

Set-Asides and Subsidies in Auctions*

Susan Athey

Jonathan Levin

Department of Economics

Department of Economics

Stanford University

Stanford University

and NBER

and NBER

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Abstract

Set-asides and subsidies are used extensively in government procurement and natural resource sales. Economic theory is ambiguous on how such policies affect both auction participation and auction prices. We study the use of these policies, targeted at small businesses, in the context of U.S. Forest Service timber auctions. Empirically, the decline in large bidders at set-aside auctions is matched by an increase in smaller bidders, with only slight revenue effects. We then compare the existing set-aside program to a proposed program of small-bidder subsidies. We find that such a change...

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1. Introduction

Government procurement programs often seek to achieve distributional goals in addition to other objectives. This point is sometimes overlooked by studies that focus on the cost and efficiency of procurement, but it is not a small one. In the United States, the federal government explicitly aims to award at least 23% of its roughly \$300 billion in annual contracts to small businesses, with lower targets for businesses owned by women, disabled veterans and the economically disadvantaged. Many state and local governments also set goals regarding small businesses or locally owned firms.

Two common methods are employed to achieve distributional goals. One approach is to set aside a fraction of contracts for targeted firms. For instance, with some exceptions, federal procurement contracts between \$25,000 and \$100,000 are reserved for small businesses.¹ An alternative is to provide bid subsidies for favored firms. Such subsidies are used by the Federal government to assist domestic firms bidding for government construction contracts under the Buy America Act, by the Federal Communications Commission to favor minority-owned firms in spectrum auctions, and in state highway procurement to assist small businesses.

Our goal in this paper is to provide evidence on the costs of these kinds of programs, in terms of both government revenue and efficiency, as well as the relative merits of set-aside and subsidy programs. We do this in the context of one particular federal program, the U.S. Forest Service’s timber sale program. During the time period we study, the Forest Service sold around a billion dollars of timber a year. In the region from which our data is drawn, about a quarter of the sales are small business set-asides.² Our basic finding is that these set-asides, which exclude a substantial number of strong potential bidders, appear to have relatively little effect on government revenue. We estimate that for an average sale, restricting participation to small businesses lowers Forest Service revenue by just over 3%; our 95% confidence interval on the revenue effect of a set-aside provision ranges from -9.6% to $+2.8\%$. We find that the inefficiency created by a set-aside is also small as well, around 4% for an average sale. Finally, we show that a well-structured bid subsidy program could achieve the same distributional outcome at lower (??) cost, and explain how such a program might work.

¹See 15 USC 644(g)(1) or the Federal Acquisitions Regulations, Section 19.502-2.

²As we discuss below, a relatively large number of small “salvage” sales are designated as set-asides, so the total value of timber sold by set-aside sale was closer to 10% of the total value of timber sold.

Basic supply and demand suggests that set-aside programs should lower revenue and decrease efficiency by reducing the number of eligible buyers. This need not be the case, however, if bidding is costly and firms are heterogeneous. In such a setting, restricting participation may increase auction revenue. Suppose there is a large bidder with a value uniformly distributed between 0 and 30 and two small firms with values uniformly distributed between 0 and 10. If it costs seventy-five cents to learn one's value and enter the auction, the large bidder will be the only entrant and will win at a zero price. If participation is restricted to the small firms, both will enter and the expected price increases to $3\frac{1}{3}$ despite the fact that expected social surplus decreases by $9\frac{1}{12}$. If there are additional large firms, however, or if entry costs are substantially lower or higher, a set-aside program both lowers revenue and decreases efficiency.³

Bid subsidies can also have ambiguous effects depending on the relative strengths of the bidders and the costs of participation. A well-known insight of Myerson (1981) is that in an auction with fixed participation, appropriately handicapping bidders can increase revenue relative to a standard open or sealed bid auction. The impact of a fixed subsidy, however, can depend subtly on bidders' value distributions, as discussed by McAfee and McMillan (1989). Moreover, with endogenous participation, a subsidy will affect entry in ways that in principle can be helpful or harmful. In the previous example, a rule that awards the object to a small bidder if its bid is at least a third that of the large bidder generates entry by all three firms. Expected revenue increases from zero to $8\frac{1}{3}$ with social surplus decreasing by $5\frac{7}{18}$. Such a program results in a small firm winning two-thirds of the time. Less dramatic subsidies have a similar qualitative effect, raising revenue while decreasing surplus. A larger subsidy, however, may discourage participation by the large firm; for some entry costs, the result can be lower revenue than a no-subsidy sale.

Getting a handle on the effect of set-asides or subsidies in a given setting requires an understanding of the relative strengths of the targeted and non-targeted bidders. Forest Service timber sales are characterized by a high degree of diversity in participating bidders. Bidders range from large vertically integrated forest products firms to small owner-operated logging companies. To simplify matters, we distinguish two types of bidders: "mills" that have manufacturing capability and "loggers" that do not. As a general rule, logging firms

³There are other cases where restricting participation can raise revenue even if bidding is not costly, for instance if there are strong "winner's curse" effects; see Bulow and Klemperer (2001).

are relatively small operations; mills may be smaller independent companies or part of larger forest product companies. The heterogeneity between the different types of bidders is substantial. While the bids of large and small mills are not significantly different, mill bids are on average 10-15% higher than logger bids in a given auction. Our estimates imply that this bid differential reflects an even greater difference in underlying values.

Because mills are larger operations, a set-aside requirement effectively restricts participation to loggers and a limited set of mills. Nevertheless, we find that total participation in set-aside auctions is on average no lower than in unrestricted sales, controlling for sale characteristics. And, as noted above, the average price paid per unit of timber is only slightly lower in set-aside auctions than in unrestricted sales. These conclusions hold in our data for both open and sealed bid auctions. Moreover, exploiting the assumption that bids are generated by Nash equilibrium bidding, we provide evidence that these findings are not contaminated by substantial unobserved differences between the set-aside and unrestricted sales.⁴ Therefore it appears that the set-aside program steers a substantial amount of business toward small firms at little cost to the Forest Service in terms of sale revenue.

To assess the overall efficiency cost of the set-aside program, we build a model of the auction process and estimate its parameters from the data. Following Athey, Levin and Seira (2004), we model each sale as a private value auction with endogenous entry. This model does a reasonable job of rationalizing bidder behavior at both small business and unrestricted sales (we suspect the fit will improve with a little more thought regarding the specification). The calibrated model predicts that a set-aside restriction will lower revenue by 3.5% for an average sale, which is very close to our direct regression estimate of 3.4%. Somewhat to our surprise, the model also predicts a non-trivial increase in total participation resulting from a set-aside restriction, on the order of 9-10%; our direct regression estimate suggests a more modest 1-2% increase in participation. The model also permits a calculation of the social surplus cost to invoking a set-aside restriction; as noted above, the model suggests this cost is rather low.

[[*Incomplete*]]The calibrated model also allows us to calculate the potential outcomes from implementing a bidder subsidy program in lieu of direct set-asides. We find that to match the distributional outcomes of the current set-aside program would require a **XX%** subsidy for

⁴As discussed in greater detail in Section 3, the Forest Service makes some effort to select as set-aside sales tracts that can be handled by local small businesses.

small bidders. Such a program would lead to a **XX%** increase/decrease in revenue relative to the current system and a **XX%** change in efficiency. A slightly bigger/smaller subsidy could achieve ...

