Bid Preference Programs and Participation in Highway Procurement Auctions

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Preliminary and incomplete draft. Please do not cite.

February 2006

Abstract

A number of states have established programs to improve small business' opportunities in public procurement. We use highway procurement auction data to analyze the California Small Business program that awards qualified firms a bidding preference on applicable projects. We study the effect of this rule on bidders' incentives to participate in procurement auctions and compute its implied efficiency and distributional costs.

In equilibrium, the bid preference program has an interesting effect on the bidding strategies. The favored treatment allows a high-cost preferred bidder to lower its bid below the level at which it would tie with the highest cost non-preferred bidder. Non-preferred bidders with very high costs can never win the auction. Therefore, the preferred type can use its favored status to squeeze out the high-cost non-preferred types firms. This effect can be substantial if the variance of the non-preferred type's cost distribution is small relative to the highest possible level of costs.

Our estimation results imply that, as a consequence of the preferential treatment, the award of contracts to small bidders increases significantly, as does their participation in the auction process. At the same time, winning bids by both types of firms and thus cost of procurement increase.

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, governments frequently modify the auction mechanism used to award public contracts to grant some form of preferential treatment to disadvantaged firms. Examples of preference programs include set-aside contracts and quotas. In this paper we focus on California's use of bid discounts in promoting the small business participation in highway procurement and study the effect of this rule on bidders' incentives to participate in procurement auctions and compute the implied efficiency and distributional costs of the bid preference program.

Despite the prevalence of industrial affirmative action programs, there are only few studies of their implications for disadvantaged firms and their competitors and the cost of the program to the government. Existing work focuses primarily on analyzing the effect of the preferential treatment of disadvantaged bidders on bid levels in highway procurement (Denes (1997) and Marion (2005)), in experimental settings (Corns and Schotter (1999)), and in FCC spectrum auctions (Ayres and Cramton (2000)). Marion (2004) provides a first attempt at estimating the effect of an affirmative action program on the number of qualified and other bidders in a comparison of bid preference auctions to a base group of auctions.

Ideally, in order to study the effects of any such program we would like to be able to compare a set of auctions with a program in place to the comparable set of auctions without any program. Unfortunately, such data are generally not available. Therefore, we cannot infer the effects of a preference program from the data directly. Instead, we uncover its effects on firm behavior and government costs by estimating a model of entry and bidding that incorporates the specific terms of the program we study and performing counterfactual experiments based on the estimated parameters of the model.

The use of preferential treatment programs in procurement auctions has several consequences for firm behavior. By improving the effective competitiveness of preferred firms, it affects bidding behavior by both preferred and non-preferred firms. The auction is also likely to attract a larger number of preferred firms, which in turn may discourage non-preferred, but potentially low-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 important variables change under 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 these changes. They also provide little guidance as to how participation decisions and their effects differ under different informational environments or how we can distinguish between these

environments in the data.

We first characterize the theoretical implications of a program similar to California's using a simple model of participation previously described in the empirical and theoretical literature (e.g. Athey, Levin, and Seira (2004)). The entry model with asymmetric firms assumes that firms observe only the number of potential bidders and their own cost of entry when making the decision to participate in an auction. However, upon entry they learn their cost of completing the project and the number of actual bidders. Firms with a cost of entry below their ex-ante expected profit decide to participate in bidding, whereas firms with higher entry cost choose not to bid.

We find that if the number of actual competitors is known at the time of bidding, a bid discount like the one used by California allows preferred firms to squeeze out non-preferred bidders with high cost realizations. Preferred bidders with project costs at the upper end of the cost distribution use the cushion of the discount to lower their effective bids below cost level. Therefore non-preferred bidders with similar cost levels can never win the auction. They have to bid their costs or to stay out of the auction. This effect can be substantial if the variance of the non-preferred type's cost distribution is small relative to the highest possible level of project costs. We consider relaxing one of the assumptions of the base model by allowing for post-entry uncertainty about the number of actual competitors in an environment with heterogeneous bidders similar to the homogeneous firm setting in Li and Zheng (2005).

As in the literature on entry into auction and product 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 then turn to an empirical assessment of the program, building upon earliers 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). 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. Based on the estimated cost distributions, we assess the effect of the program on eligible and ineligible firms' probabilities of participating and winning, as well as auction efficiency and cost of procurement. Our empirical results for the case of observed competition 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. Preliminary counterfactual results indicate that the use of a five percent bid discount significantly increases their frequency of bidding

as well as the share of projects that they win. At the same time, the average winning bid earned by both small and other firms and therefore the cost to the government increases. The estimated structural parameters allow us to analyze the program more broadly. We can, for example, derive the optimal discount rate that would allow the government to achieve stated goals for small business participation at a minimum cost and contrast the cost of this optimally designed program to the cost of the current policy.

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 winning bid normalized by the government's cost estimate of the contract 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 com-

parable 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 is available for 1,204 projects. In addition, 9 contracts were postponed, leaving a set of 1,195 awarded project contracts. These contracts cover major construction projects with a value of at least $750,000 or minor maintenance projects, such as pavement rehabilitation, with a value of more than $120,000.

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. Using California data from 1996 through 1999, Marion (2004b) assesses the cost of such a quota program to be an increase in the winning bid of between 4 and 6%.

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. Since the latter program is simpler by avoiding the need for an analysis of subcontracting relationships between the primary bidder and qualified disadvantaged subcontractors, 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 goal of California's Small Bidder Preference program is to help small businesses overcome disadvantages in obtaining credit, in hiring high-skilled employees, and in sharing information and know-how through, for example, informal business networks ("old-boy networks") that small firms do not have access to.

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, up to a maximum of $50,000. 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 participants in both federally and state-funded procurement auctions. 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

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 as the smallest geographic unit that is available for all contracts. Large-scale projects span several counties and we treat each county as one location for the project. 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 75 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 $4.25 million and a median of $643 thousand.

