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Disadvantaged business enterprise goals in government procurement contracting: An analysis of bidding behavior and costs ☆

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ABSTRACT

Programs that encourage the participation of disadvantaged business enterprises (DBE) as subcontractors have been a part of government procurement auctions for over three decades. In this paper, we examine the impact of a program that requires prime contractors to subcontract out a portion of a highway procurement project to DBE firms. We study how DBE subcontracting requirements affect bidding behavior in federally funded projects. Within a symmetric independent private value framework, we use the equilibrium bidding function to obtain the cost distribution of firms undertaking projects either with or without subcontracting goals. We then use non-parametric estimation methods to uncover and compare the cost of firm bidding on a class of asphalt projects related to surface treatment in Texas. The analysis shows little differences in the cost structure between projects that have subcontracting goals and those that do not.

1. Introduction

Minority preference policies have been a part of government procurement programs in the United States since the late 1960's. Their goal is to enhance the opportunities of minority businesses and counter the effects of past discrimination. Critics of these policies claim that they result in reverse discrimination, limit competition, and raise project costs.[1] Two incentive schemes have been used widely thus far—rules requiring participation of minority firms as subcontractors and bid preference programs.[2] Our analysis focuses on the former, policies that set minority firm participation goals. Specifically, these rules require that prime contractors subcontract out a set percentage of the overall value of a project to minority firms. Such a requirement could affect the prime contractor's make-or-buy decisions in two ways. First, it may influence the overall level of subcontracting a firm uses on a project and, second, it may influence who the firm subcontracts with on a project. Both instances impose constraints on the prime contractors, potentially raising projects costs.

This paper examines whether costs differ between projects that have subcontracting goals and projects without such goals. The paper employs a structural auction model to infer contractors' costs from observed bids in order to compare the costs across project types. Nonparametric methods developed by Guerre et al. (2000) and Haile et al. (2006) are used to estimate the distribution of latent costs, allowing us to control for project heterogeneity and selection.

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[1] See Holzer and Neumark (2000) for an overview of affirmative action programs and how they affect small and disadvantaged businesses.

[2] Bid preference programs give explicit advantage to small and minority bidders in auctions. For example, in the case of California state highway contracts with bid preferences analyzed by Krasnokutskaya and Seim (2007), small business are awarded a contract if they are within 5% of the low bid.

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Papers by Marion (2007) and Krasnokutskaya and Seim (2007) also use a structural auction approach to examine bid preference schemes for small businesses; however, these papers do not examine environments where subcontracting goals are implemented. To be sure, our empirical analysis is not an evaluation of the program itself, as the program has been in place for several decades. Rather the structural model is employed to quantify differences in costs across projects with and without subcontracting goals.

The empirical setting is low-price, sealed-bid auctions for highway construction projects let in Texas over the period 1998–2007.[3] Our findings show that, once project heterogeneity and bidder participation are controlled for, there is little difference in costs between projects that are assigned subcontracting goals and projects that are not assigned such goals. When we examine an even more homogeneous sample of projects, we find even greater similarity in costs between the two project groups. We also construct estimates of the markup of the bid above the cost and find that the magnitude of the markup is consistent with that reported in the literature and varies little between auctions with and without subcontracting requirements.

The effects of minority preference policies on bidding and costs have been examined in recent studies. Several papers deal with bid preference schemes. Denes (1997) compares bids submitted between solicitations restricted to small businesses and unrestricted solicitations. He finds that bids are no higher in restricted solicitations.[4] Krasnokutskaya and Seim (2007) analyze bid preference programs in California highway procurement by examining how bidding and participation decisions are affected by a program that provides preferential treatment to small firms. They find that the preferential treatment of small businesses creates losses in efficiency (since the small firms have higher costs on average) but no change in the overall cost of procurement. In a related study of the California state procurement auctions, Marion (2007) found that the distortion in participation patterns in bid preference programs is responsible for a 3.8% increase in procurement costs. Despite this evidence, the effect of such programs on the state's cost is ambiguous. By invoking bid preferences the state gives an advantage to minority bidders and compels the non-minority bidders to bid more aggressively and win contracts at a lower bid. At the same time, since the competitive pressure is reduced for minority bidders they bid less aggressively than otherwise; and when the item is awarded to them, they impose additional cost on the state budget (Hubbard and Paarsch, 2009; Mcafee and Mcmillan, 1989).

The potential for efficiency distortions is different for programs setting minority subcontracting goals. These programs are widely used in federal procurement contracts and may constrain the make-or-buy decision of prime contractors. Efficiency distortions could be introduced due to potentially less efficient production of tasks by subcontractors compared to the prime contractor, to the use of less efficient subcontractors on subcontracted tasks, or to changes in competition intensity in the subcontracting market. Marion (2009) using data from the California Department of Transportation spanning the period between 1996 and 1999 shows that the subcontracting goals set for highway construction contracts in California raise disadvantaged business enterprise usage significantly, so that the constraints appear to bind.[5]

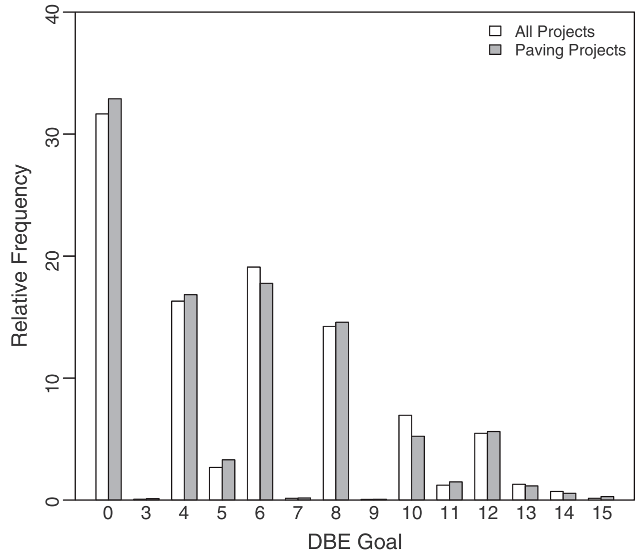

Fig. 2.1. Distribution of DBE goals for all projects and paving projects.

The paper proceeds as follows. The next section describes the disadvantaged business enterprise program and provides an overview of the data. Section 3 presents the model and structural empirical analysis. Section 4 concludes.

2. Texas auctions and bidding patterns

2.1. Data description

Our analysis utilizes data on auctions and bidding from the state of Texas. The Texas Department of Transportation (TxDOT) holds regularly scheduled highway procurement auctions that incorporate goals for the awarding of subcontracts to disadvantaged business enterprises (DBEs). DBEs are small businesses that are owned and controlled by members of a minority group including women-owned businesses. For selected federally-funded projects, TxDOT assigns a proportion of the contract value that must be performed by DBEs. Fig. 2.1 presents the distribution of the DBE goals for two groups of federally-funded projects let between 1998 and 2007—all projects and paving projects. Since paving projects are the focus of the empirical analysis that follows, we provide a separate breakout for this group of projects. Across all projects, the DBE goals range from 0 to 15% with about two-thirds of projects having DBE goals above zero. Paving projects make up about one half of the overall number of projects.

As in other states, the Department of Transportation in Texas chooses which projects to assign DBE status and the level of the DBE goal for each project. The state makes its decisions by considering a number of factors including the type of project (asphalt, bridgework, etc.), the geographic location of the project, and the availability of pre-qualified DBE subcontractors in locations that can do specific tasks. TxDOT has a separate office, Office of Civil Rights, that manages these assignments, which is distinct from the offices that design, cost out, and let the projects.

The TxDOT bid data that we have access to contain information on all road construction projects offered for bid letting in Texas for the period from September, 1998 through August, 2007.[6] Our empirical

[3] Our structural analysis only includes asphalt paving projects, as we focus on a relatively homogeneous set of projects and include those that best match the assumptions of the independent private value environment. Papers such as Bajari and Ye (2003) also focus on subsets of construction projects in order to achieve greater homogeneity in the items under study.

[4] Other studies that have been done focus on whether companies that benefit from affirmative action in procurement continue to succeed after the programs are no longer in effect (Holzer and Neumark, 2000).

[5] Marion considers federal and state funded projects. Prior to March 1998, state funded projects had both bid preference and subcontracting participation goals in place. Federal funded projects had only a program setting participation goals. Proposition 209 which was approved in November 1996 and was implemented in 1998 eliminated participation goals from state funded projects leaving bid preference goals still in place.

[6] The structure of the DBE program changed during our sample period, as the U.S. Federal Highway Administration (FHWA) moved toward more race-neutral approaches to meet DBE subcontracting objectives. In an earlier version of the paper, we tested for differences in bidding behavior associated with changes in how the DBE program was administered. We found no evidence of a change in bidding in DBE vs. non-DBE auctions in response to such program changes.

