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

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1 Introduction

Structural changes in the US economy over the past several decades have led to historically high demand for skilled labor (Autor 2014; Autor, Katz and Kearney 2008). 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, despite the high returns to college, we observe sluggish increases in postsecondary attainment, particularly among students from low-income backgrounds (Lovenheim and Reynolds 2013; Bailey and Dynarski 2011; Bound, Lovenheim and Turner 2010). For example, 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 from 31 percentage points to 45 percentage points during this period. 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). 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 (Bailey and Dynarski, 2011; Carneiro and Heckman, 2002). 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 (Hoxby and Avery 2013; Lovenheim and Reynolds 2013). In the NLSY97, only 2% of low-income 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 (Cohodes and Goodman 2014; Bound, Lovenheim and Turner 2010), time to degree (Bound, Lovenheim and Turner 2012), and subsequent earnings in the labor market (Andrews, Li and Lovenheim (2016); Hoekstra 2009; Black and Smith 2006, 2004; Brewer, Eide and Ehrenberg 1999).[2] A representative estimate from Hoekstra (2009) shows that attending the public flagship university leads to a 24% increase in earnings. 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 is necessary to understand why such gaps exist. There are five 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 (Cameron and Taber 2004; Carneiro and Heckman, 2002). 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 Avery 2013; Hoxby and Turner 2013). A third explanation is that low-income students are affected by both academic and social "mismatch" when they enroll in higher-quality schools. 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, 2014; Arcidiacono et al., 2011; Dillon and Smith 2013). Fourth, the complexity of the financial aid application may prevent students from applying for aid, and thus attending more expensive colleges (Dynarski and Scott-Clayton, 2013, 2008, 2006; Bettinger, et al., 2012). Finally, lower family resources may prevent families from investing in a higher-quality school (Lovenheim and Reynolds 2013).

[1] This is not just a reflection of the differences in enrollment. Among those who enroll in any college, 3.7% of low-income students enroll in a public flagship university, and 18.4% of high income students enroll in this school type.
[2] On the other hand, Dale and Krueger (2013, 2002) find little impact of college quality on earnings.

Prior research has found at most modest effects of policies designed to overcome one of these disadvantages on student outcomes. One reason for these modest effects is that there are interactive effects of various forms of student disadvantage, thus, making it necessary for programs to address several of these barriers simultaneously to effectively support postsecondary education among students from low-income backgrounds. In this paper, we present the first analysis in the literature of a set of interventions in Texas aimed at addressing the set of disadvantages faced by low-income students. The Longhorn Opportunity Scholarship (LOS) program at the 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, respectively.[3] The programs targeted high schools that served low-income students and traditionally sent few students to these institutions. Together, the LOS and CS programs were implemented in 110 high schools in Texas. While entirely independent, the programs offer a similar suite of interventions that attempt to overcome the multiple disadvantages faced by low-income students in the higher education system: lack of information about college quality, lower academic preparation for college, and lower financial resources. The programs contain extensive outreach and recruiting, with students going back to their high schools to share their experiences and university staff providing information sessions. 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). They also have the potential to generate "spillover" effects by inducing students in targeted schools who are not offered scholarships to attend the flagships or other higher quality institutions. Program participants also are provided scholarships to help alleviate financial strain.[4] Once enrolled, the LOS and CS programs include multiple academic support services for students as well as policies to help foster cohesion among the students. These services can help overcome social and academic mismatch. Critically, the programs did not provide students with help in the

[3] Details on the Century Scholars program can be found at https://scholarships.tamu.edu/Scholarship-Programs/Century-Scholars. The Longhorn Scholars Program has since been discontinued though a description can be found in internet archives at https://web.archive.org/web/20030622194253/http://www.utexas.edu/student/finaid/scholarships/los_index.html.

[4] 4 For example, CS scholars currently receive $5,000 per year for four years. Assuming scholarship amounts did not change, this covered most of the $5,639 cost for tuition and fees in 2004. Similarly, LOS scholars in 2002 received $4,000 per year from the program. Tuition at UT-Austin in 2005 was $7,286.

admissions process; all students who were induced to attend UT-Austin and Texas A&M were academically qualified to attend those schools.

We use administrative data from the State of Texas that links K-12 education records with higher education enrollment and performance information as well as earnings records from the Texas unemployment insurance system. Using these data, we exploit the timing differences in the roll-out of the LOS/CS programs to identify their effects on higher education outcomes and post-college 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. Our analysis focuses on high-achieving students, who we define as the top 30% of students within each high school on this performance index. We then estimate difference-in-difference models in which we compare changes in outcomes among high-ability students in treated schools to changes for high-ability students in untreated schools when the LOS/CS 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 "trimmed common support" group using the rich information we have about the demographics and college-sending patterns of each high school in Texas prior to 1999 combined with information on the criteria UT-Austin and Texas A&M say they used to select the schools. Our analysis sample consists 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 find little evidence of demographic shifts among students due to the treatments.

The results of our analysis suggest that the LOS and CS programs had large effects on the likelihood students enrolled in a flagship, with somewhat larger impacts for the LOS program. Enrollment at UT-Austin increases by 58% and Texas A&M enrollment increases by 49% among high achieving college attendees from treated schools relative to those in observationally similar untreated schools. These enrollment increases came from both reduced enrollment at two- year schools and less-selective four-year universities, which suggests these treatments increased college quality substantially for students. Further, we find evidence that many students switched from two-year to four-year schools other than UT-Austin and TAMU, and thus the programs generated spillover effects to students who did not attend the flagships. Notably, we find little impact on the likelihood of enrolling in any public school in Texas, which supports our decision to focus on a sample of college attendees. Moreover, these targeted recruitment programs were designed to incentivize students who would have gone to college to consider the flagships; it was not designed to impact students on the margin of going to college.

Our estimates consistently indicate that students from schools treated by the LOS program benefit from large increases in a range of life outcomes. Exposure to the LOS program increases the likelihood of high-achieving college attendees graduating with a four-year degree in six years by 3.5 percentage points. We also show that the LOS program did not lead high achieving students to major in less-technical subjects. In particular, there is no change in STEM majoring. These findings suggest that the extra academic support services were sufficient to overcome any academic mismatch effects. The LOS program increased earnings substantially: high-achieving college attendees in LOS high schools experienced a 4% increase in earnings 10+ years post-high school. Women experienced a larger increase in enrollment at UT, while the earnings effects are much larger among men. Male earnings increased by 7.4% 10-years after high school due to the LOS program.

For the CS program, we do not find any statistically significant effects on 6-year college graduation, although the point estimates are negative and there is some evidence of longer time to degree. We also find little evidence that the CS program increased earnings. While the enrollment effects are largest among men, male earnings do not increase as a result of the CS program. It is somewhat surprising that the CS and LOS programs have such different effects. We argue this difference is likely driven by two factors. First, the LOS program led to a much larger change in school quality because it caused students to switch from two-year schools to UT-Austin. The enrollment effects of the CS program were driven predominantly by students who otherwise would have attended less-selective four-year schools. Second, the LOS program was larger in scope and the academic support services were more intensive. All students attending UT-Austin from an LOS school received the academic support services, in contrast to the CS program that limited services to scholarship recipients. The LOS support services were much more academically-focused than in CS as well.

Our analysis cannot determine how much of the impacts we find are due to the change in school quality or the provision of supports and financial aid. We interpret our estimates as telling us whether a program that provides a full package of academic and social supports for low-income students who otherwise would not attend the flagships can successfully improve educational and labor market outcomes. Our results suggest that, if the program induces these "marginal" students to attend, they are more likely to succeed than at lower-quality institutions where they would, arguably, get less support. This finding provides evidence that attending a higher-quality school can generate substantial economic improvements for low-income and relatively high-ability students, provided they receive sufficient assistance while enrolled to offset their lack of preparation. Second, the LOS and CS programs are easily replicable beyond Texas. The pillars of the program - targeted recruitment, mentoring, special classes and financial assistance - are within the tool sets of flagship institutions in any state. The different effects of the LOS and CS programs, however, highlight the importance of understanding how the design features of these types of programs translate into student outcomes.

2 The Longhorn Opportunity and Century Scholars Programs

The Longhorn Opportunity Scholars and Century Scholars Programs were first implemented in 1999 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.[5] 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, during the period we study students ranked outside the top 10 percent of their class at high schools serving low-income students were very 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 colleges fell dramatically

[5] The ranking is determined by each high school separately, but typically is based on student grade point average.

(Kain, O'Brien and Jargowsky 2005). In response to these declines, the LOS and CS programs were developed to try to recruit students from low-SES backgrounds to the state flagships and to support their academic success whole enrolled. The LOS program targeted 70 high schools in Houston, Dallas, San Antonio, El Paso, Beaumont and Laredo that had high shares of low-income and minority students and few prior applicants to UT-Austin. The CS program similarly targeted 70 low-income schools in Houston, Dallas and San Antonio with few prior applicants to Texas A&M. There was some overlap between the two programs, with students from several high schools being eligible for both programs. Over 600 students are admitted to Texas A&M and UT-Austin under these programs each year. The high schools targeted by these programs are mostly located in the large urban centers in the state and hence the focus of these programs is on the urban poor.

