An Evaluation of a Bidder Training Program*

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Abstract

In an effort to accommodate a change in the Federal Highway Administrations 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. Our empirical models allow for potential asymmetries across various bidder groups. 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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1 Introduction

The U.S. Federal Highway Administration (FHWA) has used government policies since at least the early 1980's to encourage minority participation in procurement contracting. Many states employ bid preference programs, which discount the bids of qualified firms for the purpose of evaluation. Other programs require government agencies to set aside a certain percentage of a contract to be subcontracted out to disadvantaged business enterprises (DBEs) or other qualified firms. Over the decades and largely in response to court decisions (see, for example, the Supreme Court's 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. 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 2001. 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 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 more aggressive 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 plan for a certain project, an indirect competition effect results in which ineligible firms (by far our most frequently-observed class of bidders) behave more aggressively 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 substantially lower. These two channels generate substantial savings for the state—even our most conservative estimates involve millions of dollars saved. 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.

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. Most recently, 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.

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.[1] To begin, we describe the LINC program in more detail and, in doing so, outline the structure of our paper.

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 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

[1]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".

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 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 (in particular for maintenance contracts) 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. We present empirical models to document and help us interpret firm participation decisions in Section 4.1. 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 in Section 4.2. 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 in Section 4.3. We investigate the channels through which changes in firm behavior seem to be most important and present robustness results in Section 4.4. Further, while this 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.

Before proceeding to the empirical analysis, we describe and summarize our data in the next section. We also use the data to develop some intuition about the program's effects and to examine what drives a qualified firm to participate in the program. 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^{o} in Rhode Island) are often administered through economic or local development offices. 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 6, we consider whether firm survival in the industry has been affected by participation in LINC.

In general, such training programs seem to be on the rise. Some states have either implemented new programs (e.g., the Oklahoma Department of Transportation's Small Enterprise Training Program) or are re-emphasizing or revamping old programs (e.g., the Washington Department of

Transportation recently expanded its program targeting minority- and women-owned firms to include small businesses in general), and a number of representatives for states that do not currently have any programs indicated that they felt such opportunities would be a good idea. Moreover, these programs are not unique to Department of Transportation offices—the leading inspiration for such programs seems to be the Stempel Program for the Port of Portland in Oregon.[2] We continue our investigation of the effects of the LINC program by describing our data and determining what might drive qualified firms' participation decision.

3 Data Description

Our data comprises 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 and we construct, using each firm's past bidding behavior, other variables that might be important in driving observed behavior.

[2]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.

3.1 Basic Insights

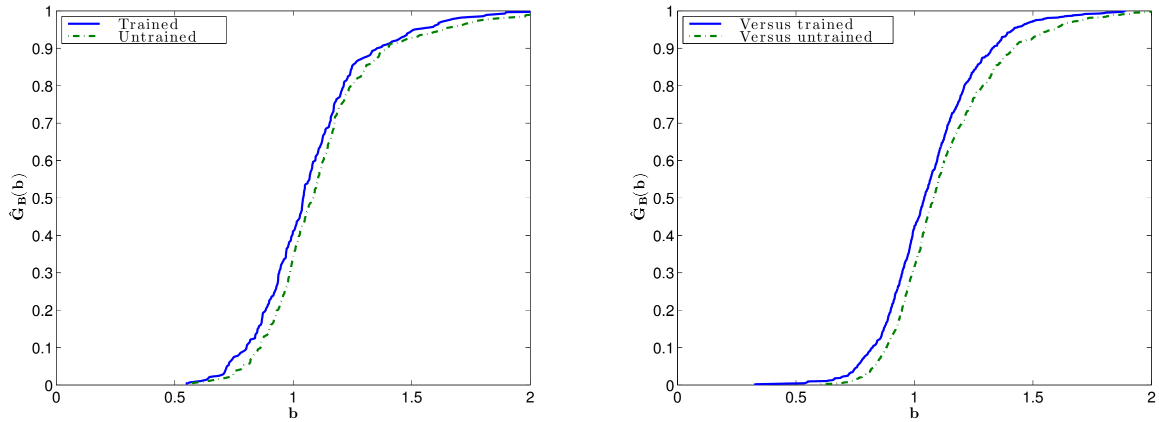
In Table 1, we present sample summary statistics for the full sample, for ineligible (non-qualified or non-LINC) firms, and for LINC-eligible firms. We further distinguish the LINC-eligible firms based on whether they participated and, if so, whether they are observed before or after enrollment in the LINC program. In the full sample, we find 1749 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 1739 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 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



(a) Qualified Firm Behavior

(b) Ineligible Firm Behavior

Figure 1: Relative Bid Distributions using Auctions with Five Bidders

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.[3]

In subplot 1a, we consider the behavior of firms that are eligible for the LINC program. The subplot suggests that LINC-trained firms behave more aggressively 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

[3]We have 5450 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.

suggests that ineligible firms behave more aggressively 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.[4] 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.

3.2 LINC Participation

Before considering the effects of LINC training, we first consider what might drive eligible firms to participate in the program.[5] The first opportunity in which eligible firms could participate was in 2001. We consider a probit model to explain the probability of an eligible firm participating in which we restrict attention to opportunities in our sample for which the training program was offered to qualified firms. Operationally, if LINC-eligible firms requested plans before a given training opportunity (i.e., were observed in our data) and chose not to participate, the firm's response variable is assigned a value of zero; if they did elect training, the response variable takes a value of one. Training is an absorbing state so our participation model is specified at the firm-LINC opportunity level, with the outcome variable taking a value of one only in the period in which a firm participates. After that period the firm is excluded from the relevant sample given graduates are ineligible.[6]

[4] 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 subplot 1a (the underlying sample size is much smaller). Both figures visually suggest a first-order stochastic dominance relationship involving graduate firms' behavior or presence.

[5] Unlike the literature which looks to measure the effects of a treatment, we do not have a randomized experiment as in our setting a group of target firms are given the opportunity to participate in a program but are not required to do so.

[6] Two alternative models might be to retain those trained firms as having a value of one for all periods thereafter or treating the model as an "ever-participate" cross-section specification. The disadvantage of the former is that it includes instances in which graduate firms cannot elect to participate again, which would introduce bias. In contrast, the latter ignores potentially valuable information involving instances in which firms repeatedly elected not to participate despite changing economic and firm-specific circumstances. For example, this approach would remove variation from the data for a firm choosing not to participate for t opportunities but then enrolls in the program at opportunity $(t + 1)$. To be clear, given our specification, a firm that never participates (or participates late) appears in the probit regression for more periods than one that participates early. Lastly, a duration-like model would get at how long it takes a firm to participate, but this is different from asking what drives firm participation.

Table 2: Decision to Participate in LINC

Variable	Probability of participation in LINC		
	(1)	(2)	(3)
Past winning-to-bidding ratio	-0.030***		
	(0.009)		
Past winning-to-plan holder ratio		-0.038***	
		(0.012)	
Past bidding-to-plan holder ratio			-0.017
			(0.011)
Log of maximum backlog	-0.005***	-0.005***	-0.004***
	(0.001)	(0.001)	(0.001)
Log distance to LINC training sessions	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Log number of rival firms faced in the market	0.023***	0.023***	0.022***
	(0.002)	(0.002)	(0.002)
Unemployment rate	-0.004	-0.004	-0.003
	(0.004)	(0.004)	(0.004)
Three-month average of the real volume of projects	-0.000	-0.000	0.001
	(0.011)	(0.011)	(0.010)
Log of firm's home district population	-0.002	-0.002	-0.002
	(0.003)	(0.003)	(0.003)
Number of observations	1,538	1,538	1,538
Wald χ^2	214.540	220.670	181.130

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

In Table 2, we present the estimates of three probit regressions as marginal effects. The models differ by various measures of a given firm's experience or success which is captured by the past winning-to-bidding, winning-to-plan holder, and bidding-to-plan holder ratios. Typically, the more experienced the LINC-eligible firm, the less likely it is for the firm to participate in LINC. The lower experience effects are more salient for firms that have won often in the past compared to those that have garnered experience primarily through simply participating (bidding) in auctions as the past bidding-to-plan holder ratio is negative but not significant in model (3).[7]

