NBER WORKING PAPER SERIES

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James W. Roberts
Andrew Sweeting

Working Paper 16650
http://www.nber.org/papers/w16650

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2010

This paper previously circulated as "Entry and Selection in Auctions". We are extremely grateful to Susan Athey, Jonathan Levin and Enrique Seira for sharing the data with us and to Coleman Doggett and Doug MacDonald for their insight on the timber industry. We appreciate useful feedback from John Asker, Phil Haile, Jakub Kastl, Brian McManus, Rob Porter, Katja Seim and numerous seminar participants as well as attendants of the 2010 NBER Summer IO program. Excellent research assistance was provided by Christoph Bauner, Yair Taylor and Huihui Wang. Both authors gratefully acknowledge financial support from Duke University. Any errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 16650
December 2010, Revised August 2013
JEL No. D44,L20,L44,L73

ABSTRACT

Governments rescue private companies partly to prevent other firms from gaining excessive market power. However, if failing firms exit, new entry may limit remaining firms' market power if there are potential entrants who can be as effective competitors as the firms leaving the market. We quantify these effects in the case of the 1984 bailout of timber companies that faced substantial losses on existing federal timber contracts. We predict that the bailout substantially increased sale prices in subsequent auctions because firms that might have might have been induced to enter without the bailout tended to have relatively low values.

James W. Roberts
Duke University
Department of Economics
213 Social Sciences Building
Durham, NC 27708
and NBER
j.roberts@duke.edu

Andrew Sweeting
Department of Economics, Tydings Hall 3266
University of Maryland
College Park MD 20742
and NBER
atsweet@duke.edu

1 Introduction

Government bailouts of struggling industrial firms are typically justified by some combination of the desire to maintain employment, the need to protect strategically important assets and the desire to avoid liquidations that could significantly enhance the market power of firms that remain in the industry. This latter argument played a significant role in debates over rescuing defense contractor Lockheed Corporation in 1971, which was the first major US bailout of an industrial firm, as well as in many other subsequent bailouts affecting, for example, the automobile (Chrysler), airline (Pan-Am and Eastern) and timber industries.[1] Surprisingly, given the controversy surrounding many of these bailouts, and economists' natural interest in the question of how market structure affects outcomes, there has been no research trying to quantify how valuable these attempts to preserve competition have been.

In this paper we attempt to understand the value of maintaining competition in the case of the Reagan administration's 1984 assistance to firms in the timber industry. This bailout was a response to a dramatic fall in timber prices as the construction industry contracted during the recession of the early 1980s. This fall left a large number of timber companies, primarily in the Western U.S., facing large losses on U.S. Forest Service (USFS) timber contracts which they had purchased at very high prices before the recession, but on which they had yet to cut the timber. In some cases, firms' expected losses on USFS contracts exceeded the net book value of the rest of their business (the government defined a firm's net book value as a firm's excess of assets over liabilities excluding any outstanding federal timber contracts). The Federal Timber Contract Payment Modification Act of 1984 (referred to throughout this paper as the "Act") allowed firms to buy out of their contract obligations in return for relatively small payments to the Treasury. In total, a mixture of local firms and large national timber companies 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)).[2] The claim that without the Act a large number of firms would

[1] Regarding Lockheed's bailout, as then Secretary of the Treasury, John Connally, noted, "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). For Chrysler's aid, as Representative John LaFalce (D-NY) put it during hearings on the government's rescue of Chrysler, "I think we should consider...the preservation of competition within the automobile industry" (House of Representatives, 96th Congress 1st Session (1979)). As for Pan-Am and Eastern interventions, as the aviation subcommittee noted in their report (House Report 103-22) to the National Commission to Ensure a Strong Competitive Airline Industry, the subcommittee hearings included "extensive discussion of actions the government" could take to "preserve competition" in the industry. It was decided in these hearings 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) or Mathiesen (1995). Prior to bailing out Lockheed, assistance to private firms was associated with economic emergencies and war-related relief (Ritholtz (2009)).

[2] Under the same legislation, firms also paid \$11.9 million to buy out of 279 Bureau of Land Management

exit and that this would cause revenues in future federal timber auctions to fall was one of the arguments used to secure broad support for the Act, and it is this claim that we seek to evaluate.

To do so, we develop and estimate a model of endogenous and selective entry into USFS auctions. We allow for endogenous entry for two reasons. First, entry into USFS auctions is widely regarded as costly, because firms perform cruises, which involve sending workers out to the tract being auctioned for several days, before they decide how much to bid. These costs may deter some firms from participating at all based on their expectations of competition in the auction. Second, it is plausible that the liquidation of some auction entrants might have encouraged other timber firms to enter in their place, reducing the loss of competition relative to the case where the entry decisions of other firms are held fixed.

By 'selective entry' we mean the simple and intuitive idea that buyers with higher values are more likely to participate in the auction. With selection, marginal entrants, who may have entered if some of the bailed-out firms had exited, tend to be less valuable to the USFS than the average entrant. We allow for selection using a model where each potential bidder receives a partially-informative signal about its value prior to deciding whether to participate in the auction by performing a cruise (the cost of which is part of the cost of entering). In equilibrium, a marginal entrant will have a lower signal, and a lower expected value, than the average entrant, and the precision of the signal (a parameter in our model) will determine the relative value of marginal entrants to the USFS. The Samuelson (1985) (S) model of auctions, where potential entrants know their values before deciding whether to enter, so selection is perfect, and the Levin and Smith (1994) (LS) model, where potential entrants only know the prior distribution of values, are limiting cases of our model.

It is also necessary to allow for selection in order to avoid two features of the LS model that are a priori unattractive given our question and also inconsistent with our data. When there are asymmetric bidder types, which is clearly the case in our data, the (type-symmetric) mixed-strategy equilibrium in the LS model[3], cannot rationalize entry by a subset of potential bidders of each type.[4] In our data, on the other hand, we do see this type of entry pattern. Second, as shown by Levin and Smith (1994) themselves, a property of the mixed strategy equilibrium is that, when not all firms enter with probability one, an increase in the number of potential entrants decreases expected revenues. This would lead to the conclusion that a bailout, which increases the number of potential competitors in future auctions, would decrease expected revenues. This result seems counterintuitive and, as we show, it is also contrary to the cross-sectional evidence in this data. Entry models with selection do not have

contracts originally priced at $436 million (U.S. GAO (1989)).

[3]This is the type of equilibrium considered, for example, by Athey, Levin, and Seira (2011).

[4]In our setting, this would mean that some, but not all, mills and some, but not all, loggers enter.

to have this feature (Menezes and Monteiro (2000)), and for the parameters that we estimate expected revenues increase with the number of potential competitors.

We estimate our model using a sample of USFS auctions held in northern California from 1982 to 1989. Northern California, together with Oregon and Washington, were the areas most affected by the bailout. We also have information on which firms bought out their contracts and at what prices. A feature of the Act provided that firms with expected losses above their net book values could buy out of contracts at particularly low prices, and we use this information to identify the firms that were most likely to exit without the policy. Having estimated the model, we compute how expected revenues would change in auctions held after the Act if these firms were removed as potential competitors.

Our estimates indicate that entry into USFS timber auctions is moderately selective and that entry costs are sufficiently high that many firms with low values, and particularly logging companies, whose values tend to be low, will not enter. Our interpretation of moderate selection is that it reflects the fact that, based on the information released by the USFS, and their own knowledge of the forests and their own capacity, potential bidders are able to form only rough approximations of their values before performing cruises.

