An Evaluation of a Bidder Training Program*

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Abstract

In an effort to accommodate a change in the Federal Highway Administration's goals towards race-neutral methods concerning the involvement of Disadvantaged Business Enterprises in contracting, the Texas Department of Transportation created a bidder training program. Using ten years of data, we examine the effects this program had on bidder behavior, project costs for the government, and the ability of these firms to compete. Unlike other policies that target these firms, we find the program generated substantial savings for the state which come at a very low cost.

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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 at least the early 1960'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 1995 ruling in *Adarand v. Peña*, U.S. Report 515 U.S. 200), the nature and administration of DBE programs has changed. Individual state agencies that administer the programs, are asked to achieve as much of the goal as possible by "race-neutral methods" before employing other perhaps identity-conscious policies.[1] For example, 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 business enterprises—SBEs) or whether such firms have received a "fair" share of state business (e.g., historically underutilized businesses—HUBs).

In response to the shift in the disposition of FHWA policy, and because the Texas Department of Transportation (TxDOT) felt having a diverse set of active firms was critical to the competitiveness of its transportation industry, TxDOT created its own Learning, Information, Networking, Collaboration (LINC) training program in September 2000. The rationale was that many DBEs, SBEs, and HUBs interested in doing business with TxDOT had not been successful and faced disproportionate barriers in doing business with the Department. As such, the program was eligible only to firms certified as DBEs, SBEs, and HUBs. The LINC program assigned participating firms a mentor from TxDOT's Business Opportunity Programs Section that helped participants understand business opportunities, provided information to assist them in bidding and executing TxDOT contracts, and introduced the firms to other contractors to foster networking opportunities. Participants received construction management training which included instruction on pre-qualification requirements and guidance on searching for contracts. Most importantly, the program's purpose

[1] Broadly speaking, affirmative action programs often seek to support underrepresented groups because they have been historically disadvantaged, have suffered from discrimination, inequalities, and/or face other injustices, and to increase the equality of opportunity. Race-conscious programs are intentional in targeting or encouraging participation of racial minorities; in contrast, race-neutral alternatives are required to be considered by public (or educational) institutions themselves as a means to meet diversity goals in a way that is not race-conscious.

was to prepare these firms to bid and perform on TxDOT contracts. For example, part of the training program involves working with “providers” which are firms on contract with TxDOT to supply marketing, estimating, and bidding services. By focusing on bidding and the execution of contracts the LINC program helps maintain and support the role such firms play in the TxDOT procurement industry.

Texas, being both large and diverse, makes for a good place to study such a program. The state boasts 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. During our ten-year sample period which spans September 1997 to August 2007, the total value of contracts awarded to LINC-eligible bidders was $1.98 billion. We use all procurement contract data from this period to examine the impact of the LINC program on the participation decisions of firms, bidding behavior, their likelihood of success, and ultimately their potential for remaining active in the industry.

We find the most convincing effects LINC has on firms is with respect to their bidding behavior—LINC-trained bidders submit more competitive tenders after graduating from the program. Average bids from LINC graduates are lower relative to firms that are ineligible for the program as well as relative to those firms which are eligible but have not undergone training. A bulletin is circulated to all prime contractors interested in working with TxDOT announcing the firms that have completed the LINC training, making other industry participants aware of which firms have graduated from the program. When rivals learn that a LINC-trained firm holds plans for a certain project, an indirect competition effect results in which ineligible firms (by far our most frequently-observed class of bidders) bid lower than they otherwise would have. 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 auctions which attract interest from LINC-trained firms, the average winning bid is also significantly lower. These two channels generate substantial savings for the state. In contrast, the LINC program requires a budget of only about $200,000. Moreover, eligible firms that do not get trained are more likely to exit the industry than firms that are not eligible, but this concerning effect goes away for firms that graduate from the LINC program.

Our program evaluation relates to the work of researchers who have investigated alternative policies at procurement auctions which target the same firms qualifying for LINC. These policies include set-asides, bid preference policies, and minority subcontracting goals. Denes [1997] compared bids submitted for solicitations restricted to small businesses with unrestricted solicitations, finding that bids were no higher in restricted settings. He suggests that costs did not increase for the government because the contracts set-aside for small businesses attracted more bidders than the open contracts.

Bid preference schemes favor bids from qualified firms for the purposes of evaluation only, thereby making favored firms more competitive within a given auction. The effect of such programs on the government's cost is ambiguous even at the theoretical level; see McAfee and McMillan [1989] and Hubbard and Paarsch [2009]. Marion [2007] found that in data from California Department of Transportation (Caltrans) 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 Caltrans 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. Rosa [2019] found that, while accounting for affiliation in firms' costs (which the previous studies did not consider), the New Mexico Department of Transportation could favor resident (in-state) bidders by even more without realizing a major increase in its project costs.

Minority subcontracting goals are often used in federal procurement contracts and may constrain the make-or-buy decision of prime contractors, could require outsourcing production of tasks to less efficient subcontractors, and can affect the competition intensity in the subcontracting market. Marion [2011] used data from Caltrans 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 projects which still involved subcontracting goals. De Silva et al. [2012] evaluated the impact of a federal subcontracting policy years after its original implementation and found that minority subcontracting goals did not increase procurement costs in Texas. Marion [2017] evaluated an exemption granted by the Iowa Department of Transportation for its subcontracting requirements to firms that had a history of actively involving DBE subcontractors. He found projects with affirmative action goals had higher bids than those without, and that this disparity increased when bidders could no longer be exempt from the subcontracting requirements. Most recently, Rosa [2020] proposed a model in which subcontracting regulations can inspire relationship building which might increase current-period costs, but can lead to savings in a later periods that are driven by relationships formed. This insight can apply to the LINC program which has networking and collaboration as important elements.

While the LINC program applies to the same class of firms as these other policies, our work and findings differ from those empirical studies. The set-aside and preference policies as well as the subcontracting goals apply for a given auction, whereas the LINC program aims to improve the behavior and outcomes for participating firms in the industry, not just within one auction. In fact, at the initial LINC meeting, participating firms must sign an agreement acknowledging that the information provided at program sessions is general and not specific to a particular project. To our knowledge, we are the first to study the effects of a bidder-training program, which we've learned exists or is being introduced with small variations in the majority of U.S. states. Given the prevalence and interest in such training programs, we hope our work has important policy implications as there is potential for our findings to suggest alternatives to meet the FHWA's original goals in a way that can actually generate clear cost savings (benefits), something that has not been demonstrated for set-asides, preference policies, and subcontracting goals.[2]

We describe the LINC program in more detail in the next section. In Section 3, we summarize our data, which we use to develop some intuition about the program's effects before considering our core empirical analysis in Section 4. While our focus is on TxDOT's LINC program, other states do have similar opportunities for DBEs, HUBs, and SBEs. We have contacted representatives at every state's Department of Transportation office and have learned two things: first, bidder training opportunities 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 which all have different names (e.g., Calmentor in California, Connect2DOT in Colorado, and Mission 360° in Rhode Island) are often administered through economic or local development offices. In

[2] The U.S. Commission on Civil Rights' 2005 report "Federal Procurement After *Adarand*" reiterated that federal agencies must consider race-neutral alternatives to race-conscious procurement programs noting the Departments of Defense, Transportation, Education, Energy, Housing and Urban Development, and State, and the Small Business Administration need to take seriously race-neutral programming efforts, emphasizing the lack of "program evaluation, outcomes measurement, empirical research and data collection".

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 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. These programs are also not unique to Department of Transportation offices—the leading inspiration for such programs seems to be the Stempel Program for the Port of Portland in Oregon.[3] Most programs have bidder training, formal mentoring, educational seminars, outreach components 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 hoping for a higher survival rate of such firms. As such, in Section 5, we consider whether firm survival in the industry has been affected by participation in LINC before concluding our research in Section 6.

2 The LINC Program

The TxDOT's LINC program began in 2001 and we observe 36 training sessions distributed throughout our sample period. The program is open only to firms that perform a category of work or supplies a type of material included in construction and maintenance contracts and has been certified as a DBE, HUB, or SBE for at least one year. While these firms are eligible for participation, they are not required to complete the LINC training. Upon electing to participate, qualified firms attend an initial meeting outlining expectations and responsibilities for enrollees. Participating firms sign a contract agreeing to partner with a mentor from TxDOT's Business Opportunity Programs section and committing to the time and efforts required of the program. The program is then structured as a set of five meetings which we briefly detail:

1. Firms receive construction management training focused on estimating and bidding, contract

[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.

administration, equipment usage, inspections, material and product testing, as well as legal issues.

2. Firms navigate TxDOT's website using on-site workstations to review project information and letting plans. A provider specializing in estimation and bidding reviews TxDOT projects with each firm. Homework is assigned: the provider works with each firm to identify one contract for which that participant must develop a bid to be submitted to the provider for review before the third meeting.

3. Firms meet with individuals from TxDOT's district and engineers' offices to learn about monitoring and inspection of job sites. Providers specializing in estimation and bidding meet with each firm to review and provide feedback on the mock bid submitted following the second meeting.

4. Firms meet with prime contractors that have been successful in working with TxDOT to develop networking opportunities. Prime contractors learn about each participating firm to better understand the participants' resources and experience. Presentations and information packets detailing each participating firm are disseminated.

5. The session highlights opportunities and discusses prequalification, certification, bonding, insurance, and contract requirements.

Beyond these five sessions, participating firms are required to contact the Business Opportunity Programs mentor following each meeting. The mentor is responsible for ensuring that the participating firm received and understood all information in each meeting, responding to questions from the participating firm, and completing reports on such interactions. Participating firms also must send copies of all bids submitted to the LINC mentor (in addition to reviewing them with the estimating and bidding provider).

Given the format and focus on the LINC program, we see a few important ways in which participants might systematically change their behavior which informs our investigation. First, firms might improve their determination of projects that are suitable to be bidding on. Second, firms could improve their estimates of how expensive a project will be for them to complete or how they will bid conditional on their estimates. Firms' estimates for a given contract will not be observable—to us, or to TxDOT. Since the first three LINC sessions focus on developing project estimates and bidding, we spend considerable time investigating the bidding behavior of firms, during which we also seek to address the selection effect noted previously. Lastly, firms could position themselves to execute the contract in a more effective way. We investigate whether changes in bidding behavior translate into savings for TxDOT by considering winning bids as well as project execution using final payments for contracts. We investigate the channels through which changes in firm behavior seem to be most important. Further, while our discussion focuses on how the behavior of LINC participants might change, there is potential for other, ineligible firms to change their behavior as well. The fourth LINC meeting explicitly involves bringing in other contractors to learn about LINC participants (and vice versa). Moreover, at the conclusion of the LINC program, information is circulated to all prime contractors interested in working with TxDOT announcing the firms that have completed the LINC program. Throughout we consider whether these firms behave any differently when potentially facing competition from LINC graduates.