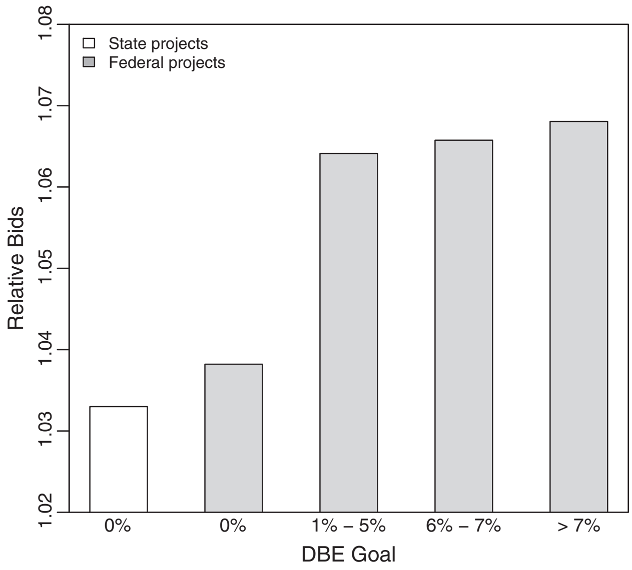

Fig. 2.2. Average relative bid for paving projects by DBE intensity.

analysis focuses on paving projects, a relatively homogeneous group of projects that previous studies have shown fit the independent private values framework well. Projects are auctioned off on a monthly basis using a low-price, sealed-bid format. For each project, we have the date of the bid letting, information on the location of the project, an overall description of the project, a detailed list of the tasks involved, the estimated length of the project (in calendar days), the state's engineering estimate of the project's total cost, whether the project is federally or state funded, and the DBE participation requirement. From the bid letting, we know the identity of the plan holders—the firms that purchase the plans for a project, which plan holders submit bids, and the dollar value of each bid submitted. State projects and federally funded projects of less than $400,000 do not have DBE goals. Projects that are less than $400,000 and over $20,000,000 are excluded from our analysis. With regard to the latter restriction, we impose the upper bound because of the nonparametric techniques used in the structural analysis. The data in this region of the distribution is quite sparse, since there are few very large projects (69) in our sample. However, the regression analysis presented in this section is not sensitive to this restriction. Our paving contract data contain 11,745 bids from 3059 auctions.

Fig. 2.2 shows bid statistics for our sample breaking out the federal projects into four DBE utilization categories: 0%, 1–5%, 6–7%, or greater than 7%. The average relative bids – the bid submitted by a firm divided by TxDOT's engineering cost estimate (ECE) for a project – is higher in projects with DBE goals. However, there are marked differences in the characteristics of DBE and non-DBE projects as shown in Table 2.1. Projects without DBE goals are generally smaller than DBE projects and contain a smaller number of bid components.

2.2. Bidding regression results

To further explore the patterns related to DBE status, we present a set of descriptive regressions where the dependent variable is the log of the bid submitted by an individual bidder. All models include a common set of basic project characteristics, including controls for the DBE status of the auction, project size (measured as the log of the engineering estimate), log of the number of plan holders, project location and time effects.[7] In some specifications, we also control for

Table 2.1
Summary statistics. DBE denotes disadvantaged business enterprises. Standard deviations are in parentheses.

Variable	Without DBE goals	With DBE goals
Number of projects	1839	1220
Number of state projects	1241	–
Average number of bidders	3.805	3.892
	(1.774)	(1.922)
Average engineer's cost estimate	2.969	4.240
(in millions of dollars)	(2.824)	(3.913)
Average relative bid	1.035	1.066
	(0.192)	(0.176)
Average number of bid components	40.506	81.560
	(30.181)	(49.509)

project characteristics including—project length (log of the calendar days to complete a project), and project type (shares of specific material components). To construct the material shares for a project, we aggregate the dollar value of bid items into 12 material groups based on item descriptions and divide each subaggregate by the project's overall engineering cost estimate. We also include the number of project components, which has been used in a number of studies as a proxy for project complexity. To control for bidder cost heterogeneity, variables that measure a bidder's capacity utilization and the distance to a project are included. A complete list of variable definitions is presented in Table A.1 in Appendix A. Two alternative DBE specifications are presented for the bid regressions—one version includes a simple indicator variable that identifies auctions with positive DBE goals, while the second version includes a set of dummy variables that control for DBE goal percentage.

The first column of Table 2.2 provides the estimates from a model that includes an indicator variable for whether a federal project has a DBE goal or not and controls for the engineering cost estimate, the number of plan holders, whether the project is a state or federal project, location and time effects. The coefficient on the DBE variable in this parsimonious specification is positive and statistically significant indicating that DBE auctions had higher average bids than those observed in non-DBE auctions (including both federal and state projects). The second column adds one additional control variable – the log of the number of bid components – the complexity variable. Adding this variable to the regression moves the coefficient on the DBE variable close to zero and it is no longer statistically significant, while the complexity variable enters the regression with a positive and statistically significant coefficient. This indicates that projects with more tasks generally have higher bids, even after controlling for project size. Column 3 incorporates additional controls for project and bidder characteristics. Project length, capacity utilized and bidder distance to project location all increase bids, while the coefficient on the DBE variable is close to zero.

Column 4 includes all the regressors in column 3 but replaces the zero–one indicator variable for DBE with a set of dummy variables that capture differences in the level of DBE goals across projects. The model includes four dummy variables for the DBE groupings reported in Fig. 2.2 and the omitted category represents the state projects. None of the DBE coefficients is statistically significant and all are close to zero in magnitude. This implies no difference in the average bid between state projects and federal projects that do not have DBE goals and no rise in the coefficients as the DBE goal increases.[8] Finally, column 5 of Table 2.2 includes bidder fixed effects in the model to control for unobserved bidder heterogeneity. Focusing on the DBE parameters, all the DBE parameters are close to zero and none are statistically significant.

How should we interpret the results on complexity and DBE status of projects? TxDOT assigns DBE goals based, in part, on the tasks involved

[7] Project location is modeled using 24 indicator variables that identify which construction district a project is in. Time effects are controlled for by a set on 119 indicator variables that identify the month and year of the project letting.

[8] We also estimated a set of models where the dependent variables were the number of bidders and the winning bids. There was no difference in participation patterns or winning bids between auctions with and without DBE goals.

Table 2.2
Descriptive bid regressions. While DBE here is an indicator variable denoting disadvantaged business enterprises, ECE denotes the value of the engineer's cost estimate. The symbol * denotes statistical significance at the 5% level. Standard errors (in parentheses) are clustered at the auction level.

Variable	Log of bids					
	(1)	(2)	(3)	(4)	(5)	(6)
DBE projects	0.052*	0.005	0.003			
	(0.008)	(0.008)	(0.008)			
State projects	−0.010	−0.002	0.005			
	(0.008)	(0.008)	(0.008)			
DBE: 0% (Fed projects)				−0.005	−0.007	0.002
				(0.008)	(0.005)	(0.036)
DBE : 1%–5%				0.001	−0.003	0.008
				(0.009)	(0.005)	(0.038)
DBE : 6%–7%				−0.003	−0.005	0.004
				(0.010)	(0.006)	(0.038)
DBE : ≥8%				−0.007	−0.008	0.000
				(0.010)	(0.006)	(0.039)
Log ECE	0.974*	0.955*	0.946*	0.946*	0.944*	0.946*
	(0.004)	(0.003)	(0.005)	(0.005)	(0.003)	(0.005)
Log complexity		0.073*	0.051*	0.051*	0.049*	0.050*
		(0.005)	(0.008)	(0.008)	(0.006)	(0.009)
Log complexity × State projects						0.002
						(0.010)
Log number of plan holders	−0.016	−0.019*	−0.034*	−0.034*	−0.041*	−0.034*
	(0.009)	(0.008)	(0.009)	(0.009)	(0.006)	(0.009)
Log days to complete the project			0.023*	0.023*	0.024*	0.023*
			(0.006)	(0.006)	(0.005)	(0.006)
Capacity utilized			0.027*	0.027*	0.021*	0.027*
			(0.006)	(0.006)	(0.005)	(0.006)
Log distance			0.010*	0.010*	0.016*	0.010*
			(0.002)	(0.002)	(0.003)	(0.002)
Bidder effects (350)	No	No	No	No	Yes	No
Division effects (24)	Yes	Yes	Yes	Yes	Yes	Yes
Material shares (11)	No	No	Yes	Yes	Yes	Yes
Time effects (119)	Yes	Yes	Yes	Yes	Yes	Yes
Number Obs	11,745	11,745	11,745	11,745	11,662	11,745
Adj R^2	0.970	0.972	0.973	0.973	0.967	0.973

in a project. Projects with a large number of tasks are more likely to have tasks appropriate for DBE subcontracting. Thus, if the state always assigned DBE status to complex projects, then our regressions would not be able to distinguish the differences in bidding due to complexity from differences in bidding due to DBE requirements. One way to see if the positive effect of complexity is merely proxying for DBE status is to examine complexity's correlation with bids in state projects. State projects are not assigned DBE goals but we can still measure the number of tasks for these projects. Column 6 of Table 2.2 presents the results of a model that includes an interaction term between a state project indicator variable and the log of complexity. This interaction term tests whether there is any difference in the relationship between bids and complexity for state versus federal projects. The coefficient on the interaction term is essentially zero (0.002) and not statistically significant. This shows that the relationship between complexity and bids is similar in state and federal projects, suggesting that the correlation between bids and complexity is not being driven by the DBE assignment process. Rather the correlation likely reflects the increase in costs associated with doing more complicated projects.

