Price Regulation, Price Discrimination, and Equality of Opportunity in Higher Education: Evidence from Texas*

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ABSTRACT

This paper assesses the importance of price regulation and price discrimination to low-income students' access to opportunities in public higher education. Following a policy change in the state of Texas that shifted tuition-setting authority away from the state legislature to public universities themselves, most institutions raised sticker prices and many began charging more for high-return majors, such as business and engineering. We find that poor students actually shifted towards higher-return programs following deregulation, relative to non-poor students. Deregulation facilitated more price discrimination and enabled supply-side enhancements, which may have partially offset the detrimental effects of higher sticker prices.

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I. Introduction

Public support for postsecondary educational investment is substantial and long-standing. For example, states spent $173 billion on higher education in 2012, permitting public institutions to provide postsecondary education to millions of students at a price well below cost (NASBO, 2013). However, tight state budgets have recently challenged states' ability to ensure both broad access to higher education and provide programs of high quality, with large funding cuts particularly during the Great Recession (Barr and Turner, 2013). Funding cuts that trigger tuition increases could widen the existing large gaps between high- and low-income students in college enrollment (Bailey and Dynarski, 2011), particularly at the most selective institutions. This would be problematic given the large returns to a college education generally (Zimmerman, 2014) and for the most selective institutions and majors specifically (Hoekstra, 2009; Hastings, Neilson, & Zimmerman, 2013; Kirkeboen, Leuven & Mogstad, 2014). Spending cuts that reduce program quality may additionally reduce degree completion (Bound, Lovenheim, & Turner, 2012; Cohodes and Goodman, 2014). How public higher education institutions balance their dual access and quality objectives has important economic consequences.

In Texas, short-term state spending cuts in 2003 were accompanied by a permanent shift in tuition-setting authority away from the state legislature to the governing board of each public university, termed "tuition deregulation." Most universities subsequently raised prices and many began charging more for high-demand or costly undergraduate majors, such as business and engineering (Kim and Stange, 2016). The presidents of major research universities claimed that tuition-setting flexibility enables institutions to expand capacity and help students succeed by enhancing program quality (Yudof, 2003). Detractors worried that price escalation would limit access to the most selective institutions and most lucrative programs for low-income students (Hamilton, 2012). This concern motivated a bundling of deregulation with additional grant aid that would partially shield low-income students from price increases, as we describe further below. More than a decade later, lawmakers in Texas and many other states continue to debate the merits of deregulation without hard evidence of its consequences. This study fills this gap by assessing how tuition deregulation – and the subsequent price increases – affects the representation of socioeconomically disadvantaged students in high-return institutions and majors.[1]

We answer this question using rich administrative data on the universe of Texas public high school graduates at Texas public universities from 2000 to 2009 matched to earnings records, financial aid, and new measures of tuition and resources at a program level. We first document substantial earnings differences across postsecondary programs (both within and across institutions) and that poor students are under-represented in the highest-return programs. Price increases were largest for the highest-return programs following deregulation, which raised the concern that deregulation would exacerbate disparities in poor student representation in these programs given low-income students' greater price responsiveness (Jacob, McCall, Stange, 2017).

We use an interrupted time series and event-study strategy to assess the effects of deregulation and compare the time path of programs chosen by poor students relative to non-poor students leading up to and following deregulation. We find that poor students shifted away from the least lucrative programs following deregulation and increase their representation in higher-earning programs relative to non-poor students. On average, poor students entered programs that generate earnings gains that are 3.7% lower than non-poor students prior to deregulation, after accounting for differences in demographics and achievement test scores. This gap closes by more than one-third following deregulation. This broad finding that poor students gained relative to non-poor students following deregulation is robust to various strategies for ruling out potential confounders, including changes in student characteristics and other policy changes – such as delayed effects of the Top 10 Percent Plan, targeted outreach, and affirmative action – that may alter the sorting of students in higher education. Encouragingly, the shift in initial program choice persists for at least two years following initial enrollment, so it is likely to result in real relative improvements in the economic wellbeing of low-income students. While estimates for longer-term outcomes such as graduation and actual earnings are noisy, taken together, they suggest that deregulation did not reduce poor students' outcomes.

Greater income-based price discrimination following deregulation permitted these programs to retain (or even expand) low-income student representation while simultaneously

[1] Flores and Shepard (2014) is the only study that examines the effects of this policy change. Using aggregate institution-level data, they find that price accelerated at seven Texas institutions following deregulation, but effects on overall enrollment of minority students and Pell Grant recipients were mixed (but underpowered).

raising sticker price and program quality.[2] Need-based grant aid increased considerably in programs with large price increases, such that the net price that low-income students paid fell relative to that for non-poor students. This was due both to an explicit provision of deregulation that required institutions to set-aside some incremental revenue for grant aid and to the presence of a large state need-based aid program, the TEXAS Grant. Program resources also improved the most for programs with the highest returns. The favorable relative changes in the price/quality package offered to poor students improved low-income students' access to the most lucrative state university programs.

Our findings contribute to three distinct literatures. First, we provide evidence on the distributional consequences of price discrimination. Prior work finds that price discrimination can be beneficial to low-income individuals both in higher education (Fillmore, 2014) and other industries by lowering relative prices. However, lacking sufficient policy change, this work has been mostly theoretical or based on simulations. There is almost no reduced-form evidence that traces the distributional consequences of a policy change that permits greater price discrimination. Price discrimination means that the greater price and resource differentiation seen among U.S. colleges (Hoxby, 2009) does not necessarily affect low-income students. Ours is the first study to look at a broad shift from a regime of broad-based subsidies (low sticker price) to one of specific subsidies (higher sticker price plus greater aid) in higher education.

Second, we provide some of the first evidence on the effects of deregulation – and university autonomy more generally – on the higher education market. Prior work has found that university autonomy is positively associated with research output (Aghion, Dewatripont, Hoxby, Mas-Colell, & Sapir, 2010), but the equity or efficiency consequences of greater institutional autonomy (and the resulting differentiation) in undergraduate education have not been previously examined. Finally, we provide further evidence that heterogeneity of human capital investment opportunities is materially important (Altonji, Blom and Meghir, 2012), even within the context of a public university system in a single state. Thus, the sorting of students across programs materially affects how a states' higher education system alters the intergenerational transmission of income.

[2] In absence of multiple "mechanism" quasi-experiments, we cannot separately identify the contribution of each potential channel – for example, sticker price, price discrimination, program resources, and admissions – to the reduced-form sorting patterns we observe without additional structure. So we view the investigation of channels as suggestive. However, since deregulation in Texas and elsewhere is a package of all of these changes, the combined effect is the primary target for policy.

This study is both timely and of broad policy importance beyond the state of Texas. Florida and Virginia recently decentralized tuition-setting authority, and several other states (New York, Washington, Wisconsin, Ohio) and Australia have all considered similar proposals (McBain, 2010; Camou and Patton, 2012). Just last year, voters in Louisiana rejected a plan that was quite similar to Texas' combination of deregulation and grant aid. The Texas experience suggests that deregulation need not adversely affect the postsecondary educational opportunities available to poor students, as many critics worried. Indeed, our findings echo the experience in England, where the end of free college was associated with increased resources and improvement in college socioeconomic gaps (Murphy, Scott-Clayton, and Wyness, 2017). Two key features of tuition deregulation in Texas case are the requirement that institutions channel some of the revenue generated by deregulation towards need-based aid and the presence of a large state-financed need-based aid program. How deregulation would have evolved absent these features remains an open question. Still, the lessons learned from Texas' deregulation policy are broadly applicable as most proposed deregulation efforts include a package of reforms – pricing independence and additional grant aid – that are similar to those offered by Texas.

This paper proceeds as follows. The next section provides background on tuition deregulation in Texas, its financial aid programs, and prior literature. Section III describes our data, sample, and student earnings across programs. Methods and results are presented in three parts. Section IV documents the large price changes following deregulation. Section V assesses changes in student sorting following deregulation. Section VI investigates both price and non-price mechanisms. Section VII concludes.

II. Background

A. Texas Context and Deregulation

Public university tuition in Texas consists of two components, statutory and designated tuition (THECB, 2010). Statutory tuition (authorized under Texas Education Code (TEC) 54.051) is a fixed rate per credit hour that differs only by residency status but is otherwise constant across institutions and programs. Designated tuition is a charge authorized by TEC 54.0513 that permits institutions to impose an additional tuition charge that the governing board of the institution deems appropriate and necessary. Though designated tuition charges are determined by institutions, the legislature historically capped designated tuition at the level of statutory tuition.[3]

Cuts to state appropriations in 2002 led many institutions to advocate for more flexibility in setting tuitions. Flagship universities argued that the existing revenue model did not adequately consider differences between institutions (Yudof, 2003). They believed that tuition flexibility would help maintain existing levels of service and increase institutions' ability to respond to educational and economic development needs. In September of 2003, the legislature passed HB 3015, which modified TEC 54.0513 to allow governing boards of public universities to set different designated tuition rates, with no upper limit. Furthermore, institutions could vary the amount by program, course level, academic period, term, credit load, and any other dimension institutions deem appropriate. Since annual price-setting occurs in the prior academic year, the Fall 2004 was the first semester that universities could fully respond to deregulation. Community colleges and private universities did not experience a similar change in their price-setting capabilities.[4]

Figure 1 depicts the price changes following deregulation. Deregulation was associated with large increases in sticker price level, growth, and differentiation immediately after deregulation. Kim and Stange (2016) demonstrate that these changes are unique to Texas – similar levels of growth were not seen in other states. The 50% increase in cross-program variability in tuition partially reflects the adoption of differential pricing across programs, particularly for Engineering and Business (Kim and Stange, 2016). Texas institutions thus followed a national trend of engaging in differential pricing for more costly and/or lucrative majors (Stange, 2015). To reduce the likelihood that tuition increases would disproportionately burden low-income students, institutions were required to set aside a share of the additional revenue for financial aid for needy students (which we describe in detail below). The legislature also mandated that institutions show progress towards performance goals (graduation, retention

[3] Universities are also allowed to charge mandatory and course fees for costs that are associated with services or activities. In fall 2002, the average mandatory fee in the state was $454, ranged from $160 (University of Houston – Victoria) to $1,175 (UT-Dallas), while the average course fee charged was $61.

[4] Tuition rates for community colleges are determined by each Community College Taxing District (CCTD), resulting in different tuition rates across CCTDs throughout our analysis period. In 2005, CCTDs were granted the authority to charge different tuition rates for different programs. However, we show in Figure A1 that subsequent changes in overall community college prices were modest relative to those at universities. Furthermore, few colleges implemented large changes in differential pricing across programs that were not already reflected in program fees.

rates, and affordability) though the oversight for this does not appear to have been put in place (McBain, 2010).

These abrupt changes in pricing and state support came against a backdrop of several other efforts to affect student choices and success. The “Top 10 Percent” rule guaranteeing admission to any public institution for students ranked in the top decile of their high school went into effect in 1998 and increased enrollment at the state’s flagships (Daugherty, Martorell and McFarlin 2012). Several targeted financial aid and outreach programs improved access to UT-Austin and Texas A&M among low-income students (Andrews, Ranchhod and Sathy, 2010; Andrews, Imberman and Lovenheim, 2016). Finally, the state’s “Closing the Gaps” initiative. was a broad effort to improve access and graduation rates for underrepresented minorities.

B. Financial Aid in Texas Before and After Deregulation

The financial impact of deregulation on poor students was a central concern of policy makers. Consequently, several features of the deregulation legislation interacted with the state’s financial aid programs to shield low-income students from the resulting price increases. Most directly, the deregulation legislation required that 15 percent of the revenue generated from designated tuition charges in excess of 46 dollars per semester hour be set aside to provide aid for needy undergraduate or graduate students in the form of grants or scholarships. Institutions have near complete discretion in determining which students receive aid from this source, referred to as “HB3015 set-asides,” with the constraint that recipients must be needy.

Also important is the Towards EXcellence Access and Success (TEXAS) Grant program, which provided $193 million to nearly 40,000 needy students in 2009 (THECB 2010b). [5] Eligibility is determined by need and having met high school curricular requirements (for initial grantees) or basic college performance (for continuing grantees). Total TEXAS Grant funds are allocated by the state to each institution annually, but institutions have discretion for determining which eligible students receive awards and how much (up to the statutory maximum). Two features of the TEXAS Grant work to shield poor students from tuition price increases. First, the statutory maximum is the statewide average of tuition and fees, so tuition increases raise the maximum award allowed by statute. This maximum does not, however, depend on the institution attended so should not be expected to differentially affect some programs more than others.

[5] Appendix Table A1 presents several measures of the TEXAS Grant program, such as number of recipients, award amounts, and EFC distribution (within our sample) over time. Funding increased considerably as the maximum and average awards increased, while the composition of students shifted to be slightly more needy.

Second, institutions are obligated to provide non-loan aid to cover the student's full tuition and fees up to demonstrated financial need to all TEXAS Grant recipients, regardless of the award amount. Increases in tuition prices thus increase institutions' grant obligations to TEXAS Grant recipients beyond the amount of the TEXAS Grant itself. [6] HB3015 set-aside funds can be used to close this gap and our discussions with higher education officials in the state suggested institutions did just that. Deregulation could thus crowd-in support from the TEXAS Grant, particularly at programs that increased prices the most. Later we show that the HB 3015 set asides were particularly large for poor students in programs that became more costly and that TEXAS Grants also expanded slightly more for these programs. Though deregulation occurred amidst a backdrop of increased funding for the TEXAS Grant, we subsequently show the TEXAS Grant (and its expansion) cannot fully explain the patterns in program choice that we document.

Student aid provided through two other large need-based grant programs – the Texas Public Educational Grant (TPEG) and the Federal Pell Grant – should have been unaffected by deregulation. TPEG is funded by a 15 percent set-aside from statutory tuition at each institution. The institutions have discretion in selecting which eligible students receive an award. TPEG distributed $88.4 million to 60,681 college students in Texas in 2009. While TPEG funds could be used to close gaps in aid packages for TEXAS Grant recipients, the funding source (statutory tuition) was unaffected by deregulation with no variation across institutions. The Federal Pell Grant Program awarded nearly $438 million to 135,623 students in Texas's public universities (THECB 2010b) in 2009. While Pell amount eligibility does increase with the cost of attendance (which depends on tuition), in practice many students already receive the federal maximum, so tuition increases are unlikely to increase Pell awards.

These programs together represent a considerable investment in making college affordable for low-income students. The HB3015 set asides and TEXAS Grant, in particular,

[6] The TEXAS grant program is somewhat unique among states. A few states (e.g., Virginia, Colorado) also allocate funds to institutions, which then pass them through to students with some degree of autonomy. Many other states (e.g., California, Minnesota, New York, South Carolina) directly determine awards, removing the institutions from decision-making. Tuition set-asides exist in a number of states, requiring institutions to use revenue dollars to fund grant aid in order to offset the effects of tuition increases on poor students. The particular set-aside in Texas, requiring that grant aid for recipients of TEXAS grants cover the full cost of tuition and fees, is more generous than most other states. Some states require that students bear at least some of the cost of tuition and fees (e.g., Minnesota), while others do not address students' unmet need net of grant aid (e.g., California, Illinois, Minnesota). See Baum et al (2012) for more details.

allow the financial aid packages for low-income students to accommodate price increases by tying need-based aid dollars directly to tuition levels.

C. Prior Literature

Prior research has established that there are returns to a college education, even among academically marginal students (Zimmerman, 2014). The benefits of a college degree are quite heterogeneous, however, as students that attend better-resourced colleges are both more likely to graduate (Cohodes and Goodman, 2014) and have higher earnings (e.g. Hoekstra, 2009; Andrews, Li, and Lovenheim, 2016, Chetty et al, 2017). Furthermore, there are substantial earnings differences across majors (Hastings, Neilson, Zimmerman, 2013; Kirkeboen, Leuven & Mogstad, 2014), with earnings differences across majors comparable to the earnings gap between high school and college graduates (Altonji, Blom and Meghir, 2012). This suggests that higher education could either narrow or widen economic inequalities depending on the nature of the institutions and programs attended by low-income and non-poor students.

Price (sticker and net) is one factor that prior evidence has demonstrated is closely linked to college enrollment, institutional choice, and persistence (Dynarski 2000; Long, 2004; Hemelt and Marcotte, 2011; Jacob, McCall, and Stange, 2017; Castleman and Long, 2016). Stange (2015) found that higher sticker prices for engineering and business is associated with fewer degrees granted in these fields, particularly for women and minorities. However, his analysis examined differential pricing generally (not just due to deregulation) and could not determine whether increased aid or supply-side factors could mitigate any adverse effects of higher price.

Furthermore, prior work has produced mixed evidence on whether tuition is actually higher when public universities have more autonomy (Lowry, 2001; Rizzo and Ehrenberg, 2004) and this work doesn't examine effects on students. The only exception is Flores and Shepard (2014), who found that at seven Texas institutions, institution-level price accelerated following deregulation but effects on enrollment of underrepresented minority students was mixed, with increased representation by blacks but reductions for Hispanic students. Pell Grant recipients increased their college enrollment rates following deregulation.

A small number of studies have directly examined price discrimination by higher education institutions and its implications for poor students. Using a structural equilibrium model of the college market, Fillmore (2014) finds that reducing institutions' ability to price discriminate lowers prices for middle- and high-income students, but raises prices for low-income students, pricing some of them out of elite institutions. Price discrimination is thus beneficial to low-income students. Epple, Romano, and Sieg (2006) also find that price discrimination significantly affects the equilibrium sorting of students into colleges, though they do not assess differential effects by income directly. Finally, Turner (2014) finds that institutions' price discrimination behavior reveals a willingness-to-pay for Pell Grant students, particularly at public institutions. Public institutions actually crowd-in institutional aid for students receiving the Pell Grant.

III. Data Sources and Sample

A. Student Data and Sample

Administrative data from the Texas Education Agency (TEA), the Texas Higher Education Coordinating Board (THECB), and the Texas Workforce Commission (TWC) are combined to form a longitudinal dataset of all graduates of Texas public high schools from 2000 to 2009. The data is housed at the University of Texas at Dallas Education Research Center.[7]

TEA data include information on students' socioeconomic disadvantage during high school, high school achievement test scores, race, gender, date of high school graduation, and high school attended.[8] Information on college attendance, major in each semester, college application and admissions, and graduation is obtained for all students attending either a community or public four-year college or university in Texas from the THECB. We categorize students as "poor" based on eligibility for free or reduced-price lunch in 12th grade, though this also includes students whose family income is at or below the federal poverty line, are TANF eligible, Pell recipients, Title II eligible, or eligible for food benefits under the Food Stamp Act of 1977. Finally, we obtain quarterly earnings for all students residing in Texas from the TWC, which are drawn from state unemployment insurance records. Thus, we expect them to be measured with little error, though they only include students who remain in the state of Texas and are covered by UI.[9]

Our main analysis focuses on the choice of first program among students who enroll in a four-year public Texas university within two years of high school graduation. We assign students

[7] We restrict attention to cohorts from 2000 onwards because key information about tuition, financial aid, application and admissions, and program resources are only available from 2000 onwards.
[8] High school exit exam scores are standardized to mean zero and standard deviation one separately by test year, subject, and test type (as the test changed across cohorts) among all test-takers in the state.
[9] Andrews, Li, and Lovenhiem (2016) find that coverage in the earnings records is quite good.

to the first four-year institution they attend and to the first declared major. Students whose first major is "undeclared" are assigned the first non-undeclared major in their academic record. Students who drop out without ever declaring a major are coded as "Liberal Arts." Some analysis also includes the full sample of Texas high school graduates. Finally, we drop some individuals with missing values for key covariates. Our final analysis sample includes 1,861,500 unique high school graduates, 580,253 of whom enroll in a Texas pubic four-year college within two years.

Table 1 presents characteristics of these samples. Approximately 30% of the full sample (19% of the college sample) is economically disadvantaged ("poor"). The middle rows of Table 1 describe the nature of the first program attended by students in our sample. As we describe in more detail later, we rank programs according to the average log earnings of enrollees relative to students that did not attend a public college in Texas. Poor students are underrepresented among the "top" earnings programs and overrepresented among the lower-earning programs. Poor students also attend programs that have lower tuition levels.

We are able to measure need-based grant aid (and thus net price) in students' first year using micro data compiled by the THECB. This micro data consistently contains financial aid award information for all students who both receive need-based aid and are enrolled in a Texas public institution from 2000 to 2011. We divide this amount in half to convert it to a semester equivalent. Unfortunately, aid received by students that did not perform a needs assessment is not consistently included in the database over time, so we are unable to create measures of net price that incorporate non-need-based aid, such as merit and some categorical grant aid.[10] The bottom of Table 1 describes the need-based grant aid received by students in our sample. Unsurprisingly, poor students receive much larger amounts of need-bases grant aid than non-poor students, nearly $2500 per semester, most prominently the Federal Pell Grant ($1330), TEXAS Grant ($870), and TPEG ($130). Average aid from the HB3015 set-aside is small ($70),

[10] The target sample for the Financial Aid Database expands over time. From 2000 to 2006 the database includes only students who received any type of need-based aid, or any type of aid which requires a need analysis. From 2007 to 2009 the database included students who are enrolled and completed either a FAFSA or TASFA (Texas Application for State Financial Aid), some of which may not have received any aid. Since 2010, the database was expanded to also include students who did not apply for need-based aid but received merit or performance-based aid. In order to keep our measures of aid consistent, we first identify students that received a positive amount of grant aid from at least one need-based aid program (Pell, SEOG, TEXAS Grant, TPEG, or HB 3015). Any student who did not receive grant aid from one of these programs or who was not matched to the FAD database is assumed to have zero need-based grants. The number of students with a positive amount of grant aid from one of these sources is relatively constant at about 21,000 students per high school cohort.

though this is misleading as these grants are mechanically zero prior to deregulation. Net tuition for poor students is very close to zero due to need-based grant aid alone.[11]

B. Program-level Data and Sample

To track changes in price following deregulation, we have assembled information on tuition and fees for each public university in Texas since 2000 separately by major/program, credit load, entering cohort, residency and undergraduate level. This level of granularity is critical, as many institutions adopted price schedules that vary according to all of these characteristics, and no prior source of data captures these features.[12] Our main price measure is the price faced by in-state juniors taking 15 credit hours, which is the minimum number of credits students would need to take in order to graduate within four years.[13] We convert all tuition prices and spending measures to real 2012 dollars using the CPI.

To measure program-level resources, we use administrative data on both the course sections offered and faculty in each department at each institution since 2000. We construct various measures of resources (faculty salary per student, average class size, faculty per student, average faculty salary) for each program in each year before and after deregulation, measured in the Fall. Since the breadth of academic programs vary by institution, we standardize them using 2-digit Classification of Institutional Program (CIP) codes, separating Economics and Nursing from their larger categories (Social Science and Health Professions, respectively) as they are sometimes housed in units which price differently. We restrict our analysis to programs (defined by 2-digit CIP codes) that enroll at least one student from each high school cohort from 2000 to 2009. Our final program-level sample includes 641 programs tracked over ten years, for a total sample size of 6,410.[14] A description of how the program-level resource measures were constructed is included in Appendix B. The average program spends nearly $3,000 on faculty salary per student, pays its main instructor $30,500 per semester, and has about 30 students per course section.

[11] As a robustness check, we also examine grants from other sources received by need-eligible students (including categorical aid and merit-based aid). Including these does not alter our estimates much. These items are not consistently available for students that did not also have a needs assessment done.

[12] This information was assembled from various sources, including university websites, archives, and course catalogs. Kim and Stange (2016) describe the price data in more detail.

[13] Unfortunately prices are only available for credit loads of 9, 12, and 15, so we are not able to construct price for the average credit load. Nonetheless, using tuition price for a different credit load will rescale our price estimates but have no substantive impact on our analysis.

[14] We exclude programs that are introduced or discontinued during our analysis window or that have a very small number of students. In practice, this restriction drops fewer than 5% of the student sample across all cohorts.

C. Program-level Earnings

We characterize each program at each institution by the average post-college earnings of its enrollees prior to deregulation, controlling for student selection into particular majors. For all individuals who both graduated from a public high school in Texas from 2000 to 2002 and were observed working in the state ten years later, we estimate:

$$LogEarnings_{ijk} = \beta_0 + \gamma_{jk} + \beta_1 CommColl_i + \beta_2 X_i + \varepsilon_{ijk} \qquad (1)$$

where γ_{jk} is a full set of fixed effects for each program (major j and institution k), $CommColl_i$ denotes students that enroll in a community college but do not transfer to a four-year institution within two years. X_i is a vector of student characteristics: achievement test scores, race/ethnicity, limited English proficient, and economically disadvantaged. The outcome $LogEarnings_{ijk}$ is the average log quarterly earnings residual for person *i* ten or more years after high school graduation, after netting out both year and quarter fixed effects. The set of program fixed effects provides an estimate of the average earnings of each program (relative to the earnings of high school graduates that did not attend public higher education in Texas) purged of any differences in student characteristics. Since we focus on initial (rather than final) program, estimates of γ_{jk} should be interpreted as the ex-ante expected returns from enrolling in each program, which includes any earnings effects that operate through changes in the likelihood of graduating.

Figure 2 shows how program earnings vary by field and institution.[15] Students in engineering, business, math, and nursing programs typically have the highest earnings. For example, students in the median engineering program in the state experience earnings gains three times as large as the gains experienced by students in the median biology program. Earnings are also highest at the state's research institutions though again there is variation across programs within the same institution. Seven of the top ten programs with the highest predicted earnings are at Texas A&M and The University of Texas at Austin. Programs associated with the lowest returns are mainly from less selective institutions and include visual/performing arts, English language, and the social sciences (excluding Economics). Since labor market outcomes vary so much across programs, disparities in access could impact economic inequality.