Project characteristics differ across federally funded contracts and state-funded contracts. Of the 1,195 contracts in the data, 47.5% are fully state-funded. Federally-funded contracts are on average longer and larger: the average duration of a federally-funded contract amounts to 230 working days, compared to 107 working days for a state-funded contract, while the average engineer's estimate for a federally-funded project is $6.92 million compared with $1.29 million for a state-funded project. The distributions of engineer's estimate and duration for state-funded projects are further skewed toward small and short projects with a median engineer's estimate of $457 thousand and median duration of 45 working days. In contrast, the same medians for federally-funded projects are $1.59 million and 125 working days.

These differences and the use of different disadvantaged bidder programs render the

state and federally funded projects incomparable. We focus on state-funded projects and the preferential treatment program administered on these projects. Table 1 summarizes the characteristics of the subset 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 up 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 to affect the bidding decision in the form of capacity utilization and the distance from the company's office to the project. 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, except for the insignificant, positive effect of distance on large bidders' participation decision in the Logit model. 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. The effect is smaller and statistically insignificant when controlling for firm fixed effects.

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. A second possible explanation is that not all plan holders are equally likely to enter. If firms have an informative signal about their cost at the time of their entry decision, large bidders that enter the auction tend to have a competitive edge over their smaller competitors. The number of large plan holders, therefore, may serve as a better indication of the intensity of competition.

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. The assumption underlying this comparison is that the effect of the first small bidder exceeds that of any subsequent bidders. 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 last 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, in particular since small bidders generally bid higher in this case. The effect is less clear in the remaining two charts in the figure. Both illustrate 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, or because the two sets of auctions differ significantly in unobserved characteristics, which confounds the effect of the participation of a small bidder.

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 bidding package. In line with the terms of the Caltrans small bidder preference program, we consider two types of companies: those that satisfy 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 the type 1 bidders. If the later is within a 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_i. Cost of entry is a private information of a potential bidder. We assume that they are distributed according to the distribution G.

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_i and project cost c_{ij} are independent draws from the distributions G and F_j.

Next, we outline the informational environment in which firms make their participation and bidding decisions. We first consider the case where firm learns the number of actual competitors after entering the auction. We then relax this assumption and study bidding strategies and participation decisions in the environment where the number of actual competitors remains unknown. We show below that this alternative specification entails significant differences in the level of the bidding strategies and thus mark-ups generated by bidders.

4.1   Non-Stochastic Number of Bidders

As in Athey, Levin and Seira (2004), we assume that in the initial participation stage, each potential bidder i knows only its own cost of entry, d_i, and the distributions of entry costs G and project costs, F_1 and F_2. 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.

4.1.1 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:

$j = 1:$

$$\pi_{i1} = (b_{i1} - c_{i1}) \Pr\left(b_{i1} < b_{k1} \; \forall k \neq i\right) \Pr\left(b_{i1} < (1+\delta)b_{k2}, k = 1, ..., n_2\right)$$

$$= (b_{i1} - c_{i1}) \left(1 - F_1\left[\beta_1^{-1}(b_{i1})\right]\right)^{n_1 - 1} \left(1 - F_2\left[\beta_2^{-1}\left(\frac{b_{i1}}{(1+\delta)}\right)\right]\right)^{n_2} \qquad (1)$$

$j = 2:$

$$\pi_{i2} = (b_{i2} - c_{i2}) \Pr\left(b_{i2} < \frac{1}{1+\delta}b_{k1}, k = 1, ..., n_1\right) \Pr\left(b_{i2} < b_{k2}, \; \forall k \neq i\right)$$

$$= (b_{i2} - c_{i2}) \left(1 - F_1\left[\beta_1^{-1}\left((1+\delta)b_{i2}\right)\right]\right)^{n_1} \left(1 - F_2\left[\beta_2^{-1}(b_{i2})\right]\right)^{n_2 - 1}$$

where $\beta_j(.) : [\underline{c}, \overline{c}] \to [\underline{b}, \overline{b}]$, 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:

$j = 1:$

$$\frac{1}{b_{i1} - c_{i1}} = \frac{(n_1 - 1)f_1\left[\beta_1^{-1}(b_{i1})\right]}{\left(1 - F_1\left[\beta_1^{-1}(b_{i1})\right]\right)} \frac{\partial \beta_1^{-1}}{\partial b_{i1}} + \frac{n_2 f_2\left[\beta_2^{-1}\left(\frac{b_{i1}}{(1+\delta)}\right)\right]}{(1+\delta)\left(1 - F_2\left[\beta_2^{-1}\left(\frac{b_{i1}}{(1+\delta)}\right)\right]\right)} \frac{\partial \beta_2^{-1}}{\partial b_{i1}}$$

$j = 2:$ $\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (2)$

$$\frac{1}{b_{i2} - c_{i2}} = \frac{n_1(1+\delta)f_1\left[\beta_1^{-1}\left((1+\delta)b_{i2}\right)\right]}{\left(1 - F_1\left[\beta_1^{-1}\left((1+\delta)b_{i2}\right)\right]\right)} \frac{\partial \beta_1^{-1}}{\partial b_{i2}} + \frac{(n_2 - 1)f_2\left[\beta_2^{-1}(b_{i2})\right]}{\left(1 - F_2\left[\beta_2^{-1}(b_{i2})\right]\right)} \frac{\partial \beta_2^{-1}}{\partial b_{i2}}$$

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)).