One potential problem with the above analysis is that it requires that the engineer's cost estimate not be influenced by DBE assignment. In Texas, the office that assigns DBE goals to auctions is clearly distinct from the parties responsible for designing and costing out a project. In addition, the setting of a project's DBE goal occurs only after a project's cost is estimated. So, DBE assignment of a project does not influence the engineer's cost estimate for the project. However, in estimating project costs, TxDOT can use information from prior bid submissions to estimate the costs of specific project components.[9] A problem with our analysis would arise if some project tasks are only performed by DBE firms and only occur in DBE auctions. Effectively there would be no cost differential to estimate in this circumstance, as differences in costs due to DBE subcontracting would simply be reflected in the engineer's cost estimate in DBE projects. From direct discussions with staff, we know that TxDOT makes DBE assignments based, in part, on the presence of specific bid items in an auction that are most suitable to subcontracting by DBE firms. A list of these items is presented in Table A.2 in Appendix A. Table A.2 shows the frequency of each task broken out by federal auctions with DBE goals, federal auctions without DBE goals, and state projects. The specific bid items presented center around landscape, traffic control and miscellaneous construction activities.[10] Most importantly, the frequency data show that these DBE tasks are not limited to DBE auctions. State projects that are not assigned DBE goals, also incorporate these tasks, and so do federal non-DBE projects. In general, we see that roughly 57% of these DBE tasks are in DBE projects while 43% are in non-DBE projects. These project percentages are similar to the overall percentage of bid items across DBE and non-DBE projects (60% vs. 40%). Thus, there does not appear to be a specialized group of tasks here that only occur in DBE projects.

Overall, the bidding patterns suggest little difference in bids submitted in auctions with DBE goals compared to auctions without DBE goals. However, these descriptive regressions do not control for the competitive

[9] For example, many projects require the use of landscaping services. TxDOT may use past seed, planting and fertilizer prices to generate an estimate of landscape costs for a project to be let.

[10] Most projects also incorporate a mobilization bid component. Mobilization tasks "include establishing and removal of offices, plants, facilities and moving personnel, equipment, and supplies to (or from) the project area to begin (or complete) work." Mobilization is given as a lump sum figure for a project and averages around 8% of a project's total estimated cost. The interquartile range is from 7% to 9%. DBE subcontractors can also be paid to perform these tasks and are; however, since mobilization tasks do not have specific price components (they are really an overhead type cost), they are not subject to the potential bias discussed here.

Table 3.1
Summary statistics for the samples of asphalt projects and surface treatment projects. DBE stands for disadvantage business enterprises. Standard deviations are in parentheses.

	Asphalt projects				Surface treatment projects			
	All bidders		3 and 4 bidders		All bidders		3 and 4 bidders	
	Non DBE	DBE	Non DBE	DBE	Non DBE	DBE	Non DBE	DBE
Bid (millions of dollars)	2.914	2.916	2.775	3.203	2.821	2.907	2.840	3.631
	(2.677)	(2.561)	(2.512)	(2.797)	(2.448)	(2.590)	(2.226)	(3.275)
Engineer's cost estimate	2.921	2.959	2.696	3.241	2.825	2.875	2.772	3.620
	(2.569)	(2.635)	(2.172)	(2.837)	(2.423)	(2.457)	(2.030)	(3.207)
Bridge work	0.005	0.006	0.004	0.008	0.004	0.005	0.005	0.009
	(0.010)	(0.012)	(0.009)	(0.013)	(0.009)	(0.011)	(0.010)	(0.014)
Earth work	0.012	0.010	0.011	0.012	0.012	0.008	0.012	0.011
	(0.014)	(0.014)	(0.013)	(0.015)	(0.015)	(0.013)	(0.014)	(0.016)
Pavement	0.062	0.031	0.064	0.021	0.006	0.014	0.007	0.025
	(0.192)	(0.118)	(0.201)	(0.086)	(0.021)	(0.061)	(0.023)	(0.092)
Concrete	0.005	0.006	0.004	0.007	0.004	0.004	0.005	0.007
	(0.010)	(0.011)	(0.009)	(0.012)	(0.009)	(0.011)	(0.010)	(0.013)
Subcontracting goals	–	6.478	–	6.287	–	6.543	–	6.578
		(2.273)		(2.350)		(2.436)		(2.819)
Complexity of the project	31.160	36.257	31.049	40.029	30.723	33.174	31.350	37.513
	(15.052)	(18.559)	(15.990)	(20.820)	(14.797)	(17.274)	(15.530)	(18.674)
Days to complete the project	81.324	83.787	74.827	84.707	70.981	71.659	67.040	77.766
	(70.698)	(55.436)	(60.644)	(52.425)	(62.592)	(34.544)	(49.821)	(35.568)
Capacity utilized	0.337	0.220	0.358	0.238	0.341	0.218	0.373	0.239
	(0.277)	(0.250)	(0.279)	(0.261)	(0.272)	(0.258)	(0.286)	(0.279)
Number of bidders	4.368	4.557	3.430	3.433	4.207	4.851	3.469	3.416
	(1.920)	(2.101)	(0.496)	(0.496)	(1.757)	(2.135)	(0.500)	(0.494)
Number of:								
Auctions	293	260	145	98	141	135	68	50
Observations	1046	924	490	332	500	534	232	170

environment or for such features as selection into the auctions. In the next section, we employ a structural approach that will allow us to control for competition, entry into the auctions and generate estimates of the latent cost distributions for bidders participating both in DBE and non-DBE auctions.

3. Structural analysis

This section uses nonparametric estimation methods to uncover the cost of firms bidding in procurement auctions. Before proceeding to the empirical analysis, we outline a simple bidding model.

3.1. Model

There are n risk neutral bidders who compete for a government contract in a low-price, sealed-bid auction. There are two types of projects, indexed by j, those that have no subcontracting goals and those that do (i.e.,$j=\{0,1\}$). The cost of contract j to a bidder i, is private and denoted by c_{ij}. The density of the private cost c_{ij} is f_j and is strictly positive on the support $[c_{L_j}, c_{H_j}]$. In a procurement auction, a bidder who is awarded contract j at a bid of b_{ij} receives a net profit of $b_{ij}-c_{ij}$. Each bidder is maximizing expected profit given by:

$$E\left[\pi_{ij}\left(b_{1j}, b_{2j}, \ldots, b_{nj}, c_{ij}\right)\right] = \left(b_{ij}-c_{ij}\right)\left(1-F_j\left(\phi\left(b_{ij}\right)\right)\right)^{n_j-1}.$$

In the symmetric independent private value (IPV) case, the equilibrium bid function is

$$\beta\left(c_{ij}|F_j, n_j\right) = c_{ij} + \frac{\beta'\left(c_{ij}\right)\left[1-F_j\left(c_{ij}\right)\right]}{\left(n_j-1\right)f_j\left(c_{ij}\right)} \tag{3.1}$$

where $b_{ij}=\beta(c_{ij})$ and $\varphi(b_{ij})=c_{ij}$.

Notice that the cost of the contract consists of the sum of the cost of various tasks comprising the project, some or potentially all of which may be undertaken by the primary contractor. In projects having subcontractor participation goals, a number of tasks representing a minimum percentage of the estimated cost, have to be undertaken by DBE subcontractors. We ask if there is a difference in bidding distributions between projects that have subcontracting goals in place and those that do not and whether the combined cost of the project is different across j's. It is obvious that, if the minority subcontractors are less efficient they will impose a cost to the state agency.

Within the symmetric independent private value framework, we use the equilibrium bidding function (3.1) to obtain the cost distribution of firms undertaking projects either with subcontracting goals or without subcontracting goals. Let $G_0(b)$ be the distribution function of bids in projects without subcontracting goals and $G_1(b)$ the distribution function of bids in projects with subcontracting goals. Let $g_0(b)$ and $g_1(b)$ be the associated densities. Considering the standard monotonicity condition imposed on the equilibrium bid function $\beta(c)$, we write $F(c)=F(\beta^{-1}(b))=G(b)$, and $f(c)=g(b)\,\beta'(c)$. If we substitute these expressions into the equilibrium bidding function, we find that the latent cost of undertaking a project without subcontracting goals can be written as,

$$c_0 = b_0 - \frac{1}{n_0-1}\frac{1-G_0(b_0)}{g_0(b_0)}, \tag{3.2}$$

where n_0 is the number of firms bidding in projects without subcontracting goals. Similarly, the latent cost associated with a project that has subcontracting goals is,

$$c_1 = b_1 - \frac{1}{n_1-1}\frac{1-G_1(b_1)}{g_1(b_1)}, \tag{3.3}$$

where n_1 is the number of firms bidding in projects with subcontracting goals. The right hand side of these equations can be estimated with nonparametric methods using the observed vector of bids.

