The Effects of Targeted Recruitment and Comprehensive Supports for Low-Income High Achievers at Elite Universities: Evidence from Texas Flagships^{*}

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Abstract

We study a set of interventions in Texas that were designed to overcome the multitude of hurdles faced by low-income, high-ability students in the higher education system. The Longhorn Opportunity Scholars (LOS) and Century Scholars (CS) programs were implemented in 1999 and 2000 and involved recruiting at specified high schools, additional financial aid, and academic supports once enrolled in college if students attended University of Texas - Austin (LOS) or Texas A&M - College Station (CS). Using administrative data on all Texas students linked with their earnings, we implement difference-in-difference estimators that examine how the outcomes of high-ability students change across treated and untreated schools when the programs were implemented. Our findings differ across programs. The LOS program led to increased enrollment at UT-Austin, higher college quality, more STEM and business majors, and higher earnings. There was no effect on college completion or time to degree, however. The CS program had little effect on student outcomes or earnings, except for a small increase in the likelihood a student majored in a STEM field. Overall, our estimates suggest these programs have some promise in supporting low-income, high ability students in the postsecondary system, but that there is much heterogeneity in program impacts to be further understood before these programs are expanded.

KEYWORDS: Postsecondary Education, Higher Education, Low-Income Students

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1 Introduction

Changes in the US economy over the past several decades have led to historically high demand for skilled labor (Autor, Katz and Kearney 2008; Autor 2014). In 1979, the gap in median yearly earnings between households with at most a high school degree and households with a worker who has a college degree was \$30,298. By 2012, this gap had nearly doubled to \$58,249 (Autor 2014). The increasing earnings premium associated with having a college degree underscores the immense and growing importance of postsecondary education in driving labor market outcomes. However, these high returns have been met with sluggish increases in postsecondary attainment, particularly among students from low-income backgrounds (Lovenheim and Reynolds 2013; Bound, Lovenheim and Turner 2010; Bailey and Dynarski 2011). For example, tabulations in Bailey and Dynarski (2011) show the college enrollment gap between those in the bottom and top income quartiles grew from 39 percentage points to 51 percentage points between the early 1980s and the turn of the 21st century. The college completion gap between these two groups also grew dramatically during this period, from 31 percentage points to 45 percentage points. The unequal investment in postsecondary education across the income distribution combined with the large earnings premium associated with college graduation suggests the current higher education system may contribute to rather than mitigate growing income inequality in the US. Indeed, some evidence suggests that changes in the earnings premium associated with college can explain between 60 and 70 percent of the rise in income inequality over the past several decades (Goldin and Katz 2007). Thus, developing policies that can support the collegiate attainment of students from low-income backgrounds is of primary policy importance.

Differences in collegiate investment between low-income and high-income students take two forms. The first is that students from low-income families are less likely to attend college at all (Carneiro and Heckman, 2002; Bailey and Dynarski, 2011). For example, tabulations from the 1997 National Longitudinal Survey of Youth (NLSY97) show that while only 13% of students from families with earnings over \$125,000 do not attend college, 56% of students from families with income below \$25,000 do not attend college. As family income increases, the likelihood of attending college increases steeply. The second type of investment gap, which has received far less attention, is that low-income students tend to enroll in schools of lower quality than their higher-income counterparts (Lovenheim and Reynolds 2013). In the NLSY97, only 2% of lowincome students attended a flagship public school, while among the highest-income students 16% did.¹ The likelihood of attending a private school also increases with income, and the proportion of students enrolling in a two-year school declines with income. There is substantial evidence of large impacts of college quality on college completion (Bound, Lovenheim and Turner 2010), time to degree (Bound, Lovenheim and Turner 2012), and subsequent earnings in the labor market (Brewer, Eide and Ehrenberg 1999; Black and Smith 2004, 2006; Hoekstra 2009; Andrews, Li and Lovenheim forthcoming). A representative estimate from Hoekstra (2009) shows that attending the public flagship university leads to a 24% increase in earnings post college graduation. Hence, differences in college quality between low-income and high-income students could significantly affect both collegiate attainment and earnings gaps.

In order to develop policies to address the gaps in postsecondary investment that exist across the income distribution, it first is important to understand why they are present. There are four main explanations for why students from low-income households tend to graduate from college in general and from more elite colleges in particular at lower rates. First, families with fewer resources at the time of college usually have fewer resources with which to invest in a child throughout his or her life. These resource differences develop into differences in academic preparation for college during students' teenage years (Carneiro and Heckman, 2002; Cameron and Taber 2004). Second, there is increasing evidence that low-income students face considerable information gaps that often preclude them from applying to and enrolling in more selective schools, even when they are academically qualified and would pay little to nothing in out-of-pocket costs (Hoxby and Turner 2013; Hoxby and Avery 2013). A third explanation is that low-income students are affected by both academic and social "mismatch" when they enroll in higher-quality schools, as, on average, such students have worse academic preparation for college and often are not part of the dominant cultural majority, particularly at more elite postsecondary institutions (Aucejo, Arcidiacono and Hotz 2013; Arcidiacono and Koedel, forthcoming; Arcidiacono et al., 2011; Dillon and Smith 2013). Finally, lower family resources may prevent families from investing in a higher-quality school (Lovenheim and Reynolds 2013).

¹This is not just a reflection of the differences in enrollment. Among those who enroll, 3.7% of low-income students enroll in a public flagship university, and 18.4% of high income students enroll in this school type.

The many hurdles faced by low-income students in the higher education system suggest that programs addressing several of these barriers simultaneously might be particularly effective at supporting postsecondary education among students from low-income backgrounds at highquality universities. In this paper, we present the first analysis in the literature of a set of interventions in Texas aimed at addressing this array of disadvantages faced by low-income students. The Longhorn Opportunity Scholarship (LOS) program at University of Texas at Austin (UT Austin) and the Century Scholars (CS) program at Texas A&M University – College Station, which are the two flagship schools of the Texas public higher education system, began in 1999 and 2000 and were targeted at high schools that served low-income students and that traditionally sent few students to a Texas flagship. Together, the LOS and CS programs were implemented at 110 high schools in Texas. While run separately, they both offer a similar suite of interventions that attempt to address the set of disadvantages faced by low-income students in the higher education system. First, high-achieving students at targeted high schools are offered scholarships to help alleviate financial concerns if they are admitted to UT-Austin or Texas A&M. Second, enrolled students are offered smaller classes and academic tutoring to help them with the more rigorous coursework at these elite public schools. Third, the programs contain extensive outreach, with students going back to their high schools to share their experiences with prospective college students. This outreach and recruitment of students from low-income high schools helps overcome information barriers that may preclude students from these schools from applying to and enrolling in an elite postsecondary school (Hoxby and Turner 2013). Thus, the CS and LOS programs are designed to address the multitude of difficulties that students from low-income backgrounds can face at very selective universities: lack of information about college quality, lower academic preparation for college, and lower financial resources.

We use administrative data from the State of Texas that allows us to link K-12 education records with higher education enrollment and performance information and earnings records from the Texas unemployment insurance system, and we exploit the timing differences in the rollout of the LOS/CS programs to identify their effects on higher education outcomes and postcollege earnings. Because these programs were targeted towards high-performing students, we first generate a performance index using the extensive set of high school test score information we have about each student. We then estimate difference-in-difference models in which we compare changes in outcomes among high-ability students according to their high school academic performance index in treated schools to those of the same ability level in untreated schools when the COS/LS programs are implemented. The main identification assumption in these models is that the trends in enrollment patterns and outcomes among high-achieving students would have been the same in treated and untreated high schools absent the programs. This assumption may be strong due to the fact that the treated schools are highly selected. In order to make this assumption more credible, we construct a "common support" group using the rich information we have about the demographics and college-sending patterns of each high school in Texas prior to 1998. Thus, our analysis sample is comprised of the set of schools that are more observationally-similar across the treatment and control groups than would be the case if we used all high schools in Texas. We also show evidence of common trends in flagship enrollment prior to the treatments, and we examine program effects among less-elite students who are less likely to be treated by the LOS and CS programs.