Our counterfactuals predict that, if the firms facing the worst losses, who were eligible for the lowest buyout rates, had exited without the Act, revenues in subsequent auctions would have fallen by an average of just over 11%. We regard this as a large effect given that the average post-Act auction had approximately nine potential entrants, and based on our criterion, only two of them would have been expected to exit without the bailout. In contrast, in many industries it is believed that only two or three firms are necessary to produce reasonably competitive outcomes (although these beliefs are related to the number of actual, not potential, entrants). For example, Bresnahan and Reiss (1991)'s analysis of firm entry suggested that most of the competitive effects of more firms in a number of service industries came from the second or third entrant. Across a wide-range of industries, mergers are now rarely challenged unless the merger will reduce the number of competitors below four (Coate and Ulrick (2005)). This large effect reflects three features of our model and our estimates. First, like other authors using timber data, we estimate that bidder values for a given tract are heterogenous, so that adding an additional competitor can increase the expected value of first- or second-highest order-statistics of bids quite substantially. This feature holds in our results even though, unlike some other authors, we allow for cross-auction heterogeneity that shifts the values of all potential bidders. Second, we allow for systematic differences in the values of mills and loggers. Mills have systematically higher values, making them more valuable to the USFS, and they were also more likely to benefit from the bailout program. Finally, selective entry plays an important role. Even though the reduction of potential bidders increases the probability that other firms enter, the marginal entrants who now participate tend to have relatively low values, and as a result their addition only increases the seller's expected revenues by a small amount. In contrast, in a model without selection, the seller's expected revenues could fall when some potential competitors exit, as noted above.

The 11% change in revenues is also large when we compare it with alternative ways of changing revenues in an auction, such as setting an optimal reserve price. Allowing for selective entry, we find that an optimal reserve price, for example, raises revenues by only about 2%, and, therefore, it could certainly not have been used to offset the loss of competition that would have been caused by a large number of bankruptcies. In doing so we illustrate, in a more general model that allows for asymmetries and endogenous entry, Bulow and Klemperer (1996)'s well-known theoretical result that additional competitors are more valuable than auction design tools. They show that adding one competitor is more valuable to the seller than choosing the optimal design in a setting with exogenous entry, symmetric bidders and independent private values. The result does not hold allowing for endogenous, but not selective entry, as adding potential competitors reduces expected revenues (the optimal reserve in the LS model is zero when the seller's value of keeping the object is zero). However, with selective entry the advantage of adding competitors can re-emerge. This illustration is particularly relevant given the large number of papers that have studied the setting of optimal reserve prices in timber auctions (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 (forthcoming)).

While we view our work as being a first attempt to study one of the arguments advanced in favor of bailouts, we should be clear that we do not view our paper as providing a thorough cost-benefit analysis of whether the bailout was an appropriate use of public funds. We do not attempt such an exercise because it is unclear what should be assumed about how much money the government would have been able to recover in the event of the firms going bankrupt or liquidating, or what would have happened in terms of local employment. Also, our sample of auctions excludes other timber sales that could have been affected by the bailout, such as those held by federal Bureau of Land Management, state agencies and private individuals. To conduct our own counterfactual we have to make strong assumptions about which firms were most likely to exit (those with large losses) and that exit would not have been followed by new entry into the industry as well as into particular auctions. We view this last assumption as plausible, because the number of sawmills in California had been in steady decline prior to the recession and the Act. In 1968 there were 216 sawmills in CA. This number fell to 176 in 1972 and 142 in 1976. In 1982 (during the recession) there were 101 sawmills, which fell to 93 in 1988. After 1991 the number of sawmills fell steeply after the courts prohibited logging in the habitats of the Northern Spotted Owl.[5]

Although we are not aware of any related papers considering the effects of a bailout, our paper is part of the literature on estimating auction models with endogenous entry. A number of papers estimate models inspired by the LS model, where it is assumed that bidders only know the distribution of values when they decide whether to enter so that there is no selection.[6] Most of the non-auction entry literature makes a similar no-selection assumption with regards to marginal costs or product qualities, assuming that if firms are asymmetric in these dimensions, these differences are only revealed once entry decisions have been taken.[7] Li and Zheng (2009) estimate an S-type of entry model with selection. Marmer, Shneyerov, and Xu (2011) and Gentry and Li (2012) consider the identification of models with imperfect selection based on the same type of signal structure that we consider. We differ from these papers in being focused on the implications of selective entry. We estimate a parametric model, employing an approach suggested by Ackerberg (2009), partly because we want to follow much of the recent auction literature (e.g., Li and Zheng (2009), Krasnokutskaya and Seim (2011)) in allowing for unobserved (to the econometrician) heterogeneity in values across auctions with endogenous bidder participation.[8]

This paper is also related to other work (Roberts and Sweeting (forthcoming) and Bhattacharya, Roberts, and Sweeting (2012)) that considers the importance of allowing for selective entry into auctions. However, those papers focus on selective entry's influence on mechanism design. Instead, in this paper, we consider a common justification for corporate bailouts and highlight the fact that while new entrants might limit increases in market power following the exit of failing firms (should the bailout not occur), their ability to do so will depend on whether they can be as effective competitors as the firms leaving the market. Exactly how competitive new entrants are depends on how selective is the entry process.

[5]See Morgan, Keegan, Dillon, Chase, Fried, and Weber (2004).

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

[7]For example, models like the one in Berry (1992) allow for there to be a shock to a firm's payoff from entering a market, which may cause some firms to enter while others do not. However, they assume that this shock does not affect the profits of other firms, so it must be interpreted as affecting sunk costs or fixed 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. Instead, the natural analogue of our model in non-auction settings would be one where firms receive noisy signals about their post-entry marginal costs or qualities.

[8]We have used this estimation approach in recent work on auctions (Roberts and Sweeting (forthcoming) and Bhattacharya, Roberts, and Sweeting (2012)) 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 (2010) 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.

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 uses them to measure the impact on USFS auction revenues from bailing out the firms that bid in these auctions. 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 The Federal Timber Contract Payment Modification Act of 1984

For over forty years the federal government, through the USFS and Bureau of Land Management, and many states have used auctions to sell contracts to the private sector for harvesting timber on federally- and state-owned land. Although we will focus on auctions held by the USFS, these other government-run auctions should also have been affected by changes in competition. The firms bidding in these auctions either have the ability to process timber themselves, or if not, will resell the timber to another firm that can. Following convention in the literature (e.g. Athey, Levin, and Seira (2011)), we refer to the former as 'mills' and the latter as 'loggers'. At a regional level, there are many firms who place bids in government-run auctions, but for a particular timber sale, the set of possible bidders is likely to be much smaller.

Auction formats have varied across agencies and over time, but frequently winners only pay the agency when the timber is cut. Prior to 1984 USFS contracts in California could last longer than five years, providing buyers with an incentive to delay cutting when they expected prices to rise. However, if prices for cut-timber fell sharply, buyers could also face large losses and this is what happened in the early 1980s, as shown in Figure 1. The thick black line in the figure is the quarterly average price for a thousand board feet (mbf) of Douglas Fir, a product common to northern California and the Pacific Northwest (prices of other products common in California, such as Sugar Pine and Hem Fir, show a similar pattern). The figure also shows the average and 75th percentile of auction sale prices and the average reserve prices of USFS auctions in California (we do not show reserve prices prior to 1978 because of a large number of missing values).