In all models, we include a set of controls to capture economic conditions facing a firm, variables characterizing the market, or those expected to obtain in the future. The maximum backlog, firm's

[7]The winning-to-plan holder ratio equals the winning-to-bidding ratio times the bidding-to-plan holder ratio, so these are not jointly considered in a model. These experience-based estimates are the ones most likely to suffer from bias given the structure of our empirical specification which gives more weight to firms who had the opportunity to participate in LINC but chose not to—a firm with many months in the data will have, by definition, a low participation rate and lower variation in these ratios than we'd likely observe across different firms.

distance to the training opportunity, and the variable concerning the number of rivals faced are firm-specific—they reflect the capacity of the firm, relative convenience of the opportunity, and the level of competition a firm has faced as represented by the number of unique plan holders that a firm has faced in the given month. Firms with higher capacity are slightly less likely to participate, though the magnitude of this effect is much lower than the effects from increased competition. Firms that faced a larger number of rivals are more likely to participate in the program—facing an additional rival in a given month makes firms 2.3% more likely to enroll. This effect is not masking something like the size of the firm's district, as we have also controlled for population in a district for which we have annual observations. The firm's distance to a training center is unimportant, suggesting that participation is not coming solely from eligible firms located near a training opportunity. The monthly unemployment rate in Texas is included to account for the economic conditions at a given time. The variable not significant, nor is the average value of future projects which is computed as a three-month moving average value of projects offered by TxDOT and reflects potential upcoming opportunities.

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 (entry into and bidding at auctions) and outcomes (likelihood of winning 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 Likelihood of Bidding

First, we examine whether participation in the LINC program affected the entry patterns for LINC-qualified bidders. To consider this, we estimated probit models characterizing the probability of bidding in a given auction, conditional on the firm holding plans, and present estimation results in Table 3 as marginal effects.[8] One of our main interests throughout our analysis will be on

[8]A reasonable precursor to this analysis might consider whether LINC training affects the probability of requesting plans. We do not present such analysis in large part because plans are of minimal cost and when comparing the

the coefficient of the dummy variable "LINC-graduate" which takes a value of one if the firm is a LINC-qualified firm that has completed the training program and is assigned a value of zero otherwise (these are our treated firms). Related, "LINC-eligible, before training" is an indicator variable that accounts for whether the firm is LINC-qualified and eventually elects to enroll in the training program, but is observed at a point in the sample *before* the firm has been trained. In contrast, "LINC-eligible, will never train" is a binary variable that takes a value of one if the firm is LINC-qualified but never participates in the training program.[9]

Most of our other independent variables serve as a set of controls and involve accounting for factors that are commonly used in the auctions literature. They can be categorized as representing auction, firm-specific, rival, and market characteristics. As project characteristics, we include the estimated cost of the project provided by state engineers, the number of potential rivals (plan holders) which all plan holders are made aware of before bidding, the number of days expected to complete a project, the complexity of a project as measured by the number of itemized components required to submit a bid, the project's materials shares for the six areas specified by TxDOT in its code book, and project division fixed effects (every project belongs to one of 25 locations) which are identified by TxDOT. The firm-specific characteristics involve the share of the firm's capacity utilized, the logarithm of the firm's distance to the project location, a dummy variable that takes the value of one if the firm has an ongoing project in the same county, and the number of past bids to account for experience. Proximity and concurrent involvement in local projects can reduce moving costs and create the opportunity to share resources more effectively across projects. As rival characteristics, we include the average rivals' past winning-to-plan holder ratio, rivals' minimum backlog, and the logarithm of the closest rival's distance to the project location. Finally, we include a set of ($12 \times 9 = 108$) month-year time dummies to account for market conditions during the letting of projects within our sample. A detailed description of all variables we employ is provided in the

likelihood of requesting plans before-and-after training, we found no important effects. As simple evidence, a t-test considering whether the average number of proposals requested per month before LINC training is the same as that of after training (considering only firms that eventually train) is rejected at conventional levels and has a p-value of 0.29.

[9] For all of our empirical results, we also combined these two LINC-eligible, but untrained groups (like we did in Figure 1) thereby generating an eligible but untreated variable. Our results are consistent, both qualitatively and quantitatively, when we replace the two variables we have presented with this aggregated, untreated variable. We have opted for the specifications we present which disentangle the untrained bidders into those who will complete the LINC program versus those who elect not to participate because we felt this allowed us to better identify the effects of the LINC program, especially when thinking about selection concerns.

Appendix.

Table 3: Probit Results for Probability of Entry

Variable	Pr[Entry|Plan holder]			
	LINC-qualified		Full sample	
	(1)	(2)	(3)	(4)
LINC-graduate (β_1)	0.111***	-0.010	-0.052***	-0.052***
	(0.018)	(0.020)	(0.009)	(0.009)
LINC-eligible, before training (β_2)	0.139***	0.078***	-0.047***	-0.019
	(0.022)	(0.024)	(0.014)	(0.014)
LINC-eligible, will never train (β_3)			-0.143***	-0.082***
			(0.013)	(0.014)
Log of ECE	0.000	0.005	0.006*	0.008**
	(0.010)	(0.010)	(0.003)	(0.003)
Log number of plan holders	-0.129***	-0.122***	-0.177***	-0.144***
	(0.022)	(0.024)	(0.007)	(0.007)
Log number of days to complete	-0.013	-0.021	0.004	0.004
the project	(0.013)	(0.013)	(0.004)	(0.004)
Log complexity	-0.025**	-0.051***	-0.011***	-0.038***
	(0.013)	(0.013)	(0.004)	(0.004)
Bidder's capacity utilized		-0.018		0.021**
		(0.033)		(0.010)
Log of bidder's distance to		-0.050***		-0.045***
the project location		(0.007)		(0.002)
Ongoing project in the same county		0.165***		0.136***
		(0.019)		(0.006)
Log number of past bids		0.069***		0.040***
		(0.006)		(0.001)
Average rivals' winning-to-plan		-0.553***		-0.334***
holder ratio		(0.161)		(0.050)
Log of rivals' minimum backlog		-0.005***		-0.003***
		(0.001)		(0.000)
Log of closest rival's distance to		0.030***		0.026***
the project location		(0.008)		(0.002)
Number of observations	6,393	6,393	53,683	53,683
Wald χ^2	552.300	899.300	2,668.000	5,424.000
χ^2 test probability: $\beta_1 = \beta_2$	0.215	0.004	0.734	0.042
χ^2 test probability: $\beta_1 = \beta_3$			0.000	0.065

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

Table 3 provides results concerning the probability of entering an auction conditional on holding plans. In models (1) and (2), we restrict attention to the bidders in our sample who are eligible for the LINC program. Controlling only for contract-specific characteristics suggests that those bidders who select into LINC behave no differently before and after the program, but these bidders are more likely to tender a bid on projects once they hold plans relative to the group of eligible bidders who never opt into the training program. In model (2), however, when we control for bidder-specific variables the results tend to differ; participating bidders are more likely to enter into projects before they are trained whereas they behave comparably with the omitted group (eligible but non-participating bidders) after training. Expanding this analysis to the full sample means we can identify the coefficient on the eligible group of bidders who choose not to participate if our omitted group is taken to be the firms that do not qualify for the LINC program. Doing so yields the same pattern we found using the LINC-qualified sample with the caveat that all of these LINC-qualified firms are less likely to submit bids conditional on holding plans relative to the set of ineligible firms. In models (3) and (4), we find that the LINC graduates behave differently from their peers who refrain from participating in the program—we reject the null hypothesis that $\beta_1 = \beta_3$ at reasonable sizes.

Beyond these observations of interest given our research focus, the other results presented accord with intuition. The estimates indicate that as the number of plan holders, project complexity, and a bidder's distance to the project location increases, a firm's probability of entering an auction decreases. Likewise, when firms face strong rivals—those with high winning-to-plan holder ratios and those with low backlogs—the probability of entry decreases. Bidders who have ongoing projects in the same bidding location (same county), those facing rivals who are located farther away from a project site, or those who have greater bidding experience have a higher probability of entry.