The results of our analysis suggest that the LOS and CS programs had different impacts on students. The LOS program significantly increased the likelihood that a high-performing student enrolled in UT-Austin. This enrollment increase came from reduced enrollment at much lower-quality public schools in-state, rather than from out-of-state or private schools. Despite the increase in college quality experienced by these students, they were just as likely (but not more likely) to graduate from college, and their time to degree also remained the same. However, they were substantially more likely to major in a STEM field and somewhat more likely to major in business. Thus, these students experienced an increase in college quality and sorted into more technical majors. These results suggest that their earnings also should have increased, which is what we show. Exposure to the LOS program increased post-college earnings by 7%-9%. On the whole, this program had a substantial impact on students' long-run educational and labor market outcomes.

In contrast, the CS program had little effect on students. We find no evidence that student enrollment choices were impact by this program, and their educational attainment also was at most minimally affected. While we do find a positive effect on the likelihood a student is a STEM major, they do not earn more in the labor market. Thus, exposure to the CS program had no more than a small effect on student behavior and on their educational and labor market outcomes.

The results from this analysis suggest that bundled programs designed to address the multitude of disadvantages faced by low income students in attending high-quality colleges and universities can be successful but that they are not universally so. While the LOS program had a large positive effect on students across a number of dimensions, the CS program did not. Understanding the reasons for these differences is critical for policy, but it is beyond the scope of this paper. We therefore leave such an investigation to future work.

2 The Longhorn Opportunity and Century Scholars Programs

2.1 Program Description

The Longhorn Opportunity Scholars and Century Scholars Programs were first implemented between 1998 and 2000, respectively, to increase enrollment rates for low-income and minority students at UT-Austin and Texas A&M in the wake of the state's affirmative action ban. The affirmative action ban went into effect in 1997 and made it illegal for schools in the state to consider race as a factor in admissions. The pre-existing affirmative action system was replaced by the Texas Top 10% Rule in 1998, which stipulated that any student in the top 10% of his or her high school class could attend any Texas public university. Post-1997, the vast majority of students in UT-Austin and Texas A&M were admitted under this rule. As a result of the Top 10% rule, students ranked outside the top 10 percent of their class, particularly at high schools serving low-income students, are unlikely to enroll in UT-Austin or Texas A&M.

Despite the fact that many students from low-income schools became eligible to attend Texas A&M and UT-Austin under this rule, minority enrollment at these schools fell dramatically. For example, Kain, O'Brien and Jargowsky (2005) show that after the affirmative action ban went into effect, enrollment amongst African American students at UT-Austin declined by 68%, and it declined by 72% at Texas A&M. Hispanic enrollment also dropped considerably, by 6% and 25% at UT-Austin and Texas A&M, respectively. The LOS program initially targeted 70 high schools that had high shares of low-income and minority students and few prior applicants

to UT-Austin. The CS program similarly targeted 40 low-income schools in Houston, Dallas and San Antonio with few prior applicants to Texas A&M, although there was some overlap between the two programs. Over 600 students are admitted to Texas A&M and UT-Austin under these programs each year.

Though administered by different universities, the two programs are very similar and are summed up best by the Longhorn Opportunity Scholarship Brochure:

"More than simply a scholarship, the program serves as the catalyst for the creation of a comprehensive academic community development package with a three-fold aim: to identify students who, through a variety of circumstances, might not have otherwise had either the opportunity or the desire to attend The University; to deploy University resources to attract them to Austin; and most importantly, to give these students the resources and attention that will help them to succeed academically and ultimately become alumni of The University of Texas at Austin."

A set number of fellowships are allocated to each high school, based on how under represented students at the given high school are at the university. Students who are awarded one of these scholarships are exposed to a multitude of treatments:

- 1. They are given additional financial aid if they enroll in the flagship school that makes the scholarship offer.
- 2. There is an active recruiting effort made at these high schools to try and overcome any information barriers about cost, the likelihood of admission, and the value of attending a higher-quality school that may have existed. After several years, the recruiters were students from the high school who attended the flagship running the program. These students thus could address issues pertaining to academic and social mismatch directly.
- 3. Once enrolled, the LOS and CS students are given priority in registration, smaller classes, access to tutoring, and mentoring. Furthermore, the LOS and CS programs establish formal communities that offer support, guidance, and resources to low-income students.

These interventions could influence several important postsecondary outcomes and earnings in ambiguous directions that point to the need for an empirical analysis. We might expect the LOS/CS programs to have a positive effect on student outcomes because of the overall positive effects of college quality on educational attainment and earnings (e.g., Bound, Lovenheim and Turner 2010; Brewer, Eide and Ehrenberg 1999; Black and Smith 2004, 2006; Hoekstra 2009; Andrews, Li and Lovenheim forthcoming). The LOS/CS programs should increase the likelihood that students enroll in UT-Austin and Texas A&M. Indeed, in interviews with ten freshmen recipients of the Longhorn Opportunity Scholarship, Bhagat (2004) finds that the financial, social, and academic supports offered by the LOS were the primary reasons that students selected the University of Texas at Austin, suggesting that the programs had positive effects on enrolling. This is consistent with the evidence in Domina (2007) and Andrews, Ranchhod and Sathy (2010) of higher flagship enrollment after the LOS/CS program implementation among students in treated high schools. We will examine the enrollment effects as well in our empirical analysis below. Outside of the flagships, the other options for these students typically are far worse in terms of the quality and resource levels of the institution, including attending lower-quality four-year schools, attending a two-year college or not attending college at all. Domina (2007) shows that while students in LOS/CS schools were more likely to enroll in a flagship, they were just as likely to attend a non-selective four-year school after the treatment was implemented. This finding suggests that the alternative for most of these students is a two year school or no college at all and that the LOS/CS treatment likely led to a substantial increase in college quality for treated students. The increased financial support for college also may help students progress through the higher education system by relaxing credit constraints.²

The ambiguity in predicted impacts of the programs arises because of the tension that exists between overall college quality effects and the potential for academic "mismatch" that arises when students of lower academic preparation are brought into a more demanding educational environment.³ The students affected by the LOS and CS programs tend to be high-achievers in their high schools, but because they come from low-income schools they still may be underprepared for the rigors of a flagship university. If the LOS/CS programs induce students to enroll in schools in which they are mismatched, they could lower these students' degree attainment, persistence, and future earnings. They also could shift these students to easier, potentially less lucrative majors. Nonetheless, the LOS and CS programs provide a system of social and academic supports that potentially mitigate the experience of mismatch. The programs provide mentors from the respective universities as well as student mentors who are scholarship recipi-

²Note, however, that there is very little evidence that credit constraints or financial aid have more than a modest impact on students' paths through college (e.g., Stinebrickner and Stinebrickner 2008; Johnson 2013; Bettinger 2004).

 $^{^{3}}$ See Arcidiacono and Lovenheim (2014) for an overview of the "quality-fit" tradeoff in higher education

ents, and who thus have similar backgrounds to the prospective students. These mentors could have eased the transition from high school to college for scholarship recipients. The academic supports – smaller classes and tutoring – could compensate for any deficits in prior academic preparation as well.

As a result of these conflicting theoretical impacts, a priori, it is not possible to determine the net effect of the supports provided by these targeted recruitment programs. The success or failure of the targeted recruitment programs must be determined empirically, and the fact that the theoretical predictions are ambiguous makes it critical for policy to examine the effect of these programs on student educational and labor market outcomes in order to determine whether or not the LOS/CS models are an appropriate way to stimulate higher attainment rates among low-income students at elite colleges and universities. These arguments underscore the importance of conducting a rigorous analysis that can identify the effects of these targeted recruitment programs on students, which is what this analysis aims to do.

2.2 Prior Literature

While no prior work exists that examines the impact of this type of multifaceted treatment aimed at addressing the multiple disadvantages faced by students from low-income backgrounds at selective higher education institutions, there are several important studies that have examined programs that contain individual components of the CS and LOS treatments. In particular, prior work has examined the impacts of college outreach programs and financial aid, with very little prior research being done on targeted college services. An important contribution of our proposed analysis stems from the fact that it may not be enough to merely address one of the disadvantages faced by low-income students. Instead, to increase the postsecondary attainment of such students, particularly at highly-selective schools, it may be necessary to provide multiple targeted interventions simultaneously. Our study will be the first to provide evidence on this type of broad intervention for a low-income and heavily minority population.

