Academic Match and the Returns to For-Profit and Public Colleges

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Abstract

Short vocational college programs can deliver substantial returns. Public subsidies for these programs are concentrated in community colleges (CCs). Yet CCs graduate only 30% of their students, while two-year for-profit alternatives graduate twice that share. Using administrative records covering all two-year for-profit and public college students in Texas, I use distance instruments to identify college sector effects among students on the for-profit/public margin. For-profits raise long-run completion rates by 32 percentage points, with effects largest among the weakest students. Higher completion rates do not come at the expense of degree value, as a within-individual design shows that for-profit and CC degrees confer similarly large and durable returns. Expected returns at enrollment exhibit substantial match effects: academically weak students gain more from for-profits because of elevated dropout risk at CCs, while the strongest earn higher returns from CCs, partly due to the option value of academic and four-year pathways. To further investigate mechanisms, I collect new data on program-level course requirements. The data show that for-profits require significantly less academic coursework, helping explain why weaker students benefit more from their attainable degree pathways. Finally, I estimate the welfare effects of extending subsidies to for-profits. Accounting for fiscal savings on substitution out of CCs and increased tax revenues, I estimate marginal values of public funds in excess of 2.

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1 Introduction

As technological change reshapes labor demand, a central challenge for the US economy is how to build relevant human capital among workers outside traditional four-year college pathways. Short vocational training programs are an important vehicle for skill formation (Holzer 2026), but access to training is only the first step in workforce development. Students of widely varying academic abilities must then navigate the path to a credential. Some students will be unable to meet standards that reflect the skill demands of their intended occupations. Others may drop out because of challenging academic requirements which do not help build in-demand skills. In designing academic standards for vocational programs, colleges must therefore weigh the value of academic requirements against the challenges they present for vocational students.

How well institutions strike this balance will shape the inclusiveness and productivity of the vocational programs at the margins of higher education. A growing body of evidence finds substantial returns to vocational college programs (Lovenheim and Smith 2023). These returns disproportionately accrue to graduates (Jepsen, Troske and Coomes 2014), yet the primary vehicles for vocational training in the US — two-year public colleges, or community colleges (CCs) — graduate only 30% of their students.[1] For-profit alternatives graduate students at twice this rate, yet they receive significantly lower tuition subsidies than CCs — raising questions about the efficiency of public spending. Of course, graduation is a limited metric of success. If for-profits achieve higher graduation rates by lowering standards and awarding degrees with little labor-market value, perhaps they merit no public support at all. I therefore ask three questions: Why are for-profit graduation rates so much higher than public graduation rates? Do their more attainable degree pathways lead to lower returns? And should subsidy policies be redesigned to expand the supply of attainable vocational programs?

I answer these questions by combining rich administrative and survey data, which I use to estimate the productivity of for-profit and public programs for students of differing academic skills. Identifying the relative effects of for-profit and public colleges is difficult because for-profits specialize in vocational programs, while CCs bundle vocational training with academic and transfer options. Naive comparisons might confound sector effects with differences in program composition and student sorting. I overcome these challenges

[1] Specifically, 30% of first-time, full-time degree- or certificate-seeking students earn a credential from their original institution within 150% of the expected program duration, based on Integrated Postsecondary Education Data System (IPEDS) data. Within 6 years, only 40% of CC students will have earned any credential from *any* college, according to the author's calculations using Beginning Postsecondary Students 2012/2017 data.

using administrative records covering the universe of two-year for-profit and public college students in Texas, which link measures of pre-college skills to program-specific enrollment, degree attainment, and earnings. I find a for-profit completion premium within nearly every narrowly defined program of study. Conditioning on student characteristics only widens the gap, as for-profit students are negatively selected on academic skills. To identify outcomes for students on the for-profit/public margin, I adapt the multiple-treatment IV framework of Mountjoy (2022), using distance to each sector as excluded cost-shifters for enrollment. Conditional on rich location controls, the instruments are unrelated to predetermined student characteristics including high-school test scores, providing support for the conditional independence assumption. I find that for-profits raise long-run any-degree completion rates by 32 percentage points, while reducing Bachelor's attainment by 13 percentage points.

Average effects mask substantial heterogeneity by pre-college academic skills. I find a significantly larger for-profit completion premium among the least academically prepared students, who disproportionately sort into for-profits, and public colleges only improve Bachelor's attainment rates among higher-skill students. These patterns point to the possibility of academic match effects and suggest that for-profits raise graduation rates by reducing the academic intensity of their programs. I evaluate this hypothesis by turning to national transcript data. For-profit students with observably similar academic backgrounds earn significantly higher grades than their community-college peers. They are also much less likely to be placed into remedial education, and they take substantially narrower courses of study, avoiding the out-of-major academic courses commonly required at CCs. Newly collected data on course requirements for more than a thousand vocational programs confirm that public programs require significantly more academic coursework. Students on the for-profit margin perform especially poorly in those academic courses. And conditional on student characteristics, for-profit GPAs are nearly 0.50 GPA points higher — one third of which is explained by their narrower vocational curriculum alone. These curricular differences help rationalize both the for-profit completion premium and the match effects in degree production.

To understand whether the for-profit completion premium dilutes the value of for-profit degrees, I next estimate the ex-post returns to different schooling and attainment outcomes using a within-person design. Flexible individual-FE models of earnings show substantial returns to both for-profit and community-college degrees even 12 years after enrollment, while the returns to those who enroll but do not graduate are small. I next identify expected returns to enrollment among students on the for-profit/public margin by integrating these individual-FE estimates of ex-post returns with IV estimates of sector effects on program choice and degree attainment. Due to higher for-profit graduation rates, for-profits yield larger expected returns to enrollment, though match effects are significant: academically

weak students earn significantly more by enrolling in for-profits, since they face elevated dropout risk at CCs, while the strongest students earn higher returns from public enrollment due in part to the option value of academic pathways. Direct IV estimates of ex-ante returns show the same patterns, though less precisely estimated.

To compare the efficiency of for-profit and public degree production technologies, I next estimate the private and social costs of schooling. College-level expenditure data show broadly similar per-student resource costs across sectors. I then return to the IV design to estimate expected lifetime schooling costs for students on the for-profit/public margin. Combining these costs with estimates of gross returns, I calculate the net present value of enrollment in each sector across the skill distribution. Estimates imply that the for-profit degree production technology is relatively efficient for low-skill students, while public programs are more socially efficient for higher-skill students.

For-profits achieve comparable — and for some, higher — net returns, yet tuition subsidies are far larger at CCs. This suggests that shifting subsidies toward for-profits on the margin might improve the value-added of higher education, particularly among lower-skill students. To understand the welfare implications of asymmetric public subsidies, I estimate the marginal value of public funds (MVPF) of extending subsidies to for-profits. To do so, I estimate a college demand model which identifies compliers under a for-profit subsidy. Students shifted into for-profits come equally from non-enrollment and CCs, but primarily from the bottom of the skill distribution — those most likely to benefit from for-profit enrollment. Subsidy costs are offset by savings from substitution out of already-subsidized CCs and by increased tax revenues. Under a benchmark with perfectly elastic long-run supply, each dollar of subsidy cost generates more than five dollars in additional earnings. MVPFs range from 2 to 15, depending on how much of the earnings gains are offset by nonpecuniary costs of schooling and work. Expanding private provision of short vocational tracks emerges as an efficient way to build human capital among low-skill students on the margins of higher education.

Related Literature My results contribute to the literature on for-profit and community colleges, educational attainment, and the returns to vocational training. Most work comparing for-profit and community colleges finds that for-profits negatively affect multiple outcomes: students pay more in tuition, take on greater debt, default at higher rates, and may face worse labor-market outcomes (Deming, Goldin and Katz 2012; Deming et al. 2016; Cellini and Darolia 2016; Cellini and Turner 2019; Armona, Chakrabarti and Lovenheim 2022).[2] These differences partly reflect the fact that for-profits must cover their costs, while community colleges use their considerable state support to offer near-zero tuition rates.

[2]The evidence for worse labor-market outcomes is not settled, as I explain below.

While prior work has compared completion rates at for-profit and community colleges, there remains no consensus about whether these gaps reflect sector effects or simply differences in student or program composition (Deming, Goldin and Katz 2012; Liu and Belfield 2014; Baum, Holzer and Luetmer 2021; Armona, Chakrabarti and Lovenheim 2022).[3] The lack of clear evidence about the for-profit completion premium has also limited our understanding of the drivers of degree attainment among students in vocational programs. I offer extensive evidence — using both nationally representative data and quasi-experimental variation in Texas — that for-profits significantly boost completion rates, and I use transcript data to highlight curricular differences as a likely mechanism.[4]

By contrast, a large literature studies the determinants of low graduation rates at community colleges. While community colleges promise gateways to human capital formation for students of lesser means, some have pointed to a tension between their open-access mission and their performance (Bailey, Jaggars and Jenkins 2015). Bound and Turner (2007) and Bound, Lovenheim and Turner (2010) find that reduced resources per student lower aggregate attainment, showing that supply-side factors significantly impact degree production — yet the evidence linking resources to completion is weaker within the two-year sector. Other studies, namely Zimmerman (2014) and Goodman, Hurwitz and Smith (2017), provide quasi-experimental evidence that low CC completion rates indeed reflect large school effects, but for students on the four-year margin. I contribute by showing that CC graduation rates reflect significant completion penalties, even relative to other two-year colleges offering similar degrees. Yet the relevant constraints on degree attainment may differ significantly on the for-profit margin, where students seek short vocational degrees and are substantially more disadvantaged in their resources, academic preparation, and socioeconomic background.

Convincing evidence on the specific drivers of low CC graduation rates remains relatively scarce. Researchers have articulated many potential barriers, including implicit capacity constraints and cohort crowding (Bound and Turner 2007), limited course offerings and flexibility (Robles, Gross and Fairlie 2021; Grosz, Kurlaender and Stevens 2022), the structure of remedial requirements (Bailey, Jeong and Cho 2010; Liu and Belfield 2014; Meiselman and Schudde 2022), insufficient advising resources to navigate complex degree requirements (Per-

[3]In particular, compare Liu and Belfield (2014) with Baum, Holzer and Luetmer (2021). The former finds a large for-profit completion premium within programs, controlling for prior academic characteristics, yet Baum, Holzer and Luetmer (2021) argue these differences disappear after accounting for student and program traits. This finding may reflect their use of an endogenous control, full-time status, which may be an important mediator of completion-rate effects. Indeed, Haygood (2026) finds sector effects on full-time status, showing that for-profit students downshift to part-time enrollment when they enroll in CCs.

[4]Some older mixed-method studies compare small clusters of two-year for-profit and public colleges, highlighting academic difficulties as potentially important mechanisms (Wilms 1974; Person, Rosenbaum and Deil-Amen 2006).

son, Rosenbaum and Deil-Amen 2006; Bahr 2008), lack of structure and "guided pathways" to degrees (Scott-Clayton 2011; Bailey, Jaggars and Jenkins 2015), and peer effects (Smith and Stange 2016), among others. Progress on empirically identifying the significance of each mechanism has been somewhat limited due to challenging identification issues and potential interactions between different barriers. Randomized evaluations of bundled interventions such as Accelerated Study in Associate Programs (ASAP) show that intensive supports can nearly double CC graduation rates, but do not separately identify the mechanisms driving these gains (Scrivener et al. 2015; Miller et al. 2020). While my evidence shares this limitation, I find patterns consistent with two additional challenges faced by academically weaker students: broad curricular requirements and relatively tough grading standards. Here I complement Denning et al. (2022), who show that grading standards have first-order effects on degree completion across US college sectors.

My primary contribution is to strengthen our understanding of the returns to for-profit colleges. Most prior work finds that for-profits deliver similar or lower gross returns relative to community colleges, and that private net returns are decidedly lower due to higher for-profit tuition (Lovenheim and Smith 2023). Using within-person estimators, Cellini and Turner (2019) find lower returns to for-profit certificate programs nationally, while Jepsen et al. (2025) find that for-profits in Missouri somewhat out-perform community colleges in gross returns. At best, these estimators identify returns for distinct self-selected populations, however, so their comparison does not identify relative returns under selection on gains. Matching students on observables and conditioning on program of study are imperfect remedies only valid under restrictions I find are rejected in practice.[5]

The few studies using instruments for enrollment are better-positioned to identify relative returns among marginal students, but existing estimates are uninformatively noisy and do not isolate returns on the for-profit/public margin without strong restrictions on sorting or treatment-effect heterogeneity (Liu and Belfield 2014; Armona, Chakrabarti and Lovenheim 2022; Kirkeboen, Leuven and Mogstad 2016). I address these challenges by adapting the multiple-treatment IV framework of Mountjoy (2022), which identifies margin-specific treatment effects in settings with multiple unordered treatments and unrestricted treatment-effect heterogeneity. My approach combines IV estimates of sector effects on educational attainment with within-person estimates of the ex-post returns to realized schooling outcomes, as in Jacobson, LaLonde and Sullivan (2005) and Dynarski, Jacob and Kreisman (2018). In distinguishing these ex-post returns from the ex-ante returns to enrollment, I draw on Altonji

[5]Randomized resume-audit studies also find null or negative effects of for-profit credentials on employer callback rates (Darolia et al. 2015; Deming et al. 2016). Yet callback rates are at best an indirect proxy for returns, and by construction these experiments do not account for how sector differences in completion rates impact expected returns.

(1993) and Stange (2012*b*). My work also relates to the broader literature on identification under essential heterogeneity (Willis and Rosen 1979; Heckman, Urzua and Vytlacil 2006; Carneiro, Heckman and Vytlacil 2011).

I also provide some of the first evidence for match effects within non-selective colleges. Most of the match and affirmative-action literature defines college quality in terms of selectivity. Arcidiacono, Aucejo and Hotz (2016) and Dillon and Smith (2020), for instance, find significant complementarities between ability and college quality in graduation rates and earnings at four-year colleges. By contrast, two-year colleges appear less differentiated in quality (Stange 2012*a*). To my knowledge, Smith and Stange (2016) provide the only existing evidence of match effects within two-year colleges, using a selection-on-observables design. They find complementarity between a student's own PSAT score and that of their peers in Bachelor's attainment, yet quality differences overwhelm match effects in scale. By contrast, I find match effects large enough to flip the sign of relative returns for different students.

Finally, my work relates to a broader literature on workforce development, including vocational training opportunities outside the walls of higher education. Indeed, many of the for-profit programs I study resemble non-college training programs far more closely than, say, four-year colleges. These alternatives include sectoral employment programs, federal workforce programs, as well as apprenticeships and on-the-job training, and are reviewed in Holzer (2026). Examples vary from relatively low-return federal initiatives like Job Corps to the more promising sectoral employment programs like Year Up and WorkAdvance reviewed in Katz et al. (2022). Sectoral employment programs typically target specific industries and occupations with strong local labor demand, mirroring how two-year for-profits adapt their programs to prevailing labor-demand conditions (Gilpin, Saunders and Stoddard 2015). Still, these employment programs operate at a much smaller scale than for-profit college programs and are typically selective, unlike the largely open-access two-year college sector. My results point to for-profits as an alternative set of workforce development programs operating at scale and offering substantial returns to a similar population of disadvantaged young adults.

I begin in Section 2 by describing the data, the landscape of two-year colleges in the US, and potential sources of the for-profit completion premium. Section 3 then describes patterns of degree attainment across sectors, followed by identification and estimation of sector effects on completion rates in Section 4. I then estimate the ex-ante and ex-post returns to for-profit and community colleges in Section 5, showing how they depend on graduation rates and pre-college skills. Section 6 then estimates the MVPF of a for-profit tuition subsidy designed to expand the provision of attainable vocational programs. I conclude with a discussion in Section 7.

2 Data and Institutional Background

I employ a combination of survey and administrative panel data, supplemented with a novel dataset of degree requirements.

Beginning Postsecondary Students Data I take nationally representative survey data from the National Center for Education Statistics' Beginning Postsecondary Students (BPS) survey, which followed a cohort of first-time undergraduate students beginning their college studies in the 2011-12 academic year through multiple waves culminating in 2017. The survey collected detailed data on students' pre-college socioeconomic and academic characteristics, their beliefs and preferences at entry and over time, as well as their enrollment and degree completion outcomes during each enrollment spell. A subset of the sample also participated in the Postsecondary Education Transcript Study (PETS), which includes data on courses and credits attempted and earned by subject, as well as grades over time and by subject. The NCES requested transcripts from 93% of the 4,360 institutions included in the BPS and received a transcript from at least one attended institution for 73% of the 35,540 BPS student participants.

I focus on the subset of 9,400 students surveyed who enroll in 2-year or less-than-2-year colleges. For the majority of the analysis, I restrict attention to the 7,200 students initially declaring a major in a career and technical education (CTE) field, since two-year for-profits offer almost exclusively CTE degrees. And since patterns of degree attainment differ significantly between certificate and Associate's programs, I further split the analysis by the student's intended degree level. This makes for primary analysis samples of 2,800 certificate and 4,400 Associate's students. For one analysis, I also employ an earlier edition of the BPS for a cohort beginning college in the 2003-04 academic year.

Texas Education Research Center Data To identify college sector effects on attainment and earnings, I use individual-level linked administrative data on the education and earnings of the universe of Texas public HS students from the Education Research Center (ERC) at UT Austin. The data include student demographic variables, HS test scores and graduation records, college enrollment and graduation for nearly all two-year Texas colleges, and quarterly earnings data from the Texas Workforce Commission (TWC), which collects data on the near-universe of wage-earners in Texas based on UI wage reports.

My primary analysis sample includes all 2.15 million Texas public HS students graduating between 2004–2012. This includes 585,000 who first enroll at one of 67 community colleges within 4 years of graduation, and 38,000 who first enroll at one of 81 two-year private colleges within the first 4 years. Approximately 37% of those public students initially enroll in a

vocational major, compared to 99% of for-profit students.[6] For within-individual earnings regressions, I use an auxiliary sample of older students who initially enroll in college from age 22 to 50 and between 2003 and 2014, and who have some pre-college earnings history. This sample contains 128,000 community-college students and 77,000 two-year for-profit students. Finally, Texas community-college transcript records are available beginning in 2011. To characterize transcript outcomes, I will therefore restrict the main analysis sample to the 2011–2012 cohorts.

The for-profit college sample contains more than 95% of all two-year for-profit college enrollment reported in the Department of Education's Integrated Postsecondary Education Data System (IPEDS), which covers all colleges participating in federal financial aid programs. Coverage of purely certificate-granting less-than-2-year for-profits is relatively weak, both because some that report to IPEDS do not report to the ERC, and because many small non-degree-granting for-profits do not belong to the IPEDS data universe, as they do not participate in federal financial aid disbursement. This is not a significant limitation for my purposes, since coverage is nearly complete for the part of the for-profit sector where overlap with CC degree programs is largest — namely, Associate's degree programs in CTE fields.

Degree Requirements Data To provide direct evidence on sector differences in degree requirements, I assemble a novel program-level dataset characterizing the course requirements of vocational programs at two-year Texas colleges. I begin with 1,481 programs identified from 2024 IPEDS completions data, where a program is a combination of college, degree level, and major (6-digit CIP code). This sampling frame covers the 50 vocational fields with the most for-profit completions nationally, which together account for 89% of Texas for-profit completions. For each program, I use an AI-assisted web-collection and extraction routine to identify the courses required for graduation, including total credits and the academic share of required credits.

Academic credits include courses designated as general-education or core curriculum, along with coursework in subjects such as English, mathematics, science, communication, and social science when its content falls outside the program's occupational domain. The resulting dataset contains complete curricular requirements for 1,078 programs, including 187 for-profit programs and 891 community-college programs. These constitute 73% of programs and account for 86% of completions in the sampling frame. Coverage includes 91% of for-profit programs and 70% of community-college programs, representing 95% and 83% of

[6] I define vocational, or CTE, fields according to the two-digit Classification of Instructional Programs (CIP) taxonomy. In particular, I include codes 11, 12, 15, 22, 43, 46, 47, 48, 50, 51, and 52, referring to computer and information sciences, personal and culinary services, engineering technologies/technicians, legal professions and studies, security and protective services, construction trades, mechanic and repair technologies/technicians, precision production, visual and performing arts, health professions, and business.

completions, respectively. Appendix D contains further details on the dataset construction.

Integrated Postsecondary Education Data System (IPEDS) Data Finally, I take institution-level data from IPEDS for national summary statistics and for supplemental information on the analysis sample of Texas colleges.

2.1 Institutional Background

The Two-Year Sector in Perspective Students in sub-baccalaureate degree programs make up more than 40% of all US undergraduates. Two-year college students enroll in typically one-year certificate programs and two-year Associate degree programs, but the majority plan to transfer to four-year colleges thereafter. Two-year public colleges in particular embrace a dual mission of providing educational opportunities for students of all academic and socioeconomic backgrounds, while serving as a launching pad for further study among more ambitious, transfer-minded students.

Though two-year for-profit colleges offer substantially higher graduation rates than two-year public colleges, for-profits have lower graduation rates among four-year colleges. And unlike many of the largest four-year for-profit colleges, two-year for-profits primarily offer in-person degree programs with limited fully online offerings. In general, the for-profit sector appears to function best in the market for short credentials with a clear connection to in-demand occupations (Deming, Goldin and Katz 2013). Consistent with this view, Gilpin, Saunders and Stoddard (2015) show that two-year for-profits' entry and program-offering patterns are highly responsive to changes in local labor demand. Still, for-profits are a diverse set of colleges, and the two-year market has also featured instances of false advertising and outright fraud (U.S. Government Accountability Office 2010).

Vocational Training Programs Two-year colleges are also the primary vehicle for vocational training in the United States.[7] Their vocational programs equip students with occupation-specific skills and prepare them for licensing exams and voluntary certifications relevant to particular occupations like medical assisting, automobile repair, and welding. Completion of a college program is itself required for entry into certain occupations, including dental hygiene and physical therapy assisting, making vocational programs a gateway into what are often relatively high-paying fields.

As examples, Figure 1 presents modal public degree pathways for two common programs: a Licensed Practical Nursing (LPN) certificate and a two-year Associate of Applied Science (AAS) degree in automobile technology. Public colleges may or may not require remediation and academic coursework for 45-credit certificates like the displayed LPN program, but

[7] On-the-job training may rival formal college programs in scope but is harder to quantify.

60-credit AAS degrees require remediation for those not achieving proficiency on placement exams, usually followed by 15 credits in academic courses like English and math. Remedial coursework can span math, reading, and writing, requiring up to three sequential math courses in some cases, none of which contribute to the degree or certificate's credit requirements.[8] Remedial and academic requirements are much reduced in the for-profit versions of these programs, as I document in Section 4.1. Graduates of programs like the LPN certificate must then pass a state-mandated licensing exam in order to practice, while graduates of other programs like automobile repair may earn voluntary certifications after graduation. Many for-profit and public programs also integrate internships with local employers into the curriculum.

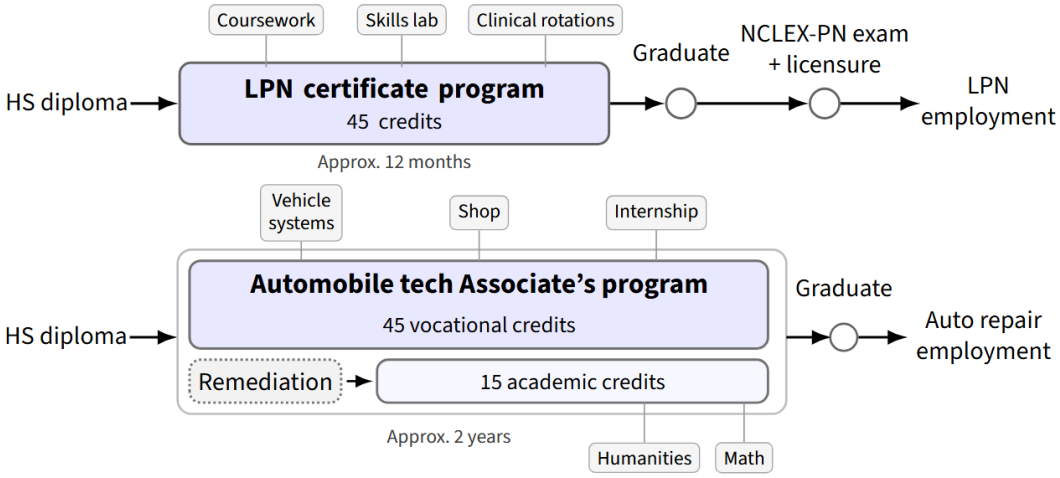


Figure 1: Paradigmatic Public Vocational Degree Pathways

Public vs. For-Profit Options Community colleges are the dominant provider of vocational programs, as they are geographically widespread and receive substantial state support. State appropriations allow CCs to offer below-cost tuition, often near zero for students of lesser means, consistent with their open-access mission (Table 1). For-profit alternatives are much smaller, commonly offering only a handful of programs in career-oriented fields and charging substantially higher tuition — in large part because they do not receive the state appropriations available to CCs. For-profits serve 17% of new two-year or less-than-two-year college enrollees each year, compared to public colleges' 80% market share.[9]

[8]Several states including Texas have since reformed their remedial requirements to a "co-requisite" model in which remediation occurs simultaneously with credit-bearing introductory academic coursework — potentially reducing remediation-related delays but not relaxing the underlying academic requirements.

[9]Based on author's calculations from 2025 IPEDS 12-month enrollment files, summing first-time and transfer-in degree-/certificate-seeking undergraduates in primarily sub-baccalaureate colleges. The remaining 3% enroll in private non-profit colleges. Primarily sub-baccalaureate colleges are those where a minority of

Table 1: Two-Year College Characteristics

	Public	For-profit
Enrollment share	80%	17%
Average net tuition	\$714	\$9,407
Vocational share	37%	99%
Certificate share	6%	74%
Graduation rate	33.5%	62.8%

Notes: The table compares primarily sub-baccalaureate institutions. Average net tuition and graduation rates estimated from 2023 IPEDS data, weighting institutions by 12-month undergraduate enrollment. Net tuition after grants computed by dividing net tuition-and-fee revenue by 12-month undergraduate enrollment. The graduation rate is the share of first-time, full-time students completing within 150 percent of normal time at the original institution. Vocational and certificate shares come from the Texas analysis sample.

Unlike for-profit providers, community colleges also offer a wide range of academic programs like history and general studies, which are typically designed to allow for four-year transfer. Serving both career-oriented and more academically inclined students presents a challenge, as CCs must design degree pathways and academic requirements suitable to a wide range of aptitudes and educational goals. By contrast, most for-profit students come to college with the goal of completing a short program relevant to a particular vocation. The lack of academic majors at for-profits and the fact that their credits are often not accepted by public institutions mean that avenues for major-switching and four-year transfer are more constrained at for-profits. Yet these narrower offerings lend themselves to more streamlined curricula centered on vocation-relevant material, while public vocational programs often require academic courses. Thus, public and for-profit programs entail different degrees of specialization at entry, and many CC students who are less sure of their desired program simply would not consider an expensive for-profit option with only a handful of programs — particularly since for-profit programs often run on accelerated timelines.[10]

Given for-profits' higher tuition and limited program offerings, for whom might a for-profit program make sense? Prior work shows that for-profits offer specific vocational programs sometimes not available at the local CC, constituting a source of differentiation com-

degrees are awarded at the Bachelor's level. This distinction matters because a portion of community colleges have officially switched from two-year to four-year status, even though they continue to primarily offer sub-baccalaureate programs. I use the 2009 institutional control classification since several for-profits have formally switched to non-profit status since then. These statistics likely understate the for-profit market share, because some non-degree-granting for-profits exist outside the IPEDS universe.

[10]While about half of community-college students enroll part-time, 90% of for-profit students enroll full-time, quickening their path to degrees. Haygood (2026) shows that these differences do reflect sector effects on enrollment intensity.

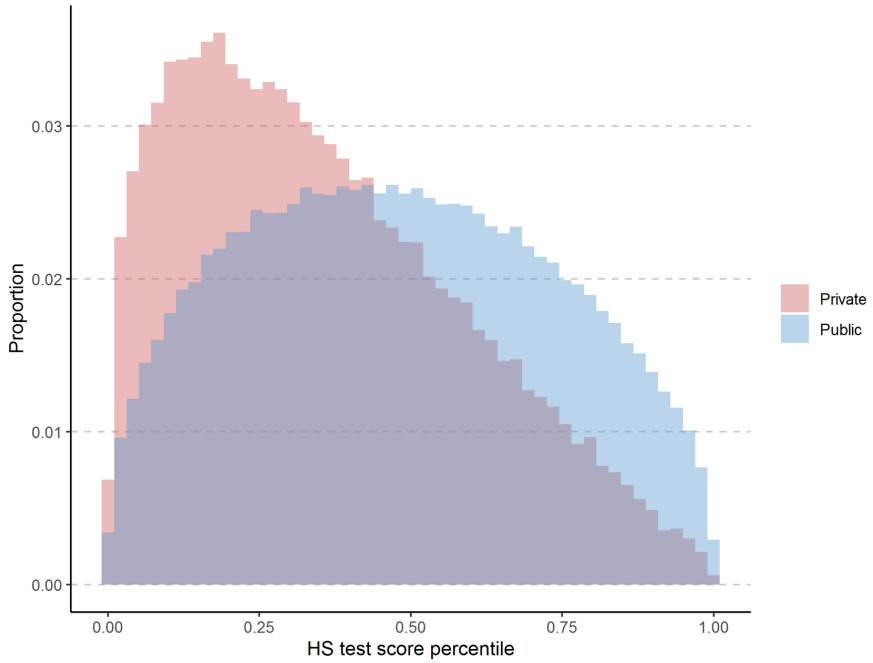


Figure 2: Distributions of Pre-College Skills

Notes: Distributions of HS test score percentiles among two-year private for-profit students and two-year public students in Texas belonging to the 2004–2012 HS graduating cohorts. Percentiles are constructed by taking within-cohort percentiles of the average of 9th- and 10th-grade math and reading test scores.

pelling to students with strong program preferences. For-profit students are also more likely to report considering graduation rates when deciding where to enroll, suggesting an awareness of for-profits' elevated graduation rates (Haygood 2026).[11] To the extent that for-profits raise graduation rates by reducing academic requirements, students with weaker academic backgrounds should be more sensitive to graduation rates than others. Consistent with this view, I find that proxies for pre-college academic skill are significantly lower among for-profit students. Figure 2 shows this by plotting the distribution of for-profit and CC students' high-school test score percentiles, which is uniform in the population of high-school graduates.[12] And for academically weak students, the option values of academic major-switching and four-year transfer offered by CCs are likely to be less valuable, as these routes entail more demanding academic coursework. And given their academic backgrounds, for-profit students are unlikely to apply or gain admission to selective colleges. They therefore are most likely to consider their local community college, a regional public four-year, a for-profit, or

[11] While preferences for distinctive for-profit program characteristics are important, other work emphasizes the role of limited information and advertising in driving for-profit enrollment (Armona and Cao 2024). Easy access to student loans also dampens students' price sensitivities.