4.2 Bidding Behavior

Our primary interest is on whether bidding has been affected by the LINC training program, for which we use formal econometric models to interpret the data. In Table 4, we provide a set of regression results in which we explain variation in the log of bids under various specifications. The table considers three samples of bid data: models (1), (2), (3), and (4) use only bids from LINC-qualified firms; model (5) considers only bids from ineligible firms; models (6) and (7) use the full sample of bid data. To account for heterogeneity across contracts, all models include the engineer's cost estimate, the project length (number of days to complete the project), complexity (number of subitems involved in the project) as well as time, material shares, and project division effects which we discussed earlier.[10]

[10] 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

Table 4: Bid Regression Results

Variable	Log of bids						
	Qualified				Unqualified	Full sample	
	OLS						Heckman
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LINC-graduate (β_1)	-0.047***	-0.045***	-0.043***	-0.023*		-0.017***	-0.021***
	(0.015)	(0.015)	(0.015)	(0.012)		(0.005)	(0.005)
LINC-eligible, before training (β_2)				0.007		-0.001	-0.002
				(0.014)		(0.007)	(0.007)
LINC-eligible, will never train (β_3)						0.007	-0.001
						(0.008)	(0.008)
Interest from LINC-trained firm	-0.004	-0.004	-0.006	0.007	-0.020***	-0.017***	-0.017***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.005)	(0.004)	(0.003)
Log of ECE	0.962***	0.962***	0.925***	0.939***	0.921***	0.931***	0.931***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.003)	(0.003)	(0.002)
Log expected number of bidders			-0.021	-0.000	-0.020***	-0.017***	-0.022***
			(0.014)	(0.017)	(0.006)	(0.006)	(0.004)
Log number of days to complete			0.026***	0.031***	0.035***	0.034***	0.034***
the project			(0.008)	(0.008)	(0.004)	(0.004)	(0.002)
Log complexity			0.068***	0.056***	0.074***	0.074***	0.072***
			(0.009)	(0.008)	(0.006)	(0.005)	(0.002)
Log total number of rivals faced		-0.003	0.001	-0.032**	-0.005**	-0.001	-0.001
in the market		(0.006)	(0.006)	(0.016)	(0.002)	(0.002)	(0.002)
Past winning-to-plan holder ratio		0.060	0.068	-0.176***	0.034**	-0.160***	-0.159***
		(0.049)	(0.048)	(0.037)	(0.014)	(0.010)	(0.009)
Bidder's capacity utilized			0.038**	0.036**	0.038***	0.038***	0.040***
			(0.017)	(0.016)	(0.005)	(0.005)	(0.005)
Bidder's distance to the project			0.014***	0.011***	0.015***	0.013***	0.009***
location			(0.005)	(0.003)	(0.002)	(0.001)	(0.002)
Ongoing project in the same county			-0.010	-0.023**	-0.014***	-0.017***	-0.005
			(0.009)	(0.009)	(0.003)	(0.003)	(0.005)
Log number of past bids			-0.005	0.003	-0.004*	0.004***	0.008***
			(0.007)	(0.004)	(0.002)	(0.001)	(0.002)
Average rivals' winning-to-plan			-0.060	-0.071	-0.036	-0.052	-0.060***
holder ratio			(0.094)	(0.101)	(0.034)	(0.035)	(0.023)
Log of rivals' minimum backlog			-0.000	-0.000	0.001**	0.001***	0.000**
			(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Log of closest rival's distance to			0.004	0.007*	-0.002	0.000	0.003**
the project location			(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Selection							
λ							0.064**
							(0.023)
Firm effects	Yes	Yes	Yes	No	Yes	No	No
Number of observations	3,278	3,278	3,278	3,303	28,222	31,783	31,783
R^2	0.985	0.985	0.985	0.983	0.986	0.985	

** 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.

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 includes firm-specific fixed effects meaning the identification of the effect of LINC training is driven by within-firm changes that come from the firms that are eligible and elect to participate.[11] However, a natural concern is that those firms who participate in the program constitute a non-random sample from the pool of eligible firms. In fact, we demonstrated in Table 2 that there was selection into the program on important observables—namely, the total number of rivals faced in the market and the firm's own winning-to-plan holder ratio. Thus, since model (1), ignores these important variables which explain LINC participation, the effect on bidding behavior would be biased. In model (2) we add these variables, not because we think these are important in explaining observed variation in bids, but because of concerns about selection on observables. The effect of LINC training changes only marginally and remains negative and statistically significant. Model (3) expands model (2) by including a host of covariates that are contract-, bidder-, or rivals-specific. 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 (rivals' winning-to-plan holder ratio) rates. Accounting for all of these variables along with firm fixed effects shows that LINC graduates still bid 4.3% less on average than untrained, but eligible firms. Moreover, we take the stability of the coefficient estimate as a good sign—as important covariates, which we know are related to selection into the program or bidding are added to the model, the estimated effect remains consistent. This gives us some hope that anything unaccounted for in our specification, would also not affect our estimate in important ways.

We observed whether untrained firms are not trained because they elect not to participate or because they are observed in the data before they opt to train. We can see whether these two types of untrained firms behave inherently different if firm fixed effects are not used. In model (4), we

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.

[11]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, we have dropped 25 observations from one-time, LINC-qualified bidders.

consider this using the sample of LINC-eligible bids where the omitted group in this model are the firms who never participate. LINC graduates bid more aggressively than both types of untrained firm, 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.

As we've discussed, there is potential for the LINC program to indirectly affect the behavior of other firms. We take advantage of 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 inspired us to create a dummy variable "Interest from LINC-trained firm" to capture how the behavior of rival firms might change when a LINC-trained firm shows interest in a project. This takes a value of one when a LINC graduate holds plans for a given auction and is assigned a value of zero otherwise.[12] Though no indirect competition effect obtains in the sample of LINC-eligible bids, those firms do not constitute the majority of firms in the market. To better investigate any indirect competition effect on bidding behavior, we first restrict attention to the sample of bids from ineligible firms. Model (5) 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 0.004 away from zero.[13]

When we consider the full sample of bids in model (6), the omitted group is now the set of ineligible firms so we can identify all variables related to the various types of LINC eligibility and

[12]To be explicit, consider an auction in which the plan holders are one LINC-trained firm, one LINC-qualified, but untrained firm, and three firms ineligible for the program. The dummy variable takes a value of one for all but the LINC-trained plan holder, in which case it takes a value of zero. If the same situation arose but there were two LINC-trained plan holders at the auction, the variable would take a value of one for all bidders at auction given everyone has at least one potential rival that is a LINC graduate. Of course, if no LINC-trained firms request plans for a given auction, the variable takes a value of zero for all firms in that auction.

[13]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. The indirect effects are almost identical to what we have presented as, conditional on there being any LINC-trained rivals, there is often only one that holds plans. See Table A3 in the Appendix.

participation. Again, LINC graduates behave more aggressively after completing the program and the presence of graduates in the market (demonstrated by their interest in a given project) generates more aggressive bids from the other firms resulting in an indirect competition effect. This finding is consistent with the bid distribution in subplot 1b of Figure 1. We take model (6) as our baseline model in going forward.

A concern one might have with bid regressions is selection bias—after controlling for covariates, those firms tendering positive bids are not randomly selected. Bid levels are only observed when firms choose to enter an auction. We presented in Table 3 some findings that suggest the decision to enter an auction conditional on holding plans is non-random. We address this concern by using a Heckman-based correction in which we specify the probability of entering an auction (the selection equation) using the same variables we use in the outcome equation given in model (6) of Table 4. Because we do not have exclusion restrictions, we leverage the nonlinearity of the functional form of the selection equation. The estimates in model (7) reflect that selection concerns are valid, and strengthen our results—LINC graduates tender bids that are 2.1% lower than all other firms and the indirect competition effects remains.