Previous research on college outreach programs has not found strong evidence they increase student academic outcomes. Using National Education Longitudinal Study of 1988 (NELS:88) data, Domina (2009) studies the effect of being exposed to a college outreach program that provides information on the college application process and, in some cases, tutoring support and college counseling services for high school students. Domina reports that about 5% of students in the NELS:88 sample are exposed to such a program. Using propensity score matching techniques, he finds little evidence that exposure to an outreach program influences high school achievement or college enrollment. In a randomized controlled trial of Upward Bound, Myers et al. (2004) find largely the same results, except for a positive four-year college enrollment effect.

These studies do not examine the impact on college quality other than the four-year/2-year margin. However, a major effect of the type of college outreach embedded in the CS/LOS programs might be to influence students to attend a flagship rather than a non-flagship school. There is some evidence that college outreach can positively influence the quality of schools to which students apply and enroll. Hoxby and Turner (2013) conduct a randomized controlled trial in which they send detailed information to high-achieving, low-income students throughout the United States on college enrollment strategies as well as information about selective schools and their likelihood of admission. They also include application fee waivers. Their findings suggest that simply providing these high-achieving, low-income students with information about their probabilities of admission to different tiers of schools as well as information about expected costs has significant effects on the types of colleges and universities to which these students apply and attend. The LOS and CS programs provide similar information and recruiting techniques, and they thus could have large effects on the school choices made by students in the targeted high schools.

Our proposed research also relates to a body of work examining the effect of financial aid on student collegiate choices and outcomes. Evidence from state merit aid programs that offer free or highly-reduced tuition to in-state students to attend a public state school suggest these programs are successful at altering the college enrollment decisions of high-achieving students (Dynarski 2000; Cornwell, Mustard and Sridhar 2006; Cohodes and Goodman 2014). However, these programs do not tend to increase students' academic performance in college and even may reduce it because they induce many students to enroll in lower-resource schools than they otherwise would have (Cohodes and Goodman 2014; Fitzpatrick and Jones 2012; Sjoquist and Winters 2012).

Importantly, the LOS and CS programs should have the opposite college quality effect to what has been found in the merit aid literature, since they use price incentives to try and attract more low-income students to attend higher quality schools. The likely alternative for these students is a less-selective and lower-resource state university, community college or no college at all. UT-Austin and Texas A&M-College Station have much higher per-student expenditures, lower student-faculty ratios and significantly higher 6-year graduation rates. In addition, both flagships have student bodies with higher measured pre-collegiate academic ability relative to other public colleges and universities in Texas, as measured by the SAT score. Any resulting peer effects, therefore, may play a role in driving the education differences across these schools and could have a positive impact on LOS/CS students (Sacerdote 2001; Zimmerman 2003; Stinebrickner and Stinebrickner 2006).

This project also relates to a sizable body of work that has been done on the Texas Top 10% plan. The Top 10% plan was implemented in 1998 as an alternative to affirmative action. It gave automatic admission to any student in the top 10% of his or her high school class to any public college or university in Texas. There is a large literature exploring the effect of the Texas Top 10% plan on enrollment and completion outcomes, especially among minority students. This research tends to find that the Texas Top 10% plan increases enrollment among high-achieving students at flagship schools (Domina 2007; Niu and Tienda 2010; Daugherty, Martorell and McFarlin 2012), especially those who were in high schools that traditionally did not send many students to these schools (Domina 2007; Long and Tienda 2008). The effects on completion are more ambiguous, with some studies finding a negative effect (Cortes 2010) and some finding no effect (Daugherty, Martorell and McFarlin 2012).

While our proposed analysis studies a set of interventions that is separate from the Texas Top 10% law, this admission policy change provides an important backdrop for our study and likely independently influenced enrollment choices among many of the students in treated high schools. We discuss in Section 4 how this policy affects our identification strategy.

3 Data

The data we use in this study come from three sources: administrative data from the Texas Education Agency (TEA), administrative data from the Texas Higher Education Coordinating Board (THECB), and quarterly earnings data from the Texas Workforce Commission (TWC). The data are housed at the Texas Schools Project, a University of Texas at Dallas Education Research Center (ERC). These data allow one to follow a Texas student from Pre-Kindergarten through college and into the workforce, provided individuals remain in Texas. We discuss each of these data sets in turn.⁴

Beginning in 1992, the TEA began collecting administrative data on all students enrolled in public schools in Texas. These data contain students' grade, the school in which he or she is enrolled, scores from state standardized tests, and a host of demographic and educational characteristics such as race/ethnicity, gender, special education status, Title 1 status, whether the student is eligible for free or reduced-price lunch, whether the student is at risk of dropping out, and enrollment in gifted and talented programs. The test score data we use are from the 11^{th} grade Texas Assessment of Academic Skills (TAAS) exams for reading, writing and mathematics. The TAAS exams are administered to all students in Texas, and they are "high stakes" in the sense that students must achieve a passing score on them in order to graduate. Because students can retake them, we use the lowest score for each student, which typically corresponds to the score from the first time students take the exam. Although the TEA data begin in 1992, in 1994 Texas redesigned the high school exams. We therefore exclude data from before the 1996 graduating cohorts and use TEA data from the high school classes of 1996-2002.

The LOS/CS programs targeted only high-ability students at each school. We estimate the students' academic ability as the first principal component of a factor analysis model that includes 11^{th} grade TAAS scores on mathematics, reading and writing. As argued by Cunha and Heckman (2008) and Cunha, Heckman and Schennach (2010), combining test scores in a factor model provides a stronger proxy for student academic ability than using any one test score alone. Using this academic ability factor, we rank students in his or her school-specific 11^{th} grade cohort. Andrews, Li and Lovenheim (forthcoming) present evidence that the within-

⁴The data used in this project are virtually identical to those used in Andrews, Li and Lovenheim (forthcoming).

high school rank on these exams is highly correlated with whether one is admitted to a flagship university through the Top 10% Rule,⁵ which is evidence that the relative rank on these exams is a good proxy for relative academic rank in each high school.

Our higher education data from the THECB contain detailed information about college enrollment and key collegiate outcomes for all students who enroll in a public college or university in the State of Texas. For these students, we observe the enrollment decision in every school in each semester, major choice, the timing of all degrees received, and credits earned that we can use to calculate GPAs. The quarterly earnings data from the TWC are from 2007-2012 and contain earnings for every worker who works in Texas. Because we are interested in examining measures of more permanent earnings, we measure earnings at 6 years after college exit for all workers. In this way, we can specify a consistent post-college time period in which to observe earnings while ensuring to the extent possible that our earnings estimates are not biased by the earnings instability that often occurs in the early 20s, especially among college graduates. Means of analysis variables among the common support sample (see Section 4) for the top 10% of students by eventual school treatment status are presented in Table 1.

A core limitation with our data is that students only are followed if they attend college in Texas and then work in the labor force in Texas post-graduation. The main concern is that the LOS/CS programs induce students who would have attended an out-of-state or private school to move to the in-state flagship.⁶ This would affect the interpretation of our estimates, as it would appear that students are "upgrading" school quality due to the programs while in actuality they are just shifting from a similar out-of-state or private school to a public flagship university. Of course, these students still would receive the increases services once enrolled as well as the scholarship money, but any college quality effects would be muted. Thus, this type of sorting likely would lead us to overstate the program impacts, especially if the students induced to switch schools have higher innate ability, desire to attend college, and/or wealth that would generate better college outcomes and earnings.

We address this potential bias in a few ways. First, we note that in the population affected by LOS and CS, very few students attend out-of-state or private schools. Indeed, in Texas

⁵They show that admission through the Top 10% Rule is highly predictive of attending UT-Austin or Texas A&M, but conditional on the relative rank on the TAAS test scores this variable loses its predictive power.

 $^{^{6}}$ Daugherty, Martorell and McFarlin (2014) show that the Top 10% Rule had just such an effect on student college-going in a low-income district.

overall only 18% of first-time 4-year college enrollees who were seniors in high school the prior year attend an out-of-state school. While similar statistics for in-state private schools are not available, only 12% of enrollment in Texas degree granting institutions is in private colleges. Given the low income of students in LOS/CS schools, we would expect these numbers to be far lower for our subpopulation of interest. Second, we show in our empirical models that LOS/CS treatment is uncorrelated with the likelihood of attending any public college in the State of Texas. The lack of an extensive margin effect on college enrollment suggests that students are not being drawn into the public sector of Texas schools from the private sector or from out-of-state institutions.

