An Evaluation of a Bidder Training Program*

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Abstract

In an effort to accommodate a change in the U.S. Federal Highway Administration's goals towards "race-neutral methods" concerning the involvement of Disadvantaged Business Enterprises in procurement contracting, the Texas Department of Transportation created a Learning, Information, Networking and Collaboration (LINC) bidder training program. 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 in the procurement contracting industry. We distinguish between ineligible firms as well as eligible firms that undergo training and those that don't, to consider empirical models which allow for potential asymmetries across these bidder groups. Unlike other programs that target these firms, we find that LINC generated substantial savings for the state through direct competition effects stemming from aggressive bidding of LINC graduates but also via indirect competition effects—by inducing other firms to bid more aggressively. These changes generate benefits to 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 1999 ruling in *Adarand v. Peña*, U.S. Report 515 U.S. 200), the nature and administration of DBE programs has changed. While they still retain their basic structure, the goal of firm participation is now described as being "aspirational." Individual state agencies that administer the programs, are asked to achieve as much of the goal 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 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 $2.04 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 work relates most closely to that 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 [forthcoming] 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 that the exemption policy allowed bidding firms to smooth demands on capacity-constrained DBE subcontractors. Marion found projects with affirmative action goals had higher bids than those without, and that the difference increased substantially 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 (plus hold TxDOT harmless in any claims, suits, or actions). To our knowledge, we are the first to study the effects of a bidder-training program. In our research, we've found bidder training programs exist or are being introduced 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. In what follows, we aim to shed light on the benefits to be had from such a program by examining firms' participation and bidding decisions, assessing the cost to the government, and considering firm survival in the industry. First, 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 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.[1] While these firms are eligible for the program, 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 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 also learn about each participating firm in a presentation.

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

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. Beyond the homework assignment of developing a bid which is reviewed with the estimating and bidding provider, participating firms must send copies of all bids submitted to the LINC mentor.

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. 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. 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 5. 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, a bulletin 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 first use the next section as an opportunity to describe and summarize our data. 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 U.S. 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 from targeting minority- and women-owned firms to include small businesses in general), and a number of representatives for states that do not currently have any programs indicated that they felt such opportunities would be a good idea. Moreover, these programs are not unique to Department of 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 such as a measure of 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

[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.

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.

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. In our sample period, 58 LINC participants went on to eventually submit bids (constituting 1739 bids) and we observe 44 of them winning at least one contract. 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 elect not to participate. This is clear from both the engineer's estimate and the number of days required to complete a project.

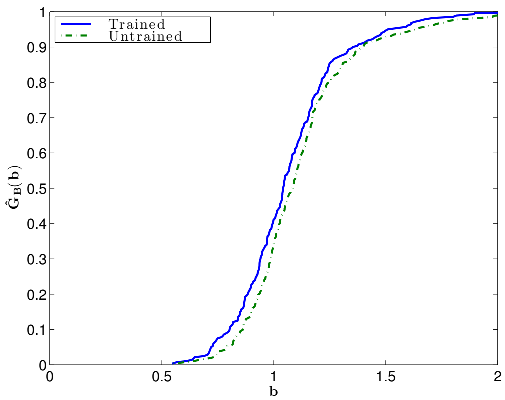
Table 1: Summary statistics

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 bidding firms	1,057	924	72	52	58
Number of bids	31,783	28,480	669	895	1,739
Number of winning firms	655	564	39	44	44
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)

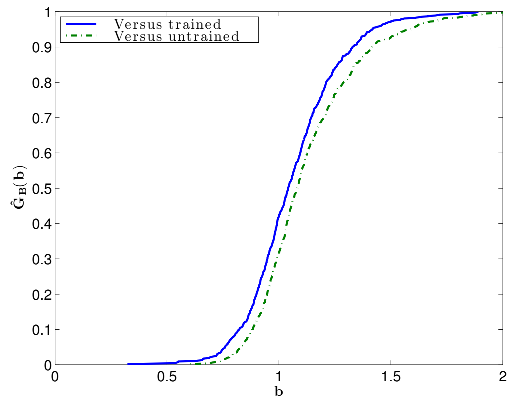
Standard deviations are in parentheses when appropriate.

In order to compare bidding across contracts of varying size and complexity, and often involving different types of work, we compute relative bids (relative winning bids) by normalizing the tendered amount by each firm, for each contract, by the state's respective engineering estimate. LINC-qualified but untrained firms submit relative bids that are about two percent higher than ineligible firms. This is true for both eligible firms that choose not to participate as well as for participating firms before they enrolled in the program. After completing the LINC program, the difference relative to the baseline group of ineligible firms goes away for graduates. Given the consistent guidance on bidding that participants receive in the LINC program, it's no surprise that firms come out of the program behaving differently. This observation suggests some potential for government savings. Indeed, we also see that after training, LINC bidders' relative winning bids are reduced—they are about one percent lower than those of other groups.

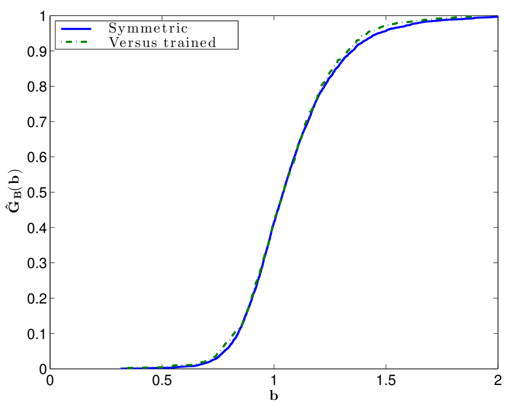
Though we will investigate a number of channels through which LINC might affect firm behavior and procurement outcomes, our primary focus in light of the program description is on how bidding behavior might change as a result of the LINC program. A snapshot of bidding patterns observed in the data helps motivate this investigation. In Figure 1, we present four 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