Our results can be usefully compared to those of Marion (2004), who studies the effect of a bid subsidy program in California highway procurement auctions. He finds that procurement costs are roughly 3.5% higher in subsidy auctions, an increase that he attributes largely to decreased participation by low-cost large firms. As Marion explains, this change in participation is hard to rationalize with the simplest models of endogenous participation. In Marion's case, unlike in ours, the participation response to subsidies harms rather than helps the auctioneer. Nevertheless, the two studies share two common themes: first that the direct costs to government set-asides and subsidies may be relatively low; and second, that accurately accounting for participation is crucial for assessing bid preference programs.

2. A Model of Set-Asides and Subsidies

This section describes our basic model of the auction process, studied previously in Athey, Levin and Seira (2004). We then use the model to informally discuss the effect of set-asides or bidder subsidy programs.

A. The Model

Consider a seller who wishes to auction a single tract of timber. She announces a reserve price r and whether the auction will be open or sealed bid. There are N potential bidders, of whom N_L are loggers and N_M are mills. A bidder must spend K to learn his private value for the timber and enter the auction. Bidder i 's value v_i is drawn independently from either F_L or F_M , depending on whether the bidder is a logger or a mill. We assume that for $\tau = L, M$, the distribution F_τ has density f_τ and support $[\underline{v} = r, \bar{v}_\tau]$, and that F_M stochastically dominates F_L in the sense that for all v , $f_M(v)/F_M(v) \geq f_L(v)/F_L(v)$.

For both open and sealed bid auctions, we assume that bidders make independent participation decisions, but learn the identities of the other participants before submitting their bids.⁵ In a sealed bid auction, participants independently submit bids, with the highest

⁵The model can be modified to allow for the case where bidders do not observe the set of entrants before submitting their bids. The stochastic dominance assumptions must be modified, but the qualitative results remain the same.

bidder winning and paying his bid. In an open auction, the price rises continuous from the reserve price until a single winner remains. A strategy for bidder i consists of a probability p_i of entering the auction, and a bidding strategy $b_i(\cdot; n)$ that specifies i 's bid as a function of his value and the set n of participating bidders.

Given a set of participants n , the bidding game between the participants has a unique equilibrium for both auction formats. The bidding equilibrium is type-symmetric in the sense that all loggers use the same strategy $b_L(\cdot; n)$ and all mills the strategy $b_M(\cdot; n)$.

The entry game may have multiple equilibria. Athey, Levin and Seira, however, identify a condition that ensures both a unique type-symmetric entry equilibrium and, up to permutations of the loggers, a unique pure-strategy entry equilibrium. The condition for uniqueness is that the value distribution for mills is sufficiently stronger than that for loggers such that the following condition holds: for all n_L, n_M ,

$$\pi_M(n_L, n_M + 1) > \pi_L(n_L, n_M), \quad (1)$$

where π_τ is the expected profits gross of entry cost for a bidder of type τ given that n_L loggers and n_M mills participate in the auction. In words, mills have a sufficient value advantage over loggers to outweigh the effects of facing an additional bidder. We assume this condition holds, and later verify it in our data.

Given condition (1), the unique type-symmetric equilibrium has the following structure. Either mills enter with probability $p_M < 1$ and no loggers enter, or mills enter with probability one and loggers enter with probability $p_L \in [0, 1]$. Because we observe loggers entering regularly in our data, we focus on the latter case. If $0 < p_L < 1$, the equilibrium requires that an entering logger makes zero profit, that is

$$\Pi_L(p_L) = \sum_{n_L=1}^{N_L} \pi_L(n_L, N_M) \Pr[n_L \mid p_L, i \text{ enters}] = K \quad (2)$$

The other possibility is an entry equilibrium in pure strategies. Under condition (1), the number of participants in such an equilibrium is uniquely determined. All mills and n_L loggers enter, where n_L satisfies:

$$\pi_L(n_L, N_M) \geq K > \pi_L(n_L + 1, N_M). \quad (3)$$

Athey, Levin and Seira focus on the type-symmetric equilibrium, but observe that a pure strategy equilibrium yields similar predictions for the comparison between open and sealed bid auctions. The two models are also similar if one is analyzing the effects of subsidies and set-asides. It is simpler to provide intuition for the effect of set-asides and subsidies in the pure-strategy case, but it seems possible that the mixed strategy equilibrium better approximates the uncertainty bidders face when entering a timber auction, so we consider that case when estimating entry costs in Section 5.

B. Set-Aside Auctions

A set-aside provision that rules out participation by some or all of the mills has two effects. First, relative an unrestricted sale, fewer mills will participate in the set-aside sale. Second, the decreased mill participation increases participation by loggers who anticipate a greater chance to win the auction. The first effect lowers revenue; the second effect raises it. Depending on the number of potential bidders, the auction format and the nature of the entry equilibrium, the net result can be either an increase or decrease in equilibrium revenue and total participation.

It is perhaps easiest to illustrate the possibilities in the context of an open auction where logger entry is determined by a pure strategy equilibrium. In this case, the entry equilibrium is socially efficient; it maximizes social surplus given the set of potential bidders. From this efficiency viewpoint, it is easy to see that a reduction in the number of eligible mills through a set-aside provision will lead to a decrease in the efficiency of the auction.

To understand the effect on participation and revenue, suppose there are initially N_M mills and N_L loggers, and that if participation is not restricted all the mills and n_L loggers will enter in equilibrium. Suppose that with the set-aside provision only $N'_M < N_M$ mills are eligible. If $n_L = 0$ so no loggers were willing to enter an unrestricted sale, then the set-aside provision may or may not induce logger entry. If $n_L > 0$, then it was profitable for a logger to enter given the entry of N_M mills and $n_L - 1$ loggers. Therefore it must be profitable for a logger to enter given the entry of N'_M mills and $n_L - 1 + (N_M - N'_M)$ loggers — the total number of entrants is the same in the latter case, but the entrants are weaker. So total equilibrium entry will increase with a set-aside provision. What about revenue? In the $n_L = 0$ case, the effect depends on whether or not the set-aside provision generates logger entry. In the $n_L > 0$ case, the first $n_L + N_M$ entrants to the set-aside sale are weaker as

a smaller fraction of them are mills, but the increase in total entry will push up expected revenue. The net effect is ambiguous.

We can illustrate the possibilities by modifying the example from the introduction. Suppose mills have values uniformly distributed on $[0, 30]$, loggers have values uniformly distributed on $[0, 10]$ and entry costs are 1. Suppose the potential bidders are one mill and three loggers. With no restrictions, only the mill will enter in equilibrium. Revenue will be zero. If the mill is restricted from participating, two loggers will enter and expected revenue will be $10/3$. So here a set-aside provision raises participation and revenue.

But what if there are two mills? In this case, an unrestricted sale will attract both mills, so the expected revenue is 10, while a restricted sale will have revenue 0 or $10/3$ depending on whether one or both mills are ineligible. Finally, if there are three mills, the unrestricted sale will attract all the mills and generate an expected revenue of 22.5. In this case, any restriction will lower both participation and revenue.

Similarly ambiguous effects arise if we consider the mixed-strategy type-symmetric entry equilibrium of the open or sealed-bid auction. Although the analysis is more complex, particularly in the sealed bidding case, the same effects arise. Prohibiting entry by some or all of the mills increases the incentive for loggers to enter. In principle, expected total participation can increase or decrease depending upon the strength of this incentive. Revenue is pushed down by the fact that if total entry is the same, the composition of bidders is weaker. But additional participation can potentially drive revenue up.