In addition to sample selection that can occur at the college choice stage, there can be selection post-college due to migration out of Texas. While it is uncommon for students to move out-of-state after college, it occurs often enough to be of concern. According to the 2008-2012 American Community Survey, 2% of individuals in Texas with a bachelor's or higher degree move to a different state each year. Assuming that this rate is cumulative, then up to 10% of college graduates may move out of state within 5 years. Of course, this measure is unlikely to be cumulative: those in a cohort with the highest propensity to leave would have already left in earlier years. Additionally, the figures do not break down whether a student gets a degree from an in- or out-of-state school. We would expect the former to have a lower leaving rate. Nonetheless, the figures also are not broken down by age, and so we might expect younger people to be more likely to leave. We note as well that Andrews, Li and Lovenheim (forthcoming) show that earnings of bachelor degree holders in Austin (home of UT-Austin) and College Station (home of TAMU) who move out-of-state do not differ meaningfully from those who remain in-state.

We address attrition in the earnings measures using several methods. First, we operate primarily under the assumption that any attrition in the earnings data is random. That is, we assume that the likelihood of earnings being absent is unrelated to whether one is treated by the COS/LS program. This is an untestable assumption, but there are certain tests we conduct to provide some support for it. In particular, we examine whether the COS/LS treatment is associated with a change in the background characteristics and pre-collegiate academic outcomes of those in the earnings sample. We also estimate whether the treatment is correlated with being missing from the earnings data. In neither case do we see evidence of differential attrition from the earnings sample due to LOS/CS treatment that point to biases in our results.

4 Methodology

Our methodological approach to examining the effect of the LOS/CS programs on student college choice, academic outcomes and labor market earnings is to estimate difference-in-difference models in which we compare changes in outcomes when students are treated to changes among students in schools that are not treated. As discussed above, the LOS and CS programs are most likely to affect higher-ability students. In our baseline model, we therefore restrict the analysis to students who are in the top 20% of their high school class in a given year according to the ability index discussed in Section 3. The difference-in-difference model is specified as follows:

$$Y_{ijt} = \alpha + \beta Treated_{ijt} + X_{ijt}\Gamma + \phi_j + \theta_t + \epsilon_{ijt}, \tag{1}$$

where Y_{ijt} is an educational or labor market outcome of interest for student *i* in from high school *j* who is in 12th grade in year *t*, and *X* is a vector of individual characteristics such as high school test scores, race, gender, and free/reduced price lunch status. The model also contains school fixed effects (ϕ_j) and year fixed effects (θ_t). Treated is an indicator for whether the 12th grade cohort in school *j* and year *t* is eligible for the LOS or CS programs.

In equation (1), the main parameter of interest is β , which how outcomes change among top 20% students in LOS/CS schools relative to top 20% students in untreated schools when the programs are implemented. The main assumption under which β is identified is that the counterfactual trends in outcomes among schools not receiving the treatment are the same as those among the treated schools. This identification assumption is potentially strong, especially since the programs are targeted at low-income schools that could have substantially different trends than non-LOS/CS schools absent the treatment.

In order to make this identification assumption more likely to hold, we restrict the analysis schools to the set of high schools schools with common support. Using data from the 1997-1998

school year (which is before either program was implemented), we estimate a logistic regression of the likelihood a high school becomes an LOS or CS school as a function of the following school-level characteristics: percent enrolling in UT-Austin or Texas A&M, percent taking the SAT or ACT, percent economically disadvantaged, percent black, percent Hispanic, and the percent scoring above either 24 on the ACT or 1120 on the math and verbal sections of the SAT. Note that the number of students enrolling in flagship schools are particularly important controls because the LOS and CS programs explicitly targeted to schools that sent few students to UT-Austin and Texas A&M, respectively. We estimate this model separately for LOS and CS treatments, and we use this model to calculate a propensity score that shows the likelihood a given high school is treated.

Our main analysis sample is comprised of treated schools that are within the propensity score distribution of the control schools and the control schools that are within the propensity score distribution of the treated schools. Figures 1 and 2 show the propensity score densities for treated and control schools by likelihood bin, separately for UT-Austin (LOS) and Texas A&M (CS) respectively. As the figures demonstrate, there are several treated schools that have a predicted likelihood of treatment that is greater than any control school. These schools are shown in green in Figures 1 and 2, and they are excluded from the main analysis. These schools are sufficiently different from any control school that it makes the identification assumptions underlying our estimator more difficult to support. And, there are many control schools that are very unlikely to be treated. These schools also are dropped from the analysis. By restricting our sample to the set of common support schools, we thus render the linear-in-parameters assumption of OLS less important and we make it more plausible that the control schools provide accurate measures of counterfactual trends for the treatment schools.

Another concern with equation (1) relates to the imposition of the Top 10% Rule in 1998. As discussed above, this rule led to most admissions to the flagship schools being from the top 10% of a class. The main assumption underlying equation (1) is that the top 20% in the treated and control schools are similarly treated by the Top 10% Plan. The trends in flagship enrollment, however, suggest the Top 10% Rule is not a serious confounder in this setup. Figures 3 and 4 show enrollment trends for UT-Austin and Texas A&M, respectively, for treated schools, untreated schools, and the common support untreated schools. In each figure, we show the trends for 3 different bins of the student ability index. In Figure 3, there are no differential pre-treatment trends that suggest the program was targeted to schools based on trends in UT-Austin enrollment, and there is no apparent increase in 1998 (the first year of the Top 10% Rule). However, there is a large and sustained increase in UT-Austin enrollment when the Longhorn Opportunity Scholars program is implemented in 1999 relative to the untreated schools, and this effect is largest for the highest-ability students. The pre-treatment trends also are similar to each other for Texas A&M in Figure 4, although here there is no evidence of an enrollment effect due to the Century Scholars program implementation in 2000. For neither university is there a relative increase in enrollment in 1998, which supports the validity of our empirical approach. Furthermore, the lack of an enrollment effect at Texas A&M does not necessarily mean the program was ineffective, because the students being offered the scholarships still paid less and received more services when enrolled.

Because the LOS and CS programs were aimed at the highest-performing students in the targeted schools, students below the top decile were much less likely to be treated by the program. They still could have been influenced by the recruitment efforts or by any spillovers from increasing the number of students enrolling in a flagship university, but students lower in the academic distribution received a much weaker treatment than students higher in the distribution. Figures 3 and 4 highlight this feature of the program. However, students in the 70^{th} to 89^{th} percentiles still are relatively high achieving and thus they are likely to be subject to any school-specific shocks or trends that are correlated with the CS/LOS rollout. Thus, we estimate equation (1) separately by measured ability decile in order to examine whether any program effects dissipate across the ability distribution. If our estimates are picking up the effects of the LOS/CS interventions, then they should be largest for the top deciles students. If they are picking up unobserved shocks or trends that are correlated with the treatments, however, then the effects should be similar across deciles.

Equation (1) is designed to identify intent-to-treat (ITT) parameters. That is, β in equation (1) shows the effect of being exposed to the LOS/CS intervention by being in a treated high school (or by being a high-performing student in a treated high school). From a policy perspective, this is an extremely important parameter for two reasons. First, universities cannot compel takeup. Thus, from the policymaker's standpoint, the ITT is the most relevant parameter. Second, there are significant opportunities for spillovers to students who do not receive the scholarships from the outreach efforts and from any peer effects of the treatment. Thus, the treatment effect on the treated (TOTE) likely understates the overall impact of the program. Nonetheless, the TOTE is a policy parameter of interest here. Unfortunately, however, we cannot calculate the TOTE because we do not have information on which students actually received the scholarships. It also is tempting to use the enrollment effects as a first-stage, but because the program can impact students without influencing enrollment decisions through financial aid and increased services once enrolled, enrollment changes cannot be used to calculate a treatment effect on the treated. We therefore restrict our attention to identifying the ITT, which we argue is the parameter of primary interest as well.