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 or if a firm has another project going on in the same county and can, perhaps, generate synergistic benefits, then lower bids are tendered. If the size, length, or complexity of the project 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. All of these effects are statistically significant at the 1% level even after controlling for time, project composition, and project division effects which, given their sign accords with intution, gives us some confidence in our empirical specifications.

4.3 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 when potentially facing LINC rivals on a contract. It would then seem that the auction outcomes should be better for the state. To examine this conjecture, in Table 5, we present similar empirical bidding models but restrict

Table 5: Descriptive Winning Bid Regression Results

Variable	Log of winning bids				
	Qualified		Unqualified	Full sample	
	OLS				Heckman
	(1)	(2)	(3)	(4)	(5)
LINC-graduate (β_1)	-0.032	-0.021		-0.027***	-0.021**
	(0.028)	(0.021)		(0.008)	(0.011)
LINC-eligible, before training (β_2)		-0.003		-0.013	-0.005
		(0.025)		(0.011)	(0.015)
LINC-eligible, will never train (β_3)				-0.006	-0.006
				(0.015)	(0.014)
Interest from LINC-trained firm	-0.032*	-0.012	-0.022***	-0.016***	-0.019***
	(0.017)	(0.016)	(0.005)	(0.005)	(0.006)
Log of ECE	0.935***	0.949***	0.935***	0.944***	0.947***
	(0.010)	(0.010)	(0.004)	(0.003)	(0.004)
Log expected number of bidders	-0.063***	-0.104***	-0.062***	-0.064***	-0.140*
	(0.023)	(0.024)	(0.007)	(0.007)	(0.073)
Log number of days to complete	0.004	-0.002	0.031***	0.026***	0.025***
the project	(0.015)	(0.014)	(0.005)	(0.004)	(0.004)
Log complexity	0.104***	0.100***	0.092***	0.094***	0.098***
	(0.013)	(0.013)	(0.006)	(0.005)	(0.006)
Log total number of rivals faced	-0.001	0.006	-0.011***	-0.005*	-0.005*
in the market	(0.010)	(0.010)	(0.004)	(0.003)	(0.003)
Past winning-to-plan holder ratio	0.058	-0.028	0.045**	-0.025*	-0.026*
	(0.083)	(0.063)	(0.021)	(0.015)	(0.014)
Bidder's capacity utilized	0.053*	0.021	0.011	0.015*	-0.011
	(0.031)	(0.027)	(0.010)	(0.008)	(0.027)
Bidder's distance to the project	-0.002	0.005	0.010***	0.006***	-0.003
location	(0.010)	(0.006)	(0.003)	(0.002)	(0.008)
Ongoing project in the same county	-0.024	-0.025*	-0.009*	-0.016***	0.012
	(0.016)	(0.015)	(0.005)	(0.004)	(0.027)
Log number of past bids	-0.014	0.004	0.000	0.007***	0.005**
	(0.015)	(0.006)	(0.004)	(0.002)	(0.002)
Average rivals' winning-to-plan	0.005	-0.015	-0.101**	-0.136***	-0.240**
holder ratio	(0.143)	(0.136)	(0.043)	(0.039)	(0.108)
Log of rivals' minimum backlog	-0.000	-0.000	0.001**	0.001**	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Log of closest rival's distance to	0.012	0.014**	-0.001	0.005**	0.013
the project location	(0.007)	(0.006)	(0.002)	(0.002)	(0.008)
Selection					
λ					0.147
					(0.140)
Firm effects	Yes	No	Yes	No	No
Number of observations	816	821	6,562	7,434	7,434
R^2	0.994	0.991	0.991	0.989	

** 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.

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 aggressively. Of course, most of the projects are won by ineligible firms and in model (3) we observe that when these firms win contracts its with bids that are 2.2% 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 2.7% lower in model (4) and winning bids from any firm that potentially faced a LINC graduate are 1.6% lower. In Table A4 in the Appendix, we present quantile regression estimates from model (6) specification of Table 4 and model (4) specification of Table 5 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 full sample of bids presented earlier.

4.4 Additional Results and Discussion

Having provided some benchmark results, we consider 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.

4.4.1 Selection into the LINC Program

After describing the LINC program, we demonstrated that some bidder-specific factors were significant in explaining the decision to participate in the LINC program. These observable factors were then controlled for in our empirical models, but 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. We present the regression results in Tables 6 and 7.

The first model in each 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 consistent across the various sample periods as well as across the various model specifications. Model (4) in the two tables shows consistent results with our discussion of model (2), though the effect of LINC training is dampened a bit given the omitted group in the full sample is the pool of ineligible firms. When participation in the auction is accounted for in the Heckman-based models (5), the effect of LINC training is negative and significant across both time periods, as is the indirect competition effect. This gives us some confidence that there is not selection into the LINC program based on important unobservables which we feel in light of this evidence would have to be affecting early and late participants in the same way.

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 aggressive 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 4 for all bids and column (4) of Table 5 for winning bids—these empirical models include the full sample of bids (winning bids) and the full set of control variables.

Table 6: Descriptive Bid Regression Results: before 2003

Variable	Log of bids				
	Qualified		Unqualified	Full sample	
	OLS				Heckman
	(1)	(2)	(3)	(4)	(5)
LINC-graduate (β_1)	-0.050**	-0.048**		-0.027***	-0.031***
	(0.019)	(0.020)		(0.009)	(0.008)
LINC-eligible, before training (β_2)		-0.013		-0.009	-0.010
		(0.018)		(0.007)	(0.007)
LINC-eligible, will never train (β_3)				0.005	-0.002
				(0.012)	(0.011)
Interest from LINC-trained firm	-0.001	0.008	-0.029***	-0.022***	-0.021***
	(0.016)	(0.017)	(0.008)	(0.008)	(0.004)
Log of ECE	0.913***	0.932***	0.908***	0.918***	0.919***
	(0.010)	(0.010)	(0.005)	(0.005)	(0.002)
Log expected number of bidders	-0.033*	0.000	-0.021***	-0.018**	-0.020***
	(0.020)	(0.023)	(0.008)	(0.008)	(0.005)
Log number of days to complete the project	0.047***	0.044***	0.058***	0.050***	0.050***
	(0.016)	(0.016)	(0.007)	(0.007)	(0.004)
Log complexity	0.066***	0.057***	0.078***	0.082***	0.079***
	(0.013)	(0.013)	(0.006)	(0.006)	(0.003)
Log total number of rivals faced in the market	0.004	-0.036	-0.005	-0.003	-0.008**
	(0.009)	(0.022)	(0.003)	(0.003)	(0.003)
Past winning-to-plan holder ratio	0.101**	-0.172***	0.031*	-0.134***	-0.110***
	(0.050)	(0.050)	(0.016)	(0.012)	(0.016)
Bidder's capacity utilized	0.010	0.014	0.025***	0.018***	0.014**
	(0.028)	(0.025)	(0.008)	(0.007)	(0.007)
Bidder's distance to the project location	0.008	0.011***	0.016***	0.016***	0.013***
	(0.007)	(0.004)	(0.002)	(0.002)	(0.002)
Ongoing project in the same county	0.003	-0.005	-0.017***	-0.020***	-0.012**
	(0.013)	(0.014)	(0.004)	(0.004)	(0.005)
Log number of past bids	-0.019	0.003	-0.009***	0.006***	0.010***
	(0.011)	(0.006)	(0.003)	(0.002)	(0.002)
Average rivals' winning-to-plan holder ratio	-0.200	-0.185	-0.058	-0.077*	-0.089***
	(0.133)	(0.145)	(0.041)	(0.043)	(0.028)
Log of rivals' minimum backlog	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Log of closest rival's distance to the project location	0.009	0.007	-0.001	0.001	0.002
	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)
Firm effects	Yes	No	Yes	No	No
Number of observations	1,689	1,698	14,053	15,869	15,869
R^2	0.985	0.982	0.987	0.985	