C. Bidder Subsidies

There are a variety of ways to offer bidder subsidies. One straightforward approach is to offer favored bidders a fixed credit of size a should they win the auction. An alternative is to specify that a favored bidder must pay only a fraction $b/(1 + \alpha)$ of its bid b for some $\alpha > 0$; this makes the bid credit a fraction of the bid rather than an absolute amount. Finally, a common system in government procurement is to run a sealed bid auction where the winner pays his or her bid, but a favored bid is given preference over an unfavored bid if $(1 + \alpha)$ times the favored bid is larger than the unfavored bid. The latter two policies are equivalent if there is only a single favored bidder.

To illustrate the effects of a subsidy, it is perhaps easiest to start with the case of an open auction with two participants, an mill with value v_M and a logger with value v_L . Suppose

the seller offers a fixed credit of size a to the logger. There are three possible outcomes from this policy. If $v_L > v_M$, the subsidy will not change the outcome of the sale, but it will lower the price by a . If $v_M > v_L > v_M - a$, the subsidy will allow the logger to win over the higher-valued mill and the price will fall from v_L to $v_M - a$. Finally, if $v_M - a > v_L$, the mill will win with or without the subsidy, but the policy will raise the price by a . These same potential outcomes also arise if there are additional bidders, although the subsidy will not matter if the two highest bidders are either both mills or both loggers.

From an ex ante standpoint, it is relatively easy to see that a small subsidy will tend to increase sale revenue. To continue with the two bidder example, a small subsidy is very unlikely to affect the allocation and conditional on the allocation being unaffected it is more likely that the mill is the winner and revenue increases. A similar logic applies even if there are more bidders, and also to percentage subsidies, although the analysis there is complicated by the fact that the size of the revenue change varies with the level of the losing bid. A small subsidy will also increase logger participation without affecting mill participation, which will create an additional force that increases revenue, though at the cost of a further distortion away from social efficiency.

The situation becomes more ambiguous if one considers larger subsidies or a subsidy that is targeted both at loggers and at a subset of mills. In either of these cases, a subsidy program can discourage participation of strong unfavored bidders. If this happens, it is possible that the both revenue and social efficiency will decrease under the subsidy policy.

3. Description of Timber Sales

This section describes the how timber auctions work, the small business set-aside program, and the data for our study. We discuss only the essentials of the sale process; more detailed accounts can be found in Baldwin, Marshall and Richard (1997), Haile (2001), Athey and Levin (2001) or Athey, Levin and Seira (2004).

A. Timber Sales and Small Business Set-Asides

A sale begins with the Forest Service identifying a tract of timber to be sold and conducting a survey to estimate the quantity and value of the timber and the likely costs of harvesting. A sale announcement that includes these estimates is made at least thirty days prior to the auction. The bidders then have the opportunity to conduct their own surveys

and prepare bids. The Forest Service uses both open and sealed bid auctions. If the auction is open, bidders first submit qualifying bids, typically at the reserve price, followed by an ascending auction. The sealed bid auctions are first price auctions. In either case, the auction winner has a set period of time, typically between one and four years, to harvest the timber.

The Forest Service designates certain sales as small business set-asides. For a standard set-aside sale, eligible firms must meet two basic criteria. First, they must have no more than 500 employees. Second, they must manufacture the timber themselves or re-sell it to another small business, with the exception of a specified fraction of the timber for which no restrictions apply. There is also a second category of set-aside sales, labeled “salvage set-aside sales”. Salvage tracts contain substantial amounts of dead, damaged or insect-infested timber; these tracts tend to be smaller than average and have lower value. More stringent eligibility criteria apply when a salvage tract is auctioned as a small business set-aside. In this case, firms must have no more than 25 employees, and they must agree to accomplish a significant fraction of the logging with their own employees or with those of another firm of similar size. In our data, there appear to be some exceptions to the eligibility criteria, and conversations with Forest Service employees confirm that the rules are occasionally loosened for various reasons.

These rules are laid out in Forest Service regulations, which also provide guidelines for which sales should be designated as set-asides.⁶ The Forest Service periodically sets targets for the amount of timber small businesses are expected to purchase in different areas. Though subject to some adjustment, the basic goal is to maintain the historical share of timber logged by small businesses in different areas, with the historical amounts corresponding to the quantities logged between 1966 and 1970. By projecting the amount of timber that will be purchased by small businesses in unrestricted sales, the Forest Service determines the quantity of timber that must be sold using set-aside sales, although forest managers have some discretion to accommodate specific local needs. Forest managers are expected to use the same sale methods for set-aside sales and to include a variety of sale sizes, terms and qualities in the set-aside program. Forest managers also have some discretion to designate tracts as set-asides based on the needs of small businesses in the area. This is important for our analysis as it suggests that the tracts designated as set-asides may be tracts that are relatively well-suited to purchase by small firms. We revisit this below.

⁶See the U.S. Forest Service Handbook, Section 2409.18 on Timber Sale Preparation.

B. Description of the Data

Our data consists of sales held in California between 1982 and 1989. For each sale, we know the identity and bid of each participating bidder, as well as detailed sale characteristics from the sale announcement. We also collected additional information to capture market conditions. We use national housing starts in the six months prior to a sale to proxy for demand conditions, and U.S. Census counts of the number of sawmills and logging companies in the county of each sale as a local measure of competition. Finally, for each sale, we construct a measure of the number of active firms in the area by counting the number of distinct firms that bid in the same forest district over the prior year. This is the most satisfactory measure of potential competition we have found but it is undoubtedly a somewhat noisy measure of how bidders actually assess their potential competition in a given auction.

In classifying bidders, we distinguish between mills, which are larger and can process at least some of the timber themselves, and logging companies that must re-sell the timber they harvest. We also have limited data on the small-business status of each firm; this data is useful for the mills, which tend to bid relatively often, but less useful for the logging companies as many appear only a few times.⁷ Of the 87 mills that appear in our data, we used the small-business status data, augmented with Google searches, to identify 34 “large” mills that are ineligible for all set-aside sales, and 53 “small” mills that are eligible at least for non-salvage set-asides. The eligibility criteria for non-salvage set-asides does not appear to rule out any of the logging companies.

Determining eligibility for salvage set-asides is messier, as our firm status data often conflicts with observed participation. Specifically, the firm status data indicates that only 633 of the 909 logging companies and only 9 of the 87 mills should be eligible to participate in salvage set-asides. The “larger” logging firms, however, account for about 20% of observed logger participation in these sales. Moreover, while we observe only a tiny amount of mill participation in salvage set-asides, more than half of what we do observe is by mills whose status should disqualify them. These discrepancies force us to make some eligibility assumptions both in estimating entry costs and in using our calibrated model to generate counterfactual predictions. We discuss these assumptions in Section 5.

⁷Of the 909 logging companies that appear in the data, 642 participate in less than five sales. Further complicating matters, logging companies often participate under different names (e.g. Bill Schmidt, Schmidt Bros., Schmidt Logging, etc.). Despite many hours devoted to obtaining reasonable groupings, it is unlikely that we have avoided all errors.

Table 1 presents summary statistics of tract characteristics and auction outcomes for the four kinds of sales: regular sales, set-aside sales, salvage sales and salvage set-asides. For a typical sale, a set-aside restriction leads to a substantial reduction in the number of eligible mills. In particular, the average number of active mills is 5.94; the average number of active small mills is just under half of this, at 2.72. The participation variables in Table 1, however, suggest that the decrease in eligible bidders does not translate directly into a change in realized participation. Although set-aside restrictions greatly reduce mill participation, total participation does not fall. Additional participation by logging companies substitutes for the absent mills. Not surprisingly, set-aside sales are, on average, much more likely to be won by loggers. The table also shows that for both regular and Salvage tracts, prices are somewhat lower when participation is restricted, but the difference is far from statistically significant.