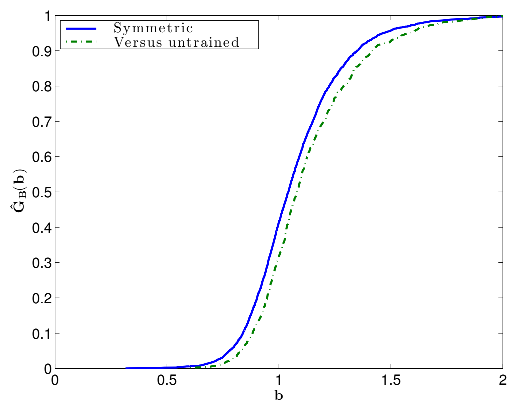
(a) Qualified Firm Behavior



(b) Ineligible Firm Behavior



(c) Ineligible Firm Behavior: Symmetric vs. Asymmetric with Trained



(d) Ineligible Firm Behavior: Symmetric vs. Asymmetric with Untrained

Figure 1: Relative Bid Distributions using Auctions with Five Bidders

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 at five-bidder auctions. The subplot suggests that LINC-trained firms behave more aggressively than eligible but untrained firms.[4] In contrast, in subplot 1b, we consider the behavior of firms that are not eligible for

[3]We have 5450 observed bids from five-bidder auctions in our sample and we observe a good mixture of symmetric (just ineligible bidders) and asymmetric auctions (ineligible bidders along with eligible, but untrained or trained bidders). Having various types of asymmetric auctions is important for this exercise as the subplots exploit distinctions in how the bidders at a given auction are classified based on whether they are eligible for and whether they participated in the LINC program by the time their bids were tendered.

[4]For this figure 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.

the LINC program and consider how they behave at two types of asymmetric auctions. The asymmetric auctions involve ineligible bidders vying for the right to complete a task against either only untrained firms or against at least one LINC graduate firm. The figure 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 other firms realize they are bidding against LINC trained firms. In subplots 1c and 1d, we consider again only the behavior of ineligible firms, but compare their bids at symmetric auctions (comprised only of ineligible firms) with their behavior at asymmetric auctions (comprised of ineligible firms and at least one LINC-eligible firm). Subplot 1c, shows that if the auction is asymmetric because a LINC-trained firm is present, behavior is not distinguishable from behavior at symmetric auctions. However, subplot 1d, shows that if the auction is asymmetric because a LINC-eligible, but untrained firm is present, bids of ineligible firms are less aggressive than at symmetric auctions. Together, these figures suggest a pattern: once firms have undergone LINC training, they appear to behave more aggressively (1a); ineligible firms which constitute the majority of the state's bidding firms, behave more aggressively when facing LINC-trained rivals than when facing untrained firms (1b); ineligible firms' bids appear no different when they face only peer ineligible firms compared to when a LINC-trained rival participates (1c), but if the rival is untrained, behavior is less aggressive (1d).[5] We investigate these effects in our empirical work by modeling firms' decisions and 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. Specifically, we consider a probit model using monthly data to explain the probability of participating. We restrict attention to LINC-qualified entrants since 2001, the inception year of the LINC program as firms that entered earlier did not have the opportunity to participate, even if they would have been willing to. We also only consider months in which qualified firms had the opportunity to participate in LINC. Operationally, the first time a LINC-eligible firm requests plans, the firm's response variable is assigned a value of zero (having not participated in LINC). Our participation model is thus specified at the firm-month level, with the participation outcome taking

[5] Kolmogorov–Smirnov tests suggest that the empirical distributions are significantly different at the one-percent level in subplots 1b and 1d; the distributions in subplot 1a are significantly different at the ten-percent level (while visually a difference appears, the underlying sample sizes are smaller than in the other subplots). Consistent with our discussion, we fail to reject a null that the distributions are the same in subplot 1c.

a value of one only in the month in which a firm participates, after which the firm is excluded from the relevant sample.[6] Becoming trained is an absorbing state and the now-trained firm is no longer eligible for participation in the program, meaning the firm is removed from the sample of participants.

Table 2: Decision to Participate in LINC

Variable	Probability of participation in LINC		
	(1)	(2)	(3)
Past winning-to-bidding ratio	-0.034***		
	(0.009)		
Past winning-to-plan holder ratio		-0.053***	
		(0.013)	
Past bidding-to-plan holder ratio			-0.016
			(0.012)
Log of maximum backlog	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)
Log number of LINC-ineligible firms	0.025***	0.025***	0.025***
faced in the market	(0.003)	(0.003)	(0.003)
Log number of LINC-eligible firms	-0.011	-0.012	-0.011
faced in the market	(0.007)	(0.007)	(0.007)
Unemployment rate	-0.004	-0.004	-0.003
	(0.004)	(0.004)	(0.004)
Three-month average of the real	0.001	0.001	0.002
volume of projects	(0.011)	(0.011)	(0.010)
Number of observations	1,538	1,538	1,538
Wald χ^2	233.760	234.970	218.210

** 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 the firm is 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

[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 again participate 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 that 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 months than one that participates early.

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, characterizing the market, or expected to obtain in the future. The maximum backlog and variables concerning the number of rivals faced are firm-specific—the maximum backlog capturing the size (capacity) of the firm and the number of rivals being the number of unique plan holders of a certain group that a firm has faced in the given month. If the firm has existing projects it is slightly less likely to participate. This finding is statistically significant and robust across specifications. The magnitude of this effect is much lower than the effects from increased competition. Firms that faced a larger number of (ineligible) rivals are more likely to participate in the program. The monthly unemployment rate in Texas is included as a control, though it is not significant nor is the average value of potential projects which is computed as a three-month moving average value of projects offered by TxDOT. We will revisit these insights in allowing for richer empirical specifications later in the paper but for now, having considered what might determine a firm's participation decision in LINC, we seek to evaluate the effects of LINC training.

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 auctions and bidding at auctions) and outcomes (likelihood of winning and project costs for TxDOT) may have changed. The firm characteristics driving LINC participation suggest important controls that must be accounted for in going forward—namely a bidder's experience, backlog, and the competitiveness of an auction. In this section, we 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

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

marginal effects.[8] Our main interest throughout our analysis will be on 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. 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), the days to complete a project, the complexity of a project as measured by the number of bid components, the project's materials shares, and the project division 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. Proximity and concurrent involvement in local projects can reduce moving costs and create the opportunity to share resources more effectively across projects. The number of past bids is used to capture any experience gathered from prior bidding. 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 time dummies to control for market fluctuations. A detailed description of all variables we employ is provided in the Appendix.

