4.2420	4.2858	4.4381	4.5171
			(0.8683)	(0.8868)	(1.3409)	(1.4110)
	Std. Dev.	2.0	1.9076	1.9194	1.9117	1.8934
			(0.2855)	(0.3024)	(0.3733)	(0.3971)

Table 6: True Importance Sampling Density Monte Carlo. The table shows the mean and standard deviation (in parentheses) for each of the parameters estimates across the 100 repetitions based on the four different definitions of the likelihood when we use the true joint distribution of the parameters as the importance sampling density, with $S = 250$ draws. See paper for descriptions of the different likelihood definitions.

			Likelihood Definition			
Parameter	Variable	True Value	1	2	3	4
Logger	Constant	2.8	2.7051	2.7102	2.6895	2.7031
Location Parameter			(0.0969)	(0.0998)	(0.1324)	(0.1333)
	x_a	1.5	1.3921	1.3807	1.3331	1.2946
			(0.1766)	(0.1810)	(0.2090)	(0.2245)
	Std. Dev.	0.2	0.2536	0.2478	0.2379	0.2312
			(0.0163)	(0.0178)	(0.0223)	(0.0238)
Difference in Mill and Logger	Constant	0.3	0.3286	0.3255	0.3532	0.3407
Location Parameters			(0.0806)	(0.0848)	(0.0970)	(0.1007)
	x_a	0.2	0.3073	0.3148	0.3536	0.3819
			(0.1465)	(0.1505)	(0.1595)	(0.1713)
	Std. Dev.	0.2	0.2487	0.2913	0.2452	0.2418
			(0.0171)	(0.0232)	(0.0204)	(0.0194)
Value Distribution	Constant	0.5	0.5727	0.5694	0.5969	0.5921
Scale Parameter			(0.0812)	(0.0423)	(0.0719)	(0.0753)
	x_a	-0.1	-0.0729	-0.0607	-0.0476	-0.0176
			(0.0762)	(0.0760)	(0.1227)	(0.1289)
	Std. Dev.	0.3	0.2895	0.2913	0.3163	0.3174
			(0.0201)	(0.0232)	(0.0326)	(0.0351)
α (Degree of selection)	Constant	0.5	0.4678.	0.4811	0.4671	0.5034
			(0.0842)	(0.1112)	(0.1052)	(0.1380)
	x_a	0.0	-0.1070	-0.1164	-0.1394	-0.1849
			(0.1526)	(0.1878)	(0.1595)	(0.2112)
	Std. Dev.	0.2	0.2590	0.3088	0.2537	0.3077
			(0.0234)	(0.0385)	(0.0311)	(0.0600)
Entry Cost	Constant	4.0	4.3744	4.0931	4.7719	4.6044
			(0.7186)	(0.7834)	(1.0344)	(1.0318)
	K	4.0	3.5605	3.8494	3.0215	3.1088
			(1.5964)	(1.5916)	(1.9387)	(1.9433)
	Std. Dev.	2.0	3.5409	3.6859	3.3704	3.5099
			(0.3358)	(0.3446)	(0.3623)	(0.4164)

Table 7: Uniform Importance Sampling Density Monte Carlo. The table shows the mean and standard deviation (in parentheses) for each of the parameters estimates across the 100 repetitions based on the four different definitions of the likelihood when we use a uniform importance sampling density, with $S = 1,000$ draws. See paper for descriptions of the different likelihood definitions.

deviation parameters are biased upwards. As in the first exercise, the alternative likelihood definitions appear to have only small effects on the precision of the estimates.

B.3 Monte Carlo Exercise 3: Two Step Estimation

As some of the parameter estimates appear to be biased using a uniform importance sampling density, the estimator we use in the paper uses the estimates based on a uniform importance sampling density to form new importance sampling densities that are used in a repetition of the estimation procedure. As long as the first step estimates are not too biased, this two step procedure should give accurate results, provided that the number of simulation draws is large enough.