Though not displayed in Table 1, the bidding behavior of mills and logging companies is quite different on average. To assess this difference, and also the difference between large and small mills, we make use of the data from unrestricted sealed bid sales. We regress the per-unit bids (in logs) on auction fixed effects and dummies indicating whether the bidder is a logger, a large mill that is ineligible for set-aside sales, or a small mill that can participate in regular set-aside sales. Our estimates indicate that small mill bids are roughly 14% higher than logger bids on average, and large mill bids roughly 10% higher than loggers. Both these differences are strongly statistically significant (t -statistics >4), but the average bids of small and large mills are not statistically distinguishable at a 10% or even 15% level. For this reason, we will treat the value distributions of small and large mills as the same when we estimate our structural model in Section 5.

A key issue for our empirical analysis is the extent to which the tracts designated as set-asides differ from those where participation is not restricted. Table 1 indicates that, at least on observable characteristics, the differences are relatively small, with one exception. The salvage tracts designated as set-asides are much smaller on average than the other salvage tracts. This suggests that controlling for sale size will be crucial to obtain good estimates of the effect of restricting participation for the salvage tracts.

To explore the differences between the set-aside and non-set-aside tracts in more detail, we regressed a dummy variable indicating whether the sale was a set-aside on a large set of observable tract characteristics, using a logit specification. The results appear in Table

2. The characteristics variables are jointly significant for both regular and salvage sales. Different forests are more or less prone to use set-aside sales, so location is the strongest predictor of whether participation will be restricted in a given sale. As noted above, sale size correlates with set-aside restrictions in the case of salvage tracts. From the logit regression, we obtained for each tract a predicted probability that the sale would be a set-aside. We use this propensity score as a control in later specifications.⁸

4. The Effect of Set-Asides

This section presents estimates of the effects of set-aside provisions on bidder participation and revenue. We start by estimating the average effects of a set-aside across different tracts, then consider how the effect varies with other characteristics of the sale.

Our basic empirical model has the form $Y = f(SBA, X, N, \varepsilon)$, where Y is an outcome of interest (participation or revenue) f is a function, SBA is a dummy equal to one if the sale is a small-business set-aside, X is a vector of observed sale characteristics, $N = (N_L, N_M)$ is the number of active logging firms and mills in the area.

This model allows the Forest Service’s choice of set-aside tracts to depend on all of the information observed in our data; we will obtain consistent estimates of the average effect of a set-aside provision so long as we adequately control for the variables used by the Forest Service. The key assumption for identification is that the choice of whether to make the sale a set-aside is uncorrelated with unobservables that might directly affect the outcome, that is ε and SBA are independent conditional on (X, N) .

We start by specifying a linear model of the form:

$$Y = \alpha \cdot SBA + X\beta + N\gamma + \varepsilon. \quad (4)$$

The two outcomes of interest are the number of participating bidders and the sale revenue. Our OLS estimates are presented in Table 3, and again on the top line of Table 4.

⁸A possibility suggested above is that the Forest Service might tend to designate tracts as set-asides that are relatively more attractive to small bidders. One way to assess that is to look at the tracts not designated as set-asides and ask whether those that look more like the set-aside tracts were more likely to be purchased by a logging firm. To measure this, we considered the non-set-aside tracts and used a logit regression to estimate the probability a tract would be won by a logging firm. For non-salvage tracts, there is a negative correlation between this probability and the tract’s propensity score; for salvage tracts, the correlation is positive.

As suggested by the earlier summary numbers, we find that set-aside restrictions do not decrease total participation despite the reduction in the number of eligible bidders. Indeed, our point estimate suggests that a set-aside provision has a slightly positive effect on participation, raising it by 1.2%; our 95% confidence interval ranges from -3.5% to +5.9%. Despite the negligible change in overall participation, the composition of bidders is weaker. This translates into a decline in revenue, but we estimate that the size of this decrease is relatively small. Controlling for other sale characteristics, we estimate that a set-aside provision lowers revenue by 3.4%; our 95% confidence interval ranges from -9.6% to +2.8%.

The specification in (4) assumes that the effect of a set-aside provision will be independent of other sale characteristics. It seems plausible that the effect is not constant. To account for this, we consider an alternative specification that interacts *SBA* with each of the control variables (X, N). We also consider a matching estimator that pairs each set-aside sale with M “similar” sales of the opposite format. The matching estimator calculates the difference between the outcome of each sale and the average outcome of its paired sales, providing an estimate of the effect of a set-aside provision for that particular tract. The average effect of a set-aside provision is the average of these differences.⁹

The estimates from both the linear specification with a full set of interactions and the matching estimator are quite close to our initial OLS estimates, suggesting that these estimates are fairly robust. In particular, we estimate a positive participation effect of 0.4% with the linear interaction specification and 1.7% with the matching estimator; our corresponding revenue estimates of the revenue decline are 2.6% and 1.9%.

The latter two specifications also allow us to examine whether the effect of a set-aside provision was larger or smaller on the tracts actually chosen for set-asides than on the tracts not chosen for set-asides. The next two lines of Table 4 report our estimates of the average effect of a set-aside provision on the tracts where a set-aside sale was in fact used. We find that the estimated effect is similar to the estimated average effect across all sales. That is, we estimate an effect on total participation that is close to zero (+2.5% or -1.5% depending on the specification) and a relatively small negative effect on revenue (a decrease of 3.2% or 4.9% depending on the specification).

⁹In our implementation of the matching estimator, we set $M = 4$ and identify matches by minimizing the metric $\|z\|_W = (z'Wz)^{1/2}$, where z is the difference between the covariates of two tracts and W is a diagonal matrix containing the inverse variances of the z s. We report robust standard errors as suggested by Abadie and Imbens (2005).

The remaining estimates in Table 4 report how the effect of a set-aside provision differ according to the characteristics of the sale. We suggested in Section 2 that the effect of a set-aside provision could vary considerably with the number of mills. Theory suggests that a set-aside provision may even increase revenue if the number of mills is small, but is likely to reduce revenue if there are a larger number of potential mills. To study this, we group the sales according to whether our measure of “active mills” is greater or less than five. We find that for tracts having a substantial number of active mills, a set-aside provision lowers total participation and results in a relatively large decline in revenue (6-8% depending on the specification). On the other hand, for tracts where there are only a few active mills, set-aside sales have substantially higher total participation controlling for other sale characteristics (8-10%) and somewhat higher revenue, although the difference is not statistically significant.

Another natural conjecture is that the consequences of a set-aside restriction will depend on whether the sale is a salvage sale. To investigate this, we estimate the linear model (4), interacting *SBA* with a dummy indicating whether the sale is a salvage sale; we also split the sample and estimate (4) separately for salvage and non-salvage sales. Our results from both approaches indicate that the effects of a set-aside provision on both total participation and revenue are similar for salvage and non-salvage sales. This is somewhat surprising because the participation requirements for a salvage set-aside are substantially more restrictive than for a regular set-aside — to participate in a salvage set-aside firms must have fewer than 25 employees, rather than fewer than 500. On the other hand, salvage sales are smaller than non-salvage sales, so the relevant firms for these sales may be smaller in any case, lessening the effect of the eligibility requirement.¹⁰

An obvious concern with these estimates is that they are confounded either by inadequate controls for observable differences between the set-aside and non-set-aside tracts or by unobservable differences for which we cannot control. The robustness of our estimates to different specifications mitigates the first concern, but there is little we can do about the second absent further assumptions. As we mention in the next section, however, the assumption that bidders are best-responding to empirical averages in the data allows us some scope to assess whether unobservable tract differences between small-business and unrestricted tracts are important.

