Bid Preference Programs and Participation in Highway Procurement Auctions*

Elena Krasnokutskaya

Department of Economics, University of Pennsylvania†

Katja Seim

Wharton School, University of Pennsylvania‡

April 2009

Abstract

We use data from highway procurement auctions subject to California's Small Business Preference program to study the effect of bid preferences on auction outcomes. Our analysis is based on an estimated model of firms' bidding and participation decisions, which allows us to evaluate the effects of current and alternative policy designs. We show that incorporating participation responses significantly alters the assessment of preferential treatment policies.

Keywords: Bid preference programs, discriminatory auction, auction participation, asymmetric bidders.

---

*Susan Athey, Phil Haile, Philip Leslie, Tong Li, Ariel Pakes, Petra Todd, Brian Viard, Joel Waldfogel, and Ken Wolpin provided helpful comments, as did conference and seminar participants at the Winter Meetings of the Econometric Society, the Toulouse Conference on the Econometrics of Auctions, the Summer Workshop at the Stanford Institute of Theoretical Economics, the Applied Microeconometrics Section of the Cowles Foundation Conference, Columbia University, Harvard University, MIT, Sauder School of Business, Stanford Graduate School of Business, Stern School of Business, University of Pennsylvania, University of Texas - Austin, and the University of Wisconsin - Madison. We thank Christine Inouye and Steven Tolle for making the data available. Cristina Fuentesa and Karam Kang provided excellent research assistance.

†3718 Locust Walk, Room 160, Philadelphia, PA 19104. Email: ekrasnok@sas.upenn.edu.

‡3620 Locust Walk, Philadelphia, PA 19104. Email: kseim@wharton.upenn.edu.

1 Introduction

Public-sector procurement accounts for over 10% of U.S. GDP. Across levels of government, preferential treatment programs are extensively used in procurement auctions. For example, in 2006, the federal government awarded 20% of its procurement dollars to favored firms.[1] One commonly used preference mechanism, a bid discount or credit, improves the bids of favored firms by a pre-established rate when determining the winner, but uses the actual amount of the winner's bid in the contract.[2] Prominent examples include a 25% bid credit granted to small firms in FCC spectrum auctions and a 50% bid penalty added to foreign bids on defense contracts. The aim of this paper is to improve our understanding of the effects of such preference programs on the government's cost of procurement and the distribution of profits between participants, as well as to provide an assessment of the likely magnitudes of these effects in practice. We do so empirically in the context of the California Small Business Preference program that grants small firms a 5% bid discount. This program aims to achieve a small-firm rate of participation in procurement of at least 25% based on the dollar amount awarded to small firms.[3]

The stated goal of most preference programs is to facilitate the integration of favored participants into the market place. These are often groups historically discriminated against, or groups considered disadvantaged due to entry barriers, or both. They are also often considered to be less cost efficient. As preference programs result in such high-cost companies performing a larger share of work, one may expect the cost of procurement to increase. At the same time, however, these programs also provide incentives to non-favored firms to bid more aggressively against the strengthened favored group, which mitigates the upward pressure on the cost of procurement. For some levels of the discount, this last effect is sufficiently strong for the cost of procurement to actually decrease (McAfee and McMillan (1989) and Corns and Schotter (1999) show this theoretically and in experiments, respectively, for assumed numbers of bidders and cost distributions).

[1] See the Federal Procurement Report 2007, available at `https://www.fpds.gov/`.

[2] With a 10% bid discount, for example, a bid by a favored firm of $400,000 is treated as a bid of $360,000 in comparing it to the remaining, non-favored, firms' bids. If the favored firm wins, its payment is the original amount of the bid, or $400,000.

[3] Other empirical studies of preference programs include Marion (2007a, 2007b) who finds two specific preference programs to be costly to governments; Denes (1997) who provides evidence of cost decreases in some set-aside auctions for dreading work; and Ayres and Cramton (1996) who argue that preference programs yielded significant revenue increases in a small sample of FCC spectrum auctions. These papers use descriptive methods, which allows them to measure the effects of the current programs, but does not permit an evaluation of alternative program designs.

The key insight of this paper is that there is a third effect neglected in the literature. Bid preference programs have potentially strong effects on firms' incentives to participate in an auction. We show that accounting for a response in participation behavior significantly alters the assessment of the preference program's cost to the government and its distributional effects. While it continues to be possible to use bid discounts to lower the cost of procurement as in McAfee and McMillan (1989), both the cost-minimizing level of the discount and the group receiving the discount may change when participation effects are taken into account. The currently accepted practice of evaluating bid preference programs holding participation fixed can yield very misleading results.

The theoretical literature suggests that the magnitudes of the program's effects crucially depend on the degree of cost asymmetries between favored and other bidders. We thus base our analysis on empirically relevant distributions of firm costs recovered from data on highway procurement auctions that were awarded under a bid preference program. We use a model of firms' participation and bidding decisions in the presence of a bid discount.[4] The firm's decision of which bid to submit reflects its private information about its cost of completing the project, which we term "project cost", and the distributions of its competitors' project costs. The participation decision instead is based on a comparison of the cost of preparing the bid, or entry cost, to the expected profit from participation. Only firms with entry costs below the expected profit ultimately submit a bid in the auction. We use this model to uncover the underlying distributions of firms' entry and project costs consistent with observed choices.

The nature and importance of our findings can be seen from Figure 1 that plots changes in the government's cost of procurement relative to no discrimination at different levels of the bid discount for a typical project in our data.[5] We contrast the cost of procurement implied by a model that does not allow firms to respond to the discount in their participation behavior with one where participation adjusts endogenously. Several patterns emerge:

1. Under fixed participation, the cost of procurement varies only by a limited amount as the discount changes from 50% to large bidders (the leftmost point in the figure) to 50%

[4] Our analysis also contributes to a small, but growing literature that empirically studies the decision to participate in an auctions. Athey, Levin and Seira (2008), Bajari and Hortacsu (2003), and Li and Zheng (2008) represent recent contributions to this literature.

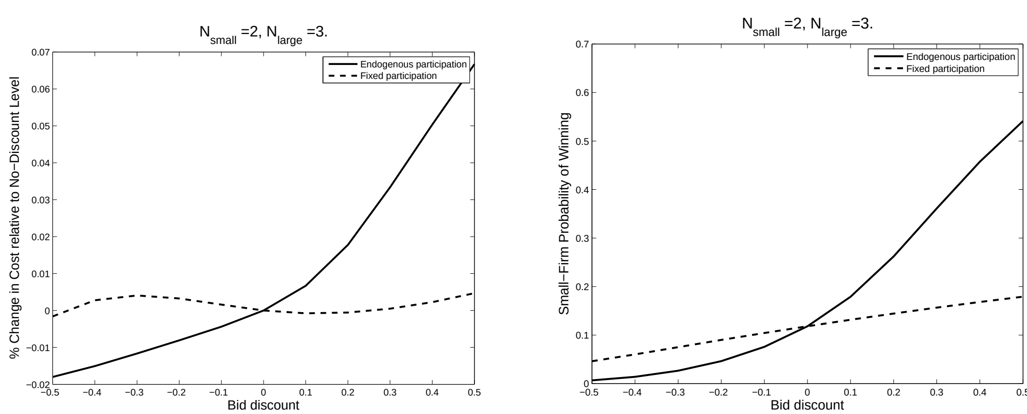
[5] The project's cost distributions are representative of approximately 30% of projects. The remaining projects are discussed in the main body of the paper.

to small bidders (the rightmost point). The cost of procurement exhibits significantly more variation when we take participation effects into account.

2. The implications for policy design differ significantly in the two cases. To minimize the cost of procurement, the model with fixed participation prescribes a discount of approximately 15% to small bidders. Relaxing the assumption of fixed participation suggests that offering such a discount to small bidders would actually increase the cost of procurement. Instead, a discount of 50% should be offered to *large* bidders to achieve substantial cost savings.

3. The California's Small Business Preference program aims to allocate 25% of procurement dollars to small firms. The fixed participation model implies that the discount required to achieve this goal is equal to 50% for this particular project. Such a discount yields a 0.6% increase in procurement cost. However, a model that takes participation adjustment into account would recognize that this substantial discount deters large-firm participation and, therefore, that the true cost increase would be 7%. Additionally, preferential treatment increases small-firm participation and in turn the group's probability of winning, hence, a bid discount of only approximately 20% is sufficient, raising the government's cost by 2%.

Figure 1: Cost of Procurement and Probability of Winning under Fixed and Endogenous Participation, Sample Project



Cost of procurement | Small firms' probability of winning

This example is based on a particular, albeit common, type of project in our data. An aggregate evaluation of California's preference policy needs to take into account heterogeneity in project characteristics and the competitive environment, which introduces heterogeneity in the effectiveness of a bid discount across projects. Our empirical results suggest significant differences in the degree of cost asymmetries between large and small firms across projects. For an important subset of projects in our data, we recover cost distributions for large and small firms that are very similar. As a result, small-firm participation and winning rates for these projects are high even in the absence of a bid discount. Because of the particular mix of projects, the aggregate cost of procurement at a discount level that awards 25% of procurement dollars to small firms is only 1.2% higher than the aggregate cost under no preferential treatment. It is important to note, however, that this result is specific to the California market. In other markets where the composition of projects is different, the cost of bid preference programs may be substantially higher or lower.

For California's current program, which uses a relatively low discount level of 5%, we find that the cost of procurement is within 1% of the cost of procurement in the absence of discrimination. However, the program induces substantial changes in small and large firms' participation and probabilities of winning. It results in a redistribution of 10 to 18% of profits from large to small firms for typical projects that differ in type of work, location, and size. At the same time the program does not achieve its allocative goal.

Interestingly, we find that an alternative preference mechanism that relies on lump-sum entry subsidies and/or taxes is more cost effective than a discount program. An appropriately chosen entry tax, for example, lowers the cost to the government significantly more than the cost-minimizing bid discount by extracting bidders' full expected surplus. Such a tax does not, however, achieve the State's allocative goal. We show instead that a combination of a subsidy to small firms and a modest tax on large firms can be used to satisfy California's allocation goals at important cost savings relative to a bid discount that achieves equivalent award levels. An entry tax or subsidy, by affecting firms' participation margins regardless of their ultimate cost of completing the project, avoids a distortion associated with bid discounts that grant higher absolute gains to bidders with high cost draws. It is through this channel that lower costs of procurement can be realized.

The paper proceeds as follows. Section 2 provides a brief overview of the highway procurement market in California and the details of the Small Business Preference program. Section 3 outlines the model of firms' joint participation and bidding decisions. Section 4 describes our estimation methodology, the results of which are in Section 5. Section 6 contains an analysis of the current and alternative programs. Section 7 concludes.

2 California's Highway Procurement Market

In this section, we describe the California highway procurement market and our data. We focus on highway and street maintenance projects auctioned by the California Department of Transportation ('Caltrans') between January 2002 and December 2005. California's Small Business Preference program is implemented on state-funded projects. During the sample period, Caltrans advertised 869 state-funded projects, of which complete data are available for 697 projects.[6] The data include information on project characteristics, the set of companies that purchased detailed project specifications and their small business status, the set of actual bidders, their bids, and finally, the identity of the winning bidder.

Letting Process. Caltrans advertises projects three to ten weeks prior to the bidding date. The project advertisement usually contains only limited information, such as type of work, location, and completion time. Interested contractors must purchase detailed project plans from Caltrans' project counter at least one week before the bid opening date. Only those firms that purchased project plans (plan holders) may submit a bid on the project. Our data suggest that purchasing a plan signals interest in bidding; we observe, for example, that in their plan purchases, companies focus on similar projects based on administrative district location and type of work. We therefore assume that the group of potential bidders on a given project coincides with the group of plan holders. The list of companies that purchased plans for a given project is posted on Caltrans' website. Therefore, potential bidders are known to each other at the time they prepare their bids.

To bid on a project, a company must submit by the bid opening date completed bid documents, which specify the bid amount, the list of subcontractors, their fees and their tasks. The preparation of bid documents requires time and effort and is, therefore, costly. We treat such bid preparation costs as entry costs in our model below.