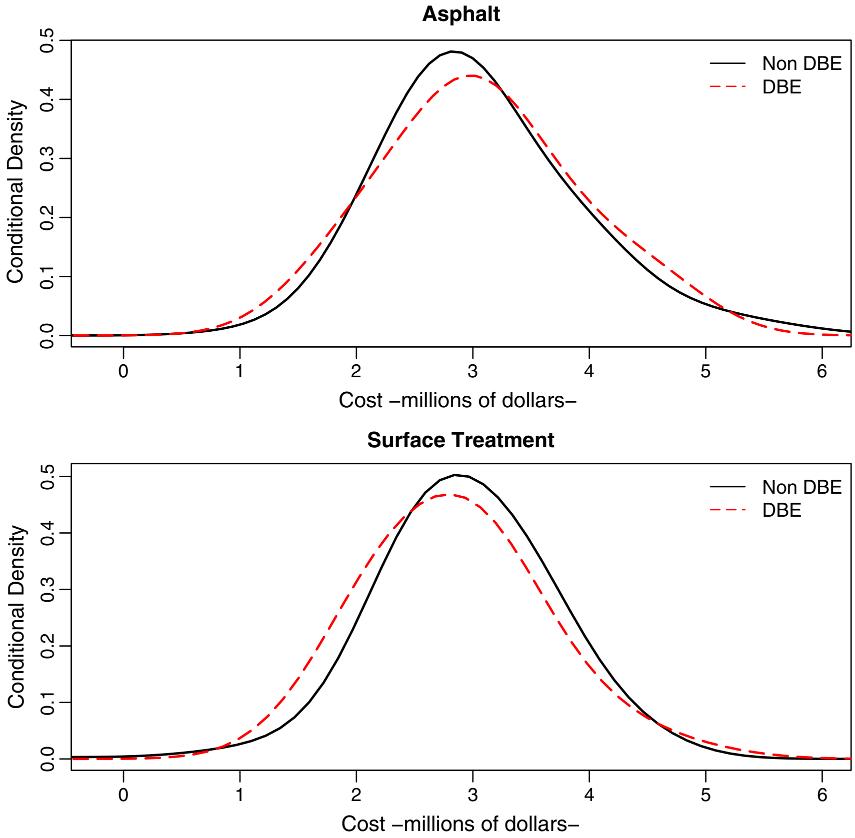

Fig. 3.1. Cost densities for DBE and non-DBE projects.

3.2. Asphalt project data

The identification and estimation of Eqs. (3.2) and (3.3) rely on the assumptions associated to the IPV framework, which are tested in Section 3.4. We require a sample of projects that are relatively homogeneous and fit the IPV framework. From related literature (see Bajari and Ye, 2003; de Silva et al., 2008) and our discussions with state highway and civil engineers, we believe that asphalt projects appear to best match these requirements. Asphalt projects rely more on the individual firm's state of equipment and internal efficiency to determine the cost and are relatively homogeneous.

Although asphalt projects are less heterogeneous than the full sample of paving projects used in Section 2, they may include work on non-asphalt components such as bridge, subgrade, etc. We made two adjustments to the sample to obtain an even more homogeneous set of projects. First, we restrict attention to asphalt paving projects with an estimated cost between \$400,000 and \$20,000,000, with an asphalt material share higher than 50% of the engineer's cost estimate, and with bridge and earthwork components of less than 5%. Bridge and earthwork components introduce uncertainty in the cost that is likely more common to all bidders. We also restricted the sample to projects with no subgrade and base course tasks.[11] Those tasks introduce common uncertainty in costs and appear most often in the construction of new roads. We present descriptive statistics for this sample in the first four columns of Table 3.1 (we call this sample Asphalt Projects). We consider the sample for all levels of participation in the first two columns and a subsample with 3 and 4 bidders in the next two columns. In the empirical analysis that follows, we will focus on samples with similar number of bidders. Second, we construct a more selected sample of contracts that relates exclusively to surface treatment.[12] The descriptive statistics for this sample are presented in the last four columns of Table 3.1. Notice that the size and number of tasks are much more similar across DBE and non-DBE projects in these subsamples compared to the differences observed in the overall paving sample used in Section 2.

3.3. Nonparametric estimation and auction heterogeneity

Standard non-parametric methods can be used to estimate $(1-G(b|\mathbf{x}))/g(b|\mathbf{x})$, where the vector $\mathbf{x}\in\mathcal{X}\subset\mathbf{R}^p$ includes variables capturing observed project heterogeneity (e.g., Guerre et al., 2000). We incorporate auction specific characteristics replacing the unconditional distribution functions $G(b)$ and $g(b)$ in Eqs. (3.2) and (3.3) by conditional distributions of a form $G(b|\mathbf{x})$ and $g(b|\mathbf{x})$, where $\mathbf{x}$ includes the engineer's cost estimate as in Marion (2007). These conditional functions can be estimated by considering the empirical version of standard definitions, $\hat{g}_{jn}(\cdot|\cdot)=\hat{g}_{jn}(\cdot,\cdot)/\hat{f}_{jn}(\cdot)$ and $\hat{G}_{jn}(\cdot|\cdot)=\hat{G}_{jn}(\cdot,\cdot)/\hat{f}_{jn}(\cdot)$, and the following estimators defined in Guerre et al. (2000):

$$\hat{g}_{jn}(b,x)=\frac{1}{nL_{jn}h_{jng}^2}\sum_{l=1}^{L_{jn}}\sum_{i=1}^{n}K_g\left(\frac{b-b_{jnil}}{h_{jng}},\frac{x-x_{jnl}}{h_{jng}}\right), \tag{3.4}$$

[11] Subgrade tasks are associated with the top surface of a roadbed upon which the pavement structure, shoulders, and curbs are constructed. Base course tasks are associated with the layers of specified material placed on a subgrade to support a surface course.

[12] Bajari and Ye (2003) analyze a model of independent private cost estimates using seal coating projects, which is class of surface treatment projects. Surface treatment may be used for primary and secondary roads that carry light traffic, as part of the original construction, or to rejuvenate old roads. Examples include overlay of asphalt, seal coats, single and multiple surface treatments. Surface treatments could be applied to concrete roads or bituminous asphalt roads.

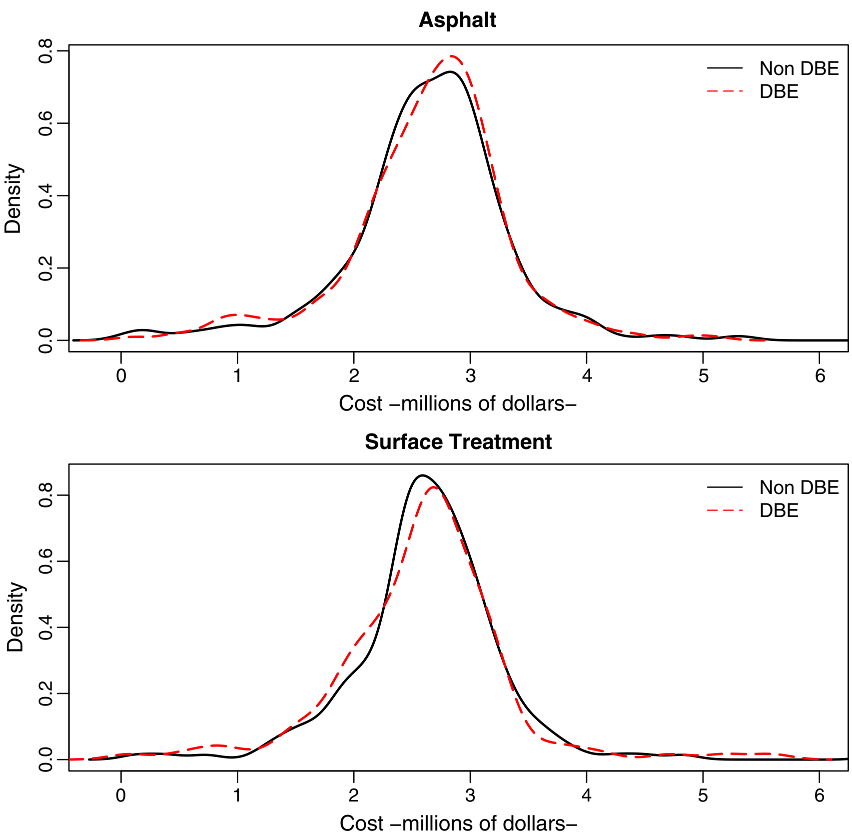

Fig. 3.2. Cost densities for DBE and non-DBE projects obtained from a sample of homogenized bids.

$$\hat{G}_{jn}(b,x) = \frac{1}{nL_{jn}h_{jnG}} \sum_{l=1}^{L_{jn}} \sum_{i=1}^{n} K_G\left(\frac{x-x_{jnl}}{h_{jnG}}\right) 1\left\{b_{jnil} \le b\right\}, \qquad (3.5)$$

$$\hat{f}_{jn}(x) = \frac{1}{L_{jn}h_{jnf}} \sum_{l=1}^{L_{jn}} K_f\left(\frac{x-x_{jnl}}{h_{jnf}}\right), \qquad (3.6)$$

where $1\{\cdot\}$ is an indicator function, $K_g(\cdot)$, $K_G(\cdot)$, and $K_f(\cdot)$ are continuously differentiable kernel functions defined over a compact support, and h_g, h_G, and h_f are the associated bandwidths. Several kernels satisfy these conditions, including the triweight kernel,

$$K(u) = \frac{35}{32}\left(1-u^2\right)^3 1\{|u| \le 1\}.$$

We use this triweight kernel to estimate the density $f_{jn}(x)$ and the distribution function $G_{jn}(b,x)$. Moreover, we consider the product of two triweight kernels for estimating the density $g_{jn}(b,x)$. Both the rates in Guerre et al. (2000) and the factors associated with the choice of the triweight kernel (see, e.g., Härdle, 1991) suggest employing bandwidths of the form $h_{jnG} = \gamma\hat{\sigma}(b_{jn})(nL_{jn})^{-1/5}$, $h_{jng} = \gamma\hat{\sigma}(b_{jn})(nL_{jn})^{-1/6}$, and $h_{jnf} = \gamma\hat{\sigma}(x_{jn})(nL_{jn})^{-1/5}$, where $\sigma(b)$ is defined as the standard deviation of b and $\gamma = 2.978 \times 1.06$.