¹⁰We also looked for differences between open and sealed bid sales. The effect of a set-aside restriction appear to be similar across these two types of sales, after controlling for other sale characteristics.

5. Estimating Economic Primitives

We now take a more structured approach to analyzing the effect of set-asides and subsidies by calibrating our theoretical model from Section 2 and using it to analyze the impact of different policies. The first step here is to estimate the parameters of the model from the sealed bidding data; this is described below. In Section 6, we use the calibrated model to investigate the effect of the set-aside program, and to study the potential impact of bidder subsidies.

Our approach to estimating the parameters of the theoretical model, and our exposition of it, follows Athey, Levin and Seira (2004). They employ a variation of two-step methods of Guerre, Perrigne and Vuong (2000) and Krasnokutskaya (2003). The first step fits a parametric model of the bid distributions; the second step uses nonparametric kernel methods to estimate the implied value distributions. Motivated by the empirical finding that bids within auctions are positively correlated conditional on observables, the model allows for an unobserved sale characteristic that is commonly observed by all bidders. The approach allows us to infer both the bidders' value distributions and the costs of participation from the sealed bidding data.¹¹

We start with a small amount of notation. Let $F_L(\cdot|X, u, N)$ and $F_M(\cdot|X, u, N)$ denote the bidders' value distributions conditional on the observed sale characteristics X , an unobserved sale characteristic u that we model as a "random effect," and the number of potential mill and logger participants $N = (N_L, N_M)$. We assume that (X, u, N) and the number of actual participants $n = (n_L, n_M)$ are common knowledge to the bidders at the time they submit their bids. Consistent with our theoretical model, we assume that bidder values are independent conditional on (X, u, N) and that participants use equilibrium bidding strategies. If there is a single entrant to the auction, we assume he bids the reserve price. With multiple entrants, we treat the reserve price as non-binding and write the equilibrium bid distributions as $G_L(\cdot|X, u, N, n)$ and $G_M(\cdot|X, u, N, n)$.

To model entry, we assume that all bidders share a common entry cost $K(X, N)$, and that entry behavior is given by a type-symmetric equilibrium. We verify below that the only outcome consistent with a type-symmetric entry equilibrium and logger entry is that all

¹¹Li (2005) and Li and Zheng (2005) also propose methods for estimating the costs of participation in auction models, and apply their approach to procurement data. In principle, the open auction data also contains relevant information but in the presence of unobservable sale characteristics, this data does not identify bidders' value distributions (Athey and Haile, 2002), so we do not use it for estimation.

potential mills enter, while loggers randomize their entry with common probability $p(X, N)$. Given an equilibrium of this form, we can infer the number of potential mill entrants from the actual number of mill entrants, as $n_M = N_M$, meaning we do not have to use our proxy for the number of “active mills” as a measure of potential mill entrants.

The parameters of interest are the value distributions $F_L(\cdot|X, u, N)$ and $F_M(\cdot|X, u, N)$, the entry cost $K(X, N)$ and the distribution of the unobserved auction characteristic $G_U(\cdot)$. We use the sealed bidding data to estimate the value distributions and the distribution of the unobserved heterogeneity, then use the equilibrium condition for optimal entry to recover the costs of participation.

A. Estimating Bidders’ Value Distributions

To recover bidders’ value distribution, we first estimate the equilibrium bid distributions G_L and G_M and then infer bidder values from the first order conditions for optimal bidding. Following ALS, we assume that the unobserved auction characteristic u is drawn from a Gamma distribution with mean one and variance θ , independent of X, N and n . We assume that conditional on (X, u, N, n) , logger and mills bids have a Weibull distribution. That is, for $k = L, M$,

$$G_k(b|X, u, N, n) = 1 - \exp\left(-u \cdot \left(\frac{b}{\lambda_k(X, N, n)}\right)^{\rho_k(n)}\right). \quad (5)$$

In equation (5), $\lambda_k(\cdot)$ is the scale of the Weibull distribution, parameterized as $\ln \lambda_k(X, N, n) = X\beta_X + N\beta_N + n\beta_{n,k} + \beta_{0,k}$, while $\rho_k(\cdot)$ the shape, parametrized as $\ln \rho_k(n) = n\gamma_{n,k} + \gamma_{0,k}$. Athey, Levin and Seira discuss the motivation both for using parametric assumptions on the bids distributions and for the specific choice of the Gamma-Weibull functional form. It is possible to test the appropriateness of the parametric assumption using Andrews’ (1997) conditional Kolmogorov test. Using this test, we cannot reject the null hypothesis that the parametric model accurately describes the data at a XX% level (35% in ALS on similar data).

Table 5 reports our estimated coefficients of the bid distribution parameters. There is strong evidence for unobserved auction heterogeneity, indicated by the estimated variance parameter θ . Consistent with the findings in ALS, mill bids stochastically dominate logger bids, and bids are increasing in the number of competitors. Note that we do not distinguish

between small-business set-asides and unrestricted sales in estimating the bid distribution; this is appropriate under the assumption that small business tracts are on average no better or worse than unrestricted tracts in terms of unobservable attractiveness. The model attributes all differences in bidding behavior between the two types of sales to differences in observable tract characteristics and in participation. Our preliminary estimates suggest this specification could be reasonable.¹²

Given estimates of the equilibrium bid distributions, we follow Guerre, Perrigne and Vuong, and Krasnokutskaya, in inferring the bidders' value distributions. If the bids observed in the data are generated by equilibrium bidding, then in an auction with characteristics (X, u, N, n) a bidder i 's bid b_i and his value v_i are related by the first order condition for optimal bidding:

$$v_i = \phi_i(b_i; X, u, N, n) = b_i + \frac{1}{\sum_{j \in n \setminus i} \frac{g_j(b_i | X, u, N, n)}{G_j(b_i | X, u, N, n)}}. \quad (6)$$

Having estimated each G_j , the only difficulty in inferring values is that we do not observe the unobserved sale characteristic u corresponding to each observed bid. We do, however, have an estimate of G_U , so we can infer the distributions $F_L(\cdot | X, u, N)$ and $F_M(\cdot | X, u, N)$ for any value of u from the relationship:

$$F_k(v | X, u, N) = G_k(\phi_k^{-1}(v; X, u, N, n) | X, u, N, n).$$

Two subtleties arise in this step. First, if bidders' value distributions are to be bounded, the equilibrium bid distributions must be as well, in contradiction to our Weibull specification. To get around this, we follow Athey, Levin and Seira (Appendix B) and truncate the estimated bid distributions. Second, the theoretical value distributions do not depend on the actual number of bidders n , but due to sampling error our estimated distributions will typically vary with n . We account for this in constructing our standard errors; in our numerical calculations in Section 6.B, we construct an average value distribution estimate, by weighting our individual estimates by the observed participation frequencies.

To provide a rough sense of the relationship between bids and values, we calculate that the median sealed bid markup in our data is 12.4%, similar to that found by Athey, Levin

¹²We have replicated our estimates included a dummy for set-aside sales as a control. The coefficient is small and not statistically significant. When we interact a dummy for set-aside sale with whether the bidder is a logger, however, the estimates become somewhat larger, and in some specifications, marginally significant. So further work is required here to settle on a final specification.

and Seira, who used a sub-set of our data that did not include the set-aside sales. That paper also includes graphs of the estimated equilibrium bid functions.