[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 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 have also consider grouping these two LINC-eligible, but untrained groups (like we did in Figure 1) and our findings are consistent, both qualitatively and quantitatively. 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.

Table 3: Probit Results for Probability of Entry

Variable	Pr[Entry|Plan holder]					
	LINC-qualified		Full sample			
	(1)	(2)	(3)	(4)	(5)	(6)
LINC-graduate (β_1)	0.112***	-0.008	-0.048***	-0.049***	-0.060***	-0.061***
	(0.018)	(0.020)	(0.009)	(0.009)	(0.009)	(0.009)
LINC-eligible, before training (β_2)	0.139***	0.078***	-0.045***	-0.017	-0.025*	-0.026*
	(0.022)	(0.024)	(0.014)	(0.014)	(0.014)	(0.014)
LINC-eligible, will never train (β_3)			-0.142***	-0.082***	-0.079***	-0.080***
			(0.013)	(0.014)	(0.014)	(0.014)
Interest from LINC-trained firm	0.001	0.021	0.024***	0.019***	0.018***	0.019***
	(0.016)	(0.017)	(0.005)	(0.005)	(0.005)	(0.005)
Log of ECE	0.000	0.007	0.008**	0.010***	0.008***	0.009***
	(0.010)	(0.010)	(0.003)	(0.003)	(0.003)	(0.003)
Log number of plan holders	-0.129***	-0.129***	-0.185***	-0.150***	-0.113***	-0.156***
	(0.023)	(0.025)	(0.007)	(0.008)	(0.008)	(0.008)
Log number of days to complete the project	-0.013	-0.022*	0.002	0.003	0.002	0.001
	(0.013)	(0.013)	(0.004)	(0.004)	(0.004)	(0.004)
Log complexity	-0.026**	-0.054***	-0.014***	-0.040***	-0.040***	-0.040***
	(0.013)	(0.013)	(0.004)	(0.004)	(0.004)	(0.004)
Bidder's capacity utilized		-0.019		0.021**	0.012	0.010
		(0.033)		(0.010)	(0.010)	(0.010)
Log of bidder's distance to the project location		-0.050***		-0.045***	-0.040***	-0.040***
		(0.007)		(0.002)	(0.002)	(0.002)
Ongoing project in the same county		0.166***		0.136***	0.133***	0.133***
		(0.019)		(0.006)	(0.006)	(0.006)
Log number of past bids		0.069***		0.040***	0.057***	0.059***
		(0.006)		(0.001)	(0.002)	(0.002)
Average rivals' winning-to-plan holder ratio		-0.560***		-0.339***	-0.362***	-0.351***
		(0.161)		(0.050)	(0.050)	(0.050)
Log of rivals' minimum backlog		-0.005***		-0.003***	-0.002***	-0.003***
		(0.001)		(0.000)	(0.000)	(0.000)
Log of closest rival's distance to the project location		0.030***		0.026***	0.025***	0.025***
		(0.008)		(0.002)	(0.002)	(0.002)
Log total number of rivals faced in the market					-0.071***	
					(0.003)	
Log total number of plans held in the month						-0.076***
						(0.004)
Number of observations	6,393	6,393	53,683	53,683	53,683	53,683
Wald χ^2	552.860	902.430	2,694.830	5,443.330	5,781.850	5,817.530
χ^2 test probability: $\beta_1 = \beta_2$	0.218	0.006	0.846	0.055	0.035	0.031
χ^2 test probability: $\beta_1 = \beta_3$			0.000	0.044	0.235	0.245

** 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 that refrain from participating in the program—we reject the null hypothesis that $\beta_1 = \beta_3$ at the 5% significance level. However, when we control for how many rivals each firm faces in the market, which we know is positively correlated with participation in the LINC program, we find graduates behave no differently than the eligible firms who never train, but both groups are less likely to tender bids than the LINC-eligible firms before they train and the ineligible firms. The same conclusion holds if we control for the number of plans each firm holds in a given month.

While our discussion has focused on variables that capture average differences in the participation between LINC-eligible and ineligible firms, as well as allow us to understand the direct effect of the LINC training program, we are also interested in any indirect effects that might result. As such, we included 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.[10] In the full sample models, firms are nearly 2% more likely to enter a contract if a LINC graduate also holds plans for that contract.

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,

[10] 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. Remember, too, that all firms are sent information about which firms participated in and completed the LINC program.

or those who have bidding experience have a higher probability of entry.

4.2 Bidding Behavior

We examine next whether bidding has been affected by the LINC training program using formal econometric models to interpret the data. In Table 4, we provide a set of least squares regression results in which we explain variation in the log of bids with the covariates we've introduced in our other models. The table considers three samples of bid data: models (1), (2), (3), and (4) use only bids from LINC-qualified firms; models (5) and (6) consider only bids from ineligible firms; models (7), (8), and (9) use the full sample of bid data.

The specification of the first two models are consistent with the participation regressions presented earlier and suggest that graduates of the LINC program bid more aggressively after completing the training—both relative to how these bidders behaved before training and relative to the eligible firms that do not participate in the training program (the omitted group). In models (3) and (4), we include 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] The effect of LINC training is strengthened as LINC graduates bid 4.5% more aggressively than untrained firms. The effects of LINC training is a direct one: those who participate in the program behave more competitively.

As noted earlier, TxDOT distributes bulletins to all contractors notifying them of the firms that participate in the LINC program. Thus, there is potential for the LINC program to indirectly affect the behavior of other firms. We again include in the empirical bidding models a dummy variable that denotes whether the bidder faced a LINC graduate as a potential rival at the auction. Though no indirect competition effect obtains in the sample of LINC-eligible bids, those firms do not constitute the majority of firms in the sample. To better investigate any indirect competition effect on bidding behavior, we first restrict attention to the sample of bids from ineligible firms. Models (5) and (6) show a significant indirect effect of the LINC program: if a LINC graduate holds plans for a project, bids of ineligible firms are on average 1.9% lower. We have confidence in this indirect competition effect as we considered other models in which we included placebo-like effects. For example, if we include a variable capturing whether plans for the auction were held by a LINC-qualified, but untrained firm (either along with or instead of the one representing our indirect competition effect) it is never statistically different

[11] Since firm fixed effects are used in models (3) and (4), 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.