3 Data Description

Our data, which come from the Procurement Division of TxDOT, comprise all 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 through measures such as workload commitment (commonly referred to in the auctions literature as backlog). Thus, our empirical analysis that follows employs the data from September 1998 through August 2007. Projects are awarded using the low-price, sealed-bid (procurement) auction format. Prior to bidding, all firms learn the location and the detailed project description, the estimated number of days to complete the project, the engineer's cost estimate (ECE) for completing the project, and the list of contractors who purchased the documents providing the initial plan description (the plan holders). The bidding process opens a minimum of 28 days after the plan for a project is posted. When the bidding period expires, the offers submitted by each bidder are revealed and the winner is announced. The winning bidder is determined solely by price—the lowest bidder is awarded the right to complete the respective task for the government. 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 assembled by the TxDOT Office of Civil Rights and we construct, using each firm's past bidding behavior, other variables that might be important in driving observed behavior.[4]

In Table 1, we present sample summary statistics for the full sample, for ineligible (non-qualified or non-LINC) firms, and for LINC-eligible firms. We further distinguish the LINC-eligible firms based on whether they participated and, if so, whether they are observed before or after enrollment in the LINC program. In the full sample, we find 1,749 unique firms holding plans. Of those firms, there are 229 unique LINC-qualified prime bidders, 90 of which participated in the LINC program. We observe 1,739 bids from LINC graduates which translated into 415 wins for these firms. The contracts that trained firms bid on appear to be, on average, much smaller than projects bid on by ineligible firms as well as eligible firms that elected not to participate. This is clear from both the engineer's estimate and the number of days required to complete a project.

Table 1: Summary statistics

Variable	Bidder category				
	All	Ineligible	LINC-eligible		
			Never participate	Trained	
				Before	After
Number of plan holder firms	1,749	1,520	139	59	90
Number of plans held	53,683	47,290	1,556	1,554	3,292
Number of bids	31,783	28,480	669	895	1,739
Number of wins	7,434	6,613	179	227	415
ECE (in millions of $)	4.072	4.269	3.512	2.167	2.195
	(11.4)	(11.800)	(6.398)	(6.953)	(8.498)
Number of days to complete the project	153.219	155.232	148.453	121.996	140.782
	(172.422)	(176.462)	(128.908)	(128.202)	(139.664)
Relative Bid	1.086	1.084	1.100	1.117	1.087
	(0.243)	(0.242)	(0.261)	(0.255)	(0.258)
Relative Winning bid	0.977	0.977	0.975	0.977	0.968
	(0.178)	(0.178)	(0.192)	(0.169)	(0.174)

Standard deviations are in parentheses when appropriate.

In order to compare bidding across contracts of varying size and complexity, often involving different types of work, we compute relative bids (relative winning bids) by normalizing the tendered

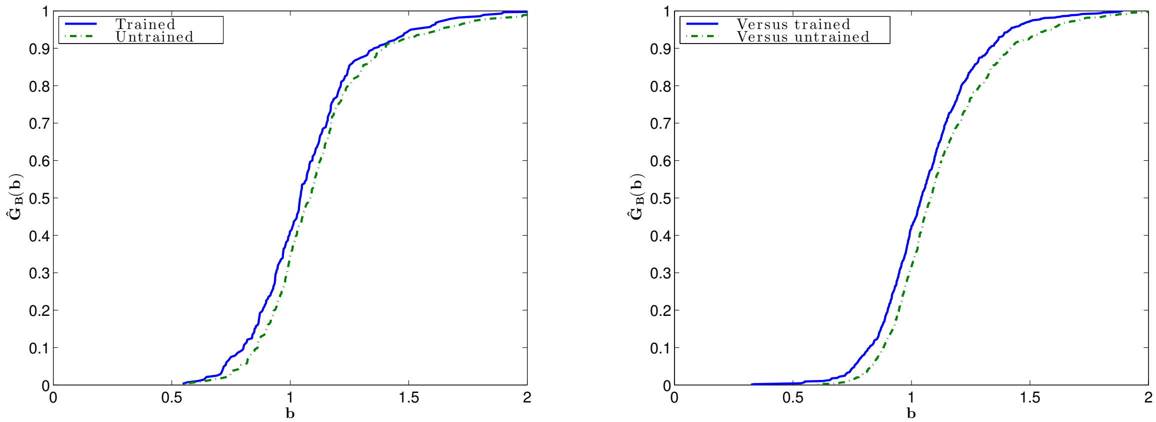
[4]In Table A1 of the Appendix, we describe each of the variables used in our work.

amount from each firm, for each contract, by the state's project-specific engineer's estimate. LINC-qualified but untrained firms submit relative bids that are about two percent higher than ineligible firms. This is true for both eligible firms that choose not to participate as well as for participating firms before they enrolled in the program. After completing the LINC program, the difference relative to the baseline group of ineligible firms goes away for graduates. Given the consistent guidance on bidding that participants receive in the LINC program, it's no surprise that firms come out of the program behaving differently. This observation suggests some potential for government savings. Indeed, we also see that after training, LINC bidders' relative winning bids are reduced—they are about one percent lower than those of other groups.

Though we will investigate a number of channels through which LINC might affect firm behavior and procurement outcomes, our primary focus in light of the program description is on how bidding behavior might change as a result of the LINC program. A snapshot of bidding patterns observed in the data helps motivate this investigation. In Figure 1, we present two subplots containing empirical distribution functions of relative bids—again, conditioning on the engineer's estimate so that the bids are at least comparable across auctions. Auction theory says that bidding behavior changes with the number of participants at auction. As such, we restrict data for this set of figures to auctions for which we observe five bidders tendering offers.[5]

In subplot 1a, we consider the behavior of firms that are eligible for the LINC program. The subplot suggests that LINC-trained firms bid lower than eligible but untrained firms. In contrast, in subplot 1b, we depict the bid distributions of firms that are not eligible for the LINC program to consider how they behave at auctions in which they face only untrained firms compared with how they behave at auctions involving at least one LINC graduate firm. The figure suggests that ineligible firms bid lower when a LINC-trained firm is present at auction than when an eligible, but untrained firm is present. This suggests that the LINC program may not only be generating more competitive bidding from its graduates, but also indirectly when ineligible firms realize they are bidding against trained firms. Kolmogorov–Smirnov tests suggest that the empirical distributions are significantly different at the one-percent level in subplot 1b and at the ten-percent level in

[5]We have 5,450 observed bids from five-bidder auctions in our sample in which we observe a mixture of auctions in which ineligible, untreated (eligible but untrained), and treated (graduate) firms are observed. For these figures we grouped eligible firms that elect not to participate with those that eventually participate in LINC but are observed before they are trained. This group is labeled and referred to as "Untrained" in these plots and this discussion.



(a) Qualified Firm Behavior

(b) Ineligible Firm Behavior

Figure 1: Relative Bid Distributions using Auctions with Five Bidders

subplot 1a (for which the underlying sample size is much smaller). Both figures visually suggest a first-order stochastic dominance relationship involving graduate firms' behavior or presence. We investigate these effects in our empirical work by accounting for many other firm-, contract-, and time-specific factors that are not accounted for in these motivating figures.

4 The Effects of LINC Training

While the summary statistics in Table 1 and subplots in Figure 1 suggest some interesting patterns, we wish to better evaluate the efficacy of the LINC program by investigating how behavior (bidding at auctions) and outcomes (winning bids and project costs for TxDOT) may have changed. In this section, we attempt to account for factors that may be varying across the sample periods, auctions, and bidders in order to better identify the effects the LINC program has had on this market.

4.1 Bidding Behavior

Our primary interest is on whether bidding has been affected by the LINC training program, for which we use econometric models to interpret the data. To do this, we introduce a dummy variable "LINC-graduate" which takes a value of one anytime a firm that has completed the program is observed bidding on a contract (after graduation), and zero otherwise. Similarly, the response of other bidders highlighted in Figure 1b suggests competitors may respond to the presence of a trained firm. Hence, we include in all of our models an additional binary variable "Interest from a LINC-trained firm" which takes a value of one if at least one of the rival planholders, which are known before bids are tendered, has completed LINC training. In Table 2, we provide a set of regression results in which we explain variation in the log of bids under various specifications using a restricted sample of the data comprising only bids from qualified firms. The direct effect of training on qualified-firm bidder behavior can most cleanly be understood using this sample as it levers trained-untrained comparisons of eligible firms. To account for heterogeneity across contracts, all models include the engineer's cost estimate, as well as time, material shares, and project division effects.[6]

The first model shows that when we account for our basic contract-specific variables so that the observed bids are at least comparable across contracts, graduates of the LINC program tender significantly lower bids than eligible firms who chose not to enroll. This model will be the most simple we present and reiterates the basic insight from Figure 1b: LINC-trained firms bid lower on average. However, given this model includes firm-specific fixed effects, here identification of the coefficient of "LINC-graduate" is driven specifically within-firm changes that come from differences in a given firm's behavior across the before-trained and after-trained auctions.[7] Note that these periods differ by firm because of the 36 training sessions spread over our sample period. If all sessions took place at once, a difference-in-difference analysis would be feasible but given the training is happening at different times, other covariates are also changing across time, contracts, locations, and so forth, which we account for going forward. Program graduates bid 4.7% lower after training than they did before training. In model (2), we include a host of other contract-, bidder-, and rivals-specific covariates which are often included in bidding regressions. For example, we compute the number of expected bidders by aggregating firm-specific participation rates on previous contracts, compute capacity-related measures, distances of all firms to the contract, experience (number of past bids) and success rates (rivals' winning-to-plan holder ratio). Accounting for all of these variables along with firm fixed effects shows that LINC graduates still bid 4.1% less on average than untrained, but eligible firms. We take the stability of the coefficient estimate as a good

[6]Time fixed effects are monthly; the project's materials shares correspond to six areas specified by TxDOT in its code book; project division fixed effects relate to the 25 project regions specified by TxDOT.

[7]In the models for which firm fixed effects are used, we include only bidders that are observed multiple times in the sample in order to identify the firm-specific fixed effects. Therefore, 25 observations from one-time, LINC-qualified bidders get dropped.