B. Estimating Bidders' Cost of Participation

We now use the equilibrium condition for logger entry to recover the bidders' costs of participation. Recall that the condition for a type-symmetric entry equilibrium is

$$\sum_{n_L=1}^{N_L} \pi_L(X, N, n_L, n_M = N_M) \Pr [n_L | p(X, N), n_L \geq 1] = K(X, N), \quad (7)$$

where $K(X, N)$ is the cost of participation, $\pi_L(X, N, n)$ is an entering logger's expected profit as a function of observed sale variables and realized participation, and

$$\Pr [n_L | p(X, N), n_L \geq 1] = \binom{N_L - 1}{n_L - 1} p(X, N)^{n_L - 1} (1 - p(X, N))^{N_L - n_L}$$

is the equilibrium probability a logger who enters assigns to total logger entry being n_L .

To recover $K(X, N)$ from the equilibrium entry condition, we require estimates of both expected profits $\pi_L(X, N, n)$, and the equilibrium entry probability $p(X, N)$. We obtain the former from the estimated value distributions. From these, we can directly calculate the equilibrium profit, $\pi_L(X, u, N, n)$ for $k = L, M$, as a function of sale characteristics and auction participation. Integrating these profits over G_U , we obtain $\pi_L(X, N, n)$. To recover loggers' equilibrium entry probabilities $p(X, N)$, we need an additional estimation step. For this, we assume that $p(X, N) = 1 - \exp(-\exp(X\beta_p + N\gamma_p))$, and estimate the unknown parameters by maximum likelihood using the observed entry behavior in the data.¹³ These estimates appear in the second column of Table 5.

Plugging our estimates of $p(X, N)$ and $\pi_L(X, N, n)$ into (7), we can easily calculate $K(X, N)$ for any set of sale characteristics X and potential bidders N . We find that for the sealed bid sales used for estimating the model, the median entry cost is in our data, the median entry cost is roughly \$3200. We get a higher estimate when we extrapolate to the open auction tracts that were not used to estimate the model (as noted by ALS, these tracts are substantially larger); the median entry cost for all tracts in the sample is roughly \$7800.

6. Welfare Analysis of Set-Asides and Subsidies (Incomplete)

¹³Maybe a better functional form would be $p(X) = \frac{\exp(X\beta)}{1 + \exp(X\beta)}$?

In this section, we use the calibrated model to provide a welfare analysis of the set-aside program, and to evaluate whether a subsidy program could achieve the same distributional goals at lower cost to the government in terms of revenue and social efficiency.

Note: this part is incomplete.

A. Assessing the Impact of Set-Asides

In this section, we perform counterfactual simulations using our estimated model parameters. For each tract, we use our model to predict the outcomes of two types of auctions: set-aside auctions and unrestricted auctions. For tracts where the actual auction was a set-aside, our prediction of the outcome of a set-aside auction can be compared to the actual outcomes in order to assess the fit of our model. Similarly, for unrestricted auctions, the actual outcomes can be compared to the predictions for unrestricted auctions to assess the model fit. After confirming that the model does reasonably well at matching actual outcomes, we then use the model to compare the effect of set-asides on participation, revenue, allocation, profits, and social surplus. We do this separately for the two types of tracts, those actually sold by set-aside and those actually sold in unrestricted sales.

Recall the primitives of the model that should be available for each sale: given observation of (X, N) , the parameters allow us to compute the entry cost $K(X, N)$ (where X does not include indicators for auction format or set-asides), the value distributions $F_L(\cdot|X, u, N)$ and $F_M(\cdot|X, u, N)$, and the distribution of the unobserved heterogeneity $G_U(\cdot)$.

Using these primitives, we can then calculate the profits from sealed bid auctions given participation ($\pi_L^S(X, N, n_L, n_M = N_M)$ and $\pi_M^S(X, N, n_L, n_M = N_M)$, where to avoid confusion we introduce superscripts to indicate the auction format) and the profits from open auctions given participation ($\pi_L^O(X, N, n_L, n_M = N_M)$ and $\pi_M^O(X, N, n_L, n_M = N_M)$). In practice, the latter profits are calculated by simulating a set of open auctions where bidders draw values from the estimated primitive value distributions, and then averaging the outcomes.

The next step is to calculate the entry equilibria for hypothetical sealed and open auctions, with and without set-aside restrictions, and use this to predict all auction outcomes. Consider first predictions for a hypothetical set-aside sale. If the sale was actually held as a set-aside, n_M is simply the actual mill participants in the set-aside. If the sale was actually held as an unrestricted auction, we construct n_M by taking the set of actual mill partici-

pants and removing those who would not qualify for a set-aside. To calculate $p^S(X, N)$ and $p^O(X, N)$, the equilibrium logger entry probabilities for sealed and open auctions, we use (7) as well as our measure of the potential number of loggers eligible for the set-aside. With these probabilities in hand (and using the primitive value distributions), we can predict all auction outcomes for both open and sealed auctions.

Second, consider predictions for a hypothetical unrestricted sale. If the sale was actually held as an unrestricted sale, n_M is simply the number of actual mill participants. If the sale was actually held as a set-aside, we must infer how many mills would have been interested in the sale. Note that this is taken as exogenous in our model, and so we simply use tract characteristics to make this prediction. In particular, we use a Poisson model to estimate the distribution of mill entrants in unrestricted sales as a function of covariates. For each possible realization of n_M , we recalculate the logger entry equilibrium using (7) as well as our measure of the potential number of loggers eligible for unrestricted sales. We then average over all predictions of the model using the distribution of n_M that we estimated (evaluated at the tract characteristics).

The results of this exercise are reported in Table 6. (*Standard errors are not yet available.*) The top panel has tracts where the actual auction was unrestricted. By comparing column (2) to column (1), we can assess the fit of the model. The perfect fit of average mill entry is guaranteed by construction. The fit of average logger entry is quite good: the predicted number is 1.76, while the actual is 1.87. This leads to a correspondingly close fit of total entry, 3.89 predicted versus 4.00 actual. The predicted sale price is also fairly close: 91.32 predicted versus 88.26 actual. The percentage of sales won by loggers is also quite close, with 41.2% predicted compared to an actual percentage of 42.4. The fit for small mills is not quite as good: our model predicts 21.1% of sales to be won by small mills, while the actual percentage is 17.3.

Comparing columns (2) and (3) for the top panel allows us to calculate the predicted effect of taking all unrestricted tracts and instead selling them using set-asides. Not surprisingly, our estimates indicate that this policy change would drastically reduce mill entry (from 2.13 to .82), but logger entry would increase so much that total entry would be higher (4.47 rather than 3.89). The sale price would fall by just over 3%, while a much higher fraction of sales would be won by loggers (73.1% versus 41.2% with unrestricted sales). Social surplus would fall by about \$30,000, a decrease of about 5%.

Now consider the bottom panel, tracts that were actually sold by set-aside. Comparing columns (1) and (3) allows us to assess the fit of the model. The model predicts too little loggers entry: the prediction is 2.63 loggers per tract, while the actual entry is 3.00 loggers per tract. This carries over into a prediction of total entry that is also too low. We believe that expanding the set of controls used for tract characteristics might improve the fit of this prediction, and we plan to incorporate this change in future drafts of the paper. The prediction of average sale price is fairly close, at \$75.97 compared to an actual price of \$76.91. Due to the low prediction of logger entry, the prediction of the percentage of sales won by loggers is also too low.