[15] Appendix Figure A4 shows the distribution of predicted program-level earnings, weighted by enrollment in 2000. Appendix Figure A5 depicts the median program earnings for each field and institution with different sets of controls. The ranking of fields and institutions by earnings are generally not sensitive to the controls used.

To characterize choices among the 641 programs more easily, we assign each program to one of twenty quantiles based on the program's predicted student earnings impact. Since quantiles are constructed with student-level data, each ventile accounts for approximately five percent of all enrollment.[16] An additional benefit of grouping programs into equally-sized ventiles is that this accounts for size differences across programs that can make interpretation difficult.

IV. Sticker Price Changes

The direct effect of deregulation was to induce substantial price increases for public bachelor's degree programs in Texas. Panel A of Figure 3 presents event-study estimates, comparing the post-deregulation growth in sticker price for programs in the top vs. bottom quartile of predicted earnings. While the price of both is growing prior to deregulation (consistent with national trends), the sticker price jumps immediately following deregulation, particularly for the most lucrative programs. Panel B plots ventile-specific price changes, with the bottom ventile omitted and serving as the reference category. Indeed, the price increase was largest for the most lucrative programs. Programs in the top half of the earnings distribution all increased tuition by a larger amount than those in the lower half, with particularly large increases among the top 15% of programs, which increased tuition by more than $400. Similarly, large increases were also seen in ventile twelve, which includes the University of Texas at Austin Liberal Arts program. This is a large increase relative to the overall average tuition of $2160 prior to deregulation. We also estimate models that interact $Post_t$ with the predicted earnings for program jk.[17] Programs with high predicted earnings (1 log point) increased their tuition price by $728 more than those whose enrollees earn no more than high school graduates. We also let high returns programs have a different initial and post-deregulation growth rate. Price increased immediately post-deregulation for the most lucrative programs (by $441), and also grew at a faster rate ($57 more per year, though insignificant) following deregulation relative to the pre-existing trend.

V. Did Student Sorting Change Following Deregulation?

A. Assessing Changes in Student Sorting

Table 1 demonstrated that poor students are overrepresented in programs in the bottom earnings quartile and are much less likely to enroll in one of the more lucrative programs. To assess how

[16] Table A3 in the Appendix lists the specific programs with the highest and lowest earnings gains, while Table A4 lists the specific programs contained in each ventile.

[17] These results are reported later in Table 6.

deregulation altered the distribution of programs attended by poor and non-poor students, we estimate models of the form:

$$Outcome_{jk(it)} = \beta_0 + \beta_1 Poor_{it} + \beta_2 Post_t * Poor_{it} + \beta_3 Time_t + \beta_4 Post_t + \beta_5 X_{it} + e_{it} \qquad (2)$$

where $Outcome_{jk(it)}$ captures the earnings potential of the program (major *j* at institution *k*) that individual *i* from cohort *t* enrolled in. While we initially examine indicators for college enrollment, our primary outcome is $PredEarn_{jk(it)}$, the predicted earnings of the program chosen by individual *i* in cohort *t.* The coefficient β_1 measures the difference in the earnings potential of programs entered by poor and non-poor students prior to deregulation. Our main parameter of interest is β_2, the differential change in average predicted earnings of the programs attended by poor students relative to non-poor students following deregulation. To describe where in the distribution of programs changes occur, we also estimated models with the outcome $VentQ_{jk(it)}$, an indicator for individual *i* in cohort *t* enrolling in a program *jk* whose predicted earnings place it in the *Q*th ventile. For instance, $Vent20_{jk(it)}$ indicates enrollment in programs that have the highest 5% (enrollment-weighted) of predicted earnings. In this case, β_2 captures any differential change in the likelihood of poor students enrolling in such programs relative to non-poor students following deregulation. To account for differential changes in the characteristics of poor and non-poor students, we control for achievement test scores, race/ethnicity, and whether the student is limited English proficient. Models that include a set of cohort fixed effects in place of the linear time trend and $Post_t$ dummy are quite similar, so we mostly focus on the more parsimonious specification. To account for the possibility that state-wide shocks may affect all students making college choices at the same time, we cluster standard errors by high school cohort.[18]

To interpret our estimates as the causal effect of deregulation on the sorting of students across programs, we require that there be no trends or simultaneous policy changes that differentially affect poor vs. non-poor students and more vs. less lucrative programs following deregulation. State-wide economic shocks or broad initiatives to increase postsecondary

[18] Other methods of clustering produce similar levels of inference. Our main estimates have p-values of 0.09 or lower if we instead cluster by cohort X poor or institution or use block or wild- bootstrap procedures (Cameron, Gelbach, Miller 2008). These results are reported in Appendix Table A5.

participation among all students will be absorbed by year fixed effects or time trends and are not a source of bias. However, delayed effects of other policies such as the Top 10 Rule or targeted scholarship and recruitment policies-for example, the Longhorn Scholars program at UT Austin-could potentially confound our estimates of the effects of deregulation.

To address this issue, we also estimate event-study models. These models include an indicator for poor, poor interacted with a set of cohort fixed effects (omitting 2003), and a full set of cohort fixed effects and individual controls.

$$Outcome_{jk(it)} = \beta_0 + \beta_1 Poor_{it} + \sum_{c=2000}^{2009} \beta_c 1(Cohort = c) * Poor_{it} + CohortFE_t + \beta_5 X_{it} + e_{it} \quad (3)$$

The coefficients, β_c ,can be interpreted as the change in poor student representation relative to non-poor students in *c* relative to the year prior to deregulation (2003). For c = 2000, 2001, and 2002 these coefficients measure any pre-trends in the outcomes that couldn't possibly be due to deregulation. Whether these pre-deregulation coefficients are equal to zero provides a suggestive test of the main assumption of specification (2) that allows for a causal interpretation.

B. Overall Enrollment and Initial Program Choice

Before examining program choice, we first examine whether deregulation is associated with overall changes in college enrollment. These results are shown in the first four columns of Table 2. We see little effect of deregulation on students' likelihood of attending any public college in Texas (including community colleges) or any 4-year public institution after controlling for a simple linear time trend, with or without other controls.[19] Deregulation does not appear to have affected overall college enrollment or students' choice between 2-year and 4-year institutions, given that the former was not subject to deregulation. Furthermore, we believe that changes in sample selection have little impact on our analysis of program choice.

The final two columns present our main results on choice of initial program for the entire sample of high school graduates (column 7) and the subset of students that enroll in four-year colleges (column 8). On average, poor students enter programs that generate earnings gains 3.7% lower than non-poor students, after controlling for demographics and achievement test scores. This gap closes by more than one-third following deregulation. Estimates are still positive but

[19] Results for any 4-year public program and a public 4-year program included in our analysis sample are quite similar, so we show the latter because this directly speaks to the importance of sample selection for our subsequent analysis on program choice.

attenuated when we include all high school graduates (including non-attendees) in column 7.[20] Results are directionally similar, though weaker and less precise, when we do not control for changes in student characteristics.

Figure 3 presents event-study estimates as described in equation (3). There is no noticeable trend in average program earnings of poor relative to non-poor students leading up to deregulation, but a noticeable and persistent uptick afterwards (Panel A). Similarly, we see no pre-existing trends in the difference between poor and non-poor students in the likelihood of enrolling in a top 20% or bottom 20% program (Panels B and C), but clear shifts following deregulation. This gives us confidence that our interrupted time-series estimates are not merely picking up the effects of pre-existing trends. The gains come from a clear relative movement of poor students away from the least lucrative programs – a reduction of 3.5 percentage points in the relative likelihood of enrolling in a bottom quintile program. Some of this movement may be to programs in the top quintile, though the magnitude does depend on controls for student test scores. There is no evidence that the representation of low-income students declined in top programs following deregulation. Appendix Figure A8 shows these trends in levels for poor and non-poor students (rather than the difference). While both groups experience similar trends prior to deregulation (towards less lucrative programs), poor students move to more lucrative programs in absolute terms, while the enrollment pattern of non-poor students is relatively more stable after deregulation.

Figure 4 examines student sorting across the whole distribution of programs. To better understand how earnings differ across this distribution, the figure plots the average predicted earnings for each ventile. Other than the tails, log predicted earnings is quite linear. Thus, even shifts in students across programs in the middle of the distribution will have important consequences for predicted earnings. The dark bars show that the unequal distribution of students across programs remains even after controlling for differences in student demographics and achievement test scores. Poor students are 1 to 2 percentage points more likely to enroll in programs in each of the bottom six ventiles and, consequently, much less likely to enroll in programs with medium to high predicted earnings. However, this pattern changed in the years following deregulation (light bars). Relative to non-poor students, poor students shift away from

[20] Since non-attendees are the baseline group against which earnings are compared, these students all receive a zero for the predicted earnings outcome. So, including them in the analysis (with no detectable change in behavior) attenuates the overall effect towards zero.

these low-earning programs after 2004 and make gains throughout the rest of the distribution. Large gains are seen particularly in ventile twelve, which includes Liberal Arts at UT Austin, one of the largest programs in our data. However, important gains are made at many other programs with above-median earnings potential.[21]

C. Robustness and Alternative Explanations

The broad pattern of sizeable shifts away from the bottom of the distribution is remarkably robust to the inclusion of different student controls or alternative specifications, as shown in Panel B of Figure 4 and in Table 3.[22] High school fixed effects account for the possibility that the high schools attended by college-goers is changing in a way that may correlate with program choice. We also control for application and admissions behavior by including a large set of indicators for all the Texas public universities to which the student applied and was accepted, which may pick up some unobservable student traits (Dale and Krueger, 2000). Neither addition impacts our estimates, though we exclude these controls from our baseline for reasons of statistical power and interpretability, respectively.[23] Given the unimportance of controlling for these observed characteristics, this gives us confidence that the results may be robust to changes in unobserved characteristics as well.

In columns (4) through (7), we systematically rule out several of the most well-known policies that might differentially affect poor vs. non-poor students following deregulation. It's worth noting that most of these policies were enacted several years prior to deregulation, so would only be a source of bias if they had delayed effects on the relative program enrollment of poor and non-poor students. Encouragingly, all of our main results are qualitatively (and often quantitatively) unaffected by these sample restrictions. Thus, we conclude that these other major policy shifts that altered the enrollment of low-income students are unlikely to explain the large shift we observe that coincides with tuition deregulation.

[21] Appendix Figure A6 shows raw histograms for poor and non-poor students in 2000 and 2008. The relative gains of poor vs. non-poor students are driven both by shifts in where poor students enroll (e.g. away from the lowest earnings programs) and the enrollment choices of non-poor students.

[22] Appendix Figure A7 presents estimates for models with fewer or richer controls than our base model. The only place where controls alter the qualitative result is for programs at very top of the distribution. Controlling for achievement test scores attenuates a negative shift at ventile nineteen and turns a negligible change at the very top ventile into a sizeable positive one when controls are included. Because of the importance of controls at these two ventiles, we are cautious about making strong conclusion about movements at the very top.

[23] Including controls for application and admission behavior may be "over controlling" for the treatment of deregulation if one of the mechanisms is through students' application behavior.

In column (4), we drop all students from the 110 high schools that participated in the Longhorn Opportunity Scholars or Century Scholars programs, which provided financial aid and enhanced support services for poor students attending UT-Austin and Texas A&M, respectively. Though these programs started in 1999 and 2000, respectively, delayed effects could be a source of bias since the LOS has been shown to have large impacts on attendance and completion at UT-Austin (Andrews, Imberman, Lovenheim, 2016). House Bill 1403, otherwise known as the "Dream Act," granted in-state tuition to undocumented students in Texas and was associated with an increase in college enrollment among foreign-born non-citizen Latino/a students (Flores, 2010). Specification (5) drops the small number of Limited English Proficient-classified students in our sample. This is an imperfect proxy for students most likely to be affected by HB1403; unfortunately, citizenship status is not available in our data.

After 1998, the "Top 10 Percent" rule guaranteed admission to any public institution in Texas for residents who graduate in the top decile of their high school class and increased enrollment at the state's flagships (Daugherty, Martorell and McFarlin 2012, Long, M, V. Saenz, and M. Tienda, 2010). Though we do not possess high school grades (or rank), in specification (6) we drop students that scored in the top 30% of their high school on the high school exit exam. This restriction likely drops most students admitted under the Top 10 given the positive correlation between high school test scores and grades.[24] Finally, in column (7) we restrict our sample only to white students, who should be unaffected by the restoration of race-conscious admissions at UT-Austin in 2003.

Our results are quite similar regardless of how we identify "poor" students in our sample, including persistent eligibility for free- or reduced-price lunch, as suggested by Dynarski and Michelmore (2017) or with Pell grant receipt. This is important as we use Pell grant receipt as a marker for poor in supplemental analysis when free or reduced-price lunch status is unavailable. Furthermore, in column (11) we distinguish very poor students (expected family contribution of zero) from moderately poor students (Pell-eligible, but EFC > 0). Though point estimates are larger for the poorest students in our sample, the share of the gap closed after deregulation is identical between these two groups. Gains are thus experienced by both the poorest and modestly

[24] Tables A7 and A8 in the Appendix shows how the sample of institutions and majors chosen by our sample changes with this restriction. As expected, dropping students in the top 30% of each high school's exit exam score distribution greatly reduces the representation of UT-Austin and Texas A&M in the analysis sample (from 32% to 11%) and also reduces the share of students in Engineering and Biology (from 22% to 11%).

poor students that attend four-year college. Finally, our results are qualitatively similar if we use the level of predicted earnings as our measure of program value-added, where the level includes observations with zero earnings (12). Poor students are enrolled in programs with lower levels of expected earnings, but this gap closes quite a bit following deregulation. Though not shown, these results are also robust to the set of controls used to construct earnings estimates for each program.[25] We also performed our main analyses on a restricted sample of students that enrolled in a four-year university directly after high school. The results are quite similar, both qualitatively and quantitatively.

Our single-state analysis cannot account for any national trends or policy changes that alter the representation of poor students relative to non-poor students at high-earning programs and institutions. For instance, if poor students were making relative inroads at high-earnings programs around the country because of Pell grant expansions, our Texas-specific estimates will overstate the gains experienced due to tuition deregulation. To address this, we complement our main analysis with a cross-state comparison between Texas and other states. We find that the difference in predicted earnings of 4-year public institutions attended by Pell students and non-Pell students shrinks in Texas following deregulation, while actually widening modestly in other states. This analysis suggests that our main within-Texas comparison is not conflating deregulation with national trends. If anything, our results are strengthened by including other states as a comparison group. Simply put, Texas is unusual in having the Poor-NonPoor gap close following deregulation relative to other states that did not deregulate tuition.[26]

D. Medium-Term Outcomes

One concern is poor students may not ultimately benefit from initially attending better programs because they do not persist, graduate, or actually experience higher earnings. Table 4 investigates several of these medium-term outcomes. Column (1) reports sorting results for the program students attend in their 3rd year after initial enrollment, where continuing enrollment and dropout are distinct outcomes for each program.[27] The patterns are quite similar to those for initial

[25] The coefficient on Post X Poor in Panel A are 0.0192, 0.0177, and 0.0112 when the earnings equation has no controls, only demographic controls, or full controls + application dummies, respectively. These are all significant at the 1% level and are quite similar to our base model estimate of 0.0129.
[26] This supplemental analysis is described in Appendix C. The results are robust to various sets of control states, including using the synthetic control approach of Abadie, Diamond, and Hainmueller (2010).
[27] We estimate predicted earnings for each program separately for students that are still enrolled and those that have dropped out, using a modified version of equation (1) that interacts each program dummy with whether the student is still enrolled in college after two years. Predicted earnings estimates are qualitatively similar to those that do not

program enrollment. On average, poor students are in programs that generate earnings gains 5.6% lower than non-poor students two years after initial enrollment, after controlling for demographics and achievement test scores. This gap closes by more than one-fifth following deregulation. These results suggest that deregulation induces poor students to not only enter more lucrative programs but to also remain and persist in them.[28]

Column (2) examines the likelihood of graduating within six years of college entry.[29] Estimates are very imprecise zeros, but directionally consistent with our conclusion that deregulation is not associated with reduced attainment. Finally, in columns (3) and (4) we examine whether deregulation is associated with an improvement in the relative position of poor students in the earnings distribution following high school and college. We calculate earnings percentiles relative to high school graduates in the same high school cohort and include all in-state quarterly earnings over the focal year, including quarters with zero earnings. Examining actual earnings raises a number of challenges, so we view analysis of this outcome with caution.[30] Nonetheless, poor students modestly closed some of the gap in their earnings rank relative to non-poor students following deregulation. One particular concern is that any long-run trends affecting poor vs. non-poor workers in the labor market in the years following deregulation may confound our estimates. To address this, Panel B presents a triple-difference estimate where we use non-attendees to control for such a trend. These estimates are even larger, though also imprecise. That is, the poor vs. non-poor gap in earnings widens for those who do not attend four-year college but poor college attendees are mostly shielded from this trend. While these medium-term outcomes are noisy, they point in the direction of poor students that attend four-year colleges being slightly better off following deregulation.

VI. Possible Channels

A. Price Mechanisms

distinguish between continued enrollees and dropouts; students in engineering and business programs and at the most selective institutions have the highest post-college earnings among both persisting and non-persisting students. Students that persist through two years have higher earnings than those in the same programs that do not persist.

[28] Table A6 in the Appendix shows that these results are also robust to the various sample restrictions.

[29] Unfortunately we lose the last two cohorts of our sample when looking at six years after initial enrollment.

[30] Specifically, (1) coverage is incomplete for later cohorts; (2) earnings at young age may not fully reflect long-run outcomes; (3) using actual earnings as an outcome raises a whole host of issues related to differential selection into the earnings sample; and (4) outcomes that are quite distant from the policy change we are exploring may be more susceptible to other influences.

To address concerns that tuition increases would burden low-income students, 15% of tuition revenue generated by deregulation was required to be set aside for need-based grant aid administered by the institutions. More price discrimination – a higher sticker price combined with more aid for low-income students – could potentially increase the representation of low-income students in more costly programs by lowering net price.[31] Figure 6 demonstrates the extent of income-based price discrimination before and after deregulation.[32] Each panel plots the poor vs. non-poor difference in need-based grant receipt each year, with the gap normalized to zero in the year before deregulation. Since poor and non-poor students face the same sticker price for each program, differences in grant aid map directly to price discrimination. Poor students experience a large increase in total need-based grant aid (relative to non-poor students) immediately after deregulation (Panel A). The increase is particularly large at top quartile programs, but still noticeable at bottom quartile programs too. Subsequent panels show the contribution of each of the largest components of need-based grant aid in Texas. HB3015 set-aside grants increased dramatically following deregulation, but only for students in the highest return programs, which experienced the largest sticker price increases (Panel B). Federal Pell Grants expanded modestly following deregulation, though increases were similar for low and high-return programs (Panel C). Furthermore, our cross-state analysis described in Appendix C suggests a minor role for the national Pell Grant expansion, as similar re-sorting patterns are not seen in other states that also experienced it.

TEXAS Grants also increased considerably across the board, particularly for students in the highest return programs (Panel D). This is partially by design; the maximum TEXAS Grant is pegged to average tuition in the state and institutions must fully cover tuition and required fees for any TEXAS Grant recipients with non-loan sources, though institutions can choose not to provide TEXAS Grants to qualified students. Taken together, Panels B and Panel D demonstrate how HB 3015 set asides along with the TEXAS Grant permit institutions to price discriminate, shielding recipients from sticker price increases.

[31]Approximately half of all programs have a poor student share that is 15% or lower. These programs should be able to perfectly offset tuition increases with additional grant aid for poor students via the 15% HB3015 set-asides, keeping net price for poor students constant or even lower. TEXAS Grants can be used to offset tuition increases even further. Institutional discretion means that the offsets we find may not reflect this theoretical ideal in practice.
[32] The following financial aid results should be interpreted cautiously, however, as data limitations require us to exclude non-need-based aid, which disproportionately benefits non-poor students. There is no specific provision of deregulation that would cause merit aid to change following deregulation, but we cannot entirely rule this out.

To further understand the contribution of the TEXAS Grant specifically to our sorting results, in Table 5 we first repeat our main analysis replacing Poor with an indicator for Texas Grant eligibility (based on the criteria as of 2005); sorting results are quite similar to our base estimates (column 1). Columns (2) and (3) restrict analysis to students that are reasonably close to the eligibility threshold. If the TEXAS Grant expansion was fully responsible for our sorting results, then the point estimate should not attenuate with narrower bandwidths. In the narrowest bandwidth, estimates are about one-quarter as large as with the full sample, though the proportionate narrowing of the predicted earnings gap is the same. This attenuation is not because poor students did not experience greater total and TEXAS Grant aid following deregulation, because they do (columns 4 to 9). We conclude that the TEXAS Grant program played an important role in expanding opportunities to low-income students following deregulation, though it cannot explain the full improvement.

The net result of these aid expansions is a widening of the gap in net tuition between non-poor and poor students following deregulation, particularly at higher return-programs. In fact, poor students actually experienced a decrease in net tuition following deregulation at several programs while non-poor students saw increases of several thousand dollars per semester.[33] Are programs that experienced the greatest increase in price-discrimination also the programs that experienced the largest increase in poor students' representation? To answer this, we estimate program-specific versions of equation (2) separately for each program for net price and an indicator for enrolling in the specific program. Using these program-level estimates, we find that each $1000 decrease in the net price that poor students pay (relative to that paid by non-poor students) following deregulation is associated with a 4% increase in the likelihood that a poor student enrolls in a specific program (relative to the time pattern for non-poor students). Thus changes in net price are a plausible mechanism through which the sorting of students across programs changes following deregulation.[34]

Note that this analysis likely understates the effect of deregulation on need-based aid, as institutions were not required to spend additional aid revenue for students in the programs that

[33] Figure A9 in the Appendix plots the net tuition for poor and non-poor students separately by program ventile.
[34] We do not place more emphasis on program-specific estimates for two primary reasons. First, programs are of very different sizes and thus enrollment changes are of such different scales that they are difficult to compare. This motivates our normalization by the program-specific poor student enrollment share and also our focus on ventile-specific estimates, since these have comparable scales. Second, program choice is inherently a multinomial decision, and thus the attributes of all alternative programs should also enter students' choices. Program-specific estimates do not account for the attributes of other programs.

generated it. For instance, additional aid dollars generated by higher business program prices could have been used to subsidize students in liberal arts.

B. Non-Price Mechanisms

Institutions that supported deregulation hoped to use the additional revenue to improve program quality, which may also have affected the sorting of students across programs. We investigate supply-side channels in Table 6. We estimate models interacting $Post_t$ with $PredEarn_{jk}$, the predicted earnings (in 2000) for program jk. A useful summary measure of program resources is total salary of all faculty per student enrollment (column 2), as improvements in several dimensions – more faculty, more highly paid faculty, more tenure-track faculty, smaller class sizes – would be reflected in this measure.[35] Estimates suggest that total salary per enrollment increased most for the more lucrative programs following deregulation. This was accomplished both via expanding the total faculty size, by increasing pay for instructors (either by shifting to a more expensive rank of instructor or increasing pay within rank), and reducing class sizes. These same qualitative patterns remain even when we let high returns programs have a different initial and post-deregulation growth rate in Panel B. Some measures demonstrate improvement immediately following deregulation, while others also improve at a faster rate following deregulation. These greater levels of instructional inputs may partially offset the detrimental effects of the price increases used to generate them.

To determine how much of the deregulation-induced re-sorting operates via shifts across- vs. within-institution, we re-estimate equation (2) but with institution- or major-average predicted earnings as the outcome (rather than institution-major predicted earnings). Estimates using institution-average predicted earnings are quite similar to our main model, suggesting that almost all of the change can be explained by gains in the relative quality of institutions attended by poor students, while cross-major shifts explains little.[36] One channel through which institutions could mitigate adverse effects of price increases on poor students is by changing admissions processes to favor poor students or by encouraging more to apply. We are not aware of any systematic changes in admissions policies that differentially affected poor vs. non-poor students at the time (other than those discussed earlier), but we also assessed this quantitatively

[35]Per-student resource measures are divided by (number of course enrollments divided by 5) to be comparable to unique students, which assumes each student takes approximately 5 classes.
[36]The results are included in Appendix Table A9. We also estimated our base model, but including first school and first major fixed effects separately, with a similar conclusion. Including first school fixed effects completely eliminates the deregulation effect but major fixed effects (without school fixed effects) does not.

by estimating institution-specific versions of equation (2).[37] We examine both the unconditional likelihood of enrolling or applying to each institution and the likelihood of being admitted (conditional on applying). There is a clear relative increase in the likelihood that poor students enroll at higher-return institutions following deregulation and a corresponding decrease at lower-return institutions. However, these gains do not appear to be systematically related to increases in the relative likelihood that poor students are admitted to these institutions (conditional on applying). Furthermore, some programs (most often Business) within institutions practice selective admissions. The stated GPA cut-offs for admissions to these programs do not change following deregulation.[38] While we cannot rule out other non-price channels as important, such as marketing or targeted outreach, we can say that our results are not due to the biggest outreach programs operated by the two flagship institutions.[39]

Finally, we examined changes in program size as a potential mechanism through which these shifts occurred (reported in Appendix D). Total enrollment in low-earning programs grew throughout our analysis period, but did not experience above-trend growth following deregulation. Enrollment in more lucrative programs was mostly stagnant both before and after deregulation. For the most lucrative programs, the lack of any aggregate enrollment change suggests poor students are (modestly) displacing their non-poor counterparts. For less-lucrative programs, there is growth in the enrollment of poor students and non-poor students, but enrollment for non-poor students is occurring at a faster rate.