[12] I construct test score percentiles by taking the average of standardized math and reading scores from 9th and 10th grade, and then taking within-cohort percentiles of the average scores.

non-enrollment.[13]

3 The For-Profit Completion Premium

Within the two-year sector, for-profit graduation rates substantially exceed community-college graduation rates across each dataset and regardless of how graduation is defined. Beginning with the full US population of two-year colleges, IPEDS shows that 62.8% of for-profit college students graduate from their original college within 150% of expected time, compared to just 33.5% of community-college students (Table 1). Appendix Figure A6 shows that CC graduation rates have been even lower historically. Incorporating transfer students only modestly shrinks this gap. Though transfer is rare at for-profits, about 18% of CC students transfer to another college. The IPEDS collection does not track the degree attainment of these students, but the NSC finds that 48% of CC transfer students earn degrees nationally. Imputing this graduation rate to the IPEDS transfer data, for-profit students remain 20 percentage points more likely to earn a degree.

To evaluate whether differences in degree programs or student characteristics can explain this gap, I next turn to nationally representative individual-level data from the Beginning Postsecondary Students (BPS) survey. This survey tracks students across multiple waves following their entry into college in 2011. I again restrict the sample to students beginning at sub-baccalaureate colleges. Given that for-profits offer exclusively vocational programs, I now restrict the sample to students intending a major in career and technical education. And since public colleges specialize in longer Associate's degrees, comparing degree outcomes without conditioning on degree intent may conflate the influence of degree program and sector. I therefore split the sample by initial degree intention.

Similar to the analysis in Deming, Goldin and Katz (2012), I present both raw mean differences and comparisons which control for observable pre-college student characteristics. Though selection-on-observables is a strong assumption in this setting, it serves as a starting point to describe key differences between sectors and understand how observable sorting impacts the completion-rate gap in the nationally representative data. I account for unobserved heterogeneity in Section 4. Table 2 presents mean public graduation rates and the for-profit graduation premium — shown both as the raw mean difference, and as the residual completion-rate gap after controlling for baseline student characteristics. These include pre-college measures of academic ability and preparedness, socioeconomic status and family

[13] Deming, Goldin and Katz (2012) and Haygood (2026) offer additional background on variation among for-profits and the kinds of students the for-profit sector educates. Haygood (2026) also estimates the second choices of for-profit students, finding that 30–50% would substitute to community colleges absent their chosen for-profit.

background, and student demographics including age at enrollment and single parenthood.[14] Panel A presents results for Certificate students, while Panel B presents those for Associate's students.

Rates of graduation — with any degree from any college, within 3 and 6 years of first enrollment — are again significantly higher at for-profit colleges. Since for-profit students have weaker academic preparedness and come from more disadvantaged backgrounds, controlling for student characteristics inflates the completion-rate gap. The for-profit premium is largest for Associate programs, where for-profit students are nearly three times as likely to graduate within 3 years. While public graduation rates catch up over time, still only 40.4% of public Associate's students graduate within 6 years, compared to a (selection-corrected) 61.6% of for-profit students. Graduation rates for public Certificate students are much higher, at 43.6% within 3 years, but Certificate programs make up a negligible share of public enrollment. And even there, for-profit students are 18.8 (12.5) percentage points more likely to graduate within 3 (6) years. Though for-profits do specialize in shorter vocational degrees, these differences do not explain a large share of the graduation-rate gap.

Next I characterize the attained degree levels of graduates. Students beginning in Certificate programs rarely graduate with a higher degree level; in those programs, the for-profit premium operates exclusively through Certificate awards. Switching degree level is more common among Associate's students, however, as half of public Associate's students who graduate end up with a degree other than an Associate's. Of those beginning in a public Associate's program and graduating within 6 years, 18.3% drop down to a Certificate program, while 30% go on to achieve a Bachelor's degree. In part because for-profit credits do not transfer across schools as easily, for-profit students are 5.4 percentage points less likely to attain a Bachelor's degree. They are also 3.3 percentage points less likely to switch down to a Certificate (conditional on observables).

Among Associate's students who complete their Associate's degree, for-profit graduates also finish much more quickly, spending nearly half as much time in school. I plot these degree-attainment dynamics in more detail in Figure 3, which shows unadjusted public completion probabilities alongside selection-corrected estimates of for-profit completion rates. Most Certificate students who graduate in either sector will earn their first credential within the first 2 years. Among Associate's students, however, while the vast majority of for-profit graduates complete their first degree within 3 years, it takes a majority of public graduates more than 3 years to earn their first degree. Finally, I show in Appendix Figures A7 and A8

[14] I do not control for full-time status, since Haygood (2026) finds that enrollment intensity is influenced by college sector and may represent an important channel underlying sector effects on degree attainment, as is also suggested by the ASAP studies (Scrivener et al. 2015; Miller et al. 2020).

Table 2: Degree Attainment by Sector

	Public mean	For-profit premium	
		Unadjusted	With controls
Panel A: Certificate students			
Any degree within 3 years	0.436	0.152	0.188
		(0.049)	(0.054)
Any degree within 6 years	0.510	0.105	0.125
		(0.047)	(0.054)
Highest degree: Certificate	0.464	0.123	0.133
		(0.048)	(0.053)
Highest degree: Associate's	0.035	-0.013	-0.010
		(0.014)	(0.015)
Highest degree: Bachelor's	0.010	-0.005	—
		(0.008)	—
Months elapsed (Certificate graduates)	16.0	-2.7	-2.4
		(1.4)	(1.5)
Months enrolled (Certificate graduates)	12.6	-1.4	-0.9
		(1.1)	(1.2)
Panel B: Associate's students			
Any degree within 3 years	0.174	0.301	0.332
		(0.042)	(0.046)
Any degree within 6 years	0.404	0.152	0.212
		(0.044)	(0.053)
Highest degree: Certificate	0.074	-0.016	-0.033
		(0.016)	(0.020)
Highest degree: Associate's	0.209	0.277	0.299
		(0.047)	(0.055)
Highest degree: Bachelor's	0.121	-0.109	-0.054
		(0.013)	(0.017)
Months elapsed (Associate's graduates)	36.6	-17.4	-18.8
		(1.2)	(1.9)
Months enrolled (Associate's graduates)	30.8	-13.9	-14.0
		(1.0)	(1.4)

Notes: Estimates from BPS 12/17. Sample includes all students enrolling in a two-year or less-than-two-year college and initially intending a CTE major. The unadjusted for-profit premium is a simple difference of means. The for-profit premium with controls represents the coefficients on for-profit indicators from regressions with the following independent variables: income percentile rank, total income by dependency status, highest level of HS math, years completed of HS math, number of HS honors subjects, number of HS science courses, whether took AP courses, HS GPA, HS degree status, family size, father's and mother's highest education level, whether first in family to attend college, parents' marital status, degree of urbanization, age at enrollment, gender, ethnicity, index of high-school dropout risk, single parenthood, and pre-college work experience. Standard errors in parentheses.

that these national patterns replicate remarkably well in the Texas administrative data, not only in terms of cumulative completion rates, but also in the timing of degree completion and the extent of switching between degree levels.

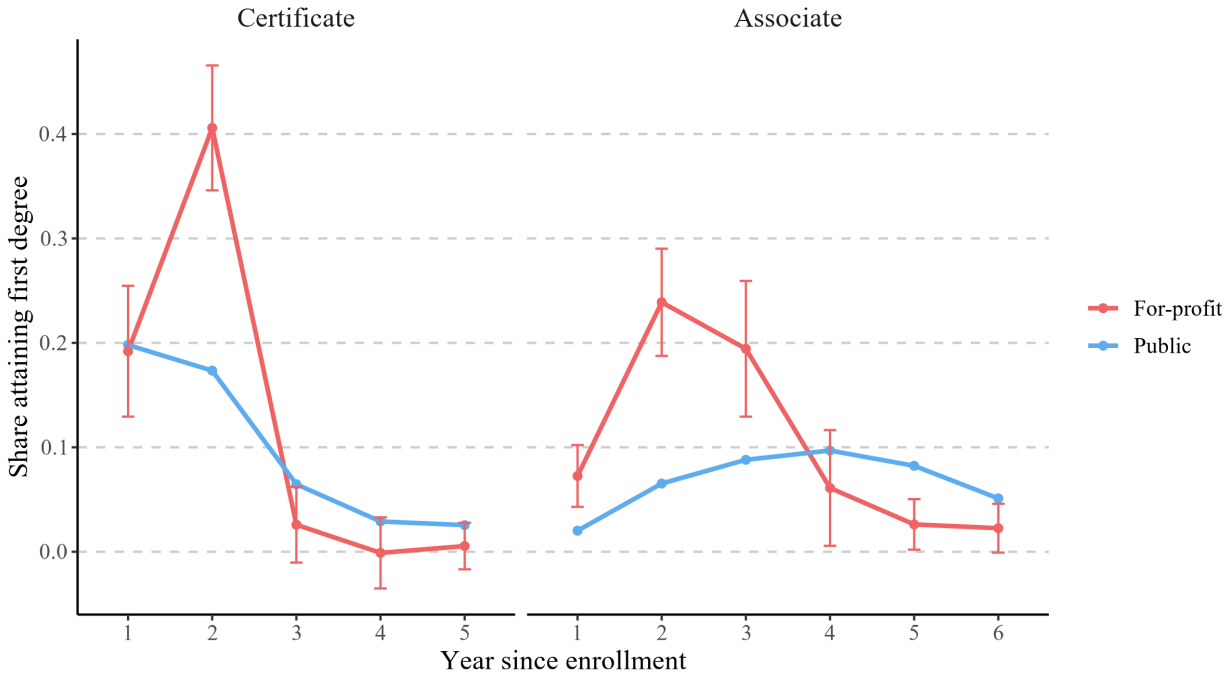


Figure 3: Flow Graduation Rates by Degree Program and Sector

Notes: Estimates from BPS 12/17. Sample includes all students enrolling in a two-year or less-than-two-year college and initially intending a CTE major. Blue dots represent the proportion of public students completing their degree each year after first enrollment. Red dots are selection-corrected proportions for for-profit students — that is, they add the for-profit coefficient from a regression with controls (where public is the omitted group) to the public mean. Controls include income percentile rank, total income by dependency status, highest level of HS math, years completed of HS math, number of HS honors subjects, number of HS science courses, whether took AP courses, HS GPA, HS degree status, family size, father's and mother's highest education level, whether first in family to attend college, parents' marital status, degree of urbanization, age at enrollment, gender, ethnicity, index of high-school dropout risk, single parenthood, and pre-college work experience. Error bars represent 90% confidence intervals.

Overall, then, although the IPEDS data underlying the aggregate graduation statistics have limitations, they paint a relatively accurate picture of sector differences in degree attainment. Incorporating transfers only modestly shrinks the for-profit completion premium, and conditioning on observable student characteristics in fact expands the gap. Although degree completion patterns do differ substantially by program — with for-profits specializing in shorter, vocational degrees — the completion-rate gap holds up even within degree levels and within vocational majors.

Lastly, to further evaluate the role of program composition I turn to the Texas administrative records, which record enrollment in even more granular programs of study. Even

within vocational programs, for-profit and community colleges offer different distributions of majors, and specific vocational majors may differ in difficulty. To account for these differences, I estimate completion-rate gaps in the Texas administrative data within finer major classifications and find large completion-rate gaps in nearly every program at both Certificate and Associate's levels (Figure 4). Reweighting the public program distribution to match the distribution of for-profit program enrollment only shrinks the for-profit completion premium by 9%.

Heterogeneity by Academic Skills Barriers to graduation may differ across students. If public graduation rates are lower due to a more academically intensive curriculum, academically weaker or less prepared students should face particularly low graduation prospects at public colleges. Here I present descriptive evidence consistent with this hypothesis, again using the larger administrative sample from Texas. While this analysis remains descriptive in nature, the remainder of the paper will show that these patterns indeed reflect sector effects that vary by pre-college skills, and Section 4.1 provides direct evidence for greater academic intensity at CCs using transcript records and degree-requirements data.

If academic standards drive the for-profit completion premium, for-profit completion probabilities should be higher across the board, yet less sensitive to their students' academic skills. Denoting G_i^j the potential sector-j graduation outcome of student i with ability A_i, we would predict $\mathbb{E}[G_i^{FP} \mid A_i = a] > \mathbb{E}[G_i^{CC} \mid A_i = a]$ for all a, while

$$0 \leq \frac{\partial \mathbb{E}[G_i^{FP} \mid A_i = a]}{\partial a} < \frac{\partial \mathbb{E}[G_i^{CC} \mid A_i = a]}{\partial a}.$$

To map this prediction to data, I link college attainment outcomes to measures of students' pre-college academic skills from 9th- and 10th-grade test scores. Figure 5 shows that public completion rates are in fact highly sensitive to pre-college skills, while the relationship between skills and graduation is significantly weaker in the for-profit sector. The more challenging Associate's programs naturally feature lower completion rates and steeper skill gradients, but the academic skill-elasticity of graduation rates remains substantially higher at CCs.

These gradients may reflect differences in other student characteristics associated with HS test scores. Yet conditioning on ethnicity, gender, HS fixed effects, and free-/reduced-price lunch (FRPL) eligibility does not significantly change the estimated slopes. Consistent with sorting on gains, Figure 5 also shows that lower-skill students are over-represented in the for-profit sector, even within degree levels. To the extent that degrees carry labor-market returns, sorting on relative graduation rates will also generate match effects in ex-ante returns, which I consider in Section 5. Finally, while the national BPS survey does not

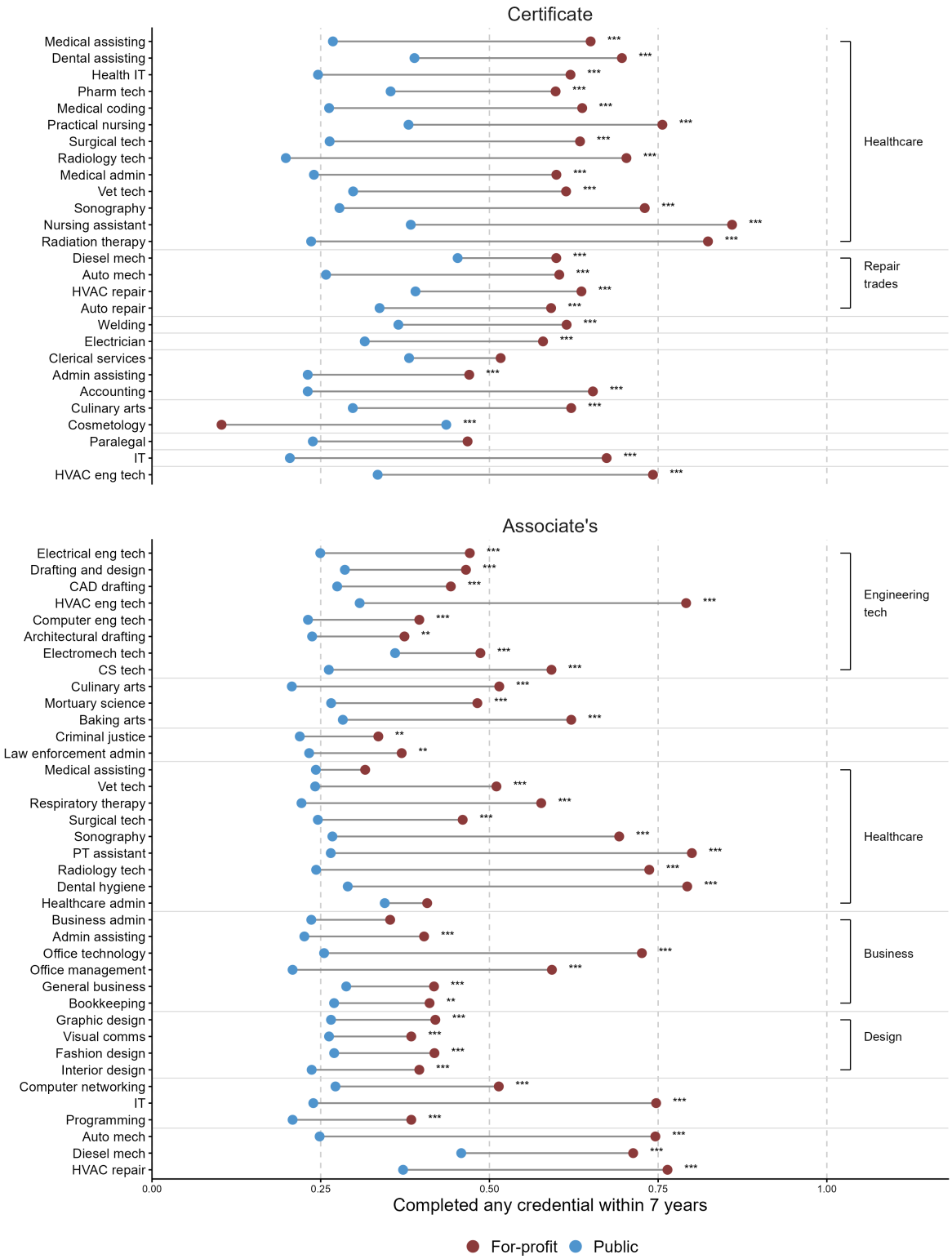


Figure 4: Completion Rates by Program of Study

Notes: Sample includes all Texas public HS students who enroll in a two-year for-profit or community college intending a certificate or Associate's degree in one of the listed majors from 2004–2012. Majors correspond to six-digit CIP codes. Outcome is completing any credential within 7 years of first enrollment. Stars indicate whether the difference of means is statistically significant; *, **, and *** correspond to 10%, 5%, and 1% significance levels, respectively.

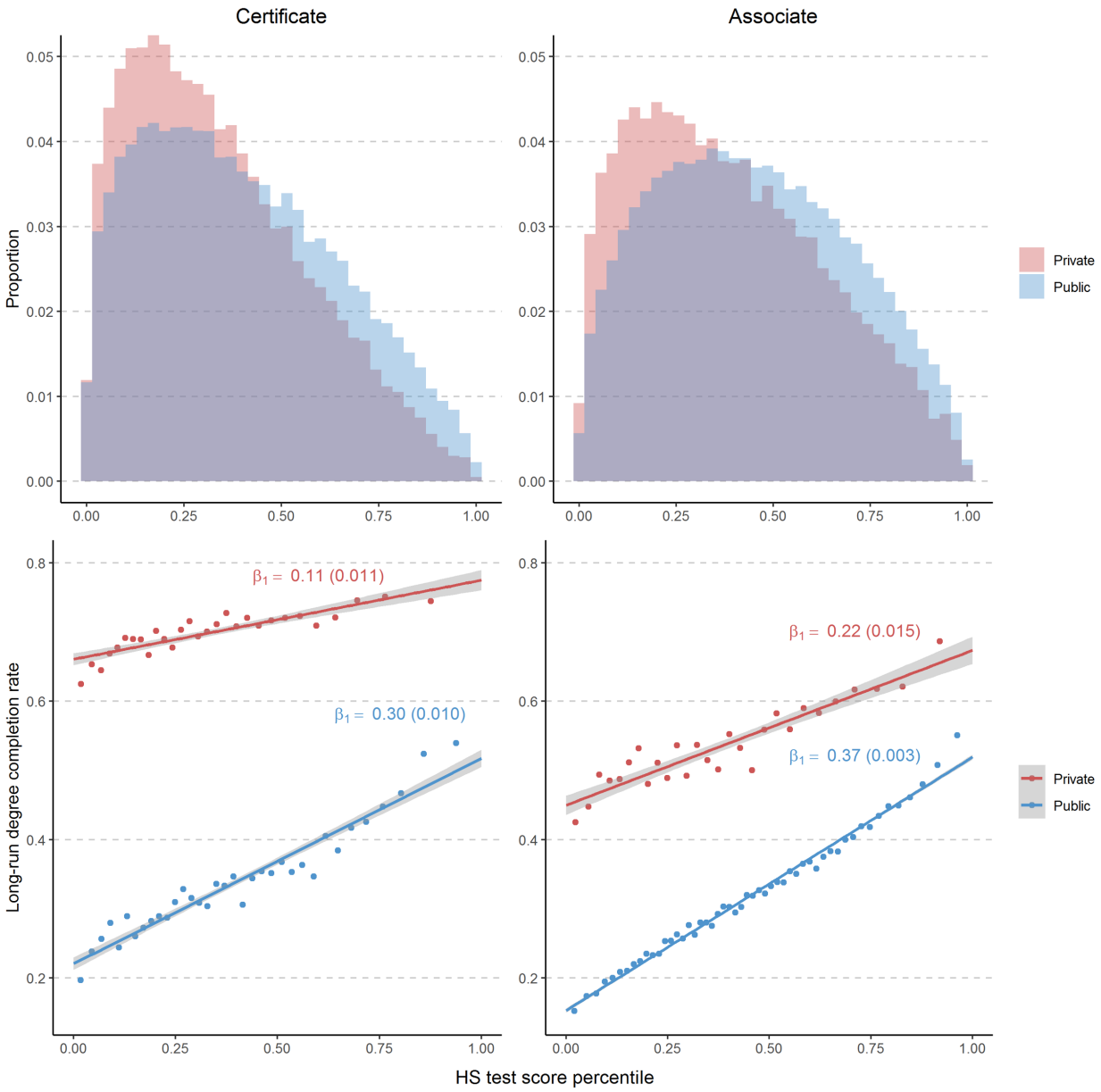


Figure 5: Graduation Rates by Pre-College Academic Skills

Notes: Sample includes all Texas public HS students who enroll in a two-year for-profit or community college intending a Certificate or Associate's degree from 2004–2012. The HS test score percentile is taken from statewide 9th- and 10th-grade tests in math and reading, which are converted to within-cohort percentile ranks. The long-run degree completion rate is the share of students completing any degree from any college within 7 years of first enrollment.

include the granular ability measures available in the Texas administrative sample, I find very similar gradients in the national survey data when using binned HS GPA as a measure of academic preparedness (Appendix Figure A3).

4 Estimating Causal Sector Effects on Completion Rates

While the for-profit completion premium remains large even conditional on a rich set of student characteristics, sorting on unobserved student heterogeneity may still compromise the interpretation of these residual completion-rate gaps as sector effects. Although for-profit students are observably less prepared to succeed in college, other determinants of graduation like motivation are challenging to measure and may bias the estimated gap in the opposite direction. For instance, a much larger share of CC students begin part-time, suggesting that they may be less committed to earning a degree than their for-profit peers. In addition, for-profit students may know their desired program of study earlier than CC students — since for-profit colleges typically only offer a handful of majors, students must be relatively certain of their major preferences when they first enroll. These and potentially other unobserved differences make selection-on-observables an unsatisfying assumption. To allay these concerns, I now turn to administrative data to estimate causal sector effects on completion rates using two different research designs.

I first use a within-person approach. Some students enroll in both for-profit and community colleges, but at different times. In fact, I observe thousands of such students with an initial enrollment spell in one sector, an interruption of their schooling for several years, followed by a separate enrollment spell in the other sector. Observing graduation outcomes for the same student in each sector purges confounding due to permanent unobserved heterogeneity. The key threat to identification is time-varying unobservables that shift students' graduation probabilities between spells.[15] For instance, students may gain skills or learn about their preferences during their first spell, improving their success rate in their next. But observing sector-switchers moving in both directions allows me to separate out a common second-spell effect using a differences-in-differences design, which identifies sector effects under a symmetry assumption. Appendix B presents the identification results in more detail along with estimates. I find a for-profit completion premium of about 40 percentage points among these switchers.

Admittedly, students who pursue similar degrees at both for-profit and public colleges are a unique subset of two-year students, and the symmetry assumption needed for identification

[15]Students' re-enrollment decisions likely depend on their prior graduation outcome too, introducing an additional self-selection problem. I account for this in Appendix B.

is difficult to empirically validate. To cement the evidence for sector effects, I next develop an alternative identification strategy which yields sector effects for the broader population of students on the for-profit/public margin under more traditional exclusion and monotonicity assumptions. Here, I identify margin-specific sector effects using multiple sector-specific cost-shifters for college enrollment, as in Mountjoy (2022).

Identification Let Y_j be potential outcomes under a set of mutually exclusive and exhaustive treatments $j \in \{0, 1, ..., N\}$. Also define potential treatments $D_j(\boldsymbol{Z}) \in \{0, 1\}$ with $\sum_j D_j(\boldsymbol{Z}) = 1$, over an instrument vector $\boldsymbol{Z} = (Z_1, ..., Z_N)$.

Under standard independence, exclusion, rank, and monotonicity conditions, variation in only a single element of $\boldsymbol{Z}$ yields a weighted average of treatment effects on different complier margins:

$$LATE_j = \sum_{k \neq j} \omega_k \mathbb{E}[Y_j - Y_k \mid j \leftarrow k \text{ complier}]$$

where the ω_k complier shares are further identified by single-IV regressions of D_k on D_j. Yet the margin-specific local average treatment effects of interest, $\mathbb{E}[Y_j - Y_k \mid j \leftarrow k \text{ complier}]$, are not separately identified. In my setting, reducing the cost of two-year for-profits brings in students not only from CCs, but also from the non-enrollment and four-year margins, which contaminates identification of the for-profit sector effect relative to CCs.

With valid instruments for every treatment level — the full $\boldsymbol{Z}$ —, multivariate TSLS has more promise. But even then the margin-specific sector effects are only identified under implausible restrictions on college preferences and/or treatment effect heterogeneity (Kirkeboen, Leuven and Mogstad 2016). Given that low-ability students sort into for-profits and have especially low completion rates at public colleges, essential heterogeneity appears to be a salient feature of my setting, rendering these standard IV estimands uninformative.

However, an alternative estimand which chains together multiple single-IV estimands does identify margin-specific treatment effects under close relatives of the standard IV assumptions. This identification is also robust to arbitrary forms of sorting and treatment effect heterogeneity. Mountjoy (2022) introduces this technique and proves identification in the case of three unordered treatments. Here, I show that identification easily generalizes to finitely many treatment levels.[16]

First, I assume that the N instruments are valid, independent of all potential outcomes and treatments and excluded from the outcome equation:

[16] I present an abbreviated exposition here and refer the reader to Mountjoy (2022) for further discussion.

Assumption (A-IE) Independence and Exclusion:

$$\mathbf{Z} \perp\!\!\!\perp \left(Y_0, ..., Y_N, \{\mathbf{D}(\mathbf{z})\}_{\forall \mathbf{z}}\right)$$

Next, I assume a natural extension of monotonicity from the binary case, requiring that the cost-shifter for j only induces complier flows from j to k, $k \neq j$.

Assumption (A-UPM) Unordered Partial Monotonicity: $\forall\, z'_j < z_j$, $\mathbf{z}'_{-j} = \mathbf{z}_{-j}$

$$D_j(\mathbf{z}') \geq D_j(\mathbf{z}),\ D_k(\mathbf{z}') \leq D_k(\mathbf{z})\ \ \forall k \neq j,$$

for all individuals, and strictly for some.

Note that a rank assumption is embedded here. As usual, this assumption requires that all students agree on the sign of the cost-shifter's utility, ruling out defiers, so that flows go in one direction. However, we impose no restriction on the composition of next-best alternatives from which students are drawn.

Under these conditions, the mean potential outcomes of each complier margin are identified at each point in the support of the instrumental variation, through local IV projections of interacted outcomes YD_k on D_k — instrumenting for D_k with Z_j.

Theorem. *Under (A-IE) and (A-UPM), for $j \neq k$, $j \geq 1$, $k \geq 1$,*

$$\underbrace{\frac{\partial \mathbb{E}[YD_k \mid \mathbf{Z}]}{\partial Z_j} \Bigg/ \frac{\partial \mathbb{E}[D_k \mid \mathbf{Z}]}{\partial Z_j}\Big|_{\mathbf{Z}=\mathbf{z}}}_{LIV_{kj}(\mathbf{z})} = \mathbb{E}[Y_k \mid j-k \text{ complier at } \mathbf{z} \text{ wrt } Z_j]$$

Proof. See Appendix A. □

Intuitively, these IV regressions isolate how sector-k outcomes change in response to changes only in the cost of sector j. While changes in Z_j induce inflows to j on multiple margins $l \neq j$, any change in Y among k enrollees must be due to outflows on the single complier margin $j \leftarrow k$, (under the stated monotonicity and exclusion restrictions). Scaling the total change in the outcome of that sector by the size of the outflow then yields the mean potential outcome among those marginal students.

One additional assumption is required to contrast these identified mean potential outcomes and form the treatment effects of interest. Within students on the $j-k$ margin, we need those induced into j by Z_k to be "comparable" to those induced into k by Z_j, in terms of potential outcomes. Formally, we require the following assumption.