During the bid preparation process, companies engage in extensive negotiations with subcontractors. As evident from the bid documents, the sets of subcontractors often overlap across companies preparing bids for the same auction. Thus, it is likely that participants learn about other companies preparing bids for the same project from subcontractors. Anecdotal evidence confirms that by the bid opening date, bidders usually know who their competitors for a given project are.

Preference Program. The Small Business Preference program sets a goal of allo-

[6] Caltrans did not preserve lists of companies that purchased bid documents for some projects.

cating 25% of state procurement dollars to small firms. The program is implemented using a discriminatory first-price sealed-bid auction mechanism. It grants small firms a 5% bid discount, a reduction in their bids for comparison purposes only when determining the winner. The winner is then paid the full amount of its bid.

To qualify for the discount, a company has to satisfy three conditions. It has to be independently owned and operated; have fewer than 100 employees; and have average annual gross receipts limited to $10 million over the previous three tax years.[7] We obtained quarterly information on the certification status of companies in our data set from the Department of General Services. In our sample, out of 672 companies that bid on at least one project, 269, or 40%, were certified as small businesses. Caltrans awarded 39.02% of contracts to qualified small businesses. The total value of these contracts accounted for only 15.45% of total procurement dollars, however. Most of the projects allocated to small firms are therefore small. It also means that Caltrans does not meet the program's allocation goal. The bid preference altered the identity of the winning bidder in only 5% of projects.

3 Model of Firms' Participation and Bidding Decisions

This section develops a model of firms' participation and bidding decisions that forms the basis for our empirical analysis below. We consider a single standalone auction. We assume that a total of N potential contractors express interest in the project offered for bid. Similar to other work on auction participation (e.g., Samuelson (1985), Levin and Smith (1994)), we model a potential bidder's decision as a two-stage process. In the first stage, each potential bidder decides whether to participate in the auction. When making this decision a firm compares the expected profit conditional on participation to the cost of preparing the bid. Only firms with an entry cost below the expected profit from participation choose to enter the auction. In the second stage, firms that choose to participate (actual bidders) submit their bids. Bids reflect firms' costs of completing the contract, which we refer to as project costs.

We assume that in awarding the contract, the government applies a discriminatory

[7] Such revenue restrictions could affect small firms' entry behavior. For example, a company may decide not to bid on a large project if winning this project brings it over or very close to the revenue threshold. In our data, however, 99% of small firms have yearly revenue below $5.4m, relative to a large project's typical size of about $1m. Therefore, in most cases winning one additional large project does not impact the small-firm status of a company.

rule similar to the one used in California. If the lowest favored bid is within δ percentage points of the overall lowest bid, the government awards the project to this favored bidder. It pays the contractor the full amount of the bid. Otherwise, the government awards the contract to the lowest non-favored bidder. A preference program thus introduces an asymmetry into the payoffs of favored firms (group 1) and other firms (group 2). The number of potential bidders in each group k is N_k, with $N_1 + N_2 = N$. We allow for the possibility that favored and other firms differ systematically in their costs of preparing bids and/or of completing the project. We denote the project cost of firm i of group k by c_{ik} and assume that it is independent of its competitors' costs and distributed according to F_k with support $[\underline{c}, \overline{c}]$. Similar to project costs, bid preparation costs, denoted by d_{ik}, differ across competitors and groups according to the distribution G_k.

We assume that in the initial participation stage, each potential bidder i knows only its own cost of entry, d_{ik}, the distributions of project and entry costs, F_k and G_k, and the numbers of potential bidders by group. By incurring bid preparation costs, the firm learns its project cost c_{ik} and the number of other firms in each group that similarly decided to participate, n_1 and n_2.[8] Both entry and project costs remain private information to each contractor throughout. The bidding stage is a discriminatory first-price sealed-bid procurement auction with asymmetric bidders.

3.1 Characterization of Equilibrium in the Bidding Stage

We begin with an analysis of the bidding stage and then use the results to analyze the participation stage. We focus on group-symmetric equilibria where bidders of group k follow the same bidding strategy, $\beta_k(.)$, mapping project cost, c_{ik}, into a bid b_{ik}, $\beta_k(.) : [\underline{c}, \overline{c}] \rightarrow [\underline{b}_k, \overline{b}_k]$. Due to the bid-preference program, a bidder i of group k wins the project if its bid b_{ik} is below all competing bids adjusted by the bid discount δ where applicable. Firm i with

[8] Athey et al. (2008) make the same assumption. Marmer, Shneyerov and Xu (2007) and Li and Zheng (2008) perform tests of alternative models of entry, including the one used here. Marmer et al. (2007) cannot reject the model we use against alternatives where bidders are not fully informed about the number of their competitors. In contrast, Li and Zheng (2008) reject this model in their data. However, they work with data from mowing auctions where bidders rarely use subcontractors, whereas Marmer et al. (2007) use data from a setting very similar to ours.

project cost c_{ik} chooses bid b_{ik} to maximize expected profit conditional on participating:

$$\begin{aligned}\pi_{ik}(c_{ik}) &= (b_{ik}-c_{ik})\Pr(b_{ik}\le\ b_{jk}\ \forall j\neq i)\Pr\left(b_{ik}\le(1+\delta)^{1-2I(k=2)}b_{j-k}, j=1:n_{-k}\right) \quad (1)\\ &= (b_{ik}-c_{ik})\left(1-F_k\left[\beta_k^{-1}(b_{ik})\right]\right)^{n_k-1}\left(1-F_{-k}\left[\beta_{-k}^{-1}\left((1+\delta)^{1-2I(k=2)}b_{ik}\right)\right]\ \right)^{n_{-k}}\end{aligned}$$

where $I(k=2)$ is an indicator variable that equals one if firm i belongs to group 2. The first-order condition of the firm's bidding problem is:

$$\begin{aligned}\frac{1}{b_{ik}-c_{ik}} &= \frac{(n_k-1)f_k\left[\beta_k^{-1}(b_{ik})\right]}{\left(1-F_k\left[\beta_k^{-1}(b_{ik})\right]\right)}\frac{\partial\beta_k^{-1}}{\partial b_{ik}} \quad (2)\\ &+ \frac{n_{-k}(1+\delta)^{1-2I(k=2)}f_{-k}\left[\beta_{-k}^{-1}\left((1+\delta)^{1-2I(k=2)}b_{ik}\right)\right]}{\left(1-F_{-k}\left[\beta_{-k}^{-1}\left((1+\delta)^{1-2I(k=2)}b_{ik}\right)\right]\right)}\frac{\partial\beta_{-k}^{-1}}{\partial b_{ik}}\end{aligned}$$

The preference program introduces two interesting features into the equilibrium, reflecting the increased competitiveness of favored bidders. First, a single favored bidder with $c_{i1}=\bar{c}$ finds it optimal to bid above his cost when bidding against several non-favored bidders since the bid discount sufficiently lowers his effective bid to result in a non-zero probability of winning the project.[9] In contrast, with multiple favored bidders, competitive pressure reduces the upper boundary bid to cost. Second, since the highest effective bid submitted by a favored bidder is given by $\frac{\bar{b}_1}{1+\delta}$, non-favored bidders with cost $c_2\in[\frac{\bar{b}_1}{1+\delta},\bar{c})$ can never win an auction where a small bidder is present and earn positive profit.

The behavior of bidders with boundary cost draws can be summarized as follows.

1. *Right-boundary condition.* Favored bidders with cost level $\bar{c}$ bid $\bar{b}_1=\bar{c}$ if $n_1>1$. If $n_1=1$, $\bar{b}_1$ is the bid level that maximizes

$$\pi_{i1}=(\bar{b}_1-\bar{c})\left(1-F_2\left(\frac{\bar{b}_1}{(1+\delta)}\right)\right)^{n_2}. \quad (3)$$

Non-favored bidders with $c_2\in[\frac{\bar{b}_1}{1+\delta},\bar{c})$ have a zero probability of winning and, therefore, bid their cost.

[9] Note that consistent with Caltrans policy, we do not impose a reserve price. If only a single bidder chose to enter the auction, there are thus no constraints on its bid. Since we do not observe infinite bids in our data, we follow Li and Zheng (2008) and assume that in such instances, the government steps in as a second bidder, drawing its project cost from the non-favored cost distribution. Since our data do not contain projects with only one bidder, this assumption is only relevant when computing the expected profit from entry by averaging over all possible bidder combinations.

2. *Left-boundary condition.* There exists a bid level $\underline{b}_1$ such that for all favored firms, $\beta_1(\underline{c}) = \underline{b}_1$. For all non-favored bidders, $\beta_2(\underline{c}) = \underline{b}_2 = \frac{\underline{b}_1}{(1+\delta)}$.

The proof of these properties follows the standard reasoning for boundary conditions in first-price auctions. Theorem 2.1 in Reny and Zamir (2004) establishes the existence and uniqueness of the bidding equilibrium in this environment.

3.2 Characterization of Equilibrium in the Participation Stage

At the participation stage, firms compare the ex-ante expected profit conditional on entry to their entry cost d_{ik}. Firms with entry costs below their expected profit decide to incur the entry fee to learn about their cost of completing the project. Ex-ante expected profit from participating is given by

$$\Pi_k = \sum_{n_k, n_{-k} \subset N_k - 1, N_{-k}} \left(\int_{\underline{c}}^{\bar{c}} \pi_k(c_{ik}; n_k, n_{-k}) dF_k(c_{ik}) \right) \Pr(n_k, n_{-k} | N_k, N_{-k}) \tag{4}$$

where $\Pr(n_k, n_{-k}|N_k, N_{-k})$ is the probability of observing n_k competitors of the firm's own type and n_{-k} competitors of the opposite type, given numbers of potential entrants of N_k and N_{-k}. $\pi_k(c_{ik}; n_k, n_{-k})$ is the expected equilibrium profit of a bidder from group k with cost realization c_{ik}. It 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, the expected profit differs only by group k, but not by firm i. The firms assess the probability that there will be n_k and n_{-k} competitors in the auction as

$$\Pr(n_k, n_{-k}|N_k, N_{-k}) = \tag{5}$$
$$\begin{pmatrix} N_k - 1 \\ n_k \end{pmatrix} \begin{pmatrix} N_{-k} \\ n_{-k} \end{pmatrix} (p_k)^{n_k} (1 - p_k)^{N_k - 1 - n_k} (p_{-k})^{n_{-k}} (1 - p_{-k})^{N_{-k} - n_{-k}}$$

The participation decision is described by group-specific entry cost thresholds, D_k, such that only firms with entry costs below their group's threshold participate in the auction. They 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

$$p_1 = G_1 \left[D_1(p_1, p_2) \right] \tag{6}$$
$$p_2 = G_2 \left[D_2(p_1, p_2) \right].$$

Brouwer's Fixed Point Theorem guarantees that the group-specific equilibrium of this game exists. In general, the entry equilibrium is not unique. There may be multiple threshold pairs that solve Equation (6). These equilibria are observationally equivalent in terms of submitted bids and differ only in entry probabilities. We verify the uniqueness of the equilibrium entry probabilities numerically within the estimation routine.[10]

4 Estimation Methodology

The model outlined above predicts group-specific participation and bidding strategies. The goal of the estimation is to recover the underlying parameters of the project cost and cost of entry distributions that best describe firms' observed bidding and entry behavior. Our estimation procedure consists of two steps. We first use generalized method of moments to estimate the entry cost and bid distributions from the data. We then recover the distributions of project costs from the estimated bid distributions.[11]

Following Krasnokutskaya (2004), we assume that bidders' project costs for project j consist of two components, $c_{ijk} = u_j \tilde{c}_{ijk}$. Here, $\tilde{c}_{ijk}$ is a firm and group-specific cost component that is private information of firm i, while u_j represents a portion of project j's cost that is known to all bidders, but is unobserved to the researcher, i.e. unobserved project heterogeneity. Let $\tilde{\beta}_k(.)$ denote the bidding strategy associated with the mean unobserved characteristic, which we normalize to $u_j = 1$. Under these assumptions, $\beta_k(c_{ijk}) = u_j \tilde{\beta}_k(\tilde{c}_{ijk})$ or $b_{ijk} = u_j \tilde{b}_{ijk}$, with $\tilde{b}_{ijk} = \tilde{\beta}_k(\tilde{c}_{ijk})$. We continue to denote the distribution of the firm-specific cost component for group-k firms by $F_k(.)$ and the distribution of unobserved project

[10] The equilibrium in the bidding stage results in non-favored bidders with $c_2 \in [\frac{\bar{b}_1}{1+\delta}, \bar{c})$ having a zero probability of winning. Since they always make zero profit, they may decide to drop out of the auction after learning their costs. In this case, Equation (6) should be adjusted to $p_k = G_k \left[D_k(p_1, p_2 p^{nb}) \right]$, $k = 1, 2$, where p^{nb} denotes the probability of non-favored bidders leaving the auction after learning their project cost realization.