Given the potential benefits of using the logarithm of bids rather than bids, we consider the logarithmic transformation for the variable of interest c_{jn} (see Li et al., 2000; Marion, 2007). We define the (i,l)-th element of the vector $\hat{\mathbf{c}}_{jn}$ as,

$$\hat{c}_{jnil} = \begin{cases} \exp\left(a_{jnil}\right)\left(1-\hat{m}_{jn}(\cdot,\cdot)\right) & \text{if } max\left\{h_{jnG},h_{jng}\right\} \le a_{jnil} \le a_{max} - max\left\{h_{jnG},h_{jng}\right\} \\ +\infty & \text{otherwise,} \end{cases} \qquad (3.7)$$

where the variable a_{jnil} denotes the logarithm of bid b_{jnil}, the variable z_{jnil} denotes the logarithm of the engineer's cost estimate x_{jnil}, the maximum value of the logarithm of bids is denoted by a_{max}, and

$$\hat{m}_{jn}(\cdot,\cdot) = \frac{1}{n_j - 1}\frac{1-\hat{G}_{jn}(\cdot|\cdot)}{\hat{g}_{jn}(\cdot|\cdot}).$$

We estimate the pseudo costs in two stages. Because the bid's distributions are not comparable in cases of different number of bidders, we estimate the vector of pseudo cost separately for $n = 3$ and $n = 4$ bidders.[13] In the first stage, we obtain $\hat{m}_{03}(\cdot,\cdot)$, $\hat{m}_{04}(\cdot,\cdot)$, $\hat{m}_{13}(\cdot,\cdot)$, and $\hat{m}_{14}(\cdot,\cdot)$ using the estimators defined in Eqs. (3.4), (3.5), and (3.6) under the restrictions imposed in Eq. (3.7).[14] To construct the pseudo costs of DBE and non-DBE projects, we evaluate $\hat{m}_{03}(\cdot,\cdot)$, $\hat{m}_{04}(\cdot,\cdot)$, $\hat{m}_{13}(\cdot,\cdot)$, and $\hat{m}_{14}(\cdot,\cdot)$ at the observed logarithm of bids and engineer's cost estimates, obtaining $\hat{c}_{03}(\cdot,\cdot)$, $\hat{c}_{04}(\cdot,\cdot)$, $\hat{c}_{13}(\cdot,\cdot)$, and $\hat{c}_{14}(\cdot,\cdot)$ as in Eq. (3.7). In the second stage, we pool the pseudo cost values $\hat{\mathbf{c}}_0 = \left(\hat{\mathbf{c}}_{03}(\cdot,\cdot)', \hat{\mathbf{c}}_{04}(\cdot,\cdot)'\right)'$ and $\hat{\mathbf{c}}_1 = \left(\hat{\mathbf{c}}_{13}(\cdot,\cdot)', \hat{\mathbf{c}}_{14}(\cdot,\cdot)'\right)'$ and the engineer's cost estimates $\mathbf{x}_0 = \left(\mathbf{x}_{03}', \mathbf{x}_{04}'\right)'$ and $\mathbf{x}_1 = \left(\mathbf{x}_{13}', \mathbf{x}_{14}'\right)'$ to estimate the conditional densities $g_0(\hat{c}_0|x_0)$ and $g_1(\hat{c}_1|x_1)$.

Fig. 3.1 presents the conditional densities evaluated at the median of the engineer's cost estimate. These empirical distributions were obtained considering the samples described in Table 3.1. The continuous lines

[13] Conditional on the pairs (j,n)'s for $j = \{0,1\}$ and $n = \{3,4\}$, the total number of observations nL_{jn} are $\{270,220,180,152\}$ in the sample of asphalt projects and $\{120,112,90,80\}$ in the sample of surface treatment projects.

[14] As explained before, we use $h_{jnG} = 2.978 \times 1.06 \times \hat{\sigma}(b_{jn}) \times (nL_{jn})^{-1/5}$, $h_{jng} = 2.978 \times 1.06 \times \hat{\sigma}(b_{jn}) \times (nL_{jn})^{-1/6}$, $h_{jnf} = 2.978 \times 1.06 \times \hat{\sigma}(x_{jn}) \times (nL_{jn})^{-1/5}$. We estimate $\sigma(b_{jn})$ as the minimum between the standard deviation of b_{jn} and a robust measure of scale, the interquartile range. For instance, in the case of 3 firms bidding in asphalt projects, we have that the bandwidths are equal to $h_{03g} = 0.987$, $h_{03G} = 0.819$, $h_{03f} = 0.988$, $h_{13g} = 1.034$, $h_{13G} = 0.870$ and $h_{13f} = 1.106$.

Table 3.2
Variability bands for the estimated densities in Fig. 3.2. The intervals were constructed considering a block bootstrap procedure. The quantiles are in millions, and we considered 10,000 bootstrap repetitions. DBE stands for disadvantage business enterprises.

	Quantiles of the cost distribution				
	1.0	2.0	3.0	4.0	5.0
Asphalt projects					
Non-DBE	[0.014, 0.095]	[0.136, 0.467]	[0.378, 0.804]	[0.010, 0.108]	[0.000, 0.027]
DBE	[0.008, 0.101]	[0.122, 0.457]	[0.412, 0.873]	[0.011, 0.121]	[0.000, 0.029]
Surface treatment projects					
Non-DBE	[0.003, 0.109]	[0.125, 0.578]	[0.275, 0.858]	[0.001, 0.119]	[0.000, 0.035]
DBE	[0.002, 0.152]	[0.129, 0.582]	[0.232, 0.833]	[0.001, 0.120]	[0.000, 0.047]

show kernel density estimates for the cost of firms bidding in projects without subcontracting goals (non-DBE), and the dashed line present estimates for the cost of firms bidding in projects with subcontracting goals (DBE). The upper panel in Fig. 3.1 shows that the cost distributions of firms bidding in asphalt projects when small bridge and earthwork components are present in the project, and the lower panel presents results from the sample of surface treatment projects. The distribution of firms undertaking DBE projects is shifted to the right, suggesting the possibility that the program generated inefficiencies. However, when we consider the more homogeneous sample of asphalt surface treatment projects, the differences in the cost distributions tend to disappear.

In our application, one needs to control for many auction-specific characteristics. Recall that the effects of project size, project complexity, and project length are statistically significant in all variants of the model estimated in Table 2.2. It is natural then to use the estimation method proposed by Haile et al. (2006). The advantage of their approach relative to the approach developed by Guerre et al. (2000) is that it enables one to control for many auction-specific characteristics without increasing the sample size.

Haile et al. (2006) propose a "homogenization" strategy that can be employed if several conditions are met. First, consider the function $\Gamma:\mathcal{X}\times\mathcal{W}\rightarrow\mathbf{R}$, then $\exists(\mathbf{x}_0,w_0)\in\mathcal{X}\times\mathcal{W}\subset\mathbf{R}^p\times\mathbf{R}$ such that $E(\Gamma(\mathbf{x},w))=\Gamma(\mathbf{x}_0,w_0)$.[15] Consider also an additively separable structure on how observable factors $\mathbf{x}$ and latent auction heterogeneity w affect costs.[16] Under these assumptions and if the variables capturing observed and unobserved heterogeneity $(\mathbf{x},w)$ are independent of cost c, the equilibrium bid function can be written as,

$$\begin{aligned}\beta(c|n,\mathbf{x},w)&=\beta(c|n,\mathbf{x}_0,w_0)+\Gamma(\mathbf{x},w)\\&=\alpha(n)+\Gamma(\mathbf{x}_0,w_0)+\tilde{\Gamma}(\mathbf{x},w)+\tilde{\beta}(c|n,\mathbf{x}_0,w_0)\end{aligned}$$

where $\tilde{\Gamma}(\mathbf{x},w)=\Gamma(\mathbf{x},w)-\Gamma(\mathbf{x}_0,w_0)$, $\alpha(n)=E(\beta(c|n,\mathbf{x}_0,w_0))$, and $\tilde{\beta}(c|n,\mathbf{x}_0,w_0)$ is a conditional zero mean term. Because in equilibrium $b^0\equiv\alpha(n)+\Gamma(\mathbf{x}_0,w_0)+\tilde{\beta}(c|n,\mathbf{x}_0,w_0)=b-\tilde{\Gamma}\,(\mathbf{x},w)$ is interpreted as the bid a firm would have submitted in equilibrium to an auction with observables characteristics $\Gamma(\mathbf{x},w)=\Gamma(\mathbf{x}_0,w_0)$. Notice that we need to control directly for the effect of w. Assuming that $\zeta(\mathbf{x},\mathbf{z})=min\{n\in N:Pr(N\leq n|\mathbf{x},\mathbf{z})\geq\tau\}$ for a quantile $\tau\in(0,1)$, we write,

$$n=\zeta(\mathbf{x},\mathbf{z})+w, \tag{3.8}$$

where $\mathbf{z}$ is a vector of instruments and w is an index that includes unobserved factors independent of $\mathbf{x}$. Conditional on $\mathbf{x}$, the instrument $\mathbf{z}$ is independent of c and w. In this paper, we take a control variate approach, estimating $w=n-\zeta(x,z)$ as suggested in Haile et al. (2006).