Table 2: Bid Regression Results: Qualified Bidders

Variable	Log of bids							
	OLS				IV		Heckman	Heckman–IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LINC-graduate	-0.047***	-0.041***	-0.023**	-0.021*	-0.041*	-0.019	-0.026**	-0.022*
	(0.015)	(0.015)	(0.012)	(0.011)	(0.024)	(0.012)	(0.012)	(0.013)
LINC-eligible, before training			0.007	0.009		0.010	0.015	0.019
			(0.014)	(0.013)		(0.014)	(0.014)	(0.016)
Interest from LINC-trained firm	-0.004	-0.006	0.006	0.007	-0.005	0.007	0.006	0.007
	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)
Log of ECE	0.962***	0.925***	0.941***	0.939***	0.925***	0.938***	0.940***	0.938***
	(0.004)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)	(0.006)
Log expected number of bidders		-0.023	-0.024*	-0.024	-0.021*	-0.019	-0.019	-0.013
		(0.015)	(0.015)	(0.015)	(0.013)	(0.014)	(0.014)	(0.014)
Log number of days to complete		0.026***	0.030***	0.031***	0.027***	0.030***	0.027***	0.026***
the project		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Log complexity		0.068***	0.057***	0.059***	0.068***	0.060***	0.052***	0.052***
		(0.009)	(0.008)	(0.008)	(0.013)	(0.008)	(0.007)	(0.009)
Log total number of rivals faced		0.002	0.003	0.003	0.002	0.003	-0.009	-0.013
in the market		(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.009)	(0.010)
Past winning-to-plan holder ratio		0.113*	-0.145***	-0.139***	0.107	-0.149***	-0.085*	-0.069
		(0.059)	(0.043)	(0.039)	(0.070)	(0.043)	(0.048)	(0.065)
Bidder's capacity utilized		0.038**	0.034**	0.037**	0.037**	0.038**	0.030*	0.029*
		(0.017)	(0.016)	(0.015)	(0.018)	(0.016)	(0.017)	(0.017)
Bidder's distance to the project		0.014***	0.010***	0.011***	0.014***	0.011***	0.005	0.003
location		(0.005)	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)	(0.005)
Ongoing project in the same county		-0.011	-0.024**	-0.024***	-0.010	-0.021**	-0.008	-0.002
		(0.009)	(0.009)	(0.009)	(0.011)	(0.009)	(0.013)	(0.015)
Log number of past bids		-0.007	0.005	0.006	-0.004	0.004	0.014**	0.018**
		(0.007)	(0.004)	(0.004)	(0.008)	(0.004)	(0.007)	(0.008)
Average rivals' winning-to-plan		-0.057	-0.025	-0.013	-0.064	-0.021	-0.065	-0.080
holder ratio		(0.093)	(0.101)	(0.100)	(0.078)	(0.099)	(0.086)	(0.097)
Log of rivals' minimum backlog		-0.000	0.000	0.000	-0.000	0.000	-0.000	-0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log of closest rival's distance to		0.004	0.007*	0.009**	0.005	0.008**	0.011**	0.013***
the project location		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Inverse mills ratio								0.116*
								(0.062)
Selection								
λ							0.088*	
							(0.052)	
Firm effects	Yes	Yes	No	No	Yes	No	No	No
Project RE	No	No	No	Yes	No	No	No	No
Number of observations	3,278	3,278	3,303	3,278	3,278	3,303	3,303	3,278
R^2	0.985	0.985	0.983	0.983	0.985	0.983		0.983
Wald χ^2							178,426.16	
F-statistics for weak identication					697.8.	6,053.00		16,308.00

** denotes statistical significance at the 5% level. * denotes statistical significance at the 10% level. Robust standard errors clustered by auction are in parentheses. All models include time, material shares, and project division effects.

sign—the estimated effect remains which gives us some hope that anything unaccounted for in our specification, would also not affect our estimate in important ways.

We observe whether untrained firms are not trained because they elect to never participate or because they are observed in the data before they are trained. We can investigate whether these two types of untrained firms behave inherently different if firm fixed effects are not used. In models (3) and (4), we consider this by introducing a new dummy variable which takes a value of one when firms that will eventually train were observed bidding before training, and so the omitted group in these models corresponds to firms who never participate. LINC graduates bid lower than both types of untrained firms, but there is no difference in the bids tendered across the different types of untrained firms, accounting for the full set of covariates we employ. Following Li and Zheng [2009], model (4) also includes project-level random effects, to control for unobserved auction heterogeneity—things observed by bidders when making their decisions but are unobserved by the econometrician.[8] In both of these models, a significant effect of LINC training is found: trained firms bids about 2.1% lower than eligible, but untrained firms.

We want to highlight two types of endogeneity concerns that can challenge our regression approach. First, a natural concern is that those participating in the program constitute a non-random sample from the pool of eligible firms. Non-random treatment assignment stems from the structure of the LINC program which allows, but does not require, eligible firms the opportunity to train. Thus, trained firms constitute a selected sample. Second, those firms that bid on a project may constitute a non-random sample from the pool of firms holding plans for a project. We seek to address these two concerns by using exclusion restrictions by employing instruments which affect selection into the program and entry into the auction, respectively, but not the outcome (bid) in either instance. We expand on these points and present results individually, before addressing both sample selection concerns in a unified approach.

Considering selection into the LINC program, first note that we do not have an incidental

[8] An alternative to including contract-specific characteristics would be to include auction-specific fixed effects which would mean these observables as well as variables that do not change within an auction (like the expected number of bidders) would not be identified, though concerns about unobserved heterogeneity would be mitigated. When we estimate such models, the correlation between the estimated auction fixed effects and the engineer's cost estimate is 0.99. If these fixed effects are used as the dependent variable in a regression, the contract-specific observables (and time and location fixed effects) explain over 99% of the variation in the project fixed effects. In short, we don't feel unobserved heterogeneity is overwhelming our models. As such, we've opted to explicitly control for observables in our research which has allowed us to investigate whether LINC participants respond differently to things like the level of competition, complexity, project length, and so forth in various empirical specifications.

truncation problem as we are able to see bids for all types of firms regardless of their training decision or eligibility. We have an endogenous dummy variable "LINC-graduate" and, as such, we seek to address this issue using an instrumental variables approach following Adams et al. [2009]. We instrument for the "LINC-graduate" dummy by running a first-stage probit model considering how likely a firm is to participate in the LINC training program given the distance to the training location from each firm's location and the time lag between concurrent training sessions. The intuition for including these variables is that firms closer to training sites or when trainings have not been offered for a while, should be more likely to train. However, these variables should not affect a given firm's bid on a TxDOT project. Following Adams et al. [2009], the fitted values from the first-stage model instrument for "LINC-graduate", the effect of which we then estimate via instrumental variables (IV). The IV results in column (5) which includes firm fixed-effects are fairly consistent with the sister model estimated in column (2). Similarly, the model without firm fixed effects estimated via IV and presented in column (6) provides estimates in line with model (4). However, both models show reduced statistical significance from bidder training.

Bidding firms also constitute a non-random sample of the firms that hold plans for a given contract, which can result in selection bias. Unlike selection into the program, for which we observe behavior regardless of the decision to train, we do not observe bids from plan-holding firms that do not tender an offer on a given contract. We address this concern by using a Heckman-based correction (a control function approach) which amounts to including a nonlinear function involving the inverse Mills ratio but also by instrumenting for entry into an auction. To instrument for entry into an auction, we use the funding status of the project (whether federal funds are used) as well as subcontracting requirements stated for the project in estimating the selection equation which corresponds to the probability of entering an auction. De Silva et al. [2005] used the funding status of a project as an exclusion restriction in a Heckman-based approach and De Silva et al. [2012] showed that subcontracting requirements do not affect bid amounts. One rationale for why subcontracting requirements could impact entry but not bids, could be that plan holders observe project requirements (in particular, subcontracting requirements), and then decide to tender a bid if their typical or planned collaborators would be sufficient in meeting the requirements; otherwise, they decide not to enter. Such a consideration would impact auction entry, but not bids. These IVs for auction entry utilize variation across projects, meaning the entry probability will be common for all bidders under this structure. This limitation is not inconsistent with how auction researchers have modeled endogenous entry; see, for example, Levin and Smith [1994] where a symmetric entry equilibrium involves mixed strategies with each potential bidder entering with a common probability. The estimates in model (7) reflect that selection concerns are valid, and that LINC graduates tender bids that are 2.6% lower than all other firms.

Lastly, we follow Wooldridge [2010], to address both of these concerns in a unified Heckman–IV approach. Specifically, (i) we estimate a selection equation using instruments for LINC program participation (distance to the training site and time since the last training session) to obtain fitted values for the probability of participating in LINC; (ii) we estimate a selection equation specifying the probability of participating in a given auction using instruments for auction participation (a binary variable indicating if federal funds are used as well as the percentage of the project that must be outsourced to qualified subcontractors) from which we compute the inverse Mills ratio; (iii) we use the data for which we observe the decision to enter the auction and the bid tendered, to estimate the bidding models via instrumental variables where the inverse Mills ratio from (ii) is also employed.[9] The estimates, presented in model (8) of Table 2 suggest that program graduates bids are 2.2% lower, on average, having controlled for the other factors presented and taken steps to address both types of sample selection concerns.

As we've discussed and demonstrated in Figure 1b, there is potential for the LINC program to indirectly affect the behavior of other firms given the structure of the LINC program which makes other contractors aware of the LINC graduates—this is a focus of training session four and the post-graduation reporting-out process that notifies all firms who have demonstrated an interest in working with TxDOT of the LINC graduate firms. This, combined with that fact that plan holders are also provided a list identifying fellow plan holders before bidding begins, suggests rivals may respond to the potential presence of a LINC trained firm. We did not find evidence of any indirect effect using the restricted sample of bids comprising firms eligible for participation in the LINC program, but those firms constitute a relatively small share of the firms active in the TxDOT procurement market. As such, only rarely do these firms hold plans for contracts where LINC-trained firms have also demonstrated interest (about 8% of contracts, for example, involve more

[9] For additional details, see Procedure 19.2 on pages 810–811 of Wooldridge [2010]. Standard errors are computed by bootstrapping the entire procedure 1000 times.

than one LINC-trained firm holding plans). To better investigate any indirect competition effect on bidding behavior, we first restrict attention to the sample of bids from unqualified (ineligible) firms. Model (1) of Table 3 shows a significant indirect effect of the LINC program: if a LINC graduate holds plans for a project, bids of ineligible firms are on average 2% lower. We have confidence in this indirect competition effect as we considered other models in which we included placebo-like effects, finding no significant results. For example, if we replace this variable with one capturing whether plans for the auction were held by a LINC-qualified, but untrained firm, it is never statistically different from zero and is always smaller in magnitude, being at most 0.005 away from zero.[10]

When we expand the sample of unqualified bids to consider the full sample of bids in model (2) of Table 3, we can now identify a new dummy variable "LINC-eligible, will never train" which takes a value of one if the bid comes from a firm qualified for the program, but never opts to enroll in training during our sample period. In these models involving the full sample of bids, the omitted group is now the set of ineligible firms so the coefficient estimates over the primary LINC-related binary variables should be interpreted as relative to the average bid from an ineligible firm. Again, LINC graduates bid lower after completing the program and the presence of graduates in the market (demonstrated by their interest in a given project) generates more competitive bids from the other firms resulting in an indirect competition effect. These findings are consistent with the bid distributions in subplots 1a and 1b of Figure 1. The estimates in model (2) are pretty comparable to the estimates in the remaining columns of Table 3, which address other concerns that we have already described, but using the full sample of bids: auction-level unobserved heterogeneity is considered in model (3), sample selection concerning LINC program participation in model (4), selection into an auction in model (5), and both sample selection concerns in model (6).

While our discussion of the bidding results has focused on the effects of training, we should note that the other coefficient estimates suggest patterns that are intuitively appealing. For example, if there are more bidders expected 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

[10]These results are provided in Table A2 in the Appendix. We also considered models in which we included the number of LINC trained rivals holding plans, rather than an indicator variable for the presence of any LINC graduates. The indirect effects are almost identical to what we have presented as, conditional on there being any LINC-trained rivals, there is only one that holds plans 80% of the time.