[11] Jofre-Bonet and Pesendorfer (2003) and Athey et al. (2008) use similar estimation methodologies. We chose not to estimate the distribution of project costs directly from the data because of the computational burden of having to simulate bidding strategies numerically for every parameter guess and every project.

heterogeneity by $H(.)$. We assume that firms observe the realization of the common unobserved project characteristic prior to making their entry decisions, whereas the individual cost-component is realized only after the entry decision has been made. As a result, probabilities of entry are functions of the realization of u_j, $p_k(u_j)$.

We assume that the distribution of the individual log-bid component $\ln(\tilde{b}_{ij})$ is normal with mean $\mu_{kj} = x_j\alpha_k^F$ and standard deviation σ_{kj}^F. We assume that u_j is distributed according to a log-normal distribution with mean one and standard deviation σ_u. Last, we assume that entry costs are distributed according to a normal distribution left-truncated at 0 with group-specific means $\mu_{kj}^G = z_j\alpha_k^G$ and standard deviation σ_k^G. Here x_j and z_j denote project characteristics that affect project and entry costs, respectively.

To estimate the parameters of the individual bid component we use the empirical counterparts to the following set of theoretical moment conditions:

$$\begin{aligned} E[1(i \in group\ k)(\ln(\tilde{b}_{ij}) - x_j\alpha_k^F)x_j] &= 0, \quad k = 1, 2 \\ E[1(i \in group\ k)(\ln(\tilde{b}_{ij}) - x_j\alpha_k^F)^2] &= {\sigma_k^F}^2, \quad k = 1, 2 \end{aligned} \tag{7}$$

We identify the standard deviation of the distribution of unobserved project heterogeneity, σ_u, from a moment condition that measures the covariance between any two bids submitted in the same auction:

$$E[(\ln(\tilde{b}_{ij}) - x_j\alpha_{k(i)}^F)(\ln(\tilde{b}_{lj}) - x_j\alpha_{k(l)}^F)] = {\sigma_u}^2, \tag{8}$$

where we use the notation $k(i)$ and $k(l)$ to indicate that the group membership of firms i and l could differ.

We integrate over the distribution of the unobservable project characteristic numerically. In doing so, we recognize a correlation between u_j and the numbers of bidders that arise because firms observe u_j at the time of entry. We thus integrate over the conditional density of u_j, given the realizations of n_1 and n_2 in the data:

$$h(u_j|n_{1j}, n_{2j}, N_{1j}, N_{2j}) = \frac{\Pr(n_{1j}(u_j), n_{2j}(u_j)|N_{1j}, N_{2j}, u_j)h(u_j)}{\int \Pr(n_{1j}(u_j), n_{2j}(u_j)|N_{1j}, N_{2j}, u_j)h(u_j)du_j dN_1 dN_2} \tag{9}$$

We compute the probabilities of observing a combination of (n_1, n_2) as in Equation (5) and include the dependence of n_k on u_j to highlight that the group-specific equilibrium probabilities of participation in Equation (6), $p_k(u_j)$, are functions of u_j.[12]

The second group of moments is used to recover parameters of the entry cost distributions. We use the empirical approximation to the following moment conditions, integrating over the unconditional distribution of the unobserved project characteristic numerically, as above:

$$E[n_{kj}|x_j, z_j] - p_k(x_j, z_j, u_j)N_{kj} = 0 \tag{10}$$
$$E[n_{kj}^2|x_j, z_j] - p_k(x_j, z_j, u_j)N_{kj}\left(1 - p_k(x_j, z_j, u_j) + N_{kj}p_k(x_j, z_j, u_j)\right) = 0,$$

where $p_k(x_j, z_j, u_j)$ denotes the group-specific equilibrium probabilities of participation in Equation (6). We use separate moment conditions for small, medium-sized, and large projects.[13] We weight observations so that we have the same mix of moment conditions across numbers of potential bidders in each size category. To compute the expected profit of entry, we follow Eyakime, Laffont, Loisel and Vuong (1993) to recover the inverse bid functions from the first-order conditions for profit maximization and express expected profit for a given (n_1, n_2) combination as a function of the submitted bid. Finally, we integrate over the distribution of actual bidders and the distribution of submitted bids.

We conclude this section with a brief discussion of the econometric identification of our parameters. Because of the relatively small size of our data set, we use parametric assumptions for the distributions of bid and entry costs, as well as unobserved project heterogeneity. However, our data identify the distributions of bids and entry costs non-parametrically. Krasnokutskaya (2004) contains a detailed discussion of the non-parametric identification of the parameters of the bid distribution in the presence of unobserved project heterogeneity. The distribution of entry costs is also identified non-parametrically. The expected profit in Equation (4), as a function of u_j, maps the distribution of unobserved project heterogeneity into the distribution of probabilities of entry. In our model, this mapping is one-to-one. As a result, it is possible to identify the probability of entry as a function of

[12] In estimation we maintain the assumption that a large bidder who can never win a given project ultimately does not submit a bid. Our estimation procedure accounts for the resulting truncation. We are able to recover the full distribution of the large-firm individual cost component because our data set contains auctions that did not attract any small bidders. The probabilities p_{2j}^{nb} are recovered from the ratios of the cumulative distribution functions of project costs for projects with $n_1 = n$, $n = 1$ or $n = 2$ and those with $n_1 = 0$ for interior cost levels.

[13] We estimate both a specification that relies only on first moments and a specification that uses first and second moments. The results are very similar across the two specifications. We report the estimation results for the first specification, together with predictions for the second moments based on the estimated coefficients.

the expected profit associated with a given realization of u_j, which gives us a cumulative distribution function of the cost of entry distribution.

In the parametric analysis, when recovering the distributions of individual bid and unobserved heterogeneity components, we use projects with different numbers of bidders. Ex-post, both distributions depend on the numbers of bidders. Therefore, we could not separately recover them from the data if we made a parametric assumption for the dependency on the number of bidders for both distributions. Instead, we assume that the distribution of unobserved project heterogeneity does not depend on the number of bidders and employ in estimation the conditional distribution of u_j, conditioning on the numbers of potential and actual bidders in Equation (9).

We use three moment conditions per group of bidders to recover three parameters characterizing the group's distribution of entry costs. These moments represent the average numbers of bidders by project size category. For each group, the moments thus trace the average number of bidders as a function of project size. The intercept of this profile identifies the constant of the distribution of entry costs; the slope identifies the coefficient for project size; and the curvature identifies the variance of the entry cost distribution.

5 Empirical Analysis

This section presents results of our empirical analysis. We first summarize descriptive patterns in the data that speak to the presence of cost asymmetries across groups of bidders, the heterogeneity of projects in our data set, and the strategic response of bidders to the bid preference program. We next implement our estimation strategy. We demonstrate that the predicted bid and entry choices based on our estimated parameters fit the data well, including for groups of projects not used in estimation. The estimated parameters of the entry cost distribution imply reasonable entry costs. The results confirm the presence of substantial asymmetries across bidder groups and important variation in the degree of asymmetries that correlates with project characteristics. Small bidders have higher project and entry costs for the majority of projects. However, we also identify a sizable set of projects where small bidders have lower project or entry costs or both.

5.1 Descriptive Analysis

Table 1 summarizes the characteristics of the set of state-funded projects that we use in estimation. Important project characteristics include the engineer's estimate of the project's total cost, the type of work involved, the project's location at the level of the administrative district, and the time allocated to complete the project. The engineer's estimate reflects Caltrans' assessment of the project's price based on similar projects auctioned in the past. We follow other procurement auction studies (e.g., Hong and Shum (2002), Jofre-Bonet and Pesendorfer (2003), Porter and Zona (1993), Bajari, Houghton and Tadelis (2007)) in using it as a proxy for the size of the project.

Projects are split into five work categories: bridge work; landscaping; road repair; signs, signals and lighting; and small building work. Road-repair projects account for 60.26% of contracts; small building work accounts for another 15.93% of contracts, while 10.04% of contracts are for bridge work. The remaining contracts are split roughly equally between landscaping and signs/lighting work. Across projects, the median project has an engineer's estimate of $464,000 (standard deviation of $740,000) and a duration of 45 working days (standard deviation of 165 days). Table 1 further highlights significant heterogeneity in the competitive environment. On average a project attracts 4 small potential bidders and 6.5 large potential bidders with 1.7 small and 2.6 large firms submitting bids.

The bottom panel of Table 1 summarizes potential and actual entry separately for small, medium, and large projects, representing the terciles of the distribution of the engineer's estimate. The small-firm participation rate declines sharply with project size. It drops from 51% of small potential bidders submitting bids in small projects to only 35% in large projects. In contrast, the participation rate of large firms is roughly constant across project sizes, ranging from 38% to 40%.

To investigate how participation rates vary with project characteristics, we conduct a probit analysis of a potential bidder's decision to submit a bid (see Table 2). We include proxies for the competitive environment and project characteristics (size, time to completion, type of work, location) and allow the coefficients to differ for small and large plan holders. We control for unobserved project characteristics by including the number of actual bidders. We divide project locations into rural and urban based on the project's administrative district, defining a project to be rural if it is located in the North Coast, North Central, South Central, or Southern Sierra districts. We also combine bridge and road work into one group, relative to the remaining contracts.

The probit analysis reveals a negative, statistically significant effect of the number of potential competitors on a firm's participation decision. This is true for potential competitors of the same type as well as of the opposite type. The presence of an additional small potential bidder decreases both a small and a large firm's propensity to submit a bid by about twice the reduction brought forth by the presence of an additional large potential bidder, a statistically significant difference. This evidence is consistent with companies' strategic response to the bid preference program.

Table 2 also suggests heterogeneity in participation across locations and type of work. We include interaction variables of the project's location (urban or rural) and the project's type of work (road repair/bridge or other) and estimate differences between small and large firms' participation rates. Across project types, small firms have statistically significantly lower participation rates than large firms. The difference is more pronounced for urban projects, which are larger on average than rural projects, in line with the results in Table 1. Small firms are also less likely to participate in road-repair than in other projects, regardless of project location; however, the difference is statistically significant for urban projects only. Large firms, in contrast, exhibit less heterogeneity in participation choices, and we cannot reject the equality of participation rates across locations and types of work.

These regularities indicate that project size, location, and type of work affect entry in a group-specific way, potentially reflecting differences in the cost of completing a particular project or the cost of preparing bid documents. To investigate the former, we conduct a regression analysis that relates log-bid levels to project characteristics.[14] Table 3 summarizes the results. The estimated coefficients have the expected signs. We find that log-bids increase in the engineer's estimate and the project's duration. In addition, we find significant variation in bid levels across work types and locations, even after controlling for project size. Conditional on project characteristics, the average bid of a small bidder is 8.1% higher than that of a large bidder.

In summary, the descriptive evidence suggests that bidding and entry behavior differ by firm group. We find that the number of small potential bidders affects participation decisions of both groups of bidders more than the number of large potential bidders. This suggests that the Small Business Preference program affects the operation of this market. At the same time, small firms submit bids significantly less frequently, and if they do, bid higher than large firms. Such participation and bidding behavior could arise due to large differences

[14] We include the numbers of potential bidders to control for unobserved project heterogeneity.

in project costs between small and large firms even if the costs of preparing bids are similar across groups. On the other hand, even without pronounced differences in project costs, small firms' bids may be higher due to the competitive advantage awarded by the preference program, while their less frequent entry is due to larger bid preparation costs.

