Bid Preference Programs and Participation in Highway Procurement Auctions

Preliminary and Incomplete.

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Abstract

We use highway procurement auction data to analyze the California Small Business program that awards a contract to a qualified small bidder provided its bid is within five percent of the overall low bid. We study the effect of this rule on bidders' incentives to participate in procurement auctions and compute its implied efficiency and distributional costs. We set-up and estimate a model of auction participation and bidding between asymmetric firms under the assumptions that (1) bidders incur a cost to participate in the auction for a particular procurement project; (2) they make the participation decision before they learn their cost of completing the auctioned project; and (3) upon incuring the entry cost, but before submitting a bid, bidders learn the number of other bidders and their cost of project completion.

With a bid discount, small bidders can improve both their mark-up and their probability of winning the project. The last effect dominates for high-cost bidders: small bidders with project costs at the upper end of the cost support exploit the cushion of the discount to squeeze large bidders out of the auction. This effect is, in general, stronger when project cost distributions differ substantially across types.

Our estimation results imply that small bidders have on average higher costs of completing projects and higher costs of participation. The differences in the cost of entry are larger in magnitude and increase with the size of the project. In this environment, the program produces a substantial increase in small bidders' probabilities of winning and participation while resulting in a small change in the cost of procurement to the government. The magnitudes of the effects and the sign of the effect on the government's cost of procurement vary across projects of different sizes.

Keywords:
Bid preference programs, highway procurement, auction participation, asymmetric bidders.

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1 Introduction

Governments use a number of programs to reduce the under-representation of identifiable groups of firms in public procurement. Under these programs, disadvantaged firms often receive some form of preferential treatment in the auction mechanism used to award public contracts. Examples of preference programs include set-aside contracts, quotas, and bid discounts. In this paper we focus on California's use of bid discounts in promoting the participation of small businesses in highway procurement and study the effect of the discounts on bidders' incentives to participate in procurement auctions and on the implied efficiency and distributional costs of the bid preference program.

Despite the prevalence of such affirmative action programs, there are only a few studies of their implications for disadvantaged firms, their competitors, and the cost of procurement to the government. Existing work focuses primarily on analyzing the effect of the preferential treatment of disadvantaged bidders on bid levels. Among others, the papers that contributed to this literature include analysis of preferential treatment in highway procurement by Denes (1997) and Marion (2005), in FCC spectrum auctions by Ayres and Cramton (2000), and in experimental settings by Corns and Schotter (1999). Marion (2004) provides an initial analysis of the effect of an affirmative action program on participation through the descriptive comparison of two types of auctions.

The use of preferential treatment programs in procurement auctions has several consequences for firm behavior. By improving the effective competitiveness of disadvantaged firms, it affects both their and other firms' bidding behavior. The auction is also likely to attract a larger number of disadvantaged firms, which in turn may discourage other, potentially lower-cost firms from participating. While theoretical models of participation (e.g. Samuelson (1985), McAfee and McMillan (1987), Levin and Smith (1994)) make clear predictions about the direction in which bid levels and other variables of interest change with a preferential treatment program, they yield ambiguous predictions for the cost of the program to the government and provide no assessment of the magnitude of the changes in participation behavior.

In order to study the effects of such favoritsm, we would ideally like to be able to compare a set of auctions with a preference program to the comparable set of auctions without any program. Unfortunately, such data are generally not available. Instead, we develop and estimate a model of entry and bidding that incorporates the specific terms of the program we study and consider the estimated model's predictions for firm behavior were the program to be eliminated.

We first characterize the theoretical implications of introducing a program similar to California's in a procurement market. Under the California Small Bidder Preference program, the lowest qualified small bidder wins a contract provided its bid is within five percent of the overall low bid. We use a simple model of participation previously described in the literature (e.g. Athey, Levin, and Seira (2004)) that considers two groups of firms that decide over participation in an auction for a single project and, if they choose to participate, the bid to submit. The firms' decisions depend on two different costs: a cost of entry and a cost of completing the project. We allow the distributions of costs to differ across groups to capture possible cost-based differences as a reason for the under-representation of disadvantaged businesses. Upon paying the entry cost, they learn their cost of completing the project and the number of actual competitors. Only firms with a cost of entry below their ex-ante expected profit from bidding decide to submit a bid. When making the participation decision, firms observe only the number of potential bidders and their own cost of entry.

In this environment, small bidders use a bid discount to improve their expected mark-up as well as their probability of winning the project. The last effect is more pronounced at the upper end of the project cost support where small bidders use the cushion of the discount to lower their effective bids below cost. Therefore, large bidders with similar cost levels can never win the auction. They either bid their costs or stay out of the auction. A simulation study shows that small bidders are able to eliminate the competition from large bidders in this fashion over a larger part of the cost support if distributions of costs differ substantially across groups of bidders.

We perform an empirical assessment of the preference program, building upon earlier studies of the highway procurement market such as Bajari and Ye (2003), Hong and Shum (2002), Jofre-Bonet and Pesendorfer (2003), Krasnokutskaya (2003) and Porter and Zona (1993). As in the literature on entry into product and auction markets (e.g. Bresnahan and Reiss (1991), Berry (1992), Mazzeo (2001), Seim (2005), Athey, Levin, and Seira (2004), Li (2005) and Li and Zheng (2005)), our estimation approach yields empirical entry and project cost distributions that match firms' observed participation and bidding decisions to the outcomes of the discrete entry game between potential bidders. We use a simulated maximum likelihood method to uncover the parameters of project and entry cost distributions. We then use our estimation results to simulate the outcome of an auction without preferential treatment and, thus, infer effects of the program on the number of important variables.

Our empirical results suggest that small bidders, the target of California's program, are indeed weak bidders in the market with on average higher costs of completing a project. However, we find that differences in the cost of completing the project are small relative to differences in the cost of entry. We estimate that a typical small bidder's cost of entering a project is on average 50% higher than the comparable cost of a large bidder, with entry costs diverging as projects increase in size. The magnitudes of the estimated entry costs depend on the specification of the entry model. We find that a model where firms pay identical, fixed entry costs and randomize over their entry decision implies higher costs than the average entry costs resulting from a model where entry costs differ across firms and are privately observed. Therefore, it is important to use a flexible specification of the parameters of the entry cost distribution that can be estimated from the data instead of *a priori* imposing restrictions on the distribution parameters in the model.

The difference in the two types' entry costs further implies a variation in the program's effects across project sizes. We find that for medium-sized projects, the program induces a substantial increase in small bidders' probabilities of winning and participation while leaving the cost of procurement unchanged. The program produces only moderate increases in small firm participation for small projects, yet increases the cost of procurement by about 4%. Finally, we find the strongest effect on participation for large projects where the cost of procurement actually decreases. Our results confirm that, across project sizes, the program increases the inefficiency of the auction mechanism in awarding the project to firms who are not the low-cost bidder. We then consider alternative mechanisms to encourage small firm participation in procurement, including alternative bid discount programs, an entry cost subsidy, and set-aside auctions.

2 Related Literature on Bid Preference Programs

Despite the prevalence of governmental programs to promote the involvement of firms of various types in procurement, there is little work studying their effects. Marion (2004a) looks at the effect of the preferential treatment program in highway procurement auctions. By granting a bid preference to high-cost firms, the government loses surplus from low-cost bidders by awarding contracts to likely higher-cost competitors. At the same time, the preferential treatment increases the competitive pressure exerted by favored bidders. Non-favored bidders respond by bidding more aggressively, possibly driving down winning bids and the cost of procurement to the government. Marion analyses this trade-off using data on highway construction contracts that the California Department of Transportation awarded between 1996 and 2002. In descriptive regressions, he shows that large firms bid 1.4% lower on preference auctions than on similar non-preference auctions. At the same time, small firms bid 1.4% higher in preference auctions than in similar non-preference auctions. He finds further that preference auctions increase procurement costs by 3.5%, possibly because the likelihood of large firm participation is smaller for preference auctions than for non-preference auctions. Marion obtains these results by comparing federally funded and state-funded projects. In California, federally funded and state-funded contracts are covered by two separate disadvantaged bidder programs that differ in the type of company they focus on. Marion's results thus compare the outcomes of the two programs. We instead conduct a counterfactual analysis to isolate the effects of the bid preference program.

Denes (1997) looks at how setting aside a share of contracts for small bidders affect the cost of government contracting. He has data on winning bids for federal dredging contracts during 1990 and 1991, as well as detailed information on the project as well as participation in the bidding process. He then compares the mean normalized winning bid for set-aside contracts (where only small businesses compete) to the mean for general contracts (where all companies can compete). He finds statistically significant differences in normalized winning bids in only one of eight contract categories, with the winning bids in set-aside auctions being lower than the comparable winning bids in general auctions. He concludes that there is no evidence to support the hypothesis that set-asides increase costs. He suggests that one possible reason that set-asides produced either no change or a lower bid price than unrestricted dredging is that more firms bid on the set-asides. On average, 3.6 firms bid on the set-asides, while only 3.1 firms bid on the unrestricted solicitations. He states that "apparently there is a large population of qualified set-aside participants who only bid on set-aside procurements. The analysis suggests that setting aside contracts for small businesses does not necessarily reduce the number of competitors bidding on the project and, in this case, increased the number of competitors."We investigate the importance of similar participation patterns in the California highway procurement market below.

3 The Highway Procurement Market

The analysis in this paper is based on data from highway and street maintenance projects auctioned by the California Department of Transportation (Caltrans) between January 2002 and April 2005. During this period, 1,491 projects were advertised, of which complete data are available for 1,204 projects. In addition, 9 contracts were postponed, leaving a set of 1,195 awarded project contracts.