C. Separating the Contribution of Different Channels

We are not able to isolate the contribution of each individual channel to the resorting that occurs following deregulation, though evidence suggests that both price and quality channels could be important, particularly if program quality is not well known. Prior work has consistently demonstrated that students are very sensitive to both sticker and net price in their enrollment, institution, and major choices (Dynarski, 2000; Long, 2004; Hemelt and Marcotte, 2011; Stange, 2015), with low-SES students being particularly price-sensitive (Jacob, McCall, and Stange,

[37] Results are reported in Table A10. Admissions data is incomplete for our first cohort, so this analysis only includes the 2001-2009 high school cohorts. Appendix Table A11 reports means for all the outcomes.

[38] The required GPA for admissions to the undergraduate Business programs at UT-Austin (GPA = 3.0), Texas A&M (3.0), University of Houston (2.75), and Texas Tech (2.75) remained constant from 2003 to 2005. That at UT-Arlington increased from 2.0 to 2.5 in this time period. Texas A&M Engineering's admission standard also remained constant (at 2.0).

[39] As shown in Table 3 (column 4), are results hold even after excluding high schools targeted by the Longhorn Opportunity Scholars (UT-Austin) and Century Scholars (Texas A&M) programs.

2017). However, evidence on responsiveness to program quality is less clear. Students are attracted to more selective institutions and high-paying majors (Dillon and Smith, 2017; Beffy et al. 2012; Long et al, 2015; Wiswall and Zafar, 2014), though appear to be less sensitive to financial resources specifically (Jacob, McCall, and Stange, 2017). Furthermore, quality differences are not well known, particularly to low-SES students (Hastings, Neilson, Zimmerman, 2017; Huntington-Klein, 2016). It is possible that deregulation made quality differences more salient, with sticker price serving as a signal of quality (e.g. Wolinsky, 1983). Increasing the salience of program quality can improve the program choices of low SES students in particular (Hastings, Neilson, Zimmerman, 2017).

To further explore the role of price and quality channels, we compare ventile-specific estimates of the change in poor student representation, tuition costs, resources, and grant aid. A benefit of such a ventile-specific analysis is that it accounts for size differences across programs that can make it difficult to interpret magnitudes for program-level analysis. Figure 7 demonstrates that the ventiles that experienced the greatest sticker price increase following deregulation - those with higher-than-average returns – also saw the greatest increase in the relative share of poor students. Panel A of Figure 8 shows the "first-stage" relationship between these tuition increases and two key mechanisms: program-level resources and need-based aid provided to poor students (relative to non-poor students).[40] Increases in resources and price discrimination were largest for programs that had the largest tuition increases following deregulation.[41] Panel B shows the "structural" relationship between changes in resources and grant aid and poor students' representation in these programs. Though noisy, the results do suggest that programs that saw the greatest increase in resources and price discrimination also saw the largest gains in the representation of low-income students. Thus, greater price discrimination (increased need-based grant aid for poor students) and resource improvements appear to be important mechanisms for the shifts we observe.

VII. Conclusion

In this paper, we've examined the consequences of a shift in price-setting authority for undergraduate education in Texas from the state legislature to the institutions themselves.

[40] Since sticker price for poor and non-poor students is the same within program, this latter measure captures the extent of price discrimination practiced by institutions.

[41] Figures A10 and A11 in the Appendix show that multiple resource measures improve most for programs that saw the greatest increase in tuition and that only expansions in HB3015 and TEXAS Grant programs are related to tuition increases, as expected.

Texas's public colleges and universities responded to this new autonomy by increasing price levels and variation across programs, with particularly sharp increases for the highest-return programs such as business and engineering at the state flagships. Contrary to the fears of deregulation opponents, we find no evidence that tuition deregulation reduced the representation of poor students in these programs. In fact, poor students shifted relative to non-poor students away from the least lucrative programs into more lucrative programs throughout the distribution. Importantly, these shifts in initial program choices are persistent, as we see similar improvements in the relative quality of programs that poor students are enrolled in two years after initial enrollment.

The Texas experience illustrates a way that higher education institutions can raise tuition revenue without magnifying the existing inequalities that already plague higher education (Chetty et al, 2017). Two countervailing responses appear to have partially offset the detrimental effects of price increases on demand by poor students. First, a significant share of deregulation-induced tuition revenue was channeled back into financial aid for needy students, shielding them from price increases. Second, additional revenue enabled supply-side improvements which made lucrative programs more desirable even as they became more expensive. These results underscore the importance of examining the use of funds generated by tuition increases when assessing effects on students. Our findings echo those of Deming and Walters (2015) who find that state subsidies have a larger impact on student enrollment and degree production at unselective colleges when used to boost aid and quality than if used for sticker price reduction. Changes appear concentrated in students' choice of institution (rather than the decision to enroll at all or in choice of major). One possible explanation is that the students make college decisions in stages: any enrollment, then institutional choice, then major choice. The price, aid, and resource changes that affect these decisions may be most salient (or influential) at the institutional choice stage.

How likely is it that other states or countries would experience a similar pattern if they were to adopt a similar tuition-setting model? Our results likely generalize to other settings where tuition increases are tied to additional grant aid (via set-asides). Direct set-asides were the main mechanism through which the relative prices of different programs was altered for poor and non-poor students. Such set asides are not unusual, as several recent deregulation proposals combine both pricing autonomy and additional grant aid. We speculate that deregulation would have had quite different effects if this provision were removed. A second factor affecting generalizability is the TEXAS Grant, the state's large need-based grant program. Some grant programs in other states similarly have institutional autonomy over its dispersion, though Texas appears to be unusual in combining this autonomy with features that make the program particularly effective at shielding poor students from tuition increases. However, our analysis suggest that the TEXAS Grant cannot explain all of the resorting we document, as much of it occurs among students that are not on the margin of TEXAS Grant eligibility. Nonetheless, the uncertain role of the large and generous state need-based grant program warrants some caution in extrapolating our results to other settings that lack such a program.

Our reduced-form results highlight three directions where more research is clearly needed. First, we have not isolated the independent contribution of the various possible mechanisms to the sorting of students to programs following deregulation. Several attributes changed following deregulation, so their contribution is difficult to separate with reduced-form methods. Future work should aim to quantify the role of various mechanisms and to perform simulations of counterfactual changes in these program attributes. This analysis would say, for instance, what the sorting of students would have looked like in the absence of changes in need-based grant aid, which would greatly aid generalizability. Second, we have taken institutions' pricing and resource allocation decisions as exogenous. Modeling the supply-side responses to this large change in the regulatory and economic environment as an endogenous process could shed light on the objectives of public universities, their production process, and the constraints they face. The fact that the institutions took some steps to partially shield low-income students from price increases suggests a desire to maintain some socioeconomic diversity at these institutions. Finally, how these countervailing factors – prices and resources – impact the success of students actually enrolling in these programs or student loan debt are questions with important welfare implications. While we find no adverse effects on the medium-run outcomes for poor students, future work should examine these long-run consequences too.

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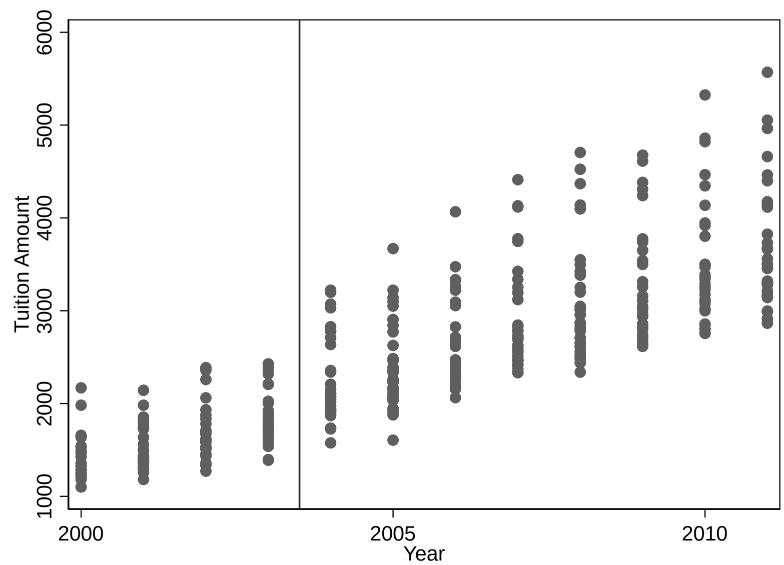
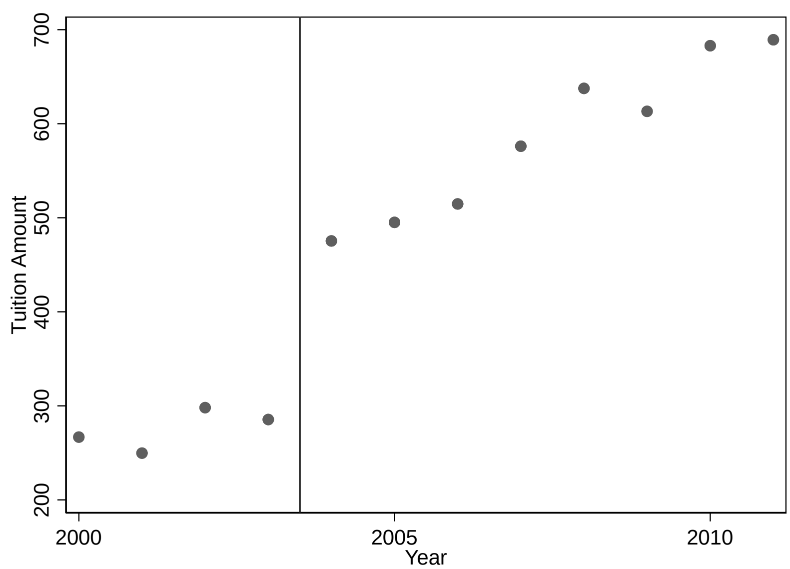
Figure 1. Trends in Fall Tuition Over time (In-state Juniors taking 15 SCH)

Panel A: Program-Specific Tuition over Time

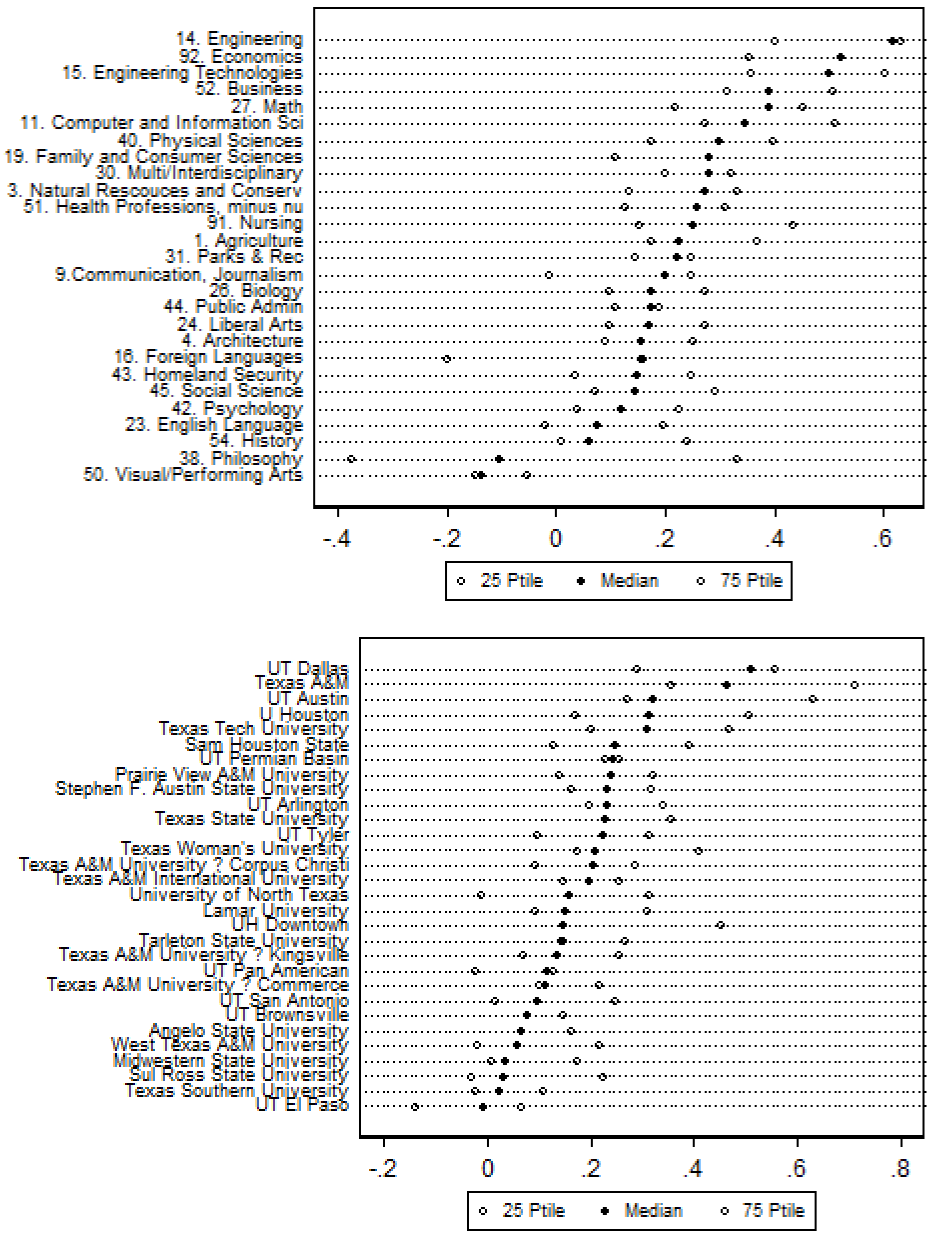


Panel B: Standard Deviation of Tuition (Across Programs)



Notes: Sample includes approximately 640 programs observed each year. Top panel plots the actual sticker price for each program each year. Bottom panel plots the standard deviation of sticker price across all programs in each year. Sticker price was obtained from course catalogs and archival sources and captured separately for each identifiable program (with a distinct tuition or fee), residency status, undergraduate level, academic year, entering cohort, and number of credit hours.

Figure 2. Predicted Earnings by Field and Institution, 2000

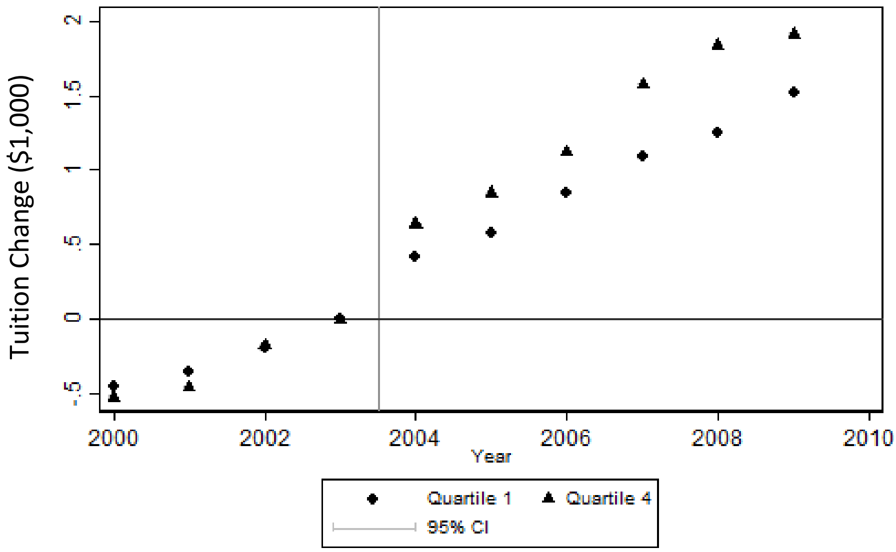


Notes: Full sample includes 643 programs, though this graph omits 68 programs that have fewer than five students enrolled from the 2000 cohort and also does not display any fields or institutions with fewer than 10 observations. The reference group consists of Texas high school students who do not begin attend any public 4-year university within 2 years of high school graduation. Programs weighted by number of enrollees from 2000 cohort when computing 25th, 50th, and 75th percentiles.

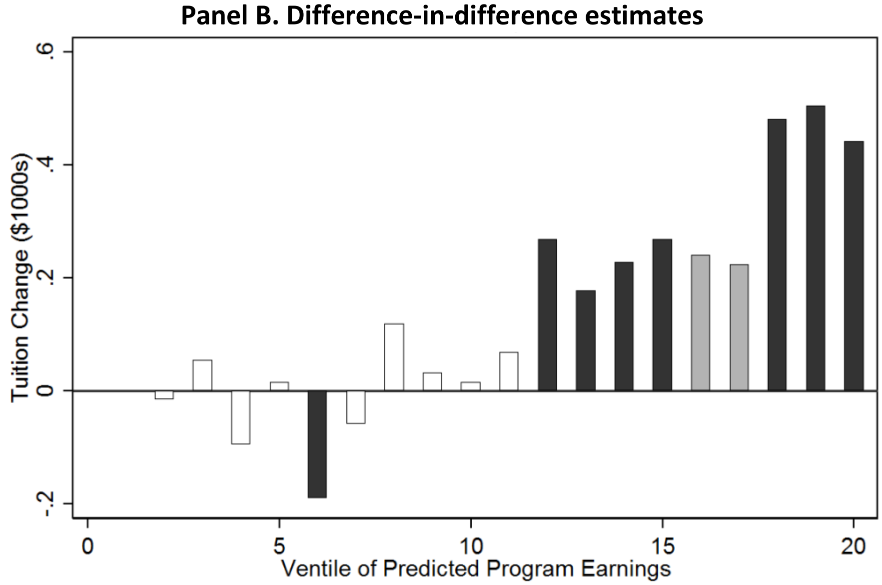
Figure 3. Sticker Price Change Post-Deregulation, by Program Earnings

In-State Juniors, 15 SCH, Fall

Panel A. Event Study Estimates



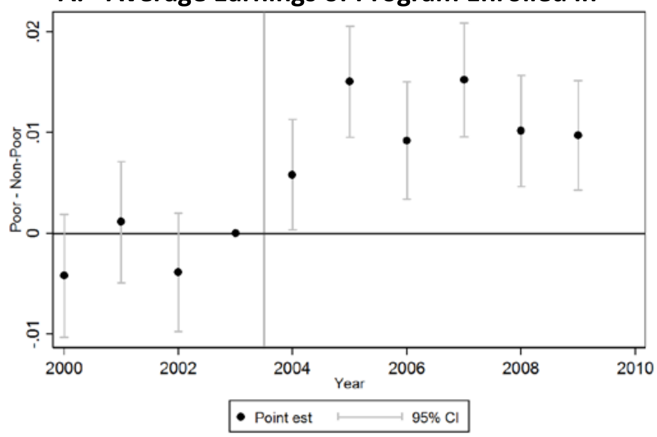
Panel B. Difference-in-difference estimates



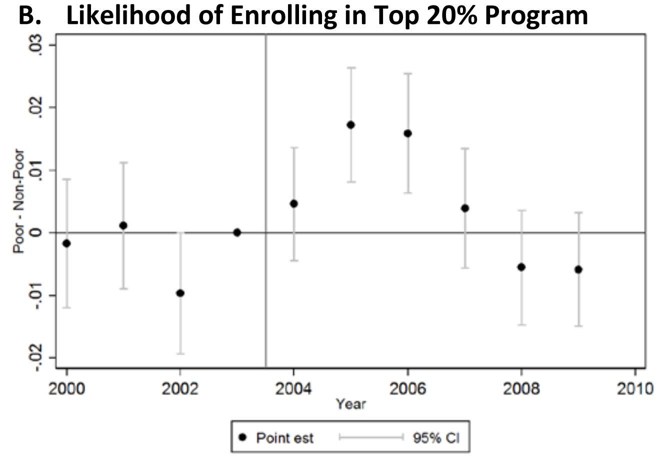
Notes: Panel A plots the change in sticker price (per semester) relative to 2003, separately for programs in the top and bottom quartile of the predicted earnings distribution. We regress sticker price on year fixed effects (omitting 2003) and program fixed effects, weighting by enrollment, separately for programs in the top and bottom quartile of the earnings distribution. The figure plots the year fixed effects. Panel B plots the change in sticker price (per semester) following deregulation by predicted earnings ventile, estimated by the coefficient on the interaction between a post indicator and indicators for each ventile. Bottom ventile is omitted and serve as a reference category. Black bars are significant at a 5% level and gray bars are significant at a 10% level. All models include program fixed effects. Full sample includes 643 programs over ten years, though analysis sample is smaller due to missing data. Standard errors clustered by program.

Figure4. Event-Study Estimates

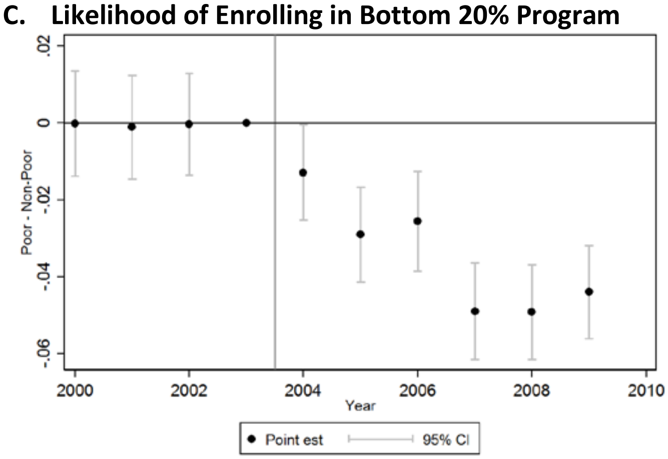
A. Average Earnings of Program Enrolled in



B. Likelihood of Enrolling in Top 20% Program



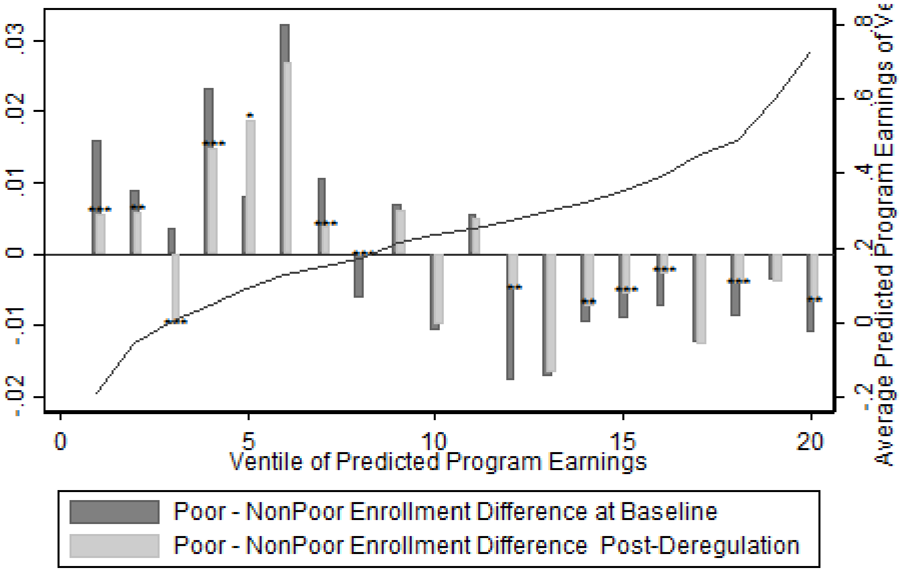
C. Likelihood of Enrolling in Bottom 20% Program



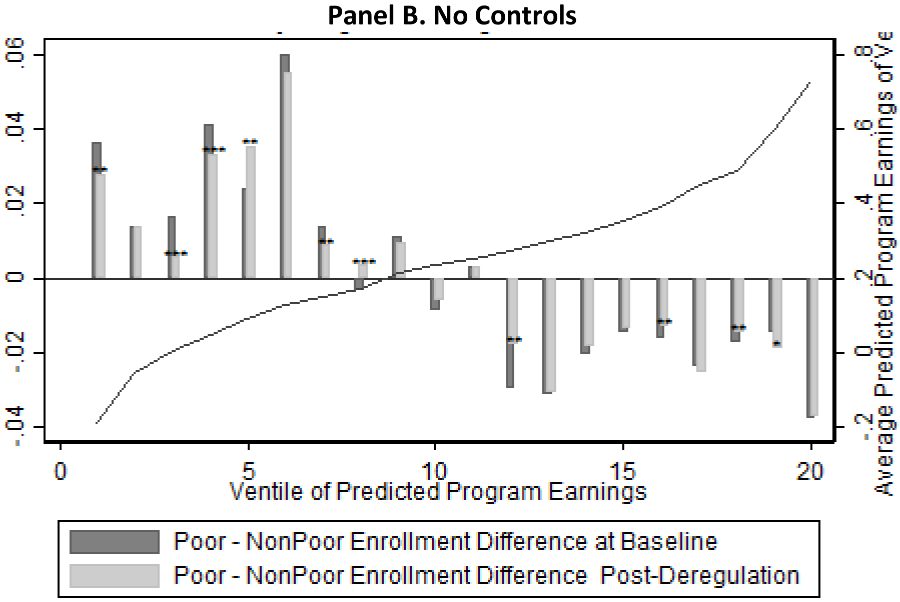
Notes: Figures plot the coefficients on the interactions between a Poor indicator and indicators for each year, as described in equation (3). The year 2003 interaction is omitted and serves as the reference category. Model also includes a full set of year fixed effects, a dummy for poor, race/ethnic indicators, indicator for limited English, and scaled reading and math scores. Outcomes are predicted earnings of the university program the student first enrolled (Panel A) and indicators for this program being in the top (Panel B) or bottom (Panel C) 20% of predicted student earnings. Standard errors are clustered by high school cohort.

