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Efficacy of a Bidder Training Program: Lessons from LINC*

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Abstract

In an effort to accommodate a change in the U.S. Federal Highway Administration's goals towards "race-neutral methods" concerning the involvement of Disadvantaged Business Enterprises in procurement contracting, the Texas Department of Transportation created a Learning, Information, Networking and Collaboration (LINC) bidder training program. We examine the costs, benefits, and efficacy of this program using ten years of data, leveraging firm-specific bidding patterns with participation dates. We study participation, entry and bidding patterns of LINC-trained relative to untrained firms. We also analyze market power effects and the survival rates of LINC graduates.

JEL Classification: C54, D44.
Keywords: auctions, bidder training, disadvantaged business enterprises.

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1 Introduction

The U.S. Federal Highway Administration (FHWA) has used government policies since the early 1980's to encourage minority participation in procurement contracting. Many states employ bid preference programs, which discount the bids of qualified firms for the purpose of evaluation. Other programs require government agencies to set aside a certain percentage of a contract to be subcontracted out to disadvantaged business enterprises (DBEs) or other qualified firms. Over the decades and largely in response to court decisions (see, for example, the Supreme Court's 1999 ruling in *Adarand vs. Peña*, U.S. Report 515 U.S. 200), the nature and administration of DBE programs has changed. While they still retain their basic structure, the goal of firm participation is now described as being "aspirational." Individual state agencies that administer the programs, are asked to achieve as much of the goal by "race-neutral methods" as possible before employing race-conscious federal procurement programs. In addition, qualified DBE firms are not simply determined by belonging to a particular demographic group (e.g., being owned by a minority, veteran, or woman) but also by their economic circumstances (e.g., small businesses). The overall regulatory response of the FHWA was to tailor programs to meet the Court's objections.

In response to the shift in the disposition of FHWA policy, the Texas Department of Transportation (TxDOT) created its own Learning, Information, Networking, Collaboration (LINC) training program in 2001 to "mentor" small and minority-owned businesses interested in doing business with TxDOT.[1] Texas has the second largest state economy in the U.S. and a diverse population with 37.62% of its residents identifying as Hispanic and 11.94% as Black in the 2010 Census. LINC's goals are to improve participation of qualified firms in a race-neutral way as well as to train these firms to bid successfully on TxDOT contracts by providing information, networking opportunities, project management, and bidding training sessions. The program allows firm owners to improve their knowledge and project management skills, thus, increasing the chances for success without explicitly constraining the decision making process. During our ten-year sample period which spans September 1997 to August 2007,

[1] LINC was established as an opportunity for DBEs as well as historically underutilized businesses (HUBs) and small business enterprises (SBEs).

the total value of contracts awarded to LINC-eligible bidders was \$2.04 billion. We examine the impact of LINC on participation, bidding, and the cost structure of qualified bidders acting as primary contractors. The LINC program description states that the targeted firms are "critical to economic competitiveness in the Transportation industry." As such, we consider whether the LINC program might improve retention of such firms in the long-run for this industry.

The efficacy of other existing minority-preference policies on procurement costs have been examined by a number of researchers with varying conclusions. Several papers deal with bid preference schemes.[2] Denes [1997] compared bids submitted between solicitations restricted to small businesses and unrestricted solicitations, finding that bids are no higher in restricted settings. Marion [2007] found that in data from California auctions for road construction contracts, the price paid by the state was 3.8 percent higher for auctions which used preferences. Krasnokutskaya and Seim [2011] also analyzed bid preference programs in California highway procurement contracts and found that the preferential treatment of small businesses creates losses in efficiency but no change in the overall cost of procurement.

While bid preference policies introduce an asymmetry among bidders (even if bidders draw costs from the same distribution), the potential for efficiency distortions stems from a different source for programs setting minority subcontracting goals. These programs are often used in federal procurement contracts and may constrain the make-or-buy decision of prime contractors. These distortions may arise because of potentially less efficient production of tasks by subcontractors compared to the prime contractor (relative to an unrestricted setting) or due to changes in competition intensity in the subcontracting market. Marion [2011] used data from the California Department of Transportation to show that the subcontracting goals set for highway construction contracts in California raise DBE usage significantly, so that the constraints appear to bind. In fact, Marion [2009] found that after California's Proposition 209 was passed (which prohibited DBE subcontracting goals concerning race or gender), state-funded contracts realized a 5.6 percent fall in prices relative to federally-funded

[2] Note that the effect of such programs on the state's cost is ambiguous even at the theoretical level; see McAfee and McMillan [1989] and Hubbard and Paarsch [2009].

projects which still involved subcontracting goals. Recently, De Silva et al. [2012] evaluated the impact of a federal subcontracting policy years after its original implementation and found that minority subcontracting goals have not increased the procurement cost in Texas.

To our knowledge, we are the first to study the effects of a bidder-training program. We have contacted representatives at every U.S. state's Department of Transportation office and have learned two things: first, these programs are quite common as more than thirty states have in place a program with many of these elements; second, Texas seems to be one of the first states to introduce such a program and its program seems to be one of the largest in terms of participation. In our correspondence with employees at state offices we have learned that these programs often go by different names (e.g., Calmentor in California, Connect2DOT in Colorado, and Mission 360^{o} in Rhode Island) and are often defined as mentor-protégé programs which are administered through economic or local development offices. Most programs have bidder training, formal mentoring, educational seminars or components, outreach such as trade shows and business fairs, technical assistance, financial and management consulting services, and/or networking as key elements. Nearly all programs have goals of promoting effective business development by improving the performance of trained firms, ultimately leading to a higher survival rate of such firms.

In general, such training programs seem to be on the rise. Some states have either implemented new programs (e.g., the Oklahoma Department of Transportation's Small Enterprise Training Program) or are re-emphasizing or revamping old programs (e.g., the Washington Department of Transportation recently expanded its program from targeting minority- and women-owned firms to include small businesses in general), and a number of representatives for states that do not currently have any programs indicated that they felt such opportunities would be a good idea. Moreover, these programs are not unique to Department of Transportations—the leading inspiration for such programs seems to be the Stempel Program for the Port of Portland in Oregon.[3] Given the prevalence and interest in such training programs, we hope our work has important policy implications as there is potential for

[3]See the very informative Wisconsin Department of Transportation [2010] report which summarized and surveyed how such programs have been operated in the U.S. and the Associated General Contractors of America's website: http://www.agc.org/cs/industry_topics/additional_industry_topics/the_stempel_plan for additional details on such programs.

our findings to suggest alternative policies to meet FHWA's original goals in a way that can actually generate clear cost savings (benefits). Mentors in the LINC program are volunteers and so the only costs for the state are administrative salaries and the costs to organize LINC-related training sessions. We have obtained expense data that reports LINC costs for fiscal years 2005 to 2012 which show that the program costs the state about $200,000 per fiscal year.[4] In what follows, we hope to shed light on the potential benefits to be had from such a program either through participation, bidding, efficiency improvements, and/or firm retention.

In general, we find the most convincing effects LINC has on bidders is with respect to bidding behavior—LINC-trained bidders behave more aggressively than firms that are not eligible for the program as well as those that are eligible but have not undergone the training program. The lower bids carry through to generate cost-savings for TxDOT in two ways: first, when LINC-trained firms win their bids are lower, on average, than those of all other firms. Second, when other firms compete at auction with LINC-trained firms, the average winning bid is also lower. These two channels generate substantial cost-savings for the state. We find LINC-trained firms that then win auctions maintain similar Lerner indexes to other firms. Moreover, eligible firms that do not get trained are more likely to exit the industry than firms that are not eligible, but this effect goes away for firms that graduate from the LINC program. We expand on and make precise these claims in what follows.

In the next section, we describe our TxDOT data and first examine what drives a qualified firm to participate in the program. In Section 3, we investigate whether trained firms are more likely to bid on a contract once they hold the plans, as well as whether they are more likely to win a contract given they've chosen to bid. We also present a set of descriptive regressions to identify bidding patterns before and after the policy was implemented and to investigate whether winning bids have been affected by the LINC program. In Section 4, we present a structural model which allows us to speak about potential changes to firms' (unobserved) cost structures, the efficiency of the auctions, and market power in the industry. The results and insights from such estimates live in Section 5. In Section 6, we consider whether firm survival in the industry has been affected by participation and, lastly, in Section

[4]The costs range from a low of $181,078 to a high of $235,234.

7, we conclude.