Though administered by different universities, the two programs are 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.

while Texas A&M describes the century scholar program as follows:

> The Century Scholars Program is more than just a monetary award; it offers students access to a first-rate education and programs that prepare students to become state, national, and world leaders. The Century Scholars Program offers academic support and hands-on contact with advisors, mentorships with faculty, freshman seminar course that focuses on academic and personal success, campus involvement, community engagement, and civic responsibility, and opportunities to serve as a Century Scholars Ambassadors. Century Scholars receive professional training in public speaking, interviewing, and presentation skills. The students may return to their former high schools to share their experiences and help continue the Texas A&M tradition of excellence. These skills are highly valued by any future employer, professional school, or graduate program.[6]

There are several consistent properties across the programs that make them worth investigating together:

[6] Reprinted from https://scholarships.tamu.edu/century_scholars.aspx.

1. Most students are given additional financial aid if they enroll in the flagship school.
2. There is an active recruiting effort made at targeted 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. Recruitment occurs through both university staff and students who have gone through the programs. These students thus could address issues pertaining to academic and social mismatch directly.
3. Once enrolled, the LOS and CS students are given access to academic support services.

Furthermore, the LOS and CS programs establish formal enrolled student and alumni communities that offer support, guidance, and resources to low-income students.

Despite these similarities, there are two substantive differences across the programs that could lead them to have different effects on student outcomes. The first is the scope of the programs. For LOS, initially the plan was to only offer services to students who received financial support from the program, restricted to a maximum number of scholarships per high school. However, in practice they allowed all enrolled students from targeted schools to receive program services (but not the scholarship money). Furthermore, an administrator of the LOS program informed us that students who did not qualify for LOS scholarship money directly usually qualified for other scholarships. For CS, students from targeted high schools only receive the academic support services if they are awarded the scholarship money. Students also must maintain a minimum GPA in order to keep their CS fellowship. That more students received academic support services under the LOS program suggests that the LOS program effects could be larger than any CS effects.

The second difference between the programs is in the type of academic support services offered. Under the LOS program, students were offered extensive support, including guaranteed spaces in residence halls, free tutoring, and peer mentoring. In addition, the LOS program had students enroll in small sections of core classes, such as Introductory Chemistry and Economics, exclusively for LOS students. Instructors for these sections taught the same content but could tailor the instruction to recognize that the students were coming from disadvantaged backgrounds and likely had a lower baseline set of skills than the average first-year student. The academic support services in the CS program were much less extensive and entailed faculty mentoring (in lieu of peer mentoring) as well as professional training in public speaking, interviewing and presentation skills. The different types of academic services offered under the LOS and CS programs could plausibly generate different impacts of the programs.

These interventions could influence several important postsecondary outcomes and earnings in ambiguous directions that point to the need for an empirical analysis. In particular, 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., Andrews, Li and Lovenheim 2016; Bound, Lovenheim and Turner 2010; Hoekstra 2009; Black and Smith 2004, 2006; Brewer, Eide and Ehrenberg 1999).[7] 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 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. Outside of the flagships, the other options for these students typically are 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. We examine the enrollment effects of these programs directly below using richer and more comprehensive data on enrollment than were used in this prior work. Our results suggest a more nuanced story that differs across LOS and CS treatments.

Increased flagship enrollment driven by the LOS and CS programs likely led to a substantial increase in college quality for treated students. To provide some context, USNews and World Report ranks UT-Austin as the 58th and TAMU as the 68th best national universities. The next highest public institutions in the state are UT-Dallas ranked 145, Texas Tech ranked 156, and University of Houston at 186. Table 1 provides information on selectivity and resources of Texas

[7] Another potential mechanism is that increased financial support provided by the programs may help students progress through the higher education system by relaxing credit constraints. However, there is very little evidence that credit constraints or financial aid have more than a modest impact on students' paths through college (e.g., Johnson 2013; Stinebrickner and Stinebrickner 2008; Bettinger 2004).

public institutions. The table compares both The University of Texas at Austin and Texas A&M to "emerging research universities" (ERUs) and other four-year schools.[8] The means in the table show that both flagships are substantially more selective than the ERUs and other 4-year institutions as measured by SAT scores of incoming students. The flagships also spend substantially more per-student, have lower student-faculty ratios, higher graduation rates and higher retention rates.

Table 1: Average Characteristics of Public 4-Year Institutions in Texas

School Characteristic	UT-Austin	Texas A&M	Emerging Research	Other 4-Year
Max USNews Ranking	53	68	145	NA
Graduation Rate	0.79	0.79	0.47	0.37
Retention Rate	0.94	0.91	0.76	0.64
Avg Full Prof Salary	$137,871	$128,367	$122,131	$87,352
UG Student/Faculty FTE	14.0	17.0	22.6	21.2
Instr Exp per UG Student	$19,320	$13,421	$7,880	$6,491
Acad Support Exp per UG Student	$5,633	$3,853	$2,865	$2,229
Student Service Exp per UG Student	$1,761	$1,914	$1,572	$1,387
SAT Math 75th Percentile	710	630	588	519
SAT Reading 75th Percentile	680	610	553	537
Institutions	1	1	7	21

Means from Integrated Postsecondary Education Data System (IPEDS) provided by the US Department of Education. Data is from 2013-14 except expenditure data which is from 2012-13 school year. "Emerging research" universities are institutions declared by state of Texas to be eligible for special funds to increase research activity. These include UT-Dallas, UT-Arlington, UT-San Antonio, UT-El Paso, Texas Tech and University of Houston.

The ambiguity in predicted impacts of the programs arises because of the potential countervailing effects of college quality effects and the potential for academic "mismatch" that can occur when students of lower academic preparation are brought into a more demanding educational environment.[9] 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 under- prepared for the rigors of a flagship university. Indeed, this is the reason that the

[8] The ERU designation is for institutions that are eligible for a special pool of state funds for increasing research output. These are sometimes called "Tier1" schools as part of the goal of the program is to increase the schools' research and academic reputations to the top tier of public universities in the US. For our purposes, this is a useful distinction as it provides a "second tier" of public institutions below the flagships but with better resources than other institutions. This group includes University of Texas at Arlington, UT at El Paso, UT at Dallas, UT at San Antonio, Texas Tech University, University of North Texas, and the University of Houston.
[9] See Arcidiacono and Lovenheim (2015) for an overview of the "quality-fit" tradeoff in higher education.

programs offer academic support services. 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.

As a result of these conflicting theoretical impacts, a priori, it is not possible to determine the net effect of the targeted recruitment programs. The success or failure of these programs must be determined empirically.

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.[10]

In 1992, the TEA began collecting administrative data on all students enrolled in public schools in Texas. These data contain students' grade level, 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, 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 11th 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

[10] The data used in this project are virtually identical to those used in Andrews, Li and Lovenheim (2014, forthcoming).

Texas redesigned the high school exams. We 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. Hence, we focus our analysis on the top of the within-school achievement distribution. We proxy for students' academic ability with the first principal component of a factor analysis model that includes 11th 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 11th grade cohort. Andrews, Li and Lovenheim (2016) present evidence that the within-high school rank on these exams is highly correlated with whether one is admitted to a flagship university through the Top 10% Rule,[11] 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 in Texas, with the exception of those working for the Federal government or US Postal Service. A core difficulty with measuring earnings is that earnings early in one's career may not be indicative of permanent earnings (Haider and Solon 2006). Because the LOS and CS programs are relatively recent, we are constrained in the length of the post-high school time period over which we can observe earnings. We construct two measures of earnings to provide insight into the role of timing. The first is average log quarterly earnings in all quarters in which earnings are observed six or more years post-high school graduation. The second uses all earnings observations that are at least ten years after high school graduation.

[11] They 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.

To construct our earnings measure, we follow the procedure use a method similar to the method used in Andrews, Li, and Lovenheim (2016). Our earnings measures can be interpreted as individual-specific average earnings that have been adjusted to account for year and quarter.

A core limitation of 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. 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.