Table 3: Bid Regression Results: All Bidders

Variable	Log of bids					
	Unqualified	Full sample				
		OLS		IV	Heckman	Heckman–IV
	(1)	(2)	(3)	(4)	(5)	(6)
LINC-graduate		-0.017***	-0.014***	-0.017***	-0.023***	-0.023***
		(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
LINC-eligible, before training		-0.001	-0.001	-0.001	-0.002	-0.002
		(0.007)	(0.005)	(0.007)	(0.007)	(0.007)
LINC-eligible, will never train		0.008	0.005	0.006	0.007	-0.002
		(0.008)	(0.007)	(0.008)	(0.007)	(0.009)
Interest from LINC-trained firm	-0.020***	-0.018***	-0.012***	-0.018***	-0.017***	-0.017***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Log of ECE	0.920***	0.929***	0.933***	0.930***	0.931***	0.931***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Log expected number of bidders	-0.023***	-0.021***	-0.029***	-0.015**	-0.020***	-0.020***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)
Log number of days to complete	0.040***	0.038***	0.034***	0.034***	0.034***	0.034***
the project	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Log complexity	0.073***	0.074***	0.070***	0.074***	0.071***	0.071***
	(0.006)	(0.005)	(0.004)	(0.005)	(0.002)	(0.003)
Log total number of rivals faced	-0.006**	-0.001	0.001	-0.001	-0.008***	-0.008***
in the market	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.003)
Past winning-to-plan holder ratio	0.033**	-0.159***	-0.165***	-0.159***	-0.112***	-0.111***
	(0.014)	(0.010)	(0.008)	(0.010)	(0.016)	(0.016)
Bidder's capacity utilized	0.033***	0.033***	0.029***	0.038***	0.037***	0.037***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Bidder's distance to the project	0.015***	0.013***	0.011***	0.014***	0.010***	0.009***
location	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Ongoing project in the same county	-0.014***	-0.017***	-0.020***	-0.017***	-0.005	-0.004
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)
Log number of past bids	-0.002	0.005***	0.004***	0.004***	0.010***	0.011***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Average rivals' winning-to-plan	-0.033	-0.047	-0.036	-0.054	-0.066***	-0.067***
holder ratio	(0.034)	(0.035)	(0.029)	(0.034)	(0.023)	(0.024)
Log of rivals' minimum backlog	0.001**	0.001**	0.000*	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log of closest rival's distance to	-0.002	0.000	-0.000	0.000	0.003**	0.003**
the project location	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Inverse mills ratio						0.080***
						(0.022)
Selection						
λ					0.077***	
					(0.020)	
Firm effects	Yes	No	No	No	No	No
Project RE	No	No	Yes	No	No	No
Number of observations	28,222	31,784	31,500	31,783	31,783	31,760
R^2	0.986	0.984	0.985	0.983		0.985
Wald χ^2					1.94e+06	
F-statistics for weak identication				6.855e+06		779,599

** denotes statistical significance at the 5% level. * denotes statistical significance at the 10% level. Robust standard errors clustered by auction are in parentheses. All models include time, material shares, and project division effects.

is larger, then higher bids are submitted. Likewise, higher bids obtain when bidders have used much of their capacity or if firms are farther from the project location. These effects are typically statistically significant at the 1% level even after controlling for time, project composition, and project division effects which, given their signs accord with intuition, gives us some confidence in our empirical specifications.

4.2 Auction Outcomes

Taken together, we see LINC alumni become more competitive in the market after graduation and we see other (primarily ineligible) firms tendering lower bids on average when potentially facing LINC rivals on a contract. While these effects might be realized on average, auctions are structured to award contracts to an extreme order statistic—the lowest bid, and so it's not clear whether the more competitive bidding implies lower winning bids as the previous results might be generated by "irrelevant" (losing) bids being closer to the winning bid. To examine this conjecture, in Table 4, we present empirical bidding models similar to those used earlier, but restrict attention to the subset of winning bids. With respect to the sample of LINC-qualified bids, being a LINC graduate does not yield significantly lower winning bids nor imply that other LINC-eligible firms behave more competitively (while the magnitude of these effects is comparable, the standard errors are larger with a smaller sample of winning bids from this group). Of course, most of the projects are won by ineligible firms and in model (3) we observe that when these firms win contracts they do so with bids that are 2.3% lower on average when a LINC graduate holds plans for the contract and serves as a potential bidder. In the full sample, we see the direct and indirect competition effects are both significant and imply cost savings for the state: winning bids from LINC graduates are at least 2.8% lower in model (4) and winning bids from any firm that potentially faced a LINC graduate are 1.8% lower. In Table A3 in the Appendix, we present quantile regression estimates from the model (2) specification of Table 3 and model (4) specification of Table 4 which show that the direct and indirect effects from the LINC training program hold not just on average, but throughout the bid and winning bid distributions, respectively. The magnitude of these coefficients is consistent with the least-squares estimates. The results indicate that the sign and significance of the other covariates are similar to those of the sample of all (not just winning) bids presented earlier. Addressing sample selection concerns, either separately or jointly, suggests these effects

Table 4: Winning Bid Regression Results

Variable	Log of winning bids						
	Qualified		Unqualified		Full sample		
	OLS				IV	Heckman	Heckman–IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LINC-graduate	-0.024	-0.022		-0.028***	-0.026***	-0.018*	-0.016*
	(0.027)	(0.021)		(0.008)	(0.008)	(0.011)	(0.009)
LINC-eligible, before training		-0.003		-0.014	-0.012	-0.003	-0.001
		(0.025)		(0.011)	(0.011)	(0.015)	(0.012)
LINC-eligible, will never train				-0.006	-0.003	-0.003	-0.004
				(0.014)	(0.014)	(0.016)	(0.014)
Interest from LINC-trained firm	-0.033**	-0.011	-0.023***	-0.018***	-0.018***	-0.020***	-0.020***
	(0.017)	(0.015)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
Log of ECE	0.930***	0.945***	0.931***	0.940***	0.943***	0.944***	0.949***
	(0.010)	(0.009)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Log expected number of bidders	-0.066***	-0.111***	-0.065***	-0.069***	-0.064***	-0.078***	-0.185***
	(0.023)	(0.022)	(0.007)	(0.007)	(0.007)	(0.010)	(0.038)
Log number of days to complete	0.017	0.008	0.040***	0.034***	0.026***	0.025***	0.023***
the project	(0.011)	(0.012)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Log complexity	0.100***	0.098***	0.089***	0.093***	0.096***	0.093***	0.100***
	(0.013)	(0.013)	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)
Log total number of rivals faced	-0.006	0.004	-0.012***	-0.006**	-0.005*	-0.009**	-0.008***
in the market	(0.010)	(0.009)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Past winning-to-plan holder ratio	0.020	-0.062	0.044**	-0.029**	-0.026*	0.020	0.257***
	(0.077)	(0.060)	(0.021)	(0.015)	(0.014)	(0.030)	(0.089)
Bidder's capacity utilized	0.060**	0.030	0.003	0.006	0.016*	0.010	-0.042**
	(0.029)	(0.026)	(0.010)	(0.008)	(0.008)	(0.009)	(0.020)
Bidder's distance to the project	0.003	0.007	0.010***	0.005***	0.006***	0.003	-0.005
location	(0.009)	(0.006)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)
Ongoing project in the same county	-0.021	-0.020	-0.009*	-0.016***	-0.016***	-0.005	0.020*
	(0.015)	(0.014)	(0.005)	(0.004)	(0.004)	(0.007)	(0.012)
Log number of past bids	-0.006	0.003	0.002	0.007***	0.006***	0.010***	0.005***
	(0.010)	(0.006)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Average rivals' winning-to-plan	-0.019	-0.007	-0.096**	-0.126***	-0.142***	-0.150***	-0.287***
holder ratio	(0.143)	(0.134)	(0.043)	(0.039)	(0.039)	(0.037)	(0.059)
Log of rivals' minimum backlog	-0.000	-0.000	0.001**	0.001**	0.001**	0.001**	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log of closest rival's distance to	0.008	0.013**	-0.000	0.005***	0.005***	0.007***	0.015***
the project location	(0.007)	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Inverse mills ratio							0.242***
							(0.075)
Selection							
λ						0.242**	
						(0.090)	
Firm effects	Yes	No	Yes	No	No	No	No
Number of observations	816	821	6,562	7,434	7,374	7,434	7,434
R^2	0.993	0.991	0.990	0.989	0.989		
Wald χ^2						410,326.76	
F-statistics for weak identification					1.425e+06		248,180

** denotes statistical significance at the 5% level. * denotes statistical significance at the 10% level. Robust standard errors clustered by auction are in parentheses. All models include time, material shares, and project division effects.

remain statistically significant, as shown by models (5), (6), and (7) of Table 4, meaning the changes in bidder behavior do translate into lower winning bids.

4.3 Additional Results and Discussion

Having provided some benchmark results, we consider deeper issues of selection into the LINC program, look to shed light on the channels through which the LINC program may be working, and hope to address other concerns in this subsection.

4.3.1 Unobservable Selection into the LINC Program

While we sought to mitigate concerns around selection bias in some of the models we presented in the previous subsections by estimating alternative models (Heckman-based corrections) and employing instruments (for example, firms' distances to training facilities), readers might worry there is selection into the program based on unobservables as well. We conduct two types of exercises to consider selection into the program on unobservables which we describe in this subsection.

First, we split our sample in two to consider whether the effects we've estimated are inherently different for early versus later participants. About half of our data come from the September 1998–January 2003 period, and half come from January 2003–August 2007 so we use January 1, 2003 as the critical date in splitting our sample, for which we re-estimate our main bidding models using the before-2003 sample and the after-2003 model separately. If the estimated models on the two subsamples appear to give similar results, then it means any unobservable driving selection must be happening throughout the entire sample—this would mean a very specific type of unobservable(s) is at play that would affect estimates in both periods in the same way. If estimates differ substantially, and differ drastically from the baseline set of results presented thus far, then unobservables may be plaguing estimation. We present the regression results in Table 5, restricting attention to the coefficients of the variables of interest but controlling for all of the auction-, bidder-, and rival-related variables from earlier models as well as time, material shares, and project division effects. Models (1) and (2) employ only the sample of bids from firms eligible for the program (like the results presented in Table 2), the results in model (3) are based off only the appropriate set of bids from ineligible firms, and the last three results use all data but are estimated using different strategies, culminating with the Heckman–IV results in the final column.