Each contract specifies provisions to encourage the participation of disadvantaged businesses. Two types of disadvantaged business programs are used in California. One program that applies to federally funded contracts attempts to increase the share of public work conducted by disadvantaged minority-, women-, or veteran-owned businesses by recommending a percentage of the contract's value to be subcontracted out to a disadvantaged business. This disadvantaged-business quota varies across contracts depending on a case-by-case assessment of the availability of disadvantaged businesses for the type of work required by the project. In our data, it ranges from 5% to 35% of the value of the contract.

A second program facilitates participation by disadvantaged businesses in procurement by granting qualified companies a bidder preference. Preferential treatment is granted to qualified small and veteran-owned bidders. We focus on the bidder preference program in this paper. We begin with an overview of the small bidder preference program before describing the contracts and bidders that it affects.

3.1 California's Small Bidder Preference Program

The California's Small Bidder Preference program arguably pursues several goals. Some of them are political such as "allocating fair proportion of contracts to different groups of bidders". Other goals have economic motivation at core such as increasing participation in govenment procurement at the expense of less efficient bidders to impose competitive pressure on the more efficient companies in the short run, or, in the long run, providing small companies with an oportunity to improve their efficiency through "learning-by-doing" or develop a reputation if these features are important in a given market.

As a Certified Small Business, the firm qualifies for a 5% bid preference on applicable state contracts and is eligible for advantageous payment terms. The small bidder preference is applied when a non-certified bidder submits the lowest bid. The contract is then awarded to the lowest certified small bidder if that firm's bid is within 5% of the overall lowest bid. The preference is used for comparison purposes only, and does not affect the amount at which the contract is awarded to the small bidder.

To be eligible for Small Business Certification, the business must be an independently owned and operated company located in California and have at most 100 employees and average annual gross receipts of $10 million or less over the previous three tax years. The certification of companies is undertaken by the California Department of General Services, which certifies eligible companies for a period of up to 4 years. The Department of General Services publishes a quarterly directory of qualified companies that allows us to identify small bidders among auction participants. Of the 672 companies that bid on at least one project from January 2002 to April 2005, 269 or 40% were certified for at least a part of this period.

3.2 Project award process

The process by which Caltrans awards a highway procurement contract to a qualified bidder proceeds in several steps. Once funding for a project has been secured and contract documents have been prepared, Caltrans advertises the project on its internet web site, which offers public access to advertised plan sets, proposals, special provisions, and wage information for prospective bidders, subcontractors or vendors. Advertising periods can range from three to ten weeks or more depending on the cost or complexity of the project.

Contractors interested in submitting bids for Caltrans contracts must purchase bid documents from the Caltrans Project Plans Counter for between $13 and $90 a set. On the bid opening date, bidders submit the completed bid forms that indicate the itemized and total amount for which the company proposes to complete the contract. In addition, they submit a bid bond of at least 10% of the total bid amount, as a promise that the bidder will accept the contract if awarded.

Within five working days following the bid opening, Caltrans awards the contract. A payment bond in the amount of the total bid guarantees that the contractor will pay any workers, subcontractors and/or suppliers, while a performance bond in the amount of 50% of the total amount of the contract assures that the contractor will complete the work satisfactorily. In the case of state-funded contracts, the small bidder preference is invoked if necessary and the winner's small business status is verified. Work on the contract commences generally several weeks after the contract award, upon official Caltrans authorization.

3.3 Contract characteristics

We focus on state-funded projects and the preferential treatment program administered on these projects. The Caltrans data contain a verbal description of the work to be carried out for the contract, which we aggregate into 8 categories: bridge work; construction and repair of buildings; new road construction; landscaping; road marking; road repair; electrical work; and maintenance work on small structures. Road-repair work accounts for 49.04% of contracts and is by far the largest category. We use counties as project locations. The duration of the project is given in working days, ranging from 8 to 2,310 working days across projects, with a median length of 45 working days. An important project descriptor is the engineer's estimate of the total cost of the project measured in $, which serves as indicator of the size of the project. Similar to the duration variable, the engineer's estimate exhibits a skewed distribution across projects with an average of $2.25 million and a median of $ 457 thousand.

Table 1 summarizes the characteristics of state-funded contracts.

3.4 Market participants

We obtained a list of companies that purchased project plan packages for each project in our data from the Project Plans Counter. Since these packages are also purchased by companies with no apparent interest in becoming a bidder on the contract, such as companies that track construction activity, we treat only those plan holders as potential bidders in the subsequent auction if the companies bid on at least one project during the period of our sample. The data furnished by Caltrans contain the name and address of the plan holders, which we use to match the plan holder information with the directory of qualified small businesses obtained from the Department of General Services and data on actual bid outcomes obtained from Caltrans' Office of Engineer. We complement the Caltrans data with information obtained from Reference USA on participant characteristics such as the number of different locations in the state, employment size categories by location, and the 6-digit SIC code corresponding to the location's primary line of business.

For a typical state-funded project in the data set, the Plans Counter issues between 5 and 16 packages, with an average of 10.33 and a median of 9. For the most popular projects in the 90th percentile, 18 packages are requested. The average project receives 4.32 requests for bidder packages from qualified small businesses, with a median of 3 packages.

The share of qualified small bidder plan holders varies with project attributes, decreasing in the project's size and increasing in its duration. This suggests that small companies are primarily interested in smaller-scale projects that require limited resources and longer projects that provide steady business.

Since Caltrans publishes the list of companies that purchase bid documents for all projects being advertised, potential bidders are aware of other companies that are sufficiently interested in the project to purchase plan packages. This serves as our motivation for the assumptions of our theoretical model that firms know the remaining potential entrants for the projects they choose to participate in.

3.5 Participation Decisions by Small and Large Contractors

While project plans are available to firms at a relatively low cost, submitting a bid to Caltrans is more costly since it requires the firm to prepare a detailed estimate of how much it would charge for each item included in the contract. Consequently, only 50.66% of plan holders submit a bid on any given auction. Small bidders are less likely to submit a bid, with a conversion rate of 43.11% on state-funded projects. This results in an average number of 4.93 bidders on each project, of which 1.90 bidders are qualified small businesses.

Conversion differs further by project attributes. Conversion is highest for the shortest projects with a duration of less than 30 working days with rates of 47.71% for small bidders and 60.53% for large bidders and decreases steadily in project duration. Small bidder conversion rates decline as well in the project's size, falling from 53.40% for projects with an engineer's estimate below $250 thousand to 33.88% for projects above $2.5 million. This trend is not nearly as pronounced for large firms, pointing again to differences in the match between project attributes and firm capabilities between the two types of firms.

Results of the analysis to submit a bid are presented in table 2, allowing coefficients to differ for small and large plan holders. We allow for company-specific factors in the form of capacity utilization and the distance from the company's office to the project to affect the bidding decision. We estimate the company's current capacity utilization using a measure proposed by Jofre-Bonet and Pesendorfer (2003). We use data on the identities of winning bidders and sizes and duration of the project to identify companies that work on any Caltrans project at any given point in time. We disregard the initial six months of data to build up a history for firms that win subsequently awarded contracts. We assume that the company allocates the work on a particular project uniformly within the allotted duration of the project. We then compute the monthly load generated by each project the company is working on in a given month. The sum of these loads is our proxy for monthly capacity utilization. The distance between company and project locations is measured as the distance between the counties in which the company and the project are located, for lack of a more finely defined project location.

We estimate both a Probit model and a fixed-effect Logit model of the participation decision. We find that distance to the project exerts a significant negative effect on the probability to bid for both types of firms. A higher distance between the bidder and the project drives up the company's cost of moving equipment and labor to the site, and the participation decision may reflect such cost considerations. A high current load consistently increases both large and small bidders' probability to submit a bid, possibly since work on any new projects would occur at future times, after the current backlog of projects has been exhausted.

Among project characteristics, both the project's size and its duration influence the bidding decision. We measure project size as the log of the engineer's estimate, scaled by the mean engineer's estimate. The effect of this size measure is of particular interest. The probability to submit a bid increases significantly with the size of the project for large firms, but decreases significantly for small firms, consistent with the descriptive evidence outlined above. At the market level, the total number of potential bidders who previously purchased plans to the projects has a negative effect on any one firm's decision to submit a bid on the project. The importance is less pronounced for small plan holders with marginal effects of -0.024 and -0.026 relative to -0.037 and -0.044 for large plan holders in the Probit and Logit models, respectively. Overall, small plan holders are less likely to become participants than large plan holders, with marginal effects of -0.461 and -0.103 in the Probit and Logit models, respectively. We reject the hypothesis that the coefficients for large and small plan holders are equal, suggesting that the participation decisions differ significantly across types of bidders.

3.6 Bidding Behavior by Small and Large Contractors

3.6.1 Bid levels

The bidder preference program can affect bid levels in several ways. It is likely to increase the probability of bidding by small businesses. With additional entry, competition in the auction increases. At the same time, the preferential treatment of small bidders imposes additional competitive pressure on large bidders.

Table 3 analyzes average bids at the bidder level as a function of bidder and project characteristics whose effects are again allowed to differ by type of firm. Among project characteristics, the engineer's estimate is the most significant determinant of bid levels, justifying its use as a proxy for project size. Projects of longer duration generate, on average, higher bid levels, however the effect is smaller and not always significant across specifications and types.

The role of company characteristics, such as distance to the project and current load, do not play a large role in determining bid levels, suggesting that they may only imperfectly capture firms' cost and capacity considerations. The average bid of a small bidder is between 10.05 and 17.91% above that of a large bidder.

We control for the competitive environment by including the number of plan holders and the number of bidders as regressors. Across types and specifications, bid levels decrease significantly in the number of bidders, but increase in the number of plan holders, as a measure of potential competition. Since we do not control for auction-specific heterogeneity beyond the project's location and the work involved, unobserved auction characteristics may confound the effect of a larger number of participants on bid levels.