As can be clearly seen in Figure 1, auction and cut-timber prices in California rose significantly in the late 1970s. Mattey (1990) attributes this increase to a mix of speculative bidding, where bidders expected prices to continue to appreciate before the timber had to be cut, and overly-optimistic USFS projections of the demand for timber lumber. Some evidence of 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 what the USFS believed the timber was worth at current prices and its estimates of likely costs.[9] The price of cut-timber fell substantially in 1980 and 1981, as the Federal Reserve aggressively sought to reduce inflation by limiting monetary growth with the federal funds rate topping 20% in 1980.[10] This policy and the accompanying recession dramatically reduced demand from sectors, such as housing and construction, that are the primary consumers of lumber (interest rates on 30 year mortgages rose 23% from 1979 to 1980, and another 21% in 1981[11] and housing starts were 26%, 38% and 39% below their 1979 level in 1980, 1981 and 1982, respectively[12]). Auction prices also fell sharply in late 1980 and 1981. One explanation for the slower response of auction prices is that bidders who did not have access to private timberlands may have been reluctant to be the first to reduce their bids out of fear that they would be without inventory if cut-timber prices started to recover (Mattey (1990)).[13] The period of data that we use to estimate the model begins in 1982 after the price declines had leveled off.

These price changes were potentially disastrous for many firms that had purchased expensive contracts before prices fell. Mattey (1990) describes that it was quite common for firms to face losses of over \$200/mbf, and, at the time, it was estimated that the industry as a whole faced losses on these contracts of \$2 billion or more (Wiegner (1984)). If a firm refused to harvest the timber on a tract, the USFS would have re-sold the contract, but the original buyer would have been liable for the difference between the original contract price and the re-sold contract price, so that large losses could not be avoided. Consequently, firms that held these contracts lobbied the government for relief. Some form of relief was potentially attractive to the government because it was likely that trying to enforce the contracts would have pushed many firms into bankruptcy in which case the government might "be lucky if it ended up collecting 25 cents on the dollar for defaulted contracts" (House of Representatives (1984)).

The federal government's initial response, in 1983, was to lengthen some sale contracts by five years.[14] However, when it appeared that this policy was not preventing some of

[9]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.

[10]See *http://www.federalreserve.gov/releases/h15/data.htm*.

[11]See *http://www.freddiemac.com/pmms/pmms30.htm*.

[12]See *http://www.huduser.org/portal/periodicals/ushmc/summer12/USHMC_2q12_historical.pdf*.

[13]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)

[14]See Federal Register 48 (1983).

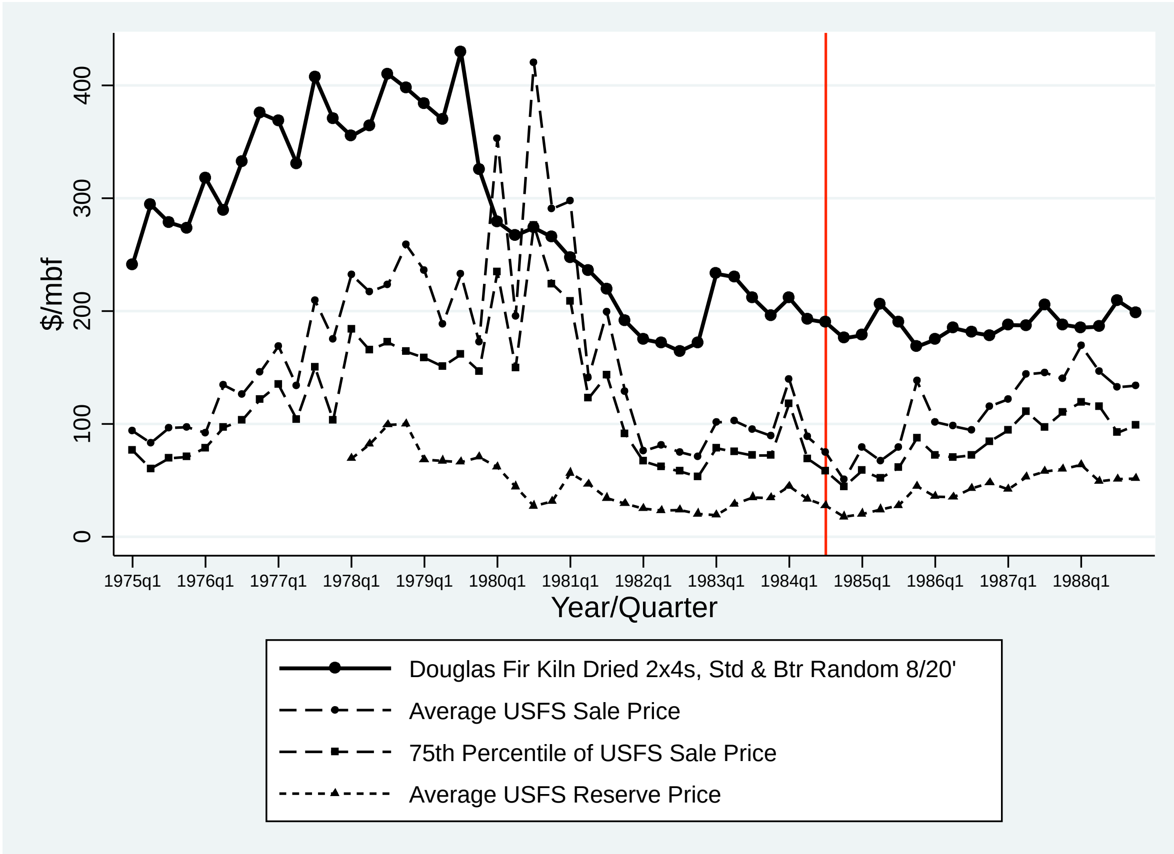

Figure 1: Prices of lumber products and USFS winning bids and reserve prices in California over time. Both are measured in $/mbf, in 1983 dollars. The vertical line is the quarter the Act was passed. The Douglas Fir prices come from Random Lengths Publishing Inc. The prices are quarterly averages of the prices, net f.o.b., received by surveyed mills in northern 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.

the most-troubled firms from shutting down[15], Congress passed the Federal Timber Contract Payment Modification Act (HR 2838), which was signed into law by President Ronald Reagan on October 16th, 1984. The bill was sponsored by several congressman from western states, including California, whose districts were most affected by the industry's downturn. A key argument made by proponents for the bill was the "enhanced competition" (Senate (1984)) that the assistance would provide for future USFS timber sales. As Representative Al Swift (D-WA) argued "Failure of these...companies will result in the increased concentration of the timber industry, which will lead to decreased competition on future contract bids" (House of

[15]Reagan (1984).

Representatives (1984)). The USFS supported the bailout (Federal Register 50 (1985)).[16]

A feature of the buyout, that is useful for our analysis, is that it was structured to give the firms in the most financial trouble the most relief. If a purchaser's potential losses would exceed 100% of net book value, it could buyout at a very low rate of $10/mbf. The rates at which firms could buy out increased as the potential losses as a fraction of net book value decreased. For firms whose losses were between 50 and 100 percent of their net book value, the buyout cost was 10% of the contract overbid (the contract price less the value, determined by the USFS, of the remaining net merchantable timber on the tract), or $10/mbf, whichever was greater. For those firms whose losses were less than 50% of net book value, the buyout cost was the greater of $10/mbf or a percent of the contract overbid, which varied with buyout volume.[17] In our data, we find that firms bought at rates that ranged from $10/mbf to $88.53/mbf. We assume throughout the paper that the firms that bought out at $10/mbf were those firms that convinced the government that absent the bailout they would be insolvent. We are comfortable with this assumption and that we are not categorizing some firms as facing insolvency, when in fact they did not, since we observe the price that each firm paid to buy out of each contract, and the firms that we identify as facing insolvency paid $10/mbf for each buyout and the average buyout price paid by other firms is $41.90/mbf. The buyout removed considerable losses from many firms' balance sheets. For example, Bohemia Corp. could have lost more than $138 million, which exceeded its net book value of $96 million. Ultimately, it reduced its losses to just under $63 million. Large firms (e.g., Weyerhaueser, 1984 net book value of $3.3 billion and Plumb Creek Timber, a subsidiary of Burlington Northern, 1984 net book value of approximately $4.0 billion) also participated in the bailout (Wiegner (1984)).