We delay a comparison of the predicted effect of auctioning the set-aside tracts using unrestricted auctions until the fit of the model on this sample is improved. We also note that due to sampling error, the predicted surplus difference has the wrong sign, though the estimate is small (2%). This is possible because the estimated value distributions are calculated separately for each n_L , and so due to a combination of sampling error and restrictions imposed by our functional form, the estimated value distributions can vary with n_L . We will also address this issue in future drafts of the paper.

Despite these issues, we provide overall averages across all tracts of the effect of using set-aside versus unrestricted sales. We find that using set-asides, average entry increases by 9.16%, average price decreases by 3.5%, and social surplus decreases by 4.1%.

In future versions of the paper, we plan to assess the effect of a set-aside sale under the hypothetical assumption that logger entry could not adjust. This calculation will help quantify the importance of the additional entry of loggers in mitigating the costs of using set-asides.

B. Assessing the Impact of Subsidies

Incomplete—awaiting computational results

Goal here is to identify what size subsidy would achieve same distributional goal as set-aside program and assess its effect. Consider subsidies where loggers (or alternatively, small mills and loggers) would pay only $1/(1 + \alpha)$ of their bids (like the FCC subsidies). Subsidy would apply to *all* sales; set-aside program would be eliminated.

1. Calculate fraction of sales that would be won by loggers/small mills/large mills with varying levels of subsidy and no set-aside (including zero subsidy).

2. Identify subsidy level for which allocation (in terms of total sales won? total timber volume won?) would match current levels.
3. For this subsidy level, compute outcomes (1)-(5). Compare to predicted outcomes under the set-aside program. This will be Table 7 (no numbers as yet!).
4. Other small stuff: Perhaps discuss one specific numerical example in detail.

7. Conclusion

To be completed

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Table 1: Summary Statistics

	Regular Sales		Salvage Sales	
	Unrestricted	Set-Aside	Unrestricted	Set-Aside
	1565	172	453	470
N				
Auction Outcomes				
	Mean	Std. Dev.	Mean	Std. Dev.
Winning Bid (\$/mbf)	90.59	123.72	88.56	58.80
Entrants	4.17	2.49	4.42	2.31
# Loggers Entering	1.82	2.01	2.58	2.02
# Small Mills Entering	0.85	1.00	1.78	1.36
# Large Mills Entering	1.49	1.37	0.06	0.29
Logger Wins Auction	0.37	0.48	0.49	0.50
Appraisal Variables				
	Mean	Std. Dev.	Mean	Std. Dev.
Volume of timber (hundred mbf)	52.29	49.84	53.02	44.84
Reserve Price (\$/mbf)	38.71	33.66	37.09	29.17
Selling Value (\$/mbf)	295.89	58.28	295.25	59.70
Road Construction (\$/mbf)	7.80	12.11	7.88	11.05
No Road Construction	0.46	0.50	0.40	0.49
Logging Costs (\$/mbf)	116.55	28.96	112.05	28.21
Manufacturing Costs (\$/mbf)	134.29	23.98	130.41	29.62
Sale Characteristics				
	Mean	Std. Dev.	Mean	Std. Dev.
Contract Length (months)	24.72	14.91	28.06	14.09
Species Herfindal	0.56	0.24	0.59	0.26
Density of Timber (hmbf/acres)	12.29	14.80	11.33	14.78
Sealed Bid Sale	0.31	0.46	0.22	0.41
Scale Sale	0.84	0.37	0.85	0.35
Quarter of Sale	2.42	1.00	2.27	1.04
Year of Sale	85.06	2.06	84.98	2.09
Housing Starts	1599.07	260.13	1597.84	292.08
Potential Competition				
	Mean	Std. Dev.	Mean	Std. Dev.
Logging companies in county	20.79	17.16	21.35	24.56
Sawmills in County	6.22	6.14	8.01	10.75
Active Loggers in district	10.50	6.75	11.81	6.98
Active Mills in district	5.80	3.09	5.90	3.04
Active Small Mills in district	2.97	1.83	3.61	1.87

Table 2: Choice of Set-Aside Sale

<i>Dependent Variable: Dummy if auction is set-aside sale (Logit regression)</i>				
	(1)		(2)	
	Regular (Non-Salvage)		Salvage	
	coefficient	s.e.	coefficient	s.e.
Appraisal Controls				
Ln(Reserve Price)	-0.126	(0.190)	-0.222	(0.161)
Ln(Selling Value)	0.800	(0.580)	-0.086	(0.079)
Ln(Logging Costs)	-1.821	(0.658)	1.049	(0.537)
Ln(Manufacturing Costs)	-0.017	(0.218)	-0.438	(0.187)
Ln(Road Costs)	-0.034	(0.143)	-1.092	(1.684)
No Road Construct. (Dummy)	-0.310	(0.402)	1.113	(3.133)
Other Sale Characteristics				
ln(Contract Length/volume)	21.428	(8.984)	2.997	(3.491)
Species Herfindal	0.007	(0.484)	-1.225	(0.444)
Density of Timber (hmbf/acres)	-0.002	(0.007)	-0.006	(0.006)
Sealed Bid (Dummy)	-0.135	(0.361)	0.823	(0.323)
Scale Sale (Dummy)	0.288	(0.334)	-0.132	(0.246)
ln(Monthly US House Starts)	0.061	(1.216)	2.756	(1.493)
Volume Controls (Dummy Variables):				
Volume: 1.5-3 hundred mbf	0.234	(0.793)	0.349	(0.292)
Volume: 3-5	1.046	(0.872)	0.173	(0.328)
Volume: 5-8	0.628	(0.928)	0.126	(0.368)
Volume: 8-12	0.525	(0.989)	-0.649	(0.407)
Volume: 12-20	0.448	(1.003)	-1.469	(0.481)
Volume: 20-40	1.304	(1.037)	-3.335	(1.199)
Volume: 40-65	1.238	(1.054)	-2.906	(1.191)
Volume: 65-90	1.489	(1.059)	dropped: never set-aside	
Volume: 90+	0.484	(1.081)	-1.529	(1.067)
Potential Competition				
ln(Loggers in County)	-0.657	(0.241)	0.240	(0.291)
ln(Sawmills in County)	0.225	(0.251)	-0.147	(0.315)
ln(Active Loggers)	0.025	(0.111)	0.717	(0.200)
ln(Active Mills)	-0.121	(0.129)	0.024	(0.102)
Constant	2.224	(9.442)	-23.582	(11.047)
Additional Controls (Dummy Variables)				
<i>Chi-Squared Statistics (p-value in parenthesis)</i>				
Years	8.35	(0.302)	13.44	(0.062)
Quarters	9.60	(0.022)	7.18	(0.066)
Species	9.64	(0.086)	10.55	(0.228)
Location	47.42	(0.000)	75.64	(0.000)
N=1326		N=901		
	LR chi2 (57)	182.6	LR chi2 (50)	398.2
	P-value	0.000	P-value	0.000
	Pseudo-R2	0.178	Pseudo-R2	0.319