Figure 5. Initial Difference and Change in Enrollment of Poor vs. Non-Poor Students Across Programs

Panel A. Full Controls

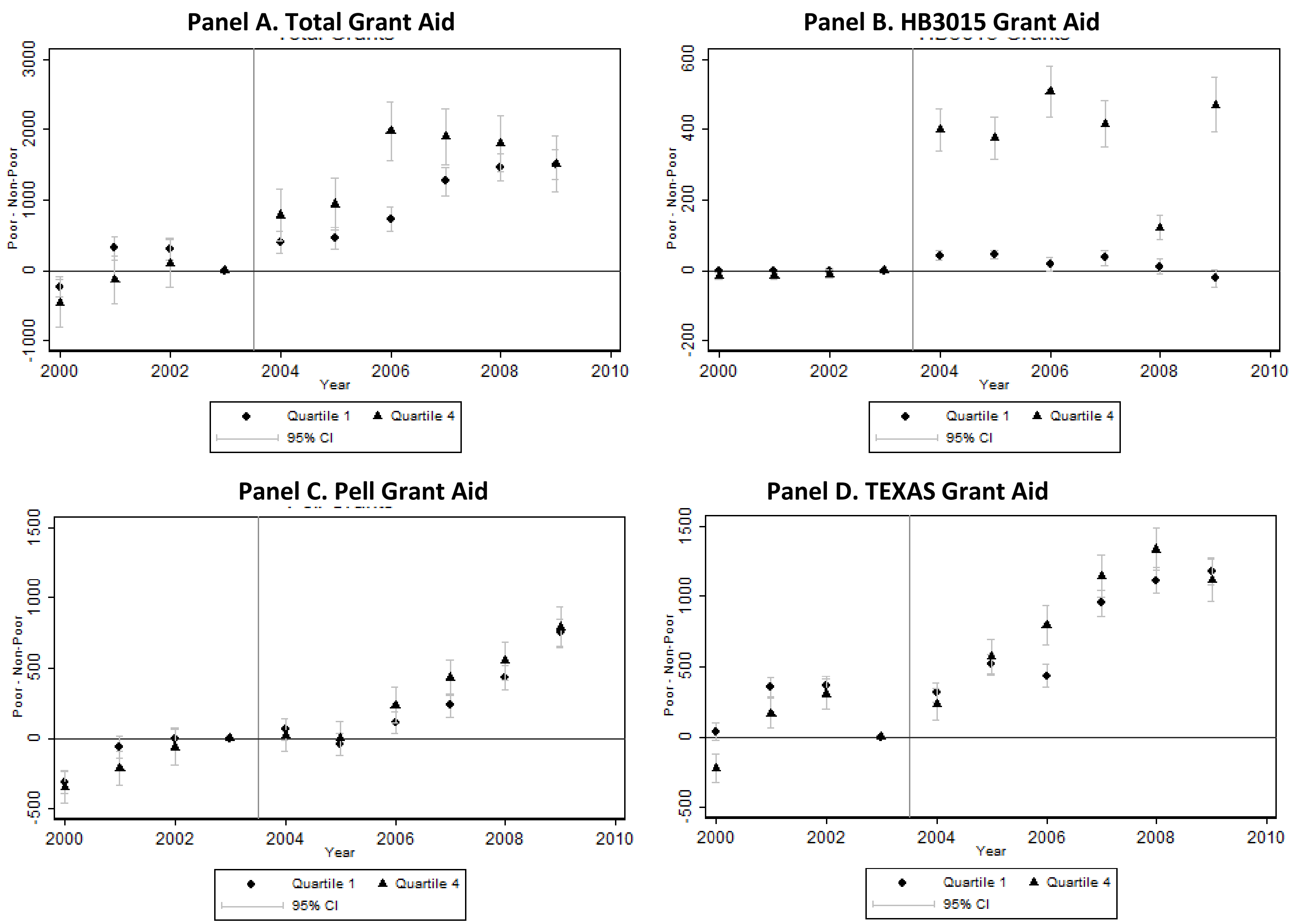


Panel B. No Controls



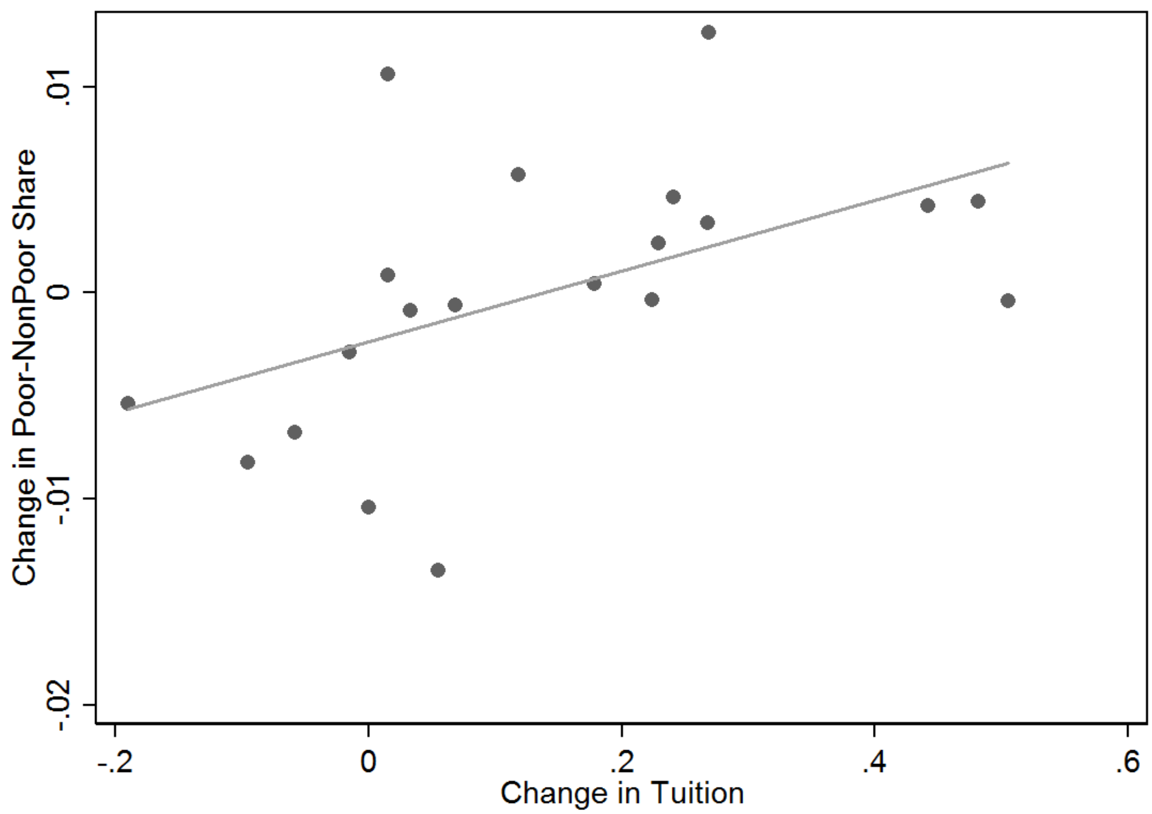
Notes: Estimates in each panel come from twenty separate regressions of indicators for enrolling in a program in each ventile on a dummy for *Poor*, *Post* X *Poor*, *Time* (linearly), *Post*, and student controls (Panel A only), as described in equation (2). Dark bars plot the coefficient on *Poor*. Light bars plot the coefficients on the *Post* X *Poor* interaction added to the coefficient on *Poor*. Markers indicate significance of the interaction coefficients at a 1% (***), 5% (**), and 10% (**) level. Standard errors are clustered by high school cohort.

Figure 6. Income-Based Price Discrimination



Notes: Estimates in each panel come from regression of each type of grant aid amount on year dummies, year dummies interacted with poor (with the 2003 interaction omitted), program fixed effects, and student demographic and achievement controls. Models are estimated separately for programs in the top and bottom quartile of predicted earnings. The *Poor*-year dummy interaction coefficients are plotted. Standard errors are clustered by high school cohort.

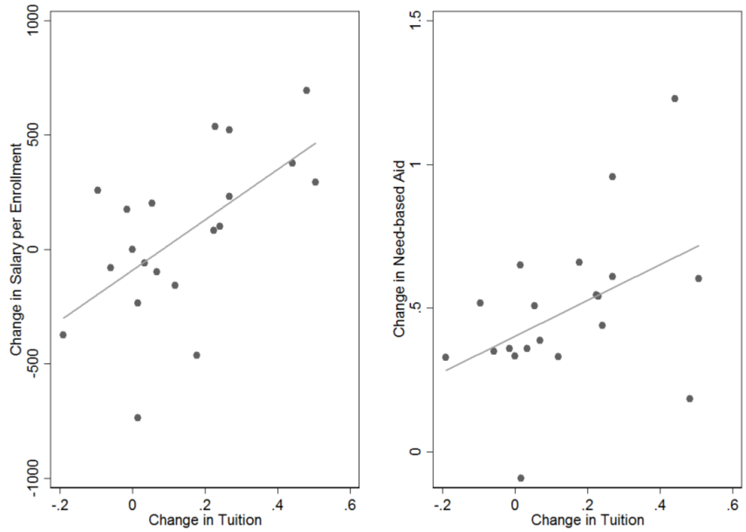
Figure 7. Enrollment Changes vs. Tuition Changes for Each Ventile of Predicted Program Earnings



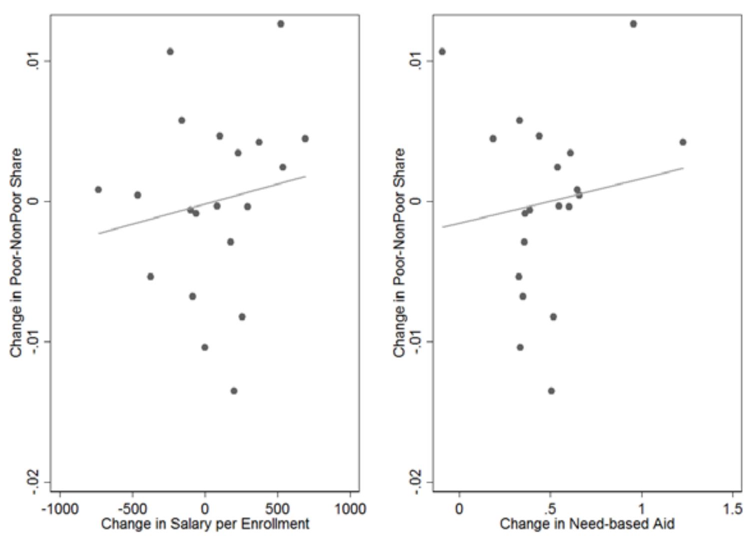
Notes: Each dot represents an estimate of the change in poor vs. non-poor share and change in tuition for a single ventile. The vertical access is the ventile-specific coefficient on PoorXPost depicted in Figure 5 and the horizontal axis is the ventile-specific coefficient on Post depicted in Figure 3B.

Figure 8. Resource and Grant Changes vs. Tuition and Enrollment Changes

Panel A. Resource and Grant Changes with Tuition



Panel B. Resource and Grant Changes with Enrollment



Notes: Each dot represents an estimate of the change in two outcomes for a single ventile. Estimates for sticker prices and salary per enrollment use program level data and are normalized to zero in the lowest ventile. Estimates for the change in poor-nonpoor share use micro student data and come from Figure 5.

Table 1. Summary Statistics of Main Student Samples

	All high school graduates		4-year college enrollees: All students		4-year college enrollees: Poor students		4-year college enrollees: Non-poor students	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Male	0.482	0.500	0.451	0.498	0.423	0.494	0.458	0.498
Black	0.121	0.327	0.119	0.324	0.213	0.410	0.098	0.297
White	0.512	0.500	0.582	0.493	0.119	0.323	0.689	0.463
Hispanic	0.326	0.469	0.235	0.424	0.611	0.487	0.148	0.355
Asian	0.038	0.191	0.061	0.239	0.055	0.229	0.062	0.242
Math test	0.007	0.994	0.465	0.764	0.200	0.848	0.526	0.730
English test	0.014	0.984	0.423	0.644	0.163	0.771	0.483	0.595
Poor	0.289	0.453	0.188	0.391	1.000	0.000	0.000	0.000
Characteristic of First 4-Year Program								
Predicted log earnings	0.079	0.169	0.241	0.216	0.174	0.200	0.257	0.216
Not enrolled in 4-year program	0.688	0.489	0.000	0.000	0.000	0.000	0.000	0.000
Top 10 %	0.031	0.172	0.097	0.295	0.052	0.222	0.107	0.309
Top 15 %	0.042	0.201	0.134	0.340	0.076	0.265	0.147	0.354
Top 20 %	0.062	0.241	0.189	0.391	0.111	0.315	0.207	0.405
Top 25 %	0.076	0.265	0.231	0.421	0.142	0.349	0.252	0.434
Bottom 25 %	0.083	0.275	0.260	0.439	0.359	0.480	0.238	0.426
Bottom 20 %	0.065	0.246	0.204	0.403	0.277	0.448	0.187	0.390
Bottom 15 %	0.049	0.215	0.156	0.362	0.200	0.400	0.145	0.352
Bottom 10 %	0.032	0.175	0.101	0.301	0.137	0.344	0.093	0.290
Tuition ($1000)			2.844	0.776	2.623	0.746	2.894	0.774
Faculty salary per student ($1000)			2.886	11.325	2.961	13.517	2.870	10.770
Need-based Grant Aid ($1000)								
Total			0.941	1.616	2.480	1.965	0.584	1.283
Pell			0.452	0.829	1.332	0.990	0.249	0.631
HB3015			0.043	0.208	0.073	0.272	0.036	0.189
TEXAS Grant			0.335	0.795	0.872	1.107	0.210	0.642
TPEG			0.080	0.255	0.129	0.307	0.069	0.241
SEOG			0.019	0.104	0.052	0.168	0.011	0.081
Tuition - Need Grant ($1000)			1.900	1.833	0.096	2.014	2.307	1.517
Number of observations	1,861,500		580,253		109,070		471,183	

Notes: Sample includes all high school graduates from public Texas high schools that enrolled in a Texas public four-year college or university within two years of high school graduation. Poor indicates elibilble for free or reduced-price lunch, family income is at/below the federal poverty line, TANF eligible, Pell recipients, Title II eligible, or eligible for food benefits under the Food Stamp Act of 1977. SEOG stands for the Federal Supplemental Educational Opportunity Grant. TEOG stands for the Texas Educational Opportunity Grant. TPEG stands for the Texas Public Educational Grant. HB3015 stands for the designated tuition grants associated with HB3015.

Table 2. Effect of Deregulation on College Enrollment and Program Choice

	Attend any public Texas college or university (mean = 0.504)		Attend 4-year college in balanced program (mean = 0.26)		Program Choice: Log(Predicted earnings) of first program			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Poor	-0.137***	-0.0860***	-0.153***	-0.0745***	-0.0604***	-0.0861***	-0.0256***	-0.0370***
	(0.00202)	(0.00277)	(0.00297)	(0.00330)	(0.00199)	(0.0018)	(0.00175)	(0.0019)
Post	0.0159	0.0148	0.00377	0.000114	0.000306	-0.0029	-0.00115	-0.0060
	(0.0287)	(0.0295)	(0.0223)	(0.0246)	(0.00759)	(0.0066)	(0.00805)	(0.0091)
Post X Poor	-0.00769*	-0.00571	-0.000780	0.00646	0.00103	0.0057**	0.00424*	0.0129***
	(0.00390)	(0.00379)	(0.00401)	(0.00406)	(0.00240)	(0.0023)	(0.00224)	(0.0018)
Controls	No	Yes	No	Yes	No	No	Yes	Yes
Sample	All HS grads	All HS grads	All HS grads	All HS grads	All HS grads	4-year enrollees	All HS grads	4-year enrollees
Outcome mean	0.504	0.504	0.26	0.26	0.079	0.241	0.079	0.241
Observations	1,861,500	1,861,500	1,861,500	1,861,500	1,861,500	580,253	1,861,500	580,253
R-squared	0.018	0.046	0.022	0.122	0.026	0.0223	0.113	0.1205

Notes: All models include time (linearly). Controls include gender, race/ethnic indicators and indicator for limited English, and scaled reading and math scores. Sample includes all students in the high school classes of 2000 to 2009 from public high schools in Texas. College enrollment is measured within two years of high school graduation. Students that attend both 2-year and 4-year colleges are counted as 4-year college attendees. Balanced program refers to the 643 programs that have non-zero enrollment during sample period. Standard errors are clustered by high school cohort (*** p<0.01, ** p<0.05, * p<0.1).

Table 3. Effect of Deregulation on Predicted Earnings of Undergraduate Program Chosen
Robustness

		Varying controls		Restricted sample to rule out other policies			
	Base Model: Log(Predicted earnings) College enrollees Full controls	Full + High school FEs	Full + Application & admissions	Drop LOS/CS Schools	Drop LEP Students	Drop top 30% at each high school	White Students Only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Poor	-0.0370***	-0.0165***	-0.0182***	-0.0420***	-0.0372***	-0.0331***	-0.0657***
	(0.0019)	(0.0018)	(0.0015)	(0.0021)	(0.0019)	(0.0023)	(0.0019)
Post X Poor	0.0129***	0.0116***	0.0073***	0.0135***	0.0124***	0.0129***	0.0109***
	(0.0018)	(0.0020)	(0.0017)	(0.0022)	(0.0019)	(0.0028)	(0.0023)
Obs.	580,253	580,253	580,253	534,366	569,664	306,645	337,721

	Identifying poor students			
	Poor = always FRPL during high school	Poor=Pell Recipient	Poor: Pell Recipient, EFC > 0 Very Poor: EFC = 0	Outcome = Level of predicted quarterly earnings
	(9)	(10)	(11)	(12)
Poor	-0.0257***	-0.0386***	-0.0318***	-193.87***
	(0.0024)	(0.0009)	(0.0014)	(13.30)
Post X Poor	0.0114***	0.0142***	0.0117***	87.07***
	(0.0023)	(0.0017)	(0.0022)	(16.27)
Very Poor			-0.0476***	
			(0.0017)	
Post X Very Poor			0.0173***	
			(0.0026)	
Obs.	580,253	580,253	580,253	580,253

Notes: All models include controls for gender, race/ethnic indicators and indicator for limited English, scaled reading and math scores, time (linearly), and a post indicator. Full sample includes students in the high school classes of 2000 to 2009 that enroll in a Texas public university within two years of high school graduation. Outcome is the predicted earnings of the university program (institution X major) the student first enrolled in. Predicted earnings is estimated using 2000-2002 cohorts and applied to all cohorts (see text). Standard errors are clustered by high school cohort (*** p<0.01, ** p<0.05, * p<0.1).

Table 4. Effect of Deregulation on Medium-term Outcomes

	Dependent Variable			
	Predicted log earnings of program enrolled in 3rd year (1)	Graduate within 6 years of college entry (2)	Earnings Percentile 8-years Post HS Grad (3)	Earnings Percentile 10-years Post HS Grad (4)
Panel A. Sample includes all 4-year enrollees within two years				
Poor	-0.0556***	-0.1020***	-1.4513***	-1.5023***
	(0.0020)	(0.0047)	(0.2780)	(0.1878)
Post X Poor	0.0121***	0.0007	0.0206	0.1917
	(0.0025)	(0.0052)	(0.3150)	(0.4087)
Observations	580,253	510,046	519,694	400,778
Panel B. Sample includes all Texas high school graduates				
Poor			-2.0358***	-2.1410***
			(0.2123)	(0.2037)
Poor X Attend			0.2809	0.6931***
			(0.1740)	(0.1527)
Post X Poor			-0.9422**	-1.0933**
			(0.2881)	(0.3576)
Post X Poor X Attend			0.6410*	0.8941
			(0.2943)	(0.5159)
Observations			1,660,825	1,286,798

Notes: All models include controls for gender, race/ethnic indicators, indicator for limited English, scaled reading and math scores, time(linearly), and an indicator for being after deregulation. Sample includes students in the high school classes of 2000 to 2009 overall (Panel B) and those that enroll in a Texas public university within two years of high school graduation (Panel A). Earnings and graduation models include fewer observations because the outcome is not available for later cohorts. Earnings percentiles are defined relative to high school graduates in the same high school cohort and include all quarterly earnings over the focal year. Zeros are included in calculating percentiles. Standard errors are clustered by high school cohort.

Table 5. Importance of TEXAS Grant to Sorting Results

	A. Predicted Earnings		
	All observations (1)	EFC +/- 6000 of TX Grant Eligible (2)	EFC +/- 3000 of TX Grant Eligible (3)
TxGrantElig	-0.0349***	-0.0189***	-0.0075***
	(0.0010)	(0.0015)	(0.0009)
TxGrantElig x Post	0.0110***	0.0041*	0.0028*
	(0.0014)	(0.0021)	(0.0013)

	B. Total Grant Awards			C. TEXAS Grant Awards		
	All observations (4)	EFC +/- 6000 of TX Grant Eligible (5)	EFC +/- 3000 of TX Grant Eligible (6)	All observations (7)	EFC +/- 6000 of TX Grant Eligible (8)	EFC +/- 3000 of TX Grant Eligible (9)
TxGrantElig	4,649***	2,584***	1,924***	1,281***	601***	456***
	(194.9)	(82.2)	(101.9)	(190.1)	(64.3)	(57.7)
TxGrantElig x Post	2,042***	1,967***	1,898***	1,179***	1,619***	1,678***
	(483.5)	(327.6)	(259.2)	(325.2)	(228.7)	(220.0)
Observations	580,253	234,608	98,139	580,253	234,608	98,139

Note: TEXAS Grant eligibility is determined by having an Expected Family Contribution of less than $4,000, enrolling within 16 months of High School Graduation, and demonstrating Financial Need – by having a Cost of Attendance which is greater than the Expected Family Contribution. Regressions also include time (linearly), a post-deregulation indicator, gender, race/ethnic indicators and indicator for limited English, and scaled reading and math scores. Robust standard errors in parentheses clustered by cohort. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Changes in Sticker Price and Resources Following Deregulation

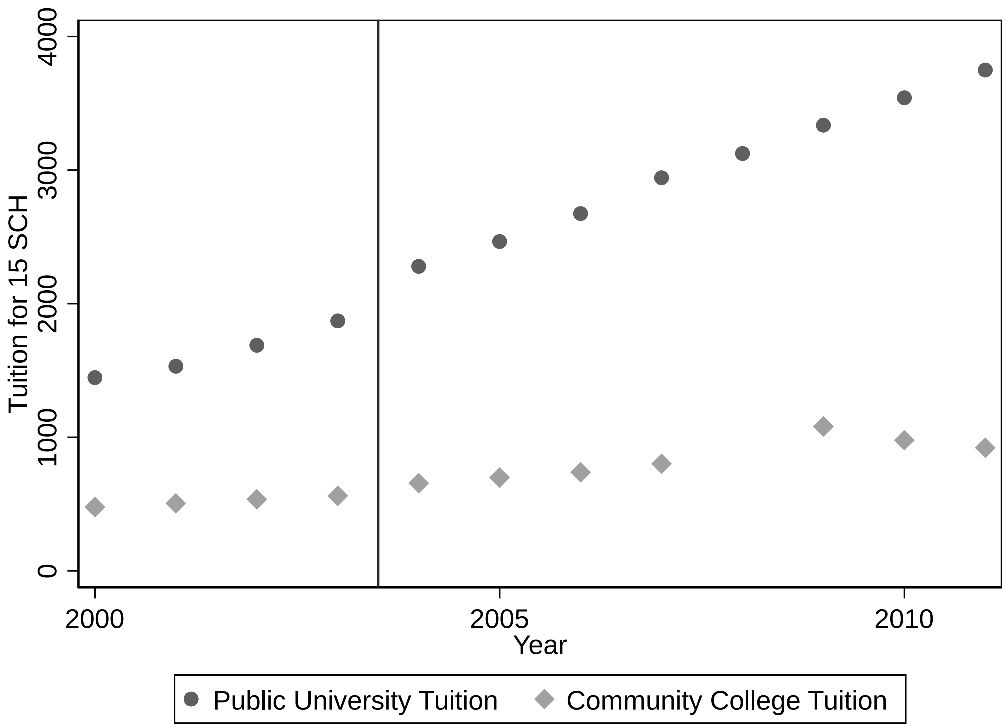
	Tuition ($1,000) for in-state junior with 15 SCH	Total salary per enrollment (trimmed)	Total faculty per enrollment (trimmed)	Average FTE salary	Average class size
	(1)	(2)	(3)	(4)	(5)
Outcome mean	2.165	2719	0.09	30,626	30.69
Panel A. Program Fixed Effects and Year Fixed Effects, No Pre-trends					
Predicted earnings X Post	0.7283***	524.82**	0.0124*	2167	-4.75
	(0.0942)	(263.23)	(0.01)	(1925)	(2.91)
Constant	2.0046***	2,965.26***	0.1006***	30,869***	30.79***
	(0.0179)	(162.97)	(0.01)	(384)	(0.90)
Panel B. Program Fixed Effects with Linear Time Trends and Pre-trends					
Predicted earnings X Post	0.4407**	461.42	0.0107	-1,418	-3.44**
	(0.1866)	(291.40)	(0.01)	(1271)	(1.63)
Time	0.1303***	-64.2	-0.0023	-160	-0.06
	(0.0095)	(65.96)	(0.00)	(191)	(0.27)
Post	0.2861***	-78.14	-0.0032	-543	1.31**
	(0.0409)	(151.99)	(0.01)	(826)	(0.55)
Post X Time	0.0099	87.98	0.0029	303*	-0.13
	(0.0116)	(68.58)	(0.00)	(170)	(0.28)
Predicted earnings X Time	0.0286	-144.34	-0.0008	739	-0.05
	(0.0459)	(154.17)	(0.00)	(777)	(1.02)
Predicted earnings X Time X Post	0.0574	313.86*	0.0023	-40	-0.42
	(0.0510)	(173.13)	(0.00)	(752)	(1.02)
Constant	2.4802***	2,479.86***	0.0884***	30,677***	30.32***
	(0.0239)	(120.20)	(0.00)	(395)	(0.40)
Observations	5,519	5,913	5,913	6,027	6,098

Notes: Full sample includes 643 programs over ten years, though analysis sample is smaller due to missing tuition and resource measures for some programs in some years. Program-specific predicted earnings control for student demographics and test scores. Standard errors clustered by program (*** p<0.01, ** p<0.05, * p<0.1). Trimmed outcomes drop observations in the top or bottom 5% of values. Regressions weighted by number of students enrolled from the 2000 high school cohort.