While the bid regressions suggest that small bidders bid higher on average, they do not directly isolate the effect of the presence of small bidders on large bidder behavior. To do so, we compare the bidding behavior of large firms in auctions where no small bidder is present to that in auctions where exactly one bidder is present. Figure 1 compares kernel density estimates of large firm bidding distributions under alternative competitive environments. Specifically, we hold the total number of bidders or participants constant and consider the effect of replacing a large bidder by a small bidder on large bidder behavior. We plot the two bid distributions under the presence of zero and one small bidder. As a comparison, we include the bid distribution of the single small bidder across projects with the same number of bidders or participants. Since small bidders are likely weaker bidders, replacing a large bidder by a small bidder may lead to an upward shift of the large-firm bid distribution. The preferential treatment of small bidders counters that effect. The change in going from auctions with no small bidders to auctions with one small bidder represents the net of these effects, as well as possibly unobserved auction characteristics that induce small bidders to stay away from a certain subset of projects. The effect of the bid preference program is most pronounced in the first chart in the figure, which shows bidding behavior in auctions with three bidders. Here, the large-firm bidding distribution shifts to the left in going from zero to one small bidder. This suggests that the bid preference significantly strengthens the competitive threat of the small bidder. The effect is less clear in the second chart in the figure. It illustrates that bidding behavior changes due to the presence of a small bidder, however, large bidders do not uniformly bid lower once a small bidder participates in the auction. This could be because small bidders in these auctions are significantly weaker so that their preferential treatment is inconsequential.

3.6.2 Winning Bid

The bidder preference program awards projects to qualified small bidders provided their bids are within a reasonable amount of the low bid. Overall, small bidders win 35.45% of all state contracts. In 4.59% of state-funded contracts, the bidder preference program alters the ranking of bidders by awarding a contract to the lowest small bidder at the expense of the non-qualified low bidder.

The median winning bid of a small bidder is below that of a large bidder, amounting to $301.65 thousand. This compares to a median winning bid for large bidders of $687.43 thousand, not controlling for sorting of small and large bidders into projects of different characteristics. We explain the winning bid more fully as a function of project and bidder characteristics in Table 4. Conditional on size, duration, and district and work categories, the results indicate that the winning bid on state contracts is on average between 3.23% higher if the winner is a qualified small business and is 6.75% higher once we control for competition proxied by the number of bidders and plan holders. The winning bid increases with the engineer's estimate and the number of working days. There are further significant differences in winning bid amounts for different work classes, reflecting both heterogeneity in the difficulty of the specific work involved and differences in the liquidity of the market for the work category. This analysis does not allow us to disentangle the effect of the preferential treatment of small bidders on winning bids from the effect of systematic differences in bidders' costs being responsible for this difference in small and large firm winning bids. The model we develop in the following section provides a more complete framework for separating these effects.

4 Model of Firms' Participation and Bidding Decisions

This section develops a model of firms' participation and bidding decisions in the presence of a bid preference program. The model forms the basis for our empirical work below. The government's goal is to procure the services of a construction company to complete a single project. We assume that there are N companies that are interested in this project (potential bidders). In our environment a company is a potential bidder if it purchases a bidding package. In line with the terms of the Caltrans small bidder preference program, we consider two types of companies: those that satisfy the requirements of the program and the rest. The number of potential bidders in each group j is N_j, with $N_1 + N_2 = N$. When deciding on the winner, an auctioneer compares the overall lowest bid and the lowest bid among type-1 bidders. If the latter is within δ percentage points of the former then the project goes to the lowest type-1 bidder. Otherwise it is awarded to the overall lowest bidder.

Similar to other work on entry into auctions (e.g. Samuelson (1985), McAfee and McMillan (1987), Levin and Smith (1994)), we frame the firm's decision as a two-stage process. Initially, each firm decides whether or not to participate in the auction. To participate firm i has to incur cost d_{ij}. We consider two alternative assumptions on the cost of entry. First, we assume that the cost of entry each firm pays differs across firms and is private information of each firm. We assume that entry costs are distributed according to the distribution G_j. We later compare the estimated average entry costs to those resulting from a specification that assumes that all firms of each type pay an identical, observed cost of entry and randomize in choosing to enter or not.

Upon entry a firm submits a bid, b_{ij}. The firm's bid depends on its cost of completing the project, which we denote by c_{ij}. We assume that the company knows its own project cost at the time of bidding, however, the cost is private information of company. Its competitors know only the distribution of firm i's project cost F_j defined on the interval $[\underline{c}, \overline{c}]$ for $j = 1, 2$.

We make three assumptions on the distributions of firm costs: (A_1) Project costs c_{ij} are mutually independent across firms; (A_2) the probability density functions of projects costs, f_1 and f_2, are continuously differentiable and bounded away from zero on $[\underline{c}, \overline{c}]$, and ($A_3$) firm i's entry cost d_{ij} and project cost c_{ij} are independent draws from the distributions G_j and F_j.

As in Athey, Levin and Seira (2004), we assume that in the initial participation stage, each potential bidder i knows only his own cost of entry, d_{ij}, and the distributions of entry costs G_j and project costs F_j. After incurring the entry cost to participate in the auction, the firm learns its own cost of completing the project c_{ij} and the number of other firms in each group who similarly decided to participate. We denote the number of participants by n_1 and n_2.

4.1 Characterization of Equilibrium in the Bidding Stage

We begin with an analysis of the bidding stage and then use the results to complete the analysis of the participation stage. Due to the bid-preference program, a participating bidder i of type j wins the project if its bid is below all competing bids adjusted by the bid discount δ where applicable. Firm i with cost c_{ij} chooses bid b_{ij} to maximize the resulting expected profit conditional on participating:

$$
\begin{aligned}
& j = 1: \\
& \quad \pi_{i1} = (b_{i1} - c_{i1}) \Pr\left(b_{i1} < \ b_{k1}\ \forall k \neq i\right) \Pr\left(b_{i1} < \ (1+\delta) b_{k2}, k = 1, ..., n_2\right) \\
& \quad\quad = (b_{i1} - c_{i1}) \left(\ 1 - F_1\left[\beta_1^{-1}(b_{i1})\right]\ \right)^{n_1 - 1} \left(\ 1 - F_2\left[\beta_2^{-1}\left(\frac{b_{i1}}{(1+\delta)}\right)\right]\ \right)^{n_2} \qquad (1) \\
& j = 2: \\
& \quad \pi_{i2} = (b_{i2} - c_{i2}) \Pr\left(b_{i2} < \frac{1}{1+\delta} b_{k1}, k = 1, ..., n_1\right) \Pr\left(b_{i2} < \ b_{k2},\ \forall k \neq i\right) \\
& \quad\quad = (b_{i2} - c_{i2}) \left(\ 1 - F_1\left[\beta_1^{-1}\left((1+\delta) b_{i2}\right)\right]\ \right)^{n_1} \left(\ 1 - F_2\left[\beta_2^{-1}(b_{i2})\right]\ \right)^{n_2 - 1}
\end{aligned}
$$

where $\beta_j(.) : [\underline{c}, \overline{c}] \rightarrow [\underline{b}, \overline{b}]$, denotes type j's bidding strategy that maps a given project cost, c_{ij}, to the firm's bid. Since we assume that the number of bidders is observed after the initial participation decision, the bidding stage is a standard first-price sealed-bid procurement auction with asymmetric bidders. The first-order condition of the firm's bidding problem is:

$$
\begin{aligned}
& j = 1: \\
& \frac{1}{b_{i1} - c_{i1}} = \frac{(n_1 - 1) f_1 \left[\beta_1^{-1}(b_{i1})\right]}{\left(1 - F_1\left[\beta_1^{-1}(b_{i1})\right]\right)} \frac{\partial \beta_1^{-1}}{\partial b_{i1}} + \frac{n_2 f_2 \left[\beta_2^{-1}\left(\frac{b_{i1}}{(1+\delta)}\right)\right]}{(1+\delta)\left(1 - F_2\left[\beta_2^{-1}\left(\frac{b_{i1}}{(1+\delta)}\right)\right]\right)} \frac{\partial \beta_2^{-1}}{\partial b_{i1}} \\
& j = 2: \\
& \frac{1}{b_{i2} - c_{i2}} = \frac{n_1 (1+\delta) f_1 \left[\beta_1^{-1}\left((1+\delta) b_{i2}\right)\right]}{\left(1 - F_1\left[\beta_1^{-1}\left((1+\delta) b_{i2}\right)\right]\right)} \frac{\partial \beta_1^{-1}}{\partial b_{i2}} + \frac{(n_2 - 1) f_2 \left[\beta_2^{-1}\left(b_{i2}\right)\right]}{\left(1 - F_2\left[\beta_2^{-1}\left(b_{i2}\right)\right]\right)} \frac{\partial \beta_2^{-1}}{\partial b_{i2}}
\end{aligned} \tag{2}
$$

We focus on type-symmetric equilibria where companies of the same type follow the same strategies. The first-order conditions, together with the boundary condition defined below, uniquely characterize optimal bidding strategies (Maskin and Riley (2000)).

The introduction of a bid discount in this setting affects small bidders in two ways. First, they increase their expected mark-ups. Second, they increase their probability of winning the project, in particular for those bidders with costs at the upper end of the cost support. These bidders use the cushion of the discount to lower their "effective" bid, $\frac{b}{(1+\delta)}$, below their cost, c. This means that large bidders with high cost levels can never win the auction. If forced to submit a bid such bidders would bid their cost.

If only one small firm is present in the auction, it chooses $\beta_1(\overline{c})$ to maximize

$$
(\beta_1 - \overline{c})\left(1 - F_2\left(\frac{\overline{\beta}_1}{(1+\delta)}\right)\right)^{n_2}.
$$

The first order condition corresponding to this problem is given by

$$
\frac{1 - F_2\left(\frac{\overline{\beta}_1}{1+\delta}\right)}{f_2\left(\frac{\overline{\beta}_1}{1+\delta}\right)} = \frac{n_2}{1+\delta}(\beta_1 - \overline{c}). \tag{3}
$$

When the auction attracts more than one small bidder, competition leads to $\beta_1 = \overline{c}$. In summary, in an auction with preferential treatment and without a reserve price, bidding strategies are characterized by:

1. If $\beta_2(\underline{c}) = b_0$ then $\beta_1(\underline{c}) = (1+\delta) b_0$;
2. $\beta_1(\overline{c}) < (1+\delta)\overline{c}$ and $\beta_1(\overline{c}) = \overline{c}$ if $n_1 > 1$
3. $\beta_2(c) = c \ \forall c \in \left[\frac{\beta_1(\overline{c})}{(1+\delta)}, \overline{c}\right]$.