Assumption (A-CC) Comparable Compliers: *for each* $\mathbf{z}$ and $\mathbf{z}'$ s.t. $z'_l = z_l$ for $l \neq j, k$,

$$\lim_{z'_j \uparrow z_j} \mathbb{E}[Y_k \mid D_j(\mathbf{z}') = 1, D_k(\mathbf{z}) = 1] = \lim_{z'_k \downarrow z_k} \mathbb{E}[Y_k \mid D_j(\mathbf{z}') = 1, D_k(\mathbf{z}) = 1]$$

This is a relatively weak condition, as we only require that students on the same indifference margin treat increases in Z_j similarly to decreases in Z_k. Mountjoy (2022) shows that virtually all standard index models of college choice immediately imply A-CC, though it does rule out certain school preferences, e.g., in which some students with systematically different levels of the outcome are insensitive to just one of the cost-shifters. Under all these assumptions, the margin-specific treatment effects are identified:

$$LIV_{jk}(\mathbf{z}) - LIV_{kj}(\mathbf{z}) = \mathbb{E}[\, Y_j - Y_k \mid j - k \text{ complier at } \mathbf{z}]$$

Estimation In practice, I partition the treatments into four levels: non-enrollment, two-year for-profit enrollment, two-year public enrollment, and four-year enrollment.[17] As in Mountjoy (2022), I use the distance to the nearest college in each sector as excluded cost-shifters. Distance instruments are highly correlated with characteristics of the locations where students grow up, so that unconditional IV independence assumptions are implausible. I therefore condition on a rich set of location characteristics and show below that, conditional on these controls, the distance IVs are approximately balanced with respect to pre-determined student characteristics.

I estimate IV systems of the following form:

$$\begin{aligned} YD_j &= \beta D_j + \sum_{l \neq k} \beta_{z,l} Z_l + \beta'_x \boldsymbol{X} + u \\ D_j &= \alpha Z_k + \sum_{l \neq k} \alpha_{z,l} Z_l + \alpha'_x \boldsymbol{X} + \nu \end{aligned}$$

The location characteristics $\boldsymbol{X}$ include fixed effects for Commuting Zone (CZ) and a 12-factor urbanicity variable, HS-level variables including the school's share of free-/reduced-price lunch students and historical industry employment shares for six different industries, as well as a large set of Census tract-level variables from the American Community Survey (ACS) relating to the area's ethnic, education, and income composition. Figure 6 shows that first stages on the FP/CC margin are strong. The right two panels show the relevant first stages, where enrollment in j is regressed on distance to k. When including controls for $\boldsymbol{Z}_{-k}$ and $\boldsymbol{X}$, the F-statistics for the exclusion of Z_{FP} and Z_{CC} in the first stages for D_{CC} and

[17] Enrollment status is determined by the first recorded sector of enrollment within four years of HS graduation.

D_{FP}, respectively, remain strong at 936.9 and 73.2.

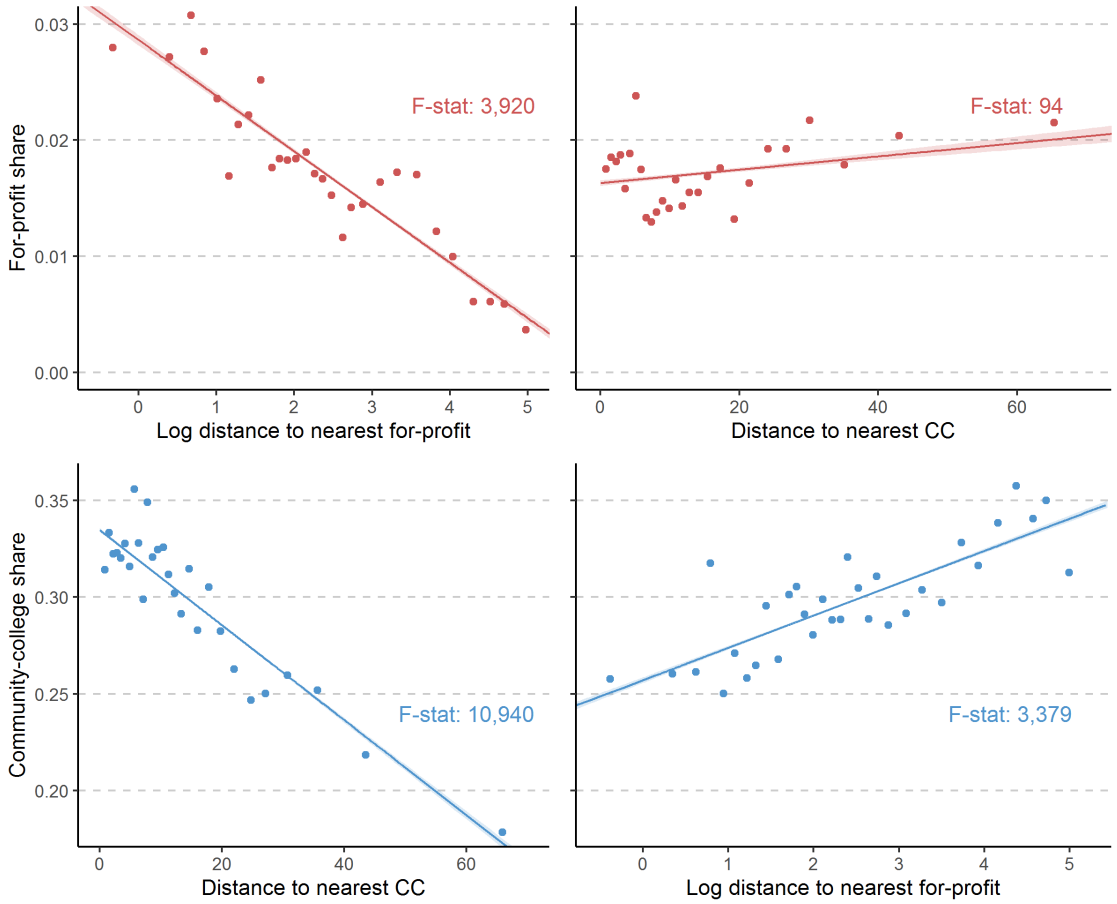


Figure 6: First-Stage Relationships

Notes: First-stage regressions of D_j on Z_j (left) and Z_k (right), overlaid with binned means. Distance is in miles.

Table 3 next evaluates the conditional independence assumptions by estimating the relationship between the instruments and pre-determined student characteristics including gender, ethnicity, FRPL as a proxy for socioeconomic status, and the HS test score percentile as a proxy for academic ability.[18] These characteristics are highly predictive of graduation outcomes and, if not balanced across values of the instruments, would indicate potential for unobserved confounding. Without any location controls, these instruments are highly correlated with baseline student characteristics. These relationships attenuate considerably when adding controls for CZ, urbanicity, and HS FRPL share in Columns (2) and (5), and they shrink even further when adding tract-level neighborhood demographics from ACS and local industry employment shares in Columns (3) and (6). The HS test score percentile — the single variable most predictive of college graduation — becomes statistically insignificant

[18]This exercise is again similar to that in Mountjoy (2022).

as a predictor of CC distance, and moving from the bottom to the top of the HS test score distribution predicts just a 0.6% difference in for-profit distance. The magnitudes of the correlations in all other cases are small once controlling for location characteristics. To show this, I also estimate first-stage and reduced-form relationships with and without individual-level control variables, finding negligible changes in estimated effects once including the full set of location controls (Appendix Table A8). That the residual distance variation is not meaningfully correlated with observed student characteristics predictive of graduation rates suggests that the location controls effectively capture other forms of unobserved confounding — though a direct test of the conditional independence assumptions is of course not feasible.

Table 3: Balance of Student Characteristics Across Distance

	Log for-profit distance			Community-college distance		
	(1)	(2)	(3)	(4)	(5)	(6)
Male	−0.001	−0.002	0.001	0.136	0.020	0.003
	(0.001)	(0.001)	(0.001)	(0.018)	(0.012)	(0.012)
Black	−0.292	0.001	−0.017	−2.228	−0.547	−0.109
	(0.003)	(0.002)	(0.002)	(0.026)	(0.018)	(0.019)
Hispanic	−0.633	−0.084	−0.034	1.938	−0.496	−0.349
	(0.002)	(0.001)	(0.001)	(0.025)	(0.017)	(0.017)
FRPL	−0.030	−0.000	−0.014	1.335	−0.151	−0.093
	(0.002)	(0.001)	(0.001)	(0.022)	(0.016)	(0.015)
HS test score pctl (0 – 1)	−0.221	−0.041	0.006	0.467	0.393	0.014
	(0.003)	(0.002)	(0.002)	(0.035)	(0.024)	(0.023)
$\boldsymbol{Z}_{-j}$	✓	✓	✓	✓	✓	✓
CZ, urbanicity FE		✓	✓		✓	✓
HS FRPL share		✓	✓		✓	✓
Neighborhood demographics			✓			✓
Industry employment shares			✓			✓
Observations	1,912,513	1,704,059	1,697,043	1,912,513	1,704,059	1,697,043
R^2	0.409	0.799	0.825	0.293	0.725	0.744

Notes: Student-level regressions of Z_j on student characteristics, distance to other sectors $\boldsymbol{Z}_{-j}$, and different sets of location-varying control variables. Distance is in miles. Standard errors in parentheses.

To probe the robustness of the Comparable Compliers assumption, I also substitute pre-determined HS test score percentiles for the outcome in the IV regressions. These regressions identify the mean HS test score percentile among for-profit students shifted by Z_{CC}, as well as among CC students shifted by Z_{FP}, providing a test of whether compliers in each direction (but on the same margin) are in fact comparable. Table 4 shows that these two sets of complier students in fact do not differ in HS test scores, providing support for the

Comparable Compliers assumption.

Table 4: Comparable Compliers

	FP	CC	Difference
HS test score percentile	0.43	0.45	-0.02
	(0.03)	(0.01)	(0.03)

Notes: Mean potential outcomes for students on the FP/CC margin, identified from distance IVs. Standard errors in parentheses.

I present estimated sector effects on program choices and completion rates for students on the FP/CC margin in Table 5, which shows both their mean potential outcomes and average sector effects, using the full set of location controls as in Column (6) of Table 3 along with student-level controls. As expected, for-profits shift students into shorter vocational programs: 30% of for-profit students shift into academic programs when they initially enroll in CCs. Still, 70% vocational program enrollment far exceeds the 37% of CC students who initially enroll in vocational programs. In addition, CCs shift students out of certificate programs into longer Associate programs: rates of certificate enrollment fall from 62% to 12% when for-profit students enroll in CCs — though again, this figure exceeds the 6% of all CC students enrolling in certificate programs.

Table 5: Effects on FP/CC margin

	Program choices		Highest degree completed			
	Vocational	Certificate	Certificate	Associate	Baccalaureate	Any degree
FP	1.00	0.62	0.42	0.20	0.07	0.69
	(0.00)	(0.05)	(0.06)	(0.04)	(0.02)	(0.06)
CC	0.70	0.12	0.05	0.13	0.20	0.37
	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Difference	0.30	0.50	0.38	0.08	-0.13	0.32
	(0.03)	(0.05)	(0.06)	(0.05)	(0.02)	(0.06)
Observations	1,697,043	1,697,043	1,697,043	1,697,043	1,697,043	1,697,043

Notes: Program choices defined based on first declared major and degree level. Degree completion measured from any college within 7 years of first enrollment. Mean potential outcomes for students on the FP/CC margin identified from distance IVs. Sample includes all Texas public HS graduates between 2004–2012. Heteroskedasticity-robust standard errors in parentheses.

For-profits also raise long-run completion rates — with any degree from any college — by 32 percentage points for students on the FP/CC margin. This estimate aligns closely

with estimates using the "switchers" design presented in Appendix B, where I find approximately 40 percentage-point gaps. Consistent with their effects on program choice, for-profits primarily promote completion of certificates (by 38 percentage points). For-profits also raise Associate-degree attainment by 8 percentage points, but they reduce Bachelor's degree completion by 13 percentage points. These effects are consistent with for-profits' narrower focus on short vocational credentials, as well as the more limited transferability of for-profit credits to the four-year public colleges where some CC students will go on to earn their Bachelor's degrees. For-profit programs therefore trade off more attainable paths to credentials with a lower attainment ceiling. These patterns also suggest scope for academic match effects: four-year pathways are primarily relevant to students with stronger academic aptitude and interests, for whom four-year option value may be more relevant, whereas elevated dropout risk may matter more among academically weaker students. I therefore evaluate heterogeneity by ability when estimating returns in Section 5.

4.1 Mechanisms: The Role of Academic Requirements

How for-profits achieve higher graduation rates will matter for whether for-profit pathways preserve the returns to college. Characterizing the contribution of different mechanisms to the for-profit completion premium is empirically challenging and an important avenue for future research. Here I present descriptive evidence that academic barriers appear to drive completion outcomes among students on the for-profit/public margin. In particular, I consider the roles of curriculum breadth and grading standards, core elements of each sector's human capital and degree production technologies.[19]

Degree Requirements I begin by describing differences in the academic content of for-profit and public degree pathways using a newly assembled dataset of program-level degree requirements, described in Section 2 and at greater length in Appendix D. Using complete course ledgers for a sample of 1,078 degree programs in Texas, I partition each program's credit requirements between academic and vocational coursework. Figure 7 plots these programs according to their number of required academic and vocational credits. It also distinguishes programs which require remediation for students not meeting the requirements for a waiver.[20]

[19]Prior work has emphasized non-academic barriers to degree completion at CCs, including implicit capacity constraints (e.g., course shutouts and inflexibility) and limited advising resources (Bound and Turner 2007; Robles, Gross and Fairlie 2021). While these constraints may also be relevant on the for-profit margin, the fact that the for-profit completion premium is largest among the academically weakest students suggests an academic mechanism (Figure 5).

[20]This includes students in all public programs of more than 42 total credits, with some exceptions.

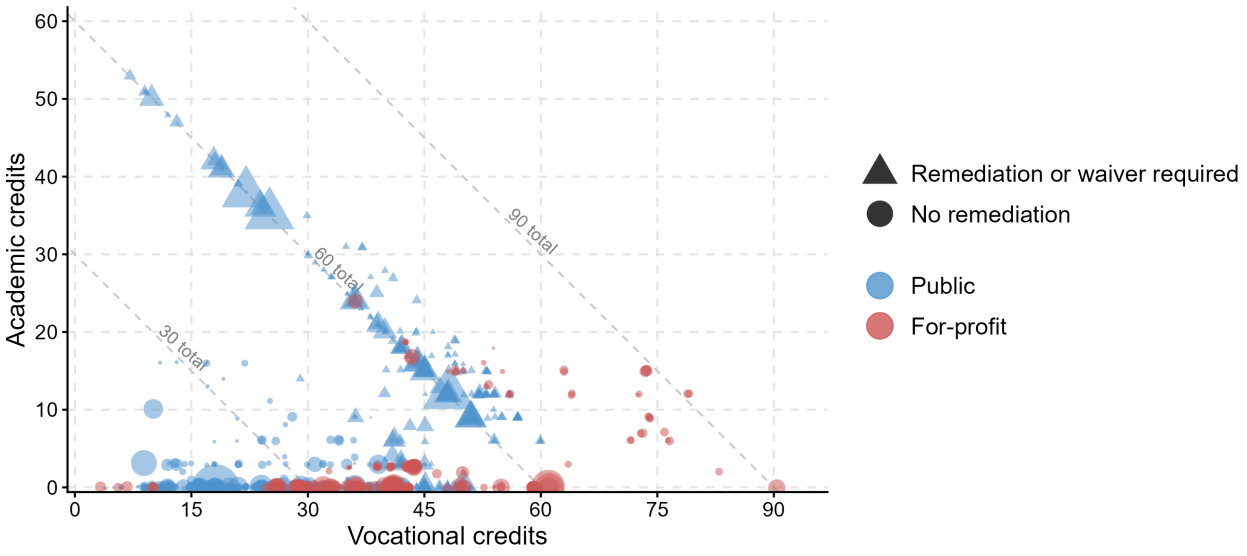


Figure 7: Program Credit Requirements

Notes: Each dot/triangle corresponds to a unique program (college × 6-digit major × degree level), for the sample of vocational programs at two-year Texas colleges. Dot/triangle size proportional to program size. Academic credits include courses designated as general-education or core-curriculum courses, as well as courses in English, math, science, communication, social science, and humanities when their content falls outside the program's occupational domain. All other credits are classified as vocational.

The data show that certificate programs vary considerably in length, with total required credits ranging between 15 and 50, while Associate's programs are typically exactly 60 credits — or more in the case of for-profit programs. Particularly in the longer programs, public colleges devote a much larger share of required credits to academic coursework than do for-profit alternatives. These gaps emerge within degree programs as well. Associate degrees in automobile repair present a particularly stark example: their modal public version requires 15 academic credits, making up 25% of the curriculum, while for-profit alternatives require no academic coursework. And these figures do not include the remedial coursework required of public students who do not qualify for a waiver.

Table 6 confirms that, while Certificate programs in both sectors require little academic coursework, public Associate's programs are relatively academically intensive on average. Reweighting to a common distribution of majors, two-year public programs require an average of 15.2 academic credits, compared to just 6.4 at for-profits — meaning that in comparable two-year programs, for-profit colleges require nearly 60% less academic coursework. These totals again do not include the additional remedial coursework often required at CCs. In addition, since for-profits shift many students from Associate's into certificate programs (Table 5), sector effects on academic requirements are in fact understated by these within-

degree-level comparisons.

Table 6: Degree Requirements at Two-Year College Programs

	For-profit	Public	
	(1)	(2)	(3)
Panel A: Certificate programs			
Total credits	37.7	28.3	32.0
Academic credits	0.4	0.8	1.7
Academic share of credits (%)	0.9	2.5	4.9
Panel B: Associate's programs			
Total credits	69.1	61.3	61.3
Academic credits	6.4	19.2	15.2
Academic share of credits (%)	9.1	31.3	24.8
Major distribution	For-profit	Public	For-profit

Notes: Observations correspond to 1,078 unique vocational programs (college × 6-digit major × degree level) at two-year Texas colleges. All statistics take completion-weighted means within 6-digit majors and average them up using the completion distribution indicated in the final row. Column (3) therefore shows public requirements under the for-profit major distribution. Academic credits include courses designated as general-education or core-curriculum courses, as well as courses in English, math, science, communication, social science, and humanities when their content falls outside the program's occupational domain.

Graduation Rates by Academic Intensity As a descriptive exercise, I next ask whether degree programs in which CCs require relatively more academic coursework are also those with relatively large for-profit completion premia. I take the program-level estimates of the for-profit completion premium shown in Figure 4 and plot them against CC programs' relative academic intensity, measured by how much their academic-credit share exceeds that of for-profit alternatives. Figure 8 shows that within both certificate and Associate's programs, the for-profit completion premium tends to be larger where public colleges impose relatively higher academic-credit burdens. Programs where CCs require substantially larger shares of academic credits, such as two-year auto mechanics programs and one-year radiology tech programs, are among those in which for-profits' graduation rates most exceed CC graduation rates. While for-profit and public programs may differ in other ways beyond their academic intensity, these patterns are consistent with CCs' more extensive academic requirements impeding the degree attainment of vocational students.

Performance in Academic Coursework To further evaluate whether academic requirements impede degree completion among for-profit students, I next estimate how students on

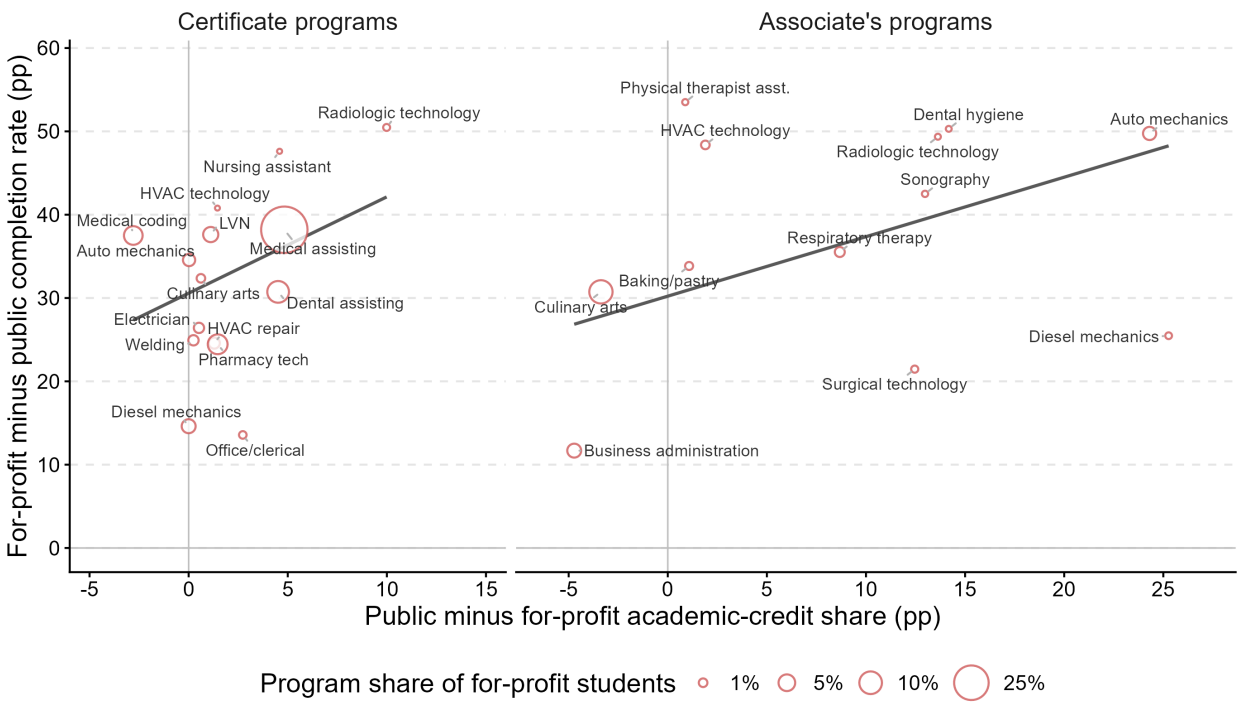


Figure 8: Completion-Rate Gaps versus Academic Requirements by Program

Notes: Each point represents a six-digit CIP field for which both completion-rate and degree-requirement estimates are available in each sector. The vertical axis is the for-profit minus public completion-rate gap, while the horizontal axis is the public minus for-profit gap in the academic-credit share. Major-specific average academic shares are weighted by program completions. Bubble size indicates the field's share of for-profit students within degree level, and fitted lines weight fields by the number of for-profit students.

the for-profit/public margin perform in academic and vocational courses using individual-level transcript data for CC students in Texas. Although the Texas data do not include for-profit transcripts, the mean CC potential outcomes of students on the for-profit/public margin are still identified using the distance-IV variation.[21] Since the transcript records only become available in 2011, I now restrict the sample to the 2011 and 2012 HS graduating cohorts. F-statistics for instrument relevance on this smaller sample remain larger than 30.

Table 7 shows that public students on the for-profit margin perform poorly, earning average GPAs of just above 2.0 on a 4.0 scale. Their weak performance is driven by the academic curriculum, in which they earn average GPAs of just 1.77. Their GPAs are 0.5 GPA points higher in vocational courses. Low grades in academic coursework place these students near the 2.0 GPA threshold which determines academic probation and below which students may lose access to financial aid. Beyond these concrete setbacks, poor performance

[21] In particular, I identify $\mathbb{E}[GPA_i^{\text{CC}} \mid \text{CC} \leftarrow \text{FP margin}]$ by regressing the interacted outcome $GPA_i D_{i,\text{CC}}$ on $D_{i,\text{CC}}$, instrumented with $Z_{i,\text{FP}}$, including the full set of location controls.

can limit degree progression by reducing the continuation value of enrollment and causing students to spend additional time retaking courses.

Table 7: Average CC GPA on FP/CC margin

	Overall	Academic courses	Vocational courses
CC GPA	2.03	1.77	2.27
	(0.11)	(0.12)	(0.15)

Notes: Entries report mean CC potential outcomes for students on the FP/CC margin, identified using the distance-IV regression framework. Sample includes Texas public HS graduates between 2011 and 2012. Heteroskedasticity-robust standard errors in parentheses.

In addition, before CC students may even begin their required academic courses, most must either satisfy academic requirements allowing them to skip remediation or enroll in one or more developmental courses in math, English, and/or writing. These additional academic courses do not contribute credits toward degree requirements and can mechanically delay degree progression by crowding out credit-bearing courses. Again using the distance-IV design, I estimate that 62% (s.e. 7%) of students on the for-profit/public margin are required to take remedial math courses upon enrolling in CCs. Appendix C presents additional transcript evidence for marginal students.

Comparing Performance across Sectors Public colleges impose heightened academic requirements which appear quite costly for students on the margin of for-profit enrollment. To further understand how such students perform in *for-profit* coursework, I next turn to the BPS PETS, a national transcript dataset covering both for-profit and public colleges. Here I lose the distance-IV-based identification of potential outcomes among marginal students, so I will simply control for observable differences using regression adjustment. Reassuringly, many of the course-taking and performance patterns observed in both the degree-requirements data and the Texas CC transcript records also emerge in this national dataset.

Among students enrolling in vocational Associate's programs, I find that for-profit GPAs are 0.47 points higher than public GPAs (s.e. 0.10), controlling for pre-college characteristics. The BPS data also record performance in academic and non-academic CTE coursework. Figure 9 shows that, as observed in the Texas transcript data, vocational CC students perform significantly worse in their academic coursework. Again controlling for student characteristics, higher for-profit GPAs are driven by performance in academic classes, where for-profit students do about 0.7 GPA points better on average. By contrast, public and for-profit students in vocational programs achieve similar assessed performance in vocational

courses. Also reflecting the higher academic requirements of public programs demonstrated in the degree-requirements data, Figure 9 shows that public students take substantially larger shares of their credits in the academic courses where they struggle most. Appendix E presents course-taking differences in more granular detail.

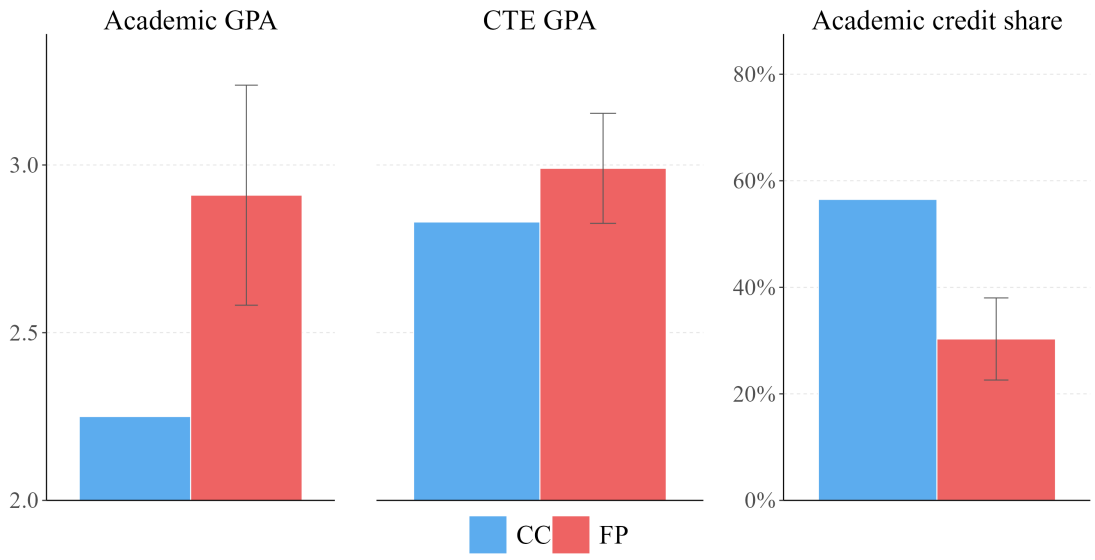


Figure 9: Average GPAs among CTE Students

Notes: Estimates from BPS 12/17. Sample includes all students enrolling in vocational Associate programs. The for-profit mean is selection-corrected by adding the for-profit coefficient from a regression with controls to the public mean. Error bars represent 90% confidence intervals.

Finally, I show how curricular differences combine with differences in assessed performance to produce the overall for-profit GPA premium using a Oaxaca-Blinder decomposition. Figure 10 shows that, in the BPS data, public colleges could make up one third of the GPA gap by narrowing their vocational curricula to have the same academic credit share taken by for-profit students. The remainder of the gap comes primarily from higher assessed performance in academic courses, with a smaller part accounted for by different grading in vocational courses. Appendix E presents additional details regarding the decomposition.

These differences in vocational program curricula and grading standards may explain why demand for for-profit programs is especially strong among students with lower pre-college skills, who may wish to avoid remediation and academic courses. They also plausibly account for academic match effects by disproportionately affecting academically weaker students' ability to achieve passing grades and complete their programs of study. Prior work has shown that shifts in grading standards can explain large shifts in college completion rates over time, suggesting these forces may have first-order effects (Denning et al. 2022). And evidence from high schools shows that grading standards bite most among students near the passing margin (Denning et al. 2026).

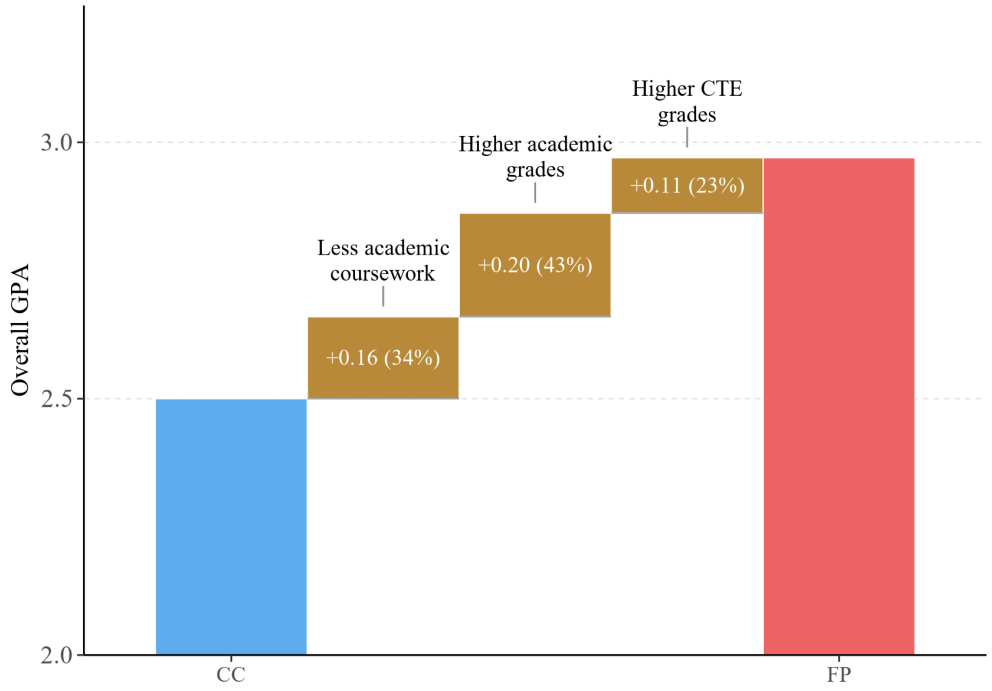


Figure 10: Oaxaca-Blinder Decomposition

Notes: Estimates from BPS 12/17. Sample includes all students enrolling in vocational Associate programs. The for-profit mean is selection-corrected by adding the for-profit coefficient from a regression with controls to the public mean.