APPENDIX A. Additional Figures and Tables

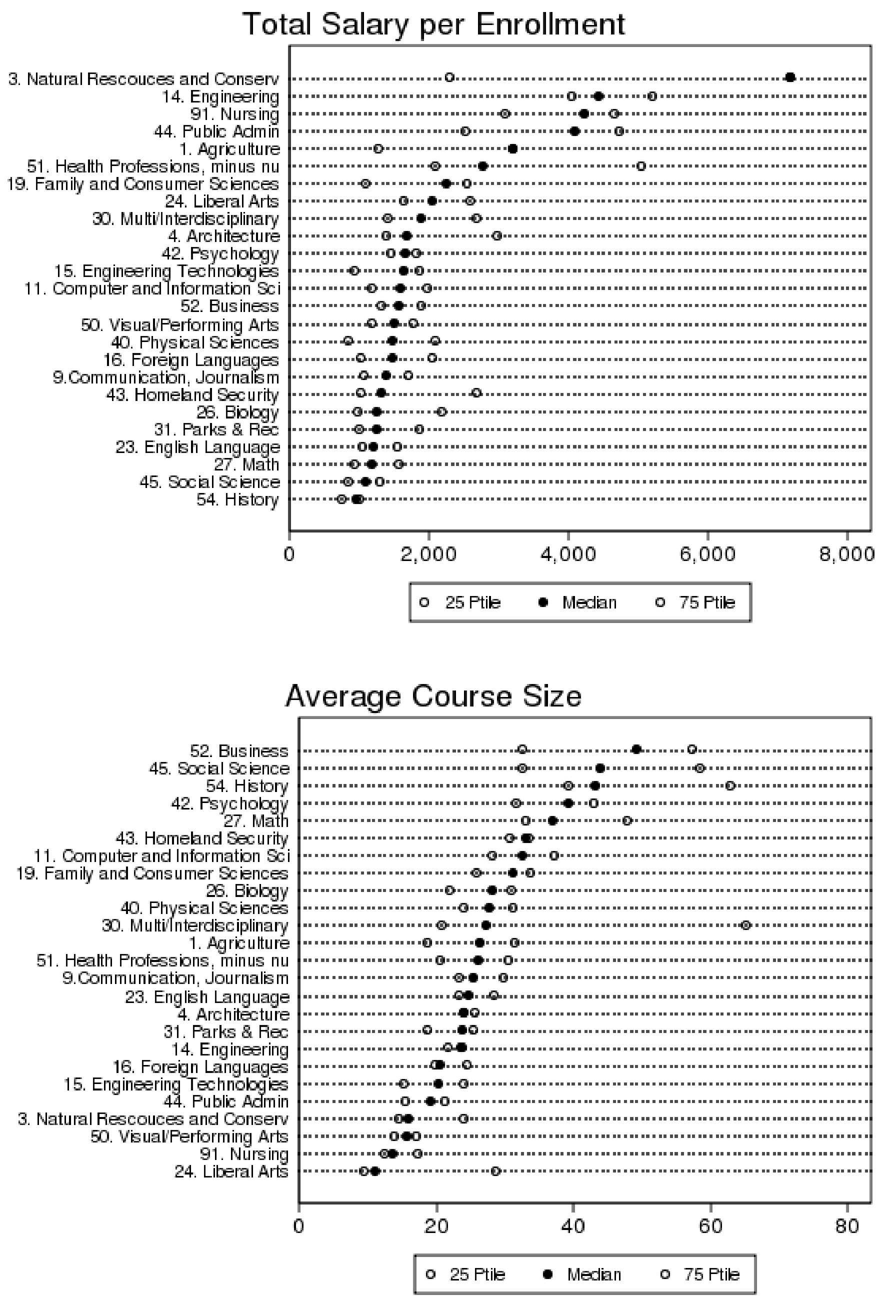
Figure A1. Tuition In Public 4-year and 2-year Colleges in Texas

Fall Semester, In-state/district students, 15 Student Credit Hours



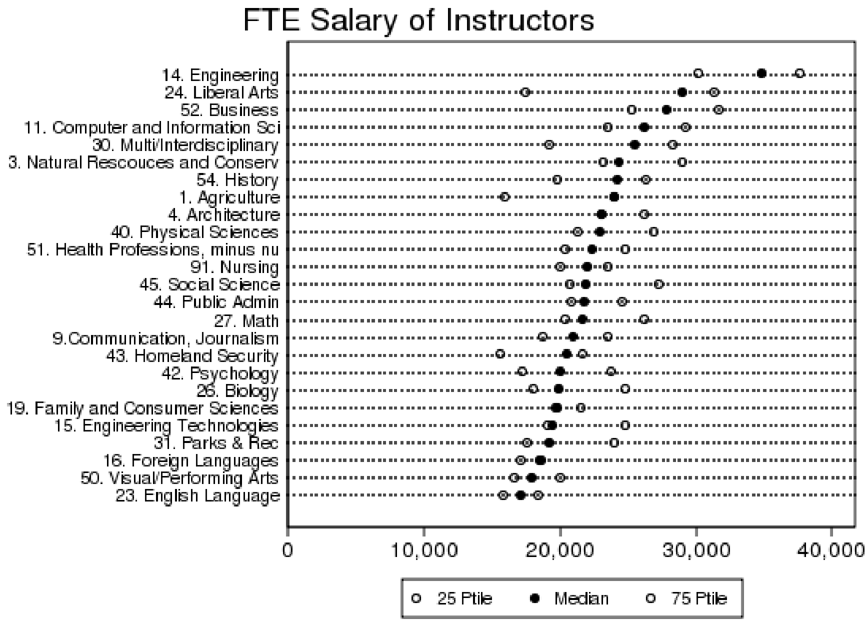
Notes: Public University sample includes approximately 640 programs observed each year. Sticker price was obtained from course catalogs and archival sources and captured separately for each identifiable program (with a distinct tuition or fee), residency status, undergraduate level, academic year, entering cohort, and number of credit hours. Community College sample includes average institution-level price for all community colleges in Texas. Tuition rates not available for 2008.

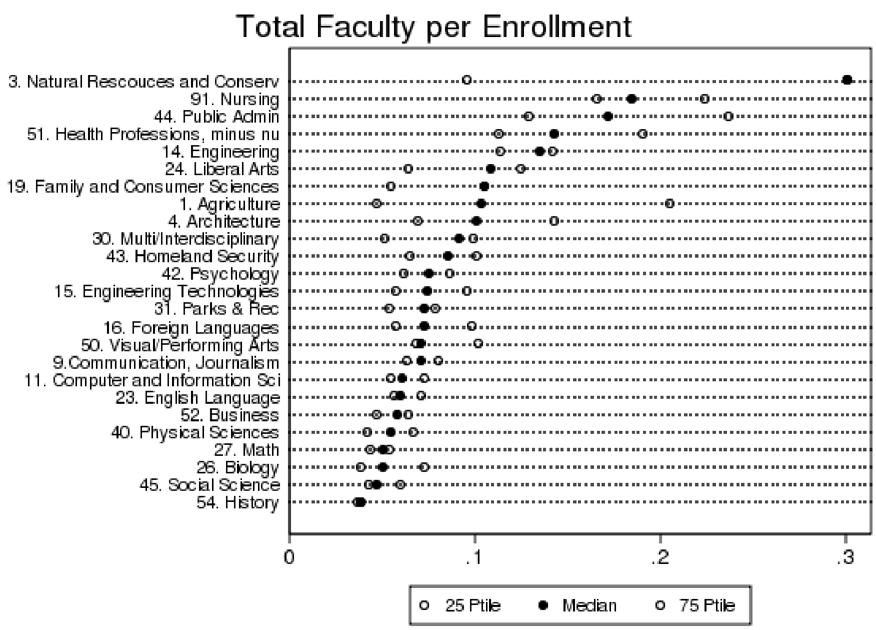
Figure A2. Resource Differences by Field, 2000



Notes: Excludes fields with fewer than 10 programs. Full sample includes 641 programs.

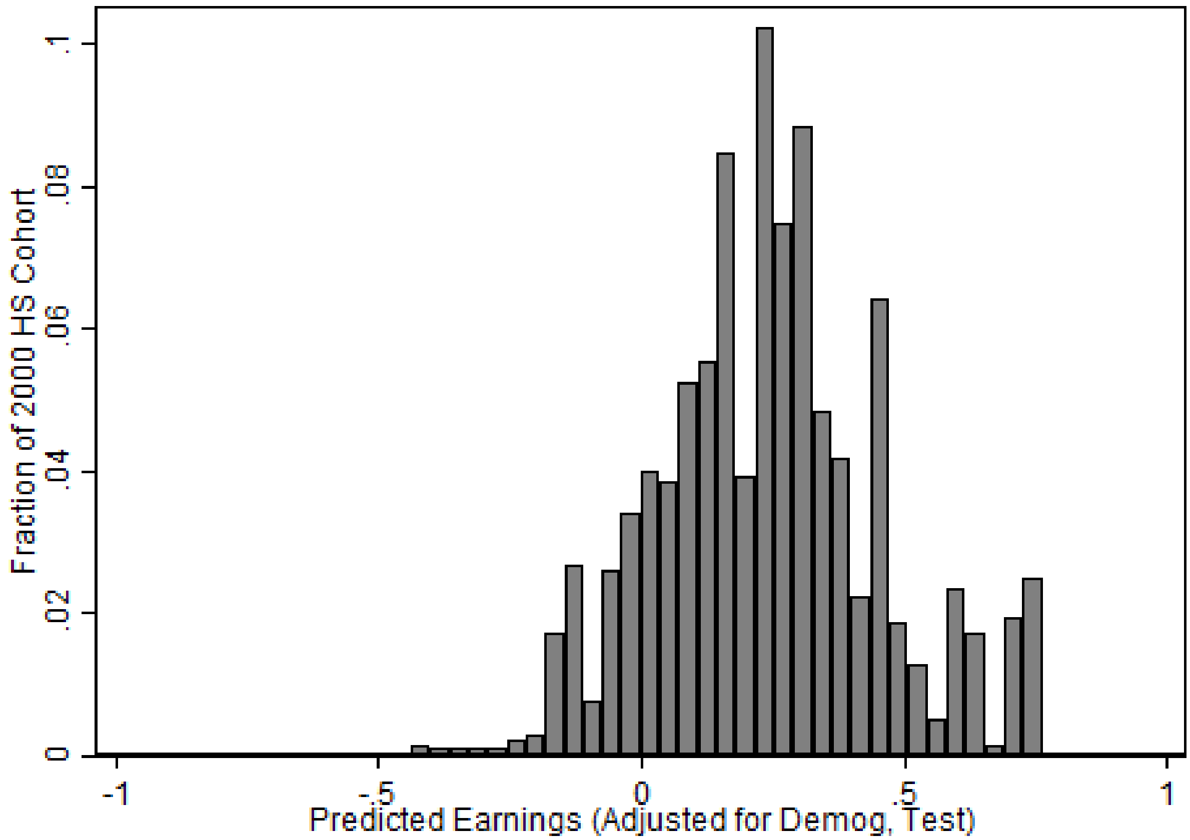
Figure A3. Resource Differences by Field, 2000





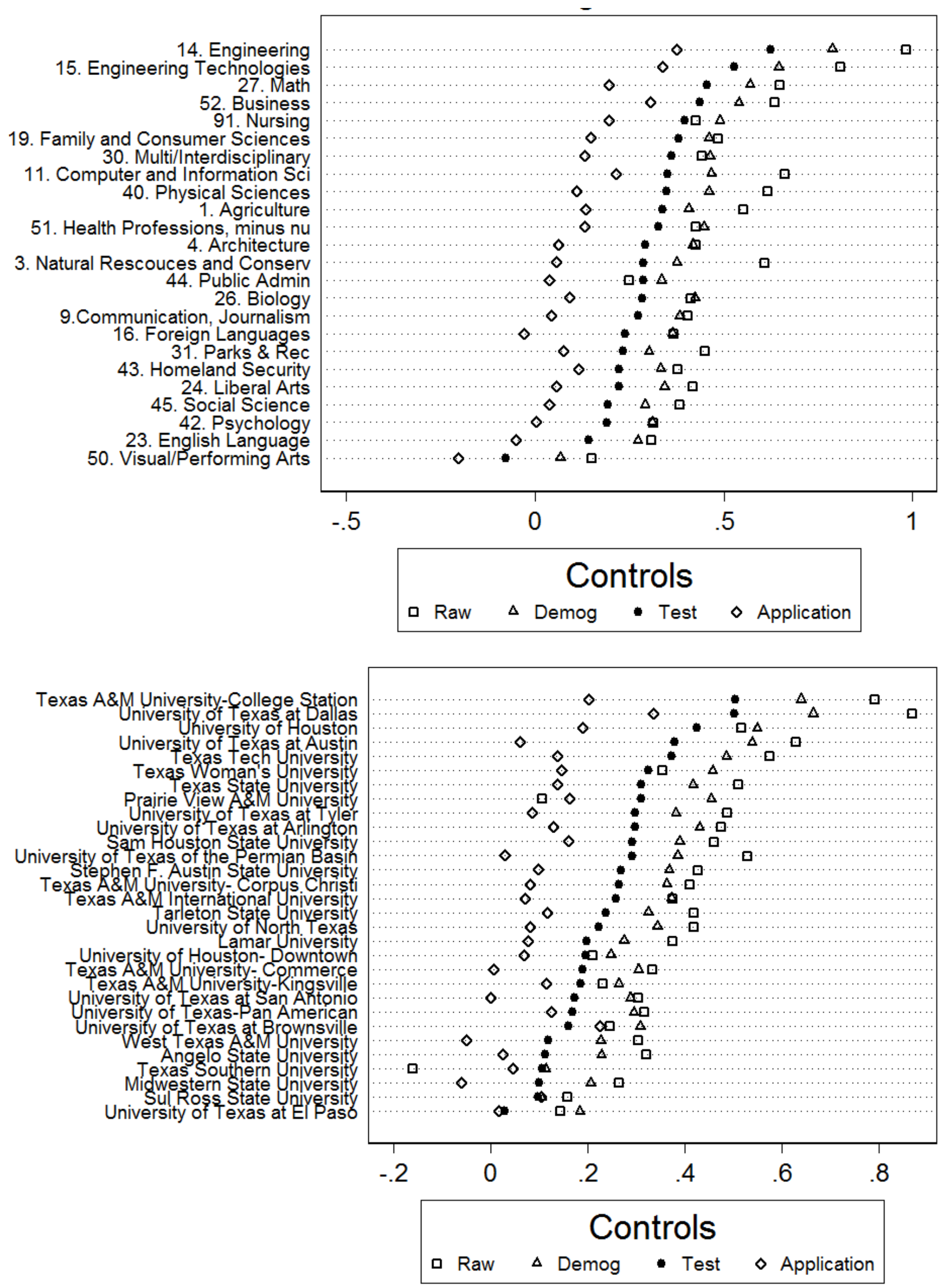
Notes: Excludes fields with fewer than 10 programs. Sample includes 641 programs.

Figure A4. Distribution of Predicted Program Earnings, 2000



Notes: Full sample includes 643 programs, though this distribution omits 68 programs that have fewer than five students enrolled from the 2000 cohort. Programs weighted by number of enrollees from 2000 high school cohort. Program-level predicted earnings control for poor, demographic controls, and standardized achievement test scores. Earnings premium is in reference to high school graduates who did not attend a Texas public university.

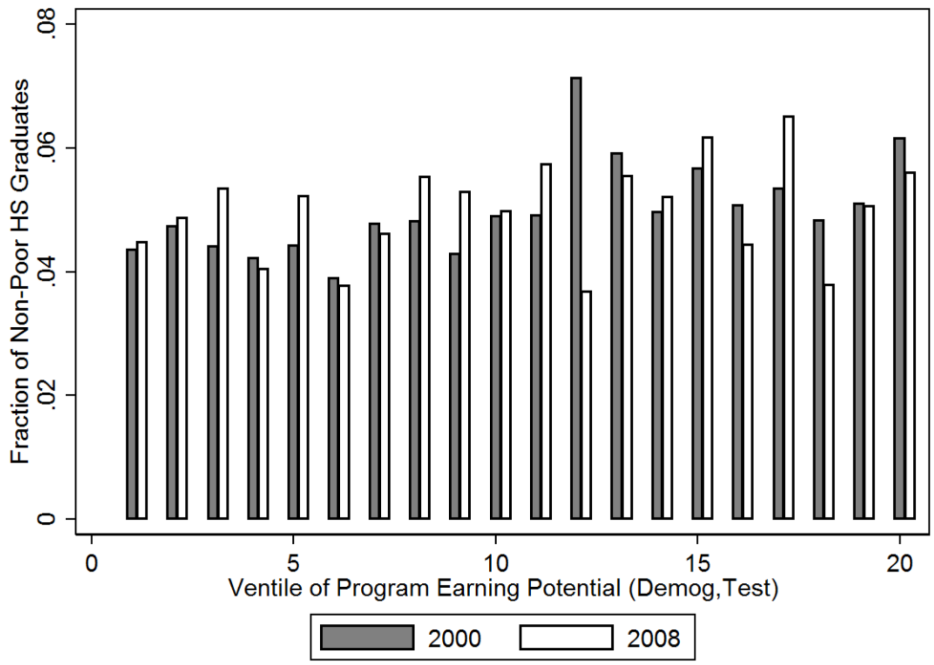
Figure A5. Earnings Differences by Field and Institution, Robustness to Controls



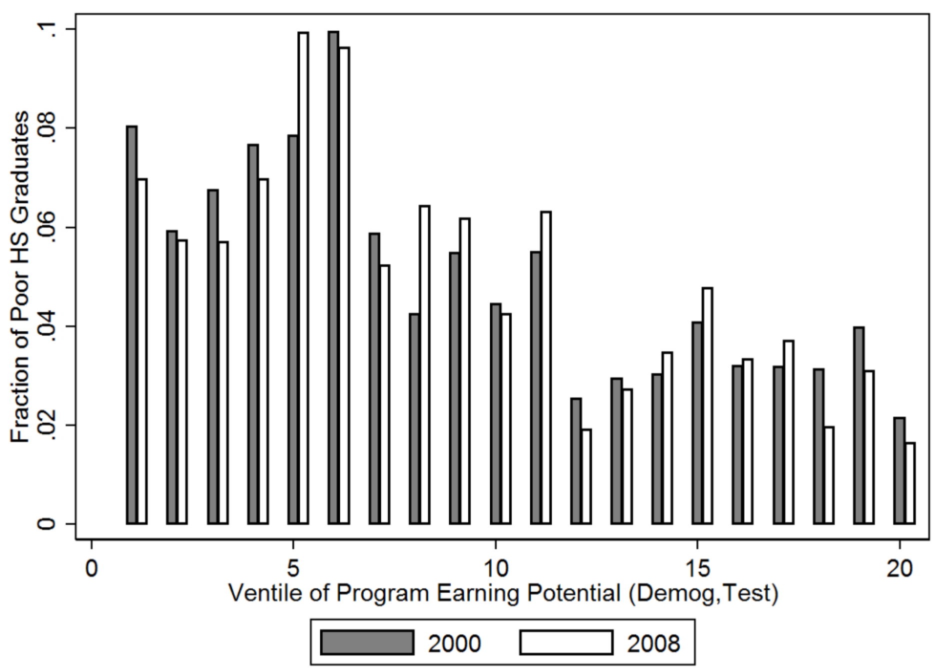
Notes: Full sample includes 643 programs, though this graph omits 68 programs that have fewer than five students enrolled from the 2000 cohort and also does not display any fields or institutions with fewer than 10 observations. Programs weighted by number of enrollees from 2000 cohort when computing 50th percentile.

FigureA6. Distribution of Students Across Programs, 2000 and 2008 Cohorts

Panel A. Non-Poor Students

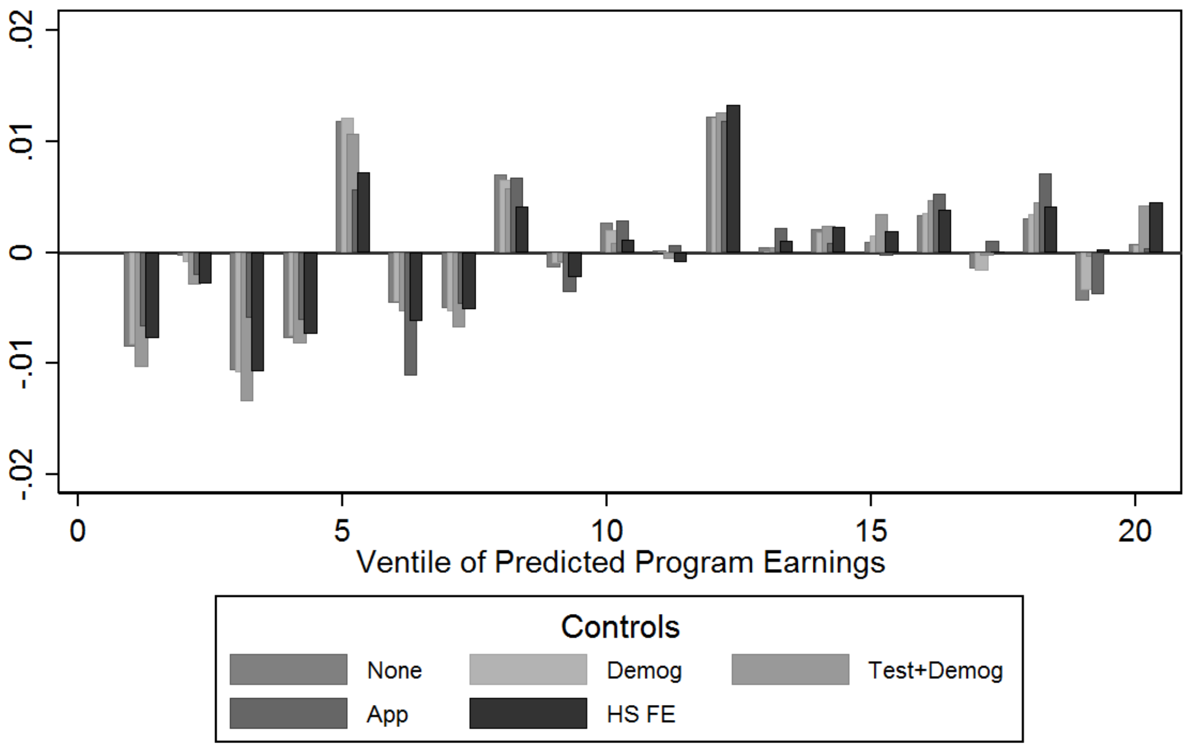


Panel B. Poor Students



Notes: Ventile of program earnings estimated via equation (1), controlling for poor, demographic controls, and standardized achievement test scores. Sample includes all 2000 graduates from Texas public high schools that enrolled in a Texas public university within two years of high school graduation.

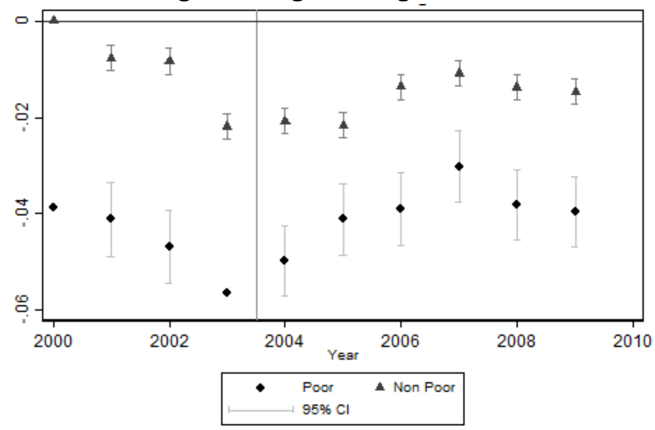
FigureA7. Change in Enrollment of Poor and Non-Poor Students Across Programs, Robustness



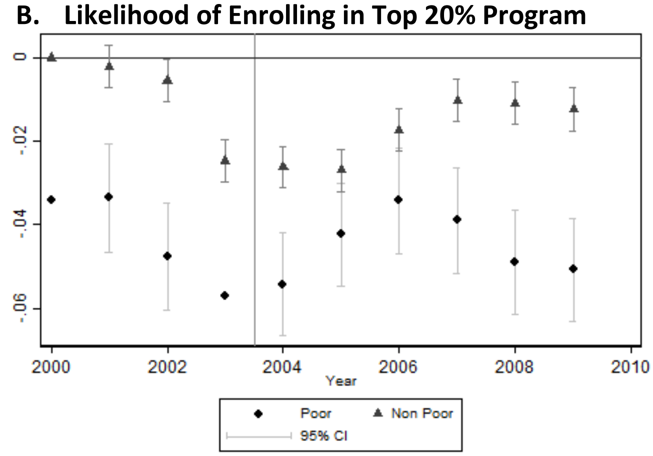
Notes: Estimates in figure come from one hundred separate regressions of indicators for enrolling in a program in each ventile on a dummy for *Poor*, *Post* X *Poor*, *Time* (linearly), *Post*, and the stated controls (if applicable), as described in equation (2). Bars plot the coefficients on the *Post* X *Poor* interaction. "None" is our specification which includes no controls. "Demog" is our specification which includes controls for student race, ethnicity, sex, and limited English proficiency. "Test+Demog" is our preferred specification, which controls for student race, ethnicity, sex, limited English proficiency, and standardized math test scores. "App" specification includes 33 indicators for whether the student applied to each university and 33 indicators for whether the student was accepted to each university, on top of controls from the base model. "HS FE" specification includes high school fixed effects on top of the controls from the preferred model.