2 Data Description and LINC Participation

We begin our investigation of the effects of the LINC program by describing our data and determining what might drive qualified firms to participate in LINC. Note that, we take as given, the set of eligible firms—these, by requirement of the LINC program, must be firms that have been certified as a DBE, HUB, or SBE for at least one year.[5]

2.1 Data Description

In our analysis, we use data from regularly-scheduled TxDOT highway procurement auctions conducted between September 1997 and August 2007. Data from September 1997 to August 1998 are used to create bidder-specific histories such as a measure of workload commitment (commonly referred to in the auctions literature as backlog). Thus, our empirical analysis in what follows employs the data from September 1998 through August 2007. Prior to bidding, all bidders learn the location and the detailed project description, the estimated number of days to complete the project, the engineer's estimate of the cost of executing the project, and the list of contractors who purchased the documents providing the initial plan description (the plan holders). Projects are awarded using the low-price, sealed-bid (procurement) auction format. The bidding process opens a minimum of 28 days after the plan for a project is posted. At the conclusion of each session, the bids submitted by each bidder are revealed and the winner is announced. For each contract, we observe the identities of the firms that requested plans, the identities of all firms that tendered a bid along with the amount of each bid, as well as the engineer's cost estimate, projected time to complete the contract, and details concerning the tasks each contract requires. We complement these data with firm-specific LINC-eligibility and LINC-participation data and we construct, using each firm's past bidding behavior, other variables that might be important in driving observed behavior. While we try to explain each variable in the

[5] There seems to be little downside, and perhaps only benefits, to claiming such DBE/HUB/SBE status. Anecdotal evidence of this might be Representative Tammy Duckworth's (D, Illinois) "questioning" during a House Oversight and Government Reform Committee hearing of federal contractor Braulio Castillo who was accused of exploiting the system of veterans benefits. During her questioning Rep. Duckworth revealed that "Iraq and Afghanistan veterans right now are waiting an average of 237 days for an initial disability rating..."

Table 1: Summary statistics

	Bidder category			
			LINC qualified	
Variable	All	Non-LINC	Untrained	Trained
Number of plan holder firms	1749	1520	198	90
Number of plans held	53683	47290	3101	3292
Number of bidding firms	1057	924	124	58
Number of bids	31783	28480	1564	1739
Number of winning firms	655	564	83	44
Number of wins	7434	6613	406	415
Bidding-to-plan holder ratio	.587	.596	.492	.549
	(.229)	(.225)	(.271)	(.208)
Relative bid	1.086	1.084	1.110	1.087
	(.243)	(.242)	(.256)	(.258)
Relative winning bid	.977	.977	.976	.968
	(.178)	(.178)	(.179)	(.174)
Engineer's estimate (in millions of $)	4.072	4.269	2.758	2.195
	(11.4)	(11.8)	(7.740)	(8.498)
Number of days to complete the project	153.219	155.232	132.880	140.782
	(172.422)	(176.462)	(128.438)	(139.664)
Complexity of the project (bid components)	64.824	65.135	61.577	63.017
	(61.329)	(62.163)	(52.199)	(47.090)

Standard deviations are in parentheses.

text, we collect all variable definitions in a table we have relegated to the Appendix.

In Table 1, we present sample summary statistics for the full sample, for ineligible/non-qualified (non-LINC) firms, and for LINC-eligible firms. We partition the LINC-eligible into two groups: untrained and trained. The untrained firms include either firms that are eligible but choose not to participate in the program and those who eventually get trained, but are observed in our data before training. In the full sample, we find 1749 unique firms holding plans. Of those firms, 229 are LINC-qualified prime bidders, 90 of which have participated in the LINC program.[6] In our sample period,

[6]Though we will not harp on this, we will remind readers since this is the time the untrained-trained distinction is applied: 229 is not equal to the number of untrained plus the number of trained bidders because some firms classify as untrained in part of our sample, then they complete LINC training and afterwards are classified as training. Thus, 229 is the number of unique LINC-eligible firms.

58 LINC participants went on to eventually submit bids (constituting 1739 bids) and we observe 44 of them winning at least one contract. The bidding-to-plan holder ratio is a measure of bidding frequency of those indicating interest in a project by purchasing a plan. When considering this ratio, participation rates for ineligible firms are about ten percent higher than those for LINC-qualified, but untrained firms. LINC training cuts this disparity in half. Note too, that if the number of wins is normalized by the number of bids, the winning-to-bidding ratio is fairly consistent across the categories. A potentially important difference is that the number of LINC-trained firms submitting these winning bids is just over half that of the number of untrained winners, indicating that training might improve success rates of a given firm.

Before training, LINC-qualified firms submit relative bids (bids normalized by engineering cost estimates) that are about two percent higher than traditional firms, though this difference goes away after LINC training. We also see that after training, LINC bidders' relative winning bids are about one percent lower than those of other groups. The last three rows of the table indicate the type of contracts in which bidding occurs may play an important role. These variables proxy for the average size or complexity of the projects on which bids are submitted. LINC-qualified bidders, on average, bid on projects that are estimated by state engineers to cost about \$1.5 million less than projects non-LINC firms bid on (and this difference increases after training). We also see that projects undertaken by qualified bidders take 15–20 days less, on average, than those by ineligible bidders. Qualified bidders also undertake projects that are typically less complex in that they have fewer components.

2.2 LINC Participation

Before considering the effects of LINC training, we first consider what might drive eligible firms to participate (or not) in the program. Specifically, we consider a probit model using monthly data to explain the probability of participating. The first time a LINC-eligible firm requests plans, the firm is assigned a response variable of zero (having not participated in LINC). If the firm completes the LINC program, the response variable changes to a one. We restrict attention to LINC-qualified entrants since 2001, the inception year of the LINC program as firms that entered earlier did not have the opportunity to participate, even if they would have been willing to. In Table 2, we present the estimates of three probit regressions as marginal effects. The models differ by various measures of a given firm's experience which is captured by the past winning-to-bidding, winning-to-plan holder, and bidding-to-plan holder ratios. Regardless of the proxy for experience, the more experienced the LINC-eligible firm, the less likely the firm is to participate in LINC. The magnitude of the effects which ranges from a 1.2 to a 5.7 percent lower probability of participating vary based on how successful the eligible firm has been—the lower participation effects are more salient for firms that have won often in the past compared to those that have experience primarily through simply participating (bidding) in auctions.[7]

Table 2: LINC Training Participation Decision

	Probability of participation in LINC		
Variable	(1)	(2)	(3)
Past winning-to-bidding ratio	-0.031***		
	(0.007)		
Past winning-to-plan holder ratio		-0.057***	
		(0.015)	
Past bidding-to-plan holder ratio			-0.012*
			(0.007)
Log (maximum backlog + 1)	-0.002***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)
Log(total number of rivals faced in the market + 1)	0.014***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)
Log(total number of LINC rivals faced in the market + 1)	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.004)
Unemployment rate	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)
Future average real value of projects	-0.003	-0.003	-0.002
	(0.006)	(0.006)	(0.006)
Number of Observations	3,027	3,027	3,027
Pseudo R^2	0.515	0.515	0.523
Wald χ^2	290.460	285.310	269.500

Robust standard errors are given below point estimates in parentheses and *** denotes statistical significance at the 1% level.

In all models, we include a set of controls to capture economic conditions facing a firm, present in the market, or expected to obtain in the future. The maximum backlog and number of rivals faced are

[7]A model with all three of the ratios is not included given that, by definition, the three are functions of each other. For example, the winning-to-plan holder ratio equals the winning-to-bidding ratio times the bidding-to-plan holder ratio.

firm-specific—the maximum backlog capturing the size (capacity) of the firm and the number of rivals being the number of unique plan holders a firm has faced in its previous participation in auctions. If the firm has existing projects it is slightly less likely to participate. This finding is statistically significant and robust across specifications. The magnitude of this effect is much lower than the effects from increased competition. Firms that faced a larger number of rivals in the past are more likely to participate in the program. The monthly unemployment rate in Texas is included as a control, though it's not significant nor is the average value of upcoming projects which is computed as the moving average value of projects offered by TxDOT in the three months that follow a point in the data. Having considered what might determine a firm's participation decision, we move on to consider the effects of LINC training.

3 The Effects of LINC Training

While the summary statistics in Table 1 suggest some interesting patterns, they provide little direct evidence of how entry, bidding, and winning may have been affected by the LINC program as we saw the types of contracts firms chose to bid on were different across the categories of firms. The firm characteristics driving LINC participation suggest important controls that must be accounted for in going forward (namely a bidder's experience, backlog, and the competitiveness of an auction). In this section, we use reduced-form methods in an attempt to control for factors that may be varying across the sample periods, auctions, and bidders in order to better gauge the effects the LINC program has had on this market. We partition our analysis into two types of results: the first concerns probabilities of actually bidding and winning while the second concerns the levels of bids and winning bids.

3.1 Likelihood of Bidding and Winning

First, we examine whether participation in the LINC program affected the entry patterns for LINC qualified bidders. To consider this, we estimated a probit model characterizing the probability of bidding in a given auction, conditional on the firm holding plans, and present estimation results in columns (1) and (2) of Table 3.[8] Our main interest is in the coefficient of the dummy variable "LINC-trained firms" which takes a value of one if the firm is a LINC-qualified firm *and* has completed the training program and takes a value of zero otherwise. Note that "LINC-qualified but untrained firm" is also a dummy variable that takes a value of one if the bidder is in fact a LINC-qualified firm, but has not participated in the training program, and zero otherwise. Again, this may involve firms that were invited but chose not to participate in the program and firms that eventually participated in LINC, but we observe them in our data before they participated. We also include a dummy variable to capture how non-LINC qualified firms bid when facing LINC trained bidders. This takes the value of one when facing a LINC-trained bidder and zero otherwise. We consider our full (September 1998 to August 2007) sample in column (1) and restrict attention to only the LINC-qualified sample in column (2).