However, the transcript evidence remains consistent with at least two underlying mechanisms which carry opposite implications for the value of for-profit degree pathways. On the one hand, higher for-profit grades might reflect genuine achievement gains as a result of a curriculum better-matched to the interests and academic skills of their students. On the other hand, these gaps might owe to grade inflation and relaxed academic standards, in which case the source of the for-profit completion premium might itself undermine for-profit returns. A more nuanced possibility is that for-profits are in fact less productive in general skill formation yet still proficient at forming occupational skills — in part by virtue of their reduced academic requirements, which encourage academically weaker students to progress, graduate, and make successful occupational transitions. To adjudicate whether for-profit degree pathways carry any labor-market value, I next estimate college returns.

5 Implications for College Returns

Next, I relate the for-profit completion premium to college returns across the ability distribution. Higher graduation rates entail a tradeoff: although more students earn credentials

which may be valued in the labor market, the quality of those credentials may fall to the extent that for-profits achieve higher graduation rates by diluting the instructional value of their programs. Different instructional levels or academic standards may therefore entail a quantity/quality tradeoff, and the implications for expected returns are therefore ambiguous. To understand how degree completion moderates the return to college, I will follow Altonji (1993) in distinguishing between ex-post returns — the returns realized from different *final* education levels, e.g., enrolling in a for-profit and dropping out — and the ex-ante returns to college enrollment, which average over ex-post returns and thus capture the option values of further education choices. These concepts differ due to the significant heterogeneity in outcomes conditional on enrollment, and the uncertainty students initially face about their prospects of graduation, their transfer probabilities, and their desired majors.

5.1 Ex-Ante Returns for Marginal Students

I begin by directly estimating the ex-ante returns to for-profit vs. public enrollment using the distance-IV framework from Section 4. I use the same specification as in Table 5 to estimate mean potential outcomes and treatment effects for students on the for-profit/public margin. Table 8 reports the degree-completion effects from before alongside earnings effects, measured in quarterly earnings at age 27–28. I find complete parity in the returns to each sector, yet the estimate is somewhat imprecise. The estimated difference between for-profit and community-college returns is just -$61 in quarterly earnings, but the 95% confidence interval is [-$1,317, $1,195].

Table 8: Mean Potential Outcomes and Sector Effects on FP/CC Margin

	Completion of $\leq$ 2-year credential	Completion of Bachelor's degree	Quarterly earnings at age 27–28 ($)
FP	0.62	0.07	4,823
	(0.06)	(0.02)	(598)
CC	0.17	0.20	4,885
	(0.02)	(0.02)	(304)
Difference	0.45	−0.13	-61
	(0.06)	(0.02)	(641)
Observations	1,697,043	1,697,043	1,697,043

Notes: Mean potential outcomes for students on the FP/CC margin, identified from distance IVs. Sample includes all Texas public HS graduates between 2004–2012. Degree completion includes graduation with any degree within 7 years of first enrollment. Earnings measured at age 27–28. Standard errors in parentheses.

Next I split the sample by initial academic skill, defining high-skill students as those scoring above the median for-profit student's HS test score (the 33rd percentile in the population).[22] Conditional on controls, F-statistics in these split samples remain larger than 32 in all cases. First, Table 9 shows that for-profit colleges graduate low- and high-skill students at similarly high rates (63% and 73%, respectively, summing completion of all degree levels), while public colleges graduate low-skill students at especially low rates. This matches the descriptive patterns documented in Figure 5 in which CC completion penalties are especially large for low-skill students, leading to significantly larger elasticities of completion rates with respect to skills in the public sector. Strikingly, Bachelor's attainment rates are nearly equal among low-skill students, while CCs raise Bachelor's completion rates by 17 percentage points among high-skill students. The option value of four-year transfer is therefore uniquely relevant for high-skill students.

Table 9: Mean Potential Outcomes and Sector Effects by Academic Skill

	Completion of $\leq$ 2-year credential		Completion of Bachelor's degree		Quarterly earnings at age 27–28 ($)	
	Low-skill	High-skill	Low-skill	High-skill	Low-skill	High-skill
FP	0.59	0.65	0.04	0.08	4,807	4,745
	(0.08)	(0.07)	(0.02)	(0.03)	(848)	(845)
CC	0.20	0.17	0.08	0.25	3,835	5,572
	(0.03)	(0.02)	(0.02)	(0.02)	(480)	(387)
Difference	0.39	0.48	−0.04	−0.17	971	−827
	(0.09)	(0.08)	(0.03)	(0.04)	(963)	(869)
Observations	465,962	1,231,081	465,962	1,231,081	465,962	1,231,081

Notes: Mean potential outcomes for students on the FP/CC margin, identified from distance IVs. High-skill students have HS test score percentiles above the median among for-profit students (0.33). Sample includes all Texas public HS graduates between 2004–2012. Degree completion includes graduation with any degree within 7 years of first enrollment. Earnings measured at age 27–28. Standard errors in parentheses.

These patterns also show up in college returns. While potential for-profit earnings are equal across skill groups, high-skill CC students earn nearly 50% more than low-skill students by age 27–28. And while high-skill students face penalties from for-profit enrollment, earning $827 less per quarter than they would have earned from CCs, low-skill students realize $971 more in quarterly earnings when they enroll in for-profits. Still, these comparisons suffer from statistical imprecision and cannot be distinguished from zero at conventional

[22] I choose the median among for-profit students to preserve power, as for-profit enrollment shares are much lower.

significance levels. The difference in the relative return to for-profit enrollment across high- and low-skill students ($-\$827 - \$971 = -\$1798$) is also imprecise ($p = 0.16$). Taken at face value, these point estimates suggest that low-skill students may be better-matched to the for-profit curriculum, while high-skill students might benefit from the option value of academic pathways and four-year transfer afforded by community colleges. Both to decompose these channels and improve precision, I next develop a minimal sequential-choice structure which expresses ex-ante returns as a combination of ex-post returns to different attainment outcomes.

5.2 Decomposing Ex-Ante Returns

Consider a layered potential outcomes model for student i, $(L_i^j, G_i^{j\ell}, Y_i^{j\ell g})$, where $L_i^j \in \mathcal{L} \equiv \{\text{Certificate}, \text{Associate}\} \times \{\text{Vocational}, \text{Academic}\}$ is i's chosen program of study in sector j, $G_i^{j\ell} \in \mathcal{G} \equiv \{0, 1, 2, 4\}$ their potential graduation outcome from enrolling in (j, ℓ), and $Y_i^{j\ell g}$ their potential earnings under (j, ℓ, g). Letting Y_i^0 indicate their potential no-college earnings, $\Delta Y_i^{j\ell g} \equiv Y_i^{j\ell g} - Y_i^0$ then equals the ex-post return to the sequence (j, ℓ, g). The ex-ante return to enrolling in sector j relative to no college, ρ_i^j, can be expressed as a combination of ex-post returns $\Delta Y_i^{j\ell g}$,

$$\rho_i^j \equiv \mathbb{E}[Y_i^j - Y_i^0 \mid i] = \sum_{\ell \in \mathcal{L}} \mathbb{P}\{L_i^j = \ell \mid i\} \sum_{g \in \mathcal{G}} \mathbb{P}\{G_i^{j\ell} = g \mid i\} \Delta Y_i^{j\ell g}.$$

While the prior section directly estimated ex-ante relative returns $\rho_i^{\text{FP}} - \rho_i^{\text{CC}}$ on the for-profit/public margin, here I combine the IV-based estimates of sector effects on program choice L_i^j and graduation $G_i^{j\ell}$ with significantly more precise estimates of the ex-post returns to different schooling sequences $\Delta Y_i^{j\ell g}$.

This framework offers a tradeoff: while direct IV estimation accommodated arbitrary sorting gains, here I will impose additional restrictions on sorting gains in ex-post returns to achieve additional precision, overcoming the key limitation of prior IV-based return estimates (Liu and Belfield 2014; Armona, Chakrabarti and Lovenheim 2022). And relative to methods relying exclusively on within-person variation (Cellini and Turner 2019; Jepsen et al. 2025), using IV estimates for sector effects on program choice resolves another issue inherent in those estimates of ex-ante returns: in particular, should estimates pool or condition on programs of study? The results from Section 4 show that the answer is neither. For-profits cause students to shift across programs of study, yet the program choices of students on the for-profit/public margin are far from representative of inframarginal students.[23] This

[23] For example, 70% of marginal students enroll in vocational programs at CCs, compared to just 37% of all

implies that neither conditioning on program choices *nor* pooling all programs can identify the relative returns to enrollment among marginal students.

Ex-Post Returns to Graduation and Dropout I first estimate ex-post returns using within-person panel estimators common in the literature, taking advantage of the fact that a significant share of two-year college students enter college with prior work experience. For those older students with pre-college earnings histories, ability bias and other forms of permanent unobserved heterogeneity driving earnings can be captured with individual fixed effects. I begin by plotting the evolution of mean quarterly earnings among graduates and dropouts of for-profit and public colleges, in time relative to their initial college enrollment, with levels fixed to zero the year before enrollment.[24] To begin with, I focus on students enrolling in vocational Associate's programs since this is the program set with greatest overlap.

Figure 11 shows that each group's earnings followed similar trajectories prior to enrollment, though pre-enrollment earnings growth is somewhat larger among public students. Following enrollment, earnings decline as students substitute schooling for work, but earnings profiles of graduates then rebound well above those of non-graduates in both sectors. Among graduates, the opportunity costs of enrollment are substantially lower for for-profit students, who earn degrees faster and therefore experience elevated earnings in the six years following enrollment. Afterwards, their earnings relative to pre-college levels fall below those of CC graduates, and for-profit non-graduates also earn less than CC non-graduates. Appendix Figure A10 shows that the pooled earnings profiles of for-profit and community-college students are more similar due to higher for-profit graduation rates.

Given the potentially large returns to four-year degrees, and since public students are much more likely to earn them, I will further split graduates into those who earn at most a 2-year degree and those who earn a Bachelor's degree. For each group $c(i) = (j(i), \ell(i), g(i))$ — combinations of enrollment sector $j(i)$, program $\ell(i)$, and attainment level $g(i)$ — I estimate the following earnings equations for those students entering college at age 22 or older with prior earnings:

$$Y_{it} = \eta_i + \theta_i t + \gamma_{t,c(i)} + f_{X_i,c(i)}(Age_{it}) + \sum_{s=-4}^{12} \tau_{s,c(i)} \mathbb{1}\{t = T_i + s\} + \varepsilon_{it} \tag{1}$$

where I fix $\tau_{-2,c} = 0$,[25] and T_i indicates the year of first enrollment. This specification com-

CC students. Yet for-profits further raise vocational program enrollment and shift students from Associate's into certificate programs.

[24]Here, students are considered to have graduated if they earned any degree from a Texas university within seven years of initial enrollment.

[25]An Ashenfelter's dip appears in the three to four quarters before enrollment. I treat this as a transitory

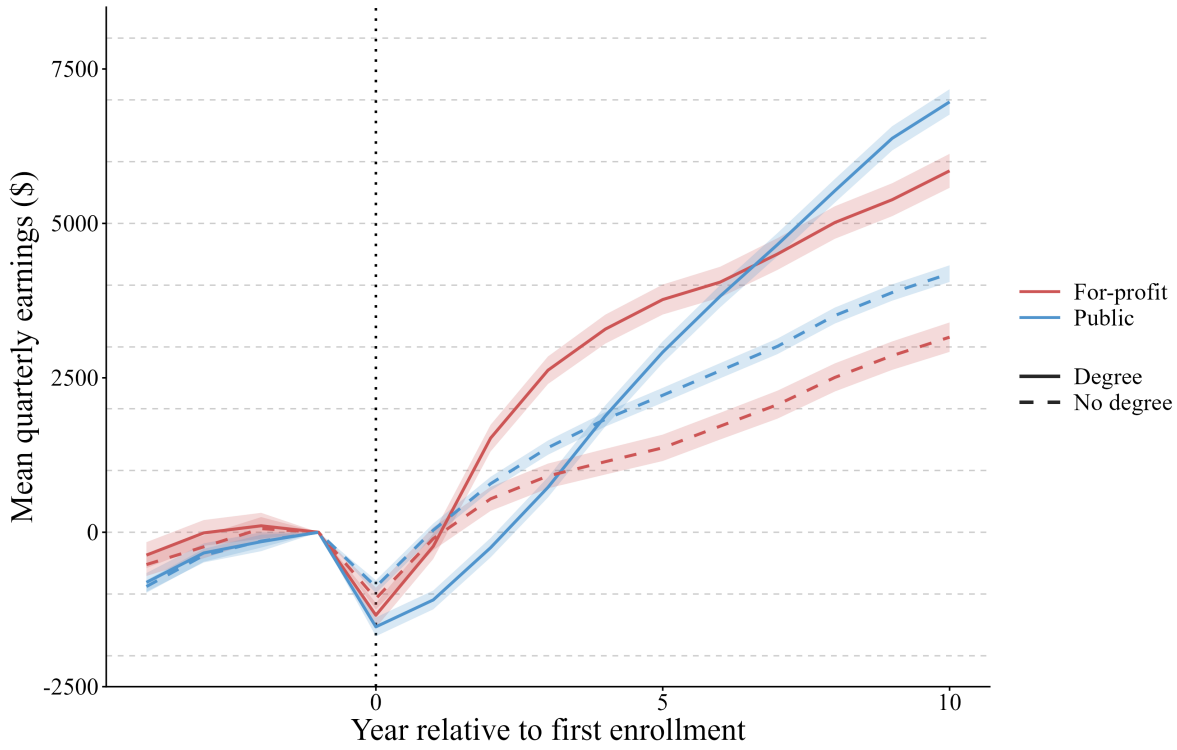


Figure 11: Raw Earnings Profiles of Associate's Degree-Seekers

Notes: Earnings are deflated to 2025 dollars. Sample includes all Texas public HS students who enroll in a two-year for-profit or community college between 2004–2012 at age 22 or older, who have some recorded prior earnings and intend an Associate's degree. Error bars represent 95% confidence intervals. Quarterly earnings profiles for each group are pegged to zero one year before enrollment.

pares treated with not-yet-treated students within the same schooling sequence $c(i)$, while allowing for quadratic age profiles specific to gender/ethnicity combinations X_i, common macroeconomic shocks $\gamma_{t,c}$, and individual-specific earnings trends $\theta_i t$.[26] Even within students enrolling in the same sector and achieving the same degree outcome, variation in enrollment timing across cohorts identifies dynamic treatment effects $\tau_{s,c}$. Across-cohort variation and heterogeneity in age-at-entry further help to identify time and age profiles. Comparing only to not-yet-treated students following the same schooling sequence is advantageous given that pre-enrollment earnings trajectories systematically differ between for-profit and public students (Figure 11).

Target estimands are the earnings effects of each education sequence on the subsample

employment shock occurring in the year before enrollment and therefore fix $\tau_{-2,c} = 0$ rather than $\tau_{-1,c} = 0$.

[26] Dynarski, Jacob and Kreisman (2018) recommend including individual trends to capture both heterogeneity in levels and predictable differences in growth rates. In practice, estimated returns are larger but qualitatively similar when excluding the individual-specific linear trends.

of those who attain that level of schooling,

$$\mathbb{E}[Y_{is}^{j\ell g} - Y_{is}^{0} \mid D_i = j, L_i = \ell, G_i = g],$$

where $Y_{is}^{j\ell g}$ are potential earnings outcomes s years after enrollment, and Y_{is}^{0} is the no-college potential outcome. Regression applied to Equation 1 identifies these treatment-effect parameters under a standard conditional parallel-trends assumption, assuming also that treatment effects are stable across cohorts. To ensure robustness to the latter assumption, I also apply the imputation-based estimator of Borusyak, Jaravel and Spiess (2024), finding nearly identical results in both for-profit and CC samples. I therefore use the traditional regression estimator in my primary specifications, as these allow estimation of longer-run returns.

The key threat to the parallel-trends assumption is that the timing of college enrollment may depend on shocks that also affect counterfactual earnings. Changes in the availability of childcare, for instance, might generate correlated shocks to labor supply and the timing of college enrollment. If such shocks systematically distinguish students enrolling in a given year from otherwise similar students who delay enrollment, estimated post-enrollment earnings effects will partly capture these contemporaneous labor-supply changes. Longer-run estimates may nevertheless remain informative if these enrollment-timing shocks are transitory. Though concerns like these are challenging to account for directly, I will examine earnings pre-trends and the durability of returns over a long horizon of 12 years after enrollment.

Under these assumptions, the parameters $\tau_{s,c}$ then characterize the value students derive from their chosen schooling sequence and attainment level — e.g., how valuable are for-profit degrees among for-profit graduates? Of most interest, however, will be the relative returns to different schooling outcomes — e.g., how much would for-profit students gain/lose had they enrolled in a CC? — yet relative returns are not identified from naive contrasts of these ATT parameters across groups c. This is because schooling choices may be correlated with unmodeled heterogeneity in college returns.

Given that women and underrepresented minorities are more likely to enroll in for-profits, as well as evidence that these groups earn lower college returns (Imberman et al. 2026), ATT contrasts may overestimate the returns to public enrollment among for-profit students. To correct for this, I apply inverse probability weighting (IPW) on gender/ethnicity combinations X_i, as well as age-at-entry and enrollment year, reweighting each sample to a common for-profit covariate distribution.[27] I assume that, conditional on X_i and the program-attainment path a student would realize under sector j, residual heterogeneity in ex-post

[27] After conditioning on CTE/non-CTE major clusters, further reweighting to match the distribution of majors does not meaningfully impact return estimates.

returns is mean-independent of sector choice:

$$\mathbb{E}[Y_{is}^{j\ell g} - Y_{is}^{0} \mid X_i = x, D_i = j, L_i = \ell, G_i = g] = \mathbb{E}[Y_{is}^{j\ell g} - Y_{is}^{0} \mid X_i = x, L_i^j = \ell, G_i^{j\ell} = g].$$

IPW-corrected estimands $\tilde{\tau}_{s,j\ell g|\text{FP}}$ then identify the returns to the schooling sequence (j, ℓ, g) among for-profit students:

$$\tilde{\tau}_{s,j\ell g|\text{FP}} = \mathbb{E}_{X|D_i=\text{FP}}\big[\mathbb{E}[Y_{is}^{j\ell g} - Y_{is}^{0} \mid X_i = X, L_i^j = \ell, G_i^{j\ell} = g]\big].$$

The assumption of no residual sorting gains is a flaw common to all panel estimators of college returns and not directly testable. The IV-based estimates from Section 5.1, while imprecise, allow arbitrary sorting gains and therefore serve as a valuable robustness check.

Figure 12 presents IPW-corrected dynamic effects $\tilde{\tau}_{s,j\ell g|\text{FP}}$ for each schooling level, among students enrolling in Associate's programs in CTE fields. I find precisely estimated and relatively flat pre-trends, preceding an Ashenfelter's dip in earnings the year prior to enrollment.[28] The returns to two-year degrees are large and similar across sectors, though for-profit returns materialize sooner as students spend less time in school. In particular, for-profit degree pathways yield significant and durable labor-market value despite higher graduation rates and potentially weaker academic standards. Degree returns show no signs of fade-out even twelve years after enrollment. If anything, graduate returns remain on an upward trajectory even through the twelfth year, particularly for public graduates, suggesting that these estimates may understate the long-run returns. On the whole, these estimates are broadly consistent with ex-post return estimates for two-year degree programs in other states (Belfield and Bailey 2017).

Mean returns to both for-profit and public dropouts are small, though public dropouts earn larger returns. If anything, for-profit students face negative returns to enrolling and dropping out, consistent with evidence from resume audit studies showing that for-profit students face reduced callback rates (Deming et al. 2016), and failing to graduate from for-profit college may constitute a particularly negative signal. Four-year graduates who begin at community colleges appear to earn somewhat larger long-run returns than two-year graduates, yet results are less precise for this sample. Very few two-year for-profit students go on to earn Bachelor's degrees, so I cannot estimate the returns to four-year graduation among this group.

Ex-Ante Returns and Match Effects Next I estimate ex-ante returns, accounting for how academic skills shape the expected return to enrollment through graduation probabil-

[28] I normalize the coefficient on the second year prior to enrollment for this reason.

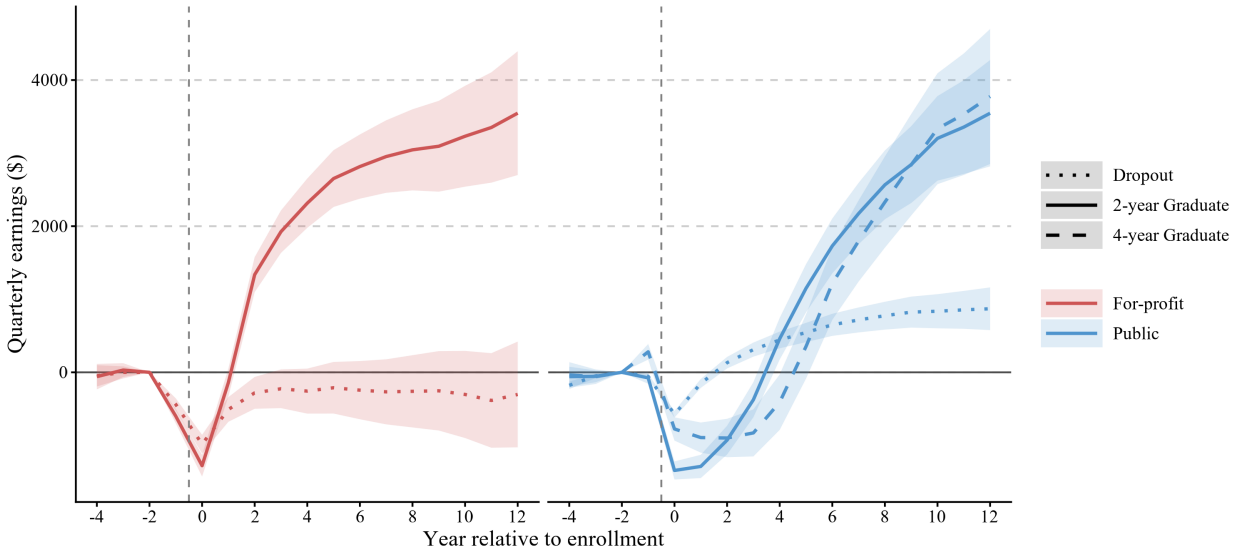


Figure 12: Gross Ex-Post Returns

Notes: Earnings are deflated to 2025 dollars. Sample includes all Texas public HS students who enroll in a two-year for-profit or community college between 2003–2014 at age 22 or older, who have some recorded prior earnings, and who intend a vocational Associate's degree. Estimates reweighted to match the for-profit distribution of gender/ethnicity. Shaded region represents 95% confidence intervals, based on standard errors clustered at the individual level.

ities. Here I incorporate the completion-rate gradients from Section 3 into the estimation along with sector effects on degree attainment and program choice. Since much of the return to enrollment lies with graduates, and since HS test scores are highly predictive of degree attainment — particularly so at CCs —, allowing for match effects through this channel significantly enriches the analysis. Incorporating heterogeneity in academic skills also takes another step toward identification of ex-ante relative returns by accounting for sorting gains, which may be generated by sector differences in academic standards.

I estimate skill-specific ex-ante returns by expressing them as a combination of long-run ex-post returns $\Delta Y_i^{j\ell g}$. The ex-ante return to enrolling in j for a student with HS test scores A_i and other covariates X_i is

$$\begin{aligned}\rho^j(A_i, X_i) &\equiv \mathbb{E}[Y_i^j - Y_i^0 \mid A_i, X_i] \\ &= \sum_{\ell \in \mathcal{L}} \mathbb{P}(L_i^j = \ell \mid A_i, X_i) \times \sum_{g \in \mathcal{G}} \mathbb{P}(G_i^{j\ell} = g \mid L_i^j = \ell, A_i, X_i) \\ &\qquad \times \mathbb{E}[\Delta Y_i^{j\ell g} \mid L_i^j = \ell, G_i^{j\ell} = g, A_i, X_i].\end{aligned}$$

To isolate the roles of program choice and completion rates, I abstract from how ability

might influence the $Y_i^{j\ell g}$ themselves,[29] assuming

$$\mathbb{E}[\Delta Y_i^{j\ell g} \mid A_i, X_i, L_i^j = \ell, G_i^{j\ell} = g] = \mathbb{E}[\Delta Y_i^{j\ell g} \mid X_i, L_i^j = \ell, G_i^{j\ell} = g].$$

To identify potential program choice and degree attainment probabilities across values of (A_i, X_i), I estimate multinomial logit models of degree attainment and program choice with a selection correction to match the IV-based estimates of mean potential outcomes on the for-profit/public margin from Section 4. Covariates include a cubic polynomial in HS test scores, race, gender, free-/reduced-price lunch status, an indicator for high-school dropout risk, and special-education status. See Appendix I for details.

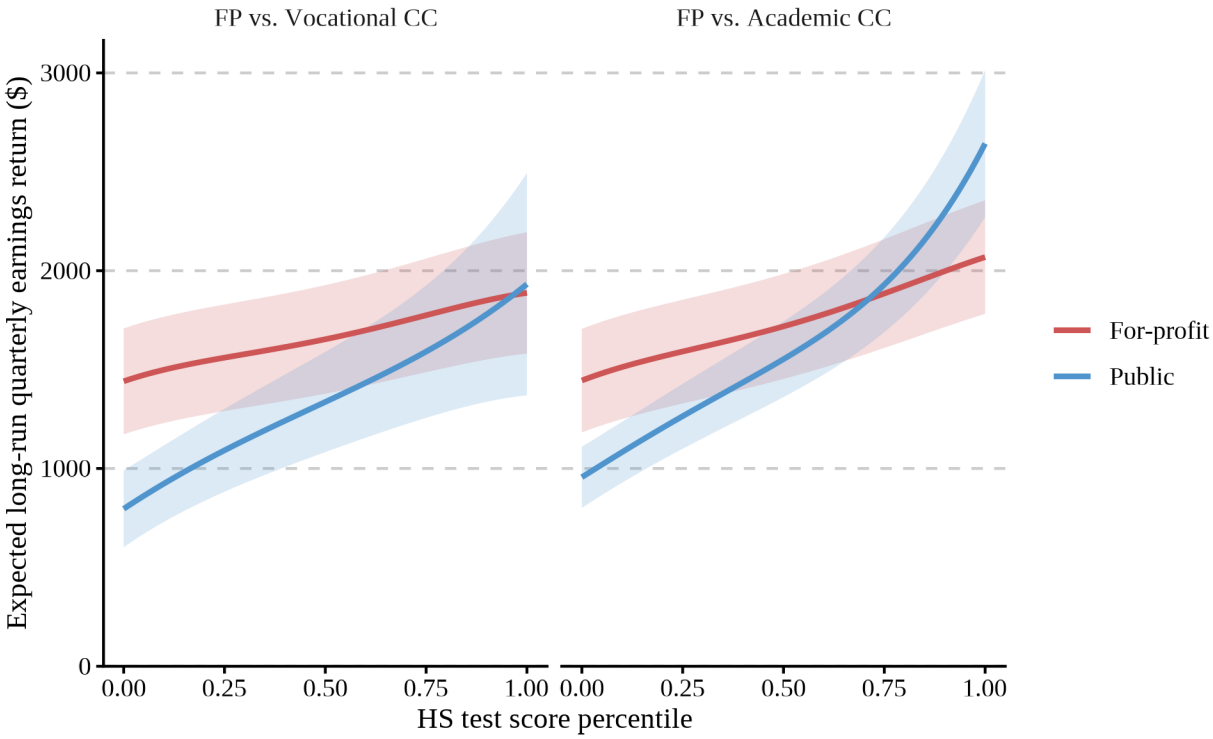


Figure 13: Ex-Ante Relative Returns by Academic Ability

Notes: Earnings are deflated to 2025 dollars. Estimates based on a sample of Texas public HS students enrolling in two-year for-profit and community colleges between 2003–2014. Shaded region represents 95% pointwise confidence intervals.

Finally, I combine these probabilities with the long-run ex-post return estimates $\tilde{\tau}_{12,j\ell g|\text{FP}}$ to form estimates of the conditional ex-ante returns among for-profit students $\bar{\rho}^j(A) \equiv$

[29] An additional source of sorting gains may come from higher-ability students deriving higher ex-post returns as well. Estimates which allow ex-post returns to vary linearly with ability yield similar qualitative conclusions but are less precise due to limited availability of HS test score data for the older event-study sample.

$\mathbb{E}_{X|D_i=\text{FP},A}\left[\rho^j(A,X)\right]$. Figure 13 plots the estimated distribution of ex-ante returns across skill levels, splitting the return estimates by CC program choice to distinguish vocational from academic programs. Recall that 70% of marginal students enroll in vocational CC programs, while the remaining 30% opt for academic CC programs. Results indicate strong complementarities between skills and college quality, even simply through the channel of completion rate differences. Sectoral differences in the relationship between graduation rates and pre-college ability introduce match effects in ex-ante returns. The lowest-skill students earn \$500–700 per quarter more by attending for-profits, while the highest-ability students on the academic margin incur long-run quarterly earnings penalties of about \$500 by attending for-profits. In addition, the long-run gross returns to college are large even for the lowest-ability students.