5 Results

Estimates of equation (1) using college enrollment outcomes as the dependent variable are shown in Table 2. In the Table, each cell is a separate regression. Panel A shows results for the 80th to 100th ability percentiles, while panels B-D show results for the top 3 deciles, separately. We examine UT enrollment for LOS schools and TAMU enrollment for CS schools. Consistent with Figure 3, in Panel A we find a positive and statistically significant effect of the LOS program on UT Austin enrollment. We show estimates using all high school graduates (column (i)) as well as all college attendees (column (ii)). Among college attendees, there is a 6.1 percentage point increase in the likelihood of enrolling in UT-Austin. In column (iii), we do not find an extensive margin effect; the LOS program does not impact the likelihood a Texas high school graduate goes to an in-state four year public school. This is an important finding, because it suggests that the program is not inducing top 20% students to attend an in-state school relative to an out-of-state or private college. Due to the lack of an extensive margin effect, we can condition on college attendance when examining college and labor market outcomes. We do so below based on this evidence.

Columns (iv)-(vi) show a similar set of estimates related to the CS program. Unlike the

Longhorn Opportunity Scholars intervention, however, there is no effect of CS exposure on enrollment at the target school (Texas A&M). The estimate among college attendees is positive, but it is small and is not statistically different from zero at conventional levels. These results are similar to those shown in Figure 4: the CS program did not affect enrollment at Texas A&M. Again, we stress that the program could have impacted other outcomes through the scholarship and college services portions of the interventions. The results below provide evidence on whether this was so.

Panel B of Table 2 shows results that use only students in the top decile. As expected, the enrollment effects are larger for UT-Austin. Here, the LOS program led to a 4 percentage point increase in UT enrollment among high school graduates and an 8 percentage point increase among college attendees. This is a 136 percent increase over the mean UT-Austin enrollment rate at these schools (Table 1). There is even less of an overall college enrollment effect among these students, and similar to Panel A there is little evidence of an effect of the CS program on Texas A&M enrollment. In Panels C and D of the table, we see the predicted result that any LOS and CS program effects on enrollment become muted when focusing on students lower in the ability distribution. However, there still is a small enrollment effect for these students, which highlights the fact that this program affects more than just the top students in these schools. That the enrollment effect declines with student measured ability suggests we are not simply picking up unobserved shocks in college enrollment among high-ability students that are correlated with the timing of the treatment implementation.

As Table 2 demonstrates, the LOS program in particular is associated with an increase in flagship enrollment that is not due to shifting of students from private and/or out-of-state schools or into the postsecondary sector more generally. It thus is important to understand from what types of colleges the increased enrollment at UT-Austin is coming. Table 3 presents estimates that can shed some light on the effect of the LOS and CS programs on college type. The table includes estimates of equation (1) in which we use whether the student attended a "Tier 1" university in Texas or any other four-year college in Texas.⁷ Across panels, it is clear that the higher UT-Austin enrollment is due to lower enrollment at much lower-ranked schools.

⁷The Tier 1 schools are those vying for Tier 1 status in Texas: Texas Tech University, The University of Houston, The University of North Texas, The University of Texas at Dallas, The University of Texas at Arlington, The University of Texas at San Antonio, and The University of Texas at El Paso. All other public four-year schools are in the "other" category.

As predicted by the lack of an enrollment effect at Texas A&M, the CS program does not shift students across public schools in Texas. However, the LOS program does, and that they are coming from the lowest-quality public four-year schools suggests that the LOS intervention leads to a large upgrade in college quality for a number of students in treated schools.

Thus far, our results indicate that students in LOS schools experienced a substantial increase in college quality by shifting from lower-resource public schools to UT-Austin, while students in CS schools did not alter their enrollment patterns. The prior literature on the educational returns to college quality suggest that the LOS intervention in particular should lead to higher BA receipt and to students obtaining a BA more quickly (Bound, Lovenheim and Turner 2010, 2012). However, the increased services associated with the CS program also could impact degree receipt and time to degree. In Table 4, we examine these outcomes to assess how the LOS and CS programs affected degree completion. Across all panels, we see little evidence of an effect on BA completion or on the time it takes students to finish. While the BA estimates are positive, they are small and are not statistically significantly different from zero at even the 10% level. Thus, our estimates are suggestive of at most a small effect of these interventions on degree attainment. Furthermore, we find little evidence that first-year GPAs are impacted by these programs. On the whole, students are performing about as well as they did before. This is an interesting finding given the fact that many students were induced to attend the flagship school rather than a lower-quality public university. Our results suggest that the academic performance of these students was not adversely affected by attending a more elite school. This finding is consistent with recent work by Hoxby and Turner (2013), who show many low-income, highability students who would likely be academically successful at more-elite schools do not apply or attend such schools. The results in Table 4 suggest that when these students are induced to attend a high-quality flagship, their educational outcomes do not suffer, as would occur if the students are academically mismatched to the more demanding educational environment.

Although the LOS and CS programs do not affect the pace or level of academic attainment, they do affect students' choice of major. Across both programs, treated students are significantly more likely to major in a STEM field and are less likely to major in humanities (Table 5). This is particularly the case for students above the 80^{th} ability percentile. The STEM effect is large: in Panel B, there is a 32% increase in the likelihood a student declares a STEM major relative to the mean for the LOS program. For the CS program, the percent effect is even larger, at 36%, due to the lower baseline mean. While the STEM effect is not statistically significant in Panel B, it is significant at the 10% level in Panels A and C and is of equal size in Panel B. Among LOS-affected students, there also is an increase in the likelihood of declaring a business major, most notably for students outside the top decile. These increases come at the expense of majoring in humanities and other subjects not listed in the table.

That the CS and LOS programs are leading to more STEM majors is an important finding. There are large socioeconomic gaps in STEM majors as well as a belief among many that the US produces too few STEM majors. The rising wage premium associated with STEM is consistent with this hypothesis. The LOS and CS interventions lead to large relative increases in STEM majors without reducing BA receipt or lengthening time to degree. These students also are completing STEM majors are more-elite schools, which recent evidence suggests is more difficult for students from lower-resource backgrounds (Aucejo, Arcidiacono and Hotz, 2013). It is likely that the effects on majors we find is driven by the increased support and educational services available to LOS and CS students. However, the bundled nature of the intervention does not allow us to test this hypothesis directly.

The large returns to college quality (Brewer, Eide and Ehrenberg 1999; Black and Smith 2004, 2006; Hoekstra 2009; Andrews, Li and Lovenheim 2012) combined with the suggestive evidence of larger returns to more technical majors (Arcidiacono 2004; Altonji, Blom and Meghir 2012; Andrews, Li and Lovenheim forthcoming) suggest that the LOS and CS interventions should raise earnings after college. In Table 6, we examine the effect of these programs on log earnings. Particularly among college graduates, there is a sizable impact of the LOS intervention on earnings, on the order of 6.5%. This effect is larger among the top decile students, at 8.7%. These estimates are consistent with the fact that these students are attending a more elite school and are more likely to major in technical subjects. The fact that the earnings effects are larger among the higher-ability students is again evidence against our estimates being biased from unobserved shocks that affect all high-ability students, since such shocks are unlikely to differentially impact the top decile. Unlike the LOS program, the CS program, is not associated

with larger earnings. In fact, most of the point estimates are negative but not statistically significant. The exception is for the 80^{th} - 90^{th} decile students, who experience sizable (but still not significant) positive returns. Overall, there is evidence that the highest-ability students earn considerably more due to exposure to the LOS program, while the returns to the CS program appear minimal.

6 Conclusion

Persistent increases in the college wage premium combined with sluggish growth in collegiate attainment, particularly among students from low-income backgrounds, make it of first-order importance to understanding what policies can reduce attainment gaps in higher education across the socioeconomic distribution. Given the evidence of the educational and labor market returns to college quality as well as the low enrollment rates among low-income students at elite schools, policies designed to raise enrollment rates of disadvantaged students at highquality colleges have the potential to reduce these disparities. We study an example of such a policy in Texas, the Longhorn Opportunity and Century Scholars programs, which were designed to address the multitude of disadvantages faced by low-income students in higher education: information, tuition subsidies, and academic support once enrolled. These programs were targeted to schools that served large numbers of low-income students and that did not historically send many students to UT-Austin or Texas A&M.