3 Model

This section describes the model of endogenous auction participation that we estimate and then use to assess the effect of removing those potential bidders who might have been forced to exit the industry without the Act.

To put the model in context, we begin by more fully describing the USFS auction process. When a sale is announced, the USFS provides its own estimate of the volume of timber for each species on the tract as well as estimated costs of removing and processing the timber.

[16] An additional worry about the bill's passage was that the government would depress future prices when it re-sold the returned timber. To avoid this problem, the resale of returned lands was spread out over a seven year period.

[17] 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)).

It also announces a reserve price and bidders must submit a bid of at least this amount to qualify for the auction. After the sale is announced, each bidder can perform its own private cruise of the tract to assess its value. 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. This paper will focus on its open outcry auctions.

In the model bidders have independent private values. This is an assumption commonly made in other papers using similar timber auction data (see for example Baldwin, Marshall, and Richard (1997), Brannman and Froeb (2000), Haile (2001) or Athey, Levin, and Seira (2011)). A bidder's private information is primarily related to its own contracts to sell the harvest, inventories and private costs of harvesting and thus is mainly associated only with its own valuation. In addition, we focus on the period 1982-1989 when contract resale, which can introduce a common value element, was limited (see Haile (2001) for an analysis of timber auctions with resale).

Consider an auction of timber tract a with $N_{\tau a}$ potential bidders (firms) of type τ with $\overline{\tau}$ types in total. In our setting $\overline{\tau}$ is 2 and the types are sawmills and loggers. Type τ firm values V 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 $[0, \overline{V}]$. The distribution can depend 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 $\mu_{1a} > \mu_{2a}$. We will also choose a value for $\overline{V}$ that is significantly above the highest price observed in our data.

Firms play a two stage game. In the first stage, each firm independently decides whether to enter the auction, which requires paying an entry cost K_a. Participation in USFS auctions is costly for numerous reasons. In addition to the cost of attending the auction, a large fraction of a bidder's entry cost is its private cruise, and people in the industry tell us that firms do not bid without doing their own cruise. There are several reasons for this. First, some information that bidders find useful, such as trunk diameters, is not provided in the pre-sale information made public by the USFS. In addition, the government's reports are seen as useful, but noisy estimates of the tract's timber. We allow for potential entrants to be imperfectly informed about their value in the model in the following way. 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. Note that the parameters σ^2_{Va}, $\sigma^2_{\varepsilon a}$ and K_a are assumed to be common across the types. We make this assumption for reasons connected with equilibrium selection, which we explain below.

Entrants can participate in the second stage of the game, and we assume that only firms that pay the entry cost can do so (as mentioned above, firms are unlikely to bid without performing their own cruise). Entrants submit bids (if their value exceeds R_a) in a second price auction, so that if a bid is submitted above the auction's reserve price, the object is sold to the bidder with the highest bid 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 view incorporating selective entry into the model as not only realistic, but also necessary for studying the question of how the Act affected revenues, because the obvious alternative modeling assumptions could lead us to effectively assume the answer in advance. For example, if all potential bidders are assumed to enter (i.e., exogenous entry), then, in a private values model, expected revenues will fall if the number of potential bidders declines. However, models with endogenous entry can also imply very particular relationships between the number of potential bidders and revenues.[18] For example, Levin and Smith (1994) show that in their model, where there is no selection, with an optimal reserve price expected revenues will increase in the number of potential bidders up to the number, n^*, where all potential bidders will enter for sure, before declining monotonically above n^* (their Corollary to Proposition 9). As in our data not all firms enter, imposing the LS model would lead to the conclusion that reducing the number of firms would reduce the USFS's revenues. In contrast, with selection the relationship between the number of potential entrants and revenues will depend on the particular parameters that we estimate.[19]

Next we describe the model's equilibrium. In doing so, we assume non-collusive bidder behavior because, although there has been some evidence of bidder collusion in open outcry timber auctions, Athey, Levin, and Seira (2011) find strong evidence of competitive bidding in these California auctions.

[18] 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.

[19] In the S model, with perfect selection, the relationship between the seller's revenue and the number of potential bidders depends on the distributions or parameters that are assumed (Samuelson (1985), Menezes and Monteiro (2000) or Li and Zheng (2009)). In our model, the pattern will also depend on the estimated degree of selection.

3.1 Equilibrium

Following the literature (e.g. Athey, Levin, and Seira (2011)), 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 in a type-symmetric equilibrium is a pure-strategy threshold rule whereby the firm enters if and only if its signal is above a cutoff, $S'^*_{\tau a}$.[20] $S'^*_{\tau a}$ 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.

[20] 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 $s > S'^*_{\tau a}$.

When there is more than one type, there may be multiple 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_v, σ_ε and K are the same across the types and to assume that firms play an equilibrium where $S_1'^* < S_2'^*$ (the type with higher mean values has the lower threshold). Under our parameter restrictions there is always exactly one equilibrium of this type. Appendix A explains the restrictions in more detail.

We choose this approach for several reasons. First, it is computationally simple to implement and it 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.[21]

Given our equilibrium selection rule it is computationally straightforward to solve for the equilibrium entry thresholds. Specifically, we use a standard non-linear equation solver (in MATLAB) to solve the zero profit conditions (Equation (2)) subject to the constraint that $S_1'^* < S_2'^*$. The integrals in Equation (2) are evaluated on a 10,000 point grid, which runs from 0.01 to 500 (significantly above the maximum price that we observe in our data).[22]

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. From the set of all such auctions held between 1982 and 1989, we drop small business set-aside auctions, salvage sales and auctions with missing USFS estimated costs. To eliminate outliers, we also remove auctions with extremely low or high acreage (outside the range of [100 acres, 10,000 acres]), volume

[21]We check whether our parameter estimates can support multiple equilibria by plotting type-symmetric "equilibrium best response functions" for mills and loggers for each auction, as we do in Figure 3 in Appendix A. Our conclusion is based on taking 10 simulated draws of the parameters for each auction. For each of these simulations, our parameter estimates support only a single equilibrium.

[22]The tolerances for solving the non-linear equations are set equal to 1e-13. Bhattacharya, Roberts, and Sweeting (2012) extend the methodology to first-price auctions where it is also necessary to solve for equilibrium bid functions.

(outside the range of [5 hundred mbf, 300 hundred mbf]), USFS estimated sale values (outside the range of [$184/mbf, $428/mbf]), maximum bids (outside the range of [$5/mbf, $350/mbf]) and those with more than 20 potential bidders (which we define below).[23] We keep auctions that fail to sell due to no bidder being willing to meet the reserve price. We are left with 887 auctions.