Most of our other independent variables serve as a set of controls and involve accounting for things that are commonly used in literature. They can be categorized as representing bidder, auction, rival, and market characteristics. The bidder characteristics involve each bidder's capacity utilization, a bidder's distance to the project location, a dummy variable that takes the value of one if the firm has an ongoing project in the same county as the current project county, and the number of past bids.[9] The number of past bids is used to capture any experience gathered from prior bidding. As project characteristics, we include the estimated cost of the project provided by state engineers, the project's materials shares, the number of potential rivals (plan holders), the days to complete a project, the complexity of a project as measured by the number of bid components, and the project division identified by TxDOT. Lastly, as rival characteristics, we include rivals' past winning-to-plan holder ratio, rivals' minimum backlog, and the closest rival's distance to the project location. Finally we include a set of time dummies to control for market fluctuations. A detailed description of these

[8] One might imagine a precursor to this analysis considering whether LINC training affects the probability of requesting plans. We do not present such analysis in large part because plans are of minimal cost and when comparing the likelihood of requesting plans before-and-after training, we found no important effects. As simple evidence, a t-test considering whether the average number of proposals requested per month before LINC training is the same as that of after training (considering only firms that eventually train and against a two-sided alternative) is rejected at conventional levels and has a p-value of 0.29.

[9] Proximity and concurrent local projects can reduce moving costs and create the opportunity to share resources more effectively across projects.

variables is provided in the Appendix.

Table 3: Results for Probability of Entry and Winning Conditional upon Entry

	Pr[Entry|Plan holder]		Pr[Winning|Entry]	
	Full sample	LINC-qualified	Full sample	LINC-qualified
Variable	(1)	(2)	(3)	(4)
LINC-qualified, but untrained firm (β_1)	-0.046***		0.013	
	(0.009)		(0.011)	
LINC-trained firm (β_2)	-0.044***	-0.029*	0.012	0.023
	(0.008)	(0.016)	(0.010)	(0.022)
Facing a LINC-trained firm	0.018***	0.019	-0.005	-0.026
	(0.005)	(0.015)	(0.006)	(0.019)
Log of engineering estimate	0.013***	0.007	0.002	-0.029***
	(0.003)	(0.008)	(0.003)	(0.011)
Log number of plan holders	-0.139***	-0.117***	-0.198***	-0.155***
	(0.007)	(0.022)	(0.008)	(0.026)
Log number of days to complete the	0.001	-0.020*	-0.000	0.013
project	(0.004)	(0.012)	(0.005)	(0.015)
Log complexity	-0.041***	-0.048***	0.002	0.037***
	(0.004)	(0.011)	(0.004)	(0.014)
Bidder's capacity utilized	0.018**	-0.021	-0.072***	-0.124***
	(0.009)	(0.029)	(0.010)	(0.035)
Bidder's distance to the project	-0.041***	-0.044***	-0.021***	-0.015**
location	(0.002)	(0.006)	(0.002)	(0.007)
Ongoing project in the same	0.129***	0.148***	0.073***	0.054***
county	(0.006)	(0.017)	(0.006)	(0.019)
Average rivals' winning-to-plan	-0.293***	-0.449***	-0.528***	-0.495***
holder ratio	(0.046)	(0.140)	(0.051)	(0.166)
Log number of past bids	0.037***	0.063***	-0.007***	-0.015**
	(0.001)	(0.005)	(0.002)	(0.008)
Rivals' minimum backlog	-0.003***	-0.004***	-0.001***	-0.003*
	(0.000)	(0.001)	(0.000)	(0.001)
Closest rival's distance to the	0.024***	0.027***	0.019***	0.000
project location	(0.002)	(0.007)	(0.003)	(0.008)
Time effects (108)	Yes	Yes	Yes	Yes
Material shares (5)	Yes	Yes	Yes	Yes
Project division effects (25)	Yes	Yes	Yes	Yes
Number of Observations	53,683	6,393	31,783	3,303
Pseudo R^2	.093	.120	.051	.082
Wald χ^2	5,379.190	888.530	1638.440	289.120
χ^2 test probability: $\beta_1 = \beta_2$	0.837		0.970	

Robust standard errors are given below point estimates in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

The results indicate that LINC-eligible firms, relative to the ineligible firms are 4.4–4.6% less likely to bid in a given auction. LINC training slightly reduces a plan holder's probability of entry, though the significance of this coefficient is marginal: using the estimates in column (1), we test whether $H_0 : \beta_1 = \beta_2$ against a two-sided alternative and our results indicate that we cannot reject the null with 95 percent confidence; however, when we restrict attention to the LINC-qualified sample in column (2), the training dummy variable is significantly different from zero at the 10% level. The estimates indicate that as the number of plan holders, project complexity, and a bidder's distance to project location increases, or when they are facing strong rivals, a firm's probability of entering an auction decreases. Bidders who have ongoing projects in the same bidding location (same county), those facing rivals who are located farther away from a project site, or those who have bidding experience have a higher probability of entry.

In columns (3) and (4) of Table 3, we consider whether the probability of winning conditional on having entered (bid at) an auction changes after a firm has graduated from the LINC program. We again estimate a probit model and report marginal effects. Our results indicate that neither being LINC qualified nor being LINC trained affects the chances of winning at auction. Bidders with higher capacity utilized, those located farther from the project location, and those facing competitive rivals are less likely to win, while those firms having ongoing projects in the same county appear more likely to win. Interestingly, experience seems to work against the likelihood of winning for firms. Of course, driving the relationship between these two sets of empirical results is the bidding behavior of firms and the question of whether bidding has changed—something we explore further in the next subsection.

3.2 Bidding and Winning Bids

Since our probit results show that entry for LINC-eligible firms is not affected by LINC participation, we examine next whether bidding has been affected by the LINC training program. In Table 4 we provide a set of descriptive regression results for the full sample and the restricted sample of LINC-qualified bidders. Specifically, in the first three columns we consider explaining variation in the logarithm of all tendered bids while in the last three columns we restrict attention to the log of only winning bids.

Table 4: Descriptive Bid Regression Results

	Log of bids			Log of winning bids		
	Full sample	LINC qualified		Full sample	LINC qualified	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
LINC-qualified, but untrained firms (β_1)	0.003			-0.008		
	(0.005)			(0.009)		
LINC-trained firm (β_2)	-0.018***	-0.029***	-0.045***	-0.027***	-0.019	-0.032
	(0.005)	(0.010)	(0.015)	(0.008)	(0.018)	(0.028)
Facing a LINC-trained firm	-0.016***	0.005	-0.006	-0.014***	-0.009	-0.026
	(0.003)	(0.009)	(0.009)	(0.005)	(0.016)	(0.017)
Log of engineering estimate	0.929***	0.943***	0.926***	0.942***	0.947***	0.938***
	(0.002)	(0.006)	(0.006)	(0.003)	(0.010)	(0.010)
Log number of plan holders	-0.019***	-0.024*	-0.014	-0.071***	-0.117***	-0.080***
	(0.004)	(0.013)	(0.013)	(0.006)	(0.021)	(0.021)
Log number of days to complete the project	0.035***	0.028***	0.026***	0.026***	-0.002	0.003
	(0.002)	(0.008)	(0.008)	(0.004)	(0.013)	(0.015)
Log complexity	0.074***	0.053***	0.066***	0.092***	0.095***	0.096***
	(0.003)	(0.008)	(0.008)	(0.005)	(0.012)	(0.013)
Bidder's capacity utilized	0.030***	0.027	0.040**	0.014*	0.023	0.055*
	(0.005)	(0.016)	(0.018)	(0.008)	(0.026)	(0.031)
Bidder's distance to the project location	0.015***	0.009***	0.014***	0.006***	0.006	-0.002
	(0.001)	(0.003)	(0.005)	(0.002)	(0.006)	(0.010)
Ongoing project in the same county	-0.022***	-0.031***	-0.010	-0.017***	-0.029*	-0.024
	(0.003)	(0.009)	(0.009)	(0.004)	(0.015)	(0.015)
Average rivals' winning to plan holder ratio	-0.067***	0.007	-0.078	-0.205***	-0.130	-0.066
	(0.024)	(0.096)	(0.091)	(0.039)	(0.137)	(0.143)
Log number of past bids	0.003***	0.004	-0.002	0.004**	0.000	-0.016
	(0.001)	(0.004)	(0.007)	(0.002)	(0.006)	(0.014)
Rivals' minimum backlog	0.001***	0.000	-0.000	0.001*	-0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Closest rival's distance to the project location	-0.001	0.007*	0.005	0.004**	0.012*	0.012
	(0.001)	(0.004)	(0.004)	(0.002)	(0.006)	(0.007)
Firm effects (133)	No	No	Yes	No	No	Yes
Time effects (108)	Yes	Yes	Yes	Yes	Yes	Yes
Material shares (5)	Yes	Yes	Yes	Yes	Yes	Yes
Project division effects (25)	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	31,783	3,303	3,278	7,434	821	816
R^2	0.984	0.983	0.985	0.989	0.991	0.994

Robust standard errors are given below point estimates in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

In model (1), the omitted group is the ineligible/non-LINC firms. We see that the estimate of the coefficient β_2 indicates that after completing LINC training, firms bid more aggressively compared to their pre-LINC training levels. There is not a statistically significant difference in the bidding behavior of LINC-qualified, but untrained firms and the ineligible firms. Thus, LINC-trained firms bid 1.8% lower than other vying firms. We also include a binary variable to indicate whether a given bid came from an auction at which a LINC-trained rival was present. When that is the case, the bid is 1.6% lower on average. In short, the training program seems to be generating aggressive bidding both directly from the program's graduates, and indirectly through more competitive behavior from rival firms when LINC graduates are present at auction.