** 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.

Table 7: Descriptive Bid Regression Results: after 2003

Variable	Log of bids				
	Qualified		Unqualified	Full sample	
	OLS				Heckman
	(1)	(2)	(3)	(4)	(5)
LINC-graduate (β_1)	-0.094**	-0.001		-0.009	-0.019**
	(0.043)	(0.016)		(0.006)	(0.008)
LINC-eligible, before training (β_2)		0.076*		0.092**	0.081**
		(0.046)		(0.040)	(0.033)
LINC-eligible, will never train (β_3)				0.004	-0.007
				(0.011)	(0.012)
Interest from LINC-trained firm	-0.013	0.008	-0.015***	-0.015***	-0.016***
	(0.012)	(0.012)	(0.006)	(0.006)	(0.004)
Log of ECE	0.925***	0.942***	0.927***	0.937***	0.936***
	(0.009)	(0.009)	(0.005)	(0.005)	(0.002)
Log expected number of bidders	0.003	0.010	-0.009	-0.007	-0.014**
	(0.021)	(0.026)	(0.010)	(0.011)	(0.007)
Log number of days to complete the project	0.021**	0.027***	0.025***	0.027***	0.028***
	(0.010)	(0.010)	(0.006)	(0.005)	(0.003)
Log complexity	0.067***	0.052***	0.068***	0.068***	0.063***
	(0.012)	(0.012)	(0.009)	(0.008)	(0.004)
Log total number of rivals faced in the market	-0.000	-0.023	-0.004	0.002	-0.010*
	(0.009)	(0.023)	(0.003)	(0.003)	(0.006)
Past winning-to-plan holder ratio	-0.101	-0.240***	0.128***	-0.209***	-0.106**
	(0.113)	(0.061)	(0.036)	(0.017)	(0.049)
Bidder's capacity utilized	0.045*	0.036	0.029***	0.050***	0.057***
	(0.027)	(0.024)	(0.008)	(0.007)	(0.007)
Bidder's distance to the project location	0.016**	0.006	0.013***	0.010***	0.004
	(0.007)	(0.005)	(0.002)	(0.002)	(0.003)
Ongoing project in the same county	-0.020	-0.035***	-0.012***	-0.014***	0.007
	(0.013)	(0.013)	(0.004)	(0.004)	(0.010)
Log number of past bids	0.017	0.005	-0.005	0.003**	0.012***
	(0.015)	(0.006)	(0.004)	(0.001)	(0.004)
Average rivals' winning-to-plan holder ratio	0.095	0.099	0.014	0.004	0.001
	(0.141)	(0.140)	(0.058)	(0.058)	(0.041)
Log of rivals' minimum backlog	-0.000	-0.001	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Log of closest rival's distance to the project location	0.001	0.005	-0.002	-0.001	0.004
	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)
Firm effects	Yes	No	Yes	No	No
Number of observations	1,589	1,605	14,169	15,914	15,914
R^2	0.986	0.984	0.987	0.985	

** 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 Table 8, 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, outweighing the average effect that the LINC-graduate experiences.

Table 8: Regression models that account for best performing firms

Variable	Log of bids			Log of winning bids		
	(1)	(2)	(3)	(4)	(5)	(6)
LINC-graduate (β_1)	-0.014**	-0.018***	-0.021***	-0.030***	-0.030***	-0.028***
	(0.006)	(0.006)	(0.005)	(0.009)	(0.010)	(0.009)
LINC-eligible, before training (β_2)	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 (β_3)	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 stars (win count in top 10%)	-0.017			-0.006		
	(0.011)			(0.019)		
LINC stars (win count in top 10%) ×	-0.001			0.024		
LINC-graduate (β_1)	(0.016)			(0.028)		
LINC stars (winning-to-bidding		-0.033***			-0.040**	
ratio in top 10%)		(0.011)			(0.018)	
LINC stars (winning-to-bidding		0.040**			0.055**	
ratio in top 10%) × LINC-graduate (β_1)		(0.016)			(0.025)	
LINC stars (win total in top 10%)			-0.007			-0.010
			(0.011)			(0.020)
LINC stars (win total in top 10%) ×			0.049***			0.023
LINC-graduate (β_1)			(0.017)			(0.037)
Firm effects	No	No	No	No	No	No
Material shares	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Distrcit effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,783	31,783	31,783	7,434	7,434	7,434
R^2	0.985	0.985	0.985	0.989	0.989	0.989

Robust standard errors clustered by auction are 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 and model (4) of Table 5, in addition to the 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 9. The various dummies 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 9: Regression models that account for the weakest firms

Variable	Log of bids			Log of winning bids		
	(1)	(2)	(3)	(4)	(5)	(6)
LINC-graduate (β_1)	-0.022***	-0.023***	-0.022***	-0.030***	-0.032***	-0.031***
	(0.005)	(0.005)	(0.005)	(0.009)	(0.009)	(0.009)
LINC-eligible, before training (β_2)	-0.002	-0.002	-0.001	-0.013	-0.013	-0.013
	(0.007)	(0.007)	(0.007)	(0.011)	(0.011)	(0.011)
LINC-eligible, will never train (β_3)	0.000	0.002	0.008	-0.006	-0.004	-0.005
	(0.008)	(0.008)	(0.008)	(0.015)	(0.014)	(0.014)
Interest from LINC-trained firm	-0.018***	-0.018***	-0.018***	-0.016***	-0.017***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
LINC stars (win count in bottom 10%)	0.055**			0.031		
	(0.024)			(0.025)		
LINC stars (win count in bottom 10%) ×	-0.003					
LINC-graduate (β_1)	(0.028)					
LINC stars (winning-to-bidding ratio		0.029			-0.016	
in bottom 10%)		(0.019)			(0.059)	
LINC stars (winning-to-bidding ratio		0.021			0.062	
in bottom 10%) × LINC-graduate (β_1)		(0.024)			(0.064)	
LINC stars (win total in bottom 10%)			-0.019			0.000
			(0.045)			(0.072)
LINC stars (win total in bottom 10%) ×			0.078			0.038
LINC-graduate (β_1)			(0.048)			(0.076)
Firm effects	No	No	No	No	No	No
Material shares	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Distrcit effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,783	31,783	31,783	7,434	7,434	7,434
R^2	0.985	0.985	0.985	0.989	0.989	0.989

Robust standard errors clustered by auction are 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 and model (4) of Table 5, in addition to the interaction terms.

4.4.2 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. The results we have presented so far suggest that many covariates, as we discussed above, might be important in driving the bidding decisions of firms. Backlog or capacity constraints as well as distance to a project location and strength of the 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].

We explore these possible channels as ways in which firms might behave differently given their classification by considering other regression models in Table 10. All of the models estimated include all covariates presented in column (6) of Table 4 but, due to space constraints, we only present coefficient estimates for our variables of interest and the relevant terms for the newly-considered cases. Specifically, we wonder 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. In all models, the estimated effects of these variables make sense: the more constrained a bidder is or the farther they are from a project, the higher a firm bids; the better the composition of rivals or if there are ongoing projects nearby for the firm, the lower the firm bids.