4.2 Characterization of Equilibrium in the Participation Stage

At the participation stage, firms compare the expected profit conditional on entry to their entry cost d_{ij}. Firms with entry costs below their expected profit decide to incur the entry fee to learn about the cost of completing the project. This yields type-specific thresholds, D_j, such that only firms with entry costs below their group's threshold learn their project cost. Since under the preferential treatment of type 1, type 2 bidders have a zero probability of winning if their cost is above $\frac{\beta_1(\bar{c})}{(1+\delta)}$, we assume that they do not submit a bid upon learning that their project cost falls into this range. The likelihood of observing a bid submitted by type-2 bidders is thus lower than the likelihood of them incurring the entry cost (*ex-ante* participation probability). Let p_j^a, p_j denote the ex-ante and ex-post probabilities of participation respectively. Thus, the ex-post probabilities of participation, p_1 and p_2, are given by:

$$\begin{aligned} p_1 &= p_1^a \\ p_2 &= \left(1 - F_2\left(\frac{\beta_1(\bar{c})}{(1+\delta)}\right)\right) p_2^a. \end{aligned} \tag{4}$$

Expected profit from participating is given by

$$\Pi_j = \sum_{k_j, k_{-j} \subset N_j - 1, N_{-j}} \left(\int_{\underline{c}}^{\bar{c}} \pi_{ij}(c_{ij}; k_j, k_{-j}) dF_j(c_{ij})\right) \Pr(k_j, k_{-j} | p_j, p_{-j}) \tag{5}$$

where $\Pr(k_j, k_{-j}|p_j, p_{-j})$ is the probability of observing k_j competitors of the firm's own type and k_{-j} competitors of the opposite type, given entry probabilities p_j and p_{-j}; $\pi_{ij}(c_{ij}; k_j, k_{-j})$ is the expected profit of a bidder from group j with cost realization c_{ij} computed on the basis of the bidding strategies described above. Expected profit reflects that at the participation stage, the firm is uncertain about both its own project cost and the competitive environment it will face upon entry. As a result, expected profit differs only by group j, but no longer by firm i. The firms assess the probability that there will be k_j and k_{-j} competitors in the auction as

$$\begin{aligned} &\Pr(k_j, k_{-j}|p_j, p_{-j}) = \\ &\quad \begin{pmatrix} N_j - 1 \\ k_j \end{pmatrix} \begin{pmatrix} N_{-j} \\ k_{-j} \end{pmatrix} (p_j)^{k_j} (1 - p_j)^{N_j - 1 - k_j} (p_{-j})^{k_{-j}} (1 - p_{-j})^{N_{-j} - k_{-j}} \end{aligned} \tag{6}$$

Entry cost thresholds are defined by a zero-profit rule so that $D_1(p_1, p_2) = \Pi_1(p_1, p_2)$

and $D_2(p_1, p_2) = \Pi_2(p_1, p_2)$. In equilibrium, bidders beliefs are correct and the equilibrium entry probabilities solve the system of equations

$$\begin{aligned} p_1 &= G\left[D_1(p_1, p_2)\right] \\ p_2^a &= G\left[D_2(p_1, p_2)\right]. \end{aligned} \tag{7}$$

Assumptions (A_1) and (A_2) guarantee that the type-specific equilibrium of this game exists. In general, the entry equilibrium is not unique. There may be multiple threshold pairs that describe equilibrium in the overall game. These equilibria are observationally equivalent, however, in terms of submitted bids and differ only in entry probabilities. In solving the model for a given set of distribution functions, we verify the uniqueness of the equilibrium entry probabilities numerically.

4.3 Computing Bidding Strategies

The first-order conditions in the bidding stage describe a system of differential equations in the firms' bidding strategies, β. Solving for equilibrium entry probabilities requires knowledge of the bid functions that map project costs to bids. The asymmetries in bidders' project costs make analytical solutions to the system of differential equations intractable. We therefore extend techniques proposed by Marshall, Meurer, Richard and Stromquist (1994) to solve the system of differential equations numerically. We use polynomial series expansion techniques, beginning at the highest project cost level, $\bar{c}$, and extrapolating backward to the lowest cost level $\underline{c}$. The solution algorithm is stable and efficient in solving the first-order conditions. Bajari (1999) and Marshall, Meurer, Richard and Stromquist (1994) provide detailed analysis of the performance and advantages of numerical solution algorithms for asymmetric auctions.

We illustrate the models' properties in the context of a specific example. We assume that bidders' project costs are distributed according to a truncated normal distribution with mean μ_j and standard deviation σ_j, defined over the interval [0,1]; entry costs are distributed uniformly on [0,0.25]. We consider the case where there are two potential entrants of both types. With a maximum of four firms in the market, there are 8 possible realizations for the number of participants, ranging from $(k_1 = 1, k_2 = 0)$ to $(k_1 = 2, k_2 = 2)$. Computing expected profit of participation entails computing optimal bidding behavior for all eight subgames defined by (k_1, k_2).

As a point of reference, we illustrate the model's properties in the absence of a bid preference program. Figure 2 depicts bidding strategies for a set of trunctaed normal distributions where type 2's project cost distribution first-order stochastically dominates that of type 1, holding the variance in costs fixed. The cost distributions are illustrated in the top left panel of figure 2. The bidding strategies end in the highest cost, reflecting that the highest cost type has no incentive to bid below the cost whereas competitive pressure does not allow him to raise his bid.

The middle left panel of figure 2 shows bidding strategies for different combinations of k_1 and k_2. Given that type 1 bidders are weak bidders in this example, they submit higher bids in distribution than type 2 bidders. At the same time, however, for a given level of cost, type 1 bidders face higher competition by the opposite type, causing them to lower their bids relative to type 2 bidders. As a result, a type 1 bidder may win the auction, despite the fact that the firm is not the lowest-cost bidder.

Figure 2 illustrates the bidding strategies for the case of a 10% bid preference. The middle right panel shows individual bidding strategies for model 1 for different firm configurations. Type 1 now moves from bidding lower to bidding higher than type 2 bidders for a given level of cost. Type 2 bidders are forced to bid their costs in the upper tail of the cost distribution. In general, a type-2 firm bids more aggressively, relative to the case without preferential treatment.

5 Empirical Implementation and Results

The predictions of the entry and bidding models outlined above consists of type-specific entry predictions as well as bidding strategies that map the distribution of firm costs into a distribution of type-specific bids. The goal of the estimation is to recover the underlying parameters of the project cost and cost of entry distributions that best explain firms' observed bidding behavior. We begin by discussing our estimation approach. We then describe the set of preliminary results.

5.1 Estimation Methodology

We estimate the parameters of the bid distributions and entry cost distributions G_j parametrically using maximum likelihood techniques. We then use the estimated bid distributions to recover the underlying project cost distributions, F_j. The likelihood of bidder i's entry and bidding decision, l_{ij}, is the joint probability of the firm's participation decision and its bidding decision conditional on entry. Assuming that the entry cost distribution, $G(\cdot)$, is independent of the project costs distributions and therefore bid distributions, this likelihood is the product of firm i's probability of entry p_j as predicted by the model times the likelihood of observing its bid to be b_{ijp} given the probability density of bids. For firms that choose not to participate, the likelihood is simply given by the probability of non-participation.

Following Krasnokutskaya (2003) we decompose the observed bid into a firm-specific and a common component. The firm-specfic component B_{ijp} captures the effect of observed project characteristics and the firm's privately observed cost of completing the project on its bid. The common component u_p represents the influence of other project characteristics on bid levels, introducing correlation in bids. We assume that $b_{ijp} = B_{ijp}u_p$ and that B_{ijp} and u_p are lognormallly distributed. This structure arises if bidders' costs are equal to the product of an individual cost component that is private information of the firm and a common component observable to all bidders. The common component may potentially be unknown to the econometrician and therefore summarizes unobserved auction heterogeneity from his/her point of view. For the distribution of unobserved auction heterogeneity, we assume a mean $m_u = 1$ and a constant standard deviation s_u. We let the mean of the distribution H_j of the firm-specific component, m_{B_j}, vary with observed auction characteristics, x_p, as well as the competitive environment in the auction, captured by n_1 and n_2. We estimate constant type-specific standard deviations s_{Bj}.

The theoretical model uses a bounded cost distribution, implying a similarly bounded bid distribution. We use the observed bid data to non-parametrically estimate a type-specific lower bound $\underline{b}_{jp}$ of the bid distributions for auctions with similar characteristics. We do not impose an upper bound during the estimation of the bid distribution, but truncate the distribution in the computation of participation probabilities.

Since the use of a lognormal distribution for u does not allow for a closed form likelihood function, we use simulation techniques to integrate over its distribution. For a given simulation draw u_{ps} from the lognormal distribution of unobserved auction heterogeneity, we first compute equilibrium entry probabilities. We then average across simulation draws, n_s, to obtain the simulated log likelihood function for participation decisions, denoted by indicator I_{ijp}, and bid levels:

$$\ln L = \sum_{s=1}^{n_s} \frac{1}{n_s} \sum_{p=1}^{P} \sum_{j=1}^{2} \sum_{i=1}^{N_{jp}} \ln l_{ijps}, \text{with} \tag{8}$$

$$l_{i1ps} = \left\{ p_{1ps} \times h_1 \left(\tilde{b}_{i1ps} \right) \right\}^{I_{i1p}} \times \{1 - p_{1ps}\}^{1-I_{i1p}}$$

$$l_{i2ps} = \left\{ p_{2ps} \times h_2 \left(\tilde{b}_{i2ps} \right) \right\}^{I_{i2p}} \times \{1 - p_{2ps}\}^{1-I_{i2p}},$$

where $\tilde{b}_{ijps}$ denotes the transformed bid of $\frac{b_{ijp}-\underline{b}_{jp}}{u_{jps}}$.