Figure A8. Event-Study Estimates in Levels

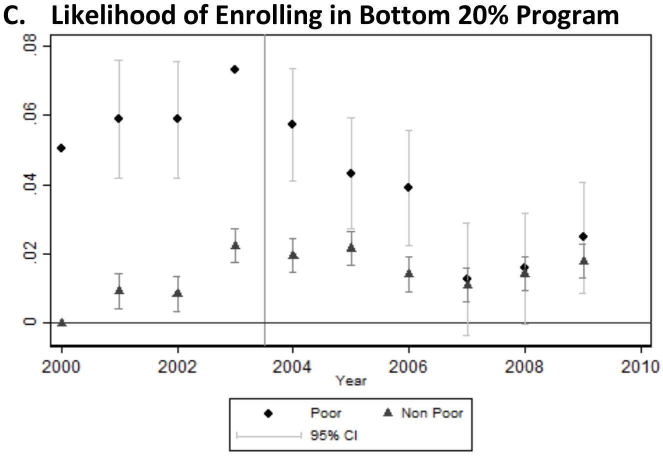
A. Average Earnings of Program Enrolled in



B. Likelihood of Enrolling in Top 20% Program

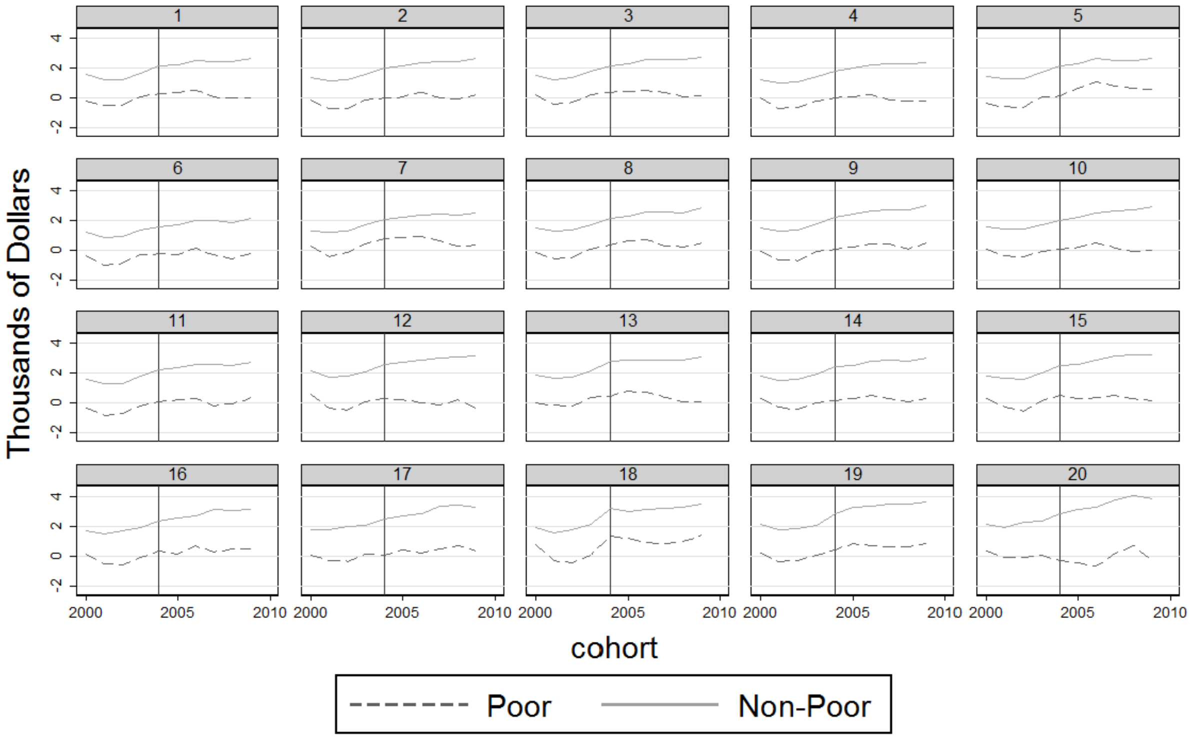


C. Likelihood of Enrolling in Bottom 20% Program



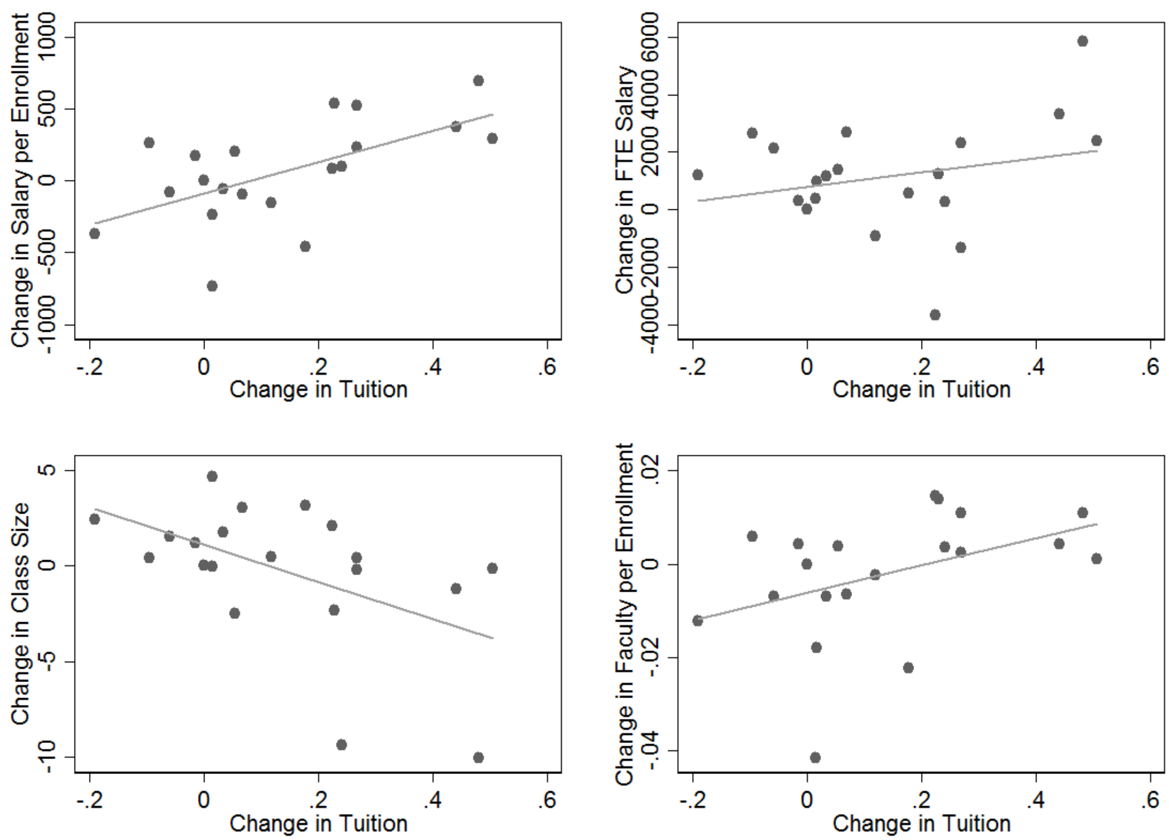
Notes: Model includes a full set of year fixed effects, a dummy for poor interacted with year effects, race/ethnic indicators, indicator for limited English, and scaled reading and math scores. Figures plot the year fixed effects (non-poor group) and the year fixed effects plus the poor-year interactions (poor group). The year 2003 fixed effect is omitted and serves as the reference category. Outcomes are predicted earnings of the university program the student first enrolled (Panel A) and indicators for this program being in the top (Panel B) or bottom (Panel C) 20% of predicted student earnings. Standard errors are clustered by high school cohort.

Figure A9. Net Tuition Over Time, Separately by Program Earnings Ventile



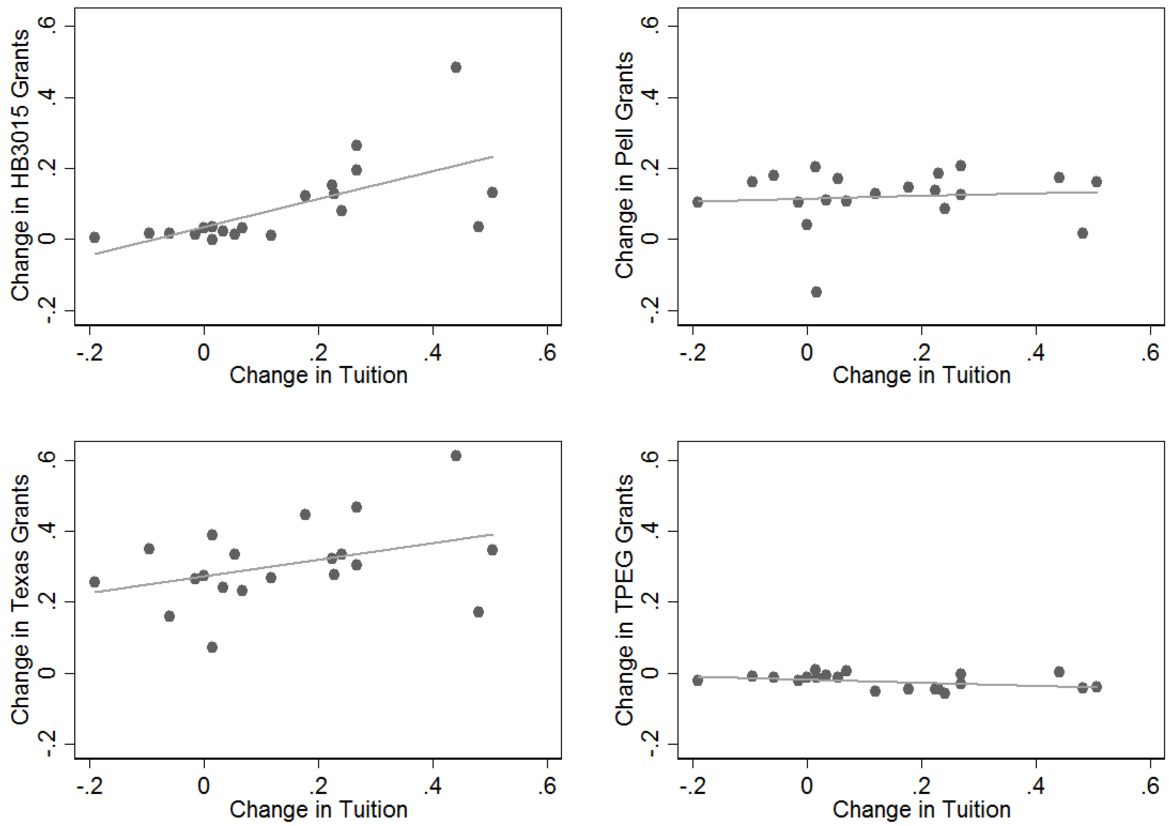
Notes: Graph plots student-level averages of tuition minus need-based grant aid in the Fall for programs in each ventile, separately for poor and non-poor students. Grant aid does not include merit, categorical, or other institutional aid that does not require a needs analysis.

Figure A10. Resource Changes vs. Tuition Changes



Notes: Each dot represents an estimate of the change in two outcomes for a single ventile.

Figure A11. Grant Aid Changes vs. Tuition Changes



Notes: Each dot represents an estimate of the change in two outcomes for a single ventile.

Table A1. TEXAS Grant Program Characteristics Over time

Panel A. Eligibility, Aggregate Numer of Recipients and Amounts, by Program Year

FY	Initial Yr. EFC Max. for Priority	# of Recipients (new and continuing)	Max. Award Amount	Average Award Amounts Disbursed	Amount Disbursed
2000	$5,000	6,108	Actual T&F	$2,315	$14,160,014
2001	$5,000	9,780	Actual T&F	$2,529	$24,820,124
2002	$5,000	26,982	$2,688	$2,685	$72,798,233
2003	$8,500	42,713	$2,950	$2,827	$121,341,457
2004	$8,500	40,379	$3,140	$2,879	$116,628,000
2005	$4,000	38,947	$3,590	$3,301	$128,814,417
2006	$4,000	38,823	$4,180	$3,815	$148,340,997
2007	$4,000	34,523	$4,750	$4,261	$147,309,274
2008	$4,000	35,633	$5,170	$4,737	$169,063,824
2009	$4,000	39,686	$5,280	$4,864	$193,445,513
2010	$4,000	41,828	$6,080	$5,546	$232,419,667
2011	$4,000	48,474	$6,780	$6,182	$300,349,881
2012	$4,000	53,335	$7,100	$4,770	$254,936,425
2013	$4,000	55,880	$7,400	$4,676	$261,915,170

Panel B. Participation and EFC Distribution in Analysis Sample, by Cohort

	EFC Distribution among TEXAS Grant Recipients				
Entering cohort	EFC=0	EFC 1 to 2000	EFC 2001 to 4000	EFC 4001 to 6000	EFC >= 6001
2000	38%	35%	18%	7%	3%
2001	29%	26%	18%	12%	15%
2002	29%	25%	16%	12%	17%
2003	35%	29%	17%	10%	9%
2004	42%	38%	19%	1%	0%
2005	40%	38%	20%	1%	0%
2006	47%	34%	19%	1%	0%
2007	48%	28%	18%	4%	2%
2008	46%	29%	19%	3%	2%
2009	62%	20%	16%	1%	1%

Notes: Top panel refer to fiscal year and include amounts for initial and continuing grant recipients. Dollar amounts are in nominal terms. Source: Texas Grant Report to Legislature June 2016. Author's analysis of Financial Aid Data.

Table A2. Summary Stats of Program-Level Panel Data

	All programs and years		All programs, 2009		Low-price program, 2009		High-price program, 2009	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Semester price ($2012, 1000s)	2.853	0.793	3.691	0.583	2.923	0.176	3.945	0.427
Total ugrad enrollments	4,790	5,080	5,300	5,468	1,822	1,741	6,411	5,782
Lower level	1,773	1,970	1,907	2,024	676	764	2,301	2,142
Upper level	2,937	3,645	3,285	3,991	1,068	1,329	3,993	4,290
Number of faculty per ugrad enrollment (/5)	0.101	0.471	0.091	0.059	0.094	0.070	0.090	0.055
New hires per ugrad enrollment (/5)	0.004	0.049	0.004	0.006	0.005	0.008	0.004	0.006
Total faculty salary per ugrad enrollment (/5)	2,989	14,645	2,814	1,999	2,375	2,118	2,948	1,945
Number of courses per enrollment (/5)	0.094	0.138	0.089	0.144	0.137	0.274	0.074	0.051
Number of sections per enrollment (/5)	0.220	0.184	0.221	0.223	0.265	0.405	0.206	0.112
FTE salary overall	30,586	9,509	31,817	11,110	26,609	7,917	33,394	11,460
Professor FTE salary	45,201	12,677	53,330	15,627	43,915	15,093	55,651	14,881
Assoc Prof FTE salary	34,012	9,042	39,675	12,102	34,573	6,188	41,140	12,969
Assist Prof FTE salary	30,673	10,087	35,655	11,090	31,239	7,437	36,813	11,597
New hire FTE salary	31,266	13,449	33,528	12,051	29,594	9,566	34,376	12,375
Average class size	30.18	15.17	29.68	14.54	25.17	11.09	31.12	15.21
Predicted program earnings (raw)	0.303	0.278	0.303	0.278	0.122	0.197	0.361	0.276
Predicted program earnings (controls)	0.252	0.217	0.252	0.217	0.116	0.175	0.296	0.211
Number of unique programs	641		641		295		346	
Number of observations	6410		641		295		346	

Notes: Sample statisitcs weighted by number of students enrolled in program from the class of 2000. Many characteristics will have fewer observations due to missing data.

Table A3. Earnings Estimates for Specific Programs, 2000 High School Graduates

Adjusting for demographics and test scores				Adjusting for demographics, test scores, application/admissions behavior			
Top 10		Log earnings premium	Number of students	Top 10		Log earnings premium	Number of students
UT Austin	52. Business	0.76	631	Texas A&M Galveston	14. Engineering	0.62	30
Texas A&M	52. Business	0.74	703	Texas A&M	92. Economics	0.56	41
Texas A&M Galveston	14. Engineering	0.72	30	UT Austin	52. Business	0.51	631
Texas A&M	15. Engineering Technologies	0.71	64	Texas A&M	52. Business	0.47	703
Texas A&M	14. Engineering	0.71	901	Texas A&M	14. Engineering	0.45	901
Texas A&M	92. Economics	0.70	41	UH Clear Lake	52. Business	0.44	35
Texas Tech University	15. Engineering Technologies	0.67	36	Texas Tech University	15. Engineering Technologies	0.44	36
UH Clear Lake	52. Business	0.67	35	Lamar University	14. Engineering	0.42	121
Sam Houston State	15. Engineering Technologies	0.65	26	Texas A&M	15. Engineering Technologies	0.39	64
UT Austin	14. Engineering	0.63	885	Texas A&M University Corpus Christi	15. Engineering Technologies	0.39	39
U Houston	14. Engineering	0.62	292	UT Dallas	52. Business	0.37	163
Bottom 10				Bottom 10			
Texas A&M University Kingsville	42. Psychology	-0.18	35	Texas A&M University Commerce	45. Social Science	-0.34	26
Midwestern State University	50. Visual/Performing Arts	-0.18	48	Texas Tech University	50. Visual/Performing Arts	-0.36	148
Tarleton State University	23. English Language	-0.19	31	Texas Woman's University	50. Visual/Performing Arts	-0.37	42
West Texas A&M University	50. Visual/Performing Arts	-0.21	81	U Houston	23. English Language	-0.38	59
Midwestern State University	45. Social Science	-0.22	35	UT Austin	50. Visual/Performing Arts	-0.40	206
Lamar University	45. Social Science	-0.22	29	UT El Paso	45. Social Science	-0.40	28
UT El Paso	45. Social Science	-0.26	28	Texas Southern University	50. Visual/Performing Arts	-0.42	33
Prairie View A&M University	50. Visual/Performing Arts	-0.32	30	Prairie View A&M University	50. Visual/Performing Arts	-0.46	30
Texas Southern University	50. Visual/Performing Arts	-0.33	33	UT El Paso	50. Visual/Performing Arts	-0.54	65
UT El Paso	50. Visual/Performing Arts	-0.44	65	Tarleton State University	23. English Language	-0.55	31

Notes: Number of students in the above table refers to the number of students from our sample enrolled in these programs from 2000 high school cohort.

Table A4. Specific Programs in Each Predicted Earnings Ventile
(Only programs with at least 100 students from high school class of 2000)

		Log earnings premium	Number of students
Ventile 20 (Top 5% of enrollment)			
U. OF TEXAS AT AUSTIN	52. Business	0.756834	873
TEXAS A&M UNIVERSITY	52. Business	0.741412	751
TEXAS A&M UNIVERSITY	14. Engineering	0.711975	1019
Ventile 19			
TEXAS TECH UNIVERSITY	14. Engineering	0.594146	366
U. OF TEXAS AT AUSTIN	14. Engineering	0.631361	813
LAMAR UNIVERSITY	14. Engineering	0.589594	133
TEXAS A&M UNIVERSITY	11. Computer and Information Science	0.586123	135
U. OF TEXAS AT AUSTIN	11. Computer and Information Science	0.541886	321
UNIVERSITY OF HOUSTON	14. Engineering	0.616315	237
U. OF TEXAS AT DALLAS	52. Business	0.581707	156
U. OF HOUSTON-DOWNTOWN	52. Business	0.549304	144
Ventile 18			
TEXAS TECH UNIVERSITY	52. Business	0.469502	1003
TEXAS A&M UNIV-KINGSVILLE	14. Engineering	0.476993	111
U. OF TEXAS AT DALLAS	11. Computer and Information Science	0.511318	159
UNIVERSITY OF HOUSTON	52. Business	0.507564	726
Ventile 17			
U. OF TEXAS AT SAN ANTONIO	52. Business	0.427202	270
TEXAS A&M UNIVERSITY	24. Liberal Arts	0.463787	1099
U. OF TEXAS AT ARLINGTON	91. Nursing	0.442971	101
TEXAS WOMAN'S UNIVERSITY	91. Nursing	0.435848	116
TEXAS STATE UNIV - SAN MARCOS	52. Business	0.462685	608
Ventile 16			
TEXAS A&M UNIVERSITY	40. Physical Sciences	0.403948	121
SAM HOUSTON STATE UNIVERSITY	52. Business	0.390754	493
U. OF TEXAS AT ARLINGTON	14. Engineering	0.401623	343
TEXAS A&M UNIVERSITY	30. Multi/Interdisciplinary	0.376928	734
UNIVERSITY OF HOUSTON	51. Health Professions, minus nursing	0.381286	215
U. OF TEXAS AT AUSTIN	40. Physical Sciences	0.398223	102
TEXAS A&M UNIV AT GALVESTON	24. Liberal Arts	0.393067	114

Table A4. Specific Programs in Each Predicted Earnings Ventile
(Only programs with at least 100 students from high school class of 2000)

		Log earnings premium	Number of students
Ventile 15			
TEXAS A&M UNIVERSITY	26. Biology	0.35496	425
U. OF TEXAS AT ARLINGTON	52. Business	0.338882	475
LAMAR UNIVERSITY	52. Business	0.355361	181
U. OF TEXAS AT AUSTIN	26. Biology	0.367627	528
TEXAS A&M UNIVERSITY	4. Architecture	0.350294	120
TEXAS TECH UNIVERSITY	11. Computer and Information Scien	0.347627	119
TEXAS STATE UNIV - SAN MARCOS	30. Multi/Interdisciplinary	0.353864	256
U. OF TEXAS AT SAN ANTONIO	14. Engineering	0.361831	150
Ventile 14			
UNIVERSITY OF NORTH TEXAS	11. Computer and Information Scien	0.316478	158
TEXAS A&M UNIVERSITY	45. Social Science	0.32932	238
STEPHEN F. AUSTIN STATE UNIV	52. Business	0.315243	434
TEXAS A&M UNIVERSITY	23. English Language	0.314094	125
UNIVERSITY OF HOUSTON	30. Multi/Interdisciplinary	0.314496	110
STEPHEN F. AUSTIN STATE UNIV	91. Nursing	0.315027	143
TEXAS A&M UNIVERSITY	31. Parks & Rec	0.322999	169
U. OF TEXAS AT AUSTIN	30. Multi/Interdisciplinary	0.319695	492
Ventile 13			
UNIVERSITY OF NORTH TEXAS	52. Business	0.312661	811
U. OF TEXAS AT DALLAS	24. Liberal Arts	0.291534	166
TEXAS TECH UNIVERSITY	19. Family and Consumer Sciences	0.282151	235
U. OF TEXAS AT AUSTIN	9.Communication, Journalism	0.300599	324
TEXAS A&M UNIV-CORPUS CHRISTI	52. Business	0.286421	176
TEXAS TECH UNIVERSITY	51. Health Professions, minus nursin	0.30923	408
U. OF TEXAS AT AUSTIN	45. Social Science	0.292939	222
Ventile 12			
TEXAS STATE UNIV - SAN MARCOS	26. Biology	0.273267	170
TEXAS A&M UNIVERSITY	9.Communication, Journalism	0.279515	104
STEPHEN F. AUSTIN STATE UNIV	51. Health Professions, minus nursin	0.26533	209
TEXAS A&M UNIVERSITY	42. Psychology	0.281518	219
U. OF TEXAS AT AUSTIN	24. Liberal Arts	0.271732	2067
U. OF TEXAS AT SAN ANTONIO	11. Computer and Information Scien	0.271584	151
SAM HOUSTON STATE UNIVERSITY	30. Multi/Interdisciplinary	0.280551	223
Ventile 11			
U. OF TEXAS-PAN AMERICAN	30. Multi/Interdisciplinary	0.255236	177
TEXAS STATE UNIV - SAN MARCOS	51. Health Professions, minus nursin	0.257261	128
STEPHEN F. AUSTIN STATE UNIV	30. Multi/Interdisciplinary	0.252774	191
UNIVERSITY OF HOUSTON	26. Biology	0.250025	253
SAM HOUSTON STATE UNIVERSITY	43. Homeland Security	0.248724	304
TEXAS TECH UNIVERSITY	4. Architecture	0.252416	273
UNIVERSITY OF NORTH TEXAS	30. Multi/Interdisciplinary	0.248585	189
U. OF TEXAS AT AUSTIN	42. Psychology	0.257893	207
TARLETON STATE UNIVERSITY	52. Business	0.264949	209
TEXAS TECH UNIVERSITY	9.Communication, Journalism	0.249035	294

Table A4. Specific Programs in Each Predicted Earnings Ventile
(Only programs with at least 100 students from high school class of 2000)