Table 4: Descriptive Bid Regression Results

Variable	Log of bids								
	Qualified				Unqualified		Full sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LINC-graduate (β_1)	-0.022**	-0.030**	-0.047***	-0.045***			-0.021***	-0.017***	-0.009
	(0.011)	(0.012)	(0.015)	(0.015)			(0.005)	(0.005)	(0.010)
LINC-eligible, before training (β_2)	0.005	-0.001					-0.006	-0.002	
	(0.014)	(0.014)					(0.007)	(0.007)	
LINC-eligible, will never train (β_3)							-0.003	0.009	
							(0.008)	(0.008)	
Interest from LINC-trained firm	0.007	0.005	-0.005	-0.006	-0.019***	-0.019***	-0.017***	-0.016***	-0.018***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Log of ECE	0.944***	0.940***	0.925***	0.924***	0.922***	0.921***	0.935***	0.931***	0.922***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log number of plan holders	-0.027**	-0.023*	-0.012	-0.013	-0.021***	-0.024***	-0.017***	-0.019***	-0.023***
	(0.013)	(0.014)	(0.013)	(0.014)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Log number of days to complete the project	0.029***	0.030***	0.026***	0.026***	0.035***	0.036***	0.034***	0.034***	0.035***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Log complexity	0.051***	0.055***	0.065***	0.068***	0.072***	0.074***	0.068***	0.073***	0.073***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Bidder's capacity utilized		0.026		0.040**		0.039***		0.030***	0.039***
		(0.016)		(0.017)		(0.005)		(0.005)	(0.005)
Bidder's distance to the project location		0.010***		0.014***		0.015***		0.015***	0.014***
		(0.003)		(0.005)		(0.002)		(0.001)	(0.001)
Ongoing project in the same county		-0.031***		-0.010		-0.014***		-0.023***	-0.013***
		(0.009)		(0.009)		(0.003)		(0.003)	(0.003)
Log number of past bids		0.004		-0.084		-0.059*		0.003***	-0.064*
		(0.004)		(0.096)		(0.034)		(0.001)	(0.033)
Average rivals' winning-to-plan holder ratio		-0.001		-0.003		-0.005**		-0.063*	-0.005***
		(0.100)		(0.007)		(0.002)		(0.035)	(0.002)
Log of rivals' minimum backlog		0.000		-0.000		0.000		0.001***	0.000
		(0.001)		(0.001)		(0.000)		(0.000)	(0.000)
Log of closest rival's distance to the project location		0.007*		0.005		-0.002		-0.001	-0.002
		(0.004)		(0.004)		(0.002)		(0.002)	(0.002)
Firm effects	No	No	Yes	Yes	Yes	Yes	No	No	Yes
Number of observations	3,303	3,303	3,278	3,278	28,222	28,222	31,783	31,783	31,500
R^2	0.983	0.983	0.985	0.985	0.986	0.986	0.984	0.984	0.986

** 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.

from zero and is always smaller in magnitude, being at most 0.004 away from zero.[12]

We consider the full sample of bids in the final three models. 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 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. The last model includes firm fixed effects and though the LINC graduation effect is no longer significant, remember that the omitted group is the ineligible firms—as opposed to models (3) and (4). This suggests graduates behave no differently, on average, than the ineligible firms which is actually consistent with the evidence presented in subplot 1c of Figure 1.

The other coefficient estimates suggest patterns that are intuitively appealing. If there are more plan holders at auction, if a firm has another project going on in the same county and can, perhaps, generate synergistic benefits, or if the rivals have been more successful in past auctions, then lower bids are tendered. If the size, length, or complexity of the project is larger/higher, then higher bids are submitted. Likewise, higher bids obtain when bidders have used much of their capacity 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.

4.3 Auction Outcomes

Taken together, we see participating firms become more competitive in the market after graduation, but so too do we see other (primarily ineligible) firms tendering lower bids when potentially facing LINC rivals on a contract. Because these effects go in the same direction it's not clear that LINC training yields more contracts for participating firms. We consider next, the probability of winning a contract, conditional on submitting a bid by constructing probit regression models. Our specifications mirror what we considered in Table 3 as we focus on the LINC-qualified sample in models (1) and (2) of Table 5 and the full sample in the remaining models. Briefly, our results indicate that once bidder- and rival-specific effects are controlled for, neither being LINC-qualified nor being LINC-trained affects the chances of winning at auction. Bidders with higher capacity utilized, those located farther from the project location, and those facing competitive rivals are less likely to win, while those firms having ongoing projects in the same county or facing rivals who are located farther away from a project appear more likely to win.

[12]Space constraints prevent us from presenting everything here, but these results are available from the authors if readers are interested.