Table 5: Bid Regression Results for Before and After 2003

Variable	Log of bids					
	Qualified		Unqualified	Full sample		
	OLS				Heckman	Heckman–IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Before 2003						
LINC-graduate	-0.050**	-0.048**		-0.027***	-0.031***	-0.024**
	(0.019)	(0.020)		(0.009)	(0.008)	(0.010)
LINC-eligible, before training		-0.013		-0.009	-0.010	-0.010
		(0.018)		(0.007)	(0.007)	(0.007)
LINC-eligible, will never train				0.005	-0.002	-0.002
				(0.012)	(0.011)	(0.013)
Interest from LINC-trained firm	-0.001	0.008	-0.029***	-0.022***	-0.021***	-0.020***
	(0.016)	(0.017)	(0.008)	(0.008)	(0.004)	(0.005)
Inverse mills ratio						0.050**
						(0.025)
Auction, bidder, and rival controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm effects	Yes	No	Yes	No	No	No
Number of observations	1,689	1,698	14,053	15,869	15,869	15,857
R^2	0.985	0.982	0.987	0.985		0.985
Wald χ^2					987 232.99	
F-statistics for weak identication						161,202.00
Panel B: After 2003						
LINC-graduate	-0.094**	-0.001		-0.009	-0.019**	-0.021***
	(0.043)	(0.016)		(0.006)	(0.008)	(0.008)
LINC-eligible, before training		0.076*		0.092**	0.081**	0.083**
		(0.046)		(0.040)	(0.033)	(0.039)
LINC-eligible, will never train				0.004	-0.007	-0.009
				(0.011)	(0.012)	(0.012)
Interest from LINC-trained firm	-0.013	0.008	-0.015***	-0.015***	-0.016***	-0.016***
	(0.012)	(0.012)	(0.006)	(0.006)	(0.004)	(0.004)
Inverse mills ratio						0.050**
						(0.025)
Inverse mills ratio						0.134**
						(0.057)
Auction, bidder, and rival controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm effects	Yes	No	Yes	No	No	No
Number of observations	1,589	1,605	14,169	15,914	15,914	15,903
R^2	0.986	0.984	0.987	0.985		0.985
Wald χ^2					948,942.84	
F-statistics for weak identication						783,265.00

** denotes statistical significance at the 5% level. * denotes statistical significance at the 10% level. Robust standard errors clustered by auction are in parentheses. All models include time, material shares, and project division effects in addition to auction, bidder, and rival controls.

The first model in each panel of the table shows that, when using variation from within a firm that participates to estimate the effect of the LINC program, graduates bid significantly less in both sample periods. Model (2) accounts for the various types of untrained firms. The effect of LINC training is nearly identical in the early period, but in the later period shows graduates don't bid differently from firms that will never train. The significance of the LINC program in model (1) of the post-2003 period stems from those graduates behaving with significantly higher bids before they were trained (than afterwards and relative to those firms that will never train). This is perhaps understandable as the sample of untrained firms looks inherently different after the program has been accepting trainees for some time. The indirect competition effects are statistically significant across the various sample periods as well as across the various model specifications. The results look even more similar across time periods when selection into the program and the auction concerns are addressed via the Heckman–IV approach, giving us some confidence that there is not selection into the LINC program based on unobservables that are changing over time.

Another concern could be that the LINC program is attracting the inherently best firms, so the estimated effect in our model captures not the effect of the training program, but rather serves as an indicator of whether the firm is one of the most successful bidding firms or not. To consider whether this story might drive the estimates, we construct variables that represent whether an eligible firm is one of the best performing (star) qualified firms. Specifically, we take the sample of all observations from eligible but untrained firms (bidders may or may not enroll in LINC at a later point) and identify the top 10% of firms according to three measures: the number of wins, the winning-to-bidding ratio of firms, and the total contract dollars allocated to the firms. We include each of these respective variables in separate regressions to consider the baseline bidding model from column (6) of Table 3 for all bids and column (7) of Table 4 for winning bids—these empirical models include the full sample of bids (winning bids) and the full set of control variables. All estimates in these tables address both sources of selection using the Heckman–IV strategy we've adopted. In Table 6, we present estimates from these specifications for the LINC- and star-related variables. Separately identifying the top performing firms does not affect our core estimates—the effect of LINC training and the indirect competition effects remain negative and significant. If anything, the top performing firms, when they become LINC trained, tender higher bids on average as the interaction of these terms is positive and significant in some models, counteracting (to a degree) the average effects that the LINC-graduate and best-performing firm experiences.

Table 6: Heckman–IV Regression Results for Best-Performing Firms

Variable	Log of bids			Log of winning bids		
	(1)	(2)	(3)	(4)	(5)	(6)
LINC-graduate	-0.019***	-0.025***	-0.029***	-0.017*	-0.021**	-0.010
	(0.006)	(0.006)	(0.006)	(0.010)	(0.010)	(0.010)
LINC-eligible, before training	0.004	0.006	0.000	-0.012	-0.001	-0.012
	(0.008)	(0.007)	(0.007)	(0.012)	(0.013)	(0.012)
LINC-eligible, will never train	0.010	0.021**	0.009	-0.004	0.018	-0.002
	(0.009)	(0.009)	(0.010)	(0.017)	(0.019)	(0.019)
Interest from LINC-trained firm	-0.017***	-0.017***	-0.017***	-0.016***	-0.016***	-0.016***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
LINC strong firm (win count in top 10%)	-0.004			0.005		
	(0.011)			(0.018)		
LINC strong firm (win count in top 10%) ×	-0.021			0.004		
LINC-graduate	(0.017)			(0.028)		
LINC strong firm (winning to bidding ratio in top 10%)		-0.034***			-0.007	
		(0.011)			(0.021)	
LINC strong firm (winning to bidding ratio in top 10%) ×		0.043***			0.027	
LINC-graduate		(0.017)			(0.029)	
LINC strong firm (win total in top 10%)			-0.005			-0.006
			(0.012)			(0.020)
LINC strong firm (win total in top 10%) ×			0.065***			-0.069
LINC-graduate			(0.019)			(0.044)
Material shares	Yes	Yes	Yes	Yes	Yes	Yes
Time effects and Distrcit effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,760	31,760	31,760	7,430	7,430	7,430
R^2	0.985	0.985	0.985	0.989	0.989	0.989
F-statistics for weak identication	251,662	279,277	308,128	113,408	42,875	45,537

Robust standard errors clustered by auction are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. These regressions are similar to the last columns presented in Tables 3 and 4 with additional interaction terms.

Since the top performing firms tend to submit higher bids, this begs the question of whether the worst-performing firms might drive the results. That is, the LINC effect is primarily obtaining because the worst performing firms select into the LINC program—the effects we estimate then represent not the effects of the training program, but that the firms who were unsuccessful have changed their behavior. We replicate the previous exercise but this time identify the worst 10% of LINC-qualified firms according to the various success measures and present the results in Table 7. The various dummy variables that represent the weakest firms are rarely significant and the interaction with the training indicator is never significant. However, the effect of the LINC program and the indirect competition effects remain negative and significant across the specifications.

Table 7: Heckman–IV Regression Results for Worst-Performing Firms

Variable	Log of bids			Log of winning bids		
	(1)	(2)	(3)	(4)	(5)	(6)
LINC-graduate	-0.036***	-0.023***	-0.022***	-0.028***	-0.030***	-0.029***
	(0.011)	(0.005)	(0.005)	(0.009)	(0.009)	(0.009)
LINC-eligible, before training	0.004	-0.001	-0.000	-0.012	-0.011	-0.012
	(0.008)	(0.007)	(0.007)	(0.011)	(0.012)	(0.011)
LINC-eligible, will never train	0.032	0.003	0.008	-0.008	-0.005	-0.009
	(0.025)	(0.009)	(0.008)	(0.015)	(0.015)	(0.014)
Interest from LINC-trained firm	-0.018***	-0.018***	-0.018***	-0.016***	-0.017***	-0.017***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)
LINC weak firm (win count in bottom 10%)	0.382			0.029		
	(0.277)			(0.027)		
LINC weak firm (win count in bottom 10%) ×	-0.189					
LINC-graduate	(0.181)					
LINC weak firm (winning to bidding ratio in bottom 10%)		0.025			-0.047	
		(0.022)			(0.078)	
LINC weak firm (winning to bidding ratio in bottom 10%) ×		0.035			0.098	
LINC-graduate		(0.026)			(0.083)	
LINC weak firm (win total in bottom 10%)			-0.020			0.010
			(0.057)			(0.079)
LINC weak firm (win total in bottom 10%) ×			0.085			0.026
LINC-graduate			(0.060)			(0.084)
Material shares	Yes	Yes	Yes	Yes	Yes	Yes
Time effects and Distrcit effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,760	31,760	31,760	7,430	7,430	7,430
R^2	0.984	0.985	0.985	0.989	0.989	0.989
F-statistics for weak identication	123.9	94,835	69,369	125,101	15,946	123,350

Robust standard errors clustered by auction are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. These regressions are similar to the last columns presented in Tables 3 and 4 with additional interaction terms.

4.3.2 Where is the Action?

We have documented that alumni of the LINC training program submit bids that are lower on average. Unfortunately, we have no data on activities or events that take place within training sessions that might allow us to speak to the efficacy of the various program elements. Instead, here we look to highlight ways in which graduates might have changed their behavior after completing training. To consider this, we present some summary statistics on bidder- and auction-specific characteristics in Table 8. To compute the means presented in this table, we employ data from only firms eligible to participate in the LINC program to allow for untrained versus trained comparisons across eligible firms. While the results we have presented so far suggest that many covariates are important in driving the bidding decisions of firms, the before versus after training distinction seems to suggest bidders behave differently in response to some of their own characteristics, as opposed to auction-level factors, as a result of training. One remarkable insight from this simple comparison of means, is that most bidder-specific characteristics look significantly different after training versus before training, while auction-specific characteristics are not significantly different across this partition. Not surprisingly, auction researchers have focused attention on these bidder-specific variables as well. Backlog or capacity constraints as well as distance to a project location and strength of competition have all been salient issues in important empirical papers concerning auctions; as examples, see Bajari and Ye [2003], Jofre-Bonet and Pesendorfer [2000, 2003], De Silva et al. [2003], De Silva et al. [2008], as well as Bajari et al. [2014]. A number of papers also note synergies which may be realized in a procurement or other context; see De Silva [2005], De Silva et al. [2005], and Gentry et al. [2016].

Table 8: Possible Asymmetries Summary Statistics

Variable	Before training	After training	p-value
Panel A: Bidder characteristics			
Bidder's capacity utilized	0.147	0.215	0.000
Bidder's distance to the project location	126.845	146.960	0.000
Average rivals' winning-to-plan holder ratio	0.141	0.139	0.156
Ongoing project in the same county	0.169	0.229	0.000
Panel B: Auction characteristics			
Engineering cost estimate (ECE)	2,758,381.000	2,195,242.000	0.293
Complexity	61.577	63.017	0.678
Number of days to complete the project	133.631	142.518	0.344
Relative subcontractor value	0.185	0.185	0.981
Number of subcontractors	4.382	4.653	0.344

We explore these possible bidder-specific channels as ways in which firms might behave differently given their training or eligibility by considering other regression models in Table 9. All of the models are estimated using the Heckman–IV approach and include all covariates presented in column (6) of Table 3 but, due to space constraints, we only present coefficient estimates for our variables of interest and the relevant interaction terms for the newly-considered cases. Specifically, we wondered if bidders might respond differently to capacity constraints, distance to the project location, the competitiveness of their rivals, or whether they have nearby work already going on.