We now turn to estimating the econometric model that allows us to disentangle the role of the preference program from inherent cost differences between firms, both of which are reflected in the observed firm choices.

5.2 Estimation Results

We assume that log-bids are normally distributed with a mean given by a linear function of the log of the engineer's estimate, duration, the numbers of actual and potential bidders and dummies for type of work and location. We allow the effects of most of these covariates to differ by bidder group. In the mean of the bid distribution we include year dummies to control for cost inflation and monthly dummies to control for seasonal fluctuations in input prices. Finally, we allow for unobserved (to the researcher) project-specific factors to impact mean log-bids. The variance of the bid distribution depends on the log of the engineer's estimate and the bidder's group. We assume that mean entry costs vary by group with project size and allow for a group-specific standard deviation.[15]

The results of estimation indicate that there are important differences in project and entry costs across groups of bidders. Table 4 reports the estimated coefficients of the bid distribution. The estimated coefficients are of the expected sign and magnitude. They reflect substantial variation in the means and variances of log-bid distributions across types of work and locations. They also imply substantial differences in log-bid levels across bidder groups. We estimate that a small firm submits a bid that is, on average, 7.7% higher than a large firm's bid for the same project. We find that the variance of the underlying log-normal distribution of bids (which equals $(\exp \sigma^{F^2} - 1) \exp(2\mu^F + \sigma^{F^2})$) increases in the engineer's estimate and is lower for small bidders. Unobserved project heterogeneity is important in our

[15]We also estimated several alternative specifications. First, we estimated a specification where the unobserved project heterogeneity, instead of the individual bid component, depends on the number of potential bidders. The coefficients for the numbers of potential bidders in the standard deviation of unobserved heterogeneity are not statistically significant; the remaining coefficients are qualitatively similar to our base specification. Second, we estimated specifications that include as additional entry cost shifters a project's number of individual tasks and nonlinear size effects. These variables do not have statistically significant effects on mean entry costs.

data. Increasing the unobserved project characteristic from a value of zero to a value equal to the estimated standard deviation of 0.1433 has an effect on mean bids that is equivalent to increasing the log-engineer's estimate by 0.33 standard deviations, an increase in the engineer's estimate of approximately $200,000. The estimation results also indicate that the effect of the numbers of potential bidders on bid levels is much smaller than the effect of the numbers of actual bidders, which favors our assumption that bidders are informed about the number of their actual competitors at the time when they submit their bids.[16] The estimated bid distributions fit the data well; see Figure A-1 in the Appendix for more detail.

We use Eyakime et al.'s (1993) methodology to recover the distribution of project costs from the distribution of bids. We use the first-order conditions to estimate inverse bid functions. Strict monotonicity of bid and inverse bid functions allows us to combine the estimated distribution of bids and inverse bid functions to obtain an estimate of the distribution of project costs. We summarize the estimated distributions of project costs in Table 5, where we report means and variances of project cost distributions as a fraction of the engineer's estimate for categories of projects defined by size, type of work, and location. With the exception of large rural other work (of which our data contain only nine projects), mean project costs are close to the engineer's estimate. Table 5 also shows important differences in means and variances of cost distributions across groups of bidders. We test for the statistical significance of these differences next.

We analyze differences in project costs across groups of bidders using a parametric bootstrap technique to test the hypothesis of the equality of the two groups' means (standard deviations) of their project cost distributions against two-sided and one-sided alternatives. Test results differ across projects. For some projects we cannot reject equality of means or standard deviations, whereas for other projects we reject equality in favor of either group having a lower mean (or standard deviation). We aggregate the test results to the level of the project category (defined in Table 5) to document how cost differences between small and large bidders vary with project characteristics. The aggregation is performed as follows. For every project j we define a random variable I_j, which is equal to one if the null hypothesis of equal means is rejected for project j at the 5% level of significance, and is equal to zero otherwise. The probability that $I_j = 1$ is thus equal to 0.05. We then calculate the number of rejections r_g for every category of projects, g. We report Prob(number of rejections $\geq r_g$),

[16] This result holds when bid distribution is estimated separately from the cost of entry distribution, i.e., when the assumption of the entry model is not imposed in the estimation.

the p-value of our test at the project category level, in Table 6.

We find that with a two-sided alternative we reject the equality of means (and standard deviations) across bidder groups for every category of projects. We, therefore, do not report the results of this test in the table. The tests with one-sided hypotheses are more interesting. We can reject an equality of means of the project cost distributions in favor of small bidders having a higher mean relative to large bidders for most categories. For rural road work and small rural other work, however, we reject the null of equal means in favor of small bidders having lower mean project costs than large bidders. We also reject the null of equal standard deviations in favor of small firms bidders having lower standard deviations than large bidders for all project categories. There are thus important project cost differences between small and large firms. However, small firms are not always weaker players in the market. With several exceptions[17], empirical auction studies rely on the assumption of symmetric bidders. In this paper, we document significant, and at times unexpected, differences between bidder groups here. Such cost differences are important in our application since the use of discrimination has the potential to restore efficiency in environments with asymmetric bidders.

Next, we turn to the estimated coefficients for the cost of entry distribution reported in Table 7. All coefficients have the expected signs and are statistically significantly different from zero. We have also estimated specifications that include conditional moments based on the type of work and location in addition to size classes. We use these additional moments to perform a test of overidentifying restrictions. The overidentifying restrictions could not be rejected on the basis of our estimates and the estimated parameters vary little across specifications.

Table 8 reports the fit for our base specification. The top panel shows the fit for the moments that we use in the estimation. The lower panel reports average and predicted numbers of actual bidders for other project groupings that were not used to form moment conditions in estimation. While the literature has not established a benchmark for assessing the fit of the entry part of our model, our fit appears to be good.

Table 9 reports the implied mean cost of entry and mean cost as a fraction of the engineer's estimate across bidder groups and project size categories. We estimate that mean entry costs amount to 2.7% to 3.7% of the engineer's estimate. This ratio increases with project size for small bidders but decreases in size for large bidders. Our estimates are

[17] For example, Bajari (2001), Athey et al. (2008), Jofre-Bonet and Pesendorfer (2003), and Asker (2009).

comparable to estimates obtained in the academic literature (Bajari, Hong and Ryan 2008) and suggested magnitudes from general construction manuals.[18] We also test the equality of the two groups' cost of entry distributions. We reject equality for all but one project size category. The results of the test are reported in the last column of Table 9.

6 Counterfactual Analysis

We use the estimation results to assess the effect of the preferential treatment of small firms on participation, the cost to the government, and the probability that a project is awarded to a small firm. After a brief overview of the counterfactual approach, we first contrast the outcomes of a discriminatory auction under endogenous and fixed participation under a wide range of discount values. This further allows us to investigate whether a bid discount could serve as an effective tool to lower the government's cost of procurement or to achieve the State's allocative goals. Due to the computational cost of numerically deriving equilibrium bidding strategies, we do so for select representative projects only. We then study the current program as a detailed example of policy effects at a relatively low discount level, before considering an entry tax or subsidy as a preferential treatment mechanism that targets the participation margin directly.

Methodology. To compare behavior in alternative environments, we need to derive the appropriate bidding strategies that solve the system of differential equations defined by the first-order conditions in Equation (2). Except for special cases, this system of differential equations does not have a closed-form solution and has to be solved numerically. We apply and extend the method proposed by Marshall, Meurer, Richard and Stromquist (1994) to our setting.[19]

[18] Halpin (2005) and others suggest that estimating costs (cost of time and effort expended to develop a total bid price and submit a proposal) typically range between 0.25% and 2% of the total project cost, but vary widely depending on the complexity, type of job, and type of work being estimated.

[19] Bajari (2001) and Marshall et al. (1994) provide details on numerical solution algorithms for asymmetric auctions. Marshall et al. (1994) use polynomial approximations to the cost distributions and employ a forward recursive algorithm to solve the resulting set of difference equations with an upper boundary condition. We extend their approach as follows. We embed the recursive algorithm in a search routine for a starting point that satisfies the upper boundary conditions. We approximate the estimated cost distributions by polynomial splines, which we found to produce more stable results than the original Taylor approximations. Finally, we extend their setup in which a single asymmetric bidder competes against a second group of bidders to settings with arbitrary numbers of bidders within the two groups, which entails solving a larger-dimensional system of differential equations.

As a performance check, we initially compare the simulated entry probabilities for the 5% discount level to the entry probabilities implied by our estimation routine. The estimation routine computes expected profits conditional on participation using the observed bid distributions directly (see Eyakime et al. (1993)), thus avoiding the simulation step. The simulation routine produces entry probabilties that match closely the ones used in estimation. Table A-1 in the Appendix contains a detailed comparison by project category.

The Role of Participation. We use the numerical routine to simulate auction outcomes under a large set of discount values for five typical projects that vary in small and large firms' relative project and entry costs.[20] We consider two scenarios, in (1) we hold participation fixed at the zero discount level, and in (2) we allow participation to adjust with the discount level. Figure 2 illustrates for two most typical (yet very dissimilar) types of projects the changes that participation adjustments introduce to the relationship between the discount and auction outcomes, such as the cost of procurement (or the expected winning bid), the small-firm probability of winning, and the expected numbers of bidders. Both the probability of small-firm award and the cost of procurement have flatter profiles under fixed than under endogenous participation. The fixed participation case isolates the response of bidding strategies to alternative discount levels. With endogenous entry, the bid response is enhanced through a decline in large-firm and an increase in small-firm participation associated with increasing discount to small firms. Hence, the probability of small-firm award rises not only because a given small bidder's probability of winning increases, but also because the proportion of small participants increases. In turn, the cost of procurement increases as a higher proportion of contracts is awarded to small bidders who charge higher prices due to their high costs and the bid discount. The fixed and endogenous participation scenarios also differ in their implications for the discount levels needed to achieve procurement cost minimizing or allocative goals.

As shown in Figure 2, the implications of accounting for endogenous participation are quite different for the two projects because they are characterized by different degrees of asymmetry between small and large bidders. Project 2 belongs to a group of projects where small firms' project and entry costs are very similar to the costs of large bidders. In addition, in these projects the variances of the project costs distributions tend to be lower than for the average project. As a result, a non-negligible share of large bidders is priced out of the auction and chooses not to bid once they observe their project cost. This effect,

[20]In this analysis negative discounts correspond to discounts given to large bidders whereas positive values correspond to discounts given to small bidders.

which is significant for this group of projects, largely mimics the participation adjustment effect. As a result, the relationships under fixed and endogenous participation are similar. Most small projects, and medium rural road work projects, share these properties.

In contrast, project 1 is exemplary of medium and large urban projects where small firms are the less efficient group in both entry and project costs. Because of substantial asymmetry there is unlikely to be a significant mass of large bidders whose bid is beaten by all, including the highest-cost, small bidders. That is why the share of large bidders dropping out after observing their project costs is much smaller relative to the case of project 2. This implies that under fixed participation the group of viable bidders does not change very much as the discount level changes. This effect underlies the stark differences between the two projects' outcomes.

Cost-Minimizing Discount. We use the five projects to explore the potential of a bid discount to lower the cost of procurement. Table 10 shows that the model with fixed participation prescribes 10% and 15% discounts to small bidders for projects 1 and 5 where small firms have higher project costs. Discounts of 10%, 15%, and 22% to large bidders for projects 2, 3, and 4, respectively, minimize government cost since large bidders are less efficient for these projects. In contrast, the cost-minimizing policy that takes participation adjustments into account does not generally favor the group with the highest project costs, but reflects entry cost differences as well. It implies that very high discounts should be given to large firms (which would induce small firms not to participate) on projects 1 and 5; that a 10% discount should be given to large firms on project 2 and small firms on project 3; and that no discount should be awarded to either firm type on project 4. It is worth noting that if the government followed the prescriptions of the fixed-participation model, the cost of procurement would increase rather than decrease in four out of the five cases after participation adjusts.