Table 10: Investigating other Possible Asymmetries through Bid Regressions

Variable	Log of bids			
	(1)	(2)	(3)	(4)
LINC-graduate (β_1)	-0.015**	-0.040***	-0.037**	-0.008
	(0.007)	(0.015)	(0.019)	(0.006)
LINC-eligible, before training (β_2)	-0.000	0.022	0.018	-0.001
	(0.009)	(0.021)	(0.019)	(0.007)
LINC-eligible, will never train (β_3)	-0.000	0.011	0.047	0.013
	(0.010)	(0.028)	(0.030)	(0.010)
Interest from LINC-trained firm	-0.017***	-0.017***	-0.017***	-0.018***
	(0.004)	(0.004)	(0.004)	(0.004)
Bidder's capacity utilized	0.037***	0.038***	0.038***	0.038***
	(0.005)	(0.005)	(0.005)	(0.005)
Bidder's capacity utilized ×	-0.006			
LINC-graduate (β_1)	(0.020)			
Bidder's capacity utilized ×	-0.006			
LINC-eligible, before training (β_2)	(0.028)			
Bidder's capacity utilized ×	0.037			
LINC-eligible, will never train (β_3)	(0.030)			
Log of bidder's distance to the project location	0.014***	0.013***	0.013***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
Log of bidder's distance to the project location ×		0.006*		
LINC-graduate (β_1)		(0.003)		
Log of bidder's distance to the project location ×		-0.006		
LINC-eligible, before training (β_2)		(0.005)		
Log of bidder's distance to the project location ×		-0.001		
LINC-eligible, will never train (β_3)		(0.007)		
Average rivals' winning-to-plan holder ratio	-0.052	-0.052	-0.049	-0.053
	(0.035)	(0.035)	(0.035)	(0.035)
Average rivals' winning-to-plan holder ratio ×			0.150	
LINC-graduate (β_1)			(0.131)	
Average rivals' winning-to-plan holder ratio ×			-0.130	
LINC-eligible, before training (β_2)			(0.113)	
Average rivals' winning-to-plan holder ratio ×			-0.292	
LINC-eligible, will never train (β_3)			(0.205)	
Ongoing project in the same county	-0.017***	-0.017***	-0.017***	-0.015***
	(0.003)	(0.003)	(0.003)	(0.003)
Ongoing project in the same county ×				-0.029***
LINC-graduate (β_1)				(0.011)
Ongoing project in the same county ×				0.001
LINC-eligible, before training (β_2)				(0.017)
Ongoing project in the same county ×				-0.020
LINC-eligible, will never train (β_3)				(0.016)
Number of observations	31,783	31,783	31,783	31,783
R^2	0.984	0.984	0.984	0.984

Robust standard errors clustered by auction are 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, in addition to the interaction terms.

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 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.[14] This suggests that alumni of the program are better able to realize synergies by bidding more aggressively on contracts where they currently have ongoing work.

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 11, we present in the first two columns Poisson pseudo-maximum likelihood estimates of models that consider variation in the number of subcontractors. We control for contract-specific characteristics and LINC classification (along with the variables important for LINC participation) in model (1) and augment this with other winner-specific covariates in model (2). In both cases, LINC graduates do not employ more subcontractors than the ineligible firms which serve as the omitted group, but graduates do use significantly more subcontractors than before they were trained as well as the group of eligible firms that never undergo training. Models (3) and (4) demonstrate that LINC graduates use subcontractors to complete more project work (measured in terms of dollars spent on subcontracting) than any of the other groups we identify—graduates before they train, eligible firms which remain untrained through our sample, as well as the ineligible firms. Relating the increase in subcontractor work to our previous findings on synergies, the amount of work outsourced is 17.1% lower if the firm has an ongoing project in the same county. Dollars spent on subcontracting are also higher for projects with more items (as measured by complexity), as the distance between a

[14] When we use a Heckman-based correction which employs the given specification in both the selection and outcome models, these, like nearly all of our results continue to hold. The LINC graduate variable remains negative and significant in all specifications at the one percent level. We present these results in Table A5 of the Appendix.

bidder and the project location increases, and as bidders have more experience.

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 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.[15] In Table 12, 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 model conditions on the engineer's initial estimate of the project while the estimates in the second instead considers the winning bid. When the engineer's estimate is considered, the estimated coefficients for our LINC-related effects are stronger than those we obtained when the winning bid was used as a dependent variable. 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 3.2% less on average and the indirect competition effect generates savings of 2.6%. 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.

Table 11: Subcontracting usage

Variable	Number of subcontractors		Log of subcontracted value	
	PPML		OLS	
	(1)	(2)	(3)	(4)
LINC-graduate (β_1)	0.034	0.039	0.292*	0.353**
	(0.026)	(0.026)	(0.159)	(0.161)
LINC-eligible, before training (β_2)	-0.052	-0.039	-0.026	0.059
	(0.039)	(0.039)	(0.263)	(0.263)
LINC-eligible, will never train (β_3)	-0.070*	-0.057	-0.543**	-0.282
	(0.037)	(0.038)	(0.246)	(0.248)
Log of ECE	0.082***	0.081***	0.746***	0.715***
	(0.014)	(0.014)	(0.057)	(0.057)
Log number of days to complete	0.034**	0.035**	-0.074	-0.060
the project	(0.014)	(0.014)	(0.076)	(0.076)
Log complexity	0.609***	0.605***	1.835***	1.813***
	(0.033)	(0.034)	(0.088)	(0.089)
Log total number of rivals faced	-0.184***	-0.217***	-0.185	-0.148
in the market	(0.059)	(0.063)	(0.304)	(0.308)
Past winning-to-plan holder ratio	0.014*	-0.004		-0.065
	(0.009)	(0.009)		(0.056)
Bidder's capacity utilized		0.068***		0.028
		(0.026)		(0.153)
Bidder's distance to the project		-0.000		0.076**
location		(0.006)		(0.036)
Ongoing project in the same county		-0.010		-0.171**
		(0.013)		(0.075)
Log number of past bids		0.014**		0.189***
		(0.007)		(0.034)
Number of observations	7,434	7,434	7,434	7,434
R^2	0.703	0.702	0.552	0.556
χ^2 test probability: $\beta_1 = \beta_2$	0.064	0.091	0.300	0.333
χ^2 test probability: $\beta_1 = \beta_3$	0.019	0.030	0.035	0.027

** 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.

Table 12: Regression Results for Final Payments

Variable	Log of final pay (1)	(2)
LINC-graduate (β_1)	-0.032**	0.001
	(0.012)	(0.008)
LINC-eligible, before training (β_2)	0.007	-0.003
	(0.020)	(0.013)
LINC-eligible, will never train (β_3)	-0.018	-0.009
	(0.019)	(0.008)
Interest from LINC-trained firm	-0.026***	-0.004
	(0.007)	(0.005)
Log of ECE	0.936***	
	(0.006)	
Log of winning bid		0.994***
		(0.004)
Log expected number of bidders	-0.077***	-0.017**
	(0.011)	(0.007)
Log number of days to complete the project	0.046***	0.013**
	(0.008)	(0.005)
Log complexity	0.086***	-0.001
	(0.008)	(0.006)
Log total number of rivals faced in the market	-0.007*	-0.003
	(0.004)	(0.003)
Past winning-to-plan holder ratio	-0.109***	-0.046***
	(0.025)	(0.017)
Bidder's capacity utilized	0.029**	0.007
	(0.013)	(0.008)
Log of bidder's distance to the project location	0.000	-0.003*
	(0.003)	(0.002)
Ongoing project in the same county	-0.011	0.004
	(0.007)	(0.004)
Log number of past bids	0.002	-0.004**
	(0.003)	(0.002)
Average rivals' winning-to-plan holder ratio	-0.123*	0.046
	(0.066)	(0.044)
Log of rivals' minimum backlog	0.001	-0.000
	(0.000)	(0.000)
Log of closest rival's distance to the project location	0.001	-0.004**
	(0.003)	(0.002)
Number of uncensored observations	4,915	4,915
R^2	0.977	0.991

** 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.

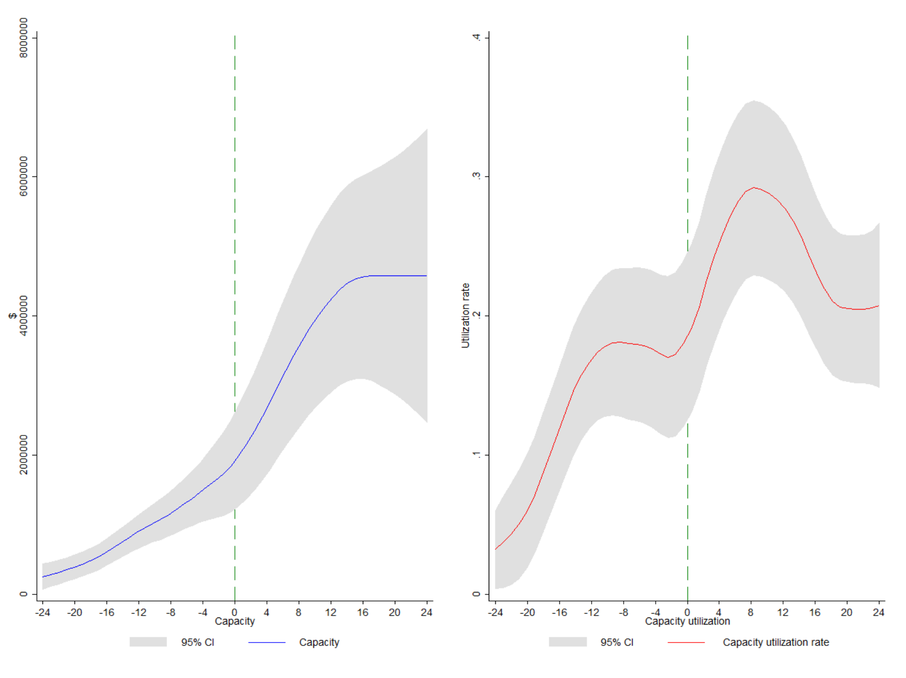


Figure 2: Changes in Capacity and Utilization for LINC Graduates

5 Firm Growth and Survival

Given that graduating firms are behaving more competitively, and final payments to these firms are about 3% 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 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

[15] 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.