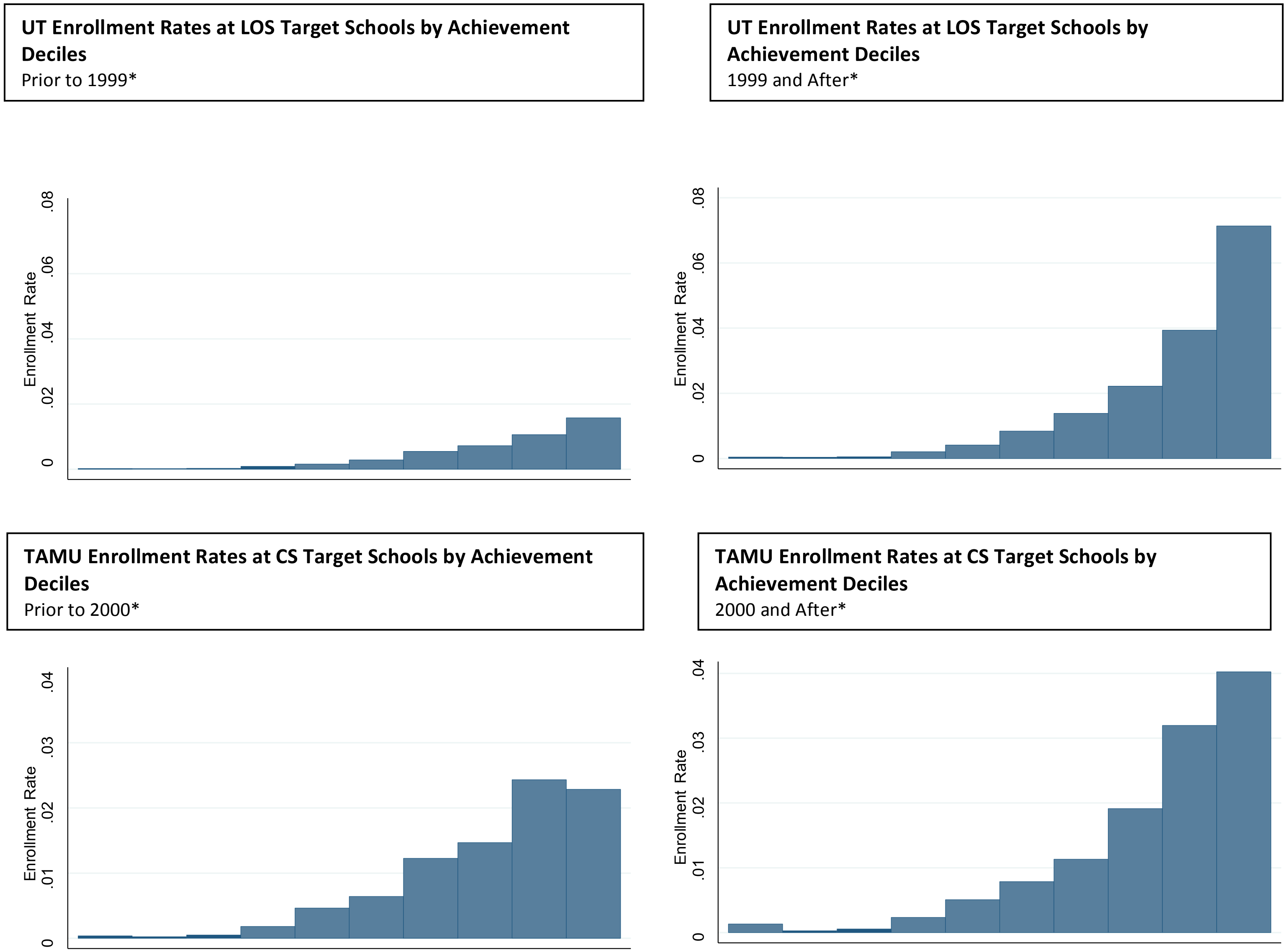
We address this potential bias in a few ways. First, we note that in the wider population affected by LOS and CS, very few students attend out-of-state or private schools. Indeed, in Texas overall only 18% of first-time 4-year college enrollees who were seniors in high school the prior year attend an 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, and most importantly, we estimate whether the LOS and CS programs have any impact on attending an in-state public school. Thus, the treatment effect is relative to not attending college, attending a 2-year college, attending a private college, or attending an out-of-state college. As we show below, we find little indication that treated students were more likely to be observed in the data. For the programs to induce private/out-of-state students to move to the flagships, there would have to be an offsetting increase in 2-year school or non-college attendance by other treated students, which is very unlikely.

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 Communities 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 (2016) 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. Given this context, we operate primarily under the assumption that any attrition in the earnings data is unrelated to whether one is treated by the CS/LOS program. In support of this assumption, we show that the LOS/CS treatment is uncorrelated with being missing from the earnings data.

4 Methodology

We estimate the effect of the LOS/CS programs on student college choice, academic outcomes and labor market earnings via difference-in-differences models in which we compare changes in outcomes when students are treated to changes among students in schools that are not treated. The LOS and CS programs are most likely to affect higher-ability students, so we restrict the analysis to students who are in the top 30% of their high school class in a given year according to the ability index discussed in Section 2. We focus on the top 30% of students rather than the top 10% because our ability index is an imperfect proxy for class rank. The top 30% of students accurately captures the large majority of groups that are potentially eligible for enrollment in a state flagship from schools in our sample. This is highlighted in Figure 1 which shows enrollment in UT-Austin from LOS targeted schools and in TAMU from CS targeted schools both before and after program implementation. The figure shows that the vast majority of enrollees in the flagships are in the top three deciles of the achievement distribution in those schools. It is also worth noting that the figures show the drastic increase in flagship enrollment from these schools after implementation of the programs. Particularly striking are the increases in the top decile of students which jump from 1.5% to 7% for UT and from a little over 2% to 4% for TAMU

Figure 1: Flagship Enrollment in LOS/CS Schools Prior to Program Start by Achievement Deciles



We estimate a difference-in-difference model that allows us to identify intention-to-treat effects of the LOS/CS programs:

$$Y_{ij\,t} = \alpha + \beta_1 \text{ LOS School}_{j\,t} + \beta_2 \text{ C S School}_{j\,t} + X_{ij\,t}\Gamma + \varphi_j + \theta_t + \varepsilon_{ij\,t}, \qquad (1)$$

where $Y_{ij\,t}$ is either an educational or labor market outcome for student i 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). The main treatment variables, LOS School and C S School, are indicators for whether the graduating cohort in school j and year t is eligible for the LOS or CS programs, respectively.

In equation (1), the parameters of interest are β_1 and β_2, which show how outcomes change among top 30% students in LOS/CS schools relative to top 30% students in untreated schools when the programs are implemented. The main assumption under which β_1 and β_2 are 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.

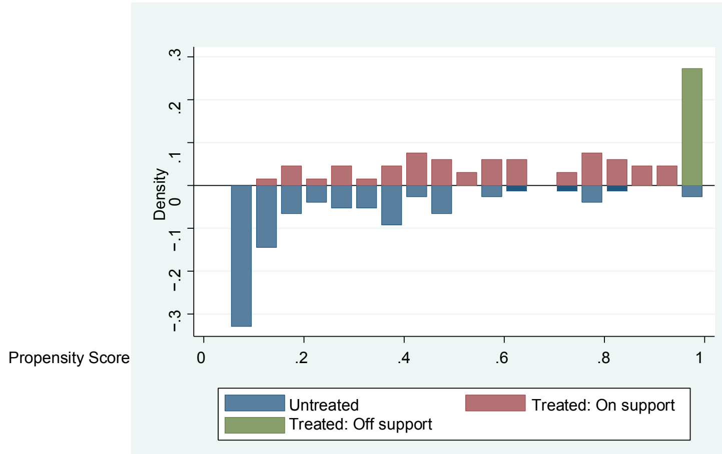
In order to make this identification assumption more likely to hold, we restrict our analysis to the set of high schools with common support amongst key observable characteristics that determine treatment, in particular low prior flagship enrollment and low income levels. Using data from the 1997-1998 school year (which is before either program was implemented but after implementation of the Top 10% rule), we estimate a probit regression of the likelihood that a high school becomes an LOS or CS school as a function of the quadratic polynomials in the following school-level characteristics: percent enrolling in UT-Austin or Texas A&M, percent taking the SAT or ACT, percent scoring above either 24 on the ACT or 1120 on the math and verbal sections of the SAT (“college ready”), percent economically disadvantaged, percent black, and percent Hispanic. The first three variables account for under-representation at the flagship by measuring how many students are potentially eligible to attend the flagships and how many actually enroll. The last three variables account for the socioeconomic makeup of students in the schools. We estimate this model separately for LOS and CS treatments. We use this model to calculate a propensity score that shows the likelihood a given high school is treated by each program.

In order to generate a common support sample that is likely to exhibit similar counterfactual trends, we first drop all treated schools with a predicted treatment likelihood higher than the highest control school and then restrict control schools to have propensity scores greater than 0.05 (there are not treated schools with propensity scores that low). We construct this trimmed analysis sample separately for the LOS treatment and for the CS treatment and then pool the two analytic samples together to estimate equation (1). Thus, our trimmed common support sample is comprised of a set of schools that have broadly similar likelihoods of being treated based on their observable characteristics.[12] Figure 2 shows the propensity score densities for treated and control schools by likelihood bin, separately for UT-Austin (LOS) and Texas A&M (CS), respectively. In the figure, we have excluded the large mass of control schools with propensity scores below 0.05 as they dominate the graph if included. Ostensibly, we are excluding a large set of high schools that serve higher-SES students and thus that have no probability of being selected for the LOS/CS treatments. As the figures demonstrate, there also are several treated schools that have a predicted likelihood of treatment that is greater than any control school. These schools are shown in green; they are excluded from the main analysis because they are sufficiently different from any comparison school that it makes the identification assumptions underlying our estimator more difficult to support. We refer to the sample that excludes these very high and low treatment likelihood schools as the "trimmed common support sample."

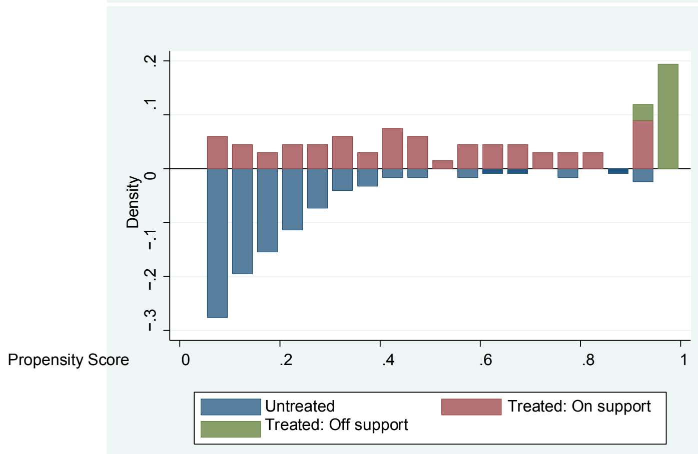
[12] We have also conducted our analyses using a sample that drop control schools below the lowest treated school and a sample trims at a propensity score of 0.10. In both cases we get very similar results.