Net Returns and Efficiency These estimates represent gross earnings effects, which do not account for the costs of schooling. For one, for-profit students earn degrees and re-enter the labor market more quickly, reducing their opportunity costs of enrollment. On the other hand, for-profits charge much higher tuition, depressing the net private return to for-profit enrollment. For evaluating the efficiency of for-profit and CC degree production technologies, however, what matters are the economic costs of their programs. This is also the relevant question for understanding whether for-profit degree pathways might serve as a model for public colleges seeking to improve attainment among low-ability students.

To estimate the expected net private and social returns to two-year college enrollment, I now quantify schooling costs. I combine IPEDS revenue and expenditure data with administrative enrollment records to infer lifetime expected tuition and costs per enrollee. Since CC students spend more time enrolled in college, simply comparing annual spending per student would be misleading. Instead, I multiply the annual average costs per student by estimates of the expected number of enrolled years from the administrative data. Since ex-ante return estimates include transfer students, I break down expected costs by sector, including enrollment spells in both the two-year for-profit and public sector and the four-year private and public sectors. Since after-grant tuition varies considerably by a student's enrollment intensity, I estimate average after-grant tuition and fees in the same way, dividing total tuition revenues net of grants by annual enrollment.

The ideal cost measure would capture all costs incurred as a consequence of the student's enrollment, including both instructional and non-instructional inputs. This spending concept is not directly observable, as IPEDS divides spending into relatively coarse categories. I consider both an expansive definition using total spending and a definition restricting to spending on instruction, academic support, student services, and institutional support. This latter concept excludes spending on activities like research, public service, and affiliated

hospital services. Net return estimates are not particularly sensitive to this choice, and below I report estimates using the more expansive total-cost definition. Hoxby (2018) discusses these and other issues with estimating higher education productivity in greater detail.

Another wrinkle in my measurement of average costs is that CC expenditures are dispersed over a wider set of students than the vocational student sample used in the gross returns estimation. If CCs' academic programs are more or less costly on average, college-level cost estimates will be biased. This issue could be ameliorated using finer-grained data on course- or program-specific costs, as in Altonji and Zimmerman (2019). Lacking program-level cost data, I identify a small set of technical public colleges which offer exclusively vocational programs, typically of less than two years, which closely resemble the short, terminal vocational programs offered by two-year for-profits. Despite not offering academic programs and transfer pathways, I find that these technical public colleges spend nearly the same amount per student as traditional public colleges (Appendix Table A7). This suggests that sectoral differences in program composition are not driving relative expenditure estimates.

Table 10 presents the expected private and social costs of for-profit and CC enrollment per year and over a student's lifetime. Public colleges spend about $1,500 less per year but about $3,000 more over the lifetime of a student. While expenditures per student are similar, tuition costs are significantly lower among CC students, who often pay near-zero tuition while enrolled in CCs.[30] By contrast, the average for-profit student pays $8,000 per year in tuition (after grants). Though relatively large, for-profits' tuition charges equal their average costs, while CCs offer steep discounts relative to their average expenditures. This wedge reflects significant state subsidization of the public sector.

I next calculate the expected net present value of enrollment for students (using tuition) and for society (using college expenditures).[31] I use the dynamic gross return estimates from before, assuming the returns plateau at their final estimated value twelve years after first enrollment. Note that the dynamic return estimates already incorporate expected opportunity costs of enrollment through reduced in-school labor supply. For each initial sector j, I assume that tuition costs T_{it}^j are deferred through federal student loans, while expenditures (social costs) C_{it}^j are borne during enrollment. I assume the full tuition balance is amortized over the ten years after exiting college.[32] Under these assumptions I calculate the expected

[30]Note that average CC tuition is only $718, compared to $7,567 at for-profits. Table 10 shows annual expected tuition costs of students initially enrolling in CCs total $2,393, which is larger because some students transfer to more expensive four-year colleges.

[31]The full social returns to education would incorporate educational spillovers and education effects on non-pecuniary outcomes. My lack of data on such outcomes and the difficulty of estimating such effects prevents this more comprehensive accounting of net benefits.

[32]Results are not sensitive to how loans and repayment are specified. The typical federal loan interest rate

Table 10: Expected Costs by Initial Two-Year Sector

	Public	For-Profit
Panel A: Per enrolled year		
Social	6,874	8,326
Private	2,393	8,063
Panel B: Per student lifetime		
Social	27,172	23,919
Private	9,461	23,164
Years enrolled	3.95	2.87

Notes: Social and private costs represent average college spending and after-grant tuition, respectively. Costs include enrollment in all colleges, regardless of sector, after first enrollment. Cost and enrollment data restricted to Texas colleges for comparability to return estimates.

net present value of enrollment in sector j as

$$\mathbb{E}[\text{PDV}_j^{social}] = \sum_{t=0}^{T} \delta^t \Big(\mathbb{E}\big[Y_{it}^j - Y_{it}^0\big] - \mathbb{E}\big[C_{it}^j\big] \Big)$$
$$\mathbb{E}[\text{PDV}_j^{private}] = \sum_{t=0}^{T} \delta^t \Big(\mathbb{E}\big[Y_{it}^j - Y_{it}^0\big] - \mathbb{E}\big[T_{it}^j\big] \Big)$$

Setting $T = 35$ and $\delta = 0.98$, I present social and private PDVs in Table 11. These results continue to use return estimates reweighted to match the for-profit demographic distribution. I find large social and private returns to both public and for-profit enrollment, ranging from \$55,000 to \$73,000 in present value. The social return to for-profit enrollment is about \$12,000 larger than that of CC enrollment. Yet due to public tuition subsidization, private returns to CC enrollment are slightly larger.

Despite community colleges' low graduation rates, and despite for-profits' high tuition, two-year college enrollment remains lucrative across the board. The social return even to students with the lowest pre-college academic performance is also positive: these students generate \$37,830 enrolling in CCs and \$54,113 at for-profits. Thus, for-profits' degree production technology is relatively efficient among academically weak students.

is approximately 3% in real terms, often with no payments or interest accrual until six months after exiting school. A student with a discount factor of 0.98 may therefore prefer to pay up front for schooling; I assume in this case that credit constraints prevent early payment.

Table 11: Expected PDV by Initial Sector

	Public	For-Profit
Panel A: Social returns		
Gross returns	81,302	91,300
Costs	26,048	23,432
Net PDV	55,254	67,868
Panel B: Private returns		
Gross returns	81,302	91,300
Costs	8,311	20,348
Net PDV	72,991	70,952

Notes: Gross returns use IPW-corrected estimates of dynamic ex-ante returns. Social costs use total expected college expenditures per student; private costs use expected tuition payments under a 10-year repayment plan. All values discounted by discount factor $\delta = 0.98$.

6 The MVPF of For-Profit Program Expansions

Since existing tuition subsidies are biased toward public colleges, closing the gap between public and for-profit tuition might lead to more efficient enrollment choices while also generating fiscal benefits. If students sort on the private benefits of enrollment, asymmetric subsidies for public colleges create a wedge that misallocates students across sectors.[33] Appendix G elaborates this result in a model with endogenous tuition and curriculum choices. I show there that the efficient benchmark can be implemented by equating the private and social costs of schooling in each sector.[34] In addition, I show that asymmetric public subsidies can generate inequality: since low-skill students earn higher gross returns to for-profit enrollment, they either enroll in the better-matched for-profit curriculum but miss out on the subsidy, or they accept the subsidy at the cost of a poorly-matched public curriculum.

Empirically, evaluating the welfare effects of a large change in subsidies would be challenging, primarily because college returns will adjust in equilibrium as the supply of college-educated workers expands. Even accounting for equilibrium price changes would not be fully satisfactory. Extending subsidies to for-profits would induce entry, and estimating the value-added of unobserved potential entrants would be difficult without significant struc-

[33]This result requires that the asymmetry of public subsidies is not correcting for some other background wedge. There may be positive externalities of college enrollment or credit constraints that warrant college subsidies, but these must apply equally to public and for-profit colleges.

[34]If public subsidies correct an underlying distortion that generates inefficiently low college enrollment, then we would apply the same subsidy to for-profit tuition; if public subsidies are themselves distortionary, we would simply eliminate the subsidy.

tural assumptions. Additionally, high for-profit tuition may contribute to completion by encouraging more intensive enrollment and faster degree progression. This mechanism could therefore alter the for-profit completion premium itself, further complicating evaluation of large tuition reductions.

I am well-positioned, however, to evaluate policy changes on the margin. To weigh effects on public spending and earnings in a coherent framework, I consider the marginal value of public funds (MVPF) associated with a corrective for-profit tuition subsidy (Hendren and Sprung-Keyser 2020). In particular, I model this policy as a voucher available to all students that can be applied toward tuition at any two-year for-profit college, reducing students' net price dollar-for-dollar before any endogenous tuition response. A for-profit subsidy is both the natural corrective to existing tuition distortions and a practical policy lever which could be easily overlaid on existing federal or state tuition grant policies.

Deriving the MVPF The MVPF is defined as the willingness to pay (WTP) for a policy among its beneficiaries per dollar of net government cost (NGC). The net government cost includes not only the direct cost of the subsidy, paid in proportion to the baseline for-profit share s_{FP}, but also indirect effects on government costs coming through substitution away from subsidized public options as well as tax revenues on any earnings gains. Next I derive the expression for the MVPF of a for-profit subsidy.

Let z denote the per-student for-profit subsidy and let $D_i(z)$ denote i's chosen sector under subsidy level z. A small for-profit subsidy draws students from enrollment margin k at rate

$$s_{\text{FP}\leftarrow k} \equiv \frac{\partial}{\partial z} \Pr(D_i(z) = \text{FP}, D_i(0) = k)\Big|_{z=0}.$$

These demand derivatives $s_{\text{FP}\leftarrow k}$ depend on tuition elasticities and how substitutable for-profits are with other sectors. Whether a subsidy primarily draws students from non-enrollment or public alternatives matters for both government costs and earnings effects.

The subsidy generates indirect effects on government spending since the government subsidizes public tuition and offers tuition grants even to for-profit students. Let f_k denote the expected government cost of enrollment in sector k. The cost of community-college enrollment is the tuition subsidy $f_{CC} = c_{CC} - (t_{CC} - g_{CC})$, where c, t, and g are the marginal resource cost of schooling, posted tuition, and tuition grants, respectively, among FP $\leftarrow$ CC compliers. While the government does not pay the resource costs of schooling at private colleges, it does incur the cost of tuition grants, primarily the federal Pell grant. The government cost of for-profit enrollment is therefore $f_{FP} = g_{FP}$, the expected grant among FP $\leftarrow$ 0 compliers. Then $\Delta f_k \equiv f_{FP} - f_k$ is the government's indirect cost per complier on

margin k.

The value of additional tax revenues represents a second indirect fiscal benefit. Letting $\Delta\rho_k \equiv \rho_{\text{FP}} - \rho_k$ be the expected change in present value of earnings among FP $\leftarrow k$ compliers and τ the average marginal tax rate, the present value of additional tax revenues $\tau\Delta\rho_k$ also enters net costs. Altogether, a dollar subsidy generates a net government cost per student of

$$\text{NGC} = s_{\text{FP}} + \sum_{k\in\{0,\text{CC},4\}} s_{\text{FP}\leftarrow k}\left[\Delta f_k - \tau\Delta\rho_k\right],$$

where margin-specific costs and revenues are weighted up according to the complier flows $s_{\text{FP}\leftarrow k}$.

The willingness to pay for the alternative subsidy regime is less straightforward. Infra-marginal for-profit students have a willingness to pay of z, as they simply receive the subsidy amount. Whether and how to value the change in earnings among compliers who switch into the for-profit sector depends on the underlying enrollment model. In the idealized benchmark described in Appendix G, students sort on private returns with full information, so by the Envelope Theorem any changes in earnings among marginal students are exactly offset by non-pecuniary costs (e.g., psychic costs of schooling) and are welfare-irrelevant. In this world, compliers have zero willingness to pay for earnings gains ($\phi = 0$).

Only if the subsidy counteracts an existing distortion should the earnings gains be priced at some rate $\phi > 0$. For instance, if students incorrectly believe the relative returns to for-profit enrollment are half of their actual value, earnings gains would be priced at $\phi = 0.5$. Alternatively, credit constraints may distort enrollment away from the for-profit sector, especially given for-profits' particularly high sticker prices. Rather than estimate students' willingness to pay for earnings gains, I will consider MVPFs under a range of WTP values $\phi \in [0, 1]$, which correspond to different underlying models of the frictions associated with for-profit enrollment.

Finally, under imperfect competition, tuition subsidies may be passed through to for-profit tuition at a rate κ, potentially dampening its enrollment impact. Here again I consider a range of scenarios. If for-profit supply is perfectly elastic in the long run, we have $\kappa = 0$ and students capture the full subsidy amount. This does not require perfect competition; in particular, $\kappa = 0$ corresponds to a free-entry equilibrium under monopolistic competition with constant costs. The for-profit sector is characterized by significant churn, making this scenario a plausible long-run benchmark. Barriers to entry will typically raise the pass-through rate. For instance, in a no-entry model with Bertrand competition and linear residual demand, we have $\kappa = 0.5$. I consider this scenario as a conservative benchmark.

When for-profits do capture part of the subsidy, we can further price any change in firm profits $\Delta\pi$ using planner weight ω_π.

More generally, subsidy incidence depends on the curvature of residual demand (Weyl and Fabinger 2013). In Appendix H I estimate equilibrium pass-through rates by combining estimates of a college-demand system with a supply model featuring Bertrand competition. There I find evidence of over-shifting: most for-profits somewhat *reduce* their posted tuition under a for-profit subsidy ($\kappa < 0$), amplifying the net tuition effect of the subsidy. This is because heterogeneity in price sensitivity generates log-convex residual demand at many colleges: as net tuition falls, the subsidy draws in more price-sensitive students, reducing optimal markups (Miravete, Seim and Thurk 2023).[35] This result, while still reliant on a particular model of competition, provides additional evidence for κ near zero. Still, I will present sensitivity analyses using pass-through rates of up to 50%.

Given the WTP for earnings gains ϕ, the pass-through rate κ, and the weight on firm profits ω_π, the MVPF is then

$$\text{MVPF}(\phi,\kappa,\omega_\pi) = \frac{\overbrace{s_{FP}(1-\kappa)}^{\text{Direct transfer}} + \phi \sum_{k\in\{0,\text{CC},4\}} \overbrace{s_{\text{FP}\leftarrow k}\left[(1-\tau)\Delta\rho_k - (t_{FP}-t_k)\right]}^{\text{Income gains on margin } k} + \overbrace{\omega_\pi \Delta\pi}^{\text{FP profits}}}{\underbrace{s_{FP}}_{\text{Direct cost}} + \sum_{k\in\{0,\text{CC},4\}} \underbrace{s_{\text{FP}\leftarrow k}\left[\Delta f_k - \tau\Delta\rho_k\right]}_{\text{Savings on CC costs and tax revenues}}}$$

To summarize, whether for-profit subsidies yield social benefits will depend on several factors. First, who shifts their enrollment in response to the subsidy, and what are their counterfactual enrollment choices? Second, what are the potential returns on each margin among those compliers? And third, what are the corresponding changes in public expenditure? The preceding sections have laid the groundwork for estimating changes in spending and returns among marginal students. To identify the first component — the composition of complier flows in response to the for-profit subsidy — I next estimate a college demand model.

College Demand Let $S(j) \in \{\text{FP}, \text{CC-V}, \text{CC-A}, 4\}$ denote college j's sector. College utilities are

$$\begin{aligned} j = 0: &\quad u_{i0} = \varepsilon_{i0}, \\ j \neq 0: &\quad u_{ij} = \delta_j + \underbrace{\alpha_{S(j)}(A_i, X_i) + \alpha_t(A_i, X_i)t_j + \alpha_d \text{Distance}_{ij}}_{\equiv \mu_{ij}} + \varepsilon_{ij}, \end{aligned} \tag{2}$$

[35] Importantly, log-convex demand is not simply a property of the mixed-logit functional form. In fact, logit models without heterogeneity in consumer preferences imply log-concave residual demand and nonnegative subsidy pass-through. Allowing student preferences and price sensitivities to vary relaxes this restriction, allowing residual demand to be either log-concave or log-convex.

where $\varepsilon_{ij} \overset{iid}{\sim} \text{T1EV}$ and

$$\delta_j = \bar{\alpha}_{S(j)} + \bar{\alpha}_t t_j + \xi_j \tag{3}$$

are mean utilities. The $\bar{\alpha}_{S(j)} + \alpha_{S(j)}(A_i, X_i)$ intercepts represent reduced-form sector preferences varying with students' academic ability and other characteristics. This captures how students sort on the perceived returns to different sectors, as well as preferences for unobserved sector characteristics. Allowing sector preferences to vary flexibly with the observed determinants of relative returns, particularly A_i, will be important for later identifying the distribution of returns on different complier margins. The $\bar{\alpha}_t + \alpha_t(A_i, X_i)$ coefficients also allow for heterogeneous tuition elasticities. Let s_{ij} denote i's implied choice probability for college j and define sector-k choice probabilities,

$$s_{ik} = \sum_{j:S(j)=k} s_{ij}.$$

The baseline for-profit share is $s_{\text{FP}} = \mathbb{E}[s_{i,\text{FP}}]$. For each margin $k \in \{0, \text{CC}, 4\}$, the mass of compliers on each margin can now be expressed as

$$s_{\text{FP}\leftarrow k} = (1-\kappa)\mathbb{E}[-(\bar{\alpha}_t + \alpha_t(A_i, X_i))s_{i,\text{FP}}s_{ik}].$$

The demand model also identifies the characteristics of students on each complier margin, which will be important for estimating their potential returns. Specifically, the distribution of (A_i, X_i) on each margin is identified from the following weighted averages,

$$\mathbb{E}[h(A_i, X_i) \mid \text{FP} \leftarrow k \text{ complier}] = \frac{\mathbb{E}[(\bar{\alpha}_t + \alpha_t(A_i, X_i))s_{i,\text{FP}}s_{ik}h(A_i, X_i)]}{\mathbb{E}[(\bar{\alpha}_t + \alpha_t(A_i, X_i))s_{i,\text{FP}}s_{ik}]}.$$

where h is some function of characteristics (e.g., a CDF).

Estimation I estimate demand in two steps. I first estimate the parameters of Equation 2 by maximum likelihood on the individual-level college-choice data, including estimated mean utilities $\hat{\delta}_j$ for each college. Beyond HS test scores, X_i includes race, gender, free-/reduced-price lunch status, an indicator of high-school dropout risk, and high-school special education status.

In a second step, I identify the mean tuition elasticity in Equation 3 using one of three different sources of variation. First, I simply project the $\hat{\delta}_j$ on sector intercepts and average after-grant tuition t_j, taking the latter to be exogenous. The tuition elasticity $\bar{\alpha}_t$ is therefore identified from within-sector heterogeneity in average after-grant tuition t_j. This approach

alone is unsatisfactory, both because average tuition masks net-tuition heterogeneity across students owing to variable tuition grants, and because tuition may be correlated with the unobserved demand-shifters ξ_j. Both of these sources of bias seem likely to understate the magnitude of price sensitivities. If predominantly classical, measurement error in prices would tend to attenuate the estimated elasticity. And the unobserved demand-shifters ξ_j — canonically, unobserved quality — often correlate positively with prices, leading to wrong-signed demand elasticities. Despite these likely sources of bias, this first approach still yields a negative mean price coefficient equal to -0.10 (s.e. 0.01). This estimate implies that CC market shares increase by 2 percentage points under a \$1,000 CC tuition reduction.

Given the importance of this parameter for the efficacy of the for-profit subsidy, I consider two alternative sources of variation for inferring the mean tuition elasticity. I first turn to quasi-experimental variation from Denning (2017), who uses variation in student net price induced by changes in the geographic boundaries determining eligibility for reduced CC tuition, also in Texas. After estimating Equation 2, I choose the value of $\bar{\alpha}_t$ to replicate the quasi-experimentally identified tuition responsiveness estimated in Denning (2017). In particular, I match my model's predicted change in CC market shares under a \$1,000 reduction in CC tuition to his reduced-form estimate of the same estimand, equal to a 5.1 percentage-point increase in CC enrollment for every \$1,000 tuition reduction. My model's price-elasticity heterogeneity then implicitly extrapolates the tuition sensitivity implied by this moment to students on the for-profit margin. This calibration yields a mean price coefficient of -0.27, larger in magnitude than the naive regression estimate of -0.10 as anticipated.

As a final alternative, I set-identify the demand elasticity by imposing the optimal-pricing conditions of a for-profit supply model. These restrictions encode the standard result that profit-maximizing firms price on the elastic side of their residual demand curve. Taking non-profit prices as exogenous, I assume that for-profits maximize profits in static Bertrand competition. The necessary first-order conditions of the pricing equilibrium impose restrictions on the size of each firm's residual demand elasticity. Though data on marginal costs would narrow the identified set, simply taking non-negative marginal costs already yields useful bounds. Appendix H elaborates further the identification result and the particular inequality constraints used to identify bounds on the tuition elasticity. I find that imposing all inequality constraints implies $\bar{\alpha}_t \leq -0.24$, while allowing 20% of for-profits to deviate from optimal pricing still implies $\bar{\alpha}_t \leq -0.10$. While dependent on the assumed model of firm conduct, these bounds are consistent with the calibrated coefficient of -0.27 from Denning (2017) and further support interpreting the naive regression estimate of -0.10 as a lower bound on the magnitude of the tuition coefficient. To remain conservative, I therefore

present MVPF results corresponding to $\bar{\alpha}_t = -0.10$.

With demand-model estimates in hand, I next simulate the implied distribution of compliers under a small for-profit subsidy in Figure 14. Marginal students disproportionately come from the lower end of the skill distribution — the region where the relative returns to for-profit enrollment are highest. Most compliers would otherwise not have enrolled in college, but somewhat less than half are diverted from CCs, and a negligible share are diverted from the four-year sector.

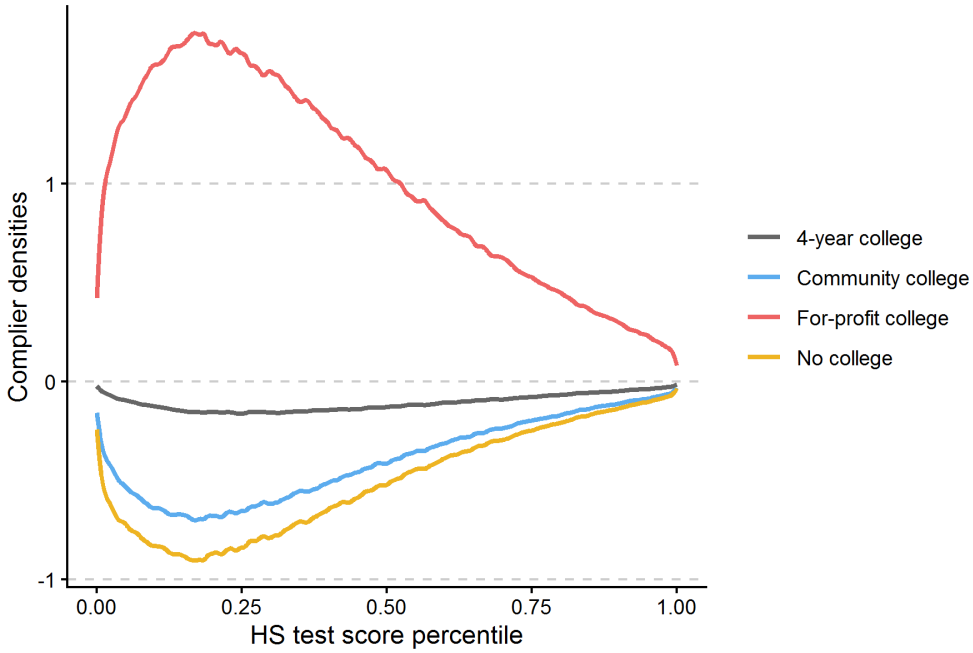


Figure 14: Complier Distributions Under a For-Profit Subsidy

Notes: Distribution of HS test scores and counterfactual enrollment choices of students induced to enroll in for-profits under a small for-profit subsidy.

Estimating the MVPF I next estimate the MVPF of a for-profit subsidy by combining estimates of the college demand model with estimates of relative returns on each complier margin. The change in expected gross returns is given by

$$\Delta\rho_k = \int \left(\rho^{\text{FP}}(A,X) - \rho^{k}(A,X)\right) dF_{\text{FP}\leftarrow k}(A,X),$$

where $F_{\text{FP}\leftarrow k}$ is the distribution of student characteristics on margin k implied by the demand model. The gross return functions ρ_k are estimated as in Section 5.2 by combining individual-FE estimates of the present value of earnings gains to each (g,ℓ) combination — reweighted to match each margin's complier distribution of race $\times$ gender — with the completion-rate and program-choice schedules estimated using distance IVs (Appendix I). I also estimate the

change in expected private costs $t_{\text{FP}} - t_k$ and the change in government costs of schooling Δf_k using distance IVs.[36] In my primary specifications, I place no weight on firm profits, $\omega_\pi = 0$. Under the $\kappa = 0.5$ pass-through benchmark — corresponding to a no-entry Bertrand supply model with linear residual demand — I will also show specifications with $\omega_\pi = 1$. This supply model yields a simple expression for the change in optimized firm profits, $\Delta\pi = s_{\text{FP}}$. Finally, I assume an average marginal tax rate of $\tau = 0.20$.

Figure 15 decomposes the numerator (WTP) and denominator (NGC) of the MVPF, in the case of perfectly elastic long-run supply. For each dollar in direct cost of the subsidy, the government spends an additional \$0.29 in Pell grants on incoming for-profit students, but it recoups \$0.49 from substitution away from subsidized public options and another \$0.34 from future tax revenues. Incorporating the behavioral effects of the subsidy therefore pushes the net government cost well below one, to just \$0.46 per dollar of direct costs. Meanwhile, WTP is at least equal to \$1.00, the direct value of the subsidy. A dollar of subsidy also generates \$5.88 in private value-added, primarily from those on the no-college margin. Those diverted from vocational and academic CC programs gain on average as well, since the subsidy draws students from the lower end of the skill distribution.

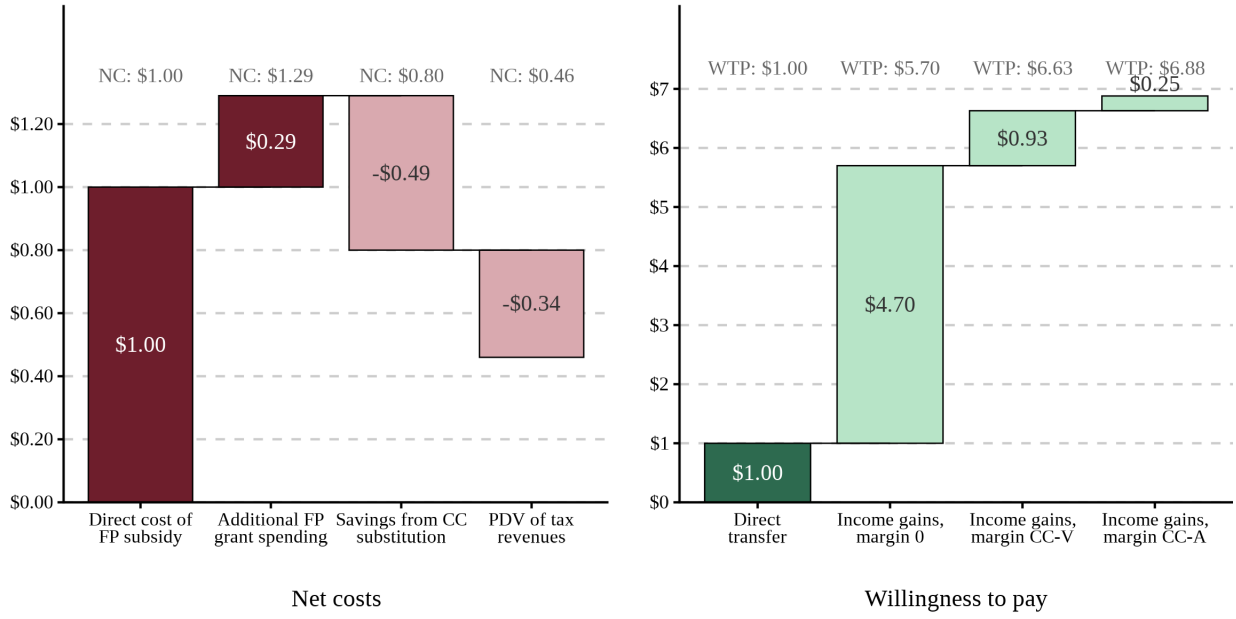


Figure 15: Costs and Benefits of a For-Profit Subsidy

Notes: Marginal costs and benefits of a for-profit tuition subsidy, under perfectly elastic long-run supply ($\kappa = 0$) and full valuation of earnings gains ($\phi = 1$). Earnings effects decomposed into three complier margins: non-enrollment (0), vocational CC (CC-V), and academic CC (CC-A).

[36] This describes the approach taken in estimating $\Delta\rho_{\text{CC}}$ and Δf_{CC}. For the non-enrollment margin, distance-IV designs are insufficiently powered. There I use the same expressions, but substituting completion-rate schedules, program-choice probabilities, and costs based on selection-on-observables estimates.

Even if students do not value any of these earnings gains ($\phi = 0$), the MVPF of the for-profit subsidy equals 2.17 in the benchmark with perfectly elastic long-run supply. These gains owe primarily to the fact that the for-profit subsidy corrects for the existing distortion of asymmetrically large public subsidies. The MVPF grows significantly larger when students value their earnings gains. Under $\phi = 0.5$, the MVPF reaches 8.56, and under $\phi = 1$ it reaches 14.95. Subsidy pass-through weakens the MVPF somewhat, as shown in Figure 16. Assuming 50% pass-through, MVPFs remain robust, between 2–6, provided the additional firm profits are fully valued ($\omega_\pi = 1$). Placing no weight on firm profits, the MVPF falls below one only if earnings gains are also valued at 0%. Even in the relatively pessimistic scenario with 50% pass-through and no weight on firm profits, MVPFs remain substantial when students value the earnings gains at 50% or more.