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 13, we present results from some of the probit regression models described above. 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 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 by 0.7%. Though this effect is small, it is statistically significant at the 1% level and robust across these three 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. 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.

Table 13: Exit Results

Variables	Exit patterns for entrants since 2001			
	All			LINC
	(1)	(2)	(3)	(4)
LINC-graduate	0.004	0.004	0.003	-0.002
	(0.003)	(0.003)	(0.003)	(0.004)
LINC-eligible, will never train	0.007***	0.007***	0.007***	
	(0.002)	(0.002)	(0.002)	
Past winning-to-bidding ratio	-0.001			0.010**
	(0.003)			(0.005)
Past winning-to-plan holder ratio		0.001		
		(0.004)		
Past bidding-to-plan holder ratio			-0.010***	
			(0.002)	
Log maximum backlog	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Log number of LINC-ineligible firms	0.021***	0.021***	0.021***	0.024***
faced in the market	(0.001)	(0.001)	(0.001)	(0.002)
Log number of LINC-eligible firms	-0.016***	-0.016***	-0.016***	-0.024***
faced in the market	(0.004)	(0.004)	(0.004)	(0.005)
Unemployment rate	0.002**	0.002**	0.002**	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Three-month average of the real	0.003	0.003	0.003	-0.001
volume of projects	(0.002)	(0.002)	(0.002)	(0.006)
Number of observations	32,448	32,448	32,448	3,661
Wald χ^2	3,414.210	3,424.190	3,308.050	406.740

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

6 Conclusion

We evaluated the effects of the TxDOT's LINC program by considering multiple channels through which the program might affect firm behavior. Some broad take-aways from our results are that firms that opt for LINC training are typically smaller, less successful in the past, and have faced many rivals in the market. LINC graduates are more aggressive in their bidding behavior than ineligible firms. They are more aggressive relative to firms that have yet to train and eligible firms that never chose to participate in the program. Our most conservative estimate in our bid regressions suggests the average bid of a LINC graduate is 1.7% lower than that of ineligible firms and when LINC graduates win they bid over 2% lower on average relative to other winning bids. That said, probit models investigating the probability of winning a contract suggest LINC graduates are no more likely to win a contract. These observations are reconciled by considering the behavior of rival firms when potentially facing a LINC graduate—an indirect competition effect results as rivals bid 1.7% more aggressively and win contracts with lower bids on average. Moreover, using quantile regressions, we showed these results hold throughout the bid distributions. Addressing sample selection concerns related to entry into an auction sharpened our findings and we found these more competitive bidding patterns actually translate into cost savings for the state.

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 often been shown to imply increased costs for the state, 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.[16] Using our estimates from model (4) of Table 5, we can provide an estimate of the benefits the LINC program has generated. Specifically, we look in the data and identify which 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. We use the coefficient point estimates from the LINC-graduate variable and the indirect competition variable to recompute how much more expensive the auctions would have been had the respective firms not been LINC trained. Aggregating the savings across the three types of winning scenarios noted implies cost savings of over $21 million per year—this amounts to 1.49% of the total value of the engineer's estimates for these contracts and 1.55% of the total value of the actual winning bids for these contracts.[17]

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

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

The negligible cost to TxDOT of running the LINC program pales in comparison to the expenses avoided and suggests large government savings. Another way to quantify the effect of the LINC program involves calculating the number of additional plan holders or bidders per auction that would be required to induce the same cost savings. Again, using the estimates from model (4) of Table 5 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.

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 aggressive behavior and cost savings for the state. Our results indicate synergies may be overlooked by qualified firms. 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). 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 aggressive 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.

References

P. Bajari and L. Ye. Deciding between competition and collusion. *Review of Economics and Statistics*, 85(4):971–989, 2003.

Patrick Bajari, Stephanie Houghton, and Steven Tadelis. Bidding for incomplete contracts: An empirical analysis of adaptation costs. *American Economic Review*, 104(4):1288–1319, 2014.

Dakshina G. De Silva. Synergies in recurring procurement auctions: An empirical investigation. *Economic Inquiry*, 43(1):55–66, 2005.

Dakshina G. De Silva, Timothy Dunne, and Georgia Kosmopoulou. An empirical analysis of entrant and incumbent bidding in road construction auctions. *Journal of Industrial Economics*, 51(3): 295–316, 2003.

Dakshina G. De Silva, Thomas D. Jeitschko, and Georgia Kosmopoulou. Stochastic synergies in sequential auctions. *International Journal of Industrial Organization*, 23(3–4):183–201, 2005.

Dakshina G. De Silva, Timothy Dunne, Anuruddha Kankanamge, and Georgia Kosmopoulou. The impact of public information on bidding in highway procurement auctions. *European Economic Review*, 52(1):150–181, 2008.

Dakshina G. De Silva, Georgia Kosmopoulou, and Carlos Lamarche. The effect of information on the bidding and survival of entrants in procurement auctions. *Journal of Public Economics*, 93 (1–2):56–72, 2009.

Dakshina G. De Silva, Timothy Dunne, Georgia Kosmopoulou, and Carlos Lamarche. Disadvantaged Business Enterprise goals in government procurement contracting: An analysis of bidding behavior and costs. *International Journal of Industrial Organization*, 30(4):377–388, 2012.

Thomas A. Denes. Do Small Business set-asides increase the cost of government contracting? *Public Administration Review*, 57(5):441–444, 1997.

Matthew L. Gentry, Tatiana Komarova, and Pasquale Schiraldi. Preferences and performance in simultaneous first-price auctions: A structural analysis, London School of Economics & Political Science, Department of Economics, typescript, 2016.

Timothy P. Hubbard and Harry J. Paarsch. Investigating bid preferences at low-price, sealed-bid auctions with endogenous participation. *International Journal of Industrial Organization*, 27: 1–14, 2009.

Mireia Jofre-Bonet and Martin Pesendorfer. Bidding behavior in a repeated procurement auction: A summary. *European Economic Review*, 44(4–6):1006–1020, 2000.

Mireia Jofre-Bonet and Martin Pesendorfer. Estimation of a dynamic auction game. *Econometrica*, 71(5):1443–1489, 2003.

Elena Krasnokutskaya and Katja Seim. Bid preference programs and participation in highway procurement auctions. *American Economic Review*, 101:2653–2686, 2011.

Justin Marion. Are bid preferences benign? The effect of Small Business subsidies in highway procurement auctions. *Journal of Public Economics*, 91:1591–1624, 2007.

Justin Marion. How costly is Affirmative Action? Government contracting and California's Proposition 209. *Review of Economics and Statistics*, 91(3):503–522, 2009.

Justin Marion. Affirmative Action and the utilization of Minority- and Women-Owned Businesses in highway procurement. *Economic Inquiry*, 49(3):899–915, 2011.

Justin Marion. Affirmative action exemptions and capacity constrained firms. *American Economic Journal: Economic Policy*, 9(3):377–407, 2017.

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

Wisconsin Department of Transportation. Disadvantaged Business Enterprise programs: A survey of state practice in operating mentor/prot eg e programs and increasing DBE participation, Transportation Synthesis Report, 2010.