Table 5: Probit Results for Probability of Winning Conditional upon Entry

Variable	Pr[Winning|Entry]					
	LINC-qualified		Full sample			
	(1)	(2)	(3)	(4)	(5)	(6)
LINC-graduate (β_1)	0.000	0.027	0.019*	0.013	0.010	0.011
	(0.023)	(0.025)	(0.011)	(0.011)	(0.011)	(0.011)
LINC-eligible, before training (β_2)	-0.009	0.007	0.025	0.022	0.021	0.021
	(0.027)	(0.028)	(0.015)	(0.015)	(0.015)	(0.015)
LINC-eligible, will never train (β_3)			0.030*	0.002	0.001	0.001
			(0.018)	(0.017)	(0.017)	(0.017)
Interest from LINC-trained firm	-0.030	-0.027	-0.007	-0.005	-0.006	-0.005
	(0.019)	(0.019)	(0.006)	(0.006)	(0.006)	(0.006)
Log of ECE	-0.038***	-0.030***	-0.002	0.004	0.004	0.004
	(0.011)	(0.012)	(0.004)	(0.004)	(0.004)	(0.004)
Log number of plan holders	-0.133***	-0.162***	-0.199***	-0.204***	-0.195***	-0.204***
	(0.026)	(0.028)	(0.008)	(0.008)	(0.008)	(0.008)
Log number of days to complete the project	0.013	0.013	-0.001	-0.001	-0.001	-0.001
	(0.016)	(0.016)	(0.005)	(0.005)	(0.005)	(0.005)
Log complexity	0.041***	0.039***	0.004	0.000	0.000	0.000
	(0.014)	(0.014)	(0.005)	(0.005)	(0.005)	(0.005)
Bidder's capacity utilized		-0.128***		-0.074***	-0.076***	-0.075***
		(0.037)		(0.011)	(0.011)	(0.011)
Log of bidder's distance to the project location		-0.016**		-0.021***	-0.020***	-0.021***
		(0.007)		(0.002)	(0.002)	(0.002)
Ongoing project in the same county		0.058***		0.078***	0.077***	0.078***
		(0.022)		(0.006)	(0.006)	(0.006)
Log number of past bids		-0.016**		-0.007***	-0.003	-0.006***
		(0.008)		(0.002)	(0.002)	(0.002)
Average rivals' winning-to-plan holder ratio		-0.523***		-0.540***	-0.545***	-0.541***
		(0.174)		(0.052)	(0.052)	(0.052)
Log of rivals' minimum backlog		-0.003*		-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		0.020***	0.020***	0.020***
		(0.009)		(0.003)	(0.003)	(0.003)
Log total number of rivals faced in the market					-0.014***	
					(0.004)	
Log total number of plans held in the month						-0.006
						(0.004)
Number of observations	3,303	3,303	31,783	31,783	31,783	31,783
Wald χ^2	252.760	288.350	1,154.920	1,638.980	1,652.840	1,641.090
χ^2 test probability: $\beta_1 = \beta_2$	0.733	0.463	0.764	0.617	0.562	0.594
χ^2 test probability: $\beta_1 = \beta_3$			0.578	0.575	0.663	0.612

** 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.

Though LINC alumni might not have a higher probability of winning contracts, because the direct and indirect effects LINC has on bidding behavior have the same direction, it would seem that the auction outcomes should be better for the state. To examine this conjecture, in Table 6, we maintain the same structure of the empirical bidding models presented earlier but restrict attention to the subset of winning bids. With respect to the sample of LINC-qualified bids, being a LINC graduate does not yield significantly lower winning bids nor imply that other LINC-eligible firms behave more aggressively. Of course, most of the projects are won by ineligible firms and in models (5) and (6) we observe that when these firms win contracts its with bids that are about 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 2.6% lower in model (8) and winning bids from any firm that potentially faced a LINC graduate are 1.4% lower. The results indicate that the sign and significance of the other covariates are similar to those of the full sample of bids presented in model (2), though the magnitude of some estimates has changed.

4.4 Additional Results and Discussion

4.4.1 Quantile Regression Analysis

The group of subplots we presented in Figure 1 suggested that the effects of the LINC training program on bidding behavior may hold not only on average, but might be important throughout the bid distribution. As such, in Table 7, we complement the bid regressions presented above by providing a portion of some quantile regression results for the models estimated in model (8) of Tables 4 and 6. We limit presentation to these two models as conveying estimates at each decile requires more space. We also limit our presentation to estimates of our primary coefficients of interest (those corresponding to the LINC-related variables in the top four rows of our bid and winning bid regression tables).[13] Table 7 has two parts: the top set of estimates concerns the log of all bids as the response variable, while the bottom relate to the log of only winning bids. The results discussed above concerning the bidding behavior of LINC-graduating firms hold throughout much of the distribution. If a firm is LINC-qualified, but never elects training, its bidding behavior is never statistically different from the ineligible firms; however, LINC-trained firms behave more aggressively by submitting bids that are 1.2–3.4% lower than the other firms throughout the first seven deciles of all tendered bids. The indirect competition effect is negative and statistically significant for every quantile presented. The magnitude of these coefficients is also consistent with the least-squares estimates. The results concerning winning bids also appear to hold not just at the mean bid, but throughout much of the distribution. Winning bids from LINC-trained firms are significantly lower than those from ineligible firms for seven of the nine deciles and the indirect competition effect is significant for all but the lowest decile of the winning bid distribution.

[13]Nonetheless, the models estimated are specified exactly as they were in column (8) of Tables 4 and 6 in the sense that all of the other covariates and fixed effects were included in the estimation.

Table 6: Descriptive Winning Bid Regression Results

Variable	Log of winning bids								
	Qualified				Unqualified		Full sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8)
LINC-graduate (β_1)	-0.021	-0.025	-0.048*	-0.034			-0.031***	-0.026***	-0.013
	(0.020)	(0.021)	(0.026)	(0.027)			(0.008)	(0.008)	(0.015)
LINC-eligible, before training (β_2)	-0.003	-0.007					-0.014	-0.011	
	(0.025)	(0.025)					(0.011)	(0.011)	
LINC-eligible, will never train (β_3)							-0.011	-0.004	
							(0.014)	(0.015)	
Interest from LINC-trained firm	-0.006	-0.009	-0.025	-0.027	-0.020***	-0.021***	-0.015***	-0.014***	-0.020***
	(0.016)	(0.016)	(0.017)	(0.017)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Log of ECE	0.945***	0.946***	0.933***	0.933***	0.935***	0.934***	0.945***	0.943***	0.935***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
Log number of plan holders	-0.113***	-0.116***	-0.081***	-0.078***	-0.064***	-0.066***	-0.069***	-0.071***	-0.069***
	(0.020)	(0.021)	(0.021)	(0.021)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Log number of days to complete the project	0.005	-0.001	0.007	0.005	0.031***	0.031***	0.026***	0.026***	0.028***
	(0.014)	(0.014)	(0.015)	(0.015)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
Log complexity	0.090***	0.096***	0.099***	0.101***	0.089***	0.091***	0.087***	0.091***	0.092***
	(0.013)	(0.013)	(0.014)	(0.013)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
Bidder's capacity utilized		0.020		0.054*		0.015		0.014*	0.021**
		(0.027)		(0.031)		(0.010)		(0.008)	(0.009)
Bidder's distance to the project location		0.006		-0.002		0.010***		0.006***	0.009***
		(0.006)		(0.010)		(0.003)		(0.002)	(0.003)
Ongoing project in the same county		-0.029*		-0.024		-0.009*		-0.017***	-0.009**
		(0.015)		(0.015)		(0.005)		(0.004)	(0.004)
Log number of past bids		0.002		-0.074		-0.157***		0.004***	-0.150***
		(0.006)		(0.143)		(0.043)		(0.002)	(0.040)
Average rivals' winning-to-plan holder ratio		-0.130		-0.014		-0.003		-0.202***	-0.006
		(0.138)		(0.014)		(0.004)		(0.039)	(0.004)
Log of rivals' minimum backlog		-0.001		-0.001		0.001		0.001*	0.000
		(0.001)		(0.001)		(0.000)		(0.000)	(0.000)
Log of closest rival's distance to the project location		0.012*		0.011		-0.001		0.004**	-0.000
		(0.006)		(0.007)		(0.002)		(0.002)	(0.002)
Firm effects	No	No	Yes	Yes	Yes	Yes	No	No	Yes
Number of observations	821	821	816	816	6,562	6,562	7,434	7,434	7,378
R^2	0.991	0.991	0.994	0.994	0.991	0.991	0.989	0.989	0.991