The other coefficient estimates suggest patterns that are intuitively appealing. If there are more plan holders at auction, if a firm has another project going on in the same county and can, perhaps, generate synergistic benefits, or if the rivals have been more successful in past auctions, then lower bids are tendered. If the size, length, or complexity of the project is larger/higher, then higher bids are submitted. Likewise, higher bids obtain when bidders have used much of their capacity, if they are farther from the project location, or if they have tendered fewer bids in the past. All of these effects are statistically significant at the 1% level even after controlling for time, project composition, and project division (locations within Texas) effects.

In columns (2) and (3) of Table 4 we restrict attention to the subsample of bids generated by LINC-qualified firms. As such, the omitted group now becomes the set of firms that opt not to undergo training. Relative to this group of untrained, but eligible firms, LINC bidding is even more competitive—the results suggesting bids that are 2.9% or 4.5% lower, depending on whether firm fixed effects are accounted for as in column (3).[10] However, when facing a LINC-trained bidder, other LINC-qualified firms do not change their bidding behavior in a significant way. The estimated coefficients of the other covariates included and discussed above are, for the most part, consistent with their respective counterparts in model (1), though significance is harder to achieve in this restricted sample.

Finally, in the last three columns of Table 4, we maintain the same structure of the three empirical models discussed but restrict attention to the subset of bids that were successful in receiving the contracts. With respect to the full sample of winning bids, being LINC-qualified alone does not suggest differences in bidding behavior relative to firms as the estimate of β_1 is not significant, but again LINC training seems to make a difference. LINC-trained firms generate bids that are, on average, 2.7% lower than that of their rivals. Moreover, the average of all winning bids is 1.4% lower when a LINC graduate

[10] Note that, in model (3), we use only bidders that are observed multiple times in the sample in order to identify the firm-specific fixed effects. Therefore, we have dropped 25 observations from one-time bidders.

is present at the auction. In column (4), the results indicate that the sign and significance of the other covariates are similar to those of the full sample of (winning and non-winning) bids. When only data from LINC-qualified winning bids is considered in columns (5) and (6), statistical significance is lost for most covariates and, in particular, for the LINC-related coefficients of interest.

In the introduction, we noted that operation of the LINC program costs the state about $200,000 per year. Using our estimates from column (4) of Table 4 we can provide an estimate of the benefits the LINC program has generated. Specifically, we look back to the raw data and identify which auctions were won by either (i) a LINC-trained firm with other LINC-trained bidders at auction, (ii) a LINC-trained firm with no other LINC-trained bidders at auction, or (iii) an ineligible firm who won an auction at against a LINC-trained firm. We use the coefficient point estimates from the LINC-trained dummy and the variable indicating whether a LINC-trained bidder was present at auction to recompute how much more expensive (because these coefficients are negative suggesting lower winning bids were realized) the auctions would have been. Aggregating the savings across the three types of winning scenarios noted implies cost savings (benefits) of over $21 million per year—this amounts to 1.49% of the total value of the engineer's estimates for these contracts and 1.55% of the total value of the actual winning bids for these contracts.[11] While there may be issues with such a back-of-the-envelope counterfactual given changes in bidder behavior are not fully internalized, the negligible cost to TxDOT of running the LINC program pales in comparison to the funds saved (and even the predicted lower bound noted in footnote 11). Another way to quantify the effect of the LINC program involves calculating the number of additional plan holders or bidders per auction that would be required to induce the same cost savings. Again, using the estimates from column (4) of the table suggests that TxDOT would need to have, on average, an additional 0.95 plan holders or 0.56 bidders per auction to yield the same cost savings.

While more aggressive bidding generates lower expenditures for TxDOT in a given auction, a concern could be that the LINC-trained firms are leaving themselves too little of a mark-up over costs

[11] We compute a 95% confidence interval for these predictions by considering the coefficient estimates plus and minus the appropriate number of standard deviations and then re-predicting cost savings. Such an exercise puts the cost savings in the range of [$7.1 million, $41.7 million].

and that their bidding behavior might not be sustainable in the long-run. Alternatively, perhaps their costs are improving which is allowing them to be more successful. In the same vein, it would be interesting to look at whether the efficiency of the procurement auctions has improved as a result of the LINC training program. Of course, analyzing bidding behavior is reasonably straightforward as bids are observed directly, but shedding light on these other issues involves understanding the (unobserved) cost structures of the firms. To investigate these questions involving firms' costs and the efficiency of the auctions, we construct a structural model of bidding behavior in the next section and present insight from estimating the latent cost distributions in the section that follows.

4 Structural Model of Bidding

In this section, we investigate further the change in observed bidding patterns by appealing to a theoretical model in which we allow for asymmetric bidders.[12] Note that we do not impose such an asymmetry in our analysis, but rather, allow for the possibility in our estimation strategy which is nonparametric and, thus, data-driven. We organize this section as follows. In the first subsection, we describe the underlying model. In the second subsection, we discuss practical issues including the pooling of many types of heterogeneous auctions in which the composition of bidders differs in our empirical work.

4.1 Asymmetric Procurement Model

Consider TxDOT would like to complete an indivisible task at the lowest possible cost. Tenders are invited from n (≥ 2) bidders (firms) and are opened only once a submission deadline has passed. The contract is awarded to the lowest bidder, who wins the right to perform the task. TxDOT pays the winning firm its bid on completion of a contract. Assume that there is no price ceiling—a maximum acceptable bid that has been imposed by the buyer; this is reasonable as, in our data, such a value

[12]While we remain agnostic as to the mechanism that might generate such an asymmetry, a number of stories are plausible for why this might be true. As an example, the networking aspect of LINC may allow prime contracts to coordinate and develop relationships with subcontractors. Such an understanding of the upstream subcontracting firms means the prime contractor (bidder) can realize cost savings (or extract potential rents) by knowing when to use various suppliers who might specialize in a smaller subset of tasks. In addition, part of the training involves learning project-management techniques. In contrast, the aggressive bidding may simply result from a better understanding of the market which might suggest more competitive bids are needed to remain successful, even in spite of higher costs.

is never imposed nor is a contract ever not awarded due to bidding behavior, even though there are instances in which the winning bid for a contract exceeds an engineer's estimate of the cost to complete a given project.[13]

Assume bidders (firms) are risk neutral and belong to one of three classes.[14] Specifically, we refer to class 0 bidders as the ineligible/non-LINC bidders, to class 1 bidders as the LINC-eligible, but untrained bidders or the never trained bidders, and to class 2 bidders as the LINC graduates or the LINC-trained firms. To be clear, class 1 includes firms who are eligible and choose to never undergo LINC training and firms who eventually partake in the LINC program, but are observed before doing so.[15] Thus, a given firm may be a class 1 bidder in some auctions that took place early, chronologically speaking, and then, after completing the LINC program, be a class 2 bidder in later auctions. In such instances, the pre-training bids are considered to be from a class 1 bidder, while the post-graduation bids belong to a class 2 bidder which is consistent with the analysis presented above in sections 2 and 3.

Let n_i denote the number of class i bidders at an auction where $n = n_0 + n_1 + n_2$. Suppose that each bidder of class i gets an independent cost draw from a distribution $F_i(c)$ which has an associated probability density function $f_i(c)$ that is strictly positive over the compact support $[\underline{c}, \overline{c}]$. The information set known to each firm includes $\{n_0, n_1, n_2, F_0(\cdot), F_1(\cdot), F_2(\cdot), \underline{c}, \overline{c}\}$ where we are explicit that the support of the cost distributions is the same for all classes of bidders. Note that each firm knows its cost draw but not the cost realizations of its rival firms; thus, since realized cost draws are privately known only to each individual firm, this is a game of incomplete information. This structure is what is known as the *asymmetric* independent private values paradigm (IPVP).[16]

[13]There are a small number of instances in which TxDOT cancels a project and then either redesigns it or combines it with other outstanding work.

[14]We are careful to refer to bidders as belonging to one of three *classes* and not as being of one of three *types* to prevent confusion with theoretical research concerning auctions. In that literature, a bidder of a certain type means a bidder having a specific cost value, regardless of which class she belongs to.

[15]We would love to consider an even finer partition by dividing up class 1 bidders but, given our estimation strategy will be nonparametric and the flexibility we are already allowing for by considering three classes of bidders, our data would be stretched far too thin to consider a distinction within this class as will be clear. Given curse-of-dimensionality issues, three classes of bidders already seems to be asking a lot of a given dataset—for example, two classes of bidders are considered by Campo et al. [2003], Flambard and Perrigne [2006], as well as Krasnokutskaya and Seim [2011].

[16]Hickman et al. [2012] provided a guide to the structural econometric analysis of auction data which is organized by informational structure.