Equilibrium with preferential treatment is characterized by an interesting behavior near the upper end of the support. Due to the cushion of the discount, the highest cost

bidder of preferred type optimally lowers its "effective" bid, $\frac{\bar{b}}{(1+\delta)}$ below its cost, $\bar{c}$. This means that non-preferred bidders with high cost levels can never win the auction. If forced to submit a bid such bidders would bid their cost. In our empirical analysis we assume that they choose to stay out of the market. Therefore, the highest cost at which the non-preferred bidder submits a bid is given by $c_0 = \beta_1(\bar{c})/(1+\delta)$. Here a bidder of type 1 chooses $\beta_1(\bar{c})$ to maximize

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

if $n_1 = 1$. The first order conditions corresponding to this problem are given by

$$\frac{1 - F_2 \left(\frac{\overline{\beta_1}}{1+\delta} \right)}{f_2 \left(\frac{\overline{\beta_1}}{1+\delta} \right)} = \frac{n_2}{1+\delta} (\beta_1 - \bar{c}) \qquad (3)$$

When $n_1 > 1$ competition leads to $\beta_1 = \bar{c}$. Hence the preferred type can use the discount to squeeze out the non-preferred type at the upper end of the support. This effect can be quite substantial if the variance of the large bidders' costs is small relative to $\bar{c}$. 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. $\beta_1(\bar{c}) < (1+\delta)\bar{c}$ and $\beta_1(\bar{c}) = \bar{c}$ if $n_1 > 1$

3. $\beta_2(c) = c \ \forall c \in \left[\frac{\beta_1(\bar{c})}{(1+\delta)}, \bar{c} \right].$

4.1.2 Characterization of Equilibrium in the Participation Stage

At the participation stage, firms compare the expected profit conditional on entry to their entry cost d_i. 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 for types 1 and

2, p_1 and p_2, are given by:

$$p_1 = p_1^a \tag{4}$$

$$p_2 = F_2 \left(\frac{\beta_1(\overline{c})}{(1 + \delta)} \right) p_2^a.$$

Expected profit from participating is given by

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

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 an expected profit of a bidder from group j with cost realization c_{ij} computed on the basis of bidding strategies described in a previous section. 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

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

Entry cost thresholds are defined by a zero-profit rule so that $D_1(p_1^a, p_2^a) = \Pi_1(p_1^a, p_2^a)$ and $D_2(p_1^a, p_2^a) = \Pi_2(p_1^a, p_2^a)$. In equilibrium, bidders beliefs are correct and the equilibrium entry probabilities solve the system of equations

$$p_1^a = G[D_1(p_1^a, p_2^a)] \tag{7}$$

$$p_2^a = G[D_2(p_1^a, p_2^a)].$$

Assumptions (A_1) and (A_2) guarantee that the type-specific equilibrium of this game exists. In general, the entry equilibrium is not unique. While for every (k_1, k_2), there is a unique set of strategies that govern bidding in the appropriate subgame, 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

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uniqueness of the equilibrium entry probabilities numerically.

5   Alternative Model of Entry

The model described above imposes a number of potentially restricting assumptions on the informational structure of the environment in which bidders make their decisions. In this section we introduce an alternative auction environment that differs along one dimension: bidders knowledge about their actual competition at the time when they prepare their bids. We analyze participants' behavior in this alternative environment.

5.1   Model with Stochastic Numbers of Bidders

We maintain the assumption that firm i knows its own cost of entry, d_i, and the distributions of project costs for the two groups, F_1 and F_2, when making the decision on whether to participate in the auction. Once the firm decides to participate, it learns its own cost of completing the project, c_{ij}, but not the number of the actual bidders. Firms choose their bid based on their assessment of the likelihood of participation by different bidders and the distributions of project costs. As above, firms' expectations about the likelihood of each firm's participation in the auction underlie its expectation about the number of actual bidders. Firms' expectations about the distribution of the number of actual bidders enters both pre- and post-entry expected profit. Post-entry, upon learning its project cost c_{ij}, firm i submits a bid to maximize expected profit of

$$
\pi_{i1} = (b_{i1} - c_{i1}) \sum_{k_1=0}^{N_1-1} \sum_{k_2=0}^{N_2} \Pr(k_1, k_2) \left(1 - F_1 \left[\beta_1^{-1} \left(b_{i1} \,|\, N_1, N_2 \right) \right] \right)^{k_1}
$$

$$
\left(1 - F_2 \left[\beta_2^{-1} \left(\left. \frac{b_{i1}}{1+\delta} \right| N_1, N_2 \right) \right] \right)^{k_2} \tag{8}
$$

$$
\pi_{i2} = (b_{i2} - c_{i2}) \sum_{k_1=0}^{N_1-1} \sum_{k_2=0}^{N_2} \Pr(k_1, k_2) \left(1 - F_1 \left[\beta_1^{-1} \left((1+\delta) b_{i2} | N_1, N_2 \right) \right] \right)^{k_1}
$$

$$
\left(1 - F_2 \left[\beta_2^{-1} \left(b_{i2} | \, N_1, N_2 \right) \right] \right)^{k_2}
$$

where $\Pr(k_1, k_2)$ is again the firm's assessment of the likelihood of facing (k_1, k_2) competitors at the bidding stage, given by the expression in equation (6). As above, $(\beta_1(c_{ij}|N_1, N_2),\ \beta_2(c_{ij}|N_1, N_2))$ denotes a pair of equilibrium strategies. *Bidders' maximization problem no longer depends on the number of actual competitors the firm faces in a given auction. Therefore its bidding strategy no longer changes with the number of actual*

competitors.

Similar to our initial setup, the entry stage is defined by entry thresholds for the two types (D_1, D_2) such that a firm enters as long as $\Pi_j(p_1, p_2) \geq D_j$, where pre-entry expected profits now equal

$$\Pi_j = \int_{\underline{c}}^{\bar{c}} \pi_{ij}(c_{ij}; k_j, k_{-j}) dF_j(c_{ij}). \tag{9}$$

While this setup relaxes the assumption that bidders learn the number of competitors they face upon entry, both models share the feature that it is the distribution of entry costs that determines which firms become active bidders. The firms' actual costs of completing a given project do not affect their participation decisions. A more realistic setup would allow both entry costs and the cost of completing the project to enter a firm's participation decision.

5.1.1 Comparing Informational Environments

We begin with a brief overview of our approach to solving the models outlined above. Firms' bidding and entry behavior in the case of exogenous entry is characterized by the solution to the system of first-order conditions (2) of the firms' bidding problem that flows into the system of equations that define equilibrium entry probabilities (7). Similarly, when entry is endogenous, bidding and entry results from jointly solving the first-order condition to the profit maximization problem in (8) and the associated entry conditions.