Table 1 shows summary statistics for our sample. For each auction, we observe the names of firms that submit bids. For any auction, we define the set of potential entrants for that auction as the auction's bidders plus those bidders who bid within 50 km of an auction over the next month. One way of assessing the appropriateness of this definition is that 98% of the bidders in any auction also bid in another auction within 50 km of this auction over the next month. On average, the median number of potential bidders in an auction is eight (mean of 8.9) and this is evenly divided 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). Note that there may have been additional firms that were 'entrants', in the sense of paying the entry cost, but subsequently found out that their values were less than the reserve price. We take this possibility into account in estimation. Mills are more likely to be willing to meet the reserve price (a median of three) than are loggers (median of one).[24]

Bids are given in $/mbf (1983 dollars). The average mill bid is 20.3% higher than the average logger bid. As suggested in Athey, Levin, and Seira (2011), mills may be willing to bid more than loggers due to cost differences or the imperfect competition loggers face in selling harvested timber.

We combine these auction data with information on firms that participated in the buyout that were provided to us by Doug MacDonald of the Timber Data Company, a company that helped the government determine buyout rates after the Act was passed. The data lists the firms that bought out of contracts and the buyout rate that they paid. Based on the Act's rules, we refer to the firms that bought out at the minimum rate, $10/mbf, as the firms which

[23] For estimation we set $\overline{V}$ = $500/mbf, which is substantially above the highest price observed in our sample.

[24] Our model assumes that differences in values explain why mills are more likely than loggers to enter an auction. However, this pattern could also be explained by differences in entry costs, which we allow to vary across auctions, but not across mills and loggers within an auction. This alternative explanation is unlikely for three reasons. First, there is little reason to believe that the cost of performing cruises differs substantially across firms for any sale since all potential entrants must attend the auction if they want to submit a bid and are interested in similar information when performing their own cruise (even if their values are different). Second, Table 1 clearly shows that mills also bid more than loggers, suggesting that the meaningful distinction between the types are their value distributions. Third, conditional on being willing to pay the reserve, which requires entry, loggers are still much less likely to win than mills (15.5% vs. 27.9%). This last point argues against the possibility that loggers enter and win less primarily because of high (relative to mills) entry costs, as this would lead them to enter only when they expect to win.

faced insolvency.

Because we are using auctions from around the time of the bailout to estimate the model, one might be concerned about the model's assumption that the firms receiving the bailout are similar to other firms of the same type. For example, a firm's willingness to pay for timber might be affected by its degree of financial distress, which may also have been affected by the bailout. Even though Figure 1 showed that, on average, auction sale prices had stabilized by the time our sample begins, the regressions in Table 2 examine bidding behavior more precisely. All regressions include auction fixed effects, thereby removing the effects of cross-auction heterogeneity, to facilitate a within-auction comparison of firms with different degrees of financial distress. The first four columns in the table look at the bidding behavior of firms within bidder-type as a function of whether they bought out of contracts, what rate they paid and whether the auction was held after the Act was passed. Standard errors are clustered at the auction level. There is no indication that the level of financial distress affected bidding behavior. There is some evidence that mills which faced insolvency were less likely to win an auction before the bailout (specification (3)), but this effect seems to be driven by two specific firms, Sierra Pacific and Schmidbauer.

4.1 Selective Entry

In this subsection we argue that the data is only consistent with a model that allows for at least some degree of selection in the entry process. As noted above, allowing for selection is important for our counterfactual as in the mixed strategy equilibrium of the symmetric LS model, expected revenues decline with the number of potential entrants unless all firms enter with probability one. This pattern is not the pattern that we see in the data. When 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, we find a positive and statistically significant coefficient on the number of potential entrants (the estimated coefficient is 0.033 with a standard error of 0.003).[25] When we include separate measures of the number of mill and logger potential entrants and their interaction, we find a large, positive effect of the number of mills and a smaller, positive effect of the number of loggers, which declines when there are more mills. This pattern makes intuitive sense as loggers tend to have lower values and, when several mills are present, it is relatively unlikely that a logger will win the auction (in 74 of the 136 times that a logger wins an auction, there are no more than 2 mill potential entrants).

[25]The full results are available on request.

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	3426
LOGGER	65.16	52.65	26.49	49.93	90.93	876
MILL	78.36	58.94	32.84	61.67	110.91	2550
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	1050
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. The term INSOLVENT means that the variable is conditioned on the firm buying out of contracts at the minimum 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)	(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 2: 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.

There is additional evidence of selection in the data. In the type-symmetric mixed strategy equilibrium of a model with non-selective entry and asymmetric bidder types, whenever the weaker type enters with positive probability, the stronger type enters with probability one. Thus, for any auction with some logger entry, a model with no selection would imply that all potential mills entrants enter. In 54.5% of auctions in which loggers participate, and there are some potential mill entrants, some but not all mills participate. A model with selective entry can rationalize partial entry of both bidder types into the same auction.

A final way of seeing whether the data is best explained by a model that allows for potential selection is by noting that a model without selection implies that bidders are a random sample of potential entrants. We can test this by estimating a Heckman selection model (Heckman (1976)) using data on the highest bid submitted by an individual firm during the auction. The second stage regression uses this bid 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 stage probit regression on 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. 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 stage results appear in column (2) of Table 3, with column (1) showing the estimates when we do not control for selection. 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 is to be expected when most mills enter, but loggers only enter when they expect their values to be high enough to compete with the mills.

The evidence presented in this section strongly suggests that the entry process is selective, but it does not pin down the degree of selection, much less guarantee that a particular degree of selection, such as perfect selection mandated by S, is appropriate. Therefore, we now turn towards estimating our model to recover the degree of selection, and other model parameters that best explain the observed bidder behavior.

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 greatly

	(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 3: Evidence of Selection. In both columns the dependent variable is log of the bid per mbf and year dummies are included. Column (2) displays the second stage results of a two step selection model. The first stage probit is of entry where the exogenous shifters are potential other mill and logger entrants, incorporated as a flexible polynomial. $\widehat{\lambda}$ is the coefficient on the Inverse Mills Ratio from the first stage.

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.

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

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.

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. We note that Li and Zheng (2009) estimate a Samuelson model 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.

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 concept 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 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. We select the bounds of the support of the structural parameters to be the same for $\phi(\cdot)$ and both stages of $g(\cdot)$ and choose them to be wide enough to include all reasonable values of the parameters. For example, we view our choice of the bounds of the support of K, $[\$0, \$20]$/mbf, to include very large realizations of entry costs, both relative to the average winning bid ($86.01/mbf, see Table 1) and plausible estimates of actual entry costs based on our conversations with industry experts (see our discussion of industry experts' opinions of actual entry costs in Section 6).[26] 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[27]; (ii) the winning bidder has a value greater than the second highest bid; (iii) both the winner and the second highest bidder entered and paid K_a; (iv) other firms that indicated that they would meet the reserve price or announced bids entered and paid K_a and had values between the reserve price and the second highest bid; and, (v) all other potential entrants may have entered (paid K_a) and found out that they had values less than the reserve, or they did not enter (did not pay 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., would pay the reserve or announce bids) out of $N_{\tau a}$ potential entrants would

[26] Our chosen support of μ_{logger} is $[2, 6]$, of $\mu_{mill} - \mu_{logger}$ is $[0, 1.5]$, of σ_v is $[0.01, 2.01]$, and of α is $[0, 1]$.