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: Regression results for placebo effect

Variable	Log of bids		Log of winning bids	
	OLS	Heckman	OLS	Heckman
	(1)	(2)	(3)	(4)
LINC-graduate (β_1)	-0.014***	-0.020***	-0.024***	-0.014
	(0.005)	(0.005)	(0.008)	(0.011)
LINC-eligible, before training (β_2)	0.000	-0.001	-0.012	-0.000
	(0.007)	(0.007)	(0.011)	(0.015)
LINC-eligible, will never train (β_3)	0.006	-0.003	-0.007	-0.004
	(0.008)	(0.008)	(0.015)	(0.017)
Interest from LINC-trained firm				
Interest from LINC-untrained firm	-0.002	-0.004	-0.001	-0.004
	(0.004)	(0.003)	(0.005)	(0.006)
Log of ECE	0.932***	0.933***	0.945***	0.951***
	(0.003)	(0.002)	(0.003)	(0.004)
Log expected number of bidders	-0.022***	-0.024***	-0.069***	-0.197***
	(0.006)	(0.004)	(0.007)	(0.047)
Log number of days to complete the project	0.033***	0.033***	0.025***	0.022***
	(0.004)	(0.002)	(0.004)	(0.005)
Log complexity	0.073***	0.069***	0.093***	0.099***
	(0.005)	(0.002)	(0.005)	(0.005)
Log total number of rivals faced in the market	-0.001	-0.008***	-0.005*	-0.008**
	(0.002)	(0.003)	(0.003)	(0.004)
Past winning-to-plan holder ratio	-0.160***	-0.114***	-0.025*	0.278**
	(0.010)	(0.016)	(0.015)	(0.113)
Bidder's capacity utilized	0.038***	0.037***	0.015*	-0.047*
	(0.005)	(0.005)	(0.008)	(0.025)
Bidder's distance to the project location	0.014***	0.010***	0.006***	-0.006
	(0.001)	(0.001)	(0.002)	(0.005)
Ongoing project in the same county	-0.017***	-0.005	-0.016***	0.022
	(0.003)	(0.004)	(0.004)	(0.015)
Log number of past bids	0.004***	0.010***	0.007***	0.005**
	(0.001)	(0.002)	(0.002)	(0.002)
Average rivals' winning-to-plan holder ratio	-0.050	-0.065***	-0.133***	-0.293***
	(0.035)	(0.023)	(0.039)	(0.076)
Log of rivals' minimum backlog	0.001***	0.001***	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Log of closest rival's distance to the project location	0.000	0.003**	0.005**	0.016***
	(0.002)	(0.001)	(0.002)	(0.005)
Number of uncensored observations	31,783	31,783	7,434	7,434
R^2	0.984		0.989	

** 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.

Table A3: Bid Regression Results

Variable	Log of bids			
	Qualified		Unqualified	Full sample
	(1)	(2)	(3)	(4)
LINC-graduate (β_1)	-0.043***	-0.022*		-0.016***
	(0.015)	(0.012)		(0.005)
LINC-eligible, before training (β_2)		0.007		-0.001
		(0.014)		(0.007)
LINC-eligible, will never train (β_3)				0.007
				(0.008)
Number of LINC-trained firms	0.000	0.012	-0.020***	-0.016***
	(0.012)	(0.011)	(0.006)	(0.005)
Log of ECE	0.926***	0.940***	0.921***	0.931***
	(0.006)	(0.006)	(0.003)	(0.003)
Log expected number of bidders	-0.023	-0.002	-0.020***	-0.017***
	(0.014)	(0.017)	(0.006)	(0.006)
Log number of days to complete	0.026***	0.031***	0.035***	0.034***
the project	(0.008)	(0.008)	(0.004)	(0.004)
Log complexity	0.068***	0.056***	0.074***	0.074***
	(0.009)	(0.008)	(0.006)	(0.005)
Log total number of rivals faced	0.001	-0.033**	-0.005**	-0.001
in the market	(0.006)	(0.016)	(0.002)	(0.002)
Past winning-to-plan holder ratio	0.068	-0.176***	0.034**	-0.160***
	(0.048)	(0.037)	(0.014)	(0.010)
Bidder's capacity utilized	0.038**	0.036**	0.038***	0.038***
	(0.017)	(0.016)	(0.005)	(0.005)
Bidder's distance to the project	0.014***	0.011***	0.015***	0.014***
location	(0.005)	(0.003)	(0.002)	(0.001)
Ongoing project in the same county	-0.010	-0.022**	-0.014***	-0.017***
	(0.009)	(0.009)	(0.003)	(0.003)
Log number of past bids	-0.005	0.003	-0.004*	0.004***
	(0.007)	(0.004)	(0.002)	(0.001)
Average rivals' winning-to-plan	-0.059	-0.071	-0.035	-0.052
holder ratio	(0.094)	(0.101)	(0.034)	(0.035)
Log of rivals' minimum backlog	-0.000	0.000	0.001**	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
Log of closest rival's distance to	0.004	0.007*	-0.002	0.000
the project location	(0.004)	(0.004)	(0.002)	(0.002)
Firm effects	Yes	No	Yes	No
Number of observations	3,278	3,303	28,222	31,783
R^2	0.985	0.983	0.986	0.985

** 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.

Table A4: 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.

Table A5: Investigating other Possible Asymmetries through Bid Regressions: Heckman

Variable	Log of bids			
	(1)	(2)	(3)	(4)
LINC-graduate (β_1)	-0.023***	-0.045***	-0.034**	-0.015***
	(0.007)	(0.015)	(0.014)	(0.006)
LINC-eligible, before training (β_2)	-0.002	0.013	0.023	-0.002
	(0.008)	(0.021)	(0.017)	(0.007)
LINC-eligible, will never train (β_3)	-0.010	0.017	0.032	0.001
	(0.009)	(0.025)	(0.023)	(0.009)
Interest from LINC-trained firm	-0.017***	-0.017***	-0.017***	-0.017***
	(0.003)	(0.003)	(0.003)	(0.003)
Bidder's capacity utilized	0.037***	0.038***	0.037***	0.037***
	(0.005)	(0.005)	(0.005)	(0.005)
Bidder's capacity utilized ×	-0.002			
LINC-graduate (β_1)	(0.019)			
Bidder's capacity utilized ×	-0.007			
LINC-eligible, before training (β_2)	(0.032)			
Bidder's capacity utilized ×	0.039			
LINC-eligible, will never train (β_3)	(0.026)			
Log of bidder's distance to the project location	0.009***	0.009***	0.010***	0.010***
	(0.001)	(0.002)	(0.001)	(0.001)
Log of bidder's distance to the project location ×		0.005		
LINC-graduate (β_1)		(0.004)		
Log of bidder's distance to the project location ×		-0.004		
LINC-eligible, before training (β_2)		(0.005)		
Log of bidder's distance to the project location ×		-0.005		
LINC-eligible, will never train (β_3)		(0.006)		
Average rivals' winning-to-plan holder ratio	-0.066***	-0.066***	-0.059**	-0.066***
	(0.023)	(0.023)	(0.024)	(0.023)
Average rivals' winning-to-plan holder ratio ×			0.080	
LINC-graduate (β_1)			(0.102)	
Average rivals' winning-to-plan holder ratio ×			-0.172	
LINC-eligible, before training (β_2)			(0.107)	
Average rivals' winning-to-plan holder ratio ×			-0.244	
LINC-eligible, will never train (β_3)			(0.158)	
Ongoing project in the same county	-0.004	-0.005	-0.005	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Ongoing project in the same county ×				-0.027***
LINC-graduate (β_1)				(0.010)
Ongoing project in the same county ×				-0.002
LINC-eligible, before training (β_2)				(0.016)
Ongoing project in the same county ×				-0.006
LINC-eligible, will never train (β_3)				(0.017)
Selection				
λ	0.0803	0.0768	0.0759	0.0753
	(0.021)	(0.021)	(0.021)	(0.021)
Number of uncensored observations	31,783	31,783	31,783	31,783

Robust standard errors clustered by auction are 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, in addition to these interaction terms.