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 uniform 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 begin with a comparison of the two models in the absence of a bid preference program. We vary μ_j and σ_j to illustrate the effect of distributional differences in project costs on firm's behavior. Figure 2 depicts bidding strategies for a set of 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. Across specifications, 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. The bottom panel of figure 2 depicts average bidding strategies for model 1. We weight a bidding strategy corresponding to a (k_1, k_2) combination by the probability of observing that particular realization of numbers of bidders, given entry probabilities p_1 and p_2 implied by the model. Since model 1 abstracts from uncertainty about competition faced in the auction, firms of a given type likely bid lower on average than they would if the number of competitors is unknown at the time of bidding. Table 5 summarizes the properties of other distributions.

The table contrasts entry probabilities, the types' probabilities of winning, their winning bid and markup, and the auction efficiency, measured as the percentage of auctions won by a firm that is not the low-cost bidder in the auction, for four sets of cost distributions. In the base case, types have the same cost distributions. Relative to symmetric types, type 1's probability of winning drops significantly once it is the weak bidder. Its winning bid, however, increases. Analogously, type 2, as the strong bidder, wins more frequently, but with lower bids than in the symmetric case. Consistent with type 1's bidding strategy lying below that of type 2, type 2's mark-ups increase while type 1's fall. Consequently, expected payoff from entry and entry probabilities for type 1 fall, while they rise for type 2. These effects are magnified once both the mean and variance of type 1's cost distribution exceed that of type 2. For these particular sets of cost distributions, auction efficiency is high. For the three sets of asymmetric bidder distributions, the low-cost bidder loses the project

in between 1.6% to 2.5% of cases only. This suggests that while type 1 firms bid more aggressively for a given level of cost, the specific cost distributions imply that their bids on average are too far above those of type 2 bidders for this competitive undercutting to lead to large inefficiencies.

The introduction of a bid preference for one type alters the types' equilibrium bidding strategies in the following ways. First, type 1, the preferred type, bids higher than before at all levels of cost. Against competitors of the opposite type, a bid of $b_{i1}(1 + \delta)$ is as competitive as a bid of b_{i1} in the absence of preferential treatment. The highest-cost bidder of type 2 bids its cost whenever it faces competition. Unlike type 2, the highest-cost bidder of type 1 is not restricted by its cost due to the discount cushion. That firm therefore chooses to lower its bid below $\overline{c}(1 + \delta)$ to increase its probability of winning. Therefore, $c \geq \frac{b^1}{(1+\delta)}$ for c in some neighborhood of $\overline{c}$, where b^1 is the highest bid ever submitted by type 1. This means that the second type can never win near the upper end of the support and therefore just bids its cost or does not submit a bid.

Figure 2 illustrates the bidding strategies for the cases of a 10% bid preference. The middle right panel shows individual bidding strategies for model 1 for different firm configurations, while the lower panels show the average bidding strategies, weighing each bidding strategy by the probability of observing the firm configuration. Since the bid preference only accrues if at least one firm of the preferred type enters the market, the average bidding strategy for model 1 and the bidding strategy for model 2 smooth out type 2's behavior at the top. In both models, the magnitude of δ correlates most strongly with the shift in type 1's bidding strategy. Type 1 now moves from bidding lower to bidding higher than type 2 bidders for a given level of cost and always bids higher in the upper tail of the cost distribution. A type-2 firm bids more aggressively, relative to the case without preferential treatment, for high levels of cost.

Table 5 summarizes the effect of the bid preference on other dimensions of firm behavior for the earlier distributions. In the case of model 1, the presence of a 10% bid preference significantly increases the probability of entry of type-1 bidders and the share of auctions they win, at the expense of type-2 bidders. Consequently, type-2 bidders enter less frequently. The average winning bid increases for most distributions, while type 2 mark-ups fall. Future work will contrast these results to the corresponding trends implied by model 2.

6 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 cost distribution and the underlying parameters of the entry distribution that best explain firms' observed bidding behavior. We begin by discussing estimation methodology for Model with non-stochastic number of bidders. We then describe the set of preliminary results.

6.1 Estimation Methodology

We estimate the parameters of the bid distributions, denoted by H_j, and entry cost distribution G parametrically using maximum likelihood techniques. We then use the estimated bid distributions to recover the underlying project cost distributions, F_j, assuming that $F_j(c_{ij}) = H_j(\beta_j(c_{ij}))$.

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, $H_1(\cdot)$ and $H_2(\cdot)$, 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, h_j. 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 component that derives from observed project characteristics and private information of the firm about it costs, B_{ijp}, and a component that captures unobserved auction heterogeneity, u_p. We assume that $b_{ijp} = B_{ijp}u_p$ and that both H_j and the distribution of unobserved auction heterogeneity follow log-normal distributions, where H_j now refers to the distribution of B_{ijp}. 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 H_j, 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 a constant standard deviation 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. As in Athey, Levin, and Seira (2004), 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 log-normal distribution of unobserved auction heterogeneity, we first compute equilibrium entry probabilities then we average across simulation draws, n_s, to obtain the simulated log likelihood function for participation decisions, denoted by indicator I_{ijp}, and bid levels:

$$\ln L = \sum_{s=1}^{n_s} \frac{1}{n_s} \sum_{p=1}^{P} \sum_{j=1}^{2} \sum_{i=1}^{N_{jp}} \ln l_{ijps}, \text{with} \tag{10}$$

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

$$l_{i2ps} = \left\{ H_2\left(\frac{\overline{b}_p}{1+\delta}\right) \times p_{2ps}^a \times h_2\left(\tilde{b}_{i2ps}\right) \right\}^{I_{i2p}} \times \left\{ 1 - H_2\left(\frac{\overline{b}_p}{1+\delta}\right) \times p_{2ps}^a \right\}^{1-I_{i2p}},$$

where $\tilde{b}_{ijps}$ denotes the transformed bid of $\frac{b_{ijp}-\underline{b}_{jp}}{u_{jps}}$ and we use the nonparametrically estimated lower bid bound and the ex-post imposed upper bid bound as limits of integration.