Each firm i chooses its bid to maximize its expected profit

$$E[\pi_i(b_i)] = (b_i - c_i)\,\Pr(\text{win}|b_i).$$

Assuming each firm is using a class-specific bidding strategy $\beta_i(c_i)$ that is monotonically increasing in its cost, the probability a class i bidder wins the auction can be written

$$\Pr(\text{win}|b_i) = \left\{1 - F_i[\beta_i^{-1}(b_i)]\right\}^{n_i - 1} \prod_{j \neq i} \left\{1 - F_j[\beta_j^{-1}(b_i)]\right\}^{n_j}$$

where $\beta_i^{-1}(\cdot)$ is the inverse-bid function characterizing behavior of class i firms.

Substituting these expressions into the expected profit objective above and taking the first-order condition for profit maximization of each class of bidder yields a system of three differential equations, each of the form

$$(b_i - c_i)\left[\left(\frac{n_i - 1}{\beta_i'[\beta_i^{-1}(b_i)]}\right)\left(\frac{f_i[\beta_i^{-1}(b_i)]}{1 - F_i[\beta_i^{-1}(b_i)]}\right) + \prod_{j \neq i}\left(\frac{n_j}{\beta_j'[\beta_j^{-1}(b_i)]}\right)\left(\frac{f_j[\beta_j^{-1}(b_i)]}{1 - F_j[\beta_j^{-1}(b_i)]}\right)\right] = 1 \qquad (1)$$

These differential equations satisfy two boundary conditions: $\beta_i(\underline{c}) = \underline{b}$ and $\beta_i(\overline{c}) = \overline{c}$ for all $i = 1, 2, 3$ given firms have the same cost support. These conditions imply that the bidding strategies of both classes involve bidders of the highest possible type ($\overline{c}$) bidding truthfully and bidders of the lowest possible type ($\underline{c}$) tendering the same low bid in equilibrium. The system does not satisfy the Lipschitz condition at the upper-end where a singularity obtains. Fortunately, existence and unqiueness of a monotone pure-strategy equilibrium (MPSE) has been shown by Lebrun [1999, 2006] as well as Maskin and Riley [2000a,b].

Another complication is that, while a unique solution exists, solving for it is often difficult; see, Hubbard and Paarsch [forthcoming] for a summary of various approaches to solving asymmetric auctions. Fortunately, the empirical strategy we employ avoids the need to solve this system explicitly. Let $G_i(b)$ denote the equilibrium bid distribution of bids from class i which has corresponding density $g_i(b)$. In the seminal work of Guerre et al. [2000, GPV] the authors recognized that

$$G_i(b) = \Pr(B_i \leq b) = \Pr[V_i \leq \beta_i^{-1}(b)] = F_i[\beta_i^{-1}(b)] = F_i(v);$$

thus,

$$g_i(b) = \frac{f_i(v)}{\beta_i'(v)}.$$

Now, using the fact that $\beta_i^{-1}(b) = v$ and substituting these terms into the system above, we can rewrite these equations as

$$c_i = b_i - \left[\frac{1}{(n_i - 1)\frac{g_i(b_i)}{1-G_i(b_i)} + \prod_{j \neq i} n_j \frac{g_j(b_i)}{1-G_j(b_i)}} \right]$$

for class i bidders. These three equations provide nonparametric identification of the model as pseudo-costs can be recovered from estimates of the right-hand side objects which depend only on observed bid and auction-composition data. This argument is more direct than that of Flambard and Perrigne [2006] who observed reserve prices which were used in their snow-removal auctions. Essentially this identification strategy can be seen as an application of Theorem 3.1 of Athey and Haile [2007] in which identities are needed only to assign an appropriate class to each bidding firm.

4.2 Practical Estimation Issues

We consider estimation of this model by adopting the two-step nonparametric estimation procedure as suggested by GPV and extended by Flambard and Perrigne [2006]. In particular, in the first step we estimate the bid distributions and densities which allow us to recover a pseudo cost corresponding with each observed bid; in the second step we recover the latent cost densities. In each step we use nonparametric estimators which have been boundary corrected as suggested by Hickman and Hubbard [2013]; thus, we adopt a boundary-corrected GPV (BCGPV) approach. In what follows we discuss some practical issues that arise when confronting the above model with real-world data.

A common practice in estimating a symmetric IPVP model is to assume the number of potential bidders equals the number of actual bidders and then restrict attention to all n-bidder auctions. Note that this assumption is not even valid for a fixed n in an asymmetric model as the composition of n-bidder auctions is likely changing based on how many bidders are from each class. For example, the bidding strategy of a class 0 bidder at an auction with two other class 0 bidders and two class 1 bidders is different than the bidding strategy of a class 0 bidder at an auction with four class 1 bidders, although the total number of bidders is the same at these auctions ($n = 5$). Thus, the "binning" approach suggested by Athey and Haile [2007] requires estimation be done separately for each set $\mathcal{N} = \{n, n_0, n_1, n_2 | n = n_0 + n_1 + n_2\}$. This is the downside of allowing flexibility and the cause for the dimensionality issues discussed earlier.

Specifically, first-step estimates $\left\{\hat{G}_0(b;\mathcal{N}), \hat{g}_0(b;\mathcal{N}), \hat{G}_1(b;\mathcal{N}), \hat{g}_1(b;\mathcal{N}), \hat{G}_2(b;\mathcal{N}), \hat{g}_2(b;\mathcal{N})\right\}$ must be constructed independently using only the bids from a given class over the set of $\mathcal{N}$ auctions. Thus, the bid distributions are estimated using empirical distribution functions

$$\hat{G}_i(b;\mathcal{N}) = \frac{1}{T_{\mathcal{N}}} \sum_{t=1}^{T_{\mathcal{N}}} \frac{1}{n_i} \sum_{\ell=1}^{n_i} 1(b_{i\ell t} \leq b),$$

where 1(A) is an indicator function that equals one if event A is true, and zero otherwise. The number of auctions $T_{\mathcal{N}}$ represents the number of auctions in the sample for which $\mathcal{N}$ is fixed and involves n_i bidders of class i. Thus, the observed bid $b_{i\ell t}$ represents the ℓth bid from a class i player at auction t which comes from a sample of $T_{\mathcal{N}}$ auctions in which (n, n_0, n_1, n_2) is the same for all auctions in this subsample. Our notation nests the symmetric model for a given n in which case $\mathcal{N} = (n, n, 0, 0)$ or $\mathcal{N} = (n, 0, n, 0)$ or $\mathcal{N} = (n, 0, 0, n)$. This is of practical importance as we often observe auctions with only class 0 bidders. Likewise, we estimate the bid density via

$$\hat{g}_i(b;\mathcal{N}) = \frac{1}{h_i^{\mathcal{N}} T_{\mathcal{N}}} \sum_{t=1}^{T_{\mathcal{N}}} \frac{1}{n_i} \sum_{\ell=1}^{n_i} \kappa\left(\frac{b - b_{i\ell t}}{h_i^{\mathcal{N}}}\right)$$

where κ is a boundary-corrected kernel function as suggested by Hickman and Hubbard [2013] and $h_i^{\mathcal{N}}$ is a class-specific bandwidth that will be different for different sets $\mathcal{N}$. We adopt the mean-integrated-squared-error-minimizing rule applied to the kernel function $\kappa(\cdot)$ as suggested by Silverman [1986].

After obtaining estimates of $\left\{\hat{G}_0(b;\mathcal{N}), \hat{g}_0(b;\mathcal{N}), \hat{G}_1(b;\mathcal{N}), \hat{g}_1(b;\mathcal{N}), \hat{G}_2(b;\mathcal{N}), \hat{g}_2(b;\mathcal{N})\right\}$ we recover pseudo costs

$$\hat{c}_{i\ell t} = b_{i\ell t} - \left[\frac{1}{(n_{it} - 1)\frac{\hat{g}_i(b_{i\ell t};\mathcal{N})}{1-\hat{G}_i(b_{i\ell t};\mathcal{N})} + \prod_{j \neq i} n_{jt} \frac{\hat{g}_j(b_{i\ell t};\mathcal{N})}{1-\hat{G}_j(b_{i\ell t};\mathcal{N})}}\right] \tag{2}$$

for class i where n_{jt} denotes the number of class j bidders at auction t such that $n_t = n_{0t} + n_{1t} + n_{2t}$ and $(n_t, n_{0t}, n_{1t}, n_{2t}) \in \mathcal{N}$. Note, too, that all pseudo costs are valid—boundary correction avoids the need to trim pseudo costs corresponding with bids observed within a bandwidth of the extremes of the sample.