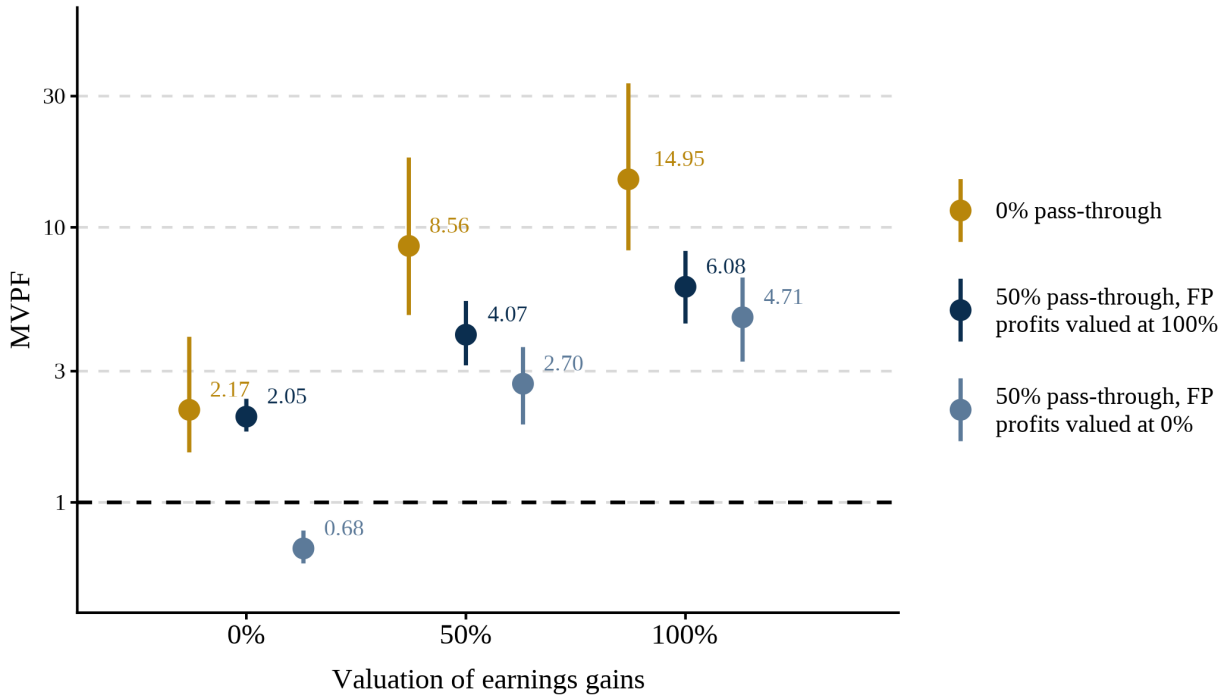


Figure 16: MVPF of a For-Profit Subsidy

Notes: Logarithmic scale. MVPF of a for-profit tuition subsidy, for different values of pass-through κ, WTP for earnings gains ϕ, and valuation of firm profits ω_π. Error bars represent 95% confidence intervals.

Looking across a variety of public programs designed to improve the labor-market outcomes of young adults, MVPF estimates of 2 or more are relatively uncommon (Hendren and Sprung-Keyser 2020). The large marginal returns I estimate for for-profit subsidies owe in part to the existing subsidy imbalance favoring public colleges. Yet shifting subsidies toward the attainable vocational tracks offered by for-profits also emerges as a relatively efficient instrument for improving human capital formation among low-skill students. Earnings gains

are so large partly because the for-profit sector draws in students who otherwise would not enroll in college, consistent with quasi-experimental evidence in Haygood (2026), but also because those it does divert from other sectors come from weaker academic backgrounds and tend to be well-suited to for-profit pathways.

7 Discussion

When choosing where to enroll, students face a significant trade-off between the ease of for-profit degree pathways and the greater option values afforded by community-college enrollment. Steep skill gradients in public-college completion rates, relaxed for-profit grading standards, and narrower for-profit degree requirements all indicate that public completion-rate penalties arise from the greater academic intensity of their vocational programs — at least for students on the for-profit margin. Academically intensive public curricula appear to create market opportunities for private colleges to offer easier degree pathways. Although one might expect the returns to such degrees to be correspondingly small, I find they still confer large long-run earnings premia. Yet differences in for-profit and public degree production technologies generate significant match effects in the ex-ante returns to enrollment: academically weaker vocational students earn more from for-profit tracks, while the opposite is true among vocational students with stronger academic backgrounds, partly due to the option value of academic pathways at CCs.

Despite the large returns to the attainable vocational pathways offered by for-profits, public subsidies heavily favor the academically intensive community-college variants of their programs. As a result, I find that shrinking the subsidy gap by expanding for-profit subsidies would, on the margin, yield public benefits even absent any earnings gains. Pricing even half of earnings gains yields MVPF estimates between 2.7–8.6, provided tuition pass-through is not too large. And the resulting earnings gains accrue primarily to lower-skill students who would not otherwise enroll in college, reducing inequality in college returns.

From the perspective of community colleges seeking to improve degree attainment among the kinds of low-skill and non-traditional students who often turn to the for-profit sector, my results suggest that the for-profit model offers a way of doing so without compromising the value of degree programs, as long as those narrower pathways are well-targeted to those likely to benefit. Redesigned pathways to vocational degrees — perhaps alternative tracks in existing programs — might do well to feature narrower curricula with fewer academic requirements, and grading standards which are suited to the purposes of terminal vocational training. Still, these possibilities are somewhat more speculative. While I find patterns across multiple sources of evidence consistent with a strong role for academic standards, separately

identifying the influence of the many differences between private and public degree pathways on the for-profit completion premium remains an important direction for future research.

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Appendix

A Additional Proofs

Extension of Mountjoy (2022) Identification

Theorem. *Under A-IE and A-UPM, for $j \neq k$, $j \geq 1$, $k \geq 1$,*

$$\underbrace{\frac{\partial \mathbb{E}[YD_k \mid \mathbf{Z}]}{\partial Z_j} \Big/ \frac{\partial \mathbb{E}[D_k \mid \mathbf{Z}]}{\partial Z_j}\Big|_{\mathbf{Z}=\mathbf{z}}}_{LIV_{kj}(\mathbf{z})} = \mathbb{E}[Y_k \mid j-k \text{ complier at } \mathbf{z} \text{ wrt } Z_j]$$

Proof. For $z_j' < z_j$, $\mathbf{z}'_{-j} = \mathbf{z}_{-j}$,

$$\begin{aligned}
\mathbb{E}[YD_k \mid \mathbf{z}'] - \mathbb{E}[YD_k \mid \mathbf{z}] &= \mathbb{E}[Y_k D_k(\mathbf{z}')] - \mathbb{E}[Y_k D_k(\mathbf{z})] \\
&= \mathbb{E}[Y_k D_k(\mathbf{z}') D_k(\mathbf{z})] - \mathbb{E}[Y_k D_k(\mathbf{z})(D_k(\mathbf{z}') + (1 - D_k(\mathbf{z}')))] \\
&= -\mathbb{E}[Y_k D_k(\mathbf{z}) D_j(\mathbf{z}')] \\
&= -\mathbb{E}[Y_k \mid D_k(\mathbf{z}) = 1, D_j(\mathbf{z}') = 1] \cdot \mathbb{P}[D_k(\mathbf{z}) = 1, D_j(\mathbf{z}') = 1]
\end{aligned}$$

$$\begin{aligned}
\mathbb{E}[D_k \mid \mathbf{z}'] - \mathbb{E}[D_k \mid \mathbf{z}] &= \mathbb{E}[D_k(\mathbf{z}')] - \mathbb{E}[D_k(\mathbf{z})] \\
&= \mathbb{E}[D_k(\mathbf{z}') D_k(\mathbf{z})] - \mathbb{E}[D_k(\mathbf{z})(D_k(\mathbf{z}') + (1 - D_k(\mathbf{z}')))] \\
&= -\mathbb{E}[D_k(\mathbf{z}) D_j(\mathbf{z}')] \\
&= -\mathbb{P}[D_k(\mathbf{z}) = 1, D_j(\mathbf{z}') = 1]
\end{aligned}$$

Combining these expressions,

$$\frac{\mathbb{E}[YD_k \mid \mathbf{z}'] - \mathbb{E}[YD_k \mid \mathbf{z}]}{\mathbb{E}[D_k \mid \mathbf{z}'] - \mathbb{E}[D_k \mid \mathbf{z}]} = \mathbb{E}[Y_k \mid j-k \text{ complier wrt } \mathbf{z}' \leftarrow \mathbf{z}]$$

Taking the limit as $z_j' \to z_j$,

$$\begin{aligned}
\lim_{z_j' \to z_j} \frac{(\mathbb{E}[YD_k \mid \mathbf{z}'] - \mathbb{E}[YD_k \mid \mathbf{z}])/(z_j - z_j')}{(\mathbb{E}[D_k \mid \mathbf{z}'] - \mathbb{E}[D_k \mid \mathbf{z}])/(z_j - z_j')} &= \lim_{z_j' \to z_j} \mathbb{E}[Y_k \mid j-k \text{ complier wrt } \mathbf{z}' \leftarrow \mathbf{z}] \\
\frac{\partial \mathbb{E}[YD_k \mid \mathbf{Z}]}{\partial Z_j} \Big/ \frac{\partial \mathbb{E}[D_k \mid \mathbf{Z}]}{\partial Z_j}\Big|_{\mathbf{Z}=\mathbf{z}} &= \mathbb{E}[Y_k \mid j-k \text{ complier at } \mathbf{z} \text{ wrt } Z_j]
\end{aligned}$$

□

Finally, comparing mean potential outcomes from different IVs requires A-CC:

$$\lim_{z_j' \uparrow z_j} \mathbb{E}[Y_k \mid D_j(\mathbf{z}') = 1, D_k(\mathbf{z}) = 1] = \lim_{z_k' \downarrow z_k} \mathbb{E}[Y_k \mid D_j(\mathbf{z}') = 1, D_k(\mathbf{z}) = 1]$$

Contrasting the identified mean potential outcomes then identifies mean sector effects on the $j - k$ margin:

$$LIV_{jk}(\mathbf{z}) - LIV_{kj}(\mathbf{z}) = \mathbb{E}[\, Y_j - Y_k \mid j - k \text{ complier at } \mathbf{z}]$$

B Identifying Sector Effects from Switchers

Here I identify sector effects using a "switchers" design. I leverage the administrative data from Texas to identify the sector-specific graduation rates of students who enroll in both sectors at different times. This approach purges any confounding due to permanent unobserved heterogeneity in traits like ability, schooling preferences, effort, and motivation. Time-varying confounders remain an issue, yet observing sector-switchers moving in both directions allows me to separate out a common time-varying switching effect and identify the sector effect under a symmetry assumption. Without imposing symmetric switching effects, I will also show that FP $\rightarrow$ CC switchers yield a lower bound on the for-profit completion premium under reasonable models of the joint decision of graduation and transfer.

Identification To formalize the identification argument, let $G_{it}^{j} \in \{0,1\}$, $j \in \{CC, FP\}$, denote potential graduation outcomes for student i in enrollment spell t. Graduation is determined by sector-specific graduation thresholds g_j, as well as permanent and transitory student characteristics (X_i, χ_{it}) and random spell-specific shocks ε_{it}:

$$G_{it}^{j} = \mathbb{1}\{g_j(X_i, \chi_{it}) > \varepsilon_{it}\}$$

Most students have either $\sum_t G_{it}^{FP}$ or $\sum_t G_{it}^{CC}$ censored, as they only ever enroll in one sector. Yet a subset of students transfer between sectors, allowing us to observe $(G_{i1}^{FP}, G_{i2}^{CC})$ or $(G_{i1}^{CC}, G_{i2}^{FP})$ (where $t \in \{1,2\}$ denotes the first and second enrollment spells). Note that χ_{i2} may include G_{i1}^{j}, the realized graduation outcome at the sector j of the initial enrollment spell.

We would like to identify $\mathbb{E}[G_{i1}^{FP} - G_{i1}^{CC} \mid i \in I]$, the average sector effect on graduation rates for different populations I. Yet these are not identified from the observed graduation rates of transfer students without further assumptions. Denoting $\beta_i = G_{i1}^{FP} - G_{i1}^{CC}$ the for-profit sector effect for student i and $\Delta G_i = G_{i2} - G_{i1}$ their observed difference in graduation outcomes, for CC $\rightarrow$ FP students we have

$$\begin{aligned}
\Delta G_i &= G_{i2}^{FP} - G_{i1}^{CC} \\
&= (G_{i2}^{FP} - G_{i1}^{FP}) + (G_{i1}^{FP} - G_{i1}^{CC}) \\
&= (G_{i2}^{FP} - G_{i1}^{FP}) + \beta_i
\end{aligned}$$

and analogously among FP $\rightarrow$ CC students, $\Delta G_i = (G_{i2}^{CC} - G_{i1}^{CC}) - \beta_i$. Taking conditional

means,

$$\begin{aligned}\mathbb{E}[\Delta G_i \mid CC \to FP] - \mathbb{E}[\Delta G_i \mid FP \to CC] &= \mathbb{E}[\beta_i \mid CC \to FP] + \mathbb{E}[\beta_i \mid FP \to CC] \\ &= 2\mathbb{E}[\beta_i \mid FP \leftrightarrow CC],\end{aligned}$$

provided that switching effects are symmetric, i.e.,

$$\mathbb{E}[G_{i2}^{FP} - G_{i1}^{FP} \mid CC \to FP] = \mathbb{E}[G_{i2}^{CC} - G_{i1}^{CC} \mid FP \to CC]. \tag{A1}$$

The second equality requires either equal shares of switchers in each direction or that sector effects don't depend on the direction of transfer (where FP $\leftrightarrow$ CC denotes all switchers). Then the mean for-profit completion premium among switchers is identified:

$$\mathbb{E}[\beta_i \mid FP \leftrightarrow CC] = \frac{1}{2}\Big(\mathbb{E}[\Delta G_i \mid CC \to FP] - \mathbb{E}[\Delta G_i \mid FP \to CC]\Big) \equiv \beta.$$

This parameter is identified under the same assumptions from a regression of graduation outcomes on individual fixed effects, an indicator for the second enrollment spell, and a for-profit sector indicator.

A1 is a reasonable assumption if the graduation-relevant factors that change between enrollment spells — like accumulated skills, schooling preferences, and motivation — are shared by all the kinds of students who ultimately re-enroll in another sector and don't depend on the particular sequence of schooling choices. There are several reasons we might expect the direction of transfer to matter, however. For instance, for-profit schools may be more likely to accept CC transfer credits, which could disproportionately raise the second-spell graduation rates of CC $\to$ FP switchers. Alternatively, FP $\to$ CC students may benefit from beginning in the sector with weaker standards before transitioning to a more advanced public program.

To avoid making any symmetry assumptions, we can also bound the for-profit sector effect by restricting the sign of the switching effect. Note that G_{i1}^{j} and G_{i2}^{j} differ for two reasons. First, transitory student characteristics χ_{it} may evolve between enrollment spells due to accumulated schooling and possibly graduation during the prior spell, as well as changes in student skills, preferences, and information. The distributions of shocks ε_{i1} and ε_{i2} may also differ, as transfer students are a self-selected sample. Selection on the prior graduation outcome may therefore alter the observed distribution of ε_{i1}.

Both of these influences are likely to overstate the graduation rates of transfer students in their second enrollment spell. Even if it ended in dropout, an initial enrollment spell arguably would not reduce a student's accumulated skills and information about their ability,

preferences, and the details of college enrollment and course selection. Thus, changes in χ_{it} seem likely to favor graduation in the second spell. In addition, earning a degree in the first spell is likely to reduce rates of re-enrollment, particularly when restricting to students switching between degree programs of the same level. Therefore, we would expect switchers to be adversely selected on ε_{i1}, as students with negative initial graduation shocks will be over-represented. Together, these predictions would indicate

$$\mathbb{E}[G_{i2}^{CC} - G_{i1}^{CC} \mid FP \to CC] \geq 0. \tag{A2}$$

Under this sign restriction, we have

$$\begin{aligned}\mathbb{E}[\beta_i \mid FP \to CC] &= \mathbb{E}[(G_{i2}^{CC} - G_{i1}^{CC}) - \Delta G_i \mid FP \to CC] \\ &\geq \mathbb{E}[G_{i1} - G_{i2} \mid FP \to CC] \equiv \beta_{LB},\end{aligned}$$

providing a lower bound for the for-profit completion premium among FP $\to$ CC switchers.

Although A2 is not a testable restriction, notice that the average switching effect across both transfer directions is identified from

$$\begin{aligned}\gamma \equiv \frac{1}{2}\Big(\mathbb{E}[\Delta G_i \mid FP \to CC] + \mathbb{E}[\Delta G_i \mid CC \to FP]\Big) = \frac{1}{2}\Big(&\mathbb{E}[G_{i2}^{CC} - G_{i1}^{CC} \mid FP \to CC] \\ &+ \mathbb{E}[G_{i2}^{FP} - G_{i1}^{FP} \mid CC \to FP]\Big),\end{aligned}$$

provided that sector effects don't depend on the direction of transfer. The average switching effect γ can therefore shed light on the sign of the switching effect among FP $\to$ CC switchers, even if switching effects are not exactly symmetric.

Estimation In practice, I restrict attention to delayed transfers, omitting students who transferred between sectors without ceasing enrollment, as arguably the ultimate origin-sector graduation outcome is censored for those students who remain continuously enrolled. I will also show estimates when restricting attention to students who seek degrees of the same level and major in each sector, to avoid comparing graduation outcomes in degree programs of differing difficulty.

First, Table A1 shows sector-specific graduation rates $\bar{G}^j$, splitting switchers by the direction of transfer. In the full sample, for-profit graduation rates are 45–62 percentage points larger depending on the transfer direction. To ensure effects are not driven by switching across degree levels of varying difficulty, Panels B and C condition on students who enroll in the same degree programs in each sector. Here the for-profit premia among CC $\to$ FP remain significant, as these students are highly unlikely to have graduated from their original CC.

The for-profit premia among FP → CC switchers fall to 20 percentage points, as those who switch to the same degree program are much less likely to have graduated from their original college. These statistics make sense given the prediction that transfer students would face adverse first-spell graduation shocks and do relatively better at their second school. Yet despite the likely positive sign of the switching effect, FP → CC students remain substantially more likely to complete the same degree at for-profits.

Table A1: Completion Rates of Switchers

	$\bar{G}^{FP}$	$\bar{G}^{CC}$	$\bar{G}^{FP} - \bar{G}^{CC}$	# students
Panel A: Full sample				
CC → FP	0.66	0.04	0.62	8,219
	(0.01)	(0.002)	(0.006)	
FP → CC	0.59	0.14	0.45	6,039
	(0.01)	(0.004)	(0.008)	
Panel B: Same degree level				
CC → FP	0.65	0.03	0.62	2,119
	(0.01)	(0.004)	(0.01)	
FP → CC	0.37	0.17	0.20	1,745
	(0.01)	(0.01)	(0.01)	
Panel C: Same degree level × major				
CC → FP	0.67	0.02	0.65	417
	(0.02)	(0.007)	(0.02)	
FP → CC	0.39	0.17	0.21	321
	(0.03)	(0.02)	(0.03)	

Notes: Sector-specific graduation rates of students enrolling in both sectors at different times, who remained out of college for more than one year between spells. Standard errors in parentheses.

Table A2 shows resulting estimates for the parameters of interest, which identify or bound the for-profit sector effect on completion rates among transfer students. Assuming symmetric switching effects (A1), $\hat{\beta}$ is a consistent estimator of the for-profit sector effect across all switchers. I find large for-profit premia of more than 40 percentage points even among students switching within the same degree programs. Under non-negative switching effects (A2), $\hat{\beta}_{LB}$ is consistent for a conservative lower bound on the for-profit sector effect among FP → CC switchers. I find lower bounds of 20 percentage points or more across all samples. Finally, to judge the sign of switching effects across all switchers, $\hat{\gamma}$ consistently estimates this parameter provided that sector effects are equal across transfer directions. I find switching effects of between 9–22 percentage points depending on the sample. These are significant and positive, consistent with the earlier predictions and the identifying assumptions required for

the lower bound β_{LB}. Finally, in heterogeneity analysis I find that the ability gradients from this within-student analysis match the descriptive ability gradients in Figure 5, indicating that sector effects are indeed larger among low-ability students (Appendix Figure A9).

Table A2: Implied Sector and Switching Effects

	$\hat{\beta}$	$\hat{\beta}_{LB}$	$\hat{\gamma}$
Full sample	0.54	0.45	0.09
	(0.005)	(0.008)	(0.005)
Same degree level	0.41	0.20	0.21
	(0.009)	(0.01)	(0.009)
Same degree level × major	0.43	0.21	0.22
	(0.02)	(0.03)	(0.02)

Notes: β gives the for-profit sector effect under A1 (symmetric switching effects). β_{LB} bounds the for-profit sector effect under A2 (non-negative switching effects among FP $\rightarrow$ CC). γ gives the average switching effect across both transfer directions under symmetric sector effects. Standard errors in parentheses.

C CC Degree Pathways for FP/CC Marginal Students

Here I evaluate how for-profit students fare when they enroll in CCs, using the administrative transcript records from Texas for public colleges. Specifically, I estimate the mean potential outcomes at CCs for students on the FP/CC margin using the distance IVs. For a range of intermediate outcomes, I estimate $\mathbb{E}[Y_{CC} \mid \text{FP} - \text{CC complier wrt } Z_{FP}]$ and compare it to the average among CC students $\mathbb{E}[Y_{CC} \mid D_{CC} = 1]$ as a benchmark. This allows for a description of the unique barriers to degree completion that for-profit students face when they do enroll in public colleges.

Table A3 presents the mean CC potential outcome among marginal students, the mean among all CC students, and the difference between the two. CC students on the for-profit margin are significantly more likely to intend shorter Certificate degrees and pursue vocational majors. This is sensible given that for-profit colleges overwhelmingly specialize in vocational Certificates. At the same time, the fact that 30% of marginal students enter with a non-vocational major illustrates the option value with respect to field of study afforded by community colleges, as these students would have had to enroll in a vocational major had they attended a for-profit.

The remedial course-taking rates at CCs significantly understate the probability that for-profit students would have to take remediation. Fully 62% of marginal students would have to take remedial math, compared to just 45% of all CC students. Despite facing larger remedial requirements, marginal students are high-effort, taking an average of 13.5 semester credit hours (SCH) in their first term. This compares to an average of just 7.9 SCH among CC students, who are much more likely to enroll part-time. This fact also makes sense given that 90% of for-profit students enroll full-time, meaning they take at least 12 SCH per term. Strikingly, for-profit students earn first-term GPAs of just 1.93, compared to a 2.25 college average. This lies below the 2.0 threshold for academic probation at many CCs and shows that for-profit students do face significant academic challenges with the public curriculum.

Marginal students attempt an average of 63 credits total, more than the 60 credits required for most Associate's degrees. Yet they only pass 37 of those credits on average. By virtue of their full-time intensity, marginal students complete degrees at somewhat above-average rates of 41%.[37] And consistent with the idea that for-profit students are more sure of their intended programs of study, more than half of graduates earn their degree in their originally declared major — compared to less than a quarter of all CC students.

[37] Note that this differs from the 37% reported in Table 8 because transcript data is only available beginning in 2011, and the sample therefore differs.

Table A3: Degree Progression Outcomes at Community Colleges

	Mean among those on FP/CC margin	Mean among all CC students	Difference
Panel A: At entry			
Intent: Certificate	0.16	0.06	0.10
	(0.02)	(0.00)	(0.02)
Intent: Vocational major	0.70	0.37	0.33
	(0.03)	(0.00)	(0.03)
Remedial math	0.62	0.45	0.16
	(0.07)	(0.00)	(0.07)
Remedial reading	0.41	0.27	0.14
	(0.06)	(0.00)	(0.06)
Remedial writing	0.40	0.30	0.10
	(0.06)	(0.00)	(0.06)
First-term SCH	13.5	7.94	5.56
	(0.62)	(0.01)	(0.62)
First-term GPA	1.93	2.25	-0.32
	(0.16)	(0.00)	(0.16)
Panel B: Cumulative performance			
Total semesters	7.00	6.53	0.47
	(0.55)	(0.01)	(0.55)
Total SCH	63.2	36.4	26.80
	(4.47)	(0.04)	(4.47)
Total SCH passed	37.1	21.4	15.70
	(3.52)	(0.04)	(3.52)
Completion rate	0.41	0.32	0.09
	(0.06)	(0.00)	(0.06)
Completion in original major	0.21	0.07	0.14
	(0.04)	(0.00)	(0.04)

Notes: Community-college mean potential outcomes for students on the FP/CC margin identified from distance IVs. Sample includes all Texas public HS graduates between 2011–2012. Degree completion includes graduation with any degree within 7 years of first enrollment. Standard errors in parentheses.

D Constructing the Degree Requirements Dataset

Degree Requirements I assemble a new dataset of course requirements using an AI-assisted data collection and processing routine. These data allow for a detailed comparison of the academic requirements of for-profit and public versions of the same degree program. I begin by defining the sampling frame: all sub-baccalaureate vocational programs at two-year for-profit and public colleges in Texas, matching the college sample used in the individual-level analyses. This program set is identified using IPEDS program-level completions as of 2024, where programs consist of college–major–credential-level combinations, using for majors the most granular six-digit CIP classification. I exclude the least prevalent for-profit fields by restricting the sampling frame to the 50 six-digit CIP fields with the most for-profit completions nationally. A total of 1,481 programs across 100 colleges meet these criteria in Texas, comprising 1,275 public programs and 206 for-profit programs. These fields cover 88.8% of for-profit vocational completions and 55.3% of public vocational completions at two-year Texas colleges (Table A4).

I divide the data assembly into two stages: source collection and requirement extraction. Separating the data assembly in this way improves replicability, as collected internet sources are frozen before their contents are evaluated. Collection is organized around 78 online catalogs, less than the 100 colleges in the sample since a single official catalog often governs multiple campuses within a public system or for-profit chain. The online source-collection protocol searches for official records that identify each credential and define its course requirements. In descending order of priority, these include the institution's current catalog and catalog archive; official program indexes, degree plans, handbooks, and course-description repositories; consumer-information and disclosure pages; older official institutional materials; and, where necessary, data retrieved from dynamic catalog systems or their underlying application interfaces. Program-level records from the Texas Higher Education Coordinating Board and Texas Workforce Commission are used to corroborate program names, credential levels, and campus coverage. This AI-assisted source-collection routine was implemented through Codex using GPT-5.6 Sol. For every successfully collected source, I preserve the original PDF or HTML material and then produce a searchable text version where feasible. This initial source-collection step identifies sources for 1,304 of the 1,481 programs, representing 90.2% of completions. This includes 97.1% of programs and 99.3% of completions in the for-profit sector and 86.6% of programs and 87.5% of completions at community colleges.

Data extraction then proceeds in several steps. Taking each college catalog in turn, I first tabulate the full set of credentials declared in its sources. I then jointly match these credentials to the college's IPEDS program records by comparing the official program name,

Table A4: Degree-Requirement Coverage

	All	For-profit	Public
Panel A: Program coverage (%)			
Target frame among all vocational programs	40.2	71.3	37.6
Complete requirements within target frame	72.8	90.8	69.9
Panel B: Completion coverage (%)			
Target frame among all vocational programs	60.6	88.8	55.3
Complete requirements within target frame	86.1	95.4	83.3

Notes: The full vocational universe includes all sub-baccalaureate vocational programs at two-year public and for-profit colleges in Texas identified in 2024 IPEDS data. The target frame restricts this universe to programs in the 50 six-digit CIP fields with the most for-profit completions nationally. Complete requirements require a credible credential match, a published credit total, a complete required-course list, and sufficient course information to apply the academic classifications.

credential level, and six-digit CIP field or field description. College-wide assignment reduces the risk that a certificate will be matched to an Associate's program or that the same credential will be wrongly assigned to multiple distinct IPEDS programs. Where a source credential could not be confidently paired with an IPEDS program, the program was left missing.

For each matched program, I next run an extraction routine that reads the program's matched source material, records its total required credits, and constructs a complete list of required courses and elective slots with their corresponding credit or contact-hour amounts.[38] Prerequisite courses, and whether they count toward the credit total, are also documented separately. Remedial requirements are excluded, as these largely follow a state-wide schedule.[39] Course codes, titles, units, elective rules, and source references are stored in an auxiliary course-level dataset. I also store course descriptions where available, for use in later course classification. A single curriculum can be linked to multiple IPEDS programs when the official source establishes that it applies across multiple campuses. Conversely, one IPEDS program can receive multiple curricular records when the official source shows versions with different total-credit, total-contact-hour, or academic-credit burdens. This occurs for 128 programs, or 8.6% of the sampling frame; in these cases, IPEDS completions are divided equally across the distinct curricula. Requirement extraction proceeds in two passes: the first applies a common routine across all catalogs, while the second revisits catalogs with

[38] Semester credits are retained as reported, while quarter credits are divided by 1.5 and contact hours by 16 to place credits in common semester-based units.

[39] At public colleges, shorter "Level 1" certificates are generally exempt, while longer "Level 2 certificates" and Associate's programs are subject to the Texas Success Initiative (TSI) remedial requirements.

limited coverage, collecting and freezing additional sources where needed and reconsidering the affected catalogs with source-specific routines. After the second pass, complete, matched requirements are available for 72.8% of programs and 86.1% of completions, including 95.4% of for-profit and 83.3% of community-college completions.