Dependent Variable	(1)		(2)	
	coefficient	s.e.	coefficient	s.e.
Small Business Sale (Dummy)	0.012	(0.024)	-0.034	(0.032)
Set-Aside Prop. Score	0.123	(0.062)	0.087	(0.082)
Appraisal Controls				
Ln(Reserve Price)	-0.039	(0.015)	0.544	(0.022)
Ln(Selling Value)	-0.007	(0.011)	-0.004	(0.013)
Ln(Logging Costs)	-0.387	(0.088)	-0.407	(0.082)
Ln(Manufacturing Costs)	0.052	(0.014)	0.098	(0.018)
Ln(Road Costs)	-0.050	(0.013)	0.001	(0.019)
No Road Construct. (Dummy)	-0.065	(0.039)	-0.104	(0.054)
Other Sale Characteristics				
Ln(Contract Length/volume)	0.656	(0.522)	-0.160	(0.562)
Species Herfindal	-0.021	(0.040)	-0.158	(0.051)
Density of Timber (hmbf/acres)	-0.008	(0.003)	0.000	(0.000)
Sealed Bid (Dummy)	0.015	(0.029)	0.050	(0.038)
Salvage Sale (Dummy)	-0.135	(0.032)	-0.087	(0.043)
Scale Sale (Dummy)	0.067	(0.026)	0.111	(0.034)
Ln(Monthly US House Starts)	0.287	(0.117)	0.049	(0.148)
Volume Controls (Dummy Variables):				
Volume: 1.5-3 hundred mbf	0.139	(0.040)	0.020	(0.042)
Volume: 3-5	0.296	(0.044)	0.118	(0.049)
Volume: 5-8	0.336	(0.048)	0.155	(0.054)
Volume: 8-12	0.379	(0.053)	0.123	(0.062)
Volume: 12-20	0.411	(0.052)	0.241	(0.064)
Volume: 20-40	0.292	(0.059)	-0.041	(0.075)
Volume: 40-65	0.333	(0.059)	-0.004	(0.077)
Volume: 65-90	0.327	(0.060)	0.014	(0.077)
Volume: 90+	0.360	(0.060)	0.076	(0.081)
Potential Competition				
Ln(Loggers in County)	-0.017	(0.022)	0.000	(0.028)
Ln(Sawmills in County)	-0.004	(0.025)	-0.027	(0.032)
Ln(Active Loggers)	0.105	(0.010)	0.063	(0.012)
Ln(Active Mills)	0.049	(0.013)	0.085	(0.014)
Constant	0.859	(0.938)	3.175	(1.126)
Additional Controls (Dummy Variables)				
<i>F-Tests (Prob>F in parentheses)</i>				
Years F(7,2601)	12.86	(0.00)	28.05	(0.00)
Quarters F(3,2601)	16.50	(0.00)	6.15	(0.00)
Species F(8,2601)	11.79	(0.00)	22.90	(0.00)
Location F(11,2601)	8.57	(0.00)	12.59	(0.00)
N=2660		N=2660		
F(58,2601)	29.7	F(58,2601)	119.8	
Prob>F	0.000	Prob>F	0.000	
R-squared	0.32	R-squared	0.64	

Table 4: Effects of Set-Aside Provision

Dependent Variable	(1)		(2)	
	ln(Entrants)		ln(Revenue)	
	coefficient	s.e.	coefficient	s.e.
Average Effect (Full Sample)				
OLS Regression	0.012	(0.024)	-0.034	(0.032)
OLS with Interactions	0.004	(0.026)	-0.026	(0.036)
Matching Estimate	0.017	(0.027)	-0.019	(0.044)
Average Effect on Set-Aside Tracts				
OLS with Interactions	0.025	(0.029)	-0.032	(0.036)
Matching estimate	-0.015	(0.028)	-0.049	(0.042)
Average Effect on Non-Salvage Tracts				
OLS with Interaction	0.000	(0.032)	-0.029	(0.042)
Split Sample OLS	-0.002	(0.033)	-0.041	(0.041)
Average Effect on Salvage Tracts				
OLS with Interaction	0.023	(0.033)	-0.038	(0.043)
Split Sample OLS	0.020	(0.034)	-0.031	(0.043)
Average Effect on Sales w/ <5 Active Mills				
OLS with Interaction	0.080	(0.035)	0.023	(0.044)
Split Sample OLS	0.099	(0.040)	0.059	(0.051)
Average Effect on Sales w/ ≥5 Active Mills				
OLS with Interaction	-0.024	(0.027)	-0.064	(0.036)
Split Sample OLS	-0.024	(0.031)	-0.073	(0.040)

Table 5: Bid and Entry Distributions for Sealed Bid Auctions

	(1)		(2)	
	Bid Distribution (Weibull)		Logger Entry (Binomial)	
	coefficient	s.e.	coefficient	s.e.
	<i>ln(λ)</i>		<i>ln(ln(1/(1-p)))</i>	
Ln(Reserve Price)	0.640	(0.021)	-0.187	(0.029)
Ln(Selling Value)	-0.018	(0.011)	-0.019	(0.018)
Ln(Manufacturing Costs)	0.021	(0.016)	0.018	(0.027)
Ln(Logging Costs)	-0.014	(0.070)	-0.330	(0.070)
Ln(Road Costs)	-0.077	(0.044)	-0.168	(0.107)
No Road Construct. (Dummy)	-0.224	(0.105)	0.053	(0.243)
Species Herfindal	-0.240	(0.048)	-0.001	(0.078)
Density of Timber (hmbf/acres)	-0.001	(0.001)	0.000	(0.000)
Salvage Sale (Dummy)	-0.031	(0.028)	-0.178	(0.042)
Scale Sale (Dummy)	0.100	(0.028)	0.097	(0.044)
Ln(Volume)	-0.017	(0.015)	-0.012	(0.023)
Active Loggers	0.003	(0.002)	-0.039	(0.003)
Active Mills	0.010	(0.005)	-0.040	(0.008)
Mill (Dummy)	0.140	(0.022)		
Min(Mill Entrants,5)	0.096	(0.013)	0.009	(0.021)
Mill (Dummy) * (Mill Entrants=1)	-0.105	(0.037)		
Min(Logger Entrants,5)	0.099	(0.012)		
Constant	1.657	(0.402)	1.813	(0.495)
<i>Binomial probability and Weibull scale parameter include forest and year dummies.</i>				
	<i>ln(p)</i>			
Mill(Dummy)	-0.011	(0.042)		
Min(Mill Entrants,5)	-0.007	(0.012)		
Mill (Dummy) * (Mill Entrants=1)	-0.113	(0.064)		
Min(Logger Entrants,5)	-0.011	(0.013)		
Constant	1.276	(0.052)		
	<i>ln(θ)</i>			
Constant	-0.290	(0.067)		
	N=4116		N=1205	
	Wald χ^2 (36)	3508.7	Wald χ^2 (33)	463.8
	Prob > chi2	0.000	Prob > chi2	0.000

Note: Bid distribution estimated on sealed bid auctions with two or more bidders (967 auctions).

Table 6: Effect of the Set-Aside Program

	(1) Actual Outcome	(2) Predicted Outcomes Unrestricted	(3) Set-Aside
<i>Tracts sold by unrestricted sale (N=2018)</i>			
Avg. Mill Entry	2.13	2.13	0.82
Avg. Logger Entry	1.87	1.76	3.65
Avg. Total Entry	4.00	3.89	4.47
Avg. Sale Price	88.26	91.32	88.34
Avg. Revenue	437,115	446,100	434,258
% Sales won by Loggers	42.4	41.2	73.1
% Sales won by Small Mills	17.3	21.1	26.9
Avg. Surplus		628,626	598,720
<i>Tracts sold by set-aside sale (N=642)</i>			
Avg. Mill Entry	0.61	1.19	0.61
Avg. Logger Entry	3.00	2.42	2.63
Avg. Total Entry	3.62	3.61	3.24
Avg. Sale Price	76.91	79.41	75.97
Avg. Revenue	143,489	169,281	148,830
% Sales won by Loggers	82.2	67.1	75.7
% Sales won by Small Mills	16.8	12.7	24.3
Avg. Surplus		204,568	209,269

Note: Bootstrap standard errors in parentheses. *Standard errors not available at this time.*