** 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: Quantile Regression Results

Variable	Log of bids								
	q10	q20	q30	q40	q50	q60	q70	q80	q90
LINC-graduate (β_1)	-0.034***	-0.022***	-0.022***	-0.020***	-0.019***	-0.019***	-0.012**	-0.011	-0.008
	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.008)	(0.009)
LINC-eligible, before training (β_2)	-0.005	-0.004	-0.010	-0.009	-0.005	-0.019***	-0.012	-0.002	0.018
	(0.010)	(0.007)	(0.007)	(0.008)	(0.006)	(0.006)	(0.010)	(0.008)	(0.017)
LINC-eligible, will never train (β_3)	-0.004	0.012	0.008	0.004	0.003	0.011	0.006	0.011	0.020
	(0.013)	(0.014)	(0.008)	(0.010)	(0.009)	(0.008)	(0.012)	(0.014)	(0.017)
Interest from LINC-trained firm	-0.017***	-0.011***	-0.014***	-0.018***	-0.018***	-0.020***	-0.020***	-0.023***	-0.020***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(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)	-0.025*	-0.039***	-0.030**	-0.026***	-0.029***	-0.029***	-0.023**	-0.007	-0.018
	(0.013)	(0.012)	(0.012)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.012)
LINC-eligible, before training (β_2)	0.018	0.002	-0.004	-0.015*	-0.026***	-0.022***	-0.025***	-0.031***	-0.028
	(0.015)	(0.012)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.010)	(0.020)
LINC-eligible, will never train (β_3)	-0.034	-0.018	-0.007	-0.004	-0.007	-0.010	-0.019	-0.006	0.014
	(0.028)	(0.027)	(0.023)	(0.019)	(0.014)	(0.014)	(0.016)	(0.019)	(0.029)
Interest from LINC-trained firm	-0.009	-0.013**	-0.011**	-0.014***	-0.019***	-0.021***	-0.018***	-0.013**	-0.015**
	(0.011)	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.007)	(0.006)
Number of observations					7,434				

Bootstrapped standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. These regressions are similar to the once presented in Tables 4 and 5 Column 7. All models include time, material shares, and project division effects.

4.4.2 Interaction Effects

One may also wonder whether LINC training (or eligibility for the program) might be affecting bidding behavior through other important channels. For example, the results in Tables 4 and 6 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]. We explore these possible channels as ways in which firms might behave differently given their classification by considering other regression models in Table 8. The table is partitioned by all bids (the first three columns of estimates) and winning bids (the last three columns). All of the models estimated include all covariates presented in column (8) of Tables 4 and 6 but, due to space constraints we only present coefficient estimates for our variables of interest and the relevant terms for the newly-considered cases.

First, note that the significance of the LINC-graduate dummy variable holds in all expanded models except for the case of winning bids when we consider asymmetric responses to distance (though the magnitude of the effect is larger than the results from Table 6, the p-value is 0.13). Second, the results concerning the indirect competition effect are consistent with our earlier discussions for all models. The estimates in columns (1) and (4) of Table 8 consider interactions between the bidder's capacity utilized and its LINC status. In short, firms eligible for the LINC program who are untrained behave no differently when it comes to capacity utilized than ineligible firms. Once a firm undergoes LINC training, behavior on average does not change but there is some evidence (significant at the 10% level) that LINC-trained winners and LINC-qualified bidders that do not become trained react to their capacity utilized in a statistically different way from ineligible firms by winning contracts with higher bids. In columns (2) and (5), we consider whether the bids of LINC-qualified firms might be different from ineligible firms based on how close the firm is to the project site. Again, there is very little difference on average in the behavior of qualified firms compared to ineligible firms. Lastly, in columns (3) and (6), we investigate whether these firms might respond differently to the perceived competitiveness of their rival firms. We consider interactions between our LINC-related dummy variables with the average of their rivals' winning-to-plan holder ratio. The interactions are never significant—suggesting response to rivals' success, though important on average, does not differ from ineligible firms, whether the LINC-qualified firm is trained or not.