We use a non-parametric approach to estimate $\left(1-G\left(\hat{b}^0\right)\right)/g\left(\hat{b}^0\right)$, where $\hat{b}^0=b-\hat{\Gamma}(\mathbf{x},\hat{w})$. The function $\Gamma(\mathbf{x},w)$ is parametrically specified and estimated by standard methods.[17] This is convenient because (a) they converge at a faster rate than non-parametric methods and (b) they offer a convenient way of incorporating a large set of covariates. We obtain $\hat{w}$ after estimating Eq. (3.8) by censored quantile regression. We use the number of plan holders as an instrument. The vector $\mathbf{x}$ includes controls for project's size (engineer's cost estimate and a quadratic term on the engineer's estimate), variables associated with the complexity of the project (number of project's component and a quadratic term on the number of project's component), controls for length of the project (calendar days to finish the project, and an interaction term between calendar days and engineer's cost estimate), controls for project's type (percentage of earthwork, percentage of bridge work, percentage of asphalt pavement work, and percentage of concrete work), and four variables indicating the location of the projects. To control for asymmetries among bidders, it is standard to include the distance to the project location and the capacity utilization of the firm in activities related to procurement (capacity utilized) in the vector $\mathbf{x}$ (Bajari and Ye, 2003; Jofre-Bonet and Pesendorfer, 2003). Finally, we estimate Eqs. (3.2) and (3.3) using the homogenized bids, and the following estimators,

$$\hat{g}_{jn}\left(\hat{b}^0\right)=\frac{1}{nL_{jn}h_{jn}}\sum_{l=1}^{L_{jn}}\sum_{i=1}^{n}K\left(\frac{\hat{b}^0-\hat{b}^0_{jnil}}{h_{jn}}\right),\hat{G}_{jn}\left(\hat{b}^0\right)=\frac{1}{nL_{jn}}\sum_{l=1}^{L_{jn}}\sum_{i=1}^{n}1\left\{\hat{b}^0_{jnil}\leq\hat{b}^0\right\},$$

where, as before, $1\{\cdot\}$ is an indicator function, L denotes the number of auctions, $K(\cdot)$ is a continuously differentiable kernel function defined over a compact support, and h is a properly chosen bandwidth. We use the triweight kernel defined above.

Fig. 3.2 presents a comparison between the cost distributions of projects with subcontracting goals and without subcontracting goals. We present the results for the sample of asphalt projects in the top panel, and the results for the sample of surface treatment projects in the bottom panel. The comparison of the cost distributions for asphalt projects presented at the top of Fig. 3.2 suggests slightly different locations and different scales. These differences tend to disappear when we consider the sample of surface treatment projects. The evidence presented in the bottom panel indicates that the differences in the cost distributions are negligible.[18]

At first glance, the results presented in Fig. 3.2 indicate that the cost distributions may not be significantly different. To examine this further, we provide 95% variability bands for several quantiles of the cost distributions in Table 3.2. Because the homogenized bids are based on estimates obtained in a first stage, standard pointwise confidence

[15] We follow closely Haile et al. (2006) notation on the normalization. The covariate value $\mathbf{x}_0$ may not need to exist.

[16] This assumption leads to a structure that it is convenient because it is preserved by equilibrium bidding. If the variables enter multiplicatively rather than additively in the cost function, it is possible to apply an approach analogous to the one developed by Haile et al. (2006).

[17] We evaluated the sensitivity of our results to the choice of the mean function, letting $\Gamma(\cdot)$ to be a smooth function. We estimated the function considering standard local polynomial regression and generalized additive methods. In our application, the evidence suggests that the conclusions are not sensitive to the choice of the conditional mean function.

[18] The motivation of controlling for endogenous participation is associated with projects with small bridge and earthwork components. We also compared the pseudo-cost distributions assuming that unobserved heterogeneity does not affect the identification of Eqs. (3.2) and (3.3). After controlling for observed heterogeneity by estimating $\Gamma(\mathbf{x})$, we obtained cost distributions that were similar to the ones presented in Fig. 3.2.

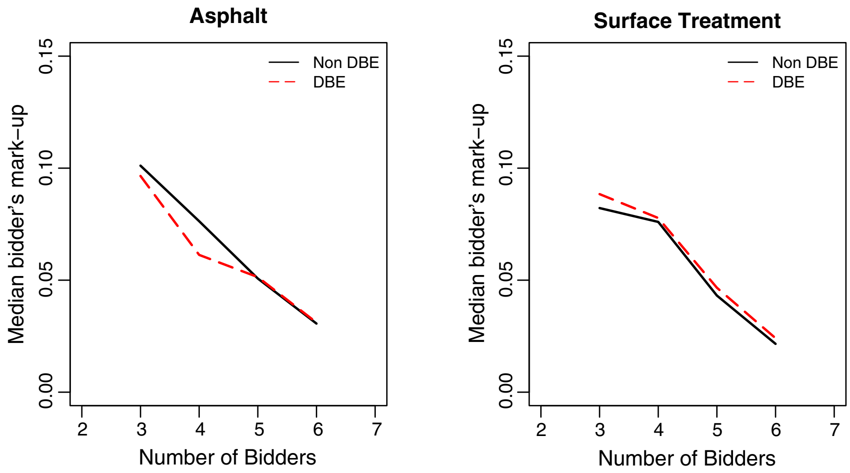

Fig. 3.3. Bidder's mark-up in projects with 3, 4, 5, and 6 bidders.

Table 3.3
Tests for invariance to number of bidders. Columns (1) present p-values of Wilcoxon tests. Columns (2) present the p-values of the standard Kolmogorov–Smirnov test.

n	Asphalt projects			Tests		Surface treatment projects			Tests	
	Median	Mean	SD	(1)	(2)	Median	Mean	SD	(1)	(2)
	Non-DBE					Non-DBE				
3	2.683	2.694	0.927	0.642	0.778	2.678	2.666	0.536	0.578	0.939
4	2.714	2.699	0.864			2.626	2.668	0.906		
	DBE					DBE				
3	2.730	2.666	0.696	0.807	0.888	2.595	2.627	0.736	0.452	0.719
4	2.716	2.625	0.653			2.594	2.485	0.657		

intervals for the densities cannot be used. Alternatively, we can use the bootstrap to provide a measure of the variability of the estimates (see, e.g., Pagan and Ullah, 1999). Specifically, a bootstrap procedure is implemented as follows.[19, 20] We draw an auction from a sample of projects and we include all bidders for that project. We continue sampling projects with replacement until we obtain a sample of L projects. Using this sample, we estimate $\Gamma(\mathbf{x}, w)$. We then construct the homogenized bids $\hat{\mathbf{b}}^0$, separately for 3 and 4 bidders. Using these samples of bids, we compute the estimates of the DBE and non-DBE densities. We iterate the procedure 10,000 times. We finally construct pointwise 95% variability bands from the quantiles of the empirical distributions. The results of the table suggest that the DBE and non-DBE distributions are not statistically different, since the variability bands overlap at different quantiles of the cost distributions.[21]

To investigate the performance of our empirical strategy, we construct estimates of the median bidders' markup $(b-\hat{c})/\hat{c}$ in auctions with 3, 4, 5, and 6 bidders. Extending the previous analysis to include auctions with 5 and 6 bidders allows us to examine in more detail the markups generated by the approach. Fig. 3.3 shows continuous lines representing the median markup in non-DBE projects, and dashed lines denoting the median markup in the DBE projects. The panels show small differences between the continuous line and the dashed line, suggesting that the program did not generate considerable differences in the levels of the markups during our sample period. Moreover, these markups are similar to the ones reported in the literature (see, e.g., Bajari and Ye, 2003), varying between 2 and 10%. Lastly, the negative slopes show the effect of competition on markups in these procurement auctions.

3.4. Testing the IPV assumptions

The IPV assumption could be violated in this context if there were costs common across bidders. One potential source of common costs could be the use of a limited set of subcontractors for specific tasks across prime contractors. While prime contractors used a large number of distinct subcontractors over the sample period, some subcontractors were employed more frequently.