The interaction terms in the first three models show that LINC graduates (and eligible but untrained firms) do not behave differently with respect to these variables—all interaction terms

Table 9: Investigating other Possible Asymmetries through Bid Regressions: Heckman–IV

Variable	Log of bids			
	(1)	(2)	(3)	(4)
LINC-graduate	-0.021***	-0.043***	-0.032*	-0.015**
	(0.007)	(0.016)	(0.019)	(0.006)
LINC-eligible, before training	-0.001	0.014	0.025	-0.001
	(0.009)	(0.020)	(0.019)	(0.007)
LINC-eligible, will never train	-0.006	0.016	0.039	0.004
	(0.011)	(0.030)	(0.032)	(0.011)
Interest from LINC-trained firm	-0.018***	-0.018***	-0.018***	-0.018***
	(0.003)	(0.003)	(0.003)	(0.003)
Bidder's capacity utilized	0.033***	0.033***	0.033***	0.033***
	(0.005)	(0.005)	(0.005)	(0.005)
Bidder's capacity utilized ×	-0.008			
LINC-graduate	(0.020)			
Bidder's capacity utilized ×	-0.006			
LINC-eligible, before training	(0.029)			
Bidder's capacity utilized ×	0.028			
LINC-eligible, will never train	(0.030)			
Log of bidder's distance to the project location	0.010***	0.010***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
Log of bidder's distance to the project location ×		0.005		
LINC-graduate		(0.004)		
Log of bidder's distance to the project location ×		-0.004		
LINC-eligible, before training		(0.005)		
Log of bidder's distance to the project location ×		-0.004		
LINC-eligible, will never train		(0.008)		
Average rivals' winning-to-plan holder ratio	-0.060**	-0.059**	-0.051**	-0.060**
	(0.023)	(0.025)	(0.024)	(0.023)
Average rivals' winning-to-plan holder ratio ×			0.065	
LINC-graduate			(0.141)	
Average rivals' winning-to-plan holder ratio ×			-0.181	
LINC-eligible, before training			(0.112)	
Average rivals' winning-to-plan holder ratio ×			-0.284	
LINC-eligible, will never train			(0.214)	
Ongoing project in the same county	-0.005	-0.006	-0.006	-0.004
	(0.005)	(0.004)	(0.004)	(0.004)
Ongoing project in the same county ×				-0.027**
LINC-graduate				(0.011)
Ongoing project in the same county ×				-0.003
LINC-eligible, before training				(0.018)
Ongoing project in the same county ×				-0.012
LINC-eligible, will never train				(0.018)
Inverse mills ratio	0.074***	0.071***	0.070***	0.069***
	(0.022)	(0.022)	(0.023)	(0.022)
Number of observations	31,760	31,760	31,760	31,760
R^2	0.984	0.984	0.984	0.984
F-statistics for weak identication	316,379	383,375	258,223	313,157

Robust standard errors clustered by auction are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
These regressions are similar to the once presented in Tables 4 and 5 Column 8 with interaction terms.

are insignificant (or very small with respect to distance). In these first three models, the effect of training remains negative and significant. However, model (4) suggests that much of the action comes from realizing synergies—when we allow for the various classes of firms to react differently to the effect of having a project in a given county, there is a negative and significant effect from LINC training because of this factor, above and beyond the average effect from LINC training. This suggests that alumni of the program are better able to realize synergies by bidding more competitively on contracts where they currently have ongoing work.

We also wondered whether professional relationships might change because of LINC training. Remember, Session 4 of the LINC program is about networking and the dissemination of information on graduate firms is likely in part done to let subcontractors know who they might be able to work with in the industry. Unfortunately our data do not contain subcontracting information for the full set of bids—only for the winning bids. Using the awarded contract data, we consider how subcontracting might have changed by considering the number of subcontractors as well as the dollar value of a project that is subcontracted out by the prime contractors. In Table 10, we present in the first two columns Poisson pseudo-maximum likelihood (PPML) estimates of models that consider variation in the number of subcontractors. The first two sets of results suggest that trained firms, when they win, do no employ a higher number of subcontractors than ineligible firms (the omitted group). There is some evidence though that more subcontractors are used by trained firms than peers observed either before training or those eligible firms that never opt to train. This holds regardless of whether we adopt an IV approach to address LINC participation or not.[11] Models (3) and (4) demonstrate that LINC graduates use subcontractors to complete more project work (measured in terms of dollars spent on subcontracting) than ineligible firms as well as eligible firms which remain untrained through our sample.

Lastly, while our focus has been primarily on the awarding of procurement contracts, readers may wonder whether post-winning behavior either differs across the various groups of bidders or somehow cancels-out the savings generated at the awarding stage. Taking an extreme (pessimistic) position, perhaps LINC graduates have somehow learned to submit deceptive bids for a project knowing that they will be able to renegotiate a higher payment after winning the contract. Such

[11] The PPML routine we employ was proposed by Santos Silva and Tenreyro [2006] and we follow Windmeijer and Santos Silva [1997] in dealing with endogeneity in count data models via an IV approach.

Table 10: Subcontracting usage

Variable	Number of subcontractors		Log of subcontracted value	
	PPML	IV-PPML	OLS	Heckman–IV
	(1)	(2)	(3)	(4)
LINC-graduate (β_1)	0.039	0.038	0.355**	0.374**
	(0.026)	(0.027)	(0.161)	(0.159)
LINC-eligible, before training (β_2)	-0.038	-0.032	0.059	0.102
	(0.039)	(0.038)	(0.263)	(0.266)
LINC-eligible, will never train (β_3)	-0.058	-0.060	-0.280	-0.286
	(0.038)	(0.038)	(0.248)	(0.253)
Log of ECE	0.081***	0.082***	0.715***	0.716***
	(0.014)	(0.014)	(0.057)	(0.060)
Log number of days to complete the project	0.034**	0.034**	-0.060	-0.075
	(0.014)	(0.014)	(0.076)	(0.084)
Log complexity	0.605***	0.605***	1.812***	1.822***
	(0.034)	(0.034)	(0.089)	(0.096)
Past winning-to-bidding ratio	-0.198***	-0.200***	-0.009	0.713
	(0.061)	(0.061)	(0.305)	(2.497)
Log total number of rivals faced in the market	-0.003	-0.004	-0.063	-0.107
	(0.009)	(0.009)	(0.056)	(0.152)
Bidder's capacity utilized	0.067**	0.067**	0.017	-0.142
	(0.026)	(0.026)	(0.152)	(0.563)
Bidder's distance to the project location	-0.000	-0.000	0.076**	0.049
	(0.006)	(0.006)	(0.036)	(0.097)
Ongoing project in the same county	-0.010	-0.010	-0.176**	-0.076
	(0.013)	(0.013)	(0.074)	(0.346)
Log number of past bids	0.014**	0.014**	0.191***	0.197***
	(0.007)	(0.007)	(0.033)	(0.037)
Inverse mills ratio				0.623
				(2.082)
Number of observations	7,434	7,434	7,434	7,430
R^2	0.702	0.702	0.556	0.557
F-statistics for weak identication				273,041
χ^2 test probability: $\beta_1 = \beta_2$	0.091	0.127	0.333	0.245
χ^2 test probability: $\beta_1 = \beta_3$	0.030	0.027	0.027	0.021

** denotes statistical significance at the 5% level. * denotes statistical significance at the 10% level. Robust standard errors clustered by auction are in parentheses. All models include time, material shares, and project division effects.

concerns were the basis of Bajari et al. [2014], in which the authors focused on the prevalence of renegotiation and post-awarding adaptation. To evaluate this, we obtained data on the final payments made to firms for contracts completed during the years of our data sample.[12] In Table 11, we provide estimates from our core regression models in which our dependent variable is now the final payment made to the winning bidder, post any renegotiation and/or adjustments to the projects. The estimates in the first two models condition on the engineer's initial estimate of the project while the estimates in the latter two instead consider the winning bid. When the engineer's estimate is considered, the estimated coefficients for our LINC-related effects is stronger than those we obtained when the winning bid was used as a dependent variable using OLS, though the effect becomes a bit muted and insignificant under the Heckman–IV approach (though indirect effects appear stronger). Importantly, these effects are not positive, easing the concerns about renegotiation or arbitrage. Thus, cost savings implied by the awarding stage are actually realized when TxDOT writes its final check to the contracting firm. LINC-trained bidders are paid less on average and the indirect competition effect generates savings. Further dismissing any concern about arbitrage in the post-awarding stage, when the winning bid is included as a covariate, there is no significant effect of being a LINC-trained firm and no indirect competition effect. This is reassuring as it suggests that behavior in the post-awarding stage is unrelated to LINC-training and does not differ across our classes of bidders. Having considered this, we are confident that LINC graduates are not somehow manipulating the system in a way that wipes out any suggested savings the state receives from the auction. Moreover, renegotiation and/or adjustments needed after the contract has been awarded appear to be independent of firms' eligibility or training status.

5 Firm Growth and Survival

Given that graduating firms are behaving more competitively, and final payments to these firms are lower on average after a firm completes the program, a natural concern is that these firms leave no room for profit and are eventually forced to exit the industry. This would challenge the attractiveness of the LINC program as, in the long-run, it could actually reduce the diversity of

[12] We have data on final payments for completed contracts from September of 1999 until August of 2007, though many of the contracts started in the later part of our data sample were not finished when this information was provided.