[27] 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.

be proportional[28] to the following, where $S'^{*}_{\tau a}$ are the equilibrium entry thresholds:

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

reflecting the contributions to the likelihood of the second highest bidder, the winning bidder, the other firms that attend the auction and those that do not attend, respectively.[29]

5.1 Identification

Gentry and Li (2012) examine nonparametric identification of the type of auction model with endogenous, and partially selective, entry that we consider in this paper.[30] They show that with sufficient exogenous variation in signal thresholds, the model is point identified. Cross-auction heterogeneity in the number, or types, of potential entrants or reserve prices, for example, may provide the necessary variation in signal thresholds. In the case where sufficient entry-threshold variation does not exist, Gentry and Li (2012) show that the model is partially identified, with bounds on the joint distribution of values and signals. Their results extend to asymmetric bidder types (as long as only one type-symmetric equilibrium is played across auctions with positive probability) and, building off ideas in Hu, McAdams, and Shum (2011), unobserved auction-level heterogeneity. Since we want to include a rich set of observed covariates and want point identification to easily quantify the potential decline

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

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

[30]The other paper that explores identification of this sort of model is Marmer, Shneyerov, and Xu (2011), who develop a nonparametric test of whether data from a first price auction with symmetric bidders and no unobserved heterogeneity is generated by a model like LS, S or one with partially selective entry.

in USFS revenues absent the bailout, we take a parametric approach to estimation.[31]

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, including controls for potential entry, and in the specifications in Table 3. We also control for species concentration since our discussions with industry experts lead us to believe that this matters to firms. We allow for auction-level unobserved heterogeneity in all parameters. 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. For the rest of the paper, we refer to these as the "mean" and "median" values of the parameters. 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. It does appear that there is both unobserved heterogeneity in values across auctions (the standard deviation of μ_{logger}) and heterogeneity in the difference between mill and logger mean values across auctions (the standard deviation of $\mu_{\text{mill}} - \mu_{\text{logger}}$).

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, a 46% difference. Figure 2 shows the value distributions for potential entrants of both types.

We estimate a mean entry cost of \$2.05/mbf. One forester we spoke with estimated current cruising costs of approximately \$6.50/mbf in 2010 dollars. In 2010 dollars our estimate of mean entry costs would be \$4.49/mbf, which is broadly consistent with research costs being the main part of entry costs into the auction. 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.

Even with the model's restrictive assumptions, made to deal with the multiple equilibria issue as well as to take a cautious approach in interpreting the data, we are able to match the data quite well. We slightly over predict logger entry. In the data, on average 0.99 loggers attend each auction. We predict that on average 1.07 loggers will enter and have values

[31] We also wish to interpret the data cautiously by not inferring that firms who submit bids are the only entrants. Gentry and Li (2012)'s results require the econometrician to observe the number of entrants, which is reasonable in some contexts. However, given the presence of reserve prices in our data, we want to allow for the possibility that firms may pay the entry cost but learn their value is less than the reserve price, in which case they will not bid.

	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
$\sim N(X_a\beta_1, \omega^2_{\mu,\text{logger}})$	(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
$\sim TRN(X_a\beta_3, \omega^2_{\mu,\text{diff}}, 0, \infty)$	(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
$\sim TRN(X_a\beta_2, \omega^2_{\sigma_V}, 0.01, \infty)$	(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
$\sim TRN(X_a\beta_5, \omega^2_K, 0, \infty)$	(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.

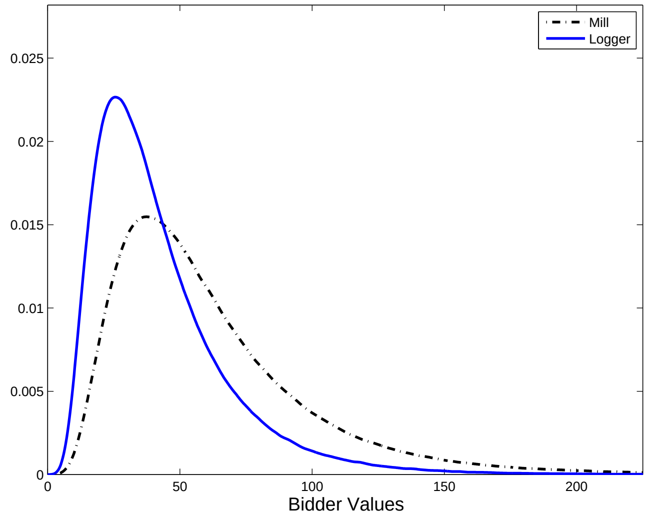

Figure 2: Comparing the value distributions for mills (dash-dot) and loggers (solid). Based on the mean value of the parameters from Table 4.

greater than the reserve. We slightly under predict mill entry. In the data, on average 2.87 mills attend each auction. We predict that on average 2.44 mills will enter and have values greater than the reserve. We slightly under predict revenues. In the data, the mean (median) revenues are \$81.89/mbf (\$65.89/mbf) and we predict them to be \$75.58/mbf (\$58.13/mbf). We do a good job of matching prices in the event of a sale. In the data, prices average \$85.76/mbf and our model predicts an average of \$86.39/mbf.

The assumptions used to generate our preferred results in Table 4, which we use in all counterfactuals below, are based on a conservative interpretation of what we know about the entry decisions of firms that do not attend the auction. An alternative assumption is that firms that did not attend the auction did not pay K. If the model is estimated under this assumption, the estimates (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.

Our estimates of the αs across auctions indicate a moderate amount of selection in the data. Based on our estimates, we find a 46% difference in mean values for potential mill and logger entrants. This is much larger than the average difference in bids across mills and loggers in Table 1, as would be expected if entry is selective. If we consider a representative auction where the reserve and the number of potential mill and logger entrants are set equal to their respective medians of \$27.77/mbf, four and four, we can compare the difference in values between a marginal bidder who observed signal $S'^{*}_{\tau a}$, and the average (inframarginal) entrant. Based on the mean parameter values, 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 entrant and marginal loggers are \$59.80/mbf and \$48.13/mbf, respectively. The difference between marginal and inframarginal bidders is indicative of the degree of selection in the entry process. Also note that, for these estimates, marginal loggers tend to have higher values than marginal mills.

7 The Value of Preserving Competition

We now use our estimated model to predict how the USFS would have been affected if the firms that received the most generous buyout terms had exited the industry, so that they were no longer potential entrants. As these firms faced losses which exceeded their net book value, it is plausible that they would have exited without the Act, or some other form of assistance. It is also possible that some other firms would have exited without the Act, so we also consider the effects if all of the firms that bought out would have exited the industry. Of course, one could argue that if a large number of timber companies had exited the industry then a number of new firms, that we do not observe in the data, would have entered, possibly using some of the capital stock from the firms that were exiting, and would therefore have been potential entrants into these auctions. This is possible, but we regard widespread new entry as unlikely given that this is an industry where the number of establishments was in steady decline (see the statistics on mills in the Introduction). It is also possible that the assets of bankrupt firms would have been bought by existing participants. In this case our assumption that the number of potential competitors would decline would still be correct, although there could be effects of additional capacity on the values of remaining bidders that our model does not capture.

Our calculations examine how changes in the set of potential entrants change the USFS's expected revenues. These are defined as being equal to auction revenues in the event of sale plus an assumed value of holding on to the tract if it is not sold, the probability of which may change with the number of entrants. Throughout the rest of the analysis, the value of holding onto the tract is assumed to be equal to the reserve price that we observe in the data. This is appropriate given that the USFS did not set reserve prices strategically during our data.[32] Expected auction revenues and the probability of sale are calculated using 5 million simulations for each auction.