To compute equilibrium entry probabilities for a given simulation draw u_{ps} we first recover the inverse bid function associated with observed bid distribution using the first order condition of the bid problem. For a given guess at (p_1^a, p_2^a), we integrate the expression for expected profit numerically as

$$\Pi_{1ps} = \sum_{k_1,k_2} \Pr(k_1, k_2 | p_1, p_2) \times \tag{11}$$

$$\left(\int_{\underline{b}}^{\overline{b}} (b_{i1} - c_{i1s}) \left(1 - H_1\left(\tilde{b}_{i1ps}\right)\right)^{n_1-1} \left(1 - H_2\left(\frac{\tilde{b}_{i1ps}}{1+\delta}\right)\right)^{n_2} dH_1 \right)$$

$$\Pi_{2ps} = \sum_{k_1,k_2} \Pr(k_1, k_2 | p_1, p_2) \times$$

$$\left(\int_{\underline{b}}^{\overline{b}} (b_{i2} - c_{i2s}) \left(1 - H_1\left((1+\delta)\tilde{b}_{i2ps}\right)\right)^{n_1} \left(1 - H_2\left(\tilde{b}_{i2ps}\right)\right)^{n_2-1} dH_2 \right).$$

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^a, are Probit probabilities:

$$p_{1ps}^a = \Phi(\Pi_{1ps}) \tag{12}$$
$$p_{2ps}^a = \Phi(\Pi_{2ps}),$$

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}^a and p_{2ps}^a. Ex-post entry probabilities are updated according to

$$p_1 = p_1^a \tag{13}$$
$$p_2 = F_2\left(\frac{\beta_1(\overline{c})}{(1+\delta)}\right) p_2^a.$$

We iterate in computing expected profit and updated entry probabilities until the fixed point of the system (12) has been found for the given draw from the distribution of u.

6.2 Preliminary Results

In this section we present some preliminary estimation results. For these results, we use non-parametric techniques proposed by Guerre, Perrigne, Vuong (2000) to estimate the distributions of bidders' costs. As suggested by Athey and Haile (2005) we initially derive bid residuals from a bid regression that removes project-specific effects. We use this distribution of residuals to uncover the distribution of costs using first order conditions implied by the model. This allow us to estimate costs of entry as given by pre-entry expected profit. We then use these estimates to simulate the outcome of the median auction under two alternative scenarios: with and without a bid preference program.

Due to small sample sizes, we are only able to estimate our model for a single configuration of small and large bidders. Model 1 assumes that bidders observe the actual number of competitors at the time when they submit their bid. Therefore, we estimate the distribution of costs using a subset of auctions that attracted one small and three large bidders.

Figure 4 shows non-parametric estimates of the bid residual densities for small and large bidders. The distribution of large-bidder residuals has a lower mean and variance than the small-bidder residual distribution. These findings are in accordance with facts

documented in the previous literature. We then use the recovered cost levels to estimate the two cost densities. We approximate the densities as fifth-order polynomials. The polynomial approximations of the density functions are depicted in figure 5. Our preliminary estimates indicate that the mean and variance of the cost distribution for small bidders are higher than those of large bidders. Therefore small bidders tend to be less efficient on average.

We use the polynomial approximations of the cost densities shown in figure 5 to simulate the bidding strategies for the two types in environments with and without preferential treatment. A typical pair of bidding strategies for 2 small bidders and 2 large bidders in the case of no preferential treatment is shown in figure 6, while the bidding strategies in an environment of a 5% bid preference are shown in figure 7. The bidding strategies have several interesting features even in the absence of any preferential treatment. First, they are highly non-linear. Second, they suggest that large bidders bid higher amounts than small bidders for low cost realizations. This tendency reverses for large cost realizations. Here small bidders submit bids that are substantially higher than those submitted by large bidders for the same level of costs. This happens because the probability of winning for small bidders is probably low and almost flat for this potion of the cost distribution. Therefore, for them it pays in expectation to raise their bid. In the case of preferential treatment, the bidding strategy of small bidders is uniformly higher than the bidding strategy of large bidders.

Table 6 presents some statistics that assess the bid preference program based on the estimated model for the cases of $\delta = 0$, $\delta = 0.05$, and $\delta = 0.10$. They are based on the outcomes of 800 simulated auctions. With increases in the rate of the preferential treatment, entry by small bidders increases from a rate of 49% to 51% for a 5% bid preference whereas participation by large bidders falls. Winning bids rise primarily for large bidders and remain nearly constant for small bidders. Since mark-ups are largely unaffected for large bidders this suggests that large bidders win at higher cost levels. At the same time, there are pronounced changes in the probability that a project is won by a small bidder. In moving from no preferential treatment to a 5% discount, the probability of winning a project increases for small bidders from 48% to 53%.

The cost of procurement to the government increases when weighing type-specific winning bids by the type's probability of winning the project, rising from \$689.50 thousand to \$706.50 on average under the 5% bid preference. Finally, the efficiency of the auction mechanism declines slightly with the introduction of a bid preference program. This is in part driven by the terms of the preferential treatment: in 3.6% of auctions, the project is awarded to a small firm that wins only due to the bid discount, but has a higher undiscounted bid than the lowest large bidder.

Interestingly, the results are partially reversed when considering a 10% bid preference. The winning bid of large firms now falls relative to the 5% case, as does the probability of winning by small firms. This effect results from (1) large firms bidding more aggressively under a larger bid discount, and (2) high-cost large firms being increasingly driven out of the market as the bid discount increases. As a result, the cost of procurement decreases, suggesting a trade-off between the cost of the bid preference program and its success in increasing project award to small bidders.

7 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 incur costs to learn about the costliness of a particular contract to the firm. These sunk cost 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 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, both in term of cost to the government, which increases by 2.5%, and the efficient allocation of projects to the lowest cost competitors in the market.