Table 11: Regression Results for Final Payments

Variable	Log of final pay			
	OLS	Heckman–IV	OLS	Heckman–IV
	(1)	(2)	(3)	(4)
LINC-graduate	-0.032**	-0.012	0.001	0.000
	(0.012)	(0.013)	(0.008)	(0.008)
LINC-eligible, before training	0.007	0.031	-0.003	-0.006
	(0.020)	(0.021)	(0.013)	(0.013)
LINC-eligible, will never train	-0.018	-0.020	-0.009	-0.009
	(0.019)	(0.020)	(0.008)	(0.009)
Interest from LINC-trained firm	-0.026***	-0.034***	-0.004	-0.001
	(0.007)	(0.008)	(0.005)	(0.006)
Log of ECE	0.936***	0.946***		
	(0.006)	(0.007)		
Log of winning bid			0.994***	0.999***
			(0.004)	(0.008)
Log expected number of bidders	-0.079***	-0.251***	-0.018***	-0.002
	(0.011)	(0.047)	(0.007)	(0.026)
Log number of days to complete the project	0.046***	0.040***	0.013**	0.007
	(0.008)	(0.008)	(0.005)	(0.009)
Log complexity	0.087***	0.096***	-0.000	-0.004
	(0.008)	(0.009)	(0.006)	(0.008)
Log total number of rivals faced in the market	-0.007*	-0.011**	-0.003	-0.002
	(0.004)	(0.004)	(0.003)	(0.003)
Past winning-to-plan holder ratio	-0.110***	0.343***	-0.047***	-0.094
	(0.025)	(0.119)	(0.017)	(0.072)
Bidder's capacity utilized	0.029**	-0.052**	0.007	0.016
	(0.013)	(0.025)	(0.008)	(0.016)
Log of bidder's distance to the project location	0.000	-0.013***	-0.003*	-0.002
	(0.003)	(0.005)	(0.002)	(0.002)
Ongoing project in the same county	-0.011	0.040***	0.004	-0.002
	(0.007)	(0.015)	(0.004)	(0.009)
Log number of past bids	0.002	0.001	-0.004**	-0.004**
	(0.003)	(0.003)	(0.002)	(0.002)
Average rivals' winning-to-plan holder ratio	-0.126*	-0.458***	0.044	0.084
	(0.065)	(0.110)	(0.044)	(0.071)
Log of rivals' minimum backlog	0.001	0.001*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Log of closest rival's distance to the project location	0.001	0.013***	-0.004**	-0.006*
	(0.003)	(0.005)	(0.002)	(0.003)
Inverse mills ratio		0.328***		-0.035
		(0.087)		(0.054)
Number of uncensored observations	4,915	4,915	4,915	4,915
R^2	0.978	0.978	0.991	0.991
		138,634		163,627

** denotes statistical significance at the 5% level. * denotes statistical significance at the 10% level. Standard errors are in parentheses. All models include time, material shares, and project division effects. Selection models are similar to the models estimated in Column 8 in Table 3 & 4.

active firms leading to an unhealthier procurement industry. Short-term savings would be obtained at the expense of fewer contracting firms in the long-run. In Figure 2 we give a snapshot of how the capacity and utilization rate has changed for LINC graduates observed for a two-year window around the date in which each firm trained. Specifically, we define each graduate firm's period 0 to be the time at which they participate in the LINC program, and we compute the average capacity and utilization rate for firms in the 24 months before and after participation. If firms are not in the market, they are not factored into the relevant months (for example, firms that train late in our sample period are not observed two years out from training). The graphs suggest that graduate firms seem to be taking on more projects and employing a great share of their capacity in the period after LINC training. In order 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 January 1, 2007 from the analysis given that we have an insufficient amount of time after that point to observe an exit. Second, we restrict attention to firms that entered the market after the LINC program was initiated so that all eligible firms in consideration had the opportunity to complete LINC training. Third, our exit date, or the last active day in the TxDOT market, is defined as the last date a firm held a plan or the last date they had an active project. Given that we do not use entrants after 2007, this gives us an opportunity to track bidders for at least 10 months since they last held plans or since their last active project day to ensure that they do not hold plans again within at least 10 months. Similar exit criteria were used by De Silva et al. [2009].

In Table 12, we present coefficient estimates from some of the probit regression models described above. The first four sets of results were obtained by estimating standard probit models, while in the second four models we instrument for LINC graduate (again using distance to the training facility and the amount of time since the previous training session). Both estimation strategies yield similar point estimates so we discuss them generally. Consistent with our previous work, in all models, the omitted class of firms is the group that is not eligible for the LINC program. Notably absent from

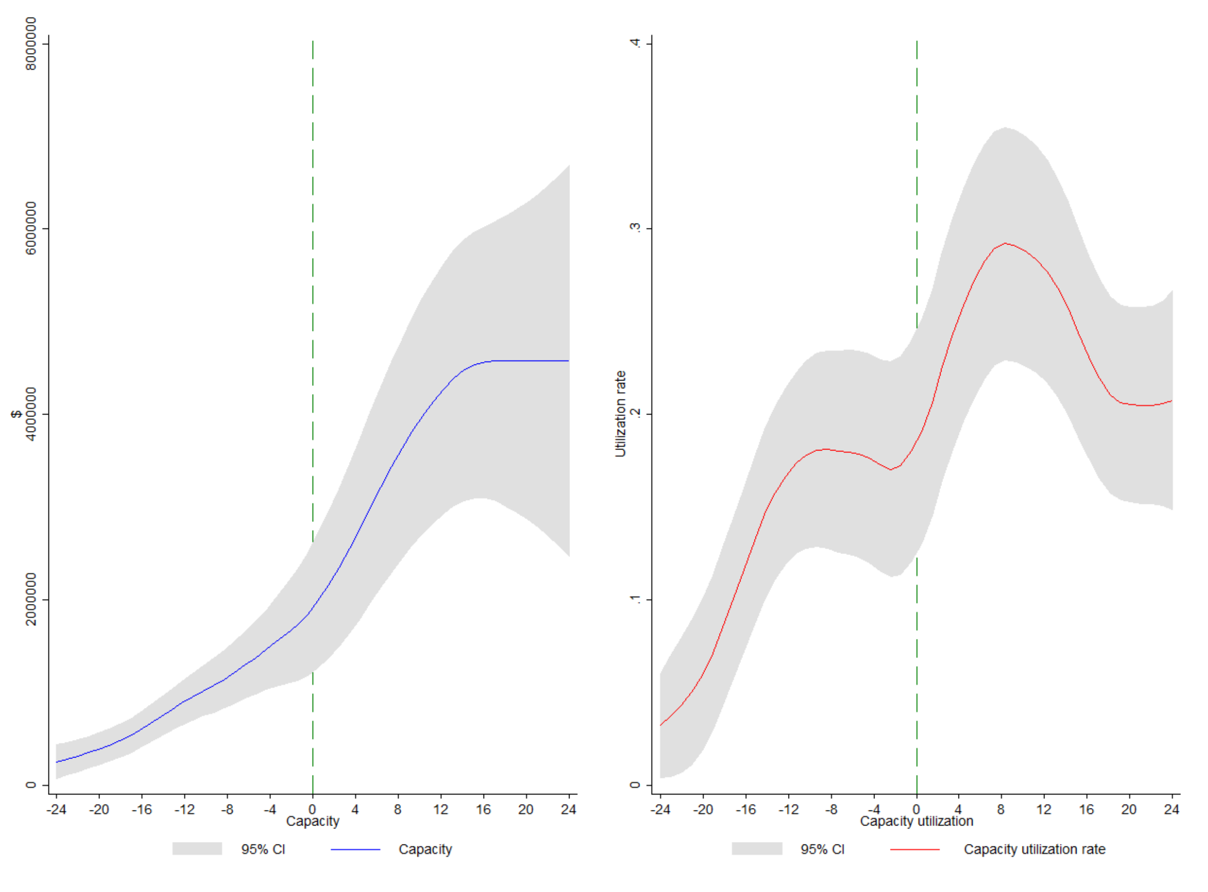


Figure 2: Changes in Capacity and Utilization for LINC Graduates

this model is the variable "LINC-eligible, before training" because no firm in this cohort is ever observed exiting the industry and, by definition, constitutes exactly the same set of firms as the "LINC-graduate" group. 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. The coefficient estimates translate to a marginal effect that is small at about 0.7%, but statistically significant at the 1% level and robust across all specifications. In contrast, firms that graduate from the LINC program are not statistically different from their ineligible rivals when it comes to exiting. If the analysis is restricted to the LINC-qualified firms only, LINC training has no significant effect on a firm's survival because of large standard errors stemming from employing a much smaller sample of data, though the coefficient estimates are consistent in sign with our full-sample findings: LINC graduates appear less likely to exit the industry. The other covariates included in this model 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 the volume of projects to be let. Larger firms are less likely to exit, while firms facing many rivals are more likely to exit—though if the rivals are LINC-eligible then the firm is less likely to exit. These effects are all robust across specifications and significant at the 1% level.

6 Conclusion

We evaluated the effects of the TxDOT's LINC program by considering multiple channels through which the program might affect firm behavior. LINC graduates are more competitive in their bidding behavior than ineligible firms. They are more competitive relative to firms that have yet to train and eligible firms that never chose to participate in the program. Estimates in our bid regressions suggests the average bid of a LINC graduate is about 2% lower than that of ineligible firms and this increase in competitiveness is true of winning bids from alumni bidders as well. Addressing sample selection concerns related to uptake of the program and entry into an auction, sharpened our findings and we found these more competitive bidding patterns remain when employing relevant instruments, different estimation strategies, and subsets or partitions of the data. Despite lower bids, winning-to-bidding ratios and models considering the probability that a LINC

Table 12: Exit Results

Variables	Exit patterns for LINC entrants since 2000							
	Probit				IV–Probit			
	All			LINC	All			LINC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LINC-graduate	0.179	0.180	0.147	-0.129	-0.035	-0.034	-0.072	-0.405
	(0.129)	(0.129)	(0.130)	(0.196)	(0.197)	(0.197)	(0.199)	(0.258)
LINC-eligible, will never train	0.309***	0.309***	0.313***		0.317***	0.318***	0.321***	
	(0.083)	(0.083)	(0.083)		(0.091)	(0.091)	(0.092)	
Past winning-to-bidding ratio	-0.010				-0.011			
	(0.138)				(0.139)			
Past winning-to-plan holder ratio		0.036				0.033		
		(0.167)				(0.175)		
Past bidding-to-plan holder ratio			-0.448***	-0.474*			-0.449***	-0.462
			(0.097)	(0.280)			(0.092)	(0.308)
Log maximum backlog	-0.149***	-0.149***	-0.137***	-0.104***	-0.149***	-0.149***	-0.136***	-0.102***
	(0.007)	(0.007)	(0.007)	(0.017)	(0.005)	(0.005)	(0.006)	(0.017)
Log number of LINC-ineligible firms	0.939***	0.939***	0.935***	1.184***	0.938***	0.938***	0.934***	1.195***
faced in the market	(0.020)	(0.020)	(0.020)	(0.064)	(0.021)	(0.021)	(0.021)	(0.085)
Log number of LINC-eligible firms	-0.709***	-0.709***	-0.705***	-1.199***	-0.704***	-0.705***	-0.699***	-1.213***
faced in the market	(0.185)	(0.186)	(0.183)	(0.217)	(0.192)	(0.192)	(0.191)	(0.210)
Unemployment rate	0.082**	0.082**	0.077**	0.096	0.078**	0.078**	0.073**	0.048
	(0.033)	(0.033)	(0.033)	(0.100)	(0.036)	(0.036)	(0.036)	(0.120)
Three-month average of the real	0.119	0.119	0.118	-0.058	0.121	0.121	0.121	-0.036
volume of projects	(0.086)	(0.086)	(0.086)	(0.292)	(0.085)	(0.085)	(0.086)	(0.288)
Number of observations	32,448	32,448	32,448	3,661	32,448	32,448	32,448	3,661
Wald χ^2	3,419.000	3,429.000	3,304.000	399.400	2,303.000	2,303.000	2,269.000	229.500

** denotes statistical significance at the 5% level. * denotes statistical significance at the 10% level. Robust standard errors are in parentheses.

graduate wins suggest no increase in the likelihood of winning a contract when a firm participates in the training program. Why? These observations are reconciled by considering the behavior of rival firms when potentially facing a LINC graduate—an indirect competition effect results as rivals also bid lower and win contracts with lower bids on average. Both of these results hold throughout the bid distributions.