Table 8: Investigating other Possible Asymmetries through Bid Regressions

Variable	Log of bids			Log of winning bids		
	(1)	(2)	(3)	(4)	(5)	(6)
LINC-graduate (β_1)	-0.016**	-0.032**	-0.046**	-0.039***	-0.038	-0.056**
	(0.007)	(0.015)	(0.019)	(0.012)	(0.025)	(0.024)
LINC-eligible, before training (β_2)	-0.002	0.030	0.002	-0.003	0.009	-0.024
	(0.009)	(0.021)	(0.019)	(0.014)	(0.032)	(0.028)
LINC-eligible, will never train (β_3)	0.003	0.009	0.055*	-0.020	0.064	0.067
	(0.010)	(0.028)	(0.030)	(0.020)	(0.054)	(0.051)
Interest from LINC-trained firm	-0.016***	-0.016***	-0.016***	-0.014***	-0.014***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Bidder's capacity utilized	0.030***	0.030***	0.030***	0.010	0.014*	0.013
	(0.005)	(0.005)	(0.005)	(0.009)	(0.008)	(0.008)
Bidder's capacity utilized ×	-0.006			0.063*		
LINC-graduate (β_1)	(0.020)			(0.037)		
Bidder's capacity utilized ×	-0.003			-0.065		
LINC-eligible, before training (β_2)	(0.028)			(0.052)		
Bidder's capacity utilized ×	0.029			0.077*		
LINC-eligible, will never train (β_3)	(0.030)			(0.042)		
Log of bidder's distance to the project location	0.015***	0.015***	0.015***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Log of bidder's distance to the project location ×		0.004			0.003	
LINC-graduate (β_1)		(0.003)			(0.006)	
Log of bidder's distance to the project location ×		-0.008*			-0.005	
LINC-eligible, before training (β_2)		(0.005)			(0.008)	
Log of bidder's distance to the project location ×		-0.000			-0.019	
LINC-eligible, will never train (β_3)		(0.007)			(0.014)	
Average rivals' winning-to-plan holder ratio	-0.063*	-0.063*	-0.065*	-0.202***	-0.202***	-0.206***
	(0.035)	(0.035)	(0.035)	(0.039)	(0.039)	(0.040)
Average rivals' winning-to-plan holder ratio ×			0.206			0.220
LINC-graduate (β_1)			(0.132)			(0.157)
Average rivals' winning-to-plan holder ratio ×			-0.032			0.084
LINC-eligible, before training (β_2)			(0.113)			(0.164)
Average rivals' winning-to-plan holder ratio ×			-0.333			-0.510
LINC-eligible, will never train (β_3)			(0.203)			(0.355)
Number of observations	31,783	31,783	31,783	7,434	7,434	7,434
R^2	0.984	0.984	0.984	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 are similar to the once presented in Tables 4 and 5 Column 8 with interaction terms.

4.4.3 Sample Selection Issues

A concern one might have with the bid regressions presented thus far is selection bias—after controlling for covariates, those firms tendering positive bids are not randomly selected. As shown in Table 3, the decision to enter an auction conditional on holding plans is non-random. Bid levels are only observed when firms choose to enter an auction. We address this concern by using a Heckman-based correction. Specifically, we specify the probability of entering an auction, as we did in models (5) and (6) in Table

3, as the selection equation and use the model in column (8) of Table 4 as the outcome equation. So that our identification is not based solely on the nonlinearity of the functional form of the selection equation, we employ exclusion restrictions. As shown in models (5) and (6) of Table 3, the total number of rivals that a firm faces in a given month (across all projects it holds) and the total number of plans held in the month were both important in explaining variation in the probability of entering an auction, but these should not affect the amount a firm bids on a given project.

We replicate the models presented in column (8) of Tables 4 and 6 following the Heckman correction procedure discussed and provide corresponding estimates in Table 9. The coefficient on the inverse-Mills ratio is statistically different from zero in both bidding models, but not for the models focused on winning bids. After accounting for sample selection concerns, the direct effect of LINC training on graduate bidding behavior is strengthened—eligible firms bid 2.2% more aggressively after completing training. The indirect effect generated by graduates holding plans still holds—rival firms bid 1.5% lower, on average, when LINC-graduates express interest in a project. Though sample selection concerns do not appear to be much of an issue when restricting attention to the sample of winning bids, the direct and indirect effects still hold and are consistent with the estimates that employ the full sample of bids.

4.4.4 Ex Post Payment Considerations

Lastly, while our focus has been 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.[14] In Table 10, we provide estimates from our core regression models (both without and with the two distinct Heckman corrections) 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 three models condition on the engineer's initial estimate of the project while the estimates in the last three columns do not but, instead consider the winning bid. When the engineer's estimate is considered, the estimated coefficients for our direct and indirect LINC-

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

Table 9: Bid Regression Results with Heckman Approach

Variable	Log of bid		Log of winning bid	
	(1)	(2)	(3)	(4)
LINC-graduate (β_1)	-0.022***	-0.022***	-0.025***	-0.022**
	(0.005)	(0.005)	(0.009)	(0.010)
LINC-eligible, before training (β_2)	-0.003	-0.003	-0.009	-0.004
	(0.007)	(0.007)	(0.012)	(0.013)
LINC-eligible, will never train (β_3)	0.002	0.001	-0.004	-0.003
	(0.008)	(0.008)	(0.013)	(0.014)
Interest from LINC-trained firm	-0.015***	-0.015***	-0.015***	-0.016***
	(0.003)	(0.003)	(0.005)	(0.005)
Log of ECE	0.931***	0.932***	0.943***	0.944***
	(0.002)	(0.002)	(0.003)	(0.003)
Log number of plan holders	-0.032***	-0.033***	-0.095***	-0.133**
	(0.005)	(0.004)	(0.035)	(0.055)
Log number of days to complete the project	0.034***	0.034***	0.026***	0.026***
	(0.002)	(0.002)	(0.004)	(0.004)
Log complexity	0.069***	0.069***	0.092***	0.092***
	(0.002)	(0.002)	(0.004)	(0.004)
Bidder's capacity utilized	0.032***	0.032***	0.005	-0.009
	(0.005)	(0.005)	(0.015)	(0.022)
Log of bidder's distance to the project location	0.011***	0.011***	0.004	-0.000
	(0.001)	(0.001)	(0.004)	(0.006)
Ongoing project in the same county	-0.011***	-0.011***	-0.008	0.006
	(0.004)	(0.004)	(0.014)	(0.021)
Log number of past bids	0.007***	0.007***	0.003*	0.002
	(0.001)	(0.001)	(0.002)	(0.002)
Average rivals' winning-to-plan holder ratio	-0.086***	-0.087***	-0.262***	-0.361**
	(0.023)	(0.023)	(0.096)	(0.147)
Log of rivals' minimum backlog	0.001***	0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Log of closest rival's distance to the project location	0.001	0.001	0.006	0.010*
	(0.001)	(0.001)	(0.004)	(0.006)
Selection				
Log total number of rivals faced in the market	Yes		Yes	
Log total number of plans held in the month		Yes		
Log total number of bids submitted in the month				Yes
λ	0.064**	0.067**	0.047	0.124
	(0.013)	(0.128)	(0.069)	(0.110)
Number of uncensored observations	31,783	31,783	7,434	7,434