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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: Effect of Preferential Treatment of Type 1

	No Preferential Treatment		Preferential Treatment			
A: Auction Efficiency						
F2 = F1	0.001		0.017			
F2 *FOSD* F1, low σ	0.025		0.027			
F2 *FOSD* F1, high σ	0.016		0.037			
F2 *SOSD* F1	0.024		0.019			

| | | | Type 1 | | Type 2 | |
| | | | | % Change from No Treatment | | % Change from No Treatment |
	Type 1	Type 2				
B: Probability of entry						
F2 = F1	0.511	0.511	0.560	0.095	0.455	-0.109
F2 *FOSD* F1, low σ	0.373	0.615	0.580	0.555	0.293	-0.524
F2 *FOSD* F1, high σ	0.153	0.763	0.413	1.704	0.288	-0.623
F2 *SOSD* F1	0.539	0.488	0.584	0.083	0.439	-0.099
C: Probability of winning						
F2 = F1	0.453	0.548	0.543	0.200	0.457	-0.165
F2 *FOSD* F1, low σ	0.324	0.676	0.520	0.606	0.480	-0.290
F2 *FOSD* F1, high σ	0.064	0.936	0.413	5.473	0.587	-0.373
F2 *SOSD* F1	0.480	0.520	0.550	0.146	0.450	-0.135
D: Average winning bid						
F2 = F1	0.744	0.812	0.729	-0.020	0.628	-0.226
F2 *FOSD* F1, low σ	0.786	0.694	0.860	0.093	0.599	-0.137
F2 *FOSD* F1, high σ	0.784	0.736	0.930	0.187	0.560	-0.240
F2 *SOSD* F1	0.744	0.687	0.746	0.003	0.626	-0.089
E: Winner's average markup (%)						
F2 = F1	0.350	0.311	0.354	0.011	0.289	-0.068
F2 *FOSD* F1, low σ	0.321	0.328	0.314	-0.020	0.283	-0.135
F2 *FOSD* F1, high σ	0.239	0.349	0.238	-0.002	0.265	-0.241
F2 *SOSD* F1	0.396	0.358	0.371	-0.063	0.282	-0.213

Notes:

The simulations use $N_1 = N_2 = 2$. Project costs are distributed according to a truncated normal distribution, $TN(\mu_j, \sigma_j)$, over [0,1]. In the base specification, bidders are symmetric and $F_1 = F_2 \sim TN(0.52, 0.23)$. In specifications 2 and 3, F_2 first-order stochastically dominates F_1, with $F_1 \sim TN(0.63, 0.23)$ and $F_2 \sim TN(0.52, 0.23)$ in specification 2 and $F_1 \sim TN(0.63, 0.27)$ and $F_2 \sim TN(0.52, 0.27)$ in specification 3. In specification 4, F_2 second-order stochastically dominates F_1 with $F_1 \sim TN(0.52, 0.27)$ and $F_2 \sim TN(0.52, 0.23)$. Probabilities of winning, average winning bids and markups, and auction efficiency are derived from outcomes of 800 simulated auctions. Auction efficiency denotes the percent of cases where the winner is not the lowest cost bidder.

Table 6: Estimation Results

	No Preferential Treatment		Pref. Treatment (δ=5%)		Pref. Treatment (δ=10%)	
	Small bidders	Large bidders	Small bidders	Large bidders	Small bidders	Large bidders
Pr(entry)	0.49	0.50	0.51	0.48	0.52	0.47
Pr(winning)	0.48	0.52	0.53	0.47	0.50	0.50
Winning Bid|Entry (ths)	729.5	652.5	730.2	679.8	747.0	649.0
Winning Bidder's Markup (%)	0.22	0.11	0.25	0.12	0.28	0.14
Cost to Government	689.5		706.5		698.0	
Efficiency	0.008		0.0100		0.0075	
% of Auctions where Program changed Winner			0.04		0.08	