The LINC training program offers an alternative approach to policies that target underutilized firms such as bidder preference policies and subcontracting goals. The latter programs have faced numerous legal challenges and have often been shown to imply increased costs for the state (despite the theoretic possibility of reducing costs), while, to our knowledge, we are the first to consider a policy like the LINC program. The only costs for the state are administrative salaries and expenses associated with organizing training-related sessions. We obtained expense data that report LINC costs for fiscal years 2005 to 2012 which show that the program costs the state about $200,000 per fiscal year.[13] However, our estimates suggest enormous benefit (cost savings) for TxDOT when auctions were won by either (i) a LINC-graduate firm for a project in which multiple LINC graduates were interested in, (ii) a LINC-graduate firm in which the winning firm was the only LINC graduate that showed interest in the project, or (iii) an ineligible firm that won a contract which attracted the interest of a LINC-graduate firm.[14] The negligible cost to TxDOT of running the LINC program pales in comparison to the expenses avoided and suggests large government savings. Using the estimates from model (7) of Table 4 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. From a policy perspective, our work is the first to consider such a program and our results suggest that such opportunities should be seriously considered by other states. Other states are perhaps aware of the potential for such programs as about 3/5 of U.S. states have a similar program in the works or already in place.

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

[14]We use the coefficient point estimates from column (7) of Table 4 for the LINC-graduate variable and the indirect competition variable to compute how much more expensive the auctions would have been had the respective firms not been LINC trained. Aggregating the savings over the seven years in our sample implies cost savings of over $16 million per year—this amounts to 1.12% of the total value of the engineer's estimates for these contracts and 1.17% of the total value of the actual winning bids for these contracts. A 95% confidence interval for these back-of-the-envelope calculations puts the cost savings in the range of [$6.7 million, $30.5 million]. While we feel the benefits certainly outweigh the costs, we remind readers that such estimated savings ignore potential behavioral changes that might have induced bidders to tender differently (for example, if the composition of rivals for each project had been different because of the LINC standing of plan holders), something a structural approach would better address.

There are a few ways in which we hope others can apply and potentially extend our research. The most natural step is investigating whether these effects are true for other states by employing an approach similar to ours. Data on firm participation in specific aspects of a training program, which was not available for our TxDOT data, could provide researchers with a source of variation that would allow for identification of the elements of a particular program that are most valuable in generating the more competitive behavior and cost savings for the state. Our results indicate synergies and to some extent subcontracting opportunities may be overlooked by qualified firms. Auction researchers are continuing to embed these types of elements in their models (for example, Kong [forthcoming] investigates synergies and Rosa [2020] considers subcontracting) and our results echo their importance. Not surprisingly, these programs differ across states which can make complementary analyses attractive in rounding out our understanding of these programs. In the Texas program, mentoring is completed by TxDOT officials but some states have programs that involve mentor firms paired with program participants. When talking with representatives from other states, a common challenge seemed to be obtaining participation from mentor firms (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). Understanding the effects of a program when firm-to-firm relationships take center stage would be an interesting direction for future work. If mentoring firms were seen in the data, one could also quantify any changes in mentor-firm behavior after participating in the program.

We see a structural econometric approach as extremely promising in understanding the channels which allow firms to behave more competitively. The description of the LINC program we gave in Section 2 is challenging to think about in a structural context; for example, in the first meeting participants learn about contract administration and in the fourth meeting they develop networking opportunities with other contractors. Both of these could lead to nontrivial cost savings which is allowing graduates to tender lower bids on average simply because their cost distribution has improved. Indeed, an asymmetric model in which firms draw costs from different distributions could explain both the more competitive bidding of program graduates (who draw types from a "better" distribution) and the indirect effect stemming primarily from ineligible firms (who would behave more aggressively against firms receiving costs from a better distribution, at least within a private values model). However, parts of the LINC program involve working with a provider specializing in estimation and bidding—remember that participants identify and develop a bid which is reviewed in detailed with the specialist. This suggests the program might be teaching firms how to bid, which could compromise the assumption of a rational bidding model being used to interpret data from periods before eligible firms are trained. Regardless, we hope that we have provided a foundation from which a structural model can be considered to investigate the effects on the latent cost distribution of LINC-eligible firms and, ultimately, the effect that LINC might have had on the efficiency of the auctions.

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7 Appendix

Table A1: Variable Definitions

Variable	Definition
Log of bids	Log value of bids
Bid dummy	Dummy to identify the bids submitted.
Win dummy	Dummy to identify the winning bid.
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-eligible, before training	Dummy to identify LINC-eligible firm before training
LINC-eligible, will never train	Dummy to identify LINC-eligible but never trained firms.
LINC-graduate	Dummy to identify LINC trained firms.
Interest from LINC-trained firm	Takes a value of one if a LINC-trained bidder (potentially other than the firm itself) holds plans for a project; otherwise it is zero.
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 ECE	The log value of the engineer's cost estimate (ECE).
Complexity	The total number of bid items (project components) in a project.
Calendar days	Number of days to complete the project 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 distance to the firm's location
Backlog	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).
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 LINC-ineligible firms faced in the market	This is the total number of unique LINC-ineligible firms faced on a given month by a plan holding firm.
Number of LINC-eligible firms faced in the market	This is the total number of unique LINC-eligible firms faced on a given month by a plan holding firm.
The total number of plan held in the month	This is the total number of plans held by a firm on a given month.
The total number of bids in the month	This is the total number of bids submitted by a firm on a given month.
Past winning-to-bidding ratio	This is bidder specific past sum of win counts as ratio of past sum of bid counts for a given month.
Past winning-to-plan holder ratio	This is bidder specific past sum of win counts as ratio of past sum of plan holder counts for a given month.
Past bidding-to-plan holder ratio	This is bidder specific past sum of bid counts as ratio of past sum of plan holder counts for a given month.
Number of past bids	Bidder specific number of past bids.
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 ratio of past wins to the past number of plans held. This variable incorporates two aspects of past rival bidding behavior. It incorporates both 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 updated monthly using the complete set of bidding data. The probabilities are initialized using data from 1997.
Unemployment rate	The monthly state-level seasonally unadjusted unemployment rate from the US BLS.
Material shares of a project.	We identify six material groups for projects based on bid items described by "Standard Specifications for Construction and Maintenance of Highways, Streets, and Bridges" code book adopted by TxDOT. These six material cost shares are constructed from this detailed information on bid items and the projects 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. highwaysign lighting fixtures).
Three-month average of the real volume of projects	This variable measures the 3-month moving average of the real volume of all projects for Texas. The real volume of projects is constructed by adding the ECE across projects up for bid in a month for Texas and deflating the current value by the CPI. Then we divide it by the average of the real volume to calculate the relative real volume. This is similar to the variable used by De Silva et al. 2008.
Future average real value of projects	This variable measures the average relative value of projects per month over the next 3 months.
Division dummies	TxDOT has 25 divisions, which are identified by division dummies
District level population	TxDOT has 25 districts, each comprising a few counties. We aggregate the U.S. Census yearly population estimates for each county.

Table A2: Bid Regression Results to Consider a Placebo Effect

Variable	Log of bids		Log of winning bids	
	OLS	Heckman–IV	OLS	Heckman–IV
	(1)	(2)	(3)	(4)
LINC-graduate	-0.014***	-0.020***	-0.025***	-0.012
	(0.005)	(0.005)	(0.008)	(0.009)
LINC-eligible, before training	0.001	-0.000	-0.012	-0.000
	(0.007)	(0.007)	(0.011)	(0.012)
LINC-eligible, will never train	0.007	-0.002	-0.006	-0.004
	(0.008)	(0.009)	(0.014)	(0.014)
Interest from LINC-untrained firm	-0.002	-0.003	-0.000	-0.005
	(0.004)	(0.003)	(0.005)	(0.005)
Inverse mills ratio		0.073***		0.268***
		(0.023)		(0.070)
Auction, bidder, and rival controls	Yes	Yes	Yes	Yes
Material shares	Yes	Yes	Yes	Yes
Time effects and Distrcit effects	Yes	Yes	Yes	Yes
Number of uncensored observations	31,784	31,760	7,434	7,430
R^2	0.984	0.984	0.989	0.989
F-statistics for weak identification		778,053		242,793

** denotes statistical significance at the 5% level. * denotes statistical significance at the 10% level. Robust standard errors clustered by auction are in parentheses. All models include time, material shares, and project division effects. Selection models are consistent with those estimated in columns (3) and (6) of Table 3 for all bids and columns (4) and (7) of Table 4 concerning winning bids.

Table A3: Quantile Regression Results

Variable	Log of bids								
	q10	q20	q30	q40	q50	q60	q70	q80	q90
LINC-graduate (β_1)	-0.040***	-0.022***	-0.022***	-0.020***	-0.021***	-0.018***	-0.012*	-0.010*	-0.009
	(0.006)	(0.008)	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)	(0.006)	(0.010)
LINC-eligible, before training (β_2)	0.000	-0.006	-0.007	-0.010	-0.008	-0.013	-0.007	-0.004	0.015
	(0.007)	(0.008)	(0.009)	(0.007)	(0.008)	(0.008)	(0.011)	(0.009)	(0.015)
LINC-eligible, will never train (β_3)	-0.006	0.006	0.003	0.004	0.006	0.005	0.009	0.010	0.015
	(0.011)	(0.011)	(0.008)	(0.009)	(0.007)	(0.007)	(0.008)	(0.013)	(0.011)
Interest from LINC-trained firm	-0.017***	-0.013***	-0.016***	-0.020***	-0.021***	-0.019***	-0.020***	-0.023***	-0.019***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)
Number of observations					31,783				

	Log of winning bids								
	q10	q20	q30	q40	q50	q60	q70	q80	q90
LINC-graduate (β_1)	-0.023*	-0.042***	-0.032***	-0.026***	-0.029**	-0.028**	-0.023	-0.013	-0.022
	(0.012)	(0.011)	(0.010)	(0.010)	(0.013)	(0.011)	(0.015)	(0.013)	(0.014)
LINC-eligible, before training (β_2)	0.015	-0.005	-0.014	-0.023	-0.020	-0.025	-0.026*	-0.034**	-0.029
	(0.021)	(0.013)	(0.015)	(0.015)	(0.018)	(0.018)	(0.015)	(0.016)	(0.027)
LINC-eligible, will never train (β_3)	-0.028	-0.014	-0.018	-0.008	-0.009	-0.011	-0.029**	-0.013	0.001
	(0.029)	(0.018)	(0.018)	(0.015)	(0.013)	(0.011)	(0.014)	(0.017)	(0.022)
Interest from LINC-trained firm	-0.012	-0.015***	-0.014***	-0.017***	-0.019***	-0.024***	-0.020***	-0.013**	-0.012
	(0.008)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
Number of observations					7,434				

Bootstrapped standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

These regressions include all variables from our richest specification—model (6) of Table 4.