Under the model with participation adjustment the program affects not only bidding behavior but also the composition of bidders' set. The bid preference generates the highest cost savings to the government for projects 1 and 5 where small firms' project and entry costs are much higher than the corresponding costs of large firms. In these projects the bid discount does not affect firms' bidding behavior because the policy effectively excludes small firms from the auction. Instead, an auction without the threat of participation by inefficient small firms attracts a sufficient number of large bidders to lower the government's cost through the increased competitive pressure that large firms impose on each other. Similarly, for project 3, small firms have lower average project costs, but face higher entry costs. The government's cost-minimizing strategy promotes their participation, which lowers the winning bid through the change in the composition of the set of actual bidders.

Other Discount Levels. Most preference programs pursue goals other than pure cost minimization and therefore are likely to produce procurement cost increases. As Figure 2 indicates, such increases can be quite large, ranging for both projects from 1% for discounts as low as 10% to as much as 5% with higher discounts of 40%.

We assess the likely magnitudes of cost increases associated with the preference programs' objectives using the allocation goal of the California Small Business Preference program as an example. The second panel of Table 10 reports the discount rates necessary to achieve this goal and the associated cost increases for the five projects discussed earlier. The resulting cost increase range from 0% to 2.3%, with the largest increases being associated with projects where small bidders are substantially less efficient than large bidders (in either project or entry costs). Significantly, the fixed participation model suggests that a much higher (by a factor of two) discount level should be used. Choosing this discount level without recognizing the changed participation incentives is costly: procurement costs rise by approximately 7% across projects.

Given the heterogeneity of cost asymmetries across projects in the data, we also compute an aggregate measure of the cost of allocating 25% of the State's procurement load to small firms. We find that a 13% discount approximately satisfies the aggregate award goal (see Table 11). This results in an approximate increase of 1.2% in the cost of procurement relative to no government intervention.[21] In contrast, if we held participation fixed, we would conclude that a much higher discount of 35% is needed to achieve the allocative goal. The model with fixed participation substantially underestimates the cost increase associated with this discount level predicting that the cost would go up by only 1.5%. This assessment ignores participation effects, which would bring the cost increase to 4.5%.

The modest aggregate cost increase for discount levels prescribed by the endogenous participation model reflects the composition of projects in the data, which contain a significant share of projects similar to project 2. In these projects small firms are efficient

[21] We find δ that sets, across projects J, $\sum_j p^{win}_{sm,j}(\delta) EngEst_j = 0.25 \sum_j EngEst_j$, where $p^{win}_{sm,j}$ denotes the small-firm probability of winning auction j. We approximate the probability of winning for each individual project by the equivalent for a representative project in its project category (for project categories, see Table 12). We similarly approximate the cost of procurement for a given project by the cost for the representative project.

competitors and have a high award rate even in the absence of a discount. It seems that the government could reduce its cost of procurement even further by granting discounts only for projects where small bidders are typically inefficient and thus have low participation and award rates.

Evaluation of Current Policy. Next we turn to an analysis of the bid preference program currently in place in California, which uses a relatively low discount of 5%. We compare auction outcomes in the current environment to the counterfactual setting where the state does not use a preference program and instead treats bidders equally. Tables 12 and 13 contain the results of this analysis. We simulate auction outcomes for a larger subset of 119 projects to capture project heterogeneity more finely based on project size, location, and type of work.[22]

Table 12 reports changes in the cost to the government measured as an expected winning bid. The cost to the government does not change very much as a result of the preferential treatment of small bidders. While the cost to the government goes up in some cases and goes down in others, these effects barely amount to 0.5% change for all project categories as well as for most individual projects.

Table 13 compares probabilities of entry by project category. The preferential treatment produces the expected increased small-firm and reduced large-firm participation. The magnitudes of these effects are economically significant, however, and differ substantially across project categories. Small-firm entry probabilities increase by between 2 and 8 percentage points, or 3.1% and 20%, while large-firm entry probabilities decline by between 3 and 6 percentage points, or 4.3% and 10.6%. The changes in the groups' participation are close to off-setting, however: total entry is virtually unchanged across project categories, with increases or decreases in overall participation of only approximately 1%.

The participation effects contribute significantly to the increase in small firms' probabilities of winning. As Table 14 shows, the change in probability of winning under endogenous participation is twice the change generated by the discount only (under fixed participation). Finally, the program also increases small potential bidder's expected profit prior to participating by 9% to 25%, with an average of 16%, while decreasing large firms' profits by 10% to 18%, with an average of 13% (see Table 12). The preferential treatment thus results in a non-trivial redistribution of profits from large to small firms at almost no cost to the government.

[22]Ten projects in each category and all nine projects for large rural other work projects.

The changes in entry and profits differ substantially in magnitude across project types. Two potential sources of such differences are (1) variation in cost asymmetries and (2) differences in market thickness, or the number of potential bidders. We investigate how these factors affect the magnitude of the program's impact on small bidders' participation in Table 15. The table reports the results of an OLS projection of the absolute change in small bidders' probability of entry on project characteristics, potential entry, and the moments of the two groups' entry and project cost distributions. The results suggest that small-firm participation responds more strongly in larger projects, for projects where small firms have lower average project costs than large firms, and for projects where the within-group variation in entry costs is lower, in particular for large firms. Last, the program has stronger effects for projects with fewer small potential bidders, but a higher number of large potential bidders. These effects are intuitive. Larger projects produce a larger absolute gain from the program that offsets entry costs. Low variance of the entry cost distribution implies that a given change in expected profit from participating affects the entry behavior of a larger mass of firms. The number of potential bidders reflects the competitive intensity and the size of the set over which the program's profit gains or losses are divided.

The second specification in Table 15 shows that after controlling for small firms' base probability of entry at $\delta = 0$, only project costs and potential competition play a statistically significant, now larger, role in promoting participation. The results also indicate that gains in small-firm participation are larger in projects where their participation would have been low in the absence of preferential treatment. The program thus appears to be more effective for projects where participation of small firms is impeded without preferential treatment.

This analysis is related to Marion (2007a) who provides an alternative estimate of the effect of the California Small Business Preference program on the cost of procurement. He measures this effect by comparing a set of state-funded projects where the program is implemented to a set of federally-funded projects. He finds that the average winning bid on state-funded projects exceeds that on federally funded projects by 3.8%. Attributing this difference to the program is complicated by the fact that federally funded projects have another preferential treatment program in place that restricts bidders' subcontracting choices. In addition, federally and state-funded projects differ along observable dimensions, suggesting that they may also differ on unobservable characteristics that would affect firms' cost distributions and, thus, the magnitudes of the effects of a preference program. If this is the case, the difference in participation patterns also would not reflect the changes in participation brought forth by the program.

Subsidy. Our analysis so far shows that increases in small-firm participation translate into increases in the group's probability of project award. This additional effect is often stronger than the direct effect of the discount, which works though the change in bidding strategies. Our analysis further suggests that differences in bid preparation costs contribute significantly to the difference in participation rates across bidder groups. Hence, a direct entry subsidy of small firms (or tax of large firms) could alternatively help to achieve small-firm award goals. A subsidy would increase the cost of procurement to the government, whereas a tax may reduce government outlays.

Table 16 summarizes lump-sum subsidy or tax policies that achieve alternative government goals for the five sample projects discussed in the beginning of the section. We find that the unconstrained cost-minimizing policy (panel 1) involves taxing both groups.[23] It reflects the trade-off between tax rate and tax base: higher tax rates increase per-firm tax receipts, but lower participation, putting upward pressure on the expected winning bid. The government minimizes its cost of procurement by choosing tax rates so only the more efficient group participates in bidding, where efficiency reflects both project and entry costs. For a detailed, graphical example of the relationship between the tax and the total cost of procurement, see Figure A-3 in the Appendix.

We next turn to a policy that achieves California's goal of allocating 25% of procurement dollars to small firms (see panel 2 of Table 16). A subsidy to small firms that achieves this objective is less costly to the government than the equivalent bid discount. It realizes cost savings of 8% on average relative to a bid discount that achieves the same small-firm award rate. These cost savings are realized in part by taxing large firms and come at the cost of substantially lowering that group's profits, which decline by between 25% to 100% relative to the bid discount case.

Since such high penalties on large firms may be undesirable, we consider an alternative scheme that achieves the small-firm award goals, but also limits the large-firm profit reductions to those under the bid discount with identical award levels. For all five projects, such a policy is feasible. In all cases, it results in procurement cost savings over the bid discount policy (see panel 3 in Table 16). This implies that the government can achieve the same small-firm award rate at lower cost, even without additional harm to large firms.

These savings arise because subsidies and taxes do not depend on firms' project cost

[23] With high tax levels, participation may drop to zero. In our simulations, we assume that the cost to the government of a non-award is equal to the engineer's estimate.

realizations. In contrast, the bid discount disproportionately rewards firms with high project costs that raise their bids by the highest absolute amount and increase their probability of winning most. A subsidy or tax, by targeting the extensive participation margin only, eliminates these distortions, resulting in a lower cost of procurement. It provides incentives for firms to submit uncompetitive bids for the sole purpose of collecting the subsidy payments, however. To avoid this, the subsidy should be awarded only to the winning bidder, while a tax can be applied to all entrants from the taxed group. The subsidy level has to be adjusted to account for this modification. However, the magnitudes of all effects remain unchanged.

7 Conclusion

This paper provides evidence based on the California Small Business Preference program on the channels through which bid discounts affect procurement outcomes, separating adjustments in firms' participation behavior from those in their bidding decisions. Within our empirical context, we find that the response in firms' bidding behavior(conditional on participation) to alternative discount levels changes aggregate procurement costs only by a limited amount relative to more substantial changes resulting from participation adjustments. This is of critical importance to policy design; we show, for example, that taking firms' participation incentives into account alters the bid discounts that achieve the government's procurement goals and the assessment of the costs increases associated with different discount levels.

California's current program generates only small increases in procurement costs. While promoting small-firm participation - at the expense of large-firm participation and profit, it does not achieve the State's allocative goal. Our results imply that for the set of projects in our data, a higher discount of 13% is needed to reach the allocative target. This discount level does not come at substantial cost increases, however, raising the aggregate cost of procurement by 1.2% relative to no intervention. It is important to note that these results depend crucially on the mix of projects in California highway procurement market. In other markets allocative goals may lead to larger or smaller cost increases.

We consider the cost implications of broader policy re-design. In line with theoretical predictions for environments with fixed participation, we find that a bid discount can be used to lower the government's cost of procurement. If the degree of cost asymmetries between small and large firms is high, the cost-minimizing auction design prevents the inefficient group

- typically small firms - from participating by granting a large discount to the other group. Since projects where small firms are very inefficient are easily identifiable by observable attributes, for these projects the government may prefer to use the set-aside auctions common in the timber industry. In our dataset, however, even the cost-minimizing discount generates only modest cost reductions, while discounts that depart from this level - but remain within the range of typically used bid discounts - can result in significant cost increases for at least a subset of projects.

We find large heterogeneity in the effect of the bid discount across types of projects. This suggests that the government should optimally employ more nuanced preferential treatment, tailoring the discount rate to the project type, similar to the approach taken by the FCC. This can result in substantial cost savings while facilitating the implementation of the State's participation goals.

Our findings suggest further that a lump-sum entry fee is more effective than a bid discount at reducing the cost of procurement. We also show that a moderate fee is sufficient to achieve the program's award goal at the same large-firm profit levels as a bid discount with the same award outcomes, while still bringing about an important reduction in the cost of procurement.

Our results demonstrate that a preference program evaluation depends critically on capturing firms' participation responses to the policy. While our findings are based on the highway procurement market, we believe that this insight, as well as our technique for predicting participation responses, is pertinent to other auction markets where discriminatory policies are used. We focus on the short-run effects of the program. Future research is needed to assess its dynamic, long-run implications, including adjustments to the set of potential bidders, which we hold fixed throughout our analysis.

References

Asker, John, "A Study of the Internal Organisation of a Bidding Cartel," *American Economic Review*, 2009. Forthcoming.

Athey, Susan, Jonathan Levin, and Enrique Seira, "Comparing Open and Sealed Bid Auctions: Theory and Evidence from Timber Auctions," Working Paper, Harvard University 2008.

Ayres, Ian and Peter Cramton, "Deficit Reduction Through Diversity: How Affirmative Action at the FCC Increased Auction Competition," *Stanford Law Review*, 1996, *48* (4), 761–815.