To compute equilibrium entry probabilities for a given simulation draw u_{ps} we first recover the inverse bid function associated with the observed bid distribution using the first order condition of the bid problem. For a given guess at (p_1, p_2), we integrate the expression for expected profit numerically over the support of the bid distribution from the nonparametrically estimated lower bid bound to the ex-post imposed upper bid bound as

$$\begin{aligned} \Pi_{1ps} &= \sum_{k_1,k_2} \Pr(k_1, k_2 | p_1, p_2) \times \\ &\left(\int_{\underline{b}}^{\bar{b}} (b_{i1} - c_{i1s}) \left(1 - H_1\left(\tilde{b}_{i1ps}\right)\right)^{n_1 - 1} \left(1 - H_2\left(\frac{\tilde{b}_{i1ps}}{1+\delta}\right)\right)^{n_2} dH_1 \right) \\ \Pi_{2ps} &= \sum_{k_1,k_2} \Pr(k_1, k_2 | p_1, p_2) \times \\ &\left(\int_{\underline{b}}^{\bar{b}} (b_{i2} - c_{i2s}) \left(1 - H_1\left((1+\delta)\tilde{b}_{i2ps}\right)\right)^{n_1} \left(1 - H_2\left(\tilde{b}_{i2ps}\right)\right)^{n_2 - 1} dH_2 \right). \end{aligned} \tag{9}$$

Given expected profits, we update the ex-ante entry probabilities. We assume that entry costs, d_j, are distributed according to a normal distribution with type-specific mean and a variance that is identical for both types. Accordingly, the ex-ante probabilities of entry, p_j, are Probit probabilities:

$$\begin{aligned} p_{1ps} &= \Phi(\Pi_{1ps}) \\ p_{2ps} &= \Phi(\Pi_{2ps}), \end{aligned} \tag{10}$$

where Φ denotes a normal pdf with mean m_{Dj} and standard deviation s_{Dj}. These entry probabilities serve as an update to our guess at p_{1ps} and p_{2ps}.

We iterate in computing expected profit and updated entry probabilities until the fixed point of the system (10) has been found for the given draw from the distribution of u.

5.2 Estimation Results

In this section we present preliminary estimation results. We use the parametric estimation techniques outlined above to estimate both the type-specific parameters of the bid distributions and the parameters of each type's cost of entry distribution. We abstract from unobserved auction heterogeneity, but assume that observed bids follow a lognormal distribution whose type-specific mean shifts with the project's size and duration and the competitive environment in auction and whose standard deviation is type-specific, but does not vary with project characteristics. We similarly allow each type's mean entry cost to vary with the project's engineer's estimate. We then use these estimates to simulate the outcome of different types of auctions in environments with alternative bid preference programs. In future work, we plan to incorporate additional bidder-heterogeneity in the estimation.

Table 5 shows parameter estimates. In line with the descriptive regressions above, the estimates suggest that qualified small bidders submit higher bids than large firms, on average. The effect is however, small in magnitude; a qualified small firm's mean log bid is approximately 1.026 times the corresponding log bid of a large bidder. In terms of practical significance, bid levels are primarily determined by the project's engineers estimate, increases of which get nearly fully passed through to bids. Mean bids decrease in more competitive auctions. While increases in participation of small and large bidders decrease bids, the number of large bidders has a stronger effect than the number of small bidders. In response to encountering one additional large bidder in an auction, firms scale down their mean log bids by a factor of 0.968, relative to a factor of 0.966 if the bidder is small. As above, the number of plan holders of either type is positively correlated with mean log bids. The results also suggest that there is larger variation in small firms' bids. The estimated standard deviation of their bid distribution is 1.037 times the standard deviation for large bidders, suggesting that there is larger heterogeneity in small bidders' cost of completing a project. In summary, the parameter estimates are in sign and statistical significance as expected: small bidders bid higher on average, with a larger standard deviation, suggesting that their costs are higher but more dispersed. The practical significance of the difference between the two bidder types is small. This is illustrated in figure 3, which shows the empirical distributions of bids for the median project with one small bidder and three large bidders. Figure 4illustrates the fit of the chosen specification. The figure plots the distribution of bid residuals in our sample across projects and bidder types and contrast it to the distribution predicted by our fitted model.

Turning to the estimated parameters of the entry cost distribution, our main estimates suggest that entry costs increase for both types of firms with the size of the project. Small firms' costs increase more in the project's size, possibly because a small firm needs to spend a larger amount of time and resources to prepare a bid for a more complex project. We also estimate the standard deviation of firms' entry costs, allowing it to vary by bidder type. In contrast to standard probit entry models, the fact that we observe multiple projects with similar numbers of potential bidders, but different entry patterns, all else equal, allows us to identify the variance in firms' entry costs. Our estimates indicate that the standard deviation of small bidders' costs exceeds that of large bidders by a factor of 3.4, suggesting that, just as with project costs, small firms are significantly more heterogeneous in their entry costs than large firms. In contrast to the estimated bid distributions, however, the differences between small and large bidders are more pronounced, both in terms of their mean entry cost, as well as their variance.

As a robustness check, we estimate several alternative specifications of the entry cost distribution. These are displayed in table 6. The table contains four sets of results: the base specification, for reference; a specification that fixes the standard deviation of the entry cost distribution to one; a specification that restricts the distribution's variance to be identical for the two types of bidders; and last a specification that assumes that entry is determined in a mixed strategy equilibrium, instead of in a game of imperfect information about competitors' entry costs. The last specification assumes that firms pay an identical entry cost that varies across types and randomize in their behavior, instead of our base specification, which imposes a distribution of entry costs on firms. The parameter estimates that result in the three alternative specifications of the game of imperfect information are similar in entailing that small firms' entry costs increase more rapidly than large firms with the size of the project. This pattern arises as well when estimating a mixed strategy game. In this specification, the fixed cost of entry is allowed to vary with the project's size as well as its duration. The results indicate that while longer projects lead to a significantly higher cost of preparing a bid, the magnitude of this effect is quite small.

5.3 Analysis of the Bid Preference Program

We use the results of estimation to evaluate the effect of preferential treatment on the cost of procurement to the government, incentives of different groups to participate in the auction and the distribution of projects and profits across groups of bidders. Here we describe results for the fixed cost of entry specification. Results for the stochastic cost of entry with estimated variance are forthcoming.

We find that preferential treatment of small bidders allows government to increase small bidders' probabilities of winning and participation with small or no change in the cost of procurement. For example, for the medium size project discount of 5% induces increase of 18% in the small bidder's probability of winning (from 32% to 37.7%). At the same time the average cost of procurement remains unchanged since the increase in the cost of procurement when project is won by one of the small bidders is almost exactly compensated by the decrease in the cost of procurement when project is won by the group of large bidders. Inefficiency of the auction doubles since due to preferential treatment the project is more often not assigned to the lowest cost bidder. Finally, the probability of participation increases from 37% to 41.9% which constitutes an increase of 13%. Therefore, the government seems to be able to achieve its goal of increased participation at no change to the cost of procurement but substantial increase in the inefficiency of auction. Performing analysis across different discount levels we find that for medium-size projects the probabilities of participation and winning further increase as the discount level increases. At the same time the cost of procurement remains roughly the same. These findings are summarized in table 7.

Next, we investigate effects of the program across project size levels. Our descriptive results indicate that small bidders express strong preference for smaller projects while large bidders prefer to participate in the larger projects. Our estimation results also indicate that differences in bidders costs grow with project size. Table 9 summarizes findings of the counterfactual analysis that underscore differences in program effects across projects of different sizes. In particular, we find that effect on small bidders' probabilities of winning and participation are strongest in the set of large projects: probability of winning goes up by 18% (from 27%), probability of participation by 13.5% (from 32%). At the same time the preferential treatment results in the decrease of the cost of procurement on average by $8000 (or 1.18%). On the other hand, in the set of small projects the increase in the probability of participation is not very large (3% up from 76%) whereas the probability of winning and the average cost of procurement go up more substantially (4% for the cost of procurement and 12% for the probability of winning). Dissecting these results even further we find that in small projects small bidders use the discount level to further improve their mark-ups whereas in the large projects they direct their efforts towards improving their chances of winning. This is consistent with unreported Monte-Carlo simulations which showed that small bidders with approximately equal chances of winning relative to large bidders with similar costs try to achieve higher mark-ups, whereas bidders with substantially lower chances target the probability of winning. The latter strategy pushes large bidders' bids down, lowering the average bid and expected winning bid in a given auction environment.

6 Conclusion

In this paper, we develop two models of participation in a first-price sealed bid auction and apply the models to study the role of bid preference programs in the award of highway procurement contracts. Both models assume that firms expend resources to learn about the costliness of a particular contract to the firm. These sunk costs of entry drive the firms' participation decisions. The two models differ primarily in their assumptions on the information available to bidders at the time of their bidding decision. We find that the assumptions on the firms' knowledge of the competitive environment entail differences in firms' optimal bidding behavior, which may affect auction outcomes under the preferential treatment of weak bidders.

The empirical results suggest that the bid preference program used in California, which grants qualified small bidders a 5% discount on their bid relative to the remaining firms in the market has significant implications for their participation and bidding behavior. To the extent that the program seeks to promote participation by disadvantaged enterprises in government procurement, it is successful: the share of projects won by qualified small bidders rises due to their preferential treatment. The increased participation comes at a cost, primarily in the efficient allocation of projects to the lowest cost competitors in the market.