To confirm that this is the case, we apply this two step procedure using likelihood definition 4 estimates from exercise 2 for each of the 100 datasets to form an importance sampling density from which we take $S = 250$ simulation draws for each auction (when we apply our estimator to the real data we use $S = 500$). We focus on likelihood definition 4 as it is the basis of our preferred estimates in the paper.

Table 8 shows the mean and standard deviation of the estimates for each of the parameters. We see that both the mean and standard deviation parameters are recovered accurately, although the estimated standard deviation of entry costs is recovered slightly less accurately than when we used the infeasible estimator in exercise 1. Overall, we regard these Monte Carlo results as providing strong support for our estimation procedure, especially as we use more than twice as many simulation draws when we apply our estimator to the actual data.

Parameter	Variable	True Value	Definition 4
Logger	Constant	2.8	2.7313
Location Parameter			(0.1389)
	x_a	1.5	1.3720
			(0.2138)
	Std. Dev.	0.2	0.1722
			(0.0349)
Difference in Mill and Logger	Constant	0.3	0.3308
Location Parameters			(0.0976)
	x_a	0.2	0.3138
			(0.1490)
	Std. Dev.	0.2	0.2039
			(0.0257)
Value Distribution	Constant	0.5	0.5741
Scale Parameter			(0.0639)
	x_a	-0.1	-0.0380
			(0.1078)
	Std. Dev.	0.3	0.2706
			(0.0292)
α (Degree of selection)	Constant	0.5	0.4725
			(0.1321)
	x_a	0.0	-0.0902
			(0.2193)
	Std. Dev.	0.2	0.2064
			(0.0590)
Entry Cost	Constant	4.0	4.2557
			(0.9945)
	K	4.0	3.5161
			(2.0808)
	Std. Dev.	2.0	2.5403
			(0.4681)

Table 8: Two Step Estimator Monte Carlo. The table shows the mean and standard deviation (in parentheses) for each of the parameters estimates across the 100 repetitions based on the fourth of the different definitions of the likelihood when we use the true joint distribution of the parameters as the importance sampling density, with $S = 250$ draws. See paper for the likelihood definition.

C Counterfactual with Strengthened Surviving Mills (FOR ONLINE PUBLICATION)

In this appendix we present results of our counterfactual simulations when we increase the value distribution of the mills that we assume survive due to what would be an increased concentration of mills, as described at the end of Section 7. We focus on the case when only the mills that bought out at \$10/mbf shut down, which corresponds to the second row in Table 5. Table 9 gives the results (the first row of this table is identical to the second row of Table 5). The last three rows correspond to different assumptions about how the value distribution of surviving mills increases after those that faced insolvency shut down. For each row, we increase $\mu_{a,\text{mill}}$ in each auction, not only those in which there is a potential entrant who we assume exits, so that at the current value of σ_{Va}, the mean of the surviving mills value distribution in an auction a is increased by $X\%$, where $X = 2$, 5 and 10%.

	Non-strategic Reserve		Optimal Reserve	
	Δ Revenues	% Change	Δ Revenues	% Change
Baseline	\$40.83 m	10.46%	\$33.19 m	8.50%
	(\$2.87 m)	(0.35%)	(\$2.60 m)	(0.36%)
Surviving Mill Mean Values ↑ by:				
2%	\$35.46 m	9.08%	\$27.59 m	7.07%
	(\$2.57 m)	(0.35%)	(\$2.27 m)	(0.34%)
5%	\$27.22 m	6.97%	\$18.86 m	4.83%
	(\$2.15 m)	(0.35%)	(\$1.78 m)	(0.31%)
10%	\$13.21 m	3.38%	\$4.20 m	1.08%
	(\$1.60 m)	(0.38%)	(\$1.09 m)	(0.29%)

Table 9: The format of the table is identical to Table 5 and all cases here correspond to the assumption that only insolvent mills shut down. The first row is identical to the second row in Table 5, and the next three rows assume that the average mill value in each auction increases by 2, 5 and 10%, respectively.