I next classify each course into one of nine categories: mathematics or statistics, natural or health science, writing or English, speech or communication, social science or humanities, occupational or technical coursework, clinical or externship instruction, orientation or academic support, and other nonacademic coursework. Academic credits are then defined according to two levels of generality. Under a conservative definition, a course is academic only when the institution designates it as general education or core curriculum, or when it teaches general content outside the program's occupational domain. Under the broader definition, any standalone course in mathematics, science, English or writing, communication, or social science or humanities is academic, even when it may be particularly relevant to the occupation (e.g., an Anatomy and Physiology course in a vocational nursing program). For elective menus, I count only the minimum number of courses and credits required by the published rule rather than treating every available option as required. The main analysis sample requires a full extracted curriculum with non-missing total credit amounts and academic-credit shares. This sample contains 1,069 programs representing 84.7% of completions in the sampling frame. It covers 87.4% of for-profit programs and 90.5% of for-profit completions, together with 69.7% of public programs and 82.9% of public completions.

Sample Statistics Table A5 presents average program requirements at two-year for-profit and public colleges in Texas. Semester-credit requirements are available for programs representing 90.5% of for-profit completions and 82.9% of public-college completions. To account for differential missingness across fields of study, I calculate each sector's completion-weighted means within two-digit CIP fields and then take weighted means across fields according to their representation in the full Texas distribution of completions. Columns (1) and (2) weight according to each sector's own major distribution, while Column (3) weights the public sample according to the for-profit distribution of two-digit CIP majors.

Under the relatively conservative definition of academic coursework, certificate programs require little academic content in either sector: academic courses account for 0.8% of for-profit requirements and 2.5% of public requirements, rising to 4.2% when public programs are reweighted to the for-profit major distribution. Under the broad definition, which also counts standalone academic courses particularly relevant to an occupation, the corresponding shares are 12.7%, 3.9%, and 8.8%. This difference is driven in part by standalone health-science coursework in for-profit certificate programs.

Associate's programs require substantially greater academic coursework in the public

Table A5: Degree Requirements at Two-Year College Programs

	For-profit	Public	
	(1)	(2)	(3)
Panel A: Certificate programs			
Total credits	38.1	28.0	31.8
Academic credits, conservative	0.4	0.8	1.4
Academic share, conservative (%)	0.8	2.5	4.2
Academic credits, broad	5.2	1.2	3.0
Academic share, broad (%)	12.7	3.9	8.8
Number of programs	129	484	484
Share of completions (%)	89.1	83.7	83.7
Panel B: Associate's programs			
Total credits	69.1	61.3	60.9
Academic credits, conservative	6.4	19.2	15.1
Academic share, conservative (%)	9.1	31.3	24.7
Academic credits, broad	9.0	23.7	17.6
Academic share, broad (%)	12.4	38.7	28.7
Number of programs	51	405	405
Share of completions (%)	95.7	82.0	82.0
Major distribution	For-profit	Public	For-profit

Notes: Sample includes all matched programs in the 2024 Texas vocational-program sampling frame. All statistics weighted by the program's share of completions. To account for differential missingness across fields of study, I calculate each sector's completion-weighted means within two-digit CIP fields and then average across fields using the full Texas completion distribution indicated in the final row. Column (3) therefore estimates public-program requirements under the for-profit completion distribution. Under the conservative academic-course classifier, academic credits consist of institutionally designated general-education or core courses and general coursework outside the program's occupational domain. The broad definition also includes standalone academic-subject courses even when they may be particularly relevant to the vocation.

sector under either definition. Under the relatively conservative classification, 31.3% of public requirements are academic, compared with 9.1% at for-profits; reweighting public programs to the for-profit major distribution reduces the public share to 24.7%. Under the broader definition, the corresponding shares are 38.7%, 12.4%, and 28.7%. Reweighting therefore narrows but does not eliminate the public–for-profit difference: the public academic share remains approximately 16 percentage points higher under either definition. For-profit Associate's programs nevertheless require more total credits, averaging 69.1 credits compared with approximately 61 credits in the public sector.

E Additional Transcript Evidence

Curricular Differences For-profit students take a substantially narrower set of courses than observably similar public-college students. Figure A1 shows remedial and out-of-major academic course-taking probabilities by sector in the same style as in Figure 3, restricting to students in vocational Associate programs. While for-profit students rarely take remedial courses, nearly 40% of public Associate's students enroll in some form of remediation, with math being the most common. Rather than a student choice, remediation at community colleges is generally the result of tracking policies which sort students into remedial courses who fail to meet academic requirements for enrolling in college-level courses. Remediation is therefore a type of academic standard which can directly lengthen the time-to-degree. Of course, remediation may also improve future course-passing rates for academically under-prepared students, though several evaluations of its effects on marginal students indicate minimal and sometimes negative effects on future performance (Martorell and McFarlin 2011; Scott-Clayton and Rodriguez 2015). Regardless of its effects, higher rates of remediation for academically similar students suggest that public degree requirements are more demanding in this dimension — either due to the remediation itself, or because of the more advanced coursework it leads to.[40]

Course-taking patterns also differ in breadth, as public-college students are more likely to take courses outside their major. Figure A1 also plots the share of students taking each of several subjects, restricting in each case to students who are not majoring in the given subject. For-profit students are less likely than comparable public-college students to take out-of-major courses in humanities, social science, statistics, and foreign languages. These differences likely reflect both differences in degree requirements and course supply. Non-major courses in humanities and social science, for instance, often form part of community colleges' general-education curriculum. And some for-profit colleges may not offer academic coursework in these subjects, given that they almost exclusively offer a handful of vocational majors.

Narrower for-profit courses of study are also evident in students' course credits. Among Associate's students intending a CTE major, public students take only 43.5% of their total credits in CTE courses, compared to 74.5% among for-profit students.[41] For-profit course-

[40] One might worry that the remedial label is a distinction without a difference — for-profits may require the same courses but choose to brand them differently. However, community colleges often do not award college credits for remedial courses, meaning that remediation increases the number of courses required for the degree, and there exists complementary case-study evidence that for-profit colleges do not require the same kinds of multi-step general-education coursework typical of community colleges (Bailey, Badway and Gumport 2001).

[41] The transcript data only provide the total CTE credits attempted anywhere through 2017, not solely at

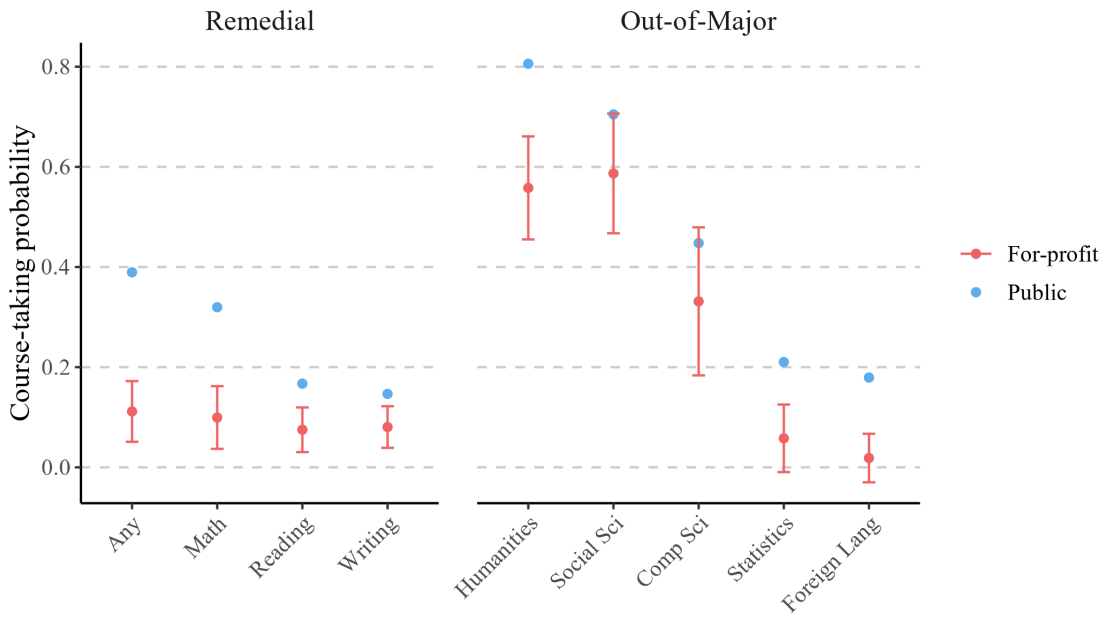


Figure A1: Out-of-Major Course-Taking

Notes: Estimates from BPS 12/17. Sample includes all students in the transcript sample who enroll in a two-year or less-than-two-year college and initially intend a CTE major at the Associate's level. Plotted are shares of students taking each subject at any point through 2017, among those whose intended major does not fall within that subject. Also see notes for Figure 3.

taking patterns are therefore more focused, both due to reduced out-of-major course-taking as well as substantially greater enrollment intensity in vocation-oriented courses. This comes at the expense of the academic coursework more likely to be required at community colleges, including remedial and general-education courses.

Grading Differences Also relevant for students' ability to graduate is their academic performance in their chosen courses. Colleges set their academic standards in part through their choice of course grade distributions and passing standards. To measure differences in grading standards, we would ideally compare how different colleges evaluate students achieving the same level of academic performance. Though the survey data do not contain objective measures of academic performance, we can compare students who enter college with observably similar levels of academic ability and preparedness. These characteristics proxy for students' baseline academic potential, which colleges then grow according to their value added. Conditional on pre-college ability, then, awarded grades may reflect both real growth

the first institution. Since transfer students may be more likely to pursue academic coursework, I use total credits at the first institution for the denominator of the CTE credit shares. Instead using the total credits attempted anywhere through 2017, the CTE shares become 30.2% and 64.8% for public and for-profit students, respectively. These differences in CTE shares are nearly identical when controlling for student characteristics.

in academic achievement (value added) and the college's subjective grading standards.

Table A6 shows that academically similar students at for-profit colleges indeed earn significantly higher grades. Adjusting for student characteristics at entry, for-profit Associate's students earn cumulative GPAs 0.47 points higher on average, while the for-profit premium among certificate students is more muted (and not statistically different from zero). Still, for-profits tend to shift students from Associate's into certificate programs (Table 5), where grades are higher across the board. Interestingly, while Associate's students' GPAs are 0.47 points higher at for-profits overall, Table A6 also shows that this gap falls to 0.16 within CTE courses (among students majoring in a CTE field). Given that for-profit students take much less academic coursework, part of the for-profit GPA premium simply comes from the narrower vocational focus of their degree programs. To quantify this channel, I next decompose the overall for-profit GPA premium into a part owing to different academic intensities and a residual part owing to different within-subject grading standards.

Table A6: Grading Standards by Sector

	Public mean	For-profit premium	
		Unadjusted	With controls
Panel A: Certificate students			
Cumulative GPA	2.717	0.178	0.125
		(0.110)	(0.097)
Cumulative GPA in CTE courses	2.891	0.118	0.063
		(0.119)	(0.121)
Panel B: Associate's students			
Cumulative GPA	2.501	0.347	0.468
		(0.085)	(0.098)
Cumulative GPA in CTE courses	2.829	0.041	0.157
		(0.078)	(0.096)

Notes: Estimates from BPS 12/17. Sample includes all students in the transcript sample who enroll in a two-year or less-than-two-year college and initially intend a CTE major. Also see notes for Table 2.

Decomposing GPA Differences: Curriculum vs. Within-Subject Grading Let the grades for student i in course c at college $j \in \{CC, FP\}$ be determined according to

$$GPA_{icj} = \beta_{0j} + \beta_{1j} A_{ic} + \varepsilon_{icj}$$

where A_{ic} is an indicator for academic (non-CTE) courses. The overall GPA premium

$\Delta\overline{GPA} \equiv \overline{GPA}_{FP} - \overline{GPA}_{CC}$ can be re-written according to the Oaxaca-Blinder decomposition, taking the public grade schedule as the reference case:

$$\begin{aligned}\Delta\overline{GPA} &= \underbrace{(\bar{A}_{CC} - \bar{A}_{FP})(-\beta_{1,CC})}_{\text{different course mix}} + \underbrace{(\beta_{0,FP} - \beta_{0,CC}) + \bar{A}_{FP}(\beta_{1,FP} - \beta_{1,CC})}_{\text{within-subject GPA gaps}} \\ &= \underbrace{(\bar{A}_{CC} - \bar{A}_{FP})(-\beta_{1,CC})}_{\text{different course mix}} + \underbrace{\bar{A}_{FP}\Delta\overline{GPA}_{A}}_{\text{academic GPA gap}} + \underbrace{(1 - \bar{A}_{FP})\Delta\overline{GPA}_{CTE}}_{\text{CTE GPA gap}}\end{aligned}$$

where $\Delta\overline{GPA}_A = (\beta_{0,FP} + \beta_{1,FP}) - (\beta_{0,CC} + \beta_{1,CC})$ and $\Delta\overline{GPA}_{CTE} = \beta_{0,FP} - \beta_{0,CC}$ represent the within-subject GPA gaps. The first term expresses how much a reduction in the academic intensity of the CC curriculum down to the for-profit level would increase grades, holding fixed the public grading schedule. The next two terms capture differences in for-profit grading within each type of course — after accounting for how the course mix changes, for-profit grades are higher still owing to the residual within-subject GPA gaps.

I next estimate these components of the for-profit GPA premium, controlling for student characteristics. Again, the overall GPA premium is 0.47 GPA points. The for-profit GPA premium within CTE courses is $\Delta\overline{GPA}_{CTE} = 0.16$, and the academic premium is $\Delta\overline{GPA}_A = 0.67$. The selection-corrected academic share of for-profit credits is $\bar{A}_{FP} = 0.30$, compared to $\bar{A}_{CC} = 0.57$ among public students. Thus, the course-composition effect totals 0.16 GPA points — reduced academic intensity alone explains 34% of the overall premium. Different within-subject grades account for the remainder of the gap, with the academic-course component totaling 0.20 GPA points and the CTE-course component totaling 0.11 GPA points, for 42.5% and 23.5% of the GPA premium, respectively.

Academic Confidence at Entry Beyond transcript outcomes, for-profit students also report higher academic confidence at entry, despite generally entering college with lesser academic preparation. Figure A2 shows that, conditional on observables, for-profit students in both degree levels are significantly more likely to anticipate academic success than CC students. Together with the transcript evidence, these facts show that for-profit students both expect and achieve higher academic performance than their CC peers, perhaps due to relaxed grading standards. Awareness of weaker academic requirements at entry may also influence student sorting, particularly among academically under-prepared students.

Ability Gradients in the National Data Figure A3 shows that, controlling for rich pre-college characteristics, for-profit graduation rates do not significantly vary with HS GPA, while CC students with HS GPAs of 3 or more are 30% more likely to graduate than those with GPAs below 3 ($p < 0.001$). Beyond degree attainment, the BPS also includes students' self-reported satisfaction with their college choices and perceived return on invest-

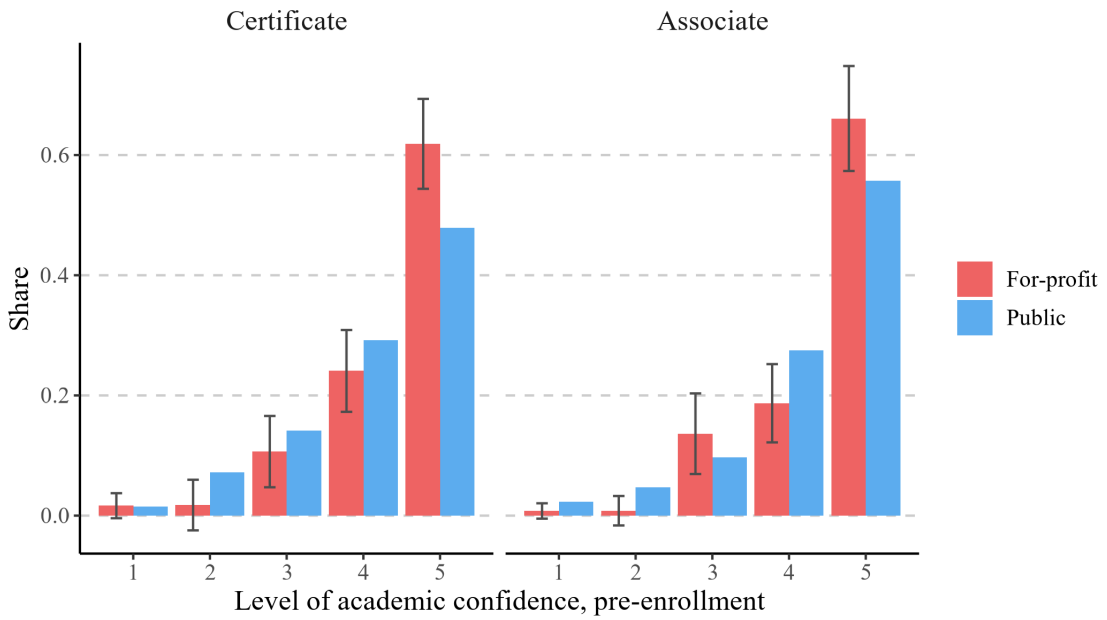


Figure A2: Academic Confidence at Entry

Notes: Estimates from BPS 12/17. Students indicated their agreement on a 1-5 scale with the statement, "Before I attended my first institution, I was confident I had the ability to succeed there as a student." Also see notes for Figure 3.

ment. While prior work has documented that for-profit students report significantly lower satisfaction with their schooling choices, Figure A3 shows that this pattern is concentrated among academically better-prepared students. Under-achieving students — those with HS GPAs below 2 — report similar rates of satisfaction with for-profit and community college quality and are equally likely to view for-profit and community college as worth the cost.

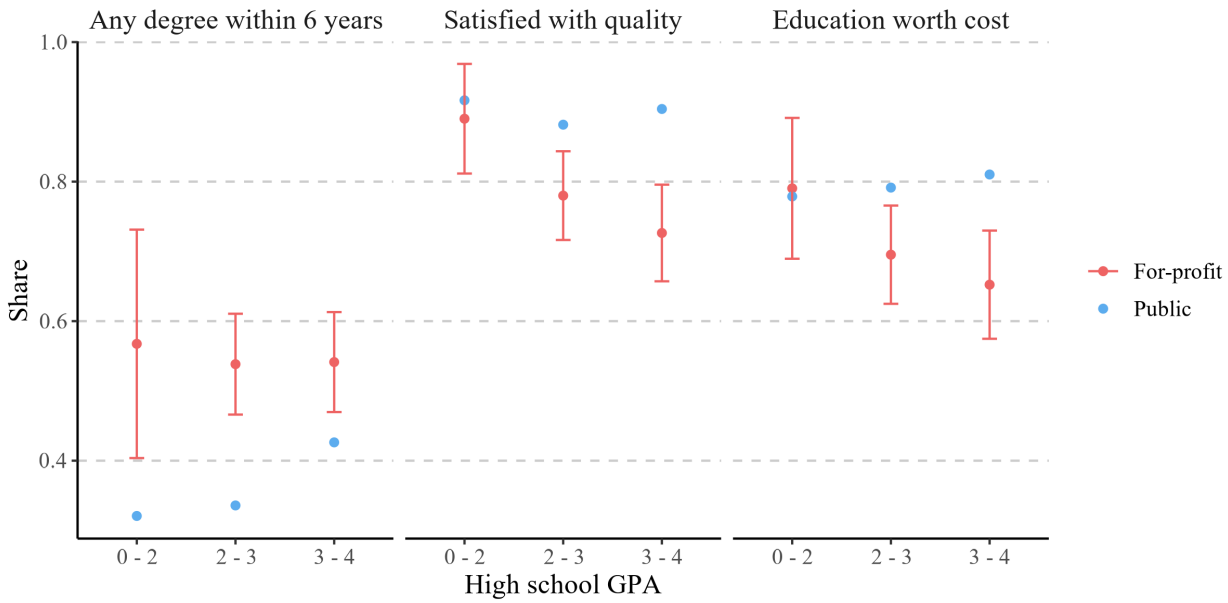


Figure A3: Relative Success by Academic Preparedness

Notes: Estimates from BPS 04/09. Sample pools students beginning college in Certificate and Associate programs at two-year and less-than-two-year colleges. High-school GPA is self-reported and binned. Satisfaction with college quality and the student's belief that their education was worth the cost were measured in a survey 6 years after initial enrollment. Blue dots represent sample proportions among public students. Red dots are selection-corrected means for for-profit students — that is, they add the for-profit coefficient from a regression with controls (where public is the omitted group) to the public mean. Controls include income percentile rank, total income by dependency status, whether parents own more than $10,000 in investments or businesses, dependency status, highest level of HS math, years of HS math, years of HS science, HS GPA, family size, father's and mother's highest education level, parents' marital status, gender, ethnicity, index of high-school dropout risk, and single parenthood. Error bars represent 90% confidence intervals.

F Public Technical Colleges

A small subset of two-year public colleges resembles two-year for-profit colleges in key dimensions. These public technical colleges specialize in the same short vocational programs offered by for-profits, and they achieve similar graduation rates. I identify these public technical colleges in IPEDS as the 279 schools which offer exclusively vocational programs of study; this definition overlaps substantially with the set of non-degree-granting, less-than-2-year public colleges.

Table A7 documents how these colleges compare to two-year for-profits and traditional public two-years. For-profits and technical publics are much more similar to one another than to traditional community colleges. They have similarly small enrollment, high full-time enrollment shares, and limited offerings of online, remedial, and four-year programming. They generally do not provide room and board services, and they rarely operate on traditional semester-based academic calendars. Consistent with their smaller size, for-profit and technical public colleges offer a much narrower set of degree programs and majors. As for outcomes, graduation rates at both for-profit and technical public colleges are nearly twice as high as those of traditional public colleges. Meanwhile, they provide significantly less four-year option value than traditional public colleges — only 1-2% of students transfer from these vocational schools, compared to 15% at traditional publics.

To achieve those higher graduation rates, technical public colleges spend significantly more than for-profit colleges. Their instructional spending per FTE student is nearly 2.5 times that of for-profits. Total spending per FTE student at technical and traditional public colleges is similar, and about 70% higher than for-profit spending. And while sticker prices at technical public colleges are about twice as high as traditional public tuition, for-profits are significantly more expensive than all public colleges.

Table A7: Two-Year College Characteristics

	For-Profit	Technical Public	Traditional Public
Total FTE enrollment	345	306	3,748
First-time enrollment	172	176	1,366
Full-time share	0.850	0.700	0.320
Offers part-time	0.480	0.640	1
% fully online	0.030	0.020	0.280
% partly online	0.130	0.020	0.270
Offers online courses	0.250	0.130	0.960
Offers online programs	0.080	0.090	0.780
Offers non-credit remediation	0.010	0.200	0.560
Offers Bachelor's programs	0.060	0.010	0.200
Offers dormitories	0.010	0.030	0.270
Offers meals	0	0.020	0.230
Continuous calendar	0.590	0.220	0.020
Semester calendar	0.050	0.120	0.890
Revenue per FTE	14,845	23,212	24,754
Total spending per FTE	12,939	22,437	21,938
Teaching spending per FTE	5,065	12,711	8,132
Services spending per FTE	2,594	3,061	4,482
Tuition	17,774	9,652	4,147
Graduation rate	0.670	0.720	0.350
Transfer rate	0.010	0.020	0.150
# programs	4.900	15.160	78.130
# majors	1.650	5.030	17.550
Number of colleges	2043	279	1026

G An Equilibrium Model of Academic Standards

This section develops a model in which a subsidized public sector competes with for-profit colleges for students of heterogeneous ability. For-profit colleges choose tuition and curricular intensity and enter until profits are driven to zero. The model rationalizes the relatively low academic standards of for-profit colleges as an equilibrium response to the students they serve. It also shows that public tuition subsidies distort student sorting by drawing some students into the steeper public curriculum even though they would generate greater surplus in the for-profit sector.

G.1 Environment

A unit mass of students has ability A_i distributed uniformly on $[0, 1]$, with mean $\bar{A} = 1/2$. Each student enrolls in either a public community college (CC) or one of N horizontally differentiated for-profit (FP) colleges. Value added in the public sector is

$$v_{\text{CC}}(A_i) = \bar{v}_{\text{CC}} + \beta_{\text{CC}}(A_i - \bar{A}), \qquad \beta_{\text{CC}} > 0. \tag{4}$$

The public sector has constant marginal cost c_{CC} and charges tuition t_{CC}. The per-student public subsidy is therefore

$$s \equiv c_{\text{CC}} - t_{\text{CC}} > 0. \tag{5}$$

Each for-profit college has average instructional quality $\bar{v}_{\text{FP}}$ and chooses the slope of its value-added schedule, $\beta_{\text{FP}} \in [\beta_{\min}, \bar{\beta})$:

$$v_{\text{FP}}(A_i; \beta_{\text{FP}}) = \bar{v}_{\text{FP}} + \beta_{\text{FP}}(A_i - \bar{A}), \qquad \bar{\beta} < \beta_{\text{CC}}. \tag{6}$$

Changing β_{FP} is thus a mean-preserving rotation of the curriculum. A higher β_{FP} raises value added for students above mean ability and lowers it for students below mean ability. The restriction $\bar{\beta} < \beta_{\text{CC}}$ captures the public sector's comparative advantage in providing a steeper, more traditional academic curriculum. For-profit colleges have constant marginal cost c_{FP} and fixed cost $F > 0$.

Horizontal differentiation gives a student who selects the for-profit sector an expected option value $\Gamma(N)$ from choosing among N varieties. This term increases the level of utility from the sector but does not vary with ability. A student therefore chooses the for-profit sector when

$$v_{\text{FP}}(A_i; \beta_{\text{FP}}) - t_{\text{FP}} + \Gamma(N) \geq v_{\text{CC}}(A_i) - t_{\text{CC}}. \tag{7}$$

Because the public value-added schedule is steeper, students sort across sectors at a single

cutoff:

$$A^* = \bar{A} + \frac{(\bar{v}_{\text{FP}} + \Gamma(N) - t_{\text{FP}}) - (\bar{v}_{\text{CC}} - t_{\text{CC}})}{\beta_{\text{CC}} - \beta_{\text{FP}}}. \tag{8}$$

Students with $A_i < A^*$ choose the for-profit sector, while students with $A_i > A^*$ choose the public sector. Hence aggregate for-profit enrollment is $D_{\text{FP}} = A^*$, and each symmetric for-profit college enrolls $d(t_{\text{FP}}; N) = A^*/N$. Here d denotes the smooth, downward-sloping residual demand facing an individual college.

G.2 Equilibrium

An active for-profit college chooses tuition and academic standards to maximize

$$\pi(t, \beta_{\text{FP}}) = (t - c_{\text{FP}})d(t, \beta_{\text{FP}}; N) - F. \tag{9}$$

Suppose the public subsidy is sufficiently large that the for-profit sector's relevant customer base lies weakly below mean ability. In particular, at the candidate symmetric equilibrium with $\beta_{\text{FP}} = \beta_{\min}$,

$$\bar{v}_{\text{CC}} - t_{\text{CC}} \geq \bar{v}_{\text{FP}} + \Gamma(N) - t_{\text{FP}}, \tag{10}$$

so that $A^* \leq \bar{A}$. This restriction captures a setting in which the low tuition charged by the public sector makes it privately attractive even to some students below mean ability.

Proposition 1 (Low-standards equilibrium)**.** *Under condition (10), and provided the students a firm can profitably attract remain below $\bar{A}$, for-profit colleges choose the lowest feasible curricular intensity in a symmetric equilibrium: $\beta^*_{\text{FP}} = \beta_{\min}$.*

Proof. Raising β_{FP} rotates a college's value-added schedule around $\bar{A}$. It therefore lowers the value offered to every student in the relevant for-profit market, all of whom have $A_i \leq \bar{A}$. The deviation makes the college less attractive both relative to other for-profit colleges and relative to the public sector. Its residual demand consequently falls at any relevant tuition. Because the college can choose its optimal tuition after selecting standards, its maximized profit is weakly decreasing in β_{FP} and is maximized at $\beta_{\min}$. □

The remainder of the equilibrium follows from the usual conditions for monopolistic

competition and free entry. In a symmetric free-entry equilibrium, $(\beta^*_{\text{FP}}, t^*_{\text{FP}}, N^*, A^*)$ solves

$$\beta^*_{\text{FP}} = \beta_{\min}, \tag{11}$$

$$d(t^*_{\text{FP}}; N^*) + (t^*_{\text{FP}} - c_{\text{FP}}) d_t(t^*_{\text{FP}}; N^*) = 0, \tag{12}$$

$$(t^*_{\text{FP}} - c_{\text{FP}}) d(t^*_{\text{FP}}; N^*) = F, \tag{13}$$

$$d(t^*_{\text{FP}}; N^*) = \frac{A^*}{N^*}, \tag{14}$$

where the cutoff A^* is given by equation (8) evaluated at $(\beta_{\min}, t^*_{\text{FP}}, N^*)$. Equation (12) is the standard markup condition, equation (13) determines entry, and equation (14) clears the market. Together these conditions characterize the equilibrium. Defining the equilibrium markup as $\mu \equiv t^*_{\text{FP}} - c_{\text{FP}} > 0$, free entry also implies

$$t^*_{\text{FP}} = c_{\text{FP}} + \frac{F}{d(t^*_{\text{FP}}; N^*)} = c_{\text{FP}} + \frac{N^* F}{D_{\text{FP}}}. \tag{15}$$

Thus for-profit tuition equals average cost: the positive markup over marginal cost covers fixed costs, while entry dissipates profits.

G.3 Efficient Sorting and the Tuition Wedge

Holding the for-profit market structure fixed, an efficient assignment compares value added net of real resource costs rather than tuition. The efficient cutoff is therefore

$$A^\dagger = \bar{A} + \frac{(\bar{v}_{\text{FP}} + \Gamma(N^*) - c_{\text{FP}}) - (\bar{v}_{\text{CC}} - c_{\text{CC}})}{\beta_{\text{CC}} - \beta_{\min}}. \tag{16}$$

Students below $A^\dagger$ are more efficiently served by the for-profit sector, while those above it are more efficiently served by the public sector. Comparing equations (8) and (16) yields

$$A^* - A^\dagger = -\frac{s + \mu}{\beta_{\text{CC}} - \beta_{\min}} < 0. \tag{17}$$

The public subsidy makes community college privately cheaper than its resource cost by s, while the for-profit markup makes for-profit college privately more expensive than its marginal resource cost by μ. The two wedges work in the same direction. As a result, students with $A_i \in (A^*, A^\dagger)$ attend community college even though the for-profit sector would generate greater surplus for them.