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

Table 10: Regression Results for Final Payments

Variable	Log of final pay					
	OLS	Heckman		OLS	Heckman	
	(1)	(2)	(3)	(4)	(5)	(6)
LINC-graduate (β_1)	-0.030**	-0.030**	-0.026**	0.001	-0.000	-0.003
	(0.012)	(0.012)	(0.013)	(0.008)	(0.008)	(0.009)
LINC-eligible, before training (β_2)	0.010	0.009	0.015	-0.002	-0.004	-0.008
	(0.020)	(0.019)	(0.019)	(0.013)	(0.012)	(0.014)
LINC-eligible, will never train (β_3)	-0.020	-0.020	-0.026	-0.010	-0.010	-0.008
	(0.019)	(0.022)	(0.023)	(0.009)	(0.014)	(0.016)
Interest from LINC-trained firm	-0.025***	-0.025***	-0.022***	-0.004	-0.003	0.000
	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.006)
Log of ECE	0.935***	0.935***	0.930***			
	(0.006)	(0.005)	(0.006)			
Log of winning bid				0.994***	1.003***	1.021***
				(0.004)	(0.011)	(0.017)
Log number of plan holders	-0.077***	-0.076***	-0.138***	-0.013**	0.010	0.053
	(0.010)	(0.028)	(0.038)	(0.006)	(0.027)	(0.041)
Log number of days to complete the	0.045***	0.045***	0.045***	0.012**	0.005	-0.008
project	(0.008)	(0.007)	(0.007)	(0.005)	(0.009)	(0.013)
Log complexity	0.083***	0.083***	0.087***	-0.001	-0.008	-0.020
	(0.008)	(0.006)	(0.007)	(0.006)	(0.009)	(0.013)
Bidder's capacity utilized	0.024*	0.024	0.004	0.005	0.016	0.037*
	(0.013)	(0.016)	(0.018)	(0.008)	(0.015)	(0.021)
Log of bidder's distance to the project	0.000	0.000	-0.008	-0.003*	-0.002	0.002
location	(0.003)	(0.004)	(0.006)	(0.002)	(0.003)	(0.004)
Ongoing project in the same county	-0.015**	-0.015	0.011	0.002	-0.006	-0.021
	(0.007)	(0.013)	(0.017)	(0.004)	(0.010)	(0.015)
Log number of past bids	-0.000	-0.000	-0.001	-0.004***	-0.004***	-0.005***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)
Average rivals' winning-to-plan holder	-0.202***	-0.199**	-0.367***	0.032	0.100	0.227*
ratio	(0.066)	(0.090)	(0.119)	(0.044)	(0.089)	(0.129)
Log of rivals' minimum backlog	0.001	0.001	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	0.000	0.000	0.008	-0.004**	-0.007*	-0.013**
project location	(0.003)	(0.004)	(0.006)	(0.002)	(0.004)	(0.006)
Selection						
Log total number of rivals faced in the market		Yes			Yes	
Log total number of plans held in the month			Yes			
Log total number of bids submitted in the month						Yes
λ		-0.002	0.107		-0.046	-0.133
		(0.043)	(0.065)		(0.054)	(0.081)
Number of uncensored observations	4,915	4,915	4,915	4,915	4,915	4,915

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

related effects are stronger (more negative) 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 the state writes its final check to the contracting firm. LINC-trained bidders are paid 3% less on average and the indirect competition effect generates savings of over 2%. 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 in saying that LINC graduates are not somehow manipulating the system in a way that wipes out any suggested savings the state receives from the auction. Moreover, renegotiation and/or adjustments needed after the contract has been awarded appear to be independent of firms' eligibility or training status.

5 Firm 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. To consider longer-term effects that the LINC program might generate, we also consider firm exit patterns. Specifically, we estimate a probit model in which the response variable takes on a value of one if a given firm exits the industry in a given period, and takes on a value of zero otherwise. The challenge in such an exercise is identifying when a firm exits the market. With this in mind, we first discuss some choices we made in our investigation. First, 75% of the projects are completed in seven months. As such, we drop firms that entered the industry (firms that hold plans for the first time) after 2007 from the analysis 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].

Table 11: 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 faced in the market	0.021***	0.021***	0.021***	0.024***
	(0.001)	(0.001)	(0.001)	(0.002)
Log number of LINC-eligible firms faced in the market	-0.016***	-0.016***	-0.016***	-0.024***
	(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 volume of projects	0.003	0.003	0.003	-0.001
	(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.

In Table 11, 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.

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 of our results are that firms that opt for LINC training are typically smaller, less experienced, 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 choose to participate in the program. The average bid of a LINC graduate is 1.7% lower than that of ineligible firms and when LINC graduates win they bid 2.6% lower on average relative to other winning bids. That said, 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 1.6% 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 reports LINC costs for fiscal years 2005 to 2012 which show that the program costs the state about $200,000 per fiscal year.[15] Using our estimates from model (8) of Table 6, which is conservative relative to final payment amounts from models (1), (2), and (3) of Table 10, 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

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

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.[16] The negligible cost to TxDOT of running the LINC program pales in comparison to the funds saved 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 (8) of Table 6 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 aspects of a particular program that are most valuable in generating the more aggressive behavior and cost savings for the state. 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 getting 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

[16] 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].

which allow firms to behave more competitively. The description of the LINC program we gave in Section 2 is both promising and 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 even 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 before the eligible firms are trained. Regardless, we hope that we have provided a foundation from which a structural model can be considered to investigate the effects on the latent cost distribution of LINC-eligible firms and, ultimately, the effect that LINC might have had on the efficiency of the auctions.

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7 Appendix

Table 12: 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	
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