Figure 2: Distribution of LOS and CS Treatment Probabilities by Treatment Status

Common Support for LOS



Common Support for CS



Tables 2 and 3 provides summary statistics for students that are both in high schools on the trimmed common support sample and who are in the top 30% of their high school class as measured by our achievement index. Throughout the study we consider two samples. Our primary focus is a sample that restricts to college attendees as these are the students who are most likely to be impacted by the programs and, as we show below, there appears to be no impact on the college attendance margin. Nonetheless, we also provide estimates for a sample of all high school graduates in the top 30% of their high school class. Table 2 provides means and standard deviations for student characteristics. The figures are similar regardless of whether we look at the full HS graduate sample or the college attendee sample, which further supports our decision to focus on college attendees. Twenty-four percent of students in the sample attend an

LOS high school after implementation and thus are eligible for the program. Eleven percent are eligible for the CS program. Looking at test scores, not surprisingly given our restriction to high achievers, the students tend to score around 90% correct on all three exam subjects. Looking at demographics, the students are mostly Hispanic - about 70% - with the rest split relatively evenly between black and white. Students have relatively high rates of gifted and talented classification at 24% but are equally likely to be at risk of dropping out of high school. Finally, approximately half of the students are economically disadvantaged.[13]

This is a relatively high rate for high school students as eligibility for free and reduced price lunch tends to be underreported amongst this age group. Indeed, in the 2000-01 school year the average economic disadvantage rate in Texas for high school students was 36%.

Table 3 displays means and standard deviations for a selection of the outcomes we investigate in this study. First we consider the student's initial college of attendance (hence, we are not accounting for transfers). Amongst this sample of high achieving high school graduates, nearly two-thirds have some post-secondary education at a public institution in Texas. Nonetheless, very few attend the flagships as was evident in Figure 2. Only 5% of top 30% graduates from these schools attend either UT or TAMU, accounting for 8% of all college attendees. A large portion attend emerging research universities or other 4-year schools and almost half of all the college attendees are observed first attending a two-year school. Of those who attend college, the choice of major field is spread widely while one-third graduate within six years.

[13] Texas considers a student to be economically disadvantaged if he or she is eligible for subsidized school lunches or is enrolled in another state or Federal anti-poverty program.

Table 2: Summary Statistics for Trimmed Common-Support Sample - Student Characteristics

	College Attendees	HS Graduates
Attends LOS HS	0.24	0.23
	(0.43)	(0.42)
Attends CS HS	0.11	0.11
	(0.31)	(0.31)
TAAS Writing	91.5	91.8
(% Correct)	(5.8)	(5.9)
TAAS Reading	91.6	91.9
(% Correct)	(5.5)	(5.5)
TAAS Math	89.3	89.7
(% Correct)	(7.6)	(7.6)
White	0.16	0.17
	(0.36)	(0.38)
Black	0.13	0.13
	(0.33)	(0.34)
Hispanic	0.69	0.67
	(0.46)	(0.47)
Gifted & Talented	0.24	0.26
	(0.43)	(0.44)
At Risk	0.26	0.25
	(0.44)	(0.44)
Male	0.45	0.46
	(0.50)	(0.50)
Econ. Disadvantaged	0.50	0.50
	(0.50)	(0.50)
Observations	28,153	61,235

Notes: Authors' tabulations using college attendees from the linked ERC-THECB data for the 1996-2002 high school graduating cohorts. Restricted to trimmed common support and top 30% of HS class as defined by TAAS achievement index.

Table 3: Summary Statistics for Trimmed Common-Support Sample - Outcomes

	College Attendees	HS Graduates
Enroll in College	-	0.63
	-	(0.48)
Enroll in UT	0.05	0.03
	(0.21)	(0.16)
Enroll in TAMU	0.03	0.02
	(0.18)	(0.14)
Enroll in Emerging	0.14	0.07
Research U	(0.34)	(0.25)
Enroll in Other	0.31	0.16
4-Yr	(0.46)	(0.36)
Enroll in 2-Yr	0.47	0.35
	(0.50)	(0.48)
Major in	0.23	0.15
Arts & Sciences	(0.42)	(0.36)
Major in	0.11	0.06
Business	(0.32)	(0.24)
Major in	0.06	0.03
Social Science	(0.24)	(0.18)
Major in	0.14	0.07
STEM	(0.34)	(0.26)
Graduate in 6 Yrs.	0.33	0.20
	(0.47)	(0.40)
Resid. Log Earn	0.14	0.12
(10+ Yrs after HS)	(0.81)	(0.83)
Observations	28,153	61,235

Notes: Authors' tabulations using college attendees from the linked ERC-THECB data for the 1996-2002 high school graduating cohorts. Restricted to trimmed common support and top 30% of HS class as defined by TAAS achievement index.

A key element in establishing the validity of a difference-in-differences identification strategy is being able to show that exogenous observable characteristics are not affected by the treatment. To address this, in Table 4 we provide balance tests using equation (1), in which we exclude the observable characteristics in X and use each observable shown in the column header as a dependent variable. In Panel A, we focus on college attendees who were in the top 30% of their high school class using our achievement index, while in Panel B we expand the sample to top 30% high school graduates. Our preferred sample is the top 30% of students restricted to college attendees, as this is the group most likely on the margin of treatment. Among these students, there is scant evidence that the observable characteristics of students change when the treatments are enacted. For LOS, there is one coefficient that is significant at the 5% level, but it is very small, suggesting a 0.6 of a percent increase in TAAS writing scores relative to the mean. Similarly, only black share is statistically significant at the 5% level for the CS treatment though a couple other estimates are significant at the 10% level. These indicate that the CS schools saw a slight shift towards lower socio-economic status enrollment relative to the comparison schools. Nonetheless, we view these as likely to be too small to substantially affect our estimates and, if anything, would bias our estimates negatively. Most crucially we do not see any indication of impacts of CS treatment on high school test scores. Estimates for the top 30% high school graduates are similar and are inconsistent with large changes in the demographic characteristics of schools surrounding treatment that would bias our results.

Table 4: Balance Tests for Trimmed Common-Support Samples

Dep. Var. →	Achievment Index	TAAS Raw Scores Writing	Read	Math	White	Black	Hisp	G&T	At-Risk	Male	Econ Disadv
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: Top 30% College Attendees (N=28,153)											
LOS	0.025	0.207**	0.046	0.321	0.016	-0.011	-0.003	0.032	0.016	-0.006	0.013
	(0.017)	(0.096)	(0.116)	(0.252)	(0.010)	(0.008)	(0.010)	(0.034)	(0.030)	(0.014)	(0.018)
CS	-0.004	0.034	-0.085	-0.065	-0.022*	0.019**	0.023*	0.030	-0.030	0.013	0.048*
	(0.017)	(0.100)	(0.119)	(0.232)	(0.012)	(0.010)	(0.012)	(0.022)	(0.034)	(0.017)	(0.024)
Sample Means	0.673	36.6	44.0	53.6	0.158	0.127	0.691	0.237	0.261	0.450	0.500
Panel B: Top 30% High School Graduates (N=61,235)											
LOS	0.019	0.127	0.005	0.347	0.017*	-0.011*	-0.004	0.015	0.010	0.016*	0.028*
	(0.016)	(0.082)	(0.109)	(0.239)	(0.009)	(0.006)	(0.008)	(0.034)	(0.028)	(0.009)	(0.017)
CS	-0.012	-0.021	-0.136	-0.130	-0.018*	0.007	0.022**	0.013	-0.014	0.008	0.040**
	(0.015)	(0.082)	(0.109)	(0.239)	(0.009)	(0.007)	(0.009)	(0.023)	(0.031)	(0.010)	(0.020)
Sample Means	0.692	36.7	44.1	53.8	0.176	0.134	0.667	0.264	0.254	0.455	0.500

Notes: Authors' estimation of equation (1) in the text using data for the 1996-2002 high school graduating cohorts, excluding all student characteristics and using the variable listed in the column title as the dependent variable. Each group of two coefficient estimates in each column comes from the same regression. Restricted to trimmed common support and top 30% of HS class as defined by TAAS achievement index. Standard errors clustered at the high school level are in parentheses: ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

The central conditions needed for identification are common to any difference-in-difference model: outcomes in the treated and control schools must be trending similarly prior to treatment and there must not be shocks in 1999-2002 that affected CS/LOS schools differently from the control schools. Our trimmed common support sample makes these assumptions more likely to hold, but it still is important to provide direct evidence on their validity. We estimate event study models in which we interact indicators for whether a school will ever be treated by the LOS or CS programs with each calendar year and estimate the impacts on flagship enrollment and graduation. This allows us to test explicitly for the existence of differential pre-treatment trends in these outcomes. As we describe in detail below, we find no evidence such trends exist, which supports our empirical strategy. It is more difficult to test for unobserved shocks that differentially impact the treated high schools. Of particular concern is the imposition of the Top 10% Rule in 1998. As a result of this rule, most admissions to the flagship schools were from the top 10% of a class. Equation (1) is identified under the assumption that the top 30% in the treated and control schools are similarly affected by the Top 10% Plan. This assumption is made more palatable by the use of the trimmed common support sample, since both treated and control schools serve low-SES students with low historical flagship enrollment rates (see Table 2). However, our event study estimates also shed light on any bias from the Top 10% Plan as this law went into effect in 1998 while the LOS/CS treatments were not rolled out until 1999-2000. We therefore should see effects in 1998 if the Top 10% Rule is driving our estimates, but as shown below the time pattern of effects much more closely matches the timing of the LOS/CS rollout than the Top 10% Plan implementation.