The nature of our data forces us to focus on short-term measures of the success of the program. We assess arguments that rationalize the favoritism of disadvantaged firms in procurement based on possible cost reductions for the government from putting competitive pressure on the remaining, more efficient competitors. The short time horizon of our data makes it difficult to assess the longer term goals of the California Small Bidder Preference program of allowing disadvantaged firms to grow. Work by Branco (2002) suggests that favoring higher cost firms may provide them with sufficient incentives to improve their efficiency, in particular if efficiency improvements are very costly to them. An interesting avenue for future research would be a more complete analysis of the long-term impacts of affirmative action programs in procurement to shed light on the empirical relevance of such efficiency enhancing arguments for the use of discriminatory practices.

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Tables and Figures

Table 1: Summary Statistics, Caltrans Projects and Bidders

	Proportion	10th Pctile	25th Pctile	Median	75th Pctile	90th Pctile
Panel A: All Projects (n=1195)						
State-funded projects	0.47					
Panel B: State-funded Projects (n=567)						
Engineer's Estimate ($000)		165.80	264.66	457.00	657.00	1234.40
Working Days		20	30	45	90	240
Type of Project						
Bridge	0.10					
Landscaping	0.07					
Road Repair	0.55					
Signs, Signals, Lighting	0.06					
Small Structures	0.14					
Plan holders*		5	6	9	12.25	17.90
Small plan holders*		1	2	3	6	9
Bidders		2	3	4	6	8
Small bidders		0	0	1	3	5
Percent small bidders		0	0	0.33	0.50	0.75
Small winners						
Overall	0.35					
Due to bid preference	0.05					

* Plan holder information only available for 490 projects.

Table 2: Discrete Choice Model of the Decision to Bid

	Probit				Logit			
	Coefficient		Robust Std Error	Marginal Effect	Coefficient		Std Error	Marginal Effect
(1) ln(Scaled Eng. Estimate), LB	0.1520	***	0.0277	0.0603	0.2416	***	0.0659	0.0602
(2) Working Days, LB	-0.0518	**	0.0235	-0.0206	-0.0518		0.0462	-0.0129
(3) # of plan holders, LB	-0.0918	***	0.0114	-0.0365	-0.1754	***	0.0129	-0.0437
(4) # of bidders, LB	0.1850	***	0.0180	0.0735	0.3635	***	0.0257	0.0906
(5) Distance to Project, LB	-0.3294	***	0.1179	-0.1308	0.5426		0.4840	0.1353
(6) Current Load, LB	0.0086	***	0.0014	0.0034	0.0160	***	0.0054	0.0040
(7) Qualified Small Business	-1.2539	***	0.1624	-0.4608	-0.4139		0.4342	-0.1026
(8) ln(Scaled Eng. Estimate), SB	-0.1541	***	0.0418	-0.0612	-0.3260	***	0.0964	-0.0813
(9) Working Days, SB	0.0373	*	0.0205	0.0148	-0.0075		0.0525	-0.0019
(10) # of plan holders, SB	-0.0599	***	0.0077	-0.0238	-0.1036	***	0.0147	-0.0258
(11) # of bidders, SB	0.1660	***	0.0150	0.0659	0.2848	***	0.0267	0.0710
(12) Distance to Project, SB	-0.6930	***	0.2416	-0.2751	-1.8484	***	0.5789	-0.4608
(13) Current Load, SB	0.0565	***	0.0112	0.0224	0.0625	**	0.0244	0.0156
Test of equal coefficients:								
(χ^2-test statistic, p-value)			(78.57, 0.0000)				(47.02, 0.000)	
Company fixed effects			No				Yes	
Number of observations			4656				4656	
R^2			0.1096				0.1282	

Note:

Dependent variable equals one if plan holder becomes bidder. Fixed effects for project location at the district level, type of contract, months, and years included. The test statistic tests the joint hypothesis that $b_1=b_8$, $b_2=b_9$, $b_3=b_{10}$, $b_4=b_{11}$, $b_5=b_{12}$ and $b_6=b_{13}$.

Table 3: Ordinary Least Squares Model of Submitted Bid

	Model 1		Model 2	
	Coefficient	Robust Std Error	Coefficient	Std Error
(1) ln(Scaled Eng. Estimate), LB	0.9546 ***	0.0142	0.9492 ***	0.0108
(2) Working Days, LB	0.0116 *	0.0068	0.0089	0.0079
(3) # of plan holders, LB	0.0102 ***	0.0022	0.0100 ***	0.0019
(4) # of bidders, LB	-0.0245 ***	0.0048	-0.0266 ***	0.0037
(5) Distance to Project, LB	0.1058 **	0.0491	0.0939	0.0775
(6) Current Load, LB	-0.0005 *	0.0003	-0.0009	0.0007
(7) Qualified Small Business	0.1791 ***	0.0489	0.1005	0.0669
(8) ln(Scaled Eng. Estimate), SB	0.9790 ***	0.0183	0.9676 ***	0.0161
(9) Working Days, SB	0.0044	0.0081	0.0324 ***	0.0081
(10) # of plan holders, SB	0.0107 ***	0.0028	0.0090 ***	0.0024
(11) # of bidders, SB	-0.0349 ***	0.0057	-0.0315 ***	0.0042
(12) Distance to Project, SB	-0.0664	0.0642	0.0083	0.0802
(13) Current Load, SB	-0.0088 ***	0.0033	-0.0067 *	0.0037
Test of equal coefficients:				
(F-test statistic, p-value)	(4.12, 0.0005)		(2.39, 0.0262)	
Company fixed effects	No		Yes	
Number of observations	2323		2323	
Adjusted R^2	0.9262		0.8974	

Note:

Dependent variable is log of submitted bid. Fixed effects for project location at the district level, type of contract, months, and years included. The test statistic tests the joint hypothesis that $b_1=b_8$, $b_2=b_9$, $b_3=b_{10}$, $b_4=b_{11}$, $b_5=b_{12}$ and $b_6=b_{13}$.

Table 4: Ordinary Least Squares Model of Winning Bid

	Model 1			Model 2		
	Coefficient		Robust Std Error	Coefficient		Robust Std Error
Winner Qualified Small Business	0.0323		0.0258	0.0675	***	0.0262
ln(Scaled Eng. Estimate)	0.9939	***	0.0156	0.9908	***	0.0144
Working Days	0.0172	**	0.0084	0.0081		0.0080
# of small bidders				-0.0433	***	0.0060
# of large bidders				-0.0333	***	0.0065
Bridge	-0.1621	***	0.0475	-0.1716	***	0.0424
Buildings	0.0310		0.0638	-0.0140		0.0518
Construction	-0.0170		0.1938	-0.0252		0.1245
Landscaping	-0.1686	**	0.0816	-0.1638	**	0.0739
Marking	-0.3032	***	0.1015	-0.4146	***	0.0902
Rest Area	0.0486		0.0757	0.0410		0.1042
Road Repair	0.0001		0.0333	-0.0451		0.0304
Signs, Signals, Lighting	0.0846		0.0577	0.0022		0.0534
Number of observations	567			567		
Adjusted R^2	0.9398			0.9486		

Note:
Dependent variable is log of winning bid. Fixed effects for project location at the district level, for months, and for years included.

Table 5: Estimated Bid and Entry Cost Distribution Parameters

Parameters of Log-Normal Distribution of Bids		
Mean Log-Bids	Parameter	Standard Error
Constant	0.14863	0.01684 ***
Small business dummy	0.02579	0.01319 *
ln(Eng. Estimate)	0.96614	0.00951 ***
Working Days	0.00004	0.00004
# of small bidders	-0.03230	0.00536 ***
# of large bidders	-0.03447	0.00455 ***
# of small plan holders	0.00921	0.00301 ***
# of large plan holders	0.01356	0.00241 ***
Std. Dev. of Log-Bids[1]	Parameter	Standard Error
Constant	-1.3528	0.0134 ***
Small business dummy	0.0370	0.0221 *
Parameters of Normal Distribution of Entry Costs		
Mean Entry Cost	Parameter	Standard Error
Constant, SB	-0.43730	0.04345 ***
ln(Eng. Estimate), SB	0.71065	0.06496 ***
Constant, LB	-0.10679	0.00163 ***
ln(Eng. Estimate), LB	0.25115	0.00081 ***
Std. Dev. of Entry Cost	Parameter	Standard Error
Small bidders	2.06463	1.11946 **
Large bidders	0.60386	0.00864 ***
n, bidders	2282	
n, potential bidders	4828	

[1] Standard deviation of log-bids estimated as $\sigma=\exp(b_0+b_1 I\,(\text{small bidder}))$.