The first two columns of Table 5 give the main results when we assume that the USFS

[32]Li and Zheng (2010), and Paarsch (1997), in one of his specifications, also make this assumption. Moreover, in practice this is very similar to assuming that USFS's value is the its estimated sale value less costs, which is the approach taken by Aradillas-Lopez, Gandhi, and Quint (forthcoming).

keeps the same reserve price. The first line shows that when all of the firms that faced insolvency are removed as potential entrants, USFS revenues across the 489 auctions in which at least two potential entrants would have remained are expected to drop by \$43.52 million (m.) dollars, or by 11.11%, relative to its value with the full set of potential entrants that we actually observe. These changes are statistically significant at any conventional significance level.[33] The final row of the table shows the predicted change in revenues when we remove all of the firms that bought out of their contracts at any rate. Since we focus on auctions for which at least two potential entrants still would have existed, the total number of auctions that we compute changes in revenues for in this counterfactual falls to 458. The decrease in revenues rises to almost 20%.

Returning to our base case assumption where only the minimum buyout rate firms are assumed to exit without the Act, the 11% revenue effect seems large given that on average these auctions have over nine potential entrants, with only two of them buying out at the minimum rate. In many markets, particularly with homogenous products, we would be believe that having six firms would be enough to generate quite competitive outcomes, so that the benefits to adding additional firms would be small.

There are three reasons why we find large effects. The first reason is that within-auction values are estimated to be quite heterogenous, which implies that adding additional bidders (entrants) can increase the expected value of the first- or second-order statistics quite substantially.[34] As an illustration of this point, consider an auction with exogenous entry where there are six bidders with values drawn 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 there is significant within-auction heterogeneity in values even though we are explicitly allowing for cross-auction heterogeneity in mean values. In this regard our results are consistent with Athey, Levin, and Seira (2011) and Aradillas-Lopez, Gandhi, and Quint (forthcoming), who also allow for cross-auction heterogeneity in timber auctions.

The second reason is that our estimated model implies that there is (moderate) selection

[33] The drop in revenues comes mainly from a decline in prices since the average probability that a tract fails to sell when these firms are no longer potential entrants only increases from 0.041 to 0.057.

[34] Similarly, in a standard homogenous goods market with Bertrand Nash price setting, the decline in the expected price when a new competitor is added will typically increase with the variance of the distribution from which marginal costs are drawn.

in entry. Recall that in LS, where there is no selection, expected revenues increase when a potential entrant is removed (a result which would hold even when the variance of the value distribution is large). The reason for this is that the removal of a potential entrant will cause the entry probabilities of the remaining firms to increase, and, with no selection, the additional entrants that this effect causes are just as likely to be valuable to the seller as any other entrant.[35] In contrast, with selection, when other firms enter only because another potential entrant has been removed, they are likely to have relatively low values and be less valuable to the seller. This fact also, of course, reduces the incentives of marginal non-entrants to enter the auction.

To see this, let's 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, but expected revenues fall to \$71.25/mbf (a decline of 6.9%).

This reflects the fact that 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.[36] If entry were more selective, then the revenue decrease might be larger. For example, if $\alpha = 0.10$, then reducing the number of potential entrants from 6 to 5 would lower revenues by 7.3%.

The third reason for the large revenue change is that most of the potential entrants that bought out their contracts are mills (on average, 1.76 mills potential entrants were eligible to buyout at the minimum rate, compared with 0.40 loggers) and, to the USFS, mills are more valuable than loggers because they tend to have higher values, so that they enter and win or set the price more often. The importance of mills is illustrated in the second row of Table 5, which shows that revenues decline by almost as much as in the base case when we remove only affected mills as potential entrants.

The final two columns of Table 5 consider how far the drops in revenues associated with a smaller number of potential entrants would be offset if the USFS set an optimal reserve price, where we assume that the USFS knows the true parameters associated with each auction (although it does not know the bidders' signals). As previously mentioned, the possible

[35] The reason that expected revenues actually increase is that, with fewer potential entrants, each of whom is more likely to enter, the probability of very few firms entering falls even though the expected number of entrants may fall as well.

[36] 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 % change than when the scale parameter is 0.5763.

Set of Exiting Firms	Non-strategic Reserve Δ Revenues	Non-strategic Reserve % Change	Optimal Reserve Δ Revenues	Optimal Reserve % 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%)
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%)
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%)

Table 5: The table shows the post 1984 change in USFS revenues in our sample of USFS 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.

value of setting optimal reserve prices in timber auctions, under the assumption of exogenous entry, has been widely studied in the literature.[37] In an IPV model where (1) bidders are symmetric, (2) all bidders must participate, (3) the marginal revenue curves associated with each bidder are downward sloping and (4) every bidder is willing to bid at least the seller's value of holding onto the object, Bulow and Klemperer (1996) show that an additional bidder is more valuable to the seller than an optimal reserve price. Our calculations illustrate how this result, which potentially has important implications for how much effort sellers should devote to designing the auction rather than encouraging interest in the object being sold, can still hold in a setting where bidders are asymmetric and entry is endogenous and selective. For example, when all firms that buy out at the minimum rate are removed, the USFS's value falls by 9.07% when it sets an optimal reserve after exit, which is only 18% smaller than the fall when it uses the reserve price observed in the data both before and after exit.[38]

The numbers in Table 5 are based on the assumption that the value distributions of surviving firms are unchanged when some of their competitors shut down. This may be a strong assumption if the failure of some firms alters the competitive structure of downstream markets for surviving firms. For example, surviving mills might have faced less competition for their processed timber had the Act not passed, and if this enabled them to raise prices,

[37]For example, 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 (forthcoming). Athey, Cramton, and Ingraham (2003) contains practical advice to timber sellers on how to set reserve prices.

[38]The optimal reserve price is found by searching over a fine grid of reserve prices based on a fixed set of 5 million simulations for each auction.

their value for USFS timber might also rise. Thus, the loss in auction revenue due to a reduction in the number of potential bidders could be offset by the fact that surviving mills have higher values and consequently could bid more. Note that increased concentration of mills might also have reduced the price they needed to pay loggers for their wood. If this translated to loggers reducing their bids, the findings in Table 5 would be strengthened.

While it is unlikely that the exit of some potential bidders in a particular auction could increase the values of surviving potential entrants into that same auction, since prices for finished wood are not set at such a local level, it is less obvious whether the exit of a large number of mills from the entire region would have altered the values of surviving firms in that area. However, based on long-term industry trends since the Act was passed, as well as our discussions with industry experts about this possibility, we do not view this as a first-order concern for the numbers in Table 5. The steady decline in the number of mills since the 1970s suggests that at the time of the Act's passing the industry was characterized by excess capacity, which would have limited surviving firms' pricing power had insolvent firms shut down. Additionally, our contacts at Random Lengths, the leading source for information and analysis of the forest products industry, think it is unlikely that, absent the bailout, surviving mills would have had substantially higher values for USFS timber.[39] They view the market for processed timber as fairly competitive. Mills in northern California will often ship their products to major distribution hubs, say in Denver or Los Angeles, where the products will then make their way to buyers all over the country. These buyers are price sensitive and are often able to substitute the mill they are ultimately buying from and even switch from one kind of timber product to another.