		Log earnings premium	Number of students
Ventile 10			
TEXAS STATE UNIV - SAN MARCOS	24. Liberal Arts	0.229603	692
PRAIRIE VIEW A&M UNIVERSITY	91. Nursing	0.245463	120
U. OF TEXAS AT ARLINGTON	24. Liberal Arts	0.231254	264
SAM HOUSTON STATE UNIVERSITY	13. Education	0.245777	113
TEXAS STATE UNIV - SAN MARCOS	9.Communication, Journalism	0.235092	219
ANGELO STATE UNIVERSITY	52. Business	0.231611	163
UNIVERSITY OF HOUSTON	9.Communication, Journalism	0.233144	102
STEPHEN F. AUSTIN STATE UNIV	11. Computer and Information Science	0.231451	142
TEXAS A&M UNIVERSITY-COMMERCE	52. Business	0.234772	118
U. OF TEXAS AT SAN ANTONIO	30. Multi/Interdisciplinary	0.245648	198
Ventile 9			
TEXAS TECH UNIVERSITY	30. Multi/Interdisciplinary	0.19969	100
TEXAS STATE UNIV - SAN MARCOS	31. Parks & Rec	0.228398	142
U. OF TEXAS-PAN AMERICAN	14. Engineering	0.229355	163
U. OF TEXAS AT ARLINGTON	26. Biology	0.216236	201
WEST TEXAS A&M UNIVERSITY	52. Business	0.214884	159
TEXAS TECH UNIVERSITY	31. Parks & Rec	0.190173	114
UNIVERSITY OF HOUSTON	42. Psychology	0.225448	147
Ventile 8			
STEPHEN F. AUSTIN STATE UNIV	24. Liberal Arts	0.184776	309
UNIVERSITY OF HOUSTON	24. Liberal Arts	0.170931	399
UNIVERSITY OF NORTH TEXAS	24. Liberal Arts	0.162854	482
TEXAS TECH UNIVERSITY	45. Social Science	0.163918	105
PRAIRIE VIEW A&M UNIVERSITY	52. Business	0.164168	179
Ventile 7			
TARLETON STATE UNIVERSITY	24. Liberal Arts	0.144712	202
TEXAS A&M INTERNATIONAL UNIV	24. Liberal Arts	0.146506	127
LAMAR UNIVERSITY	24. Liberal Arts	0.149164	410
TEXAS A&M UNIVERSITY-COMMERCE	30. Multi/Interdisciplinary	0.15386	102
UNIVERSITY OF NORTH TEXAS	26. Biology	0.146522	163
TEXAS A&M UNIV AT GALVESTON	26. Biology	0.160241	104
U. OF HOUSTON-DOWNTOWN	24. Liberal Arts	0.146414	470
SAM HOUSTON STATE UNIVERSITY	42. Psychology	0.149385	119
Ventile 6			
TEXAS STATE UNIV - SAN MARCOS	45. Social Science	0.144579	127
TEXAS TECH UNIVERSITY	42. Psychology	0.119664	154
TEXAS A&M UNIV-KINGSVILLE	52. Business	0.14345	124
U. OF TEXAS-PAN AMERICAN	52. Business	0.116592	358
SAM HOUSTON STATE UNIVERSITY	24. Liberal Arts	0.125919	127
U. OF TEXAS AT EL PASO	52. Business	0.128472	211
U. OF TEXAS-PAN AMERICAN	51. Health Professions, minus nursing	0.127493	336
TEXAS A&M UNIV-KINGSVILLE	24. Liberal Arts	0.116254	129
SAM HOUSTON STATE UNIVERSITY	9.Communication, Journalism	0.138233	124
TEXAS SOUTHERN UNIVERSITY	51. Health Professions, minus nursing	0.134407	121

Table A4. Specific Programs in Each Predicted Earnings Ventile
(Only programs with at least 100 students from high school class of 2000)

		Log earnings premium	Number of students
Ventile 5			
U. OF TEXAS-PAN AMERICAN	91. Nursing	0.088538	137
TEXAS A&M UNIVERSITY-COMMERCE	24. Liberal Arts	0.099854	156
TEXAS A&M UNIV-CORPUS CHRISTI	26. Biology	0.091717	190
UNIVERSITY OF NORTH TEXAS	42. Psychology	0.0944	184
U. OF TEXAS AT EL PASO	13. Education	0.095916	101
TEXAS STATE UNIV - SAN MARCOS	42. Psychology	0.092641	124
U. OF TEXAS AT ARLINGTON	45. Social Science	0.095301	59
TEXAS TECH UNIVERSITY	26. Biology	0.108173	121
U. OF TEXAS AT BROWNSVILLE	24. Liberal Arts	0.07872	173
U. OF TEXAS AT SAN ANTONIO	26. Biology	0.096274	363
U. OF TEXAS AT SAN ANTONIO	42. Psychology	0.082556	153
Ventile 4			
ANGELO STATE UNIVERSITY	30. Multi/Interdisciplinary	0.065623	113
U. OF TEXAS AT SAN ANTONIO	4. Architecture	0.035616	104
UNIVERSITY OF HOUSTON	45. Social Science	0.070085	137
STEPHEN F. AUSTIN STATE UNIV	9.Communication, Journalism	0.067484	129
ANGELO STATE UNIVERSITY	24. Liberal Arts	0.063743	361
U. OF TEXAS AT EL PASO	51. Health Professions, minus nursin	0.065665	111
U. OF TEXAS AT ARLINGTON	4. Architecture	0.054068	108
TEXAS A&M UNIV-KINGSVILLE	26. Biology	0.069663	116
U. OF TEXAS AT EL PASO	14. Engineering	0.026901	256
Ventile 3			
U. OF TEXAS AT SAN ANTONIO	9.Communication, Journalism	0.021003	118
UNIVERSITY OF NORTH TEXAS	9.Communication, Journalism	-0.0114	270
MIDWESTERN STATE UNIVERSITY	24. Liberal Arts	0.008185	159
U. OF TEXAS AT EL PASO	30. Multi/Interdisciplinary	-0.00714	119
UNIVERSITY OF NORTH TEXAS	45. Social Science	-0.00041	115
TEXAS SOUTHERN UNIVERSITY	30. Multi/Interdisciplinary	0.022367	268
U. OF TEXAS AT SAN ANTONIO	24. Liberal Arts	0.015896	455
Ventile 2			
SAM HOUSTON STATE UNIVERSITY	50. Visual/Performing Arts	-0.03009	190
TEXAS TECH UNIVERSITY	24. Liberal Arts	-0.05045	168
U. OF TEXAS-PAN AMERICAN	42. Psychology	-0.06245	104
UNIVERSITY OF HOUSTON	50. Visual/Performing Arts	-0.06302	193
STEPHEN F. AUSTIN STATE UNIV	50. Visual/Performing Arts	-0.05159	139
TEXAS SOUTHERN UNIVERSITY	52. Business	-0.02561	145
TEXAS STATE UNIV - SAN MARCOS	50. Visual/Performing Arts	-0.04912	241
Ventile 1 (bottom 5% of enrollment)			
U. OF TEXAS AT AUSTIN	50. Visual/Performing Arts	-0.13624	222
TEXAS TECH UNIVERSITY	50. Visual/Performing Arts	-0.14105	156
U. OF TEXAS AT EL PASO	24. Liberal Arts	-0.13846	558
UNIVERSITY OF NORTH TEXAS	50. Visual/Performing Arts	-0.1499	538
U. OF TEXAS-PAN AMERICAN	24. Liberal Arts	-0.14312	104

Table A5. Robustness to Different Inference Procedures

	Clustering on		
	Cohort	Poor X Cohort	Institution
Robust			
Poor	-0.0370	-0.0370	-0.0370
	(0.000)	(0.0000)	(0.0006)
PostXPoor	0.0129	0.0129	0.0129
	(0.000)	(0.0526)	(0.0134)
Observations	580,253	580,253	580,253
Block - Bootstrapping			
Poor	-0.0370	-0.0370	-0.0370
	(0.000)	(0.0000)	(0.0003)
PostXPoor	0.0129	0.0129	0.0129
	(0.000)	(0.0852)	(0.0139)
Observations	580,253	580,253	580,253
Wild - Bootstrapping			
Poor	-0.0370	-0.0370	-0.0370
	(0.0040)	(0.0040)	(0.0080)
PostXPoor	0.0129	0.0129	0.0129
	(0.0000)	(0.0880)	(0.0240)
Observations	580,253	580,253	580,253

Note: P-Values are reported in parentheses. Controls include gender, race/ethnic indicators and indicator for limited English, and scaled reading and math scores. Sample includes students in the high school classes of 2000 to 2009 that enroll in a Texas public university within two years of high school graduation. Outcome is the predicted earnings of the university program (institution X major) the student first enrolled in. Predicted earnings is estimated using 2000-2002 cohorts and applied to all cohorts (see text).

Table A6. Characteristic of Program Attending Two Years After Initial Enrollment
Robustness

	Base Model	No controls	Drop LOS/CS Schools	Drop LEP Students	Drop top 30% of graduating class	Poor = always FRPL	Poor = ever FRPL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Average Predicted earnings							
Poor	-0.0556***	-0.1075***	-0.0612***	-0.0371***	-0.0533***	-0.0388***	-0.0594***
	(0.0020)	(0.0030)	(0.0021)	(0.0018)	(0.0028)	(0.0027)	(0.0030)
Post X Poor	0.0121***	0.0025	0.0150***	0.0124***	0.0125**	0.0150***	0.0086**
	(0.0025)	(0.0037)	(0.0028)	(0.0018)	(0.0046)	(0.0025)	(0.0028)
B. Top 10% of Programs							
Poor	-0.0200***	-0.0423***	-0.0230***	-0.0154***	-0.0072**	-0.0143***	-0.0178***
	(0.0021)	(0.0025)	(0.0024)	(0.0016)	(0.0023)	(0.0031)	(0.0019)
Post X Poor	0.0027	-0.0028	0.0067*	0.0039	0.0076*	0.0060	0.0033
	(0.0035)	(0.0033)	(0.0035)	(0.0032)	(0.0034)	(0.0045)	(0.0038)
C. Top 20% of Programs							
Poor	-0.0369***	-0.0704***	-0.0488***	-0.0359***	-0.0186***	-0.0212***	-0.0320***
	(0.0013)	(0.0017)	(0.0022)	(0.0021)	(0.0020)	(0.0037)	(0.0016)
Post X Poor	0.0094***	0.0024	0.0111**	0.0069	0.0158***	0.0172***	0.0141***
	(0.0023)	(0.0024)	(0.0037)	(0.0041)	(0.0035)	(0.0044)	(0.0026)
D. Bottom 20% of Programs							
Poor	0.0687***	0.0314***	0.0110***	0.0500***	0.0147***	0.0054	0.0154***
	(0.0033)	(0.0014)	(0.0027)	(0.0036)	(0.0031)	(0.0040)	(0.0020)
Post X Poor	-0.0260***	-0.0171***	-0.0193***	-0.0332***	-0.0218***	-0.0243***	-0.0179***
	(0.0065)	(0.0035)	(0.0040)	(0.0064)	(0.0049)	(0.0047)	(0.0028)
E. Bottom 10% of Programs							
Poor	0.0471***	0.0317***	0.0142***	0.0241***	0.0202***	0.0051*	0.0131***
	(0.0028)	(0.0005)	(0.0015)	(0.0020)	(0.0020)	(0.0027)	(0.0012)
Post X Poor	-0.0162***	-0.0131***	-0.0132***	-0.0126***	-0.0152***	-0.0088**	-0.0082***
	(0.0048)	(0.0022)	(0.0024)	(0.0038)	(0.0028)	(0.0028)	(0.0017)
Controls							
Demographics	Yes	No	Yes	Yes	Yes	Yes	Yes
Test Scores	Yes	No	Yes	Yes	Yes	Yes	Yes
Time Controls	Time, Post	Time, Post	Time, Post	Time, Post	Time, Post	Time, Post	Time, Post
Obs.	580,253	580,253	534,366	570,688	306,645	580,253	580,253

Notes: Controls include race/ethnic indicators and indicator for limited English, and scaled reading and math scores. Sample includes students in the high school classes of 2000 to 2009 that enroll in a Texas public university within two years of high school graduation. Outcome is the predicted earnings or indicator for predicted earnings rank of the university program (institution X major) the student first enrolled in. Predicted earnings is estimated using 2000-2002 cohorts and applied to all cohorts (see text). Standard errors are clustered by high school cohort.

Table A7. Distribution of Students Across First School

	Test score in Top 30% of high school		Test score in bottom 70% of high school		Full Sample	
First School	Frequency	Percent	Frequency	Percent	Frequency	Percent
Sul Ross State University Rio Grande College	83	0.03	178	0.05	261	0.04
Angelo State University	4,871	1.73	8,612	2.5	13,483	2.15
Texas A&M University-Commerce	3,091	1.1	5,013	1.46	8,104	1.29
Lamar University	6,079	2.16	10,449	3.03	16,528	2.64
Midwestern State University	3,115	1.1	6,036	1.75	9,151	1.46
University of North Texas	16,588	5.88	24,048	6.98	40,636	6.49
The University of Texas-Pan American	10,973	3.89	15,854	4.6	26,827	4.28
Sam Houston State University	8,606	3.05	16,717	4.85	25,323	4.04
Texas State University-San Marcos	15,168	5.38	22,714	6.59	37,882	6.05
Stephen F. Austin State University	8,143	2.89	15,344	4.45	23,487	3.75
Sul Ross State University	793	0.28	2,408	0.7	3,201	0.51
Prairie View A&M University	2,328	0.83	9,454	2.74	11,782	1.88
Tarleton State University	4,706	1.67	9,580	2.78	14,286	2.28
Texas A&M University	44,837	15.9	22,492	6.53	67,329	10.75
Texas A&M University-Kingsville	3,285	1.16	6,439	1.87	9,724	1.55
Texas Southern University	1,823	0.65	9,068	2.63	10,891	1.74
Texas Tech University	20,272	7.19	25,657	7.45	45,929	7.33
Texas Woman’s University	2,288	0.81	5,287	1.53	7,575	1.21
University of Houston	15,325	5.43	20,620	5.99	35,945	5.74
The University of Texas at Arlington	12,183	4.32	14,373	4.17	26,556	4.24
The University of Texas at Austin	45,821	16.25	14,771	4.29	60,592	9.67
The University of Texas at El Paso	7,754	2.75	12,305	3.57	20,059	3.2
West Texas A&M University	3,895	1.38	6,146	1.78	10,041	1.6
Texas A&M International University	2,545	0.9	3,172	0.92	5,717	0.91
The University of Texas at Dallas	6,430	2.28	4,579	1.33	11,009	1.76
The University of Texas of the Permian Basin	1,453	0.52	1,838	0.53	3,291	0.53
The University of Texas at San Antonio	14,298	5.07	26,116	7.58	40,414	6.45
Texas A&M University at Galveston	1,373	0.49	2,179	0.63	3,552	0.57
Texas A&M University-Corpus Christi	4,976	1.76	7,263	2.11	12,239	1.95
The University of Texas at Tyler	3,432	1.22	3,563	1.03	6,995	1.12
University of Houston-Clear Lake	563	0.2	913	0.27	1,476	0.24
University of Houston-Downtown	2,112	0.75	7,660	2.22	9,772	1.56
University of Houston-Victoria	222	0.08	300	0.09	522	0.08
Texas A&M University-Texarkana	218	0.08	292	0.08	510	0.08
The University of Texas at Brownsville	2,354	0.83	2,994	0.87	5,348	0.85
Total	282,003		344,434		626,437	

Sample includes all students in the high school classes of 2000 to 2009 that enroll in a Texas public university within two years of high school graduation. Sample is slighlty larger than sample used in analysis because it is not restricted to students in the "balanced panel" of programs or to those that have non-missing control variables.

Table A8. Distribution of Students Across Majors

	Test score in Top 30% of high school		Test score in bottom 70% of high school		Full Sample	
First Major	Frequency	Percent	Frequency	Percent	Frequency	Percent
1. Agriculture	5,365	1.9	8,564	2.49	13,929	2.22
3. Natural Rescouces and Conservation	1,315	0.47	1,893	0.55	3,208	0.51
4. Architecture	4,541	1.61	4,912	1.43	9,453	1.51
5. Area, Ethnic Cultural, and Gender St	158	0.06	156	0.05	314	0.05
9.Communication, Journalism	10,631	3.77	15,663	4.55	26,294	4.2
10. Communications Tech	155	0.05	149	0.04	304	0.05
11. Computer and Information Sciences	7,423	2.63	6,321	1.84	13,744	2.19
13. Education	1,129	0.4	2,405	0.7	3,534	0.56
14. Engineering	33,049	11.72	15,940	4.63	48,989	7.82
15. Engineering Technologies	2,242	0.8	3,344	0.97	5,586	0.89
16. Foreign Languages	1,180	0.42	1,087	0.32	2,267	0.36
19. Family and Consumer Sciences	2,682	0.95	4,413	1.28	7,095	1.13
22. Legal Professions	612	0.22	906	0.26	1,518	0.24
23. English Language	5,507	1.95	5,923	1.72	11,430	1.82
24. Liberal Arts	41,578	14.74	58,791	17.07	100,369	16.02
26. Biology	27,840	9.87	23,343	6.78	51,183	8.17
27. Math	4,088	1.45	2,124	0.62	6,212	0.99
30. Multi/Interdisciplinary	17,894	6.35	26,820	7.79	44,714	7.14
31. Parks & Rec	6,588	2.34	13,276	3.85	19,864	3.17
38. Philosophy	610	0.22	435	0.13	1,045	0.17
40. Physical Sciences	5,615	1.99	4,074	1.18	9,689	1.55
42. Psychology	10,724	3.8	15,236	4.42	25,960	4.14
43. Homeland Security	4,342	1.54	11,147	3.24	15,489	2.47
44. Public Admin	966	0.34	1,905	0.55	2,871	0.46
45. Social Science	8,142	2.89	9,891	2.87	18,033	2.88
49. Transportation	48	0.02	97	0.03	145	0.02
50. Visual/Performing Arts	13,486	4.78	17,639	5.12	31,125	4.97
51. Health Professions, minus nursing	12,599	4.47	18,049	5.24	30,648	4.89
52. Business	41,027	14.55	51,939	15.08	92,966	14.84
54. History	912	0.32	1,777	0.52	2,689	0.43
91. Nursing	8,241	2.92	14,933	4.34	23,174	3.7
92. Economics	1,314	0.47	1,282	0.37	2,596	0.41
Total	282,003		344,434		626,437	

Sample includes all students in the high school classes of 2000 to 2009 that enroll in a Texas public university within two years of high school graduation. Sample is slighlty larger than sample used in analysis because it is not restricted to students in the "balanced panel" of programs or to those that have non-missing control variables.

Table A9. Contribution of Institutions and Majors to Enrollment Shifts

Initial Program Chosen

	(1)	(2)	(3)	(4)	(5)
A. Program-Specific Predicted earnings					
Poor	-0.0861***	-0.0415***	-0.0370***	-0.0182***	-0.0165***
	(0.0018)	(0.0021)	(0.0019)	(0.0015)	(0.0018)
Post X Poor	0.0057**	0.0063**	0.0129***	0.0073***	0.0116***
	(0.0023)	(0.0022)	(0.0018)	(0.0017)	(0.0020)
B. Institution-average Predicted earnings					
Poor	-0.0896***	-0.0466***	-0.0406***	-0.0118***	-0.0188***
	(0.0016)	(0.0020)	(0.0019)	(0.0013)	(0.0018)
Post X Poor	0.0083***	0.0085***	0.0122***	0.0044***	0.0108***
	(0.0021)	(0.0019)	(0.0019)	(0.0013)	(0.0017)
C. Major-average Predicted earnings					
Poor	-0.0026**	0.0020*	0.0011	0.0015	0.0015
	(0.0011)	(0.0010)	(0.0008)	(0.0010)	(0.0010)
Post X Poor	-0.0035*	-0.0031*	0.0009	-0.0010	0.0012
	(0.0018)	(0.0017)	(0.0017)	(0.0019)	(0.0016)
Controls					
Demographics	No	Yes	Yes	Yes	Yes
Test scores	No	No	Yes	Yes	Yes
Application, admission indica	No	No	No	Yes	No
High school FEs	No	No	No	No	Yes
Time controls	Time, Post	Time, Post	Time, Post	Time, Post	Time, Post

Notes: Controls include gender, race/ethnic indicators and indicator for limited English, and scaled reading and math scores. Sample includes 580,253 students in the high school classes of 2000 to 2009 that enroll in a Texas public university within two years of high school graduation. Outcome is the predicted earnings or indicator for predicted earnings rank of the university program (institution X major) the student first enrolled in. Predicted earnings is estimated using 2000-2002 cohorts and applied to all cohorts (see text). Standard errors are clustered by high school cohort. Our preferred model is specification 3.

Table A10. Institution-Specific Changes in Enrollment, Application, and Admission

		Coeff on Post X Poor for outcome:					Coeff on Post X Poor for outcome:		
Institution (ranked by institution-level predicted earnings)	Predicted Earnings	Pr(Enroll) (1)	Pr(Apply) (2)	Pr(Admit | Apply) (3)	Institution (ranked by institution-level predicted earnings)	Predicted Earnings	Pr(Enroll) (1)	Pr(Apply) (2)	Pr(Admit | Apply) (3)
Texas A&M University	0.49	0.0076*	0.0264***	-0.0249	Tarelton State Univerisy	0.18	-0.0015	-0.0029*	-0.0349
		(0.0035)	(0.0044)	(0.0229)			(0.0010)	(0.0014)	(0.0206)
UT - Austin	0.40	0.0233**	0.0246***	0.0688**	Lamar State University	0.18	0.0087***	0.0119***	0.0059
		(0.0080)	(0.0050)	(0.0227)			(0.0016)	(0.0016)	(0.0064)
UT - Dallas	0.37	-0.0009	0.0020	-0.0044	Texas A&M University - Corpus Christi	0.17	0.0023***	0.0122***	0.0160
		(0.0007)	(0.0012)	(0.0274)			(0.0006)	(0.0019)	(0.0163)
Texas A&M University - Galveston	0.37	-0.0002	-0.0009***	0.1038***	Texas A&M University - Kingsville	0.17	-0.0090**	-0.0087**	0.0035
		(0.0006)	(0.0002)	(0.0137)			(0.0029)	(0.0029)	(0.0052)
University of Houston	0.31	-0.0013	0.0017	0.0107	University of North Texas	0.14	-0.0066***	-0.0044	-0.0449**
		(0.0032)	(0.0038)	(0.0071)			(0.0018)	(0.0033)	(0.0190)
Texas Tech university	0.30	0.0046*	-0.0007	-0.0281	UT - Brownsville	0.14	0.0165**	0.0212***	0.0000
		(0.0021)	(0.0043)	(0.0288)			(0.0062)	(0.0053)	0.0000
UT - Arlington	0.25	0.0124***	0.0118**	0.0193*	UT - San Antonio	0.14	-0.0292***	-0.0219***	-0.0145*
		(0.0033)	(0.0041)	(0.0099)			(0.0064)	(0.0048)	(0.0069)
Texas Woman's University	0.25	0.0014**	0.0034**	0.0319*	Texas A&M University - Commerce	0.13	0.0014*	0.0035***	0.0150
		(0.0006)	(0.0014)	(0.0164)			(0.0006)	(0.0010)	(0.0228)
Texas State University	0.25	0.0012	-0.0062	0.0540**	Midwestern State University	0.09	-0.0000	-0.0039***	-0.0174
		(0.0015)	(0.0049)	(0.0199)			(0.0007)	(0.0009)	(0.0240)
University of Houston - Downtown	0.24	-0.0068***	-0.0042	-0.0179**	Angelo State University	0.08	-0.0012	-0.0043**	0.0935**
		(0.0020)	(0.0024)	(0.0055)			(0.0011)	(0.0014)	(0.0329)
UT - Permian Basin	0.24	-0.0021***	-0.0013	-0.0370*	UT - Pan America	0.08	0.0017	0.0596***	0.0083
		(0.0006)	(0.0009)	(0.0178)			(0.0075)	(0.0143)	(0.0071)
Sam Houston State University	0.22	-0.0035	-0.0070	0.0125	West Texas A&M University	0.07	0.0010	-0.0004	0.0268
		(0.0027)	(0.0039)	(0.0173)			(0.0010)	(0.0009)	(0.0353)
Texas A&M University - International	0.22	-0.0018	0.0060	-0.0368	Sul Ross State University	0.06	-0.0030***	-0.0048**	0.0135
		(0.0030)	(0.0035)	(0.0267)			(0.0009)	(0.0016)	(0.0178)
Stephen F. Austin State University	0.20	0.0024	0.0100**	-0.0435**	Texas Southern University	-0.02	-0.0018	-0.0061	0.0004
		(0.0019)	(0.0035)	(0.0155)			(0.0041)	(0.0061)	(0.0013)
Prairie View A&M University	0.19	-0.0010	0.0064	-0.0071	UT - El Paso	-0.04	-0.0126**	-0.0112***	0.0014
		(0.0021)	(0.0036)	(0.0043)			(0.0042)	(0.0028)	(0.0020)
UT- Tyler	0.19	-0.0026**	-0.0025**	-0.0198					
		(0.0011)	(0.0009)	(0.0255)					

Notes: Each cell is a separate regression. All specifications control for gender, race/ethnic indicators and indicator for limited English, and scaled reading and math scores. Sample includes 580,253 students in the high school classes of 2001 to 2009 that enroll in a Texas public university within two years of high school graduation. Outcomes are indicators for enrollment at, application to, admission to, or conditional enrollment at each institution. Universities are ranked here by their predicted earnings in table 7. Standard errors are clustered by high school cohort.