5 Results

Estimates of equation (1) using college enrollment outcomes as the dependent variable are shown in Table 5. In the table, each set of two estimates in a column is from a separate regression. Panel A shows estimates for college attendees and Panel B shows estimates for high school graduates. All estimates shown in Table 6 and throughout the remainder of the paper use the trimmed common support sample and are restricted to the top 30% of students in their high school class.

In Panel B of the first column of results, we provide estimates of the effect of the CS/LOS treatments on attending a public college in Texas. Recall that we only have data on students who attend public colleges in Texas; if the programs induce students to enter the public university system from other places - such as private schools, out-of-state schools, or from not attending college at all - this could generate a sample selection bias. The estimates in column (1) show no evidence of a change in enrollment in a public Texas 2-year or 4-year college or university due to the CS/LOS programs. The coefficients are small with small standard errors and are not statistically significantly different from zero at conventional levels. These results support our focus on the college attendee sample when we examine collegiate outcomes and earnings.

Columns (2) and (3) of Table 5 provide estimates of the impact of attending an LOS or CS high school on enrollment at a flagship. We find an increase in attendance of 2.78 percentage points in UT-Austin due to LOS exposure and an increase of 1.6 percentage points in Texas A&M enrollment due to CS exposure. Relative to the sample means, these estimates imply an increase in UT-Austin enrollment of 56% and an increase in Texas A&M enrollment of 46%. The effects in Panel B are similar, showing significant increases in enrollment in the requisite flagships from both programs. Importantly, in the college attendee sample the CS treatment did not affect enrollment in UT-Austin, nor did LOS treatment affect enrollment in Texas A&M. This result suggests these programs were not simply moving students across flagship schools, and they are inconsistent with differential secular enrollment trends confounding our estimates, as these would likely affect enrollment in both flagships.

Table 5: The Effect of Attending a Longhorn Opportunity or Century Scholar High School on College Enrollment

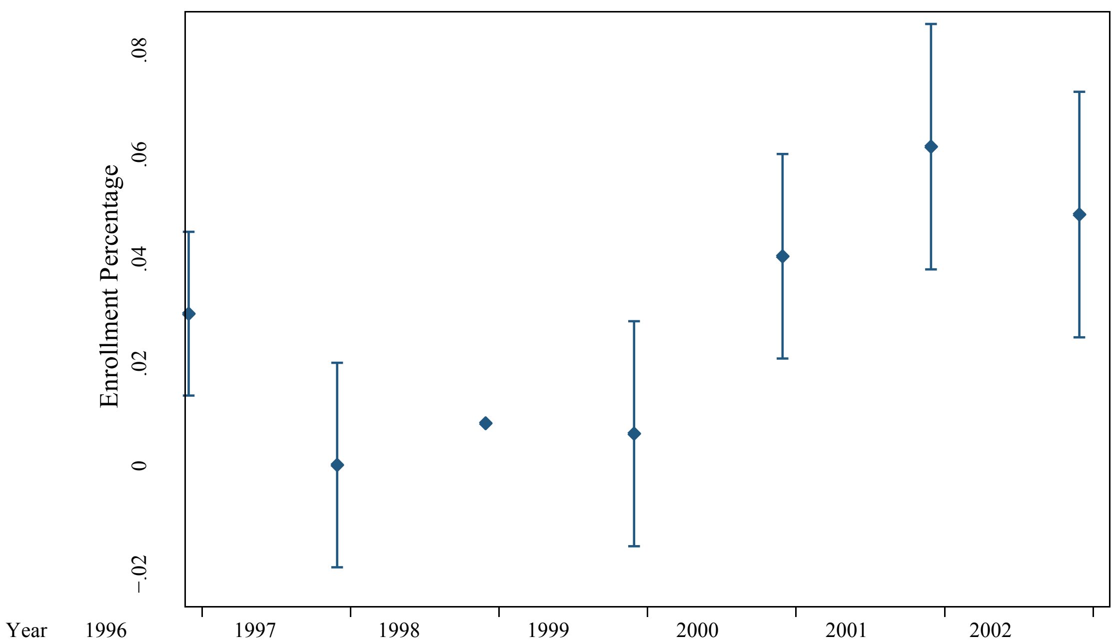
Treatment	Attend Any TX College (1)	Attend UT (2)	Attend TAMU (3)	Attend Other Research U (4)	Attend Other 4 Yr (5)	Attend 2yr (6)
Panel A: College Attendees						
LOS	-	0.027***	-0.005	-0.012	0.025	-0.037*
	-	(0.007)	(0.005)	(0.010)	(0.017)	(0.020)
CS	-	-0.003	0.016**	-0.003	-0.011	-0.001
	-	(0.008)	(0.006)	(0.011)	(0.015)	(0.016)
Mean	-	0.048	0.035	0.137	0.307	0.472
Panel B: High School Graduates						
LOS	0.007	0.023***	0.006*	0.001	0.034***	-0.060***
	(0.015)	(0.004)	(0.003)	(0.006)	(0.010)	(0.019)
CS	-0.016	0.001	0.008**	-0.012	0.014	-0.027
	(0.018)	(0.004)	(0.004)	(0.007)	(0.010)	(0.021)
Mean	0.627	0.026	0.020	0.069	0.157	0.354

Notes: Estimation of equation (1) in the text using the linked ERC-THECB data for the 1996-2002 high school graduating cohorts. Each group of two coefficient estimates in each column comes from the same regression. 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. Restricted to trimmed common support and top 30% of HS class as defined by TAAS achievement index. Sample sizes for the college attendee and HS grad samples are 28,153 and 61,235, respectively. Note that sample means do not necessarily sum to one as do not include health science campuses. Standard errors clustered at the high school level are in parentheses: ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

As discussed above, a core identification assumption embedded in equation (1) is that the treatment and control schools are trending similarly prior to the treatment rollout. In order to provide evidence in support of this assumption, Figures 3 and 4 show event study estimates of enrolling in UT-Austin and Texas A&M for the top-30% college and high school samples, respectively. Across all figures, there is little evidence of a differential upward trend in UT-Austin or Texas A&M enrollment prior to treatment. In both samples, there is a clear increase in flagship enrollment after 1999 among students in treated schools when the LOS and CS programs first began that is not predictable from pre-treatment relative trends. Furthermore, these estimates suggest that the Top 10% Rule is not a serious confounder in this setup, as there is no apparent increase in 1998 (the first year of the Top 10% Rule). That is, any differential changes in enrollment between treated and untreated schools start to occur in 2000 after LOS and CS were implemented, not in 1998 when Texas Top 10% Rule is implemented. Overall, Figures 3 and 4 are consistent with the identification assumptions underlying our difference-in- difference approach of common pre-treatment trends or shocks between treatment and control.

Figure 3: Flagship Enrollment Trends by Treatment Status - Top 30% College Attendees Sample