We combine the timing of the implementation of the LOS and CS programs with detailed administrative data from K-12 records, higher education records and earnings as long as workers remain in Texas and attend a public university. We implement a set of difference-in-difference estimators that compare how the enrollment behavior, educational outcomes and earnings of high-ability students change among those attending a treated or control high school when the programs are implemented in 1999 and 2000. While we focus on high-ability students, we also provide evidence of heterogeneous treatment effects across the upper part of the academic achievement distribution.

Our estimates suggest that these types of bundled interventions can better outcomes among targeted students. The LOS program induced many students to enroll in UT-Austin, which was a large quality upgrade relative to the schools they would have attended in the absence of the program. While we find no effect on college graduation, students were much more likely to major in STEM or business, and their earnings increased by 7-9 percent. We also show that the effects are largest among the highest-ability students, but students in the 70th percentile still experience small positive effects of the LOS program. However, we do not observe similar effects related to the Century Scholars treatment. Students in schools treated with this program exhibited no change in enrollment, completion outcomes, or earnings.

The results from this analysis suggest programs like the Longhorn Opportunity Scholarship hold some promise in promoting better postsecondary outcomes among high-ability, low-income students. While the intervention includes a bundle of services, such a bundle would be straightforward for another flagship university in another state to replicate. However, the extent to which our findings are generalizable is called into question by the lack of effects in the CS treatment. A primary question raised by our results is why the programs have such different effects. Understanding these differences and what lessons they have for these types of policies is needed in order to determine how to design an intervention that will have similar effects to the LOS program in other states. We view such an analysis as an important avenue for future research.



Figure 1: Distribution of LOS Treatment Probabilities by Treatment Status



Figure 2: Distribution of CS Treatment Probabilities by Treatment Status

Figure 3: Enrollment Trends by Ability and LOS Treatment Status





Figure 4: Enrollment Trends by Ability and CS Treatment Status

	LOS	Sample	CS S	Sample	
Variable	LOS	Non-LOS	\mathbf{CS}	Non-CS	
TAAS Writing	37.77	38.77	37.97	38.75	
TAAS Reading	45.22	46.50	45.58	46.47	
TAAS Math	56.17	57.78	56.57	57.74	
White	0.133	0.738	0.243	0.729	
Black	0.270	0.033	0.256	0.033	
Hispanic	0.570	0.173	0.454	0.184	
Gifted & Talented	0.484	0.243	0.377	0.477	
At Risk	0.188	0.056	0.132	0.061	
Male	0.443	0.447	0.439	0.448	
Economically Disadvantaged	0.501	0.124	0.408	0.133	
Enroll UT/TAMU	0.059	0.111	0.071	0.110	
Enroll Tier 1	0.136	0.120	0.183	0.115	
Enroll Other	0.771	0.659	0.692	0.667	
STEM Major	0.176	0.199	0.171	0.199	
Business Major	0.052	0.070	0.047	0.070	
Social Science Major	0.034	0.033	0.029	0.033	
Humanities Major	0.063	0.093	0.050	0.095	
Graduate College	0.243	0.340	0.244	0.340	
4-Year Graduate	0.062	0.144	0.072	0.143	
6-Year Graduate	0.185	0.297	0.195	0.297	
Quarterly Earnings	7559	9476	7979	9439	

 Table 1: Means of Analysis Variables

Notes: Authors' tabulations using of college attendees using the linked ERC-THECB data for the 1996-2002 high school graduating cohorts. All means are from the common support sample described in the text.

		Papel A.	80th 100th	Porcontilo S	tudonte		
	L	OS Program	-100	CS Program			
	Enro		Δnv	Enroll Te	Δ ηγ		
	HS Grads	Any Coll	College	HS Grads	Any Coll	College	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	
	0.026**	0.061**	0.015	0.009	0.022	0.008	
Treated	(0.007)	(0.018)	(0.021)	(0.006)	(0.015)	(0.018)	
	()	/	/	()	()		
		Panel B:	$90^{th} - 100^{th}$	Percentile S	tudents		
	\mathbf{L}	OS Program		(CS Program		
	Enro	ll UT	Any	Enroll Te	xas A&M	Any	
	HS Grads	Any Coll.	College	HS Grads	Any Coll.	College	
	(i)	(ii)	(iii)	(iv)	(\mathbf{v})	(vi)	
Troated	0.040^{**}	0.080^{**}	0.005	0.014	0.029	-0.007	
Ileateu	(0.009)	(0.022)	(0.024)	(0.009)	(0.020)	(0.019)	
			ooth ooth				
	т	Panel C:	80°~-89°~	Percentile St	udents		
		US Program					
	Enro		Any	Enroll Te	xas A&M	Any	
	HS Grads	Any Coll.	College	HS Grads	Any Coll.	College	
	(1)	(11)	(111)	(1V)	(v)	(V1)	
Treated	0.013***	0.033*	0.018	0.004	0.009	0.023	
	(0.006)	(0.018)	(0.020)	(0.004)	(0.014)	(0.024)	
		Panel D.	70th 70th	Porcontilo St	udonte		
	L	OS Program	10 -19	i ercentne St	TS Program		
	Enro		Any	Enroll To	voc AleM	Anv	
	HS Crode	Any Coll	Colloro	HS Crode	Any Coll	Colloro	
	(i)	(ii)	(iii)	(iv)	(\mathbf{v})	(vi)	
	0.011**	(11)	0.007	0.006	-0.027	0	
Treated	(0.003)	•	(0.007)	(0.004)	(0.021)	(0.003)	
	(0.000)	•	(0.011)	(0.004)	(0.020)	(0.011)	

Table 2: The Effect of the Longhorn Opportunity and CenturyScholars Programs on College Enrollment

Notes: Authors' estimation of equation (1) in the text using the linked ERC-THECB data for the 1996-2002 high school graduating cohorts. All models include high school and year fixed effects as well as the demographic, high school and test score controls discussed in Section 4 of the text. Standard errors clustered at the high school district level are in parentheses: ** indicates significance at the 5% level and * indicates significance at the 10% level.

	Panel A: 80^{th} - 100^{th} Percentile Students							
	LOS Program			CS Program				
	Enroll	Tier 1	Enroll	Other	Enroll	Tier 1	Enroll Other	
	HS Grads	Any Coll.	HS Grads	Any Coll.	HS Grads	Any Coll.	HS Grads	Any Coll.
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Treated	0.011	-0.010	0.015	-0.046**	-0.005	-0.026	0.005	0.035
Ileated	(0.014)	(0.024)	(0.020)	(0.050)	(0.016)	(0.023)	(0.019)	(0.027)
	Panel B: 90^{th} - 100^{th} Pe				th Percentile	Students		
		LOS P	rogram			CS I	Program	
	Enroll	Tier 1	Enroll	Other	Enroll	Tier 1	Enroll Other	
	HS Grads	Any Coll.	HS Grads	Any Coll.	HS Grads	Any Coll.	HS Grads	Any Coll.
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Treated	0.001	-0.022	-0.049^{**}	-0.074	-0.015	-0.024	0.020	0.046
iicatea	(0.013)	(0.026)	(0.019)	(0.050)	(0.016)	(0.027)	(0.020)	(0.032)
			-	, a seth set	h =	~ .		
		TOGO	Pane	$1 \text{ C: } 80^{\iota n} - 89^{\iota}$	^{<i>n</i>} Percentile	Students		
		LOS P	rogram	0.1		CS I	rogram	
	Enroll	Tier I	Enroll	Other	Enroll	Tier I	Enroll Other	
	HS Grads	Any Coll.	HS Grads	Any Coll.	HS Grads	Any Coll.	HS Grads	Any Coll.
	(1)	(11)	(111)	(1V)	(v)	(V1)	(V11)	(V111)
Treated	(0.018)	(0.012)	-0.022	(0.012)	(0.006)	-0.022	(0.012)	(0.024)
	(0.017)	(0.050)	(0.021)	(0.050)	(0.019)	(0.028)	(0.014)	(0.027)
			Domo	ID. zoth zot	h Dencentile	Studente		
		LOS D	Falle	1 D: 70 -79	Percentile	Students	Ducanom	
	Enroll	Tior 1	Fnroll	Othor	Enroll	Tior 1	Fnroll (Other
	HS Grade	Any Coll	HS Grade	Any Coll	HS Grade	Any Coll	HS Grade	Any Coll
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
	0.011	0.047**	-0.027**	(1)	-0.015	-0.038	0.007	(*****)
Treated	(0.048)	(0.024)	(0.010)		(0.010)	(0.028)	(0.011)	
	(0.010)	(0.021)	(0.010)	•	(0.010)	(0.020)	(•

Table 3: The Effect of the Longhorn Opportunity and Century Scholars Programs on College Quality

Notes: Authors' estimation of equation (1) in the text using the linked ERC-THECB data for the 1996-2002 high school graduating cohorts. Tier 1 colleges are UT-Dallas, University of Houston, UT-Arlington, Texas Tech, University of North Texas, UT-San Antonio and UT-El Paso. "Other" colleges are all other four-year public schools in Texas. All models include high school and year fixed effects as well as the demographic, high school and test score controls discussed in Section 4 of the text. Standard errors clustered at the high school district level are in parentheses: ** indicates significance at the 5% level and * indicates significance at the 10% level.