Bajari, Patrick, "Comparing competition and collusion: a numerical approach," *Economic Theory*, 2001, *18* (1), 187–205.

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

___**, Han Hong, and Stephen Ryan**, "Identification and Estimation of a Discrete Game of Complete Information," Working Paper, University of Minnesota 2008.

___**, Stephanie Houghton, and Steve Tadelis**, "Bidding for Incomplete Contracts: An Empirical Analysis of Adaptation Costs," Working Paper, University of Minnesota 2007.

Corns, Allan and Andrew Schotter, "Can Affirmative Action Be Cost Effective? An Experimental Examination of Price-Preference Auctions," *American Economic Review*, 1999, *89*, 291–305.

Denes, Thomas A., "Do Small Business Set-Asides Increase the Cost of Government Contracting?," *Public Administration Review*, 1997, *57* (5), 441–444.

Eyakime, Bernard, Jean-Jacques Laffont, Patrice Loisel, and Quang Vuong, "First-Price Sealed-Bid Auctions with Secret Reservation Prices," *IDEI Working Paper Series*, 1993, *27.*

Halpin, Daniel, *Construction Management, 3rd Edition*, Wiley, November 2005.

Hong, Han and Matthew Shum, "Increasing Competition and the Winner's Curse: Evidence from Procurement," *Review of Economic Studies*, 2002, *69* (4), 871–898.

Jofre-Bonet, Mireia and Martin Pesendorfer, "Estimation of a Dynamic Auction Game," *Econometrica*, 2003, *71* (5), 1443–1489.

Krasnokutskaya, Elena, "Identification and Estimation in Highway Procurement Auctions under Unobserved Auction Heterogeneity," Working Paper, University of Pennsylvania May 2004.

Levin, Dan and James L. Smith, "Equilibrium in Auctions with Entry," *American Economic Review*, 1994, *84* (3), 585–599.

Li, Tong and Xiaoyong Zheng, "Entry and Competition Effects in First-Price Auctions: Theory and Evidence from Procurement Auctions," *Review of Economic Studies*, 2008. Forthcoming.

Marion, Justin, "Are bid preferences benign? The effect of small business subsidies in highway procurement auctions," *Journal of Public Economics*, 2007, *91* (7-8), 1591–1624.

——, "How Costly is Affirmative Action? Government Contracting and California's Proposition 209," *Review of Economics and Statistics*, 2007. Forthcoming.

Marmer, Vaden, Art Shneyerov, and Pai Xu, "What Model for Entry in First-Price Auctions? A Nonparametric Approach," Working Paper, University of British Columbia 2007.

Marshall, Robert C., Michael J. Meurer, Jean-Francois Richard, and Walter Stromquist, "Numerical Analysis of Asymmetric First Price Auctions," *Games and Economic Behavior*, 1994, *7* (2), 193–220.

McAfee, R. Preston and John McMillan, "Government procurement and international trade," *Journal of International Economics*, 1989, *26* (3/4), 291–308.

Porter, Robert H. and J. Douglas Zona, "Detection of Bid Rigging in Procurement Auctions," *Journal of Political Economy*, 1993, *101* (3), 518–538.

Reny, Philip J. and Shmuel Zamir, "On the Existence of Pure Strategy Monotone Equilibria in Asymmetric First-Price Auctions," *Econometrica*, 2004, *72* (4), 1105–1125.

Samuelson, William F., “Competitive bidding with entry costs,” *Economics Letters*, 1985, *17* (1-2), 53–57.

Tables and Figures

Table 1: Summary Statistics, Caltrans Projects and Bidders

	Mean	Std. Dev.	10^{th} Pctile	Median	90^{th} Pctile
Engineer's estimate	615.416	738.560	165.250	464.130	1086
Working days	96.598	165.071	20	45	180
N^o of small plan holders	3.947	3.485	0	3	9
N^o of large plan holders	6.574	4.324	3	5	11
N^o of small bidders	1.745	1.890	0	1	4
N^o of large bidders	2.623	1.597	1	3	5
Small projects (n=229; median engineer's estimate=$207,000)					
N^o of small plan holders	4.886	3.656			
N^o of large plan holders	5.904	3.501			
N^o of small bidders	2.502	2.137			
N^o of large bidders	2.349	1.652			
Medium projects (n=235; median engineer's estimate=$464,000)					
N^o of small plan holders	4.260	3.536			
N^o of large plan holders	6.723	3.922			
N^o of small bidders	1.762	1.882			
N^o of large bidders	2.668	1.561			
Large projects (n=233; median engineer's estimate=$787,186)					
N^o of small plan holders	2.714	2.829			
N^o of large plan holders	7.651	6.649			
N^o of small bidders	0.954	1.219			
N^o of large bidders	2.929	1.645			

Note: 697 projects. Engineer's estimate reported in $1000s and duration in days.
Small projects denote the bottom one-third, medium projects the middle one-third, and large projects the top one-third of engineer's estimates. Plan holders are our measure of potential entrants.

Table 2: Discrete Choice Model of the Decision to Bid

	Coefficient	Std Error	Marg. Effect
ln(Eng. Estimate) × LB	0.0563	0.0291	0.0223
Working Days × LB	-0.0300	0.0170	-0.0119
N^o of large plan holders × LB	-0.0537***	0.0136	-0.0213
N^o of small plan holders × LB	-0.0944***	0.0089	-0.0374
ln(Eng. Estimate) × SB	-0.1458***	0.0338	-0.0578
Working Days × SB	0.0538***	0.0144	0.0213
N^o of large plan holders × SB	-0.0412***	0.0074	-0.0163
N^o of small plan holders × SB	-0.0783***	0.0081	-0.0310
Rural district × Road repair × SB	-0.7594***	0.1488	-0.2724
Rural district × Other work × SB	-0.6199***	0.1609	-0.2273
Urban district × Road repair × SB	-0.8823***	0.1466	-0.3135
Urban district × Other work × SB	-0.7030***	0.1619	-0.2554
Rural district × Road repair × LB	0.2898*	0.1366	0.1152
Rural district × Other work × LB	0.2282	0.1804	0.0909
Urban district × Road repair × LB	0.2516	0.1490	0.1000
Urban district × Other work × LB	0.2062	0.1605	0.0821
Observations	6538		

Dependent Variable: indicator of participation decision. Year and month effects included. Number of competing bidders included to control for unobserved project characteristics. Standard errors account for clustering at the project level. LB denotes a large firm; SB a small firm. Road repair includes bridge projects. * p<0.10, ** p<0.05,*** p<0.01.

Table 3: Ordinary Least Squares Model of Submitted Bid

	Coefficient	Std Error
Small-firm indicator	0.0813	0.0357**
ln(Eng. Estimate)	0.9571	0.0127***
Working Days	0.0002	0.0001***
N^o of small bidders	-0.0320	0.0074***
N^o of large bidders	-0.0329	0.0069***
N^o of small plan holders	0.0097	0.0041**
N^o of large plan holders	0.0190	0.0038***

Observations: 3034. Adjusted R^2: 0.8996. Dependent Variable: log of submitted bid. Controls for year, month, districts, and type of work by bidder type included. Standard errors account for clustering at the project level. * p<0.10, ** p<0.05, *** p<0.01.

Table 4: Estimated Parameters of Log-Normal Distribution of Bids

	Coefficient	Std Error
Constant	0.0367	0.0410
Small-firm indicator	0.0767	0.0253***
ln(Engineer's Estimate)	0.9528	0.0087***
Working Days	0.0001	4.25E-5***
N^o of small bidders	-0.0328	0.0045***
N^o of large bidders	-0.0344	0.0038***
N^o of small plan holders	0.0009	0.0026
N^o of large plan holders	0.0018	0.0022
Type of work		
Bridge	-0.1369	0.0182***
Landscaping	-0.1299	0.0212***
Road Repair	-0.0618	0.0147***
Signs, Signals, Lighting	0.0343	0.0245
Location of work		
Central Coast	-0.0265	0.0306
East Central	0.0907	0.0467*
Los Angeles	-0.0072	0.0261
North Central	0.0567	0.0338*
North Coast	0.0322	0.0333
Northern Sierras	0.0484	0.0291*
San Bernardino	0.0097	0.0284
San Diego	-0.0690	0.0303**
San Francisco	-0.0157	0.0266
South Central	0.0956	0.0302***
Southern Sierras	-0.0123	0.0380
North Central × Small	-0.1027	0.0325***
North Coast × Small	-0.0744	0.0337**
South Central × Small	-0.1072	0.0311***
Southern Sierras × Small	-0.0922	0.0419**
Std. dev. of log-bids[1]		
Constant	-1.1525	0.0356***
Small-firm indicator	-0.1188	0.0296***
Engineer's estimate	-0.2606	0.0244***
Std. dev. of unobs. proj. char., σ_u	0.1433	0.0109***

3,034 observations. Specification includes year and month effects by bidder type. Log-bids and the log of the unobserved project heterogeneity are assumed to be normally distributed.

[1] Standard deviation of log-bids estimated as $\sigma=\exp(b_0 + b_1\text{Small}+b_2\text{Engineer's Estimate})$.

* p<0.10, ** p<0.05, *** p<0.01.

Table 5: Estimated Project Costs by Project Type

		Mean		Std. Dev.	
		Small	Large	Small	Large
Project Type	# proj	Bidder	Bidder	Bidder	Bidder
Small, rural, rd repair / bridge	50	0.8910	0.9540	0.3034	0.3075
Medium, rural, rd repair / bridge	59	0.8917	0.9288	0.2355	0.2435
Large, rural, rd repair / bridge	55	0.8570	0.9062	0.2141	0.2144
Small, urban, rd repair / bridge	73	0.9601	0.9375	0.3035	0.3202
Medium, urban, rd repair / bridge	89	0.9696	0.9435	0.2290	0.2428
Large, urban, rd repair / bridge	88	0.9481	0.9333	0.1998	0.2099
Small, rural, other work	39	0.9518	1.0101	0.3025	0.3121
Medium, rural, other work	13	0.9342	0.9581	0.2059	0.2234
Large, rural, other work	9	0.8192	0.8292	0.1320	0.1594
Small, urban, other work	55	1.0401	1.0084	0.3114	0.3300
Medium, urban, other work	51	0.9683	0.9542	0.2462	0.2579
Large, urban, other work	35	0.9916	0.9850	0.2112	0.2237

Means and standard deviations of project costs are averaged across projects of within project type and scaled by the engineer's estimate before averaging.

Table 6: Summary of Tests of Equality of Means of Cost Distributions by Project Type

		H_1:sm>lg		H_1:sm<lg		
Project Type	# proj	# rej	Pr(# rej)	# rej	Pr(# rej)	conclusion
Small, rural, rd repair / bridge	50	1	0.92	28	0.00	sm<lg
Medium, rural, rd repair / bridge	59	7	0.13	22	0.00	sm<lg
Large, rural, rd repair / bridge	55	7	0.12	16	0.00	sm<lg
Small, urban, rd repair / bridge	73	35	0.00	4	0.50	sm>lg
Medium, urban, rd repair / bridge	89	44	0.00	2	0.94	sm>lg
Large, urban, rd repair / bridge	88	31	0.00	1	0.99	sm>lg
Small, rural, other work	39	4	0.13	26	0.00	sm<lg
Medium, rural, other work	12	3	0.02	2	0.12	sm>lg
Large, rural, other work	9	3	0.01	1	0.37	sm>lg
Small, urban, other work	55	33	0.00	6	0.16	sm>lg
Medium, urban, other work	51	25	0.00	3	0.47	sm>lg
Large, urban, other work	35	10	0.00	0	0.17	sm>lg

Columns 2 and 4 contain the count of projects for which we reject with 95% confidence the null hypothesis of equality of mean costs against the stated alternatives. Columns 3 and 5 contain the binomial probability of observing that number of rejections or more. Similar tests for the difference in the estimated standard deviations yield rejections of the null hypothesis in favor of the standard deviation of small-firm costs being smaller than that of large-firm costs at above 99% levels of confidence.