Panel A: UT Enrollment − LOS Treatment



Panel B: TAMU Enrollment − CS Treatment

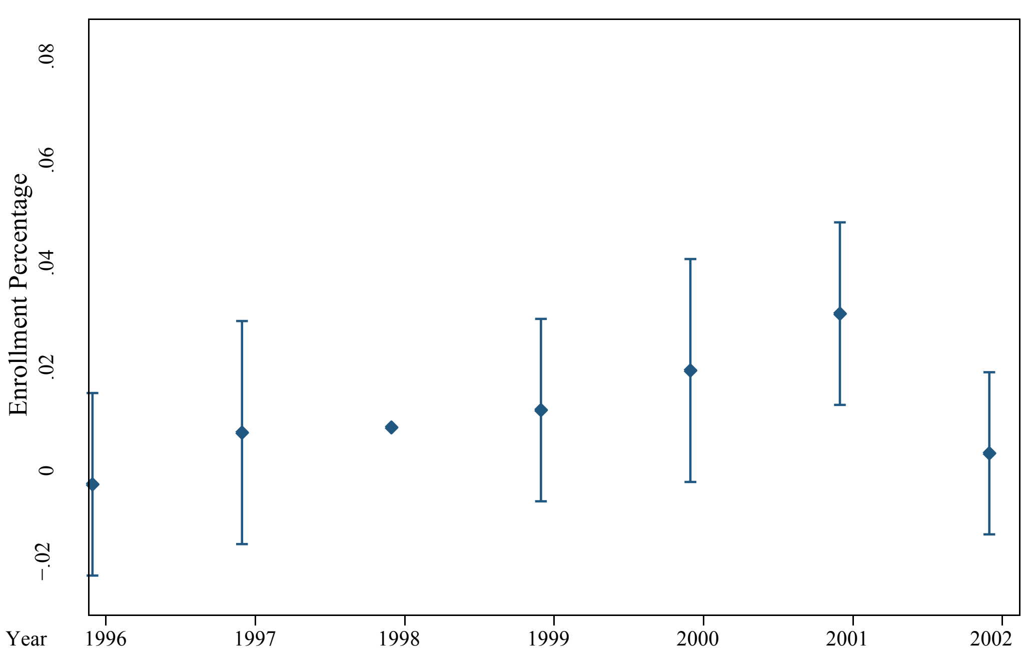
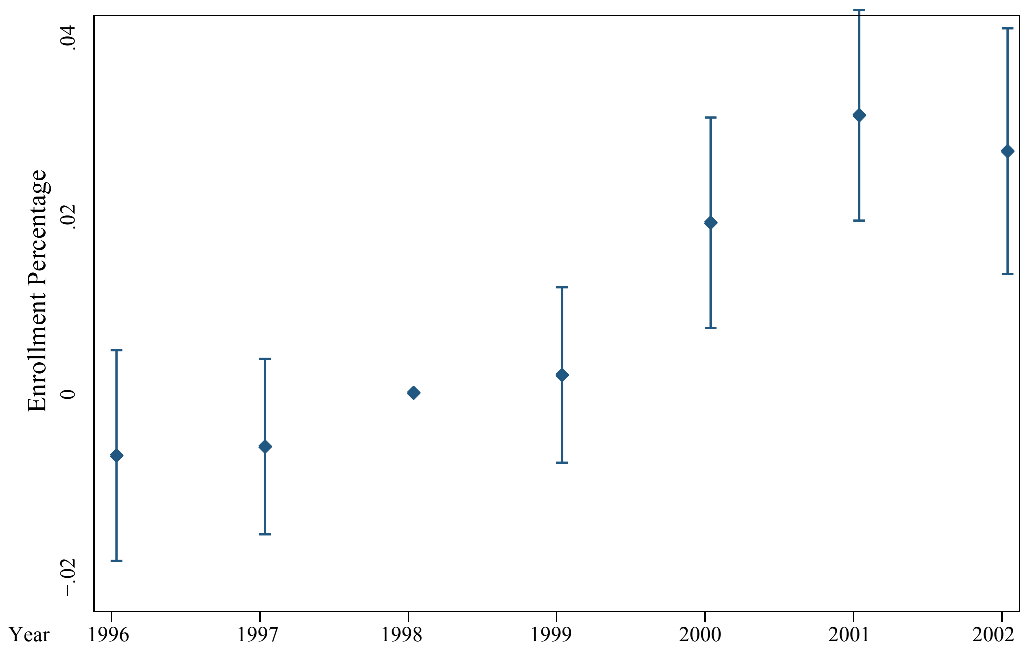
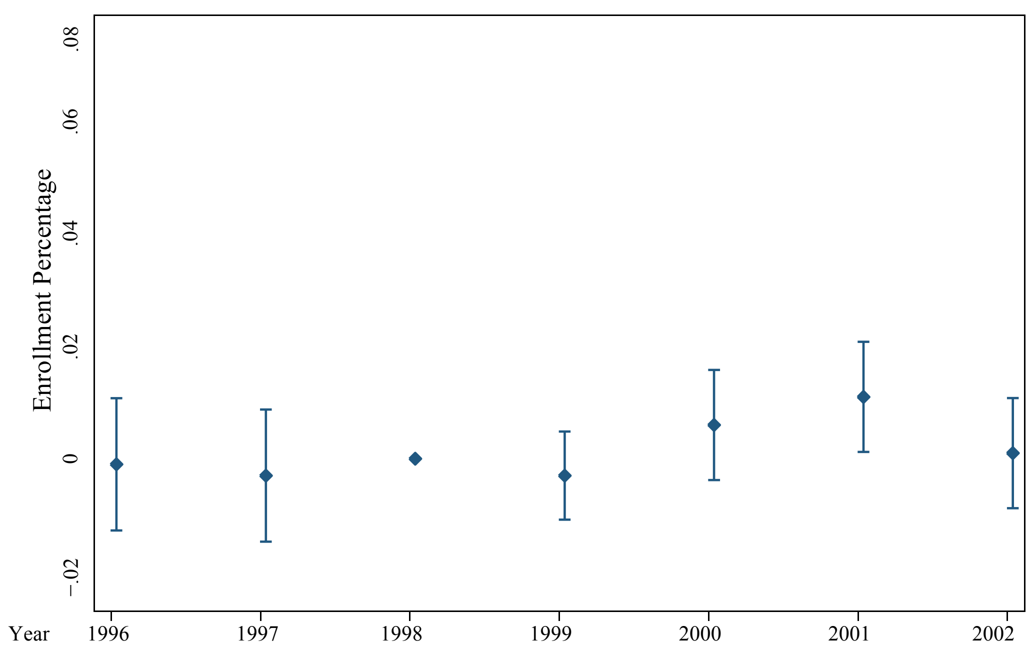


Figure 4: Flagship Enrollment Trends by Treatment Status - Top 30% HS Graduates Sample

Panel A: UT Enrollment − LOS Treatment



Panel B: TAMU Enrollment − CS Treatment



Since the LOS/CS programs did not affect the extensive margin of college enrollment and did not shift students across flagship schools, it is important to understand where the changes in enrollment came from. The remainder of Table 5 explores this question. We split non- flagship colleges and universities into 3 sectors: emerging research universities,[14] other four-year universities, and community colleges.[15] Although there is some variability across samples, three general patterns emerge. First, much of the increase in UT enrollment for the LOS treatment is driven by declines in two-year enrollment. Thus, the LOS program takes many students who would have enrolled at a local community college and induces them to enroll at UT-Austin. This represents a dramatic increase in college quality for these students. That the LOS treatment shifts students from a two-year to a flagship school is a very important finding given that these students were not given admission help; they were eligible to attend UT-Austin before the LOS program was implemented but chose not to. This finding is consistent with evidence from Hoxby and Avery (2013) that low-income, high-achieving students systematically choose less-selective schools than their higher-income counterparts and suggests that programs like the LOS scholarship can successfully get these students to enroll in more-selective schools.

Second, the CS treatment increases flagship enrollment more at the expense of emerging research enrollment than two-year enrollment. Thus, the CS treatment led to a smaller increase in college quality than did the LOS treatment. The third pattern evident in Table 5 is that there are spillovers from the LOS, though not the CS, program to students who do not enroll in flagships, as enrollment in non-flagship four-year schools increases at the expense of 2-year school enrollment. While unexpected, we believe this is a result of the recruitment efforts that UT-Austin made under this program. These recruitment efforts plausibly induced many students to attend a four-year rather than a two-year college, even if they either could not get into or chose not to attend UT-Austin.[16]

Thus far, our results indicate that students in LOS and CS schools experienced a substantial increase in college quality by shifting from lower-resource public schools to UT-Austin and

[14] These emerging research universities are listed in Section 2.
[15] A very small number of students attend health science campuses that we do not separately identify in this analysis.
[16] In results available upon request, we have estimated equation (1) using the bottom 70% of students. We find that enrollment in non-flagship four-year schools increases more among the bottom 70% students due to LOS treatment. This finding reinforces the conclusion that we are picking up spillover effects, because these students are very unlikely to be admitted to a flagship university in Texas. For bottom 70% students, there also is a small shift away from enrolling in any college due to CS treatment, highlighting a potential unintended cost of the program.

Texas A&M. The prior literature on the educational returns to college quality suggest that these interventions should lead to higher BA receipt (Cohodes and Goodman 2014; Bound, Lovenheim and Turner 2010). In Table 6, we examine how the LOS and CS programs affected four- and six-year degree completion. The structure of the table is almost identical to that of Table 5, except here we provide both ITT. First, we examine first-year GPA to see whether students are performing better or worse when they attend a more-selective school. The effects are of opposite sign across programs, with those coming from LOS high schools experiencing an increase of 0.11 GPA points and GPAs among students from CS schools declining by 0.08 points.