Table 4: The Effect of the Longhorn	n Opportunity and Century Schol-
ars Programs on College	Completion and First-Year GPA
Among College Attendees	

	Panel A: 80^{th} - 100^{th} Percentile Students							
		LOS I	Program			CS Pr	ogram	
		BA 4	BA 6	1^{st} Yr.		BA 4	BA 6	1^{st} Yr.
	BA	Years	Years	GPA	BA	Years	Years	GPA
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Treated	0.025	0.006	0.027	0.042	0.011	-0.006	0.011	-0.011
ITeateu	(0.022)	(0.010)	(0.029)	(0.038)	(0.020)	(0.010)	(0.023)	(0.044)
				ooth 100th	D (1)	G. 1 .		
		LOGI	Panel B:	90 ^{<i>cm</i>} -100 ^{<i>cm</i>}	Percentile	Students		
		LOSI	'rogram	1 st 1r		CS Pr	ogram	1 st 1r
	DA	BA 4	BA 6	1^{sv} Yr.	DA	BA 4	BA 6	1^{st} Yr.
	BA	Years	Years	GPA	BA	Years	Years	GPA
	(1)	(11)	(111)	(1V)	(v)	(V1)	(V11)	(v111)
Treated	0.022	0.019	0.029	0.059	0.026	0.006	(0.039)	0.020
	(0.028)	(0.020)	(0.045)	(0.069)	(0.025)	(0.019)	(0.027)	(0.048)
			Panel C	$80^{th} - 89^{th}$	Percentile	Students		
		LOS F	rogram			CS Pr	ogram	
		BA 4	BA 6	1^{st} Yr.		BA 4	BA 6	1^{st} Yr.
							3.7	
	BA	Years	Years	GPA	BA	Years	Years	GPA
	BA (i)	Years (ii)	Years (iii)	GPA (iv)	BA (v)	Years (vi)	Years (vii)	GPA (viii)
	BA (i) 0.031	Years (ii) -0.016	Years (iii) 0.026	GPA (iv) -0.003	BA (v) -0.004	Years (vi) -0.016	Years (vii) -0.014	GPA (viii) -0.050
Treated	BA (i) 0.031 (0.025)	Years (ii) -0.016 (0.019)	Years (iii) 0.026 (0.024)	GPA (iv) -0.003 (0.067)	BA (v) -0.004 (0.029)	Years (vi) -0.016 (0.018)	Years (vii) -0.014 (0.031)	GPA (viii) -0.050 (0.068)
Treated	BA (i) 0.031 (0.025)	Years (ii) -0.016 (0.019)	Years (iii) 0.026 (0.024)	GPA (iv) -0.003 (0.067)	$ \begin{array}{c} BA \\ (v) \\ -0.004 \\ (0.029) \\ \end{array} $	Years (vi) -0.016 (0.018)	Years (vii) -0.014 (0.031)	GPA (viii) -0.050 (0.068)
Treated	$\begin{array}{c} \text{BA} \\ (\text{i}) \\ \hline 0.031 \\ (0.025) \end{array}$	Years (ii) -0.016 (0.019)	Years (iii) 0.026 (0.024) Panel D	GPA (iv) -0.003 (0.067) : 70^{th} - 79^{th}	$\begin{array}{c} \text{BA} \\ (v) \\ \hline -0.004 \\ (0.029) \end{array}$ Percentile	Years (vi) -0.016 (0.018) Students	Years (vii) -0.014 (0.031)	GPA (viii) -0.050 (0.068)
Treated	$\begin{array}{c} \text{BA} \\ (i) \\ \hline 0.031 \\ (0.025) \end{array}$	Years (ii) -0.016 (0.019) LOS H	Years (iii) 0.026 (0.024) Panel D Program	$\begin{array}{c} \text{GPA} \\ (\text{iv}) \\ \hline -0.003 \\ (0.067) \\ \vdots \ 70^{th} \text{-} 79^{th} \\ \hline 1 \text{ st} \ V \end{array}$	$\frac{BA}{(v)}$ -0.004 (0.029) Percentile	Years (vi) -0.016 (0.018) Students CS Pr	Years (vii) -0.014 (0.031)	GPA (viii) -0.050 (0.068)
Treated	BA (i) 0.031 (0.025)	Years (ii) -0.016 (0.019) LOS F BA 4	Years (iii) 0.026 (0.024) Panel D Program BA 6	$\begin{array}{c} \text{GPA} \\ (\text{iv}) \\ \hline -0.003 \\ (0.067) \\ \vdots \ 70^{th} \text{-} 79^{th} \\ 1^{st} \ \text{Yr.} \\ \hline \end{array}$	$\begin{array}{c} \text{BA} \\ (v) \\ \hline -0.004 \\ (0.029) \end{array}$ Percentile	Years (vi) -0.016 (0.018) Students CS Pr BA 4	Years (vii) -0.014 (0.031) ogram BA 6	GPA (viii) -0.050 (0.068)
Treated	BA (i) 0.031 (0.025) BA	Years (ii) -0.016 (0.019) LOS F BA 4 Years (ii)	Years (iii) 0.026 (0.024) Panel D Program BA 6 Years	GPA (iv) -0.003 (0.067) : 70^{th} - 79^{th} 1 st Yr. GPA GPA	$\begin{array}{c} BA\\ (v)\\\hline -0.004\\ (0.029)\\\end{array}$ Percentile BA	Years (vi) -0.016 (0.018) Students CS Pr BA 4 Years	Years (vii) -0.014 (0.031) ogram BA 6 Years	GPA (viii) -0.050 (0.068) 1^{st} Yr. GPA (
Treated	BA (i) 0.031 (0.025) BA (i)	Years (ii) -0.016 (0.019) LOS F BA 4 Years (ii)	Years (iii) 0.026 (0.024) Panel D Program BA 6 Years (iii)	$\begin{array}{c} \text{GPA} \\ (\text{iv}) \\ \hline -0.003 \\ (0.067) \\ \hline \\ : 70^{th} - 79^{th} \\ 1^{st} \text{ Yr.} \\ \text{GPA} \\ (\text{iv}) \\ \hline \end{array}$	$BA \\ (v) \\ -0.004 \\ (0.029) \\ Percentile \\ BA \\ (v) \\ 0.022 \\ Parcel ($	Years (vi) -0.016 (0.018) Students CS Pr BA 4 Years (vi)	Years (vii) -0.014 (0.031) ogram BA 6 Years (vii)	GPA (viii) -0.050 (0.068) 1 st Yr. GPA (viii)
Treated	BA (i) 0.031 (0.025) BA (i) -0.001	Years (ii) -0.016 (0.019) LOS F BA 4 Years (ii) 0.008 (0.004)	Years (iii) 0.026 (0.024) Panel D Program BA 6 Years (iii) 0.033 (2.032)	$\begin{array}{c} \text{GPA} \\ (\text{iv}) \\ \hline -0.003 \\ (0.067) \\ \hline \end{array}$ $\begin{array}{c} \text{:} 70^{th}\text{-}79^{th} \\ 1^{st} \text{ Yr.} \\ \text{GPA} \\ (\text{iv}) \\ \hline 0.129^{**} \\ \hline \end{array}$	$\begin{array}{c} BA \\ (v) \\ \hline -0.004 \\ (0.029) \end{array}$ Percentile $\begin{array}{c} BA \\ (v) \\ \hline -0.018 \\ (0.029) \end{array}$	Years (vi) -0.016 (0.018) Students CS Pr BA 4 Years (vi) -0.009 (0.009)	Years (vii) -0.014 (0.031) ogram BA 6 Years (vii) -0.035 (0.035)	GPA (viii) -0.050 (0.068) 1 st Yr. GPA (viii) -0.089*

Notes: Authors' estimation of equation (1) in the text using the linked ERC-THECB data for the 1996-2002 high school graduating cohorts. All models include high school and year fixed effects as well as the demographic, high school and test score controls discussed in Section 4 of the text. Standard errors clustered at the high school district level are in parentheses: ** indicates significance at the 5% level and * indicates significance at the 10% level.