Our analysis was performed using the symmetric independent private value framework, which essentially implies exchangeability of marginal distributions and independence (Athey and Haile, 2007). Under exogenous variation of bidders, this framework suggests that the marginal distributions for $n=3$ and $n=4$ must be equal, because the costs are invariant to n (Lemma 1, Haile et al., 2006).

In Table 3.3, we present evidence on estimates for the marginal distributions of projects with different number of bidders. While the columns marked as (1) provide p-values corresponding to Wilcoxon tests, the columns marked as (2) provide p-values corresponding to Kolmogorov–Smirnov tests.[22] The first statistic is a common test suggested in the literature to evaluate difference in location, and it is applied to evaluate if the cost distributions have similar locations. The second statistic is a test for independence, and it is applied in this case to evaluate if the cost distributions in auctions with 3 and 4 bidders are significantly different. The testing procedures are described in Appendix A.

The tests seem to suggest that the sample of projects exclusively related to surface treatment fits the framework better. The cost distributions obtained using the surface treatment projects vary less in the number of bidders, and therefore, they appear to satisfy the condition on the marginal distributions associated to the IPV framework.

The IPV framework also relies on the independence of the bids submitted to an auction. We employed three testing procedures to evaluate conditional independence on pairs of bids (i,j) in auctions with 3 and 4 bidders: (i) the non-parametric test proposed by Blum et al. (1961); (ii) Kendall τ rank correlation coefficient; (iii) a Kolmogorov–Smirnov test

[19] Other bootstrap procedures have been implemented in the literature (see, e.g., Hendricks et al. (2003) and Krasnokutskaya (2011)). Hendricks et al. (2003) use a slightly different bootstrap procedure.

[20] In principle, we can use a simpler bootstrap procedure, because we might not account for dependence of any form and/or heteroscedastic errors. We evaluate the assumptions in Section 3.4.

[21] It is important to note that inference is based on estimated costs, and therefore, the limiting distribution of the test may be affected. To the best of our knowledge, the literature offers one approach. An earlier version of Haile et al. (2006) investigated a Kolmogorov–Smirnov test based on a resampling approach. According to the authors, the test performance was poor in small samples. Issues associated with inference using estimated costs are out of the scope of the paper.

[22] The tests are based on estimated costs, which might lead to incorrect inference. The estimation of costs may influence the limiting distribution of our tests. To the best of our knowledge, there is not well-established correction to this difficult problem. This issue is out of the scope of our paper.

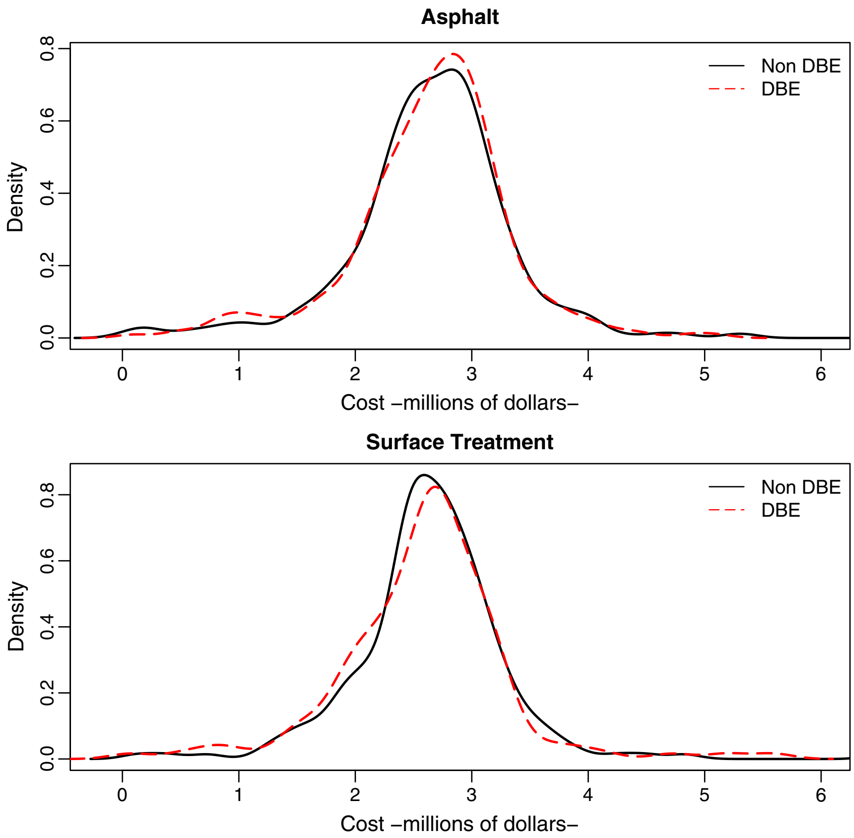

Fig. 3.4. Cost densities for DBE and non-DBE projects and selection bias.

for independence. The findings can be summarized as follows: (a) we failed to reject the null hypothesis at 5% in 98 tests out of the 108 performed tests, and (b) surface treatment projects provided a better fit to the assumptions of the model relative to the sample of asphalt projects.

3.5. Additional considerations on selection issues

The previous analysis shows that there is little difference in project costs between projects that are assigned subcontracting goals versus projects that are not assigned goals. This section discusses a few additional issues associated with bidder's participation and project heterogeneity. We previously addressed endogenous participation influenced by project unobserved heterogeneity using the method proposed by Haile et al. (2006). In the analysis of the DBE program however, one needs to consider that the program may affect costs, and therefore, the participation of bidders in an auction. The DBE program might be affecting participation in auctions with and without DBE subcontracting goals. In order to address this issue, we restricted attention to bidders participating in both DBE and non-DBE auctions.[23]

The samples of asphalt projects and surface treatment projects presented in Table 3.1 exclude bidders who participated in DBE or non-DBE auctions alone. The vast majority of bidders participate in both auctions. The asphalt sample includes 84% of all bidders participating in the auctions throughout the period of analysis, and the surface treatment sample includes 82% of all bidders. Although the sample sizes are reduced, these sample refinements minimize and potentially eliminate issues associated with bidder participation and heterogeneity.

A more important issue seems to be associated with DBE assignments. As we discussed earlier, it is likely that the state would assign DBE status to a project with a large number of tasks involved.[24, 25] The possibility of this type of selection bias could be incorporated into the analysis by replacing the selection probability by a non parametric function (Das et al., 2003). A more convenient approach for this setting with a relatively large number of covariates, is to estimate the selection probability by the propensity score. The propensity score s is the conditional probability of selection estimated by standard parametric models (e.g., probit). We use the total number of bid items in a project, the number of days to complete the project and indicators for the location of the project to estimate the conditional probability of selection. We observe that these first two effects have the expected sign and are significant at 5%. To obtain the homogenized bid, we now condition on $\hat{s}$, and therefore the first stage regression is now $\mathbf{b}=\tilde{\Gamma}(\mathbf{x},\hat{w},\hat{s})+\mathbf{u}$.

[23] As a robustness check, we also estimated the models including all bidders. Our findings revealed that the results presented in this paper are not affected dramatically. We continued to find small differences in costs in the asphalt sample and no apparent differences in costs in the surface treatment sample. The mark-ups ranged from 2 to 10%, as in Fig. 3.3. We do not present the results to avoid repetition, but they are available upon request.

[24] A natural concern in the first stage regression is the suspected endogenous indicator for DBE assignment (see, e.g., Marion, 2011). It is important to note that by the nature of the exercise, the first stage regression does not include a suspected endogenous variable, but of course, the non-random assignment $j=\{0,1\}$ may create biases.

[25] More formally, the state would assign DBE status to a project if $1\left\{\mathbf{d}'\delta+\eta>0\right\}$, where $1\{\cdot\}$ is an indicator function. The vector $\mathbf{d}$ includes the total number of bid items (project components) in a project and the availability of minority firms given by the geographic location of the project. The variable η is assumed to be an error term that could be correlated with the error term in the model for $\mathbf{b}$ but it is independent of $\mathbf{d}$. Because in the first stage $\mathbf{b}=\tilde{\Gamma}(\mathbf{x},\hat{w})+\mathbf{u}$, it is then possible that $E\{\mathbf{u}|\mathbf{x},w,\mathbf{d}'\delta>\eta\}\neq 0$ generates selection bias even in the case that $\mathbf{u}\perp\mathbf{x}$. Although they seem to represent two different issues, addressing observed heterogeneity is related in our case to correcting for selection bias. For identical projects with characteristics $(\mathbf{x}_0',w_0)'$, one would expect $\tilde{\Gamma}(\mathbf{x},w)=\Gamma(\mathbf{x},w)-\Gamma(\mathbf{x}_0,w_0)=0$, and also $E\{\mathbf{u}|\mathbf{x},w,\mathbf{d}'\delta>\eta\}=0$, simply because $\mathbf{d}'\delta$ would tend to be constant.

The panels in Fig. 3.4 present estimates of 2 and 3 that use these samples of bids $\hat{\mathbf{b}}^0$. After controlling for observed and unobserved heterogeneity and the possibility of selection bias, we again find that the cost distributions present small differences, which turn out to be negligible when we consider the sample of surface treatment projects.