The second step is more direct as the observed bids required us to account for different bidding strategies, even for a particular class of bidders depending on the composition of the bidders at auction, which required a binning procedure. Given our focus on a model within the IPVP, the recovery of the pseudo costs strips the composition effects from the model providing us with three independent samples of costs each from a respective density. As such, second-step estimation of the latent cost distributions is much easier because, for a given class, we can pool data from auctions not only across $\mathcal{N}$ for a given number of bidders n, but also across all the realized values of n in the sample (an issue we've, admittedly, not formally recognized until now to avoid complicating our notation). Specifically, take the sample of class-i pseudo costs $\{\hat{c}_i\}$ and estimate the cost density via

$$\hat{f}_i(c) = \frac{1}{T_i} \sum_{t=1}^{T_i} \frac{1}{n_{it}} \sum_{\ell=1}^{n_{it}} \frac{1}{h_i^c} \kappa \left(\frac{c - c_{i\ell t}}{h_i^c} \right)$$

where h_i^c is a second-step class-i bandwidth, κ is, again, a boundary-corrected kernel function, and now T_i represents the total number of auctions observed in the sample (across all $\mathcal{N}$) involving at least one class i bidder and n_{it} represents the number of class i bidders at auction $t \in \{1, 2, \ldots, T_i\}$.

The model and theory underneath the presentation above is built on the assumption that the contract at auction is identical and that the variation across observed bids is driven by variation in the cost draws of the bidding firms, which allows for the latent cost distributions to be identified from the observed bids. In real-world data, however, there is heterogeneity across the objects at auction—both observed and potentially unobserved auction-specific heterogeneity. While observed heterogeneity can be controlled for by conditioning the bids on observed auction covariates, it is also important to account for the fact that bidders may have access to some information about the object being auctioned that is unobserved to the econometrician. Accounting for such heterogeneity is important in order to obtain unbiased estimates.

In our application, we have data from a wide range of contract types and so it is important to control for many auction-specific characteristics. Recall the statistical importance of project size, project complexity, and project length in the bid regressions reported in Table 4. Moreover, the engineer's cost estimate is always statistically significant and accounts for why so much of the variation in observed bids is explained by the set of controls considered. It is natural then to use the estimation method proposed by Haile et al. [2006] to control for factors other than the latent costs that will generate different bids. The advantage of their approach relative to an alternative suggested by GPV which kernel smooths over the covariates is that it reduces the dimensionality and enables one to control for many auction-specific characteristics without increasing the sample size. This, of course, requires additional structure be imposed concerning how covariates affect costs. Haile et al. assumed additive (or multiplicative, log-additive) separability which is attractive in that the additivity is preserved by equilibrium bidding, meaning the effects of the covariates can be controlled for via a regression of the observed bids on the covariates.[17]

Consider the function $\Gamma\colon \boldsymbol{\mathcal{X}} \times \boldsymbol{\mathcal{W}} \rightarrow \mathbb{R}$ and assume $\exists\ (\mathbf{x_0}, w_0) \in \boldsymbol{\mathcal{X}} \times \boldsymbol{\mathcal{W}} \subset \mathbf{R}^p \times \mathbf{R}$ such that $\mathbb{E}[\Gamma(\mathbf{x},w)] = \Gamma(\mathbf{x_0}, w_0)$. Under assumptions of separability, the equilibrium bid function can be written

$$\begin{aligned} \beta(c|n, \mathbf{x},w) &= \beta(c|n, \mathbf{x_0}, w_0) + \Gamma(\mathbf{x},w) \\ &= \alpha(n) + \Gamma(\mathbf{x_0},w_0) + \tilde{\Gamma}(\mathbf{x},w) + \tilde{\beta}(c|n, \mathbf{x_0},w_0) \end{aligned}$$

where $\tilde{\Gamma}(\mathbf{x},w) = \Gamma(\mathbf{x},w) - \Gamma(\mathbf{x_0},w_0)$, $\alpha(n) = \mathbb{E}[\beta(c|n, \mathbf{x_0},w_0)]$, and $\tilde{\beta}(c|n, \mathbf{x_0},w_0)$ is a conditional zero mean term. Because in equilibrium we have that $b = \beta(\cdot)$,

$$b^0 \equiv \alpha(n) + \Gamma(\mathbf{x_0},w_0) + \tilde{\beta}(c|n, \mathbf{x_0},w_0) = b - \tilde{\Gamma}(\mathbf{x},w)$$

is interpreted as the bid a firm would have submitted in equilibrium to an auction with characteristics $\Gamma(\mathbf{x},w) = \boldsymbol{\Gamma}(\mathbf{x_0},w_0)$. Notice that we need to control directly for the effect of w. Assuming that $\zeta(\mathbf{x}, \mathbf{z}) = \min\{n{\in}N\colon \Pr(N{\le}n|\mathbf{x}, \mathbf{z}) \geq\tau\}$ for a quantile $\tau{\in}(0, 1)$, we write,

$$n = \zeta(\mathbf{x}, \mathbf{z}) + w, \tag{3}$$

where $\mathbf{z}$ is a vector of instruments and w is an index that includes unobserved factors independent of $\mathbf{x}$. We take a control function approach, estimating $w = n - \zeta(x, z)$ as suggested by Haile et al. In doing so, we are allowing for endogenous participation and assuming the number of firms that bid is

[17] Haile et al. [2006] admitted this is a strong, but often employed assumption and that it may be more natural when valuations (costs) are normalized by an engineer's estimate, something we do in what follows.

an increasing function of the unobserved heterogeneity as suggested by (3) which can be inverted to recover the latent unobserved w.[18]

This procedure allows us to construct a sample of *homogenized* bids of the form $\hat{b}^0 = b - \hat{\Gamma}(\mathbf{x}, \hat{w})$ after estimating (3). Note, too, that because we specified a parametric form for $\Gamma(\cdot)$, the asymptotic distribution of our nonparametric estimators (using the homogenized bids) does not change as $\hat{\Gamma}(\cdot)$ converges at a faster rate. While this structure is needed to control for observed covariates, our estimation of the latent distribution of private costs from bids, conditional on the heterogeneity across auctions, remains nonparametric.

We estimate the participation equation (3) by censored quantile regression to explain the number of bidders using the number of project components, the number of calendar days given to finish the project, the percentage of various common tasks required by the contract, as well as locational zone and time fixed effects. We also include the number of plan holders and the engineer's estimate as instruments. The residuals of this represent an index of unobserved factors that are independent of the covariates. We then estimate a regression of bids normalized by the engineer's estimate via least squares using these same covariates (except for the instruments), along with the residuals $\hat{w}$ to account for unobserved heterogeneity. Lastly, we obtain a sample of homogenized bids by adding the least squares residuals to the n-specific average bid (fixed effect). Importantly, note that this homogenization procedure accounts for auction-specific covariates, controls for unobserved heterogeneity, and deals with endogenous entry, but still allows for asymmetric bidders. That is, by not including any bidder-specific effects or bidder-related covariates, we allow asymmetries to remain.[19] Having constructed a sample of homogenized bids, we use the nonparametric estimation procedure described above, replacing $b_{i\ell t}$ with its associated homogenized bid $\hat{b}_{i\ell t}$.

[18] Roberts [forthcoming] makes a similar assumption by considering reserve prices to be monotonically related to the unobserved heterogeneity.

[19] Before proceeding to estimation, as a quick check that asymmetries might still exist across the classes of bidders even after homogenizing bids, we consider the behavior of class 0 bidders at an auction for a fixed n. Specifically, we conduct a Kolmogorov–Smirnov test for each n to see if the distribution of homogenized bids tendered by class 0 bidders when only other class 0 bidders are present at auction is significantly different from the distribution of homogenized bids from class 0 bidders when a non-class 0 bidders is present. Consider a null hypothesis that the observed (albeit, homogenized) bids from the symmetric and asymmetric auctions come from the same distribution against an alternative that the two samples come from different distributions. Such a test rejected the null in six of the eight cases in which $n = \{2, 3, \ldots, 8\}$.

5 Structural Estimates and Results

As described above, we partitioned (binned) our data by $\mathcal{N}$. Table 5 provides some insight into which bins are reasonable, sample-size wise, to use in nonparametric analysis. Specifically, Table 5 indicates that the majority of our auctions are symmetric auctions involving only ineligible bidders. In contrast, we discard six auctions involving only LINC-graduate bidders and four auctions with LINC-eligible but untrained firms only, all of which involved two bidders at auction. There are a good deal of asymmetric auctions involving two or more bidders, but very few of them involve all three classes of bidders. The column "$n_1 = 0$" represents non-LINC (class 0) bidders and LINC-trained (class 2) bidders both present at auction. The column "$n_2 = 0$" represents auctions involving non-LINC (class 0) and LINC-eligible, but untrained (class 1) bidders. Ignoring auctions with a bidder from each class means each auction in the data will involve bidders representing no more than two classes. As such, one could construct matrices with the number of bidders at auction along the rows and the number of class 1 or class 2 bidders along the columns. Doing so, indicates that nearly all of the asymmetric auctions involve only one bidder from the LINC-related classes. Thus, we discard auctions with more than one of the LINC-related class bidders at auction.[20] We restrict attention to settings involving two to seven bidders as this ensures that there are at least 55 observations for every possible $\mathcal{N}$-bin needed for first-step estimation.[21]

[20]Remember, first-stage estimation is the most constraining data-wise for us as it must be done for each realization of $\mathcal{N}$.

[21]As discussed, the number of auctions for each instance in Table 5 is slightly lower than we've presented after we throw out the $n_1 > 1$ and $n_2 > 1$ asymmetric auctions. The minimum number of observations (55) corresponds to the number auctions involving six ineligible bidders and one class 1 bidder, for which we observe $55 \times 6 = 330$ class 0 bids and we have 55 observations from class 1 bidders.