Figure 1: Kernel Density Estimates of Large Firm's Bidding Distributions, Alternative Competitive Environments
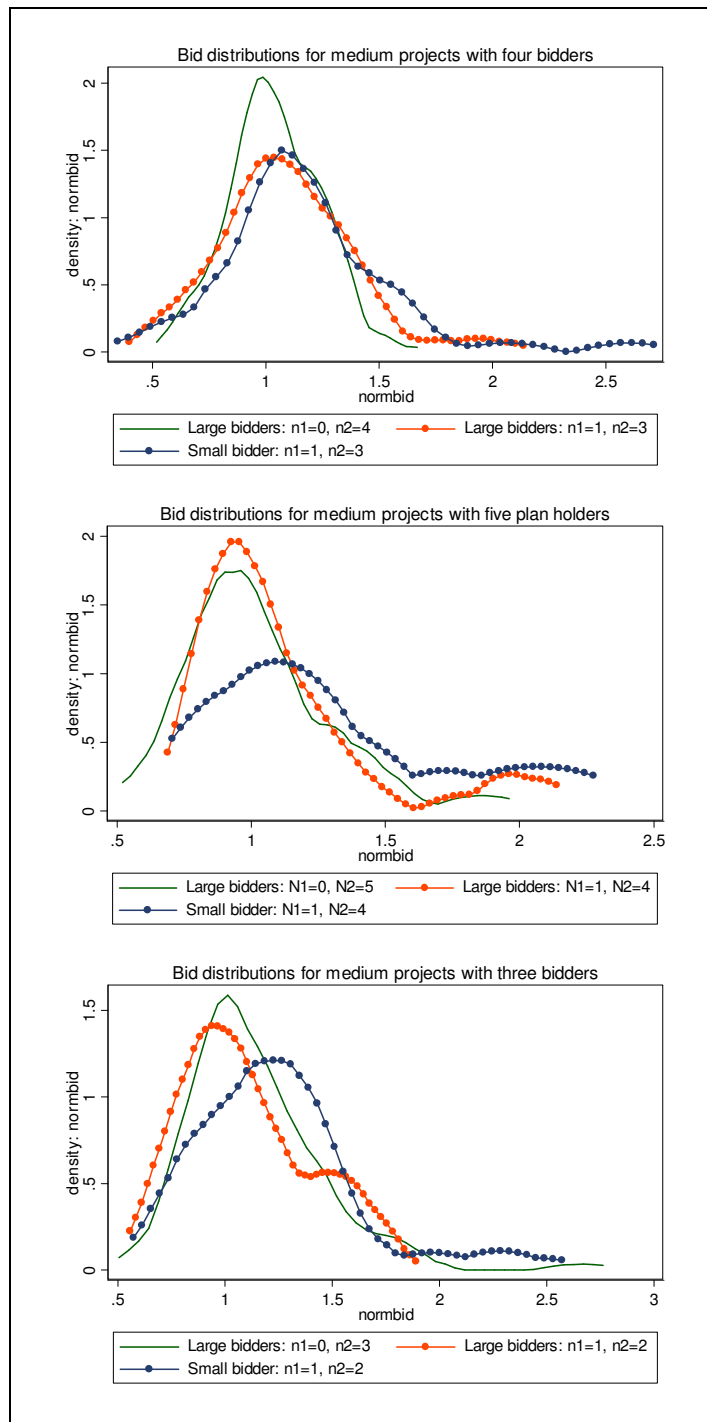
Figure 2: Bidding Strategies under Preferential Treatment of Type 1
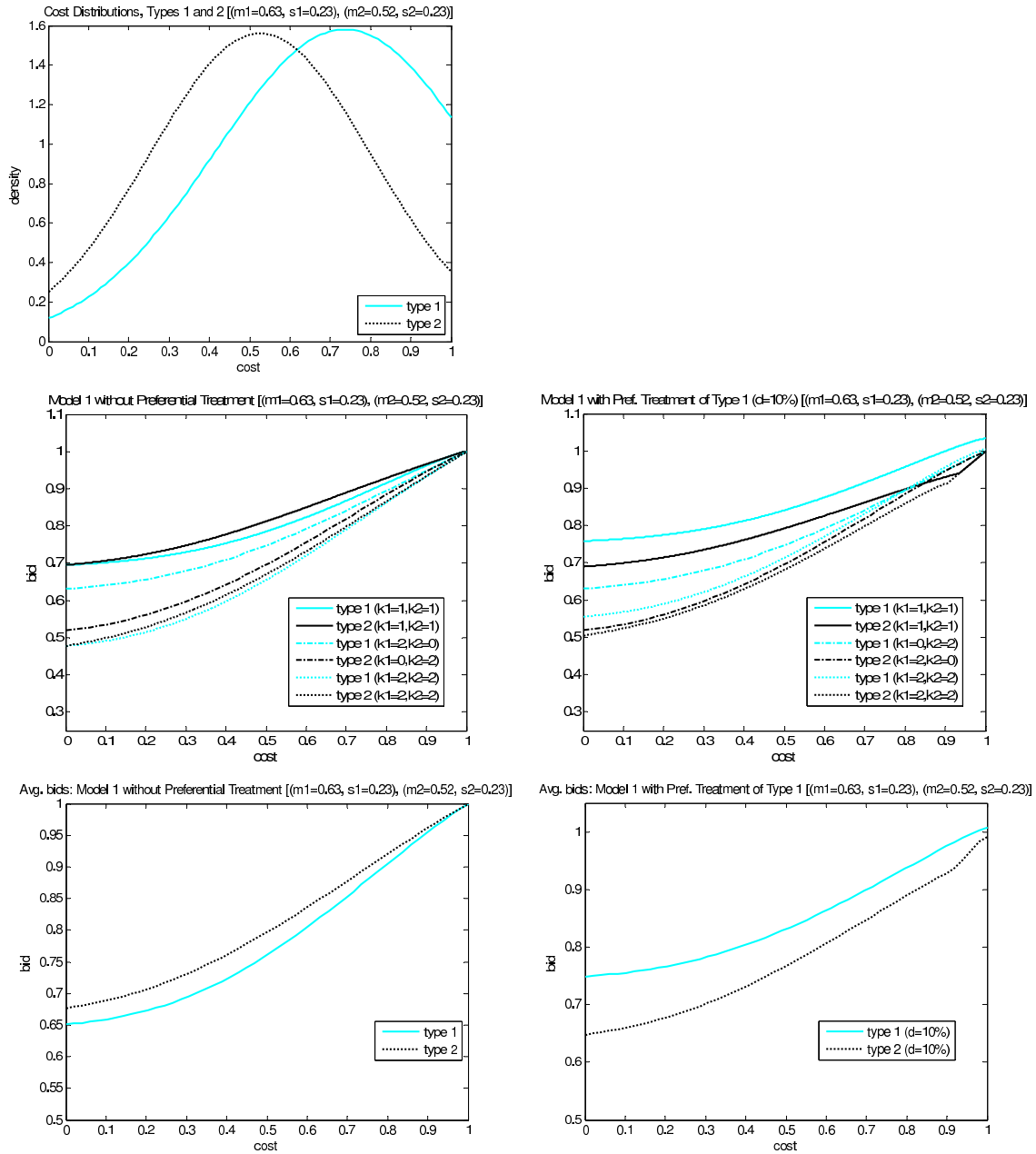
Figure 3: Bidding Strategies under Preferential Treatment of Type 1, continued
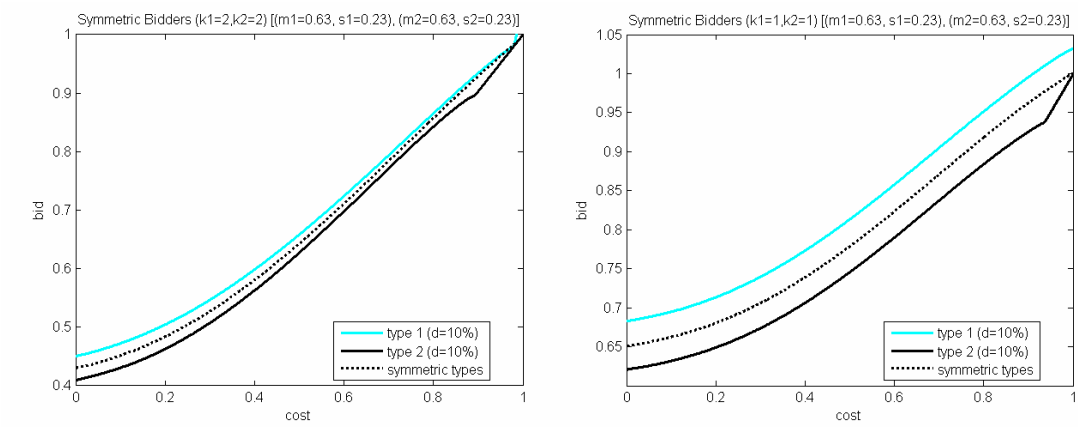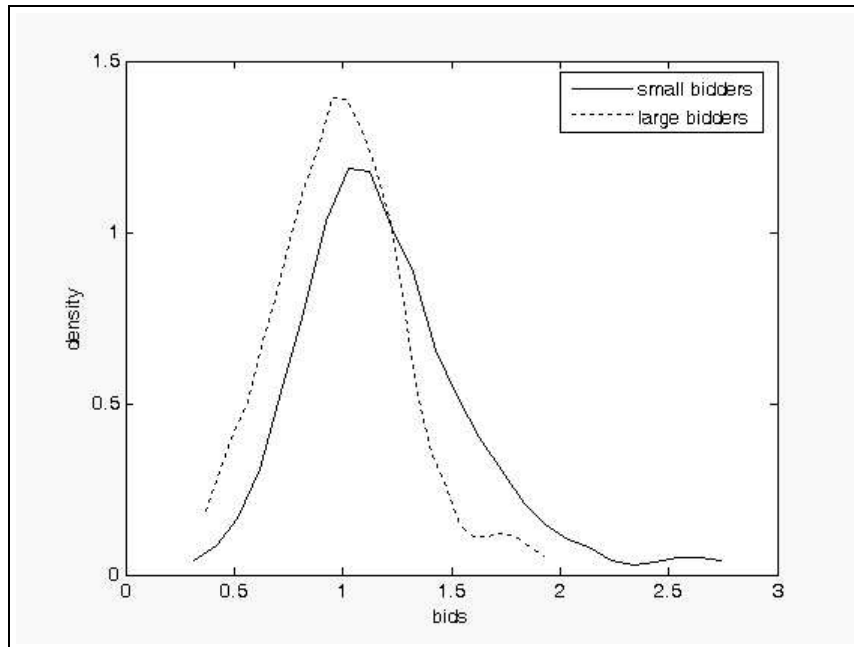
Figure 4: Empirical Bid Densities