4. Conclusion

This paper examines the differences in bidding and costs between projects that have subcontracting goals and projects that do not. The analysis uses the nonparametric structural approach developed by Haile et al. (2006) that allows one to control for many auction-specific characteristics and endogenous participation without increasing the sample size. This is particularly important in our setting as project size, complexity, materials use and other characteristics vary markedly across projects. Our empirical results show little difference in the level of bids submitted or in the estimated costs between projects with subcontracting goals and projects without such goals. When we utilize an even more homogeneous sample of projects, the differences are even less. Finally, we show that the implied markups generated from the Haile, Hong and Shum approach are consistent with those reported in the literature and do not differ substantially for auctions with and without subcontracting goals.

Our results stand in contrast to Marion (2009) who shows a substantial decline in winning bids with the elimination of a state-level DBE participation program in California. The environment analyzed here is much different; we are not evaluating a discrete change in policy. Moreover, it appears that controls for project heterogeneity explain well the observed difference in bids between DBE and non-DBE projects (Fig. 2.2) in Texas, whereas in California additional controls for project heterogeneity do not substantially mute the estimated program effects.

A simple interpretation of the Texas results is that the supply and quality of DBE subcontractors were sufficient during our period of analysis so that prime contractors were effectively unrestricted in their bidding due to the presence of DBE requirements. The Census Bureau's 2002 Survey of Business Owners indicates that Texas has a relatively large number of minority-owned construction firms in comparison to the average state, reflecting, at least in part, the large minority population of the state. Moreover, our findings do not necessarily mean that the program has had no effects on contracting. The program may have encouraged the formation and success of minority and women-owned businesses increasing the supply of DBE subcontractors, something that we cannot test with our data. Alternatively, the program may have affected project costs but the effects may have occurred outside our window of observation. Specifically, they may have occurred when the program was introduced—several decades before our period of analysis. That said, our results suggest that during the period under study DBE subcontracting requirements did not substantially raise the bids or costs of prime contractors.

Appendix A

A.1. Testing procedures

Let $\{(Z_i,V_i)\}_{i=1}^{n}$ be random samples with densities g_Z, g_V, and joint density $f(z,v)$. Hájek et al. (1999) suggest the following tests for independence and location.

1. B test: This test, which was employed in Campo et al. (2003), was proposed by Blum et al. (1961). The test statistic is equal to,

$$B_n = (F(z,v)-G_Z(z)G_V(v))^2 dF(z,v),$$

where $F(z,v)=n^{-1}{}_{i=1}^{n}I(Z_i\leq z,V_i\leq v)$, $G_Z(z)=n^{-1}{}_{i=1}^{n}I(Z_i\leq z)$, and $G_V(v)=n^{-1}{}_{i=1}^{n}I(V_i\leq v)$. This test is consistent and distribution free.

2. Kolmogorov–Smirnov test: Using the previous definitions, we can write this test as $KS_n = sup|F(z,v)-G_Z(z)G_V(v)|$.
3. Wilcoxon rank test: We set $Z_{n+j}=V_j$ for $j=1,\ldots n$ and $N=2n$. Let R_i $(i=1,\ldots N)$ be the rank of the observation Z_i in the ordered sequence $Z^{(1)}<Z^{(2)}<\ldots<Z^{(N)}$. This test is based on the statistic $S={}_{i=1}^{n}R_i$. Another form of the test is called Mann–Whitney statistic, which is based on the number of pairs (Z_i,V_i) such that $Z_i<V_j$. Under the null hypothesis of no differences in location, the standardized version of S is asymptotically normal as $n\rightarrow\infty$.
4. Kendall τ rank correlation test: Let R_i $(i=1,\ldots n)$ be the rank of the observation Z_i in the ordered sequence $Z^{(1)}<Z^{(2)}<\ldots<Z^{(n)}$ and Q_i $(i=1,\ldots n)$ be the rank of the observation V_i in the ordered sequence $V^{(1)}<V^{(2)}<\ldots<V^{(n)}$. This test is based on the following statistic: $\tau=(n(n-1))^{-1}_{i\neq j}sgn(R_i-R_j)sgn(Q_i-Q_j)$, where $sgn(A)$ denotes the sign of A. Under H_0, the standardized version of τ tends to a Gaussian distribution.

Variable definitions.

Variable	Definition
Log of bids	Log value of bids.
Log of ECE	The log value of the engineer's cost estimate (ECE.)
DBE projects	Indicator variable where DBE = 1 for projects with DBE goals; DBE = 0 otherwise
DBE: 0% (fed projects)	An indicator variable that takes the value of 1 when the project is federally funded and DBE goal is = 0. Otherwise it takes the value 0.
DBE : 1%–5%	An indicator variable that takes the value of 1 when DBE goal is between 1%–5% and 0 otherwise.
DBE : 6%–7%	An indicator variable that takes the value of 1 when DBE goal is between 6%–7% and 0 otherwise.
DBE : ≥8%	An indicator variable takes the value of 1 when DBE goal is greater than or equal to 8% and 0 otherwise.
State projects	State Project Dummy: indicator variable where State = 1 for state projects; State = 0 for federal projects.
Number of plan holders	Number of firms that hold plans for a project prior to submitting bids.
Number of bidders	The number of bidders in an auction.
Complexity	The number of bid items in a project.
Calendar days	Number of days to complete the project assigned by TxDOT.
Distance to the project location	The distance between the county the project is located in and the distance to the county of the firm's location [log(distance + 1)]
Capacity utilized	The utilization rate is the current project backlog of a firm divided by the maximum backlog of that firm during the sample period. Note that the backlog is constructed by summing across the non-completed value of the contract of existing contracts. The backlog variable is similar to the variables used by Bajari and Ye (2003) and Jofre-Bonet and Pesendorfer (2003). For firms that have never won a contract, the utilization rate is set to zero.
Bridge work percentage	The value of the bridge work bid items relative to the ECE.
Earth work percentage	The value of the earth work bid items relative to the ECE.
Pavement work percentage	The value of the pavement work bid items relative to the ECE.
Concrete work percentage	The value of the concrete work bid items relative to the ECE.
Material shares of a project	We identify 12 material groups for projects in "Standard Specifications for Construction and by Maintenance of Highways, Streets, and Bridges", a code book adopted by TxDOT. The following shares are obtained from information on bid items and engineering cost estimates: 1) asphalt surface work; 2) other asphalt surface items; 3) earth work; 4) other earth work items; 5) miscellaneous work; 6) other miscellaneous related work; 7) structures; 8) other structures items; 9) subgrade; 10) other subgrade related items; 11) lighting and signaling work; 12) other lighting and signaling related work.
Division dummies	TxDOT has 25 divisions, which are identified by division dummies.
Zone dummies	TxDOT divides Texas into five major geographic zones. We identify these zones using zone dummies.

Bid items in federal and state projects. Percentages are in brackets.

Item description	Federal projects		State projects
	With DBE goals	Without DBE goals	
Preparing right of way	2249 [59.01]	789 [20.70]	773 [20.28]
Embankment	2835 [59.81]	970 [20.46]	935 [19.73]
Topsoil	888 [57.33]	287 [18.53]	374 [24.14]
Compost	244 [49.90]	114 [23.31]	131 [26.79]
Sodding for erosion control	1064 [59.91]	316 [17.79]	396 [22.30]
Seeding for erosion control	5020 [59.64]	1718 [20.41]	1679 [19.95]
Fertilizer	466 [61.48]	139 [18.34]	153 [20.18]
Vegetative watering	2528 [56.62]	986 [22.08]	951 [21.30]
Soil retention blankets	851 [66.07]	218 [16.93]	219 [17.00]
Irrigation system	174 [40.47]	73 [16.98]	183 [42.56]
Wildflower seeding	43 [44.79]	21 [21.88]	32 [33.33]
Landscape planting	1791 [44.95]	521 [13.08]	1672 [41.97]
Landscape establishment	142 [31.91]	33 [7.42]	270 [60.67]
Salvaging, stockpiling asphalt pavement	817 [72.36]	144 [12.75]	168 [14.88]
Barricades, signs, and traffic handling	3106 [39.83]	2073 [26.58]	2619 [33.59]
Erosion and environmental controls	6664 [47.95]	3300 [23.75]	3933 [28.30]
Constructing detours	1061 [78.59]	149 [11.04]	140 [10.37]
One-way traffic control	148 [45.40]	42 [12.88]	136 [41.72]
Portable concrete traffic barrier	3996 [77.55]	576 [11.18]	581 [11.27]
Permanent concrete traffic barrier	1024 [81.66]	111 [8.85]	119 [9.49]
Textured concrete and landscape pavers	203 [61.70]	34 [10.33]	92 [27.96]
Concrete curb and gutter	2366 [67.75]	440 [12.60]	686 [19.64]
Right of way markers	203 [66.78]	86 [28.29]	15 [4.93]
Crash cushion attenuators	1181 [76.69]	188 [12.21]	171 [11.10]
Chain link fence	376 [79.49]	50 [10.57]	47 [9.94]
Wire fence	423 [60.52]	186 [26.61]	90 [12.88]
All DBE items	39,863 [56.95]	13,564 [19.38]	16,565 [23.67]
All items	300,680 [59.76]	88,459 [17.58]	114,035 [22.66]

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