Table 5: Partitioning the Data by Symmetric vs. Asymmetric Auctions

Number of Bidders	Number of Auctions					
			Asymmetric			
	Total	Symmetric Non-LINC	Total	Ineligible v LINC $n_1 = 0$	Ineligible v Untrained $n_2 = 0$	All 3
2	1138	946	182	73	108	1
3	1689	1262	427	192	215	20
4	1457	934	523	266	236	21
5	1090	643	447	216	196	35
6	810	417	393	214	143	36
7	466	207	259	137	84	38
8	257	98	159	82	54	23

In both steps of the estimation we used the triweight kernel

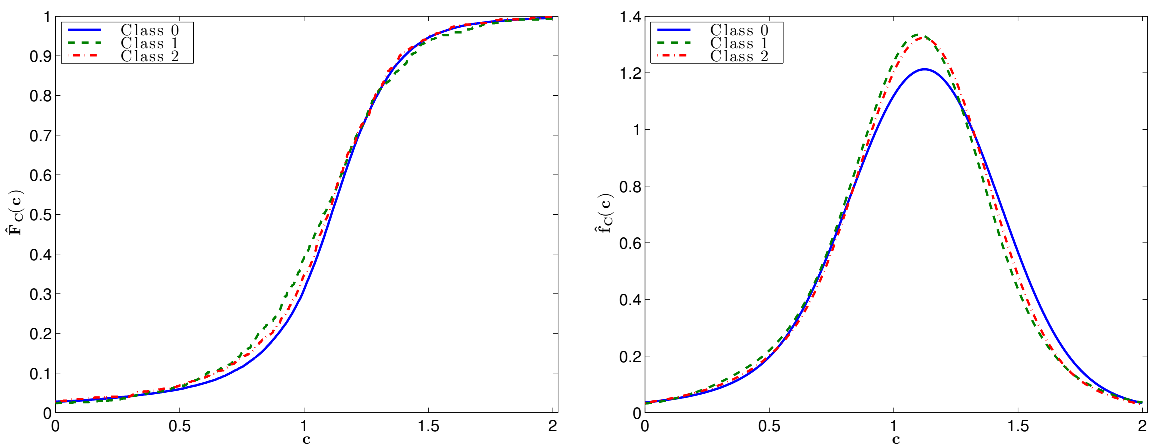
$$\kappa(u) = \frac{35}{32}(1 - u^2)^3 1\left\{|u| \le 1\right\}$$

within a boundary-corrected estimator. We present the estimated cost distributions and cost densities in Figures 1a and 1b, respectively. The estimates reveal some separation of the three the cost distributions between $c = 0.5$ and when c is just greater than one. There is no clear stochastic dominance relationship—further evidence of the type of behavior of interest to Kirkegaard [2009] as well as Hubbard et al. [2013]. Because the curves are hard to distinguish we provide the quantile values of the pseudo costs in Table 6.

Table 6: Some Percentiles of the Estimated Cost Distributions

Percentile	Ineligible (class 0)	LINC-Qualified, but Untrained (class 1)	LINC-Trained (class 2)
10	0.70	0.61	0.64
20	0.90	0.82	0.87
30	0.99	0.93	0.97
40	1.06	1.01	1.04
50	1.11	1.08	1.10
60	1.16	1.15	1.15
70	1.22	1.21	1.21
80	1.29	1.29	1.29
90	1.40	1.42	1.39

The estimated densities show that the modal cost of each class is quite similar and that the LINC-



(a) Estimated Cost Distributions

(b) Estimated Cost Densities

Figure 1: Estimates of Latent Cost Distributions and Densities

related classes are hard to distinguish. To test where there is a statistical difference between pairs of the cost distributions, we considered two-sample Kolmogorov–Smirnov tests in which the null hypothesis is that the cost distributions of the classes of firms being considered come from the same distribution, against an alternative that the two samples come from different distributions. The results of these tests are presented in Table 7. The cost distribution of ineligible firms is significantly different from the LINC-qualified, but untrained distribution any standard test size, and is significantly different from the LINC-trained distribution, though only at the 10% level. The two LINC-related cost distributions are not significantly different from one another—the test results in a p-value that just misses the 10% mark.

Table 7: Two-Sample Kolmogorov–Smirnov Tests for Asymmetric Cost Distributions

Hypothesis	KS Test Statistic	p-value
H_0: $F_0(c) = F_1(c)$; H_1: not H_0	0.0832	0.0000
H_0: $F_0(c) = F_2(c)$; H_1: not H_0	0.0398	0.0963
H_0: $F_1(c) = F_2(c)$; H_1: not H_0	0.0563	0.1094

In estimating the structural model we recovered a project cost associated with each observed bid. This allows us to look a bit deeper at the effect of market power in this procurement industry.

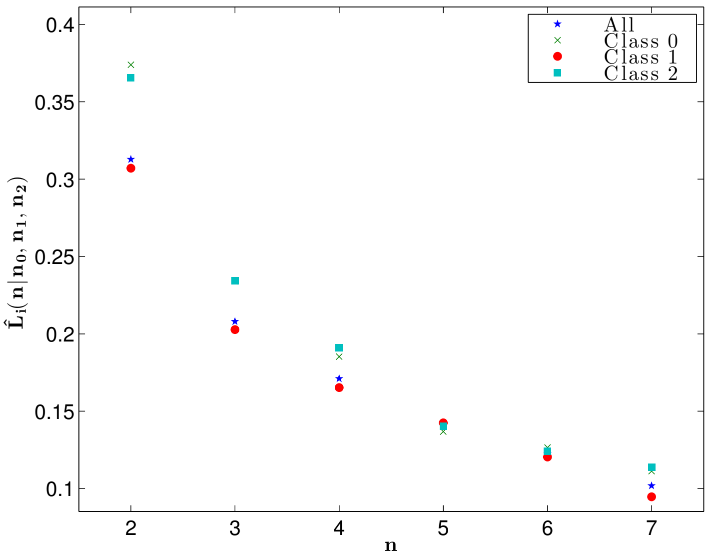


Figure 2: Lerner Index for Various Categories of Bidders

Specifically, we computed Lerner's index for each winning bidder observed in the data by computing $(b_t - \hat{c}_t)/b_t$. This, of course is typically difficult for industrial organization economists to estimate in large part because costs are unobserved. We compute the mean Lerner's index for each type of winner (for each class of bidders) and for each value of n used in the structural estimation. We provide a scatter plot of these mean values in Figure 2.[22] The figure makes clear that the behavior of the winning firms approaches that of a competitive market as the number of bidders at auction increases. We also dissected the Lerner index for ineligible (class 0) bidders further by computing the value conditional on the composition of the rivals, but did not incorporate these points in the figure so as not to congest things too much. In general, the Lerner's index of winning, LINC-ineligible firms is always slightly larger in asymmetric auctions than in the symmetric auctions. Moreover, it does not seem the mark-ups (relative to the bids submitted) are consistently higher or lower for LINC-trained firms relative to the ineligible or the LINC-qualified, but untrained firms.

We complement this figure with some summary measures concerning inefficiencies and profitability

[22]We computed standard errors on these point estimates as well but there was not a statistically significant differences between points for a given value of n.

Table 8: Summary of Structural Findings

		All	Symmetric Non-LINC	Ineligible v LINC ($n_1 = 0$)	Ineligible v Untrained ($n_2 = 0$)
$n = 2$	#Inefficient/Total	3/1076	0/902	0/70	3/104
	Winning homogenized bid	1.18	1.18	1.16	1.20
	Winner's cost	0.55	0.53	0.56	0.74
	Rivals' cost	1.07	1.08	1.02	1.07
$n = 3$	#Inefficient/Total	5/1614	0/1241	1/176	4/197
	Winning homogenized bid	1.12	1.13	1.13	1.09
	Winner's cost	0.78	0.76	0.84	0.83
	Rivals' cost	1.13	1.14	1.13	1.10
$n = 4$	#Inefficient/Total	4/1357	0/920	0/243	4/194
	Winning homogenized bid	1.10	1.10	1.10	1.10
	Winner's cost	0.85	0.83	0.86	0.88
	Rivals' cost	1.17	1.17	1.17	1.18
$n = 5$	#Inefficient/Total	2/994	0/636	1/190	1/168
	Winning homogenized bid	1.08	1.08	1.07	1.08
	Winner's cost	0.86	0.88	0.87	0.81
	Rivals' cost	1.16	1.16	1.16	1.18
$n = 6$	#Inefficient/Total	1/713	0/413	1/184	0/116
	Winning homogenized bid	1.07	1.08	1.05	1.08
	Winner's cost	0.84	0.85	0.81	0.88
	Rivals' cost	1.17	1.18	1.16	1.18
$n = 7$	#Inefficient/Total	1/379	0/205	1/120	0/54
	Winning homogenized bid	1.05	1.06	1.04	1.04
	Winner's cost	0.90	0.91	0.90	0.88
	Rivals' cost	1.17	1.18	1.15	1.18

in the observed auctions. Specifically, we provide some summary values in Table 8 by partitioning the findings based on the number of bidders at auction n. Remarkably, there are relatively few inefficiencies realized in the data given the number of auctions conducted. Still LINC does seem to reduce the frequency of an inefficient allocation slightly—of the 16 inefficient allocations, 75% of them involved a LINC-qualified, but untrained firm with a higher cost than a ineligible firm being awarded the contract. The winning bid for all firms gets smaller as competition increases, though the costs of these firms and of their rivals' at auction does not suggest a clear pattern.