Nevertheless, while a complete analysis of how changes in competition in the downstream market for wood products translates to bids in USFS auctions is beyond the scope of this paper, we can check the robustness of our results to possible increases in surviving mill values. To do so, we re-simulate the second row of Table 5, which modeled the possibility that only insolvent mills shut down, when we increase the average surviving mill values in all auctions (not just those in which a potential entrant is assumed to shut down). We do this by increasing the mean of surviving mill values by 2, 5 and 10% while holding other parameters constant. The higher is the percent increase, the smaller will be the drop in USFS revenues as surviving mills will be more likely to enter auctions and will submit higher bids when they do. Table 9 in Appendix C gives the results of these simulations. There would still be a 9.08% (s.e. 0.35%) drop in revenues absent the bailout if mill values had increased by 2%. Even if surviving mill values had risen 10%, an increase we view as extreme in light of the industry's excess capacity at the time and our discussions with industry experts, our model predicts

[39]Conversation with Tim Cochran of Random Lengths, April 2013.

the USFS auction revenues would still have declined 3.38% (s.e. 0.38%). Thus, while it may be possible that stronger surviving mills could have mitigated the drops in USFS revenue presented in Table 5, these mills' values would have had to drastically increase (i.e. by more than 10%) to completely offset the decline in revenues stemming from fewer potential buyers.

8 Conclusion

This article has estimated the value of additional competition, considering the example of the Reagan administration's 1984 bailout of the timber industry. This intervention, which, like most bailouts, was controversial, was aimed at preventing the closure of a large number of sawmills and logging companies that faced heavy losses on USFS timber contracts that they had purchased at high prices when the price of cut timber fell dramatically during the recession of the early 1980s. One of the aims of preventing bankruptcy was that this would increase competition in future federal timber sales, increasing the government's expected revenues. On the other hand, given the large number of firms in the timber industry that were not bailed out, one might expect the gains to preserving the endangered firms to be small.

To perform our analysis we develop and estimate a model of auctions with endogenous and selective bidder entry. Allowing for endogenous entry is necessary because entry into timber auctions is widely regarded as costly, and it is plausible that if some timber companies had exited the industry, other firms might have entered auctions in their place, reducing the effects on the USFS. Our structural estimates imply a moderate degree of selection, consistent with timber companies having some but imperfect information about how they value tracts prior to performing their own detailed cruise.

Assuming that all firms with potential losses above their net book value would have exited the industry without the bailout, we predict that the additional competition created by the bailout raised revenues by over 11%. This is a relatively large change in prices 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, like other authors, we estimate that bidder values for a given tract are heterogenous, so that adding an additional competitor can increase the expected value of first- or second-highest order-statistics quite substantially. Second, we allow for systematic differences in the values of mills and loggers. Mills have systematically higher values, making them more valuable to the USFS, and they were also more likely to benefit from the bailout program. Finally, selective entry plays an important role. Even though the addition of potential bidders reduces the probability that other firms enter, the 'marginal' entrants who are lost tend to have relatively low values, and as a result their loss only reduces the seller's expected revenues by a small amount. In contrast, in a model without selection, the seller's expected revenues could fall when more potential competitors are added. We also show that the 11% change in revenues through the change in the number of competitors is many times larger than the seller could achieve through using a design tool such as the reserve price. In doing so we illustrate, in a more general model that allows for asymmetries and a particular form of endogenous entry, Bulow and Klemperer (1996)'s classic theoretical result that additional competitors are more valuable than design tools.

We focus on the value of the bailout in increasing the revenues in subsequent auctions under a strict assumption about which firms would have exited without the bailout. While this assumption is reasonable given the way in which the bailout worked, a more complete analysis would need to work out whether the exit of bankrupt firms would have led to significant new entry, possibly using the same plant and equipment. A more complete cost-benefit analysis would also have to consider the effects on revenues in private and state timber sales and the value of preserving employment in local communities, many of which are dependent on timber-related industries. The same types of issues arise in bailouts of much larger firms in other industries, and understanding their effects seems to be an important, and topical, direction for future research.

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A Multiple Equilibria and Equilibrium Selection

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 3, 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.[40] 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 3 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 3.

The result that 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.[41] 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 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

[40]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'.

[41]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.

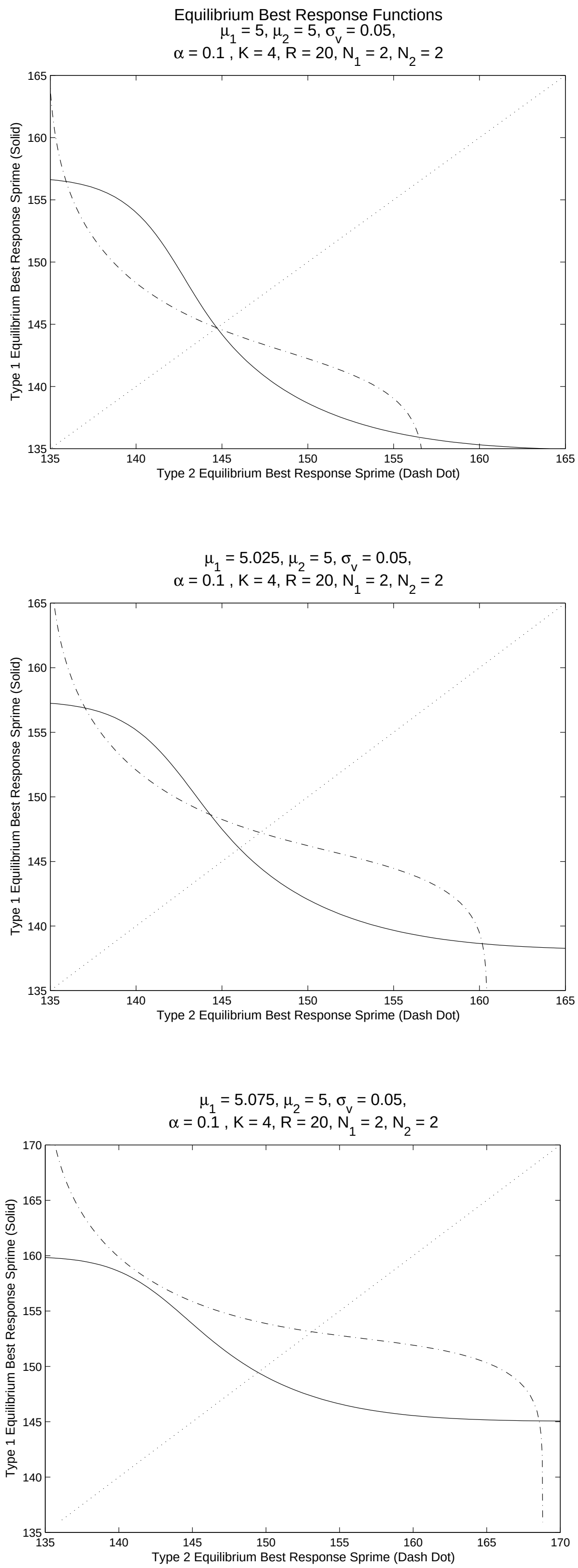

Figure 3: Reaction functions for symmetric and asymmetric bidders. In the top panel, the types are identical so that $\mu_1 = \mu_2 = 5$ and there are two firms of each type, $\sigma_V = 0.05, K = 4, \alpha = 0.1$ ($\sigma_\varepsilon = 0.0167$). In the next two panels firms are asymmetric in means only 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.

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 sawmills (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

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 satisifies 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 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.

			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.

Parameter	Variable	True Value	Likelihood Definition 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.

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

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.