*** significant at 99% level, ** at 95% level, and * at 90% level.

Table 6: Comparison of Estimated Entry Cost Parameters, Alternative Specifications

Entry Costs $\sim N(m_i, s_i)$

Mean Entry Cost	Parameter	Std. Error
Constant, SB	-0.43730	0.04345 ***
ln(Eng. Estimate), SB	0.71065	0.06496 ***
Constant, LB	-0.10679	0.00163 ***
ln(Eng. Estimate), LB	0.25115	0.00081 ***

Std. Dev. of Entry Cost	Parameter	Std. Error
s, small bidders	2.06463	1.11946 **
s, large bidders	0.60386	0.00864 ***

Entry Costs $\sim N(m_i, s=1)$

Mean Entry Cost	Parameter	Std. Error
Constant, SB	-0.29407	0.00409 ***
ln(Eng. Estimate), SB	0.49110	0.00209 ***
Constant, LB	-0.10765	0.00379 ***
ln(Eng. Estimate), LB	0.26122	0.00162 ***

Std. Dev. of Entry Cost	Parameter	Std. Error
s, all bidders	1.00000	-

Entry Costs $\sim N(m_i, s)$

Mean Entry Cost	Parameter	Std. Error
Constant, SB	-0.27061	0.00432 ***
ln(Eng. Estimate), SB	0.46100	0.00353 ***
Constant, LB	-0.09313	0.00303 ***
ln(Eng. Estimate), LB	0.24801	0.00136 ***

Std. Dev. of Entry Cost	Parameter	Std. Error
s, all bidders	0.88547	0.02413 ***

Entry Costs $= X'\beta$

Mean Entry Cost	Parameter	Std. Error
Constant, SB	-0.09750	0.00193 ***
ln(Eng. Estimate), SB	0.20460	0.00377 ***
Duration, SB	0.00020	0.00002 ***
Constant, LB	-0.03120	0.00388 ***
ln(Eng. Estimate), LB	0.04140	0.00651 ***
Duration, LB	0.00010	0.00003 ***

Std. Dev. of Entry Cost	Parameter	Std. Error
s, all bidders	0.00000	-

*** significant at 99% level, ** significant at 95% level, and * significant at 90% level.

Table 7: Counterfactual Analysis of Bid Discount Program: Alternative Discounts

		Bid discount			
		δ=0%	**δ=5%**	**δ=10%**	**δ=20%**
Pr(entry)	Small bidder	0.37	0.42	0.43	0.49
	Large bidder	0.67	0.64	0.62	0.57
Cost of entry (ths)	Small bidder	4.90	4.90	4.90	4.90
	Large bidder	3.00	3.00	3.00	3.00
Average bid (ths)	Small bidder	431.74	438.60	446.00	455.80
	Large bidder	433.00	426.30	423.10	411.00
Prob of winning	Small bidder	0.32	0.38	0.41	0.49
Winning bid (ths)	overall	417.30	417.10	417.20	419.10
	Small bidder	411.70	419.80	426.40	440.20
	Large bidder	424.10	416.90	410.74	399.20
Switch of award		0.0%	4.4%	8.2%	14.6%
Efficiency	Frequency	1.0%	2.0%	3.2%	5.2%
	% of cost	3.3%	6.7%	8.0%	8.2%

Simulation results use estimated parameters for mixed-strategy entry model with fixed entry costs. Results apply to median medium-sized project in the the data.

Table 8: Counterfactual Analysis of Bid Discount Program: Comparison of Size Categories

		Small Projects		Medium Projects		Large Projects	
		δ=0%	**δ=5%**	**δ=0%**	**δ=5%**	**δ=0%**	**δ=5%**
Pr(entry)	Small bidder	0.75	0.79	0.37	0.42	0.32	0.37
	Large bidder	0.87	0.84	0.67	0.64	0.68	0.65
Cost of entry (ths)	Small bidder	2.10	2.10	4.90	4.90	7.20	7.20
	Large bidder	1.70	1.70	3.00	3.00	3.90	3.90
Average bid (ths)	Small bidder	222.10	230.40	431.74	438.60	682.50	687.96
	Large bidder	234.50	229.20	433.00	427.30	708.50	694.33
Prob of winning	Small bidder	0.49	0.55	0.32	0.38	0.28	0.32
Winning bid (ths)	Overall	218.70	222.40	417.30	417.10	676.28	668.20
Switch of award			7.3%		4.4%		3.9%
Efficiency	Frequency	0.5%	4.2%	1.0%	2.0%	1.0%	2.0%
	% of cost	2.1%	5.1%	3.3%	6.7%	4.1%	3.7%

Small projects denote projects with an engineer's estimate in the 20th percentile of engineer's estimates across projects. Medium projects are defined to fall between the 20th and 60th percentile of the distribution of the enginner's estimate. The counterfactual is conducted for the median project within each of the three size categories and uses the estimated parameters of the mixed strategy entry game with fixed entry costs.

Figure 1: Kernel Density Estimates of Large Firm's Bidding Distributions, Alternative Competitive Environments