Table 7: Estimated Parameters of Truncated Normal Distribution of Entry Costs

	Coefficient	Std Error
Small-firm indicator	-0.7111	0.0515***
(ln(Eng. Estimate))×Small firm	0.4740	0.0277***
Large-firm indicator	-0.4438	0.0436***
(ln(Eng. Estimate))×Large firm	0.2958	0.0226***
Standard deviation ×Small firm	0.1798	0.0069***
Standard deviation ×Large firm	0.1620	0.0071***

1,313 observations. *$p<0.10$, ** $p<0.05$, *** $p<0.01$.

The estimated specification allows for unobserved heterogeneity in the bid distribution, the estimated parameters are recorded in Table 4.

Table 8: Model Fit: Entry Predictions by Project Type

	Number	Small firms		Large firms	
	of projects	Predicted	Actual	Predicted	Actual
Moment conditions: number of bidders					
Small projects	229	2.5688	2.5616	2.3919	2.3877
Medium projects	235	1.8991	1.8962	2.6996	2.6766
Large projects	233	1.2067	1.2222	2.8167	2.8528
Out of sample fit: number of bidders					
Bridge projects	70	1.9592	2.0714	2.3929	2.9286
Road-repair projects	420	1.6379	1.5578	2.8178	2.8565
Small & road-repair projects	107	2.5287	2.2844	1.9103	2.3527
Medium & road-repair projects	143	1.5805	1.7215	3.0694	2.8115
Large & road-repair projects	170	2.1374	2.0612	2.5652	2.6321
Rural projects	258	1.7513	1.6167	2.8171	2.9091
Urban projects	439	1.1491	1.1172	2.9766	2.9527
Out of sample fit: second moments					
Small projects	229	1.9496	2.2449	1.7123	1.7164
Medium projects	233	1.2542	1.5427	1.7264	1.6997
Large projects	235	0.9072	0.9237	2.1296	1.7500

Note: The second moments compare the expectation of the number of small and large bidders squared as predicted by the model to the sample equivalent.

Table 9: Estimated Entry Costs by Project Size

Project Size	Small Firms Avg. Cost	Small Firms SD Cost	Small Firms Cost/ Est	Large Firms Avg. Cost	Large Firms SD Cost	Large Firms Cost/ Est	K-S test (p-val)
Small	6.635	6.020	0.032	7.325	6.420	0.035	0.081 (0.002)
Medium	14.954	11.136	0.032	13.300	9.949	0.029	0.078 (0.004)
Large	27.830	15.466	0.037	20.412	12.720	0.027	0.235 (0.000)

Note: Costs reported in \$1,000s. The K-S test reports the test statistic and corresponding p-value of a Kolmogorov-Smirnov test of the equality of the estimated cost distributions within each size category.

Table 10: Bid Preference Program Designs under Alternative Objectives, Sample Projects

	Project 1	2	3	4	5
(N_{sm}, N_{lg})	(2,3)	(2,4)	(3,3)	(2,4)	(2,4)
Project cost diff.: $\bar{c}_{sm} - \bar{c}_{lg}$	0.50	-0.10	-0.20	-0.40	0.90
Entry cost diff.: $\bar{d}_{sm} - \bar{d}_{lg}$	0.05	-1E-03	0.06	0.18	0.14
Cost to the Government, $\delta = 0$	4.85	1.18	4.68	10.50	8.50
Cost-minimizing Policy					
(1) Endogenous Entry					
δ^E (%)	-90	-10	10	0	-90
Change in Gov. Cost (%)	-1.85	-0.28	-0.32	0	-1.69
(2) Entry fixed at $\delta = 0$-levels					
δ^F (%)	10	-10	-15	-22	15
Change in Gov. Cost under fixed entry (%)	-0.08	-0.22	-1.50	-2.20	-0.50
Change in Gov. Cost under endogenous entry at δ^F (%)	0.65	-0.28	1.80	1.30	0.82
Policy targeting 25% Small-Firm Award Rate					
(1) Endogenous Entry					
δ^E (%)	20	0	0	5	25
Change in Gov. Cost (%)	2.10	0	0	0.50	2.30
(2) Entry fixed at $\delta = 0$-levels					
δ^F (%)	50	0	0	45	40
Change in Gov. Cost under fixed entry (%)	0.52	0	0	1.90	0.94
Change in Gov. Cost under endogenous entry at δ^F (%)	7.00	0	0	6.80	6.70

Note: All costs reported in \$100,000s. Change in government cost computed relative to cost under $\delta = 0$. The change in government cost with endogenous entry in the fixed-participation panels measured the cost change that results from using δ chosen under fixed entry, but allowing participation to respond to the discount. Project 1 is in the category of medium urban road-repair work, project 2 in small rural road-repair work, 3 in medium rural road-repair work, 4 in large urban road-repair work, and 5 in large urban other work.

Table 11: Effect of Discount Level on Aggregate Procurement Cost and Allocation of Work to Small Firms

δ (%)	Agg. Cost to Gov't	Small Firms' % of Work
-25	0.991	4.5
-15	0.994	6.1
-10	0.996	8.2
-5	0.998	11.5
0	1.000	13.4
5	1.005	15.6
10	1.008	20.3
15	1.017	25.8
25	1.036	35.6

Note: The cost to the government is reported as a percent of the cost under no government intervention.

Table 12: Counterfactual Analysis of Preference Program: Comparison of Profit and Government Cost by Project Type

	$\delta = 0$			Avg Change (%) $\delta = 0 \rightarrow 0.05$		
Project type	E[Π_{sm}]	E[Π_{lg}]	E[win bid]	E[Π_{sm}]	E[Π_{lg}]	E[win bid]
Small, rural, rd repair / bridge	0.069	0.059	1.739	16.040	-14.188	0.351
Medium, rural, rd repair / bridge	0.148	0.111	4.225	11.089	-16.712	0.381
Large, rural, rd repair / bridge	0.155	0.201	6.497	10.680	-11.172	0.417
Small, urban, rd repair / bridge	0.043	0.063	1.745	13.753	-13.694	0.103
Medium, urban, rd repair / bridge	0.056	0.137	4.005	22.500	-10.542	0.242
Large, urban, rd repair / bridge	0.141	0.234	6.471	19.190	-14.970	0.470
Small, rural, other work	0.046	0.033	1.799	8.696	-18.485	0.234
Medium, rural, other work	0.120	0.139	4.836	25.000	-11.359	0.010
Small, urban, other work	0.042	0.064	1.998	13.735	-13.064	0.005
Medium, urban, other work	0.064	0.167	4.416	25.197	-10.365	0.168
Large, urban, other work	0.206	0.259	7.830	11.779	-11.292	-0.074

Note: E[Π_{sm}] (E[Π_{lg}]) denote small (large) firms' expected profits. E[win bid] denotes the expected winning bid, which measures the expected cost of procurement to the government. Expected profits and winning bid in \$100,000s.

Table 13: Counterfactual Analysis of Preference Program: Comparison of Predicted Entry by Project Type

	Potential Bidders		$\delta = 0$					Avg Change $\delta = 0 \rightarrow 0.05$				
			Entry Prob		Actual Bidders							
Project type	small	large	p_{sm}	p_{lg}	n_{sm}	n_{lg}	n_{total}	Δp_{sm}	Δp_{lg}	$\%\Delta p_{sm}$	$\%\Delta p_{lg}$	$\%\Delta n_{total}$
Small, rural, rd repair / bridge	3.500	3.500	0.703	0.661	2.420	2.310	4.730	0.034	-0.039	4.895	-6.019	-0.532
Medium, rural, rd repair / bridge	3.714	4.571	0.620	0.586	2.024	2.564	4.588	0.051	-0.042	8.105	-7.338	-0.791
Large, rural, rd repair / bridge	3.143	4.714	0.472	0.636	1.290	2.961	4.251	0.079	-0.050	20.043	-8.552	-0.406
Small, urban, rd repair / bridge	4.250	5.000	0.543	0.648	2.186	2.964	5.150	0.032	-0.029	6.587	-4.306	0.292
Medium, urban, rd repair / bridge	4.667	5.000	0.397	0.655	1.821	3.075	4.896	0.042	-0.033	11.019	-5.111	0.765
Large, urban, rd repair / bridge	4.000	4.000	0.404	0.721	1.516	2.805	4.321	0.056	-0.049	15.418	-6.873	0.383
Small, rural, other work	8.111	4.333	0.553	0.499	4.080	1.940	6.020	0.017	-0.041	3.116	-8.433	-0.576
Medium, rural, other work	6.857	3.143	0.537	0.496	3.309	1.592	4.900	0.020	-0.050	4.311	-10.272	-0.169
Small, urban, other work	6.200	4.300	0.529	0.655	2.968	2.698	5.666	0.027	-0.033	5.279	-5.171	0.245
Medium, urban, other work	4.429	4.571	0.412	0.693	1.713	3.034	4.747	0.047	-0.031	11.553	-4.707	1.092
Large, urban, other work	4.667	3.167	0.518	0.705	2.397	1.813	4.210	0.038	-0.056	8.640	-10.602	0.818

Note: p_{sm} (p_{lg}) denote small (large) firms' entry probabilities. n_{sm}, n_{lg}, and n_{total} denote the expected number of small, large, and total bidders, respectively. Δ denotes absolute changes in going from $\delta = 0$ to $\delta = 0.05$, while $\%\Delta$ denotes percent changes expressed in percentages.

Table 14: Counterfactual Analysis of Preference Program: Small-Firm Award Rate by Project Type

		$\delta = 0.05$	
	$\delta = 0$	Fixed Entry	Endog. Entry
Small, rural, rd repair / bridge	0.461	0.500	0.535
Medium, rural, rd repair / bridge	0.314	0.331	0.349
Large, rural, rd repair / bridge	0.219	0.229	0.243
Small, urban, rd repair / bridge	0.290	0.317	0.330
Medium, urban, rd repair / bridge	0.148	0.160	0.182
Large, urban, rd repair / bridge	0.091	0.101	0.117
Small, rural, other work	0.413	0.435	0.449
Medium, rural, other work	0.174	0.197	0.226
Small, urban, other work	0.312	0.339	0.355
Medium, urban, other work	0.128	0.141	0.161
Large, urban, other work	0.088	0.091	0.099

Note: Column 2 shows average small-firm probabilities of winning when entry is held fixed at the levels under $\delta = 0$. Column 3 shows probabilities of winning when entry is allowed to adjust to the bid discount.

Table 15: Analysis of the Magnitude of Counterfactual Effects: Small Firms' Entry Response

	Coefficient	Std Error	Coefficient	Std Error
Small-Firm Project Cost	0.0450***	0.0091	0.0610***	0.0110
Δ Project Costs	0.0590***	0.0110	0.0800***	0.0140
Small-Firm Entry Cost	1.3700***	0.4200	0.7440	0.5800
Small-Firm Std. Dev. Entry Cost	-8.8200***	3.6300	-4.6600	3.9200
Δ Std. Dev. Entry Costs	-19.1600***	8.3100	-12.1900	8.5400
N^o of small plan holders	-0.0020***	0.0006	-0.0030***	0.0006
N^o of large plan holders	0.0051***	0.0008	0.0050***	0.0007
Prob. entry at δ=0, SB			-0.0340***	0.1400

Note: Dependent variable is the change in the probability of entry for small firms. Δ Costs denotes the difference between large and small costs.