The last type of effect we look for LINC to have on firms in the market is in their propensity to remain active in the market, something we investigate in the next section.

6 Firm Survival

To consider longer-term effects that the LINC program might generate, we also consider firm exit patterns. Specifically, we estimate a probit model in which the response variable takes on a value of one if a given firm exits the industry in a given period, and takes on a value of zero otherwise. The challenge in such an exercise is identifying when a firm exits the market. With this in mind, we first discuss some choices we made in our investigation. First, 75% of the projects are completed in seven months. As such, we drop firms that entered the industry (firms that hold plans for the first time) after 2007 from the analysis. Second, we restrict attention to firms that entered the market after the LINC program was initiated. Third, our exit date or the last active day in the TxDOT market is defined as the last date a firm held plan or the last date they had an active project (the firm's backlog was zero.) Given that we do not use entrants after 2007 this gives us an opportunity to tract bidders for at least 10 months since their last plan holder or active project day to ensure that they do not hold plans again (participate) within at least 10 months. Similar exit criteria were used by De Silva et al. [2009].

In Table 9, we present results from some of the probit regression models described above. In all models, the omitted class of firms is the group that is not eligible for the LINC program. The first three models consider all firms in the data and differ in how a firm's experience is captured. In each model, being eligible for the LINC program, but not having undergone training, increases the likelihood of a given firm exiting relative to the ineligible group. In contrast, firms that graduate from the LINC program are not statistically different from non-LINC firms when it comes to exit. If the analysis is restricted to the LINC-qualified firms only, LINC training has no significant effect on a firm's survival. The other covariates included capture a firm's size (maximum backlog), competition in the market (based on how many rivals a firm has faced for a given month), economic conditions in Texas (the unemployment rate), and expectations about future projects. Larger firms are less likely to exit, firms facing many rivals are more likely to exit—though if the rivals are LINC-trained then the firm is less likely to exit. These effects are all robust across specifications and significant at the 1% level.

Table 9: Exit Results

Variables	Exit Patterns for Entrants since 2001			
	All			LINC
	(1)	(2)	(3)	(4)
LINC-qualified, but untrained firm (β_1)	0.012*	0.012*	0.011*	
	(0.006)	(0.006)	(0.006)	
LINC-trained firm (β_2)	0.006	0.007	0.004	-0.006
	(0.010)	(0.010)	(0.010)	(0.011)
Past winning-to-bidding ratio	-0.012			0.009
	(0.011)			(0.020)
Past winning-to-plan holder ratio		-0.000		
		(0.015)		
Past bidding-to-plan holder ratio			-0.034***	
			(0.006)	
Log (maximum backlog + 1)	-0.009***	-0.009***	-0.008***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.001)
Log(total number of rivals faced	0.047***	0.048***	0.046***	0.056***
in the market + 1)	(0.001)	(0.001)	(0.001)	(0.005)
Log(total number of LINC rivals	-0.038***	-0.038***	-0.038***	-0.059***
faced in the market + 1)	(0.012)	(0.012)	(0.012)	(0.012)
Unemployment rate	0.001	0.001	0.000	0.003
	(0.002)	(0.002)	(0.002)	(0.006)
Future average real value of	0.007	0.007	0.006	-0.004
projects	(0.006)	(0.006)	(0.006)	(0.016)
Number of observations	10,843	10,843	10,843	1,322
Pseudo R^2	0.436	0.436	0.442	0.497
Wald χ^2	1507.680	1525.380	1443.860	258.140

Robust standard errors are given below point estimates in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

7 Conclusion

We considered an eclectic approach to investigate effects of the TxDOT's LINC program from different perspectives. Some broad take-aways of our results are that firms that opt for LINC training are typically less experienced and face many rivals in the market. After completing LINC training, graduates are not too different from the larger set of LINC-qualified firms when it comes to their likelihood of entering an auction once they hold plans nor winning once they've entered. That said, LINC graduates are more aggressive in their bidding behavior than ineligible firms and LINC-qualified, but untrained firms. The average LINC bid is 1.8% lower than non-LINC firms and 2.9% (or 4.5% in one model) lower than LINC-qualified, but untrained firms. Moreover, winning bids from LINC-trained firms are

2.7% lower than bids from ineligible firms. How to reconcile this with the fact that LINC firms are no different from other firms in their chances of winning an auction once they've bid? Well, we found LINC training had spillover benefits—on average, other firms bid more aggressively when facing a LINC rival. The combined effects of this more aggressive bidding has led to massive cost savings for TxDOT relative to the cost of operating the program. A concern might be whether firms can continue to operate in this way. Our structural analysis suggested that LINC-trained firms have Lerner indexes that are on par with that of other firms and that efficiency of the auction has modestly improved. Our firm survival analysis suggested that LINC-qualified, but untrained firms are more likely to exit in a given period than ineligible firms, but that this effect goes away after LINC training.

Researchers have focused attention on bidder preference policies and subcontracting goals. A commonality between our work and this line of research is the targeted firms—LINC-qualified firms in Texas would typically qualify for such treatment in other states. From a policy perspective, our results suggest that such bidder training programs should be seriously considered by other states. As we noted, about 3/5 of U.S. states have a mentor-protégé program in the works or already in place.

There are a few ways in which we hope others can improve on our research immediately. First, data on firm participation in specific aspects of a given program could provide researchers with a source of variation which would allow for identification of which aspects of a particular program are most valuable. Second, it would be interesting to see if mentoring firms indirectly gain from participation. When talking with state representatives, a common challenge seemed to be getting mentor participation (some states, like Ohio, require a minimum number of hours from the mentor each month and independent quarterly reports from both the mentor and protégé). If mentoring firms were seen in the data, one could quantify any improvement in mentor-firm performance after participating in the program. If there was a clear cost to participating, it might suggest compensation or justify state incentives to mentors for participating. Lastly, although we did not discuss the issue in our work, given that such programs not only allow for but explicitly encourage communication and foster relationship development across mentors and protégés, a concern of the program might be that it could lead to collusive behavior. Data on which firms were paired with other firms would be important in documenting or dismissing any concerns about collusion.

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8 Appendix

Table 10: Variable Definitions.

Variable	Definition
Log of bids	Logarithm of bids
Entrant	Any firm that is a first time plan holder since the beginning of fiscal year 2001 in TxDOT auctions are considered as an entrant.
LINC-qualified, but untrained firms	Dummy to identify LINC-qualified, but untrained firms.
LINC-trained firms	Dummy to identify LINC-trained firms.
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.
Log of engineer's estimate	The log value of the engineer's cost estimate.
Complexity	The total number of bid items (components) in a project.
Calendar days	Number of days to complete the project which is assigned by TxDOT
Ongoing project in the same county	This dummy variable identifies bidders when they are bidding on projects where they have an ongoing project in the same county.
Distance to the project location	The distance between the county the project is located in and the county of the firm's location.
Backlog	Backlog is constructed by summing the non-completed value of outstanding contracts. The backlog variable is similar to the variables used by Bajari and Ye (2003) and Jofre-Bonet and Pesendorfer (2003).
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. For firms that have never won a contract, the utilization rate is set to zero.
Number of rivals faced in the market	This is the total number of unique plan holders faced in given month by a firm.
Number of LINC rivals faced in the market	This is the total number of unique LINC-qualified rivals faced in given month by a firm.
Past winning-to-bidding ratio	The number of previous wins divided by the number of previous bids at a point in time.
Past winning-to-plan holder ratio	The number of previous wins divided by the number of previous plans held at a point in time.
Past bidding-to-plan holder ratio	The number of previous bids divided by the number of previous plans held at a point in time.
Number of past bids	The number of previous bids a firm has submitted.
Average rivals' winning-to-plan holder ratio	The measure of rivals' past average success in auctions is constructed as the average across rivals of the variable "Past winning-to-plan holder ratio." This variable incorporates two aspects of past rival bidding behavior: the probability of a rival bidding given they are a plan holder and the probability the rival wins an auction given that they bid. These probabilities are initialized using data from 1997 and are updated monthly using the complete set of bidding data.
Unemployment rate	The monthly state-level, seasonally-unadjusted unemployment rate from the U.S. Bureau of Labor Statistics.
Material shares of a project	We identify six material groups for projects based on bid items described by the "Standard Specifications for Construction and Maintenance of Highways, Streets, and Bridges" code book adopted by TxDOT. These six material cost shares are constructed from detailed information on bid items and the project's overall engineering cost estimate. These include: 1) asphalt surface work (i.e., hot-mix asphalt); 2) earth work (i.e., excavation); 3) miscellaneous work (i.e., mobilization); 4) structures (bridges); 5) subgrade (i.e., proof rolling); and 6) lighting and signaling work (i.e., highway sign lighting fixtures).
Division dummies	TxDOT has 25 locational divisions in the state, which are identified by these dummy variables.