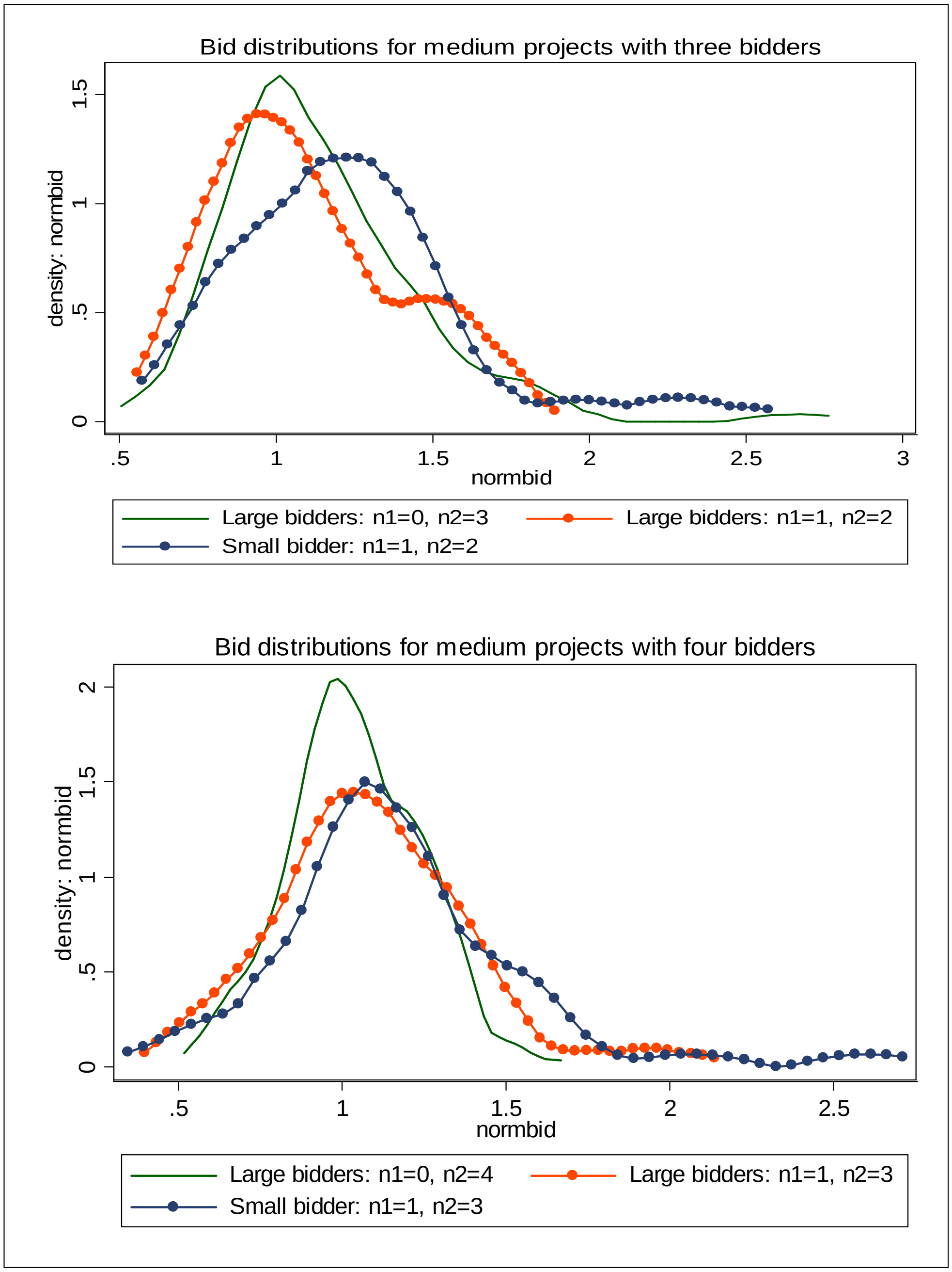

Figure 2: Bidding Strategies under Preferential Treatment of Type 1

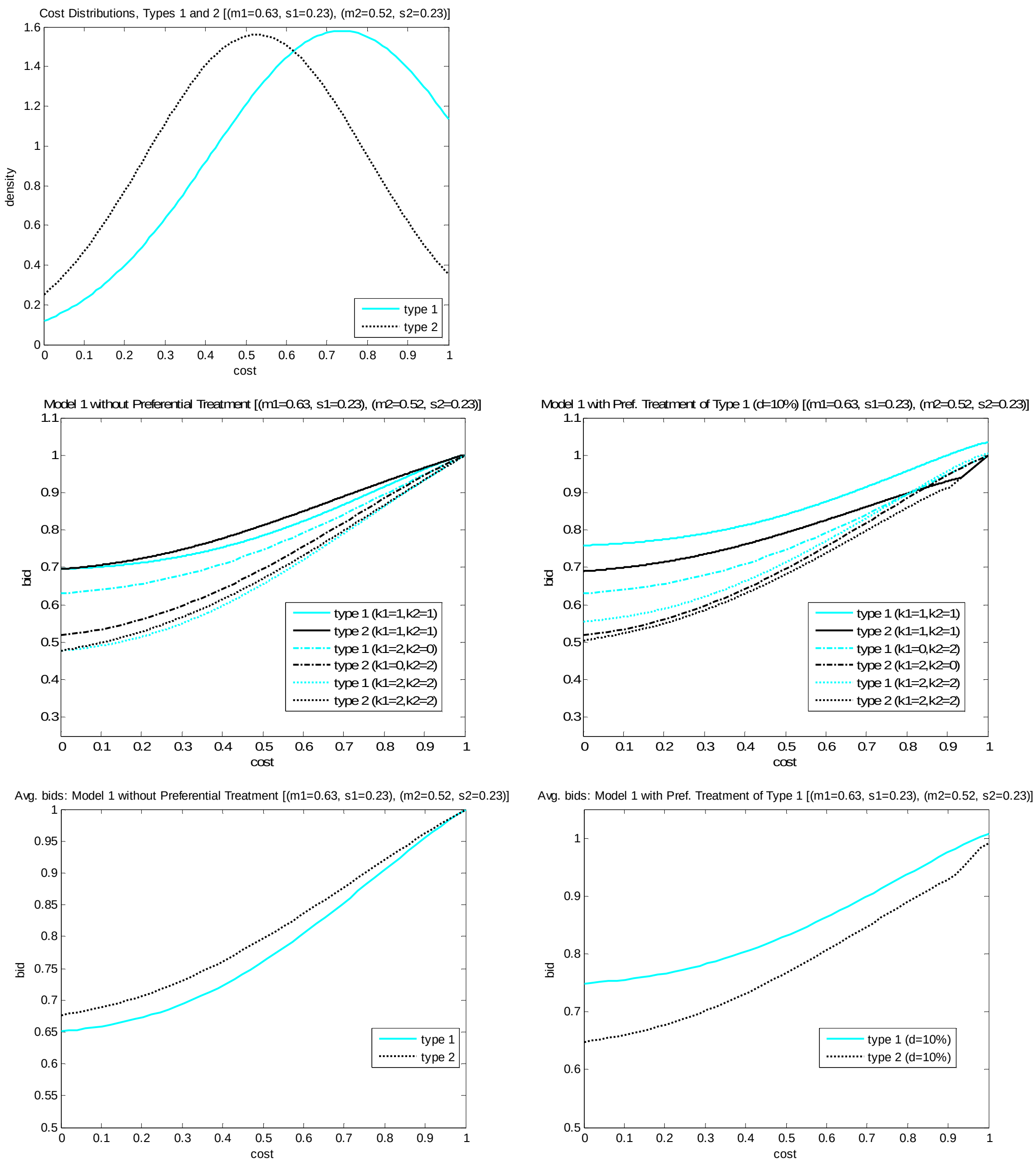

Figure 3: Predicted Bid Distributions for Median Project, Large and Small Bidders

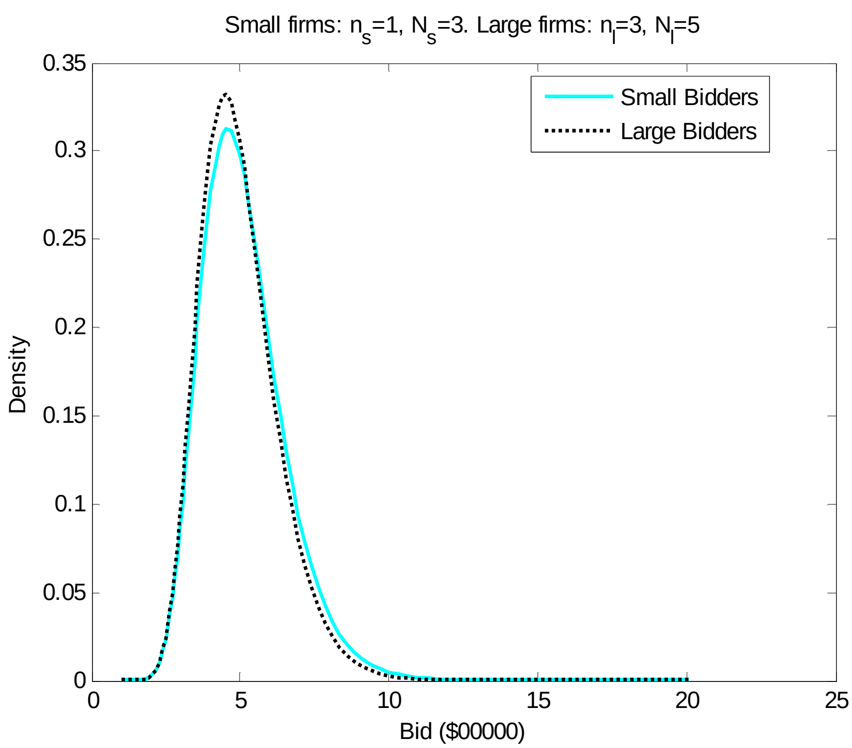

Figure 4: Predicted and Actual Bid Residuals

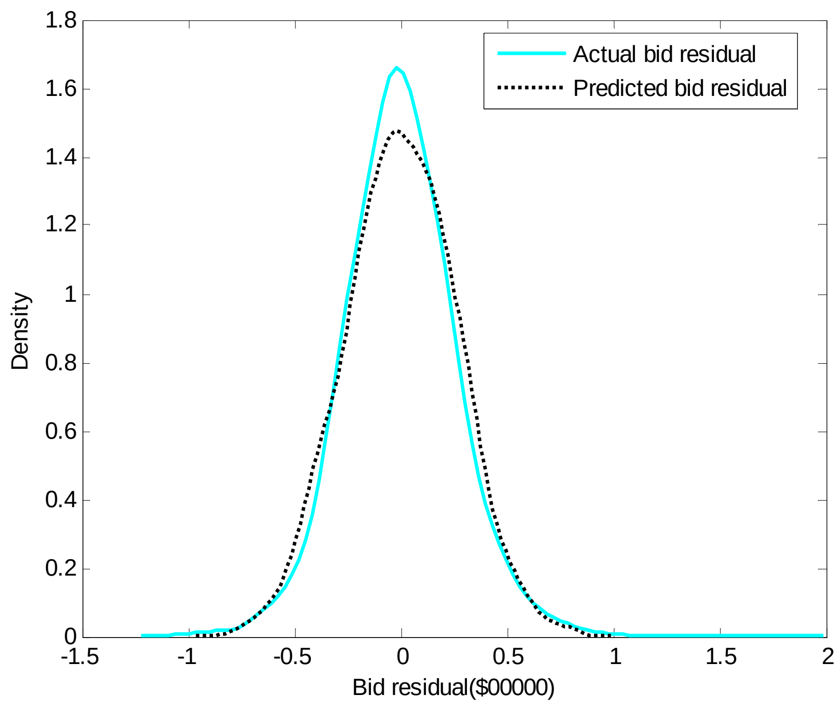

Figure 5: Comparison of Predicted Small Firm Bid Strategies, δ=5% and δ=10%

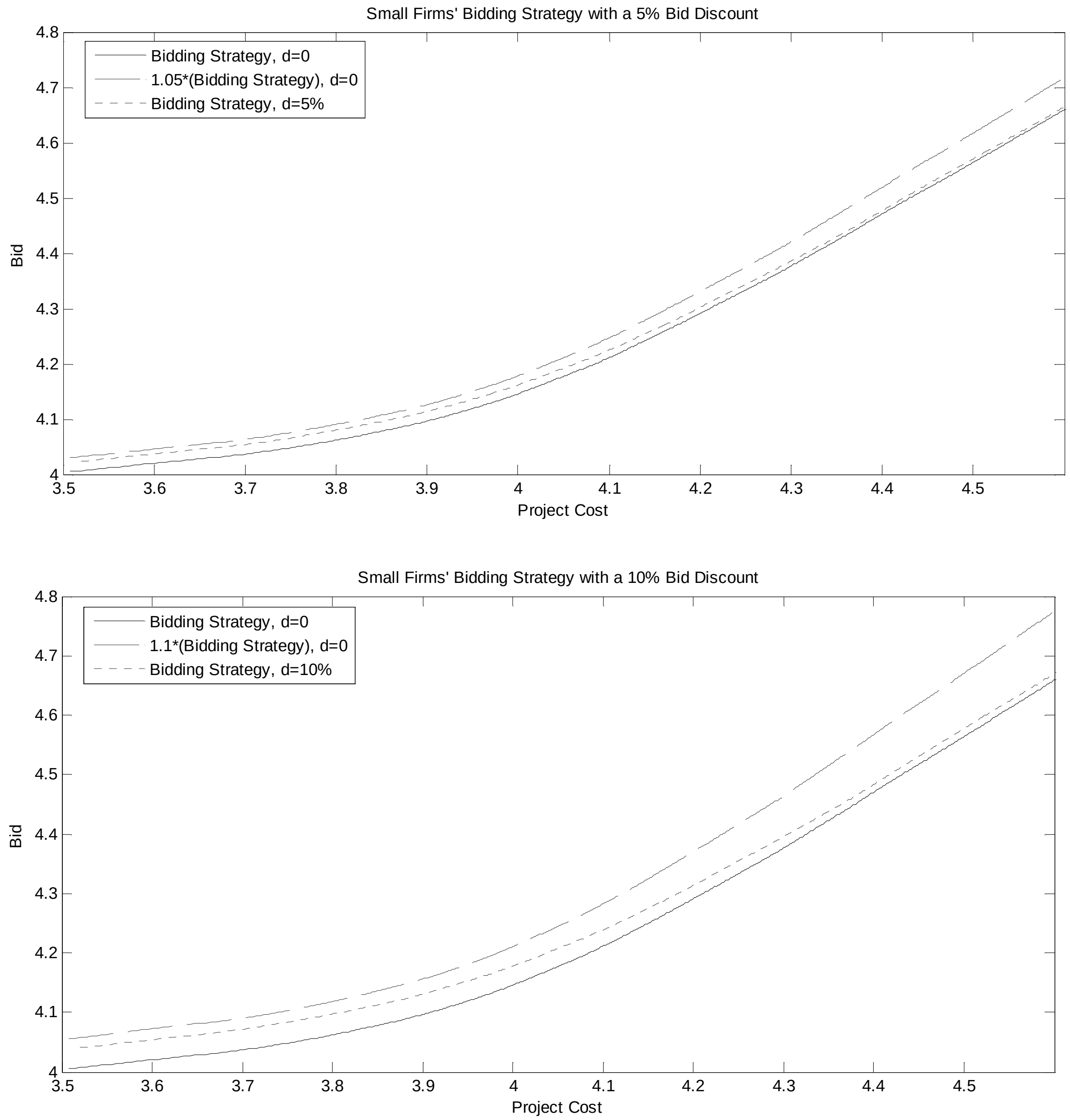

Figure 6: Predicted Probabilities of Winning, Alternative Discounts