Table 6: The Effect of Longhorn Opportunity and Century Scholar Pro- grams on College Graduation and First-Year GPA – College Attendees

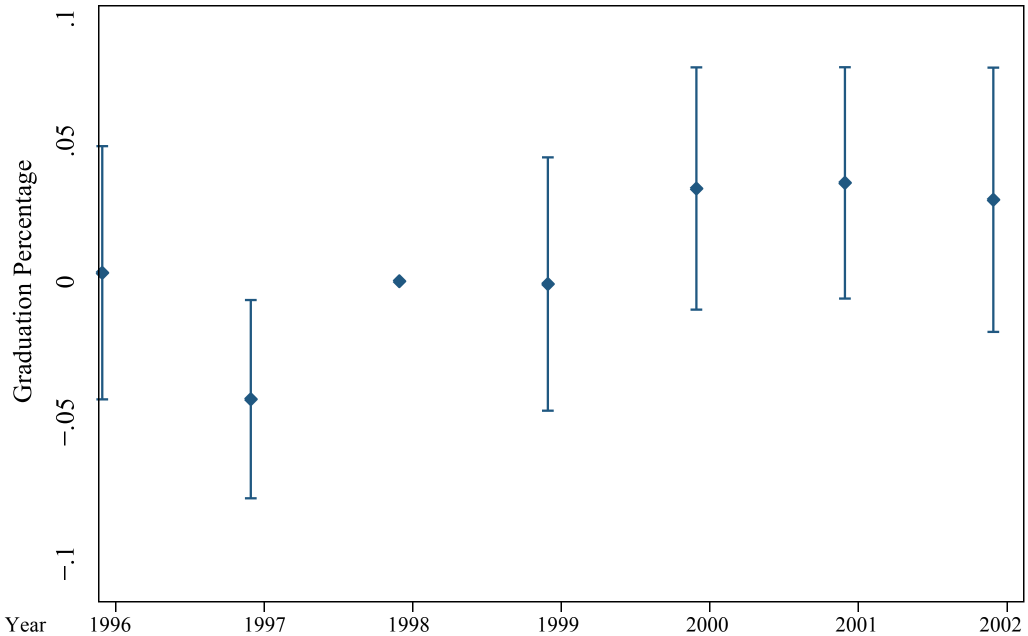
		ITT Estimates				
	Treatment	First Year GPA (1)	Grad TX College in 4 Years (2)	Grad TX College in 6 Years (3)	Grad UT in 6 Years (4)	Grad TAMU in 6 Years (5)
Panel A: College Attendees						
	LOS	0.108***	0.002	0.037***	0.019***	-0.003
		(0.033)	(0.008)	(0.011)	(0.005)	(0.005)
	CS	-0.069**	-0.030***	-0.018	0.003	0.008*
		(0.030)	(0.009)	(0.013)	(0.007)	(0.005)
	Mean	2.308	0.127	0.333	0.035	0.025
	Obs	26,746	28,153	28,153	28,153	28,153
Panel B: High School Graduates						
	LOS	-	0.015***	0.030***	0.013***	-0.001
		-	(0.005)	(0.008)	(0.003)	(0.003)
	CS	-	-0.010*	-0.008	-0.003	0.000
		-	(0.006)	(0.009)	(0.004)	(0.003)
	Mean	-	0.073	0.197	0.025	0.020
	Obs	-	61,235	61,235	61,235	61,235

Notes: Estimation of equations (1) in the text using the linked ERC-THECB data for the 1996-2002 high school graduating cohorts. Each group of two coefficient estimates in each column comes from the same regression. 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. Restricted to trimmed common support and top 30% of HS class as defined by TAAS achievement index. Standard errors clustered at the high school level are in parentheses: ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

The different effects of the LOS and CS programs on first-year GPA are similar to the differences in program effects on BA completion. In the college attendee sample, there is a large, statistically significant effect on six-year graduation of 3.7 percentage points. This is a 11.1% increase relative to the mean for this group. In contrast, the CS treatment has a negative effect on the four-year graduation rate that is substantially attenuated and statistically insignificant by six years. Thus, the CS program leads to a delay in graduation and it may also decrease graduation rates slightly. However, both programs increase the likelihood that students graduate from the respective flagship university. We hypothesize that the different graduation and grade point effects across treatments relates to the scope of the two different programs as well as the fact that the LOS program led to a much larger change in college quality than CS. Alternatively, as we will show below, the CS program appeared to induce a shift towards students choosing more difficult majors which could also drive down on-time completion and grades. Figures 5 and 6 present event study estimates that are consistent with these results. Critically, as in Figures 3 and 4, there is no evidence in these figures of differential pre-treatment trends that could bias the estimates in Table 6.

Figure 5: 6-Year Bachelor Attainment Trends by Treatment Status - Top 30% College Attendees Sample

Panel A: Graduate in 6 Years − LOS Treatment



Panel B: Graduate in 6 Years − CS Treatment

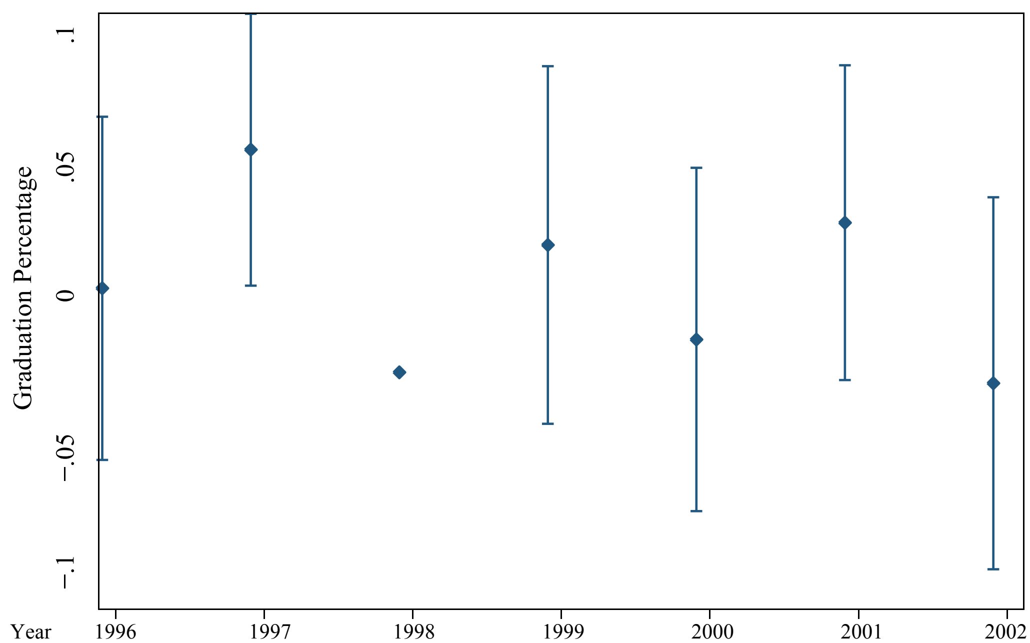
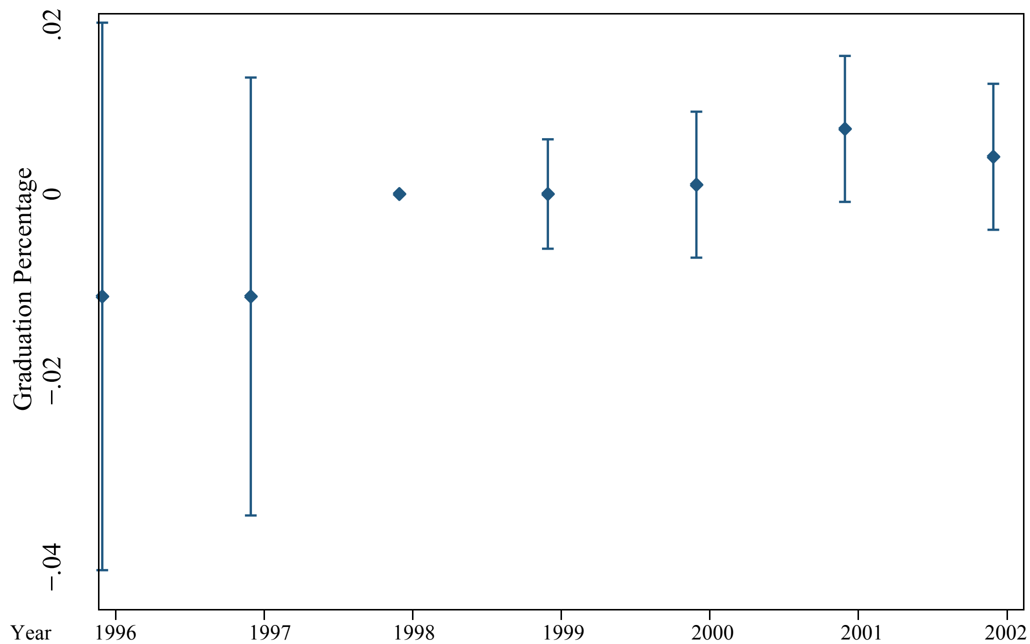
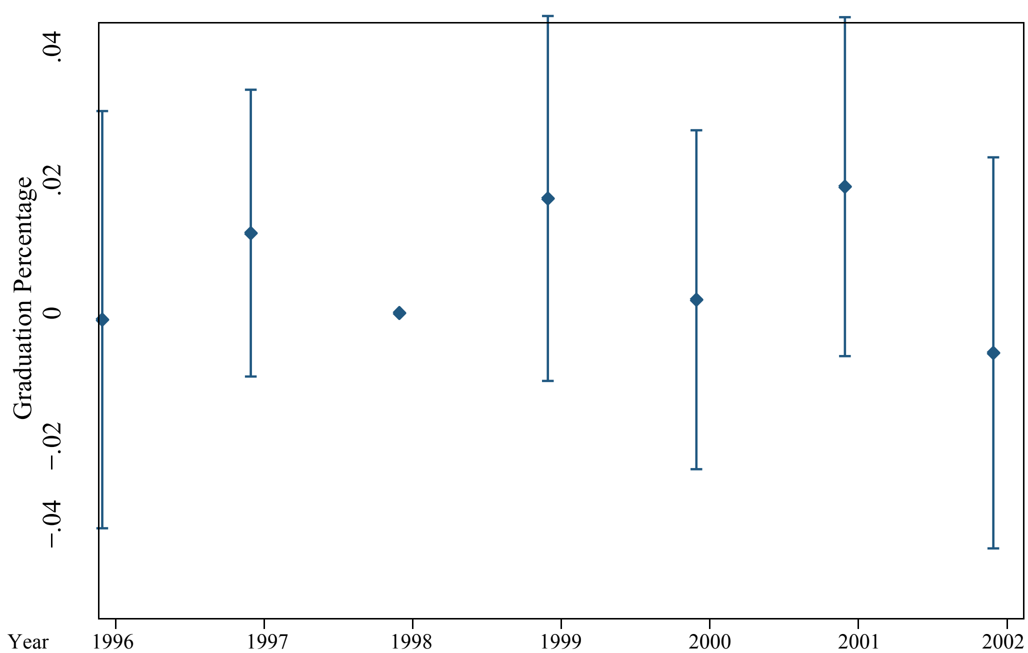