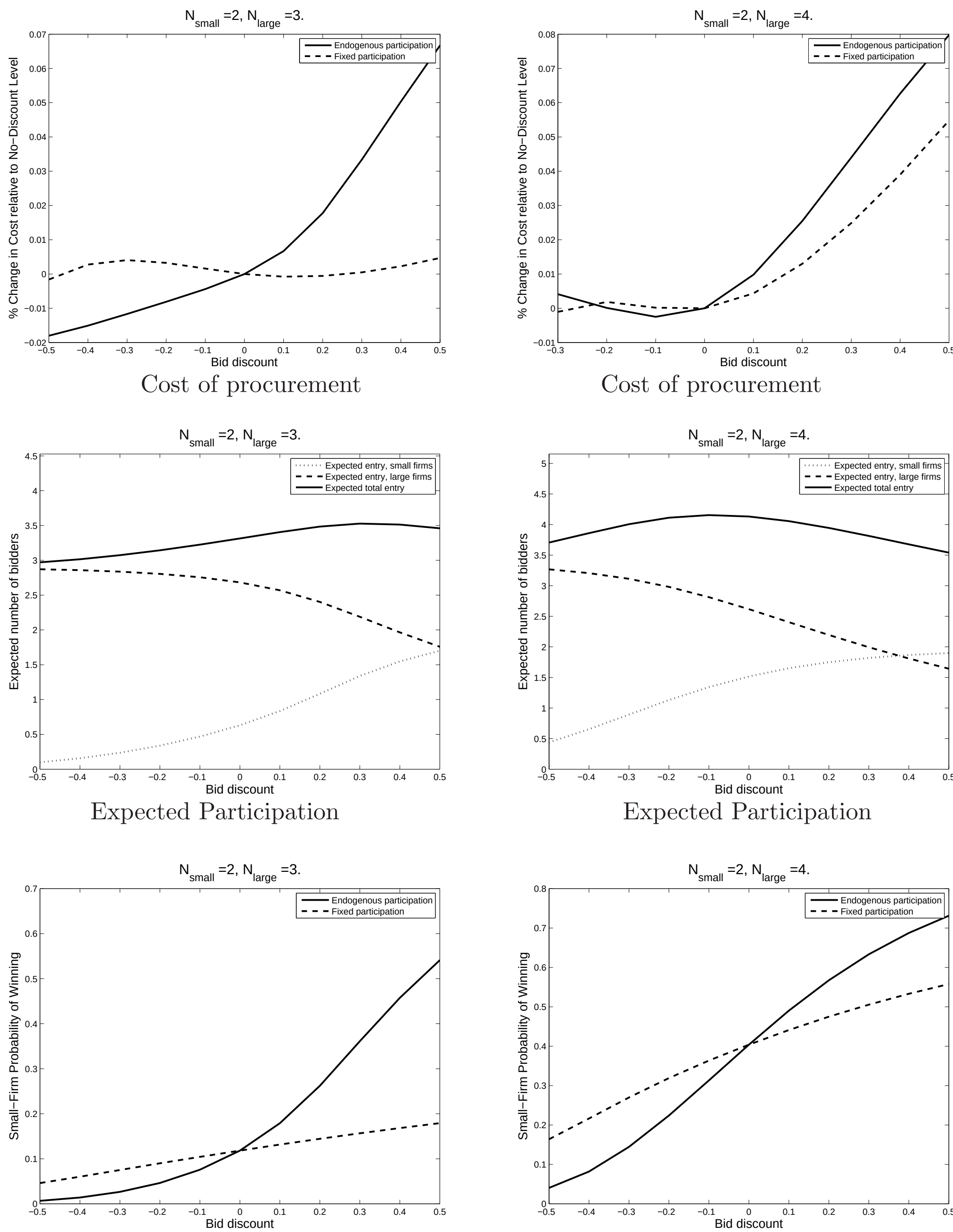
Table 16: Comparison of Alternative Subsidy Programs, Sample Projects

			Project				
			1	2	3	4	5
Optimal subsidy							
	Gov't Cost		4.21	1.03	4.20	9.42	7.67
	Subsidy	Small	-0.39	-0.09	-0.43	-0.62	-0.51
		Large	-0.35	-0.17	-0.31	-0.73	-0.33
	Exp. N^o bidders	Small	0	1.64	0	1.82	0
		Large	1.84	0	1.89	0	2.51
Subsidy targeting small-firm probability of winning							
Case 1	ΔGov't Cost (%)		-7.60	-8.40	-8.01	-8.50	-7.10
	ΔLarge-Firm Profit (%)		-25.60	-100	-33.20	-100	-37.20
	Subsidy	Small	-0.31	-0.09	-0.39	-0.62	-0.28
		Large	-0.41	-0.17	-0.35	-0.73	-0.35
Case 2	ΔGov't Cost (%)		-1.02	-1.27	-1.90	-2.50	-0.75
	ΔLarge-Firm Profit (%)		0	0	0	0	0
	Subsidy	Small	0.01	-0.04	-0.11	0	0.02
		Large	0.10	0.10	0	-0.08	0.05
Benchmarks							
	Gov't Cost ($\delta = 0$)		4.85	1.18	4.79	10.54	8.50
	Gov't Cost (allocation target)		4.95	1.18	4.82	10.6	8.67

Note: The subsidy amounts denote a subsidy payment to an individual firm was it to enter, with negative amounts denoting a tax. Government cost and subsidy payments in \$100,000s.
Case 1 shows subsidy levels that produce a 25% probability of winning for small firms. Case 2 displays subsidy levels which achieve that same small firm probability of winning as above but also constrain large-firm profits to be at least as large as those under a bid discount with a 25% small-firm probability of winning. The changes in costs and expected profits are computed relative to the respective magnitudes under the above bid discount.

Figure 2: Expected Cost and Entry under Alternative Bid Discounts, Sample Projects

(a) Project 1 (b) Project 2



Cost of procurement | Cost of procurement

Expected Participation | Expected Participation

Small Firms' Probability of Winning | Small Firms' Probability of Winning

Negative bid discounts correspond to discounts to large bidders. Information on the projects in Table 10.

Appendix (Not for Publication)

Table A-1: Comparison of Entry Probabilities, Estimation and Simulation Analysis

	Entry Probabilities			
	Estimation		Simulation	
Project type	Small Firms	Large Firms	Small Firms	Large Firms
Small, rural, rd repair / bridge	0.7287	0.5909	0.7377	0.6211
Medium, rural, rd repair / bridge	0.7164	0.5429	0.7018	0.5795
Large, rural, rd repair / bridge	0.6643	0.5492	0.6487	0.5816
Small, urban, rd repair / bridge	0.6196	0.5617	0.6277	0.5924
Medium, urban, rd repair / bridge	0.5590	0.5726	0.5818	0.5996
Large, urban, rd repair / bridge	0.5373	0.5875	0.5624	0.6110
Small, rural, other work	0.5422	0.5546	0.5636	0.5850
Medium, rural, other work	0.5442	0.5409	0.5630	0.5688
Small, urban, other work	0.5362	0.5434	0.5591	0.5730
Medium, urban, other work	0.5223	0.5559	0.5503	0.5810
Large, urban, other work	0.5220	0.5621	0.5507	0.5858

Note: the table compares predicted probabilities of entry generated by our simulation routine with $\delta = 0.05$ and by the estimation procedure. The small discrepancy in the predicted probabilities of entry arises because in the simulation routine, we have to trim the support of the project cost distribution to ensure that the density is sufficiently far away from zero.

Figure A-1: Predicted and Actual Bid Residuals

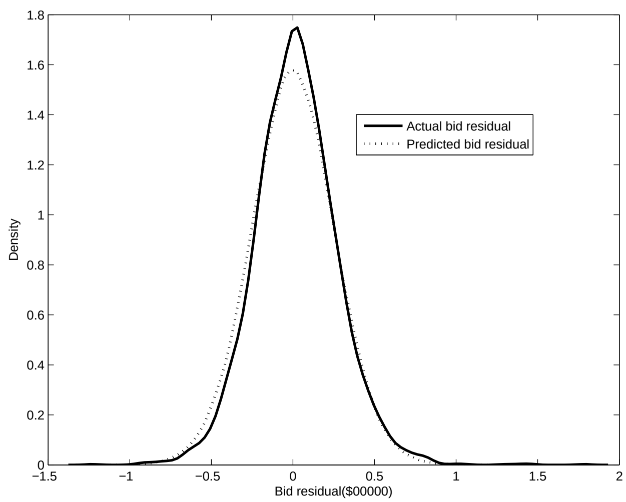
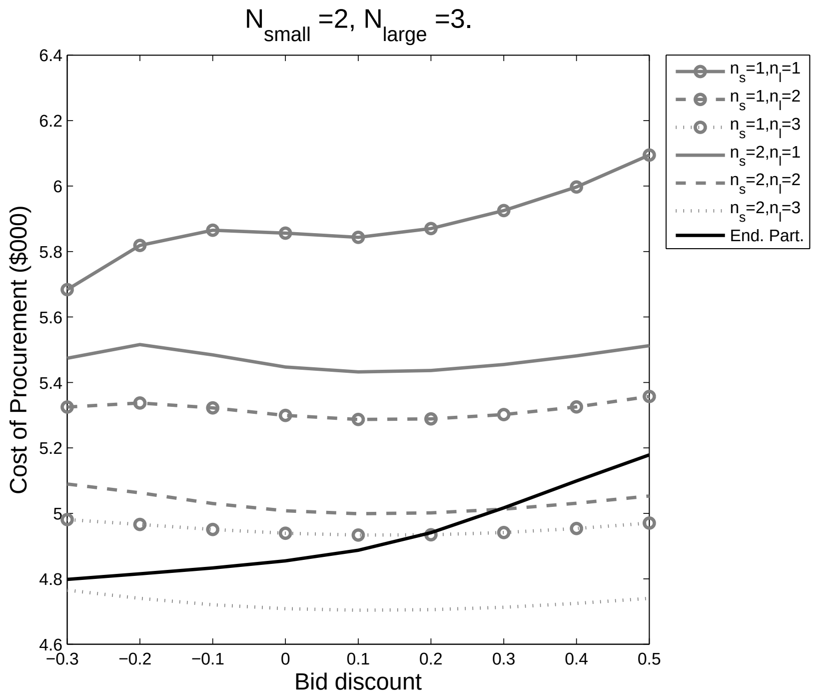
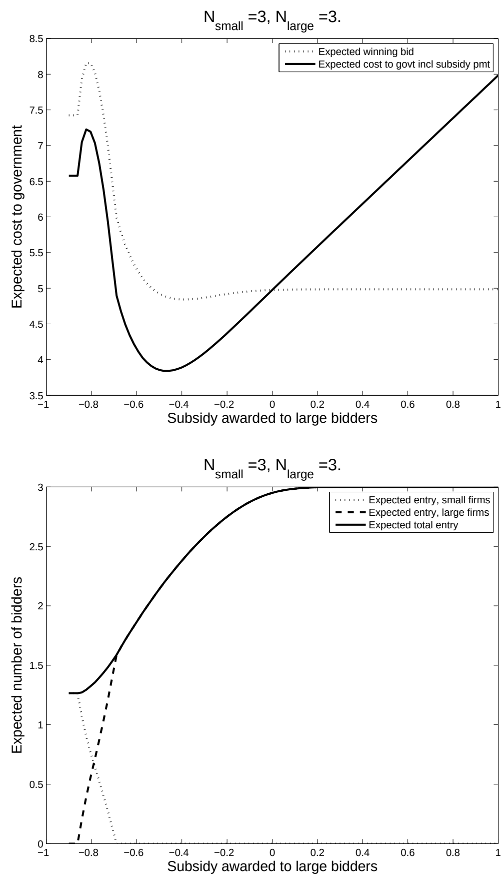


Figure A-2: Expected Cost under Fixed and Endogenous Participation, Sample Project 1



Note: the figure compares the relationship between discount levels and the cost to the government under alternative assumptions on the competitive environment. We depict in gray profiles that arise when regardless of discount, we hold the number of bidders fixed at one of six possible bidder combinations that could arise with 2 small and 3 large potential entrants. We depict in black the profile under endogenous entry. It is steeper than the other profiles, reflecting that as the discount increases, it becomes more likely that the number of bidders is composed of a larger number of small bidders and a lower number of large bidders obtain. These competitve environments correspond to the higher gray profiles.

Figure A-3: Expected Cost and Entry under Alternative Subsidy Levels, Sample Project 3



Note: the panels display the cost to the government and entry as a function of the subsidy to large bidders, holding the subsidy for small bidders fixed at the cost-minimizing tax level. Negative subsidy levels correspond to taxes. The expected winning bid reflects the following interplay of participation and bidding decisions. For subsidy levels below -0.85, only small firms are in the market and pay their optimal subsidy, resulting in a constant winning bid. As the tax charged to large bidders starts declining, large bidders begin entering the market and initially replace small bidders. For this particular project, large bidders are less efficient, pushing up the winning bid. Once taxes fall below -0.8, entering large bidders more than displace non-participating small firms, resulting in an overall increase in the number of bidders. This causes the winning bid to begin declining again.