Table A11. Means of Institution-specific Enrollment and Application Outcomes

Institution (ranked by institution-level predicted earnings)	Predicted Earnings	Outcome Mean: Pr(Enroll) (1)	Pr(Apply) (2)	Pr(Admit | Apply) (3)	Pr(Enroll | Admit) (4)
Texas A&M University	0.49	0.101	0.165	0.754	0.682
UT - Austin	0.40	0.100	0.139	0.778	0.745
UT - Dallas	0.37	0.018	0.029	0.655	0.617
Texas A&M University - Galvest	0.37	0.006	0.008	0.948	0.523
University of Houston	0.31	0.058	0.078	0.837	0.618
Texas Tech university	0.30	0.074	0.120	0.802	0.564
UT - Arlington	0.25	0.043	0.047	0.887	0.655
Texas Woman's University	0.25	0.012	0.014	0.810	0.639
Texas State University	0.25	0.062	0.096	0.739	0.574
University of Houston - Downtc	0.24	0.015	0.012	0.934	0.806
UT - Permian Basin	0.24	0.005	0.005	0.961	0.706
Sam Houston State University	0.22	0.040	0.070	0.636	0.576
Texas A&M University - Interna	0.22	0.009	0.009	0.910	0.704
Stephen F. Austin State Univers	0.20	0.038	0.065	0.899	0.496
Prairie View A&M University	0.19	0.018	0.017	0.958	0.701
UT- Tyler	0.19	0.012	0.013	0.898	0.649
Tarelton State Univerisy	0.18	0.020	0.021	0.873	0.756
Lamar State University	0.18	0.027	0.028	0.978	0.702
Texas A&M University - Corpus	0.17	0.020	0.031	0.893	0.526
Texas A&M University - Kingsvil	0.17	0.015	0.020	0.993	0.554
University of North Texas	0.14	0.067	0.088	0.879	0.576
UT - Brownsville	0.14	0.009	0.008	1.000	0.681
UT - San Antonio	0.14	0.066	0.086	0.966	0.621
Texas A&M University - Comme	0.13	0.013	0.013	0.809	0.675
Midwestern State University	0.09	0.015	0.014	0.951	0.640
Angelo State University	0.08	0.021	0.026	0.752	0.807
UT - Pan America	0.08	0.044	0.032	0.948	0.785
West Texas A&M University	0.07	0.015	0.014	0.888	0.788
Sul Ross State University	0.06	0.005	0.005	0.907	0.637
Texas Southern University	-0.02	0.017	0.025	0.997	0.572
UT - El Paso	-0.04	0.032	0.030	0.991	0.855

Notes: Sample includes 580,253 students in the high school classes of 2001 to 2009 that enroll in a Texas public university within two years of high school graduation. Outcomes are indicators for enrollment at, application to, admission to, or conditional enrollment at each institution.

Appendix B. Data on Program-level Resources

To measure program-level resources we utilize previously unused administrative data on all the course sections offered and faculty in each department at each institution since 2000. This information is obtained from Reports 4 and 8 published by the Texas Higher Education Coordinating Board. We construct various measures of resources, quality, and capacity (average class size, faculty per student, faculty salary per student, capacity of course offerings) for each program at each institution in each year before and after deregulation. We aggregated the merged course-faculty micro data to the level of academic program at each Texas university from Fall 2000 to Fall 2009. Since the breadth of academic programs vary by institution, we standardize them using 2-digit Classification of Institutional Program (CIP) codes. Two-digit CIP codes often translate to what are conventionally known as "departments" (e.g. Mathematics and Statistics) but sometimes are broader ("Social Sciences" or "Engineering"). We have separately broken out Economics and Nursing from their larger categories (Social Science and Health Professions, respectively) as they are sometimes housed in units which price differently. We restrict our analysis to programs (defined by 2-digit CIP codes) that enroll at least one student from each high school cohort from 2000 to 2009. Thus we exclude programs that are introduced or discontinued during our analysis window or that have a very small number of students. In practice, this restriction drops fewer than 5% of the student sample across all cohorts. Our final program-level sample includes 641 programs tracked over ten years, for a total sample size of 6,410. Some analysis will have fewer observations due to missing data on prices or program resources in some years.[1]

The program-level panel dataset is summarized in Table A2, with each observation weighted by program enrollment from the 2000 high school cohort. The average program has about 4,800 course enrollments, with the majority being upper-division.[2] Average tuition is $2,853 for the semester. Many resource measures we normalize by the number of course enrollments divided by five. This makes these measures on a per-student basis, assuming that each student takes approximately 5 classes in a semester. The average program has about 1 faculty member per 10 students and spends $2989 on faculty salary per student. The average FTE salary of the main course instructor is $30,500 per semester and the average class size is about 30 students per section. More expensive programs are larger, more lucrative (which we define later), and have greater levels of faculty salary per student, though also tend to have larger classes. A full description of how resources vary across programs is beyond the scope of this paper, but Figures A2 and A3 depict the resource differences across and within fields in our sample. Engineering tends to be among the most resource-intensive, with high-paid faculty, modest class sizes, and high faculty salary per student. Business, by contrast, has very large classes, which offsets the high faculty salaries. These patterns echo prior descriptive work by Johnson and Turner (2009). Interestingly, while there are consistent patterns by field across institutions, there is also substantial variation across institutions for a given field.

[1] There may be some discrepancies between the level at which the price and resource measures are captured. Tuition price is typically reported for each "school" or "college" within each university. We have applied this tuition level to all two-digit CIP codes that appear to fall within this school/college at this university. The school-CIP relationship often varies across universities. For instance, some universities include the Economics major in the College of Liberal Arts (typically a low-priced program) while others include it in Business (sometimes a high-priced program). Since we treat Economics as a stand-alone category, it receives the Liberal Arts or Business price depending on the university. Resource measures, by contrast, are generated from course-level data. CIP codes are directly available for each course from 2005 onwards. Prior to this, we generate a two-digit CIP code based on the course subject prefix or administrative code of the faculty member teaching the course. Faculty are assigned to CIP codes based on the most common major code among the courses they teach. Non-teaching faculty are assigned CIP codes based on the two-digit CIP code most commonly associated with each administrative code.

[2] Since the statistics are weighted by the number of enrollees from the 2000 high school class, these statistics give the program characteristics experienced by the "typical" student rather than the characteristics of the typical program. Thus the typical student will be in a much larger program than the typical program.

Appendix C. Control State Analysis

Our single-state analysis cannot account for any aggregate trends altering the representation of poor students relative to non-poor students at high-earning programs and institutions. For instance, if poor students were making inroads at high-earnings programs around the country because of expansions to Pell or other changes differentially affecting the enrollment of poor vs. non-poor students, our Texas-specific estimates may overstate the gains experienced due to tuition deregulation. To address this, we complement our main analysis with cross-state triple-difference comparison between Texas and other states that did not deregulate tuition-setting authority. We test whether the gap in predicted earnings of institutions attended by poor and non-poor students changes in Texas relative to other states after tuition deregulation in Texas.

Unfortunately comparably rich micro student data including extensive student controls does not exist for many states (and cannot be easily combined with our Texas data). Instead, we compare the public 4-year institutions attended by Pell students to non-Pell students in each state. We combine three data sources to characterize the average predicted earnings of institutions attended by Pell and non-Pell students at a state level over time. First, we start with the universe of public 4-year institutions from IPEDS, which includes total undergraduate enrollment. Second, we merge on the number of Pell recipients at each institution in each year.[1] Finally, mean earnings of students working and not enrolled 10 years after entry for each institution was obtained from the College Scorecard data for the 2001 and 2002 entering cohorts.[2] Having average mean earnings by institution for all institutions in the country was not possible prior to the release of the College Scorecard data in 2015. From these sources we construct for each state and each year the predicted earnings of institutions attended by Pell students and non-Pell students, as well as the difference. Across all years and states in our sample, the mean Pell-NonPell difference is about -$2,650, but is -$4,640 in Texas prior to deregulation.[3] The question we ask is how this gap changes following deregulation in Texas.

Table C1 presents our results. In column (1), we approximate our main (micro-sample- based) analysis using data just from Texas. We find that the Pell-NonPell gap shrank by $270 following deregulation in Texas. While not directly comparable to estimates from our micro sample, the pattern is directionally consistent with our earlier analysis. Pell students attended slightly more lucrative programs following deregulation relative to non-Pell students.[4] The next five columns include other states, which are used to

[1] This data comes from US Department of Education, Office of Postsecondary Education. We are grateful to Lesley Turner for sharing this data with us.
[2] The student sample includes financial aid students in AY2001-02 and AY2002-03 pooled cohort measured in CY2012, CY2013, inflation adjusted to 2015 dollars. Average earnings may be misleading to the extent that the average earnings of aided and non-aided students are different. We drop the state of New York, as the number of Pell recipients is not broken out by individual CUNY and SUNY institutions in the early years. Wyoming and the District of Columbia are also excluded because they do not have multiple public 4-year institutions.
[3] This average weights each state-year observation by the total number of students. Unweighted average is similar.
[4] Results may not be directly comparable to our main analysis for four main reasons. First, our main analysis relies on eligibility for free- or reduced-price lunch in 12th grade as the marker for poor. Results using Pell receipt as a marker for poor are similar, but not identical. Second, our measures of Pell and non-Pell enrollment do not distinguish by residency status or undergraduate level. These measures include both in- and out-of-state students, from freshmen to seniors. Our main analysis tracks the enrollment choices of students that attended public high schools in Texas and enrolled in university within two years. Treatment here will thus not be as "sharp" as in our earlier analysis. Third, the earnings measure pertains to the raw average earnings of students receiving financial aid

control for aggregate trends that could have altered the Pell-Non-Pell institutional gap using a triple-difference. The coefficient on PostXTexas quantifies how much the Pell-NonPell gap in Texas changed post-deregulation relative to the Pell-NonPell gap in other states over the same time period. The pattern is remarkably robust across multiple specifications: Pell students in Texas gained relative to non-Pell students following deregulation at a greater rate than in other states. This pattern is robust to flexibly controlling for year effects (specification 3), weighting states by total enrollment (4), and restricting the control group to geographically proximate states (5 to 7). We exclude Florida in the last two specifications as that state also experienced deregulation towards the end of our sample.

Table C1. Texas vs. Non-Texas Comparison of Change in Pell-NonPell Earnings Gap

Dept variable: Difference in mean predicted earnings of institutions attended by Pell vs. NonPell students in state ($1,000) (= 4.64 in Texas in 2003)

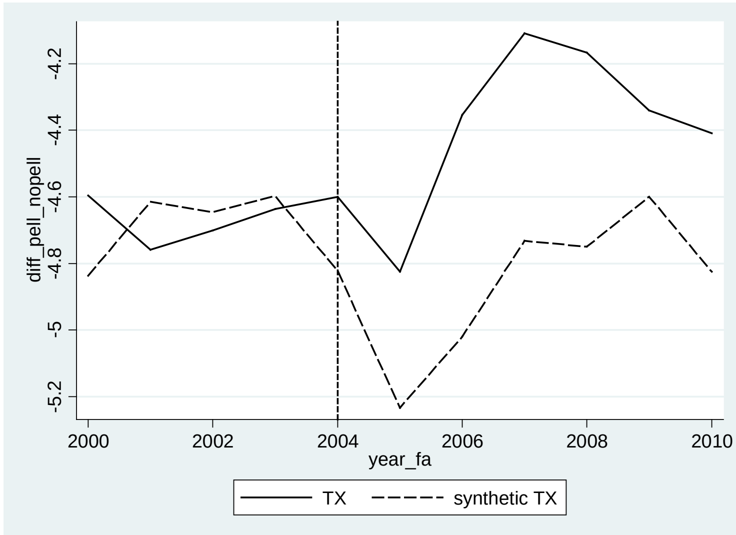
	Texas Only	Texas and Non-Texas States						Synthetic control method
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Texas		-2.348***						0.000737
		(0.283)						(0.0798)
Post	0.273**	-0.133**						
	(0.102)	(0.0608)						
PostXTexas		0.405***	0.410***	0.417***	0.601***	0.531**	0.503***	0.453***
		(0.0608)	(0.0656)	(0.0832)	(0.175)	(0.172)	(0.136)	(0.105)
Observations	11	527	527	527	142	131	164	22
R-squared	0.331	0.024	0.971	0.958	0.938	0.954	0.963	0.905
Year FEs	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Sample	TX only	All	All	All	SE	SE no FL	SESW no FL	synthetic controls
State FE	No	No	Yes	Yes	Yes	Yes	Yes	No
Weighted	No	No	No	Yes	No	No	No	No

Notes: Sample includes 47 states from 2000 to 2010 (New York, DC, and Wyoming are excluded).
Robust standard errors in parentheses. Specifications with multiple states are clustered standard errors by state.

Finally, we implement the synthetic control method described in Abadie, Diamond, and Hainmueller (2010). This method finds a set of states whose weighted behavior most closely match the treated one (here, Texas) on a number of characteristics in the pre-treatment period. We match on the Pell-NonPell earnings gap (our outcome), the Pell share of students, the overall mean predicted earnings (for all students), and the number of institutions per student (to capture the level of differentiation in the public higher education sector). For Texas, this algorithm assigns a weight of 31.2% to California, 26.3% to Delaware, 12.3% to Mississippi, 10.4% to New Mexico, 2.4% to Virginia, 1.1% to Georgia, 1.0% to Oklahoma, and less than 1% to all remaining states. The Pell-NonPell gap for Texas and this synthetic control group is displayed in Figure C1. The two groups do not deviate much from eachother prior to deregulation, but diverge noticeably from 2004 onwards. The implied treatment effect of deregulation from this method is $450 (reported in column (8) of Table C1), which is quite comparable to our standard triple difference estimates.

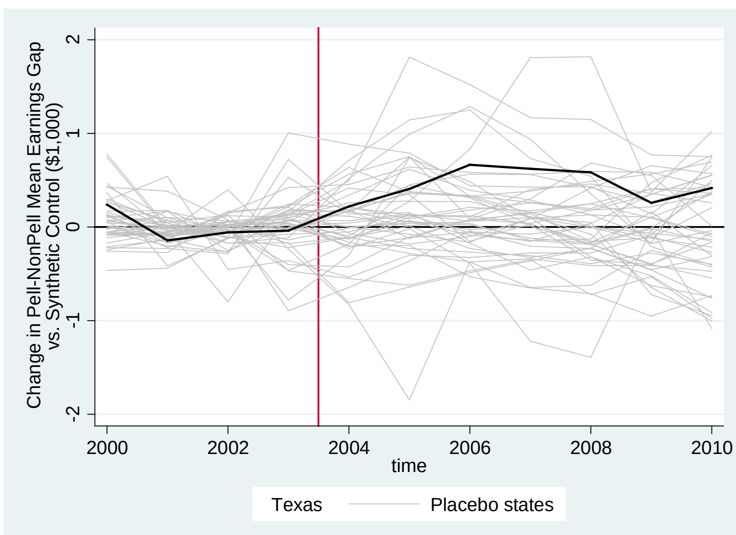
who are working and not enrolled, anywhere in the U.S.. Our Texas-specific analysis uses log earnings for all enrollees working in Texas ten years after enrollment. Finally, we are unable to control for changes in student characteristics, either in the earnings estimates or when assessing changes in program choice. So the estimates from the cross-state analysis are most comparable to column (1) in Table 3 that does not control for changes in student characteristics.

Figure C1. Texas vs. Synthetic Texas



To assess whether the experience of Texas (relative to the synthetic controls) is atypical of the variation one would see, we repeat the synthetic control analysis but assign treatment to all other 47 states as a placebo test. Figure C2 plots the treatment minus synthetic control difference for Texas (in bold) and all other 47 states (in gray) . The Texas experience of modest and sustained gains for Pell students relative to non-Pell students is fairly unusual relative to what would be expected by chance.

Figure C2. Texas-Synthetic Controls and Placebo States



All together, this analysis suggests that our main within-Texas comparison is not conflating deregulation with aggregate trends shifting the institutions attended by Pell vs. NonPell students. In anything, our results are strengthened by including other states as a comparison group.

Appendix D. Program Size Analysis

Our main analysis suggests that the fraction of poor students that enroll in higher-earning programs in post-deregulation increases relative to non-poor students and that the fraction of non-poor students increases relative to poor students at lower-earning programs. This supplementary analysis will determine whether the relative increase in the fraction of poor students enrolled is a result of either enrollment growth in these programs with more growth in the poor student population, enrollment declines with non-poor students leaving high-earning programs at a faster rate than their poor counterparts, or that the fractional changes are a result of poor students displacing non-poor students in the programs with higher earnings. For this analysis, we construct a balanced program-level dataset containing the number of juniors enrolled each program in each academic year, overall and by residency status. [1] We also merge the predicted earnings for freshmen enrolled in these same programs from our main analysis.

To flexibly determine whether program enrollment changed following deregulation, we estimate the post-deregulation deviation from enrollment trend separately for each program earnings ventile using models of the form:

$$Y_{jt} = \beta_1 Time_t + \beta_2 Post_t + \delta_j + \varepsilon_{it}$$

Y_{it} is the log junior enrollment for program *j* at time *t*, overall and by residency status. $Time_t$ is a linear time trend, δ_j is a program fixed effect, and $Post_t$ is an indicator variable which takes a value of 1 for those observations that occur after 2006 and zero otherwise. We weight observations by the level of junior enrollment in 2001 in order to adjust for the influence of small and volatile programs and also cluster standard errors by program.

Figure D1 plots the ventile-specific coefficients on *Time*, which shows that overall enrollment in public 4-year institutions has been steadily growing over time, particularly for programs in the bottom half of the earnings distribution. Higher-earning programs have seen very little growth over the decade. For non-resident students there is little evidence of changes in overall student enrollment, with slight increases in the middle ventiles (Panel B). Figure D2 plots coefficients associated with the *Post* dummy. This figure suggests that the enrollment of students in Texas – overall and non-residents **-** in the post-period do not differ substantially from the pre-period growth trajectory. Nor is there any obvious systematic relationship between the post-deregulation enrollment change and the earnings potential (as measured by the ventile) of the program.

Since ventile-specific estimates are noisy, we also estimate a more parsimonious model that assumes any differences across programs in the time trend or post-deregulation change are linear in predicted program earnings. Specifically, on the entire sample of programs we estimate the following regression:

$$Y_{jt} = \beta_1 Time_t + \beta_2 (Time_t\ X\ Pred_j) + \beta_3 POST_t + \beta_4 \left(Post_t\ X\ Pred_j\right) + \delta_j + \varepsilon_{jt}$$

where $Pred_j$ is the level of predicted earnings for program j, after controlling for student demographics and test scores. The mean of this variable in our analysis sample is 0.29. Again we weight observations

[1] We determined residency status based on the receipt of in-state tuition; all students who receive in-state tuition are considered residents, and all other students are non-residents. From this measure, approximately 93% of our sample is made up of Texas Residents. We use Pell Grant receipt to distinguish poor from non-poor students as this measure is available for all enrolled students; free-lunch eligibility is only available for students that graduated from in-state public high schools. We drop programs that have zero total, Pell, or non-Pell enrollment in any year. Our balanced panel contains 556 programs from 2001 to 2008.

by the level of junior enrollment in 2001 in order to adjust for the influence of small but highly volatile programs and also cluster standard errors by program.

Table D1 displays the results from this pooled model, which echo the results shown in the figures. We find that overall enrollment is increasing over time for the average program (predicted earnings = 0.29) and that total program enrollment increases just slightly above trend following deregulation (column (1)). These two features are most substantial for the least lucrative programs (with predicted earnings no greater than high school graduates), with little growth or change post-deregulation for the most lucrative programs. Non-resident enrollment, by contrast, experiences a steeper pre-deregulation growth rate and a more positive change post-deregulation, particularly for the more lucrative programs (though estimates are imprecise). This suggests that some of the programmatic changes following deregulation (e.g. higher prices and more spending) coincided with greater non-resident enrollment.

These program size patterns combined with our main sorting results suggests two proximate channels through which the relative shares of poor and non-poor students across programs are changing post-deregulation. For the most lucrative programs, the lack of any aggregate enrollment change suggests poor students are (modestly) displacing their non-poor counterparts. For programs from the bottom half of the distribution of predicted earnings, there is growth in the enrollment of poor students and non-poor students, but enrollment for non-poor students is occurring at a faster rate.

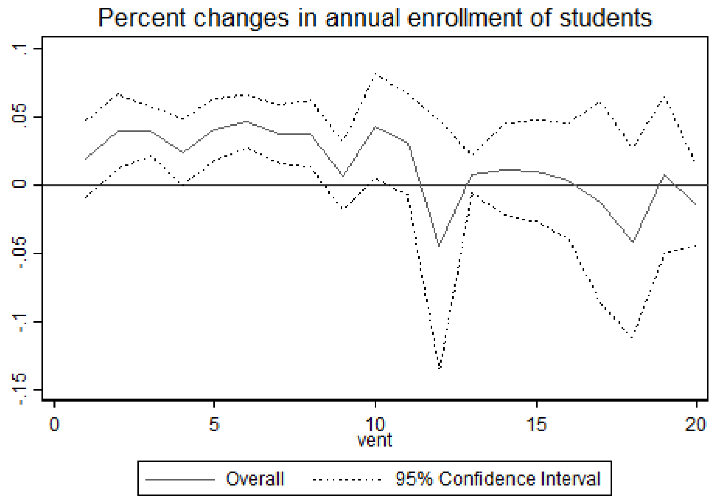
Table D1. Differences in Program-specific Enrollment Trends, by Program Predicted Earnings

	(1)	(2)
VARIABLES	Overall	Non-Resident
Time	0.0267***	0.0624***
	(0.00535)	(0.0147)
Time X Predicted Earnings	-0.0653***	-0.0975**
	(0.0186)	(0.0394)
Post	0.0301	0.0848
	(0.0201)	(0.0585)
Post X Predicted Earnings	-0.0654	0.0699
	(0.0661)	(0.166)
Constant	5.683***	2.595***
	(0.0178)	(0.0431)
Observations	3,583	3,583
R-squared	0.968	0.880

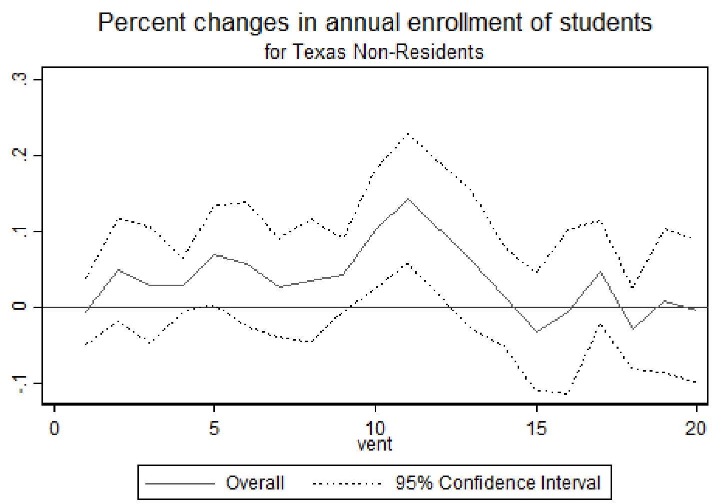
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure D1: Ventile-specific annual enrollment time trend

A. Overall



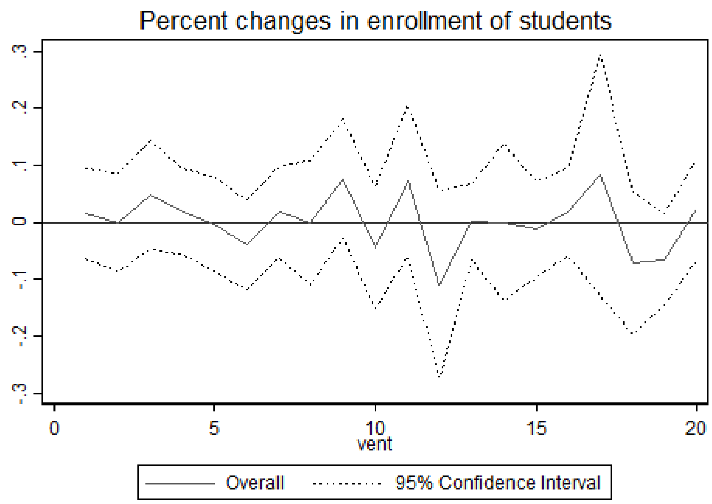
B. Non-residents



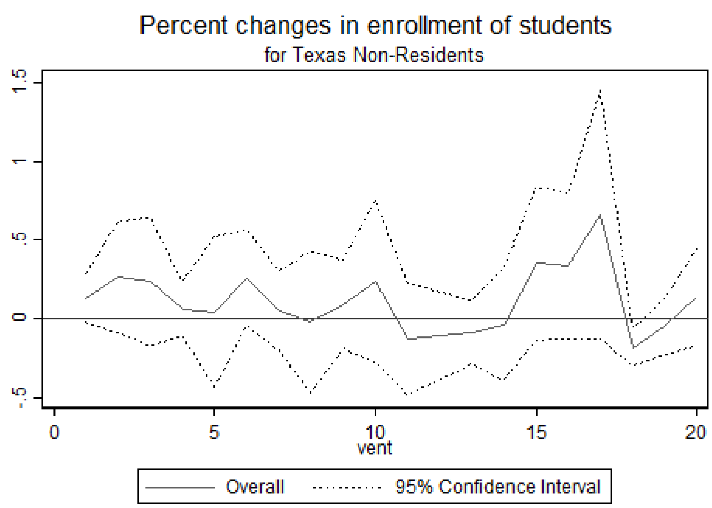
Notes: Each point on each figure corresponds to the coefficient on *Time* from a separate regression described in equation (1), where the log of junior enrollment (overall or for specific group) is the dependent variable. Sample in Panel A includes 556 programs from 2001 to 2008. Panel B omits programs that do not have at least one non-resident enrollment in each year, resulting in a sample of 82 programs. Standard errors clustered by program.

Figure D2: Ventile-specific post-deregulation enrollment change

A. Overall



B. Non-Resident Students



Notes: Each point on each figure corresponds to the coefficient on *Post* from a separate regression described in equation (1), where the log of junior enrollment (overall or for specific group) is the dependent variable. Sample in Panel A includes 556 programs from 2001 to 2008. Panel B omits programs that do not have at least one non-resident enrollment in each year, resulting in a sample of 82 programs. Standard errors clustered by program.