Figure 6: 6-Year Bachelor Attainment Trends by Treatment Status - Top 30% HS Graduates Sample

Panel A: Graduate in 6 Years − LOS Treatment



Panel B: Graduate in 6 Years − CS Treatment



Another prediction of mismatch theory is that under-prepared students will gravitate to easier majors when they are overmatched. If anything we find the opposite pattern. In Table 7, we examine whether enrolling in the CS or LOS programs induces students to alter their chosen course of study. We focus in this table on the student's "final major," which is either the major at graduation or the last observed major for students who do not graduate from a public Texas college by the end of our sample period.[17] Table 7 shows that for LOS, students are more likely to major in arts and humanities and are less likely to major in "other" subjects. This other category is comprised of education along with mainly vocational and technical support majors, and thus these major changes reflects the fact that students are switching out of two-year and less-selective four-year schools. Importantly, there is no negative effect on STEM majoring for the LOS program. Hence, at worst we can say that LOS students are not taking easier majors than they would have otherwise.

For the CS program we see a substantial shift from "other" to arguably more difficult majors, in particular STEM and social sciences. Communications and arts and humanities increase as well, but not at the expense of the more technical majors. Hence, on average, CS students choose more technically demanding majors which could provide some explanation for the longer time-to-degree and lower initial grades.

These are important findings because of the growing evidence that mismatch leads to students shifting to easier majors (Arcidiacono, Aucejo and Hotz 2013; Arcidiacono, Aucejo and Spenner 2012). We find little evidence to support such mismatch effects here for these high achieving low-income students. On net, students' major choice is not highly affected by the LOS program and CS, if anything, leads students to choose harder majors. That students are not majoring in easier subjects but are attending more elite schools and graduating at higher rates suggests the programs led to large increases in human capital accumulation.[18]

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[17] In results available upon request, we show that these patterns are similar for initial major.
[18] When we look at the bottom 70% sample, the spillover effects appear to induce some students who switch to higher quality colleges to move away from STEM majors. This further highlights the potential for the extra academic supports - which are not available to the bottom 70% sample - to offset mismatch

Table 7: The Effect of Longhorn Opportunity and Century Scholar Programs on Last Major Recorded - College Attendees

Treatment	Arts & Humanities (1)	Business (2)	Social Science (3)	STEM (4)	Agri-culture (5)	Commun-ications (6)	Other (7)
Panel A: Intention-to-Treat Estimates of CS/LOS Programs							
LOS	0.033	-0.004	0.003	-0.002	-0.000	0.000	-0.029*
	(0.020)	(0.008)	(0.007)	(0.010)	(0.001)	(0.004)	(0.017)
CS	0.022*	-0.001	0.021*	0.016*	0.002	0.014**	-0.073***
	(0.013)	(0.010)	(0.013)	(0.009)	(0.001)	(0.005)	(0.017)

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Notes: Estimation of equations (1) in the text using the linked ERC-THECB data for the 1996-2002 high school graduating cohorts. Each group of two coefficient estimates in each column comes from the same regression. 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. Restricted to trimmed common support and top 30% of HS class as defined by TAAS achievement index. Sample size is 28,153. Standard errors clustered at the high school level are in parentheses: ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

The large returns to college quality (Andrews, Li and Lovenheim forthcoming; Hoekstra 2009; Black and Smith 2004, 2006; Brewer, Eide and Ehrenberg 1999) combined with the suggestive evidence of larger returns to more technical majors (Andrews, Li and Lovenheim, forthcoming; Altonji, Blom and Meghir 2012; Arcidiacono 2004) suggest that the LOS and CS interventions should raise earnings after college. In Table 8, we examine the effect of these programs on earnings, using the adjusted log quarterly earnings measures discussed in Section 3. In the first two columns, we examine whether being in an LOS or CS high school affected the likelihood that one appears in the earnings data. The estimates are close to zero and are precisely estimated, suggesting treatment does not cause a sample selection problem.

In the remaining columns of Table 8, we show both short-term and medium-term effects using all earnings after 6 and 10 years post high school graduation. Arguably, given that many students take more than 6 years to complete college and may attend graduate school, the 10+ year results should be more reflective of lifetime earnings. Both sets of estimates show large effects of the LOS program on earnings. Being in an LOS high school increases earnings after 6 years by 3.8% and after 10 years by 4.3%. The large size of these estimates is consistent with the dramatic shift in college quality and the sizable increase in the likelihood of graduating from college. The results among top-30% high school graduates are qualitatively similar but are smaller and less precise. This occurs because there is far more earnings variance among the high school sample, and the proportion of students who are on the margin of treatment is smaller. We therefore favor the college attendee sample of high ability students. In contrast to the LOS estimates, there appears to be less earnings gains from the CS program. The ITT estimates are relatively small and statistically insignificant at 2.1% after 6 years and 0.7% after 10 for the college attendee samples. Overall, these results indicate that the LOS program have a positive effects on the long-run labor market outcomes of the targeted low-SES students while the effects of the CS program are less clear, but unlikely to be negative.

Table 8: The Effect of Longhorn Opportunity and Century Scholar Programs on Ln(Earnings)

ITT Estimates

	Treatment	In 6+ Years Earnings Sample	In 10+ Years Earnings Sample	6+ Years After HS Grad	10+ Years After HS Grad
Panel A: College Attendees					
	LOS	-0.005	-0.005	0.037**	0.042**
		(0.006)	(0.008)	(0.019)	(0.019)
	CS	-0.002	0.007	0.021	0.007
		(0.006)	(0.008)	(0.018)	(0.020)
	Obs	28,153	28,153	26,258	23,911
Panel B: High School Graduates					
	LOS	-0.002	-0.005	0.009	0.011
		(0.005)	(0.008)	(0.014)	(0.014)
	CS	-0.004	0.007	0.009	-0.006
		(0.005)	(0.008)	(0.013)	(0.014)
	Obs	61,235	61,235	54,614	49,255

Notes: Estimation of equation (1) in the text using the linked ERC-THECB data for the 1996-2002 high school graduating cohorts. Each group of two coefficient estimates in each column comes from the same regression. 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. Restricted to trimmed common support and top 30% of HS class as defined by TAAS achievement index. Earnings are adjusted for college graduating cohort year and quarter fixed effects as discussed in the text. Standard errors clustered at the high school level are in parentheses: ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

6 Conclusion

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 using a trimmed common support sample of treated and comparison schools that compare how the enrollment behavior, educational outcomes and earnings of high-ability students change when the programs are implemented in targeted high schools in 1999 and 2000.

Our estimates suggest that these types of bundled interventions can generate better outcomes among targeted students. Both the LOS and CS programs induced many students to enroll in UT-Austin and Texas A&M instead of lower-resource four-year and two-year institutions. This shift towards the flagship provided a large quality upgrade relative to the schools the students would have attended in the absence of the program. High-achieving students affected by the LOS program saw large and statistically significant increases in graduation likelihood, and we find no evidence of academic mismatch in the form of students switching to "easier" majors. We find no statistically significant effect of CS treatment on the likelihood of graduating from college, however. College students from LOS high schools experienced an increase in earnings. For the CS program, earnings estimates are positive but not statistically significant.

The differences in outcomes between these programs have two likely explanations. First, is that while we see no impact from LOS on students entering more technically advanced majors like STEM and social sciences, we do see increases in majoring in these fields from the CS program. The increased difficulty of the fields entered for CS students may have reduced completion. The second explanation is that the services provided by the LOS program were more comprehensive and included special course sections, guaranteed housing, and free tutoring. Similar services were not provided by the CS program. Even so, despite the longer time-to-degree it is encouraging that we see little to indicate that the CS program reduced earnings.

The results from this analysis suggest that programs like the Longhorn Opportunity Scholarship hold much promise in promoting better postsecondary and labor market outcomes among high-ability, low-income students. Furthermore, while it is unclear if the students treated by the program are actually “undermatched” for the state flagships, the results suggest that mismatch problems can be overcome with sufficient support services. Crucially, programs like these and the supports they provide can easily be replicated in any state flagship institution. The estimates for the Century Scholar program, however, provides a cautious note as it is not automatic that such a program will succeed in affecting postsecondary and labor market outcomes. More work focusing on the specific ways in which these programs were implemented and the implications for effectiveness would be of high value in order to better understand how to structure these programs to maximize their positive effects on students.

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