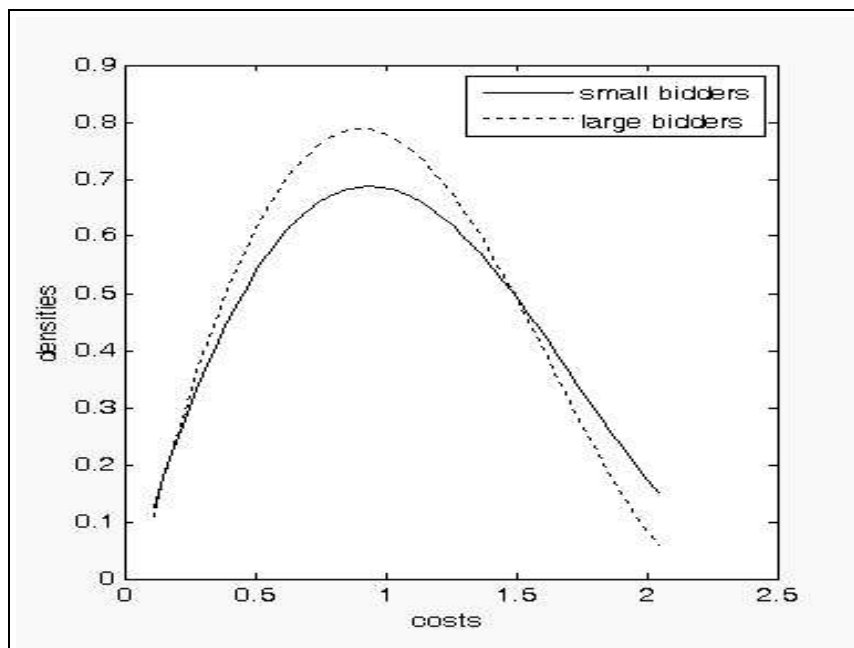Figure 5: Empirical Cost Densities (Polynomial Representation)

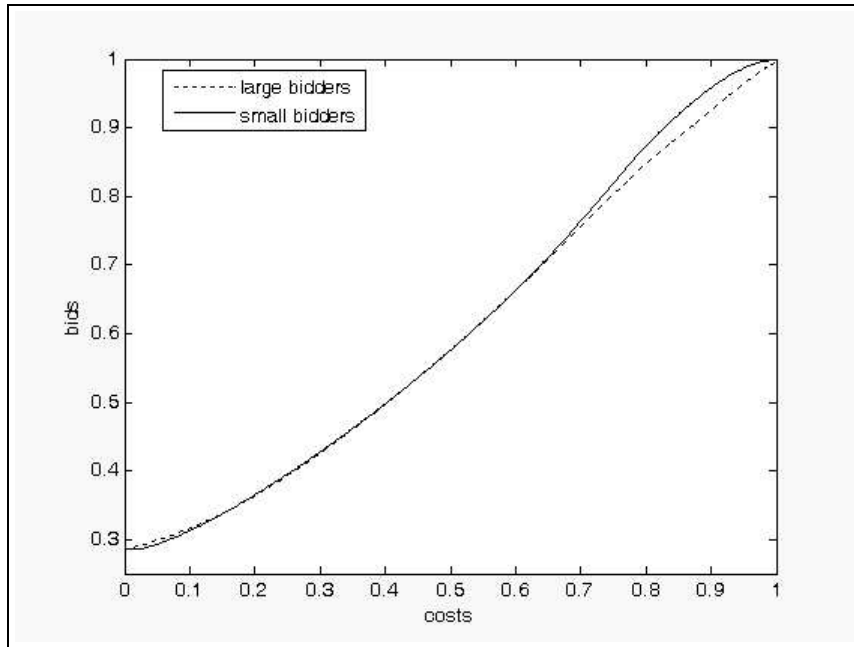Figure 6: Bidding Strategies (No Preferential Treatment)

Figure 7: Bidding Strategies (Preferential Treatment of δ=5%)