			Panel A:	$80^{th}-100^{th}$	Percentile	Students		
		LOS Pi	rogram			CS Pr	ogram	
			Social	Humani-			Social	Humani-
	STEM	Business	Science	ties	STEM	Business	Science	ties
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Trastad	0.033^{**}	0.022^{*}	0.006	-0.018	0.028^{*}	-0.005	-0.015	-0.014
Ileated	(0.015)	(0.012)	(0.011)	(0.016)	(0.015)	(0.009)	(0.016)	(0.009)
			Derest D	ooth 100th	D	Cturd and a		
		LOG D.	Panel B:	90**-100***	Percentile	Students		
		LOS PI	Secial	II		C5 Pr	Secial	II
	STEM	Ducinoca	Social	numani-	STEM	Ducinoca	Social	numani-
		Dusiliess (;;)	(iii)	(irr)		Dusiliess (i)	(ii)	(wiii)
	(1)	0.012	0.000	0.017	()	0.018	0.012	0.012
Treated	(0.030)	(0.013)	(0.015)	-0.017	(0.020)	-0.018	(0.012)	-0.013
	(0.022)	(0.019)	(0.013)	(0.014)	(0.020)	(0.013)	(0.021)	(0.012)
			Panel C	$: 80^{th} - 89^{th}$	Percentile	Students		
		LOS Pi	ogram			CS Pr	ogram	
			Social	Humani-			Social	Humani-
	STEM	Business	Science	ties	STEM	Business	Science	ties
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
	-0.002	0.096	0.010	0.040				
Irootod	-0.002	0.020	0.010	-0.019	0.034^{*}	0.017	-0.014	-0.020*
Treated	(0.016)	(0.026)	(0.016) (0.014)	-0.019 (0.026)	0.034^{*} (0.019)	0.017 (0.016)	-0.014 (0.013)	-0.020^{*} (0.012)
Treated	(0.016)	(0.026) (0.027)	(0.016 (0.014)	-0.019 (0.026)	0.034^{*} (0.019)	$\begin{array}{c} 0.017 \\ (0.016) \end{array}$	-0.014 (0.013)	-0.020^{*} (0.012)
Treated	(0.016)	0.026 (0.027)	0.016 (0.014) Panel D	-0.019 (0.026) $: 70^{th} - 79^{th}$	$\begin{array}{c} 0.034^{*} \\ (0.019) \end{array}$ Percentile	0.017 (0.016) Students	-0.014 (0.013)	-0.020* (0.012)
	(0.016)	0.020 (0.027) LOS Pr	(0.016 (0.014) Panel D	$\begin{array}{c} -0.019 \\ (0.026) \end{array}$ $\begin{array}{c} : \ 70^{th} - 79^{th} \end{array}$	$\begin{array}{c} 0.034^{*} \\ (0.019) \end{array}$ Percentile	$0.017 \\ (0.016)$ Students CS Pr	-0.014 (0.013)	-0.020* (0.012)
	(0.016)	0.026 (0.027) LOS Pr	0.016 (0.014) Panel D cogram Social	-0.019 (0.026) : 70^{th} - 79^{th} Humani-	0.034* (0.019) Percentile	0.017 (0.016) Students CS Pr	-0.014 (0.013) ogram Social	-0.020* (0.012) Humani-
	(0.016)	LOS Pr Business	0.016 (0.014) Panel D cogram Social Science	-0.019 (0.026) :: $70^{th} - 79^{th}$ Humani- ties	0.034^{*} (0.019) Percentile STEM	0.017 (0.016) Students CS Pr Business	-0.014 (0.013) ogram Social Science	-0.020* (0.012) Humani- ties
	(0.016) STEM (i)	LOS Pr Business (ii)	0.016 (0.014) Panel D cogram Social Science (iii)	-0.019 (0.026) :: 70^{th} -79 th Humani- ties (iv)	$\begin{array}{c} 0.034^{*} \\ (0.019) \end{array}$ Percentile $\begin{array}{c} \text{STEM} \\ (v) \\ \end{array}$	$\begin{array}{c} 0.017\\ (0.016) \end{array}$ Students CS Pr Business (vi)	-0.014 (0.013) ogram Social Science (vii)	-0.020* (0.012) Humani- ties (viii)
Treated	(0.016) STEM (i) -0.001	(0.020 (0.027) LOS Pr Business (ii) 0.036**	0.016 (0.014) Panel D cogram Social Science (iii) 0.008 (0.016)	$\begin{array}{c} -0.019 \\ (0.026) \end{array}$:: $70^{th} - 79^{th} \\ \text{Humani-ties} \\ (iv) \\ -0.009 \\ (0.017) \end{array}$	0.034* (0.019) Percentile STEM (v) -0.024 (0.014)	0.017 (0.016) Students CS Pr Business (vi) -0.004	-0.014 (0.013) ogram Social Science (vii) 0.017 (0.017)	-0.020* (0.012) Humani- ties (viii) -0.014 (0.014)

Table 5: The Effect of the Longhorn Opportunity and Century Scholars Programs on College Majors

Notes: Authors' estimation of equation (1) in the text using the linked ERC-THECB data for the 1996-2002 high school graduating cohorts. All models include high school and year fixed effects as well as the demographic, high school and test score controls discussed in Section 4 of the text. Standard errors clustered at the high school district level are in parentheses: ** indicates significance at the 5% level and * indicates significance at the 10% level.

Table 6: The Effect of the Longhorn Opportunity and Century Scholars Programs on Log Earnings

	Panel A:	$80^{th} - 100^{th}$	Percentile Students				
	LOS P	rogram	CS Pr	ogram			
	Any	College	Any	College			
	College	Grad	College	Grad			
	(i)	(ii)	(iii)	(iv)			
Treated	0.063**	0.065^{*}	-0.003	-0.028			
Treated	(0.026)	(0.038)	(0.033)	(0.038)			
	Panel B:	$90^{tn} - 100^{tn}$	Percentile	Students			
	LOS Pi	rogram	CS Pr	ogram			
	Any	College	Any	College			
	College	Grad	College	Grad			
	(i)	(ii)	(iii)	(iv)			
Troated	0.016	0.087^{*}	-0.038	-0.057			
ITeateu	(0.060)	(0.055)	(0.056)	(0.049)			
	Panel C:	80 th -80 th	Percentile	Students			
	I allel C.	-09 rogram	CS Pr	ogram			
	Any	Colloro	Any	Colloro			
	Colloro	Conege	Colloro	Conege			
	(i)	(ii)	(iii)	(in)			
	(1)	(11)	0.055	(10)			
Treated	(0.099)	(0.018)	(0.035)	(0.023)			
	(0.008)	(0.052)	(0.040)	(0.052)			
	Panel D.	$70^{th} - 70^{th}$	Percentile	Students			
	LOS P	rogram	CS Program				
	Any	College	Any	College			
	College	Grad	College	Grad			
	(i)	(ii)	(iii)	(iv)			
	0.051	0.003	-0.031	-0.085			
Treated	(0.040)	(0.054)	(0.047)	(0.067)			
	. ,	. /	. /	. /			

Notes: Authors' estimation of equation (1) in the text using the linked ERC-THECB data for the 1996-2002 high school graduating cohorts. Earnings are measured 6 years after college exit. All models include high school and year fixed effects as well as the demographic, high school and test score controls discussed in Section 4 of the text. Standard errors clustered at the high school district level are in parentheses: ** indicates significance at the 5% level and * indicates significance at the 10% level.