Proposition 2 (Misallocation and deadweight loss)**.** *The equilibrium assigns too few stu-*

dents to the for-profit sector. The resulting deadweight loss is

$$\text{DWL} = \frac{\beta_{\text{CC}} - \beta_{\min}}{2}(A^\dagger - A^*)^2 = \frac{(s+\mu)^2}{2(\beta_{\text{CC}} - \beta_{\min})}. \tag{18}$$

Proof. For a misallocated student of ability A_i, the surplus advantage of the for-profit sector is

$$\left[v_{\text{FP}}(A_i; \beta_{\min}) + \Gamma(N^*) - c_{\text{FP}}\right] - \left[v_{\text{CC}}(A_i) - c_{\text{CC}}\right] = (\beta_{\text{CC}} - \beta_{\min})(A^\dagger - A_i).$$

Integrating this expression from A^* to $A^\dagger$ gives the first equality in (18); substituting equation (17) gives the second. □

The efficient policy closes the full relative price wedge directly. If the public subsidy remains s and a subsidy s_{FP} reduces the price paid by a for-profit student to $t^*_{\text{FP}} - s_{\text{FP}}$, the decentralized and efficient cutoffs coincide when

$$s^*_{\text{FP}} = s + \mu. \tag{19}$$

The efficient for-profit subsidy equals the public subsidy plus the for-profit markup: s eliminates the differential subsidy across sectors, while μ closes the remaining gap between for-profit tuition and marginal resource cost. This calculation holds the for-profit price and market structure fixed; allowing firms or entry to respond would additionally require accounting for subsidy pass-through and entry.

G.4 Illustration

Figure A4 illustrates the decentralized and efficient allocations for one set of parameters. The equilibrium for-profit enrollment D_{FP} lies below efficient enrollment $D^\dagger_{\text{FP}}$. The gray triangle is the welfare loss from assigning the students between the two cutoffs to the public sector.

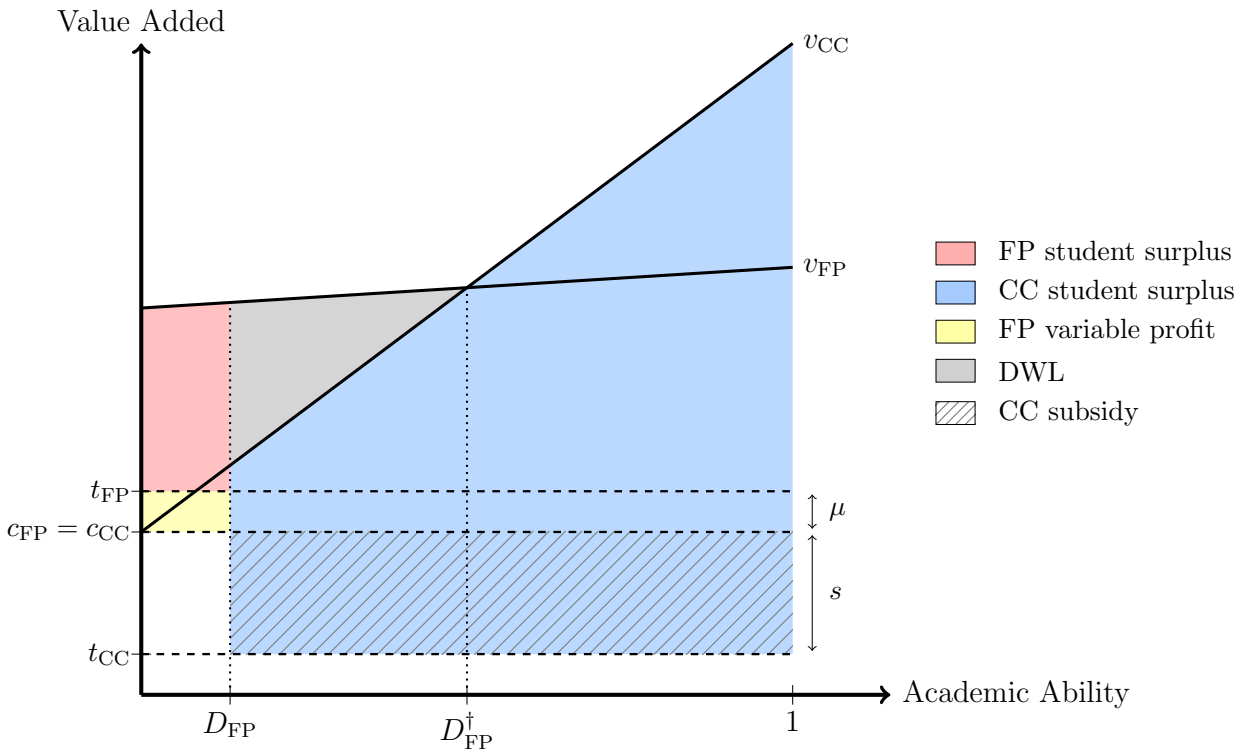


Figure A4: The Decentralized Equilibrium and Efficient Sorting

H Additional Details on MVPF Estimation

Pass-Through Estimation In Section 6 I present MVPF results in the case of two theoretical pass-through benchmarks, perfectly elastic long-run supply ($\kappa = 0$) and no-entry price-setting under linear demand ($\kappa = 0.5$). Here I supplement these benchmarks with pass-through estimates. Rather than assuming linear demand as in the latter example, I now use my estimated demand model in conjunction with the Bertrand competition model to identify equilibrium pass-through rates under a for-profit subsidy.

Hold fixed the set of colleges and their non-price characteristics, and suppose each for-profit firm operates at constant marginal cost c_j. Let p_j denote the total per-student tuition revenue received by college j, including outside grants g_j. Then under a subsidy amount z, students face net price

$$t_j(z) = p_j(z) - g_j - z.$$

Before any tuition response, net tuition therefore falls dollar-for-dollar with the subsidy. Non-profit tuition prices are held fixed throughout.

Write $s_j(\mathbf{t}) = \mathbb{E}[s_{ij}(\mathbf{t})]$ for college j's enrollment share. Holding competitors' net tuition fixed, the demand model yields demand derivatives

$$\begin{aligned} s_j' &\equiv \frac{\partial s_j}{\partial t_j} = \mathbb{E}[\alpha_i s_{ij}(1 - s_{ij})], \\ s_j'' &\equiv \frac{\partial^2 s_j}{\partial t_j^2} = \mathbb{E}[\alpha_i^2 s_{ij}(1 - s_{ij})(1 - 2s_{ij})], \end{aligned}$$

where $\alpha_i \equiv \bar{\alpha}_t + \alpha_t(A_i, X_i) < 0$ are the individual-specific price coefficients. The first-order condition for profit maximization is

$$s_j + (p_j - c_j)s_j' = 0.$$

The implied best-response functions can then be evaluated under a small for-profit subsidy. Holding competitors' prices fixed, differentiating the first-order condition gives pass-through rate

$$\kappa_j^{\text{BR}} \equiv \left.\frac{\partial p_j^*(z)}{\partial z}\right|_{z=0} = \frac{1 - C_j}{2 - C_j}, \qquad C_j \equiv \frac{s_j s_j''}{(s_j')^2}.$$

Linear residual demand corresponds to $C_j = 0$, giving $\kappa_j^{\text{BR}} = 1/2$. Locally log-convex residual demand has $C_j > 1$; when $1 < C_j < 2$,[42] college j optimally *reduces* its posted tuition under the subsidy, leading net tuition to fall by more than the subsidy amount. Indeed, my demand

[42] The second-order condition requires $C_j < 2$ at the optimum.

model estimates imply demand curvature consistent with negative κ_j^{BR} for most for-profits.

I then solve for the new equilibrium prices under a common for-profit subsidy z. Letting $\boldsymbol{\Psi}(\mathbf{p}, z)$ denote the stacked first-order conditions from above, equilibrium pass-through is given by

$$\boldsymbol{\kappa}^{\text{EQ}} = -\left(\frac{\partial \boldsymbol{\Psi}}{\partial \mathbf{p}}\right)^{-1} \frac{\partial \boldsymbol{\Psi}}{\partial z},$$

evaluated at $(\mathbf{p}^0, 0)$. I solve for this new equilibrium, finding pass-through estimates ranging from -0.35 to 0.10 across for-profit colleges. Again, the predominantly negative pass-through estimates owe to log-convex demand. These results indicate that the $\kappa = 0$ benchmark corresponding to perfectly elastic supply is in fact plausible, even without allowing for entry. Pass-through of $\kappa = 0.50$ is retained as a conservative benchmark.

Set-Identification of Tuition Elasticities The same pricing conditions provide bounds on the mean tuition coefficient. Set-identification of $\bar{\alpha}_t$ proceeds with the same two-step technique as before. This is possible since the mean utility parameters δ_j identified in the first step absorb the average tuition component $\bar{\alpha}_t t_j$. Holding fixed the model choice probabilities s_{ij} and preference-heterogeneity parameters identified in the first step, I next use supply-side restrictions to bound $\bar{\alpha}_t$.

Define

$$\Gamma_j = \mathbb{E}[s_{ij}(1 - s_{ij})], \qquad \Lambda_j = \mathbb{E}[\alpha_t(A_i, X_i) s_{ij}(1 - s_{ij})].$$

Since $\alpha_i = \bar{\alpha}_t + \alpha_t(A_i, X_i)$, the negative own-price derivative of college j's enrollment share is

$$-s_j' = -\bar{\alpha}_t \Gamma_j - \Lambda_j.$$

For a profit-maximizing college with tuition revenue $p_j > 0$, the pricing first-order condition therefore implies

$$c_j = p_j - \frac{s_j}{-\bar{\alpha}_t \Gamma_j - \Lambda_j}.$$

Imposing only nonnegative marginal costs, $c_j \geq 0$, therefore gives

$$-\bar{\alpha}_t \geq \frac{s_j/p_j + \Lambda_j}{\Gamma_j}.$$

This is the familiar restriction that a profit-maximizing firm prices on the elastic side of its residual demand curve:

$$p_j \frac{-s_j'}{s_j} \geq 1.$$

Applying this restriction for every for-profit yields the following bound on the mean tuition

elasticity:

$$\bar{\alpha}_t \leq -\max_{j \in \mathcal{J}_{\text{FP}}} \left\{ \frac{s_j/p_j + \Lambda_j}{\Gamma_j} \right\}.$$

I also consider alternatives allowing for the optimal-pricing restriction to fail for a fraction r of for-profit college-year observations. Suppressing time indices, the corresponding identified set is

$$\mathcal{I}_r = \left\{ \bar{\alpha}_t : \frac{1}{|\mathcal{J}_{\text{FP}}|} \sum_{j \in \mathcal{J}_{\text{FP}}} \mathbb{1}\left\{ -\bar{\alpha}_t \Gamma_j - \Lambda_j \geq \frac{s_j}{p_j} \right\} \geq 1 - r \right\}.$$

Thus, imposing the restriction for every college uses the largest college-specific lower bound on $-\bar{\alpha}_t$, while allowing a fraction r of violations replaces this maximum with the corresponding empirical $(1-r)$-quantile. Imposing all restrictions yields $\bar{\alpha}_t \leq -0.24$, while allowing 20% of for-profits to deviate from optimal pricing yields $\bar{\alpha}_t \leq -0.10$.

While still dependent on a particular model of firm conduct, these estimates are fully consistent with the calibrated coefficient of -0.27 from Denning (2017), and they further suggest that the regression estimate of -0.10 assuming exogenous tuition is too low to rationalize profit-maximizing behavior, at least for 20% of firms.

I Program-Choice and Completion-Rate Schedules

Identifying Completion-Rate Schedules Having identified the mean for-profit completion premium among marginal students, next I estimate how this premium varies across the distribution of student characteristics. This will be useful for estimating potential completion rates among different complier groups under policy-relevant counterfactuals. This framework also allows for decomposing the completion-rate effect into within- and across-degree-level components, helping assess what portion of the completion-rate premium owes simply to program composition. I take a straightforward approach, involving an adjustment to the observed graduation-rate schedules to match the IV-implied mean potential outcomes.

In particular, I identify graduation-rate schedules $\pi_{j\ell g}^{j\leftrightarrow k}(X_i)$ by combining observed gradients with selection-corrected levels. I first assume that graduation outcomes in each sector j and degree level ℓ follow a multinomial logit model:

$$\pi_{j\ell g}^{obs}(x) \equiv \mathbb{P}\{G_i^{j\ell} = g \mid D_i = j, L_i^j = \ell, X_i = x\} = \frac{\exp(x'\eta_{j\ell g})}{1 + \sum_{g' \in \{1,2,4\}} \exp(x'\eta_{j\ell g'})}$$

Next, I assume that selection bias in graduation rates is uniform in log odds. That is, there are constants γ_{jg} such that

$$\pi_{j\ell g}^{j\leftrightarrow k}(x) \equiv \mathbb{P}\{G_i^{j\ell} = g \mid j \leftrightarrow k, L_i^j = \ell, X_i = x\} = \frac{\exp(x'\eta_{j\ell g} + \gamma_{jg})}{1 + \sum_{g' \in \{1,2,4\}} \exp(x'\eta_{j\ell g'} + \gamma_{jg'})}$$

The γ_{jg} are then identified from the following moment conditions:

$$\mathbb{E}\left[\sum_{\ell \in \mathcal{L}} q_{j\ell}^{j\leftrightarrow k} \cdot \pi_{j\ell g}^{j\leftrightarrow k}(X_i; \boldsymbol{\gamma_j})\right] = \mathbb{E}[\mathbb{1}\{G_i^j = g\} \mid j \leftarrow k \text{ compliers}],$$

where $q_{j\ell}^{j\leftrightarrow k} \equiv \mathbb{E}[L_i^j = \ell \mid j \leftarrow k \text{ compliers}]$ and $\mathbb{E}[G_i^j = g \mid j \leftarrow k \text{ compliers}]$ are identified by distance IVs. Figure A5 shows the resulting graduation-rate schedules for Associate programs across the distribution of HS test score percentiles.

Identifying Program-Choice Probabilities I identify program-choice probabilities for students on the for-profit/public margin in a similar fashion. Again, I estimate a multinomial logit model for the choice of program in each sector and then shift the program-choice probabilities to match the IV-based mean potential outcomes.

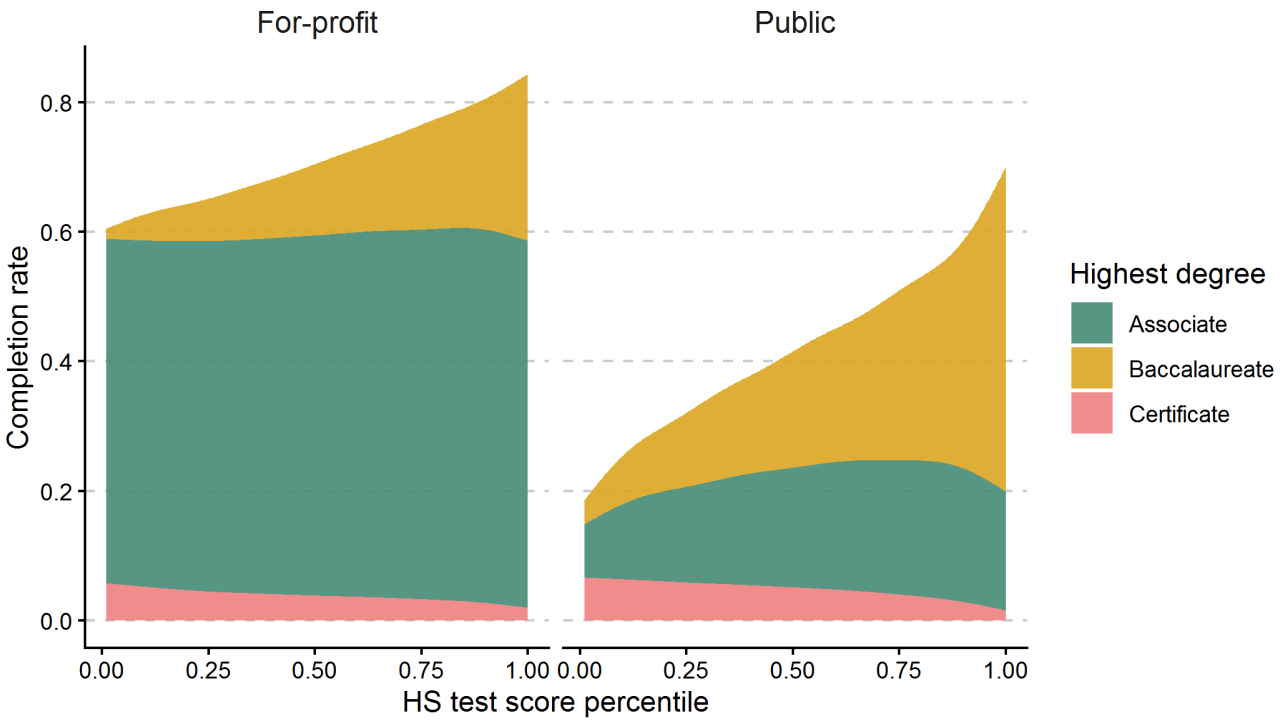


Figure A5: Selection-corrected completion rates by ability (Associate programs)

Notes: Predicted completion rates by final degree, among students on the FP/CC margin who initially enroll in Associate programs. Degree completion includes awards from any college within 7 years of first enrollment. Covariates X_i include a cubic polynomial in HS test scores, race, gender, free-/reduced-price lunch status, an indicator for high-school dropout risk, and special-education status.

J Additional Figures and Tables

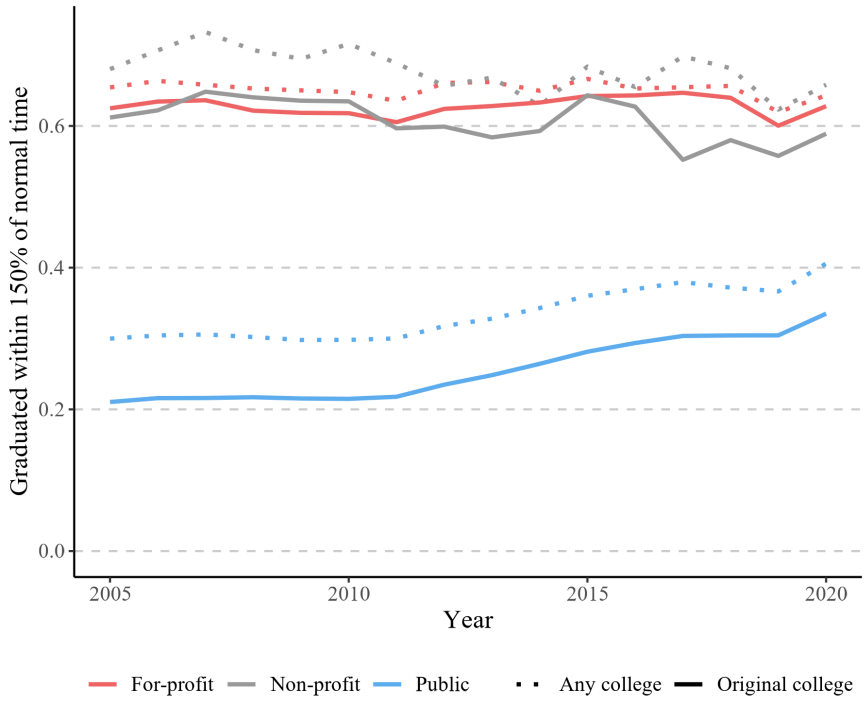


Figure A6: Degree Completion Rates by Sector

Notes: Graduation rates weighted by full-time equivalent undergraduate enrollment. Primarily sub-baccalaureate colleges only. Estimates of the share graduating from any college add in 48% of those transferring within 150% of the expected degree date, consistent with NSC estimates.

Table A8: First Stages, Reduced Forms, and IV Estimates with Student Controls

	Control set	
	Location only	Location and student
Panel A: First stages		
$D_{CC} \sim Z_{FP}$	0.0145	0.0152
	(0.0006)	(0.0006)
$D_{FP} \sim Z_{CC}$	0.118	0.123
	(0.001)	(0.001)
Outcome: Long-run completion rate		
Panel B: Reduced forms		
$Y \times D_{CC} \sim Z_{FP}$	0.0057	0.0056
	(0.0004)	(0.0004)
$Y \times D_{FP} \sim Z_{CC}$	0.0080	0.0085
	(0.0011)	(0.0011)
Panel C: IV		
Y_{CC}	0.394	0.369
	(0.023)	(0.022)
Y_{FP}	0.680	0.691
	(0.057)	(0.056)
Outcome: Quarterly earnings		
Panel D: Reduced forms		
$Y \times D_{CC} \sim Z_{FP}$	76.5	76.9
	(5.8)	(5.7)
$Y \times D_{FP} \sim Z_{CC}$	548.6	587.5
	(104.0)	(104.0)
Panel E: IV		
Y_{CC}	5,285	5,067
	(303)	(289)
Y_{FP}	4,641	4,793
	(621)	(596)

Notes: Z_{FP} is log distance to the nearest for-profit; Z_{CC} is the distance in thousands of miles to the nearest CC. All specifications include the full set of location controls described in Section 4, as well as distance to other sectors $\boldsymbol{Z}_{-j}$. The second column adds as controls predetermined student characteristics including ethnicity, gender, HS test score percentile, and FRPL status. First stages regress sector enrollment on distance to the competing sector. Reduced forms replace sector enrollment with the corresponding interacted outcome. Standard errors in parentheses.

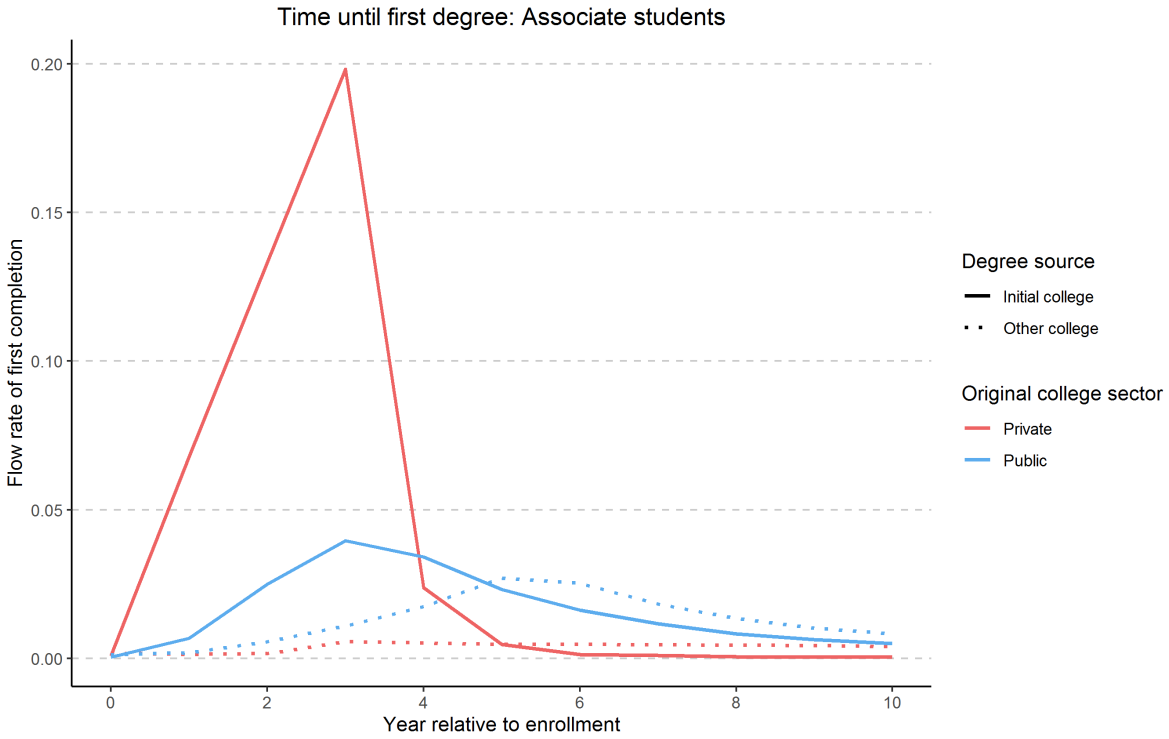


Figure A7: Flow Completion Rates by Initial vs. Transfer School

Notes: Sample includes all Texas public HS students who enroll in a two-year for-profit or community college intending an Associate's degree in a vocational field from 2005-2011.

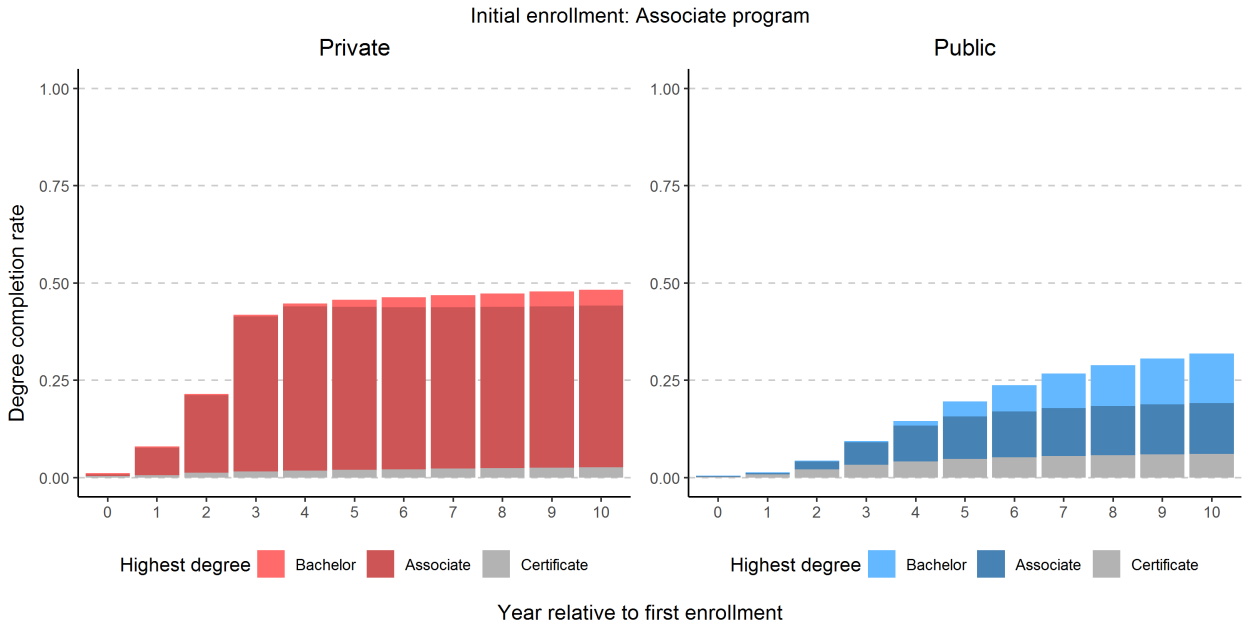


Figure A8: Composition of Degrees Earned among Initially Associate's Students

Notes: Sample includes all Texas public HS students who enroll in a two-year for-profit or community college intending an Associate's degree in a vocational field from 2005-2011.

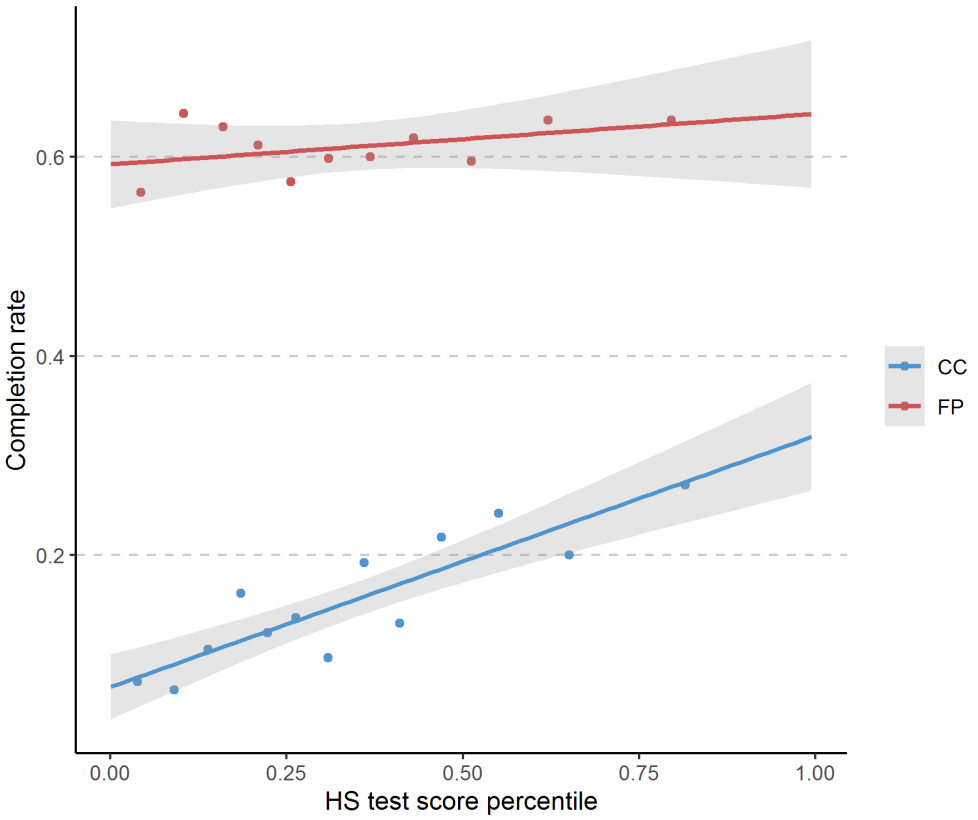


Figure A9: Completion Rates of FP → CC Switchers

Notes: Sector-specific graduation rates of students first enrolling in a for-profit and later enrolling in community college, with more than one year between enrollment spells. Shaded regions represent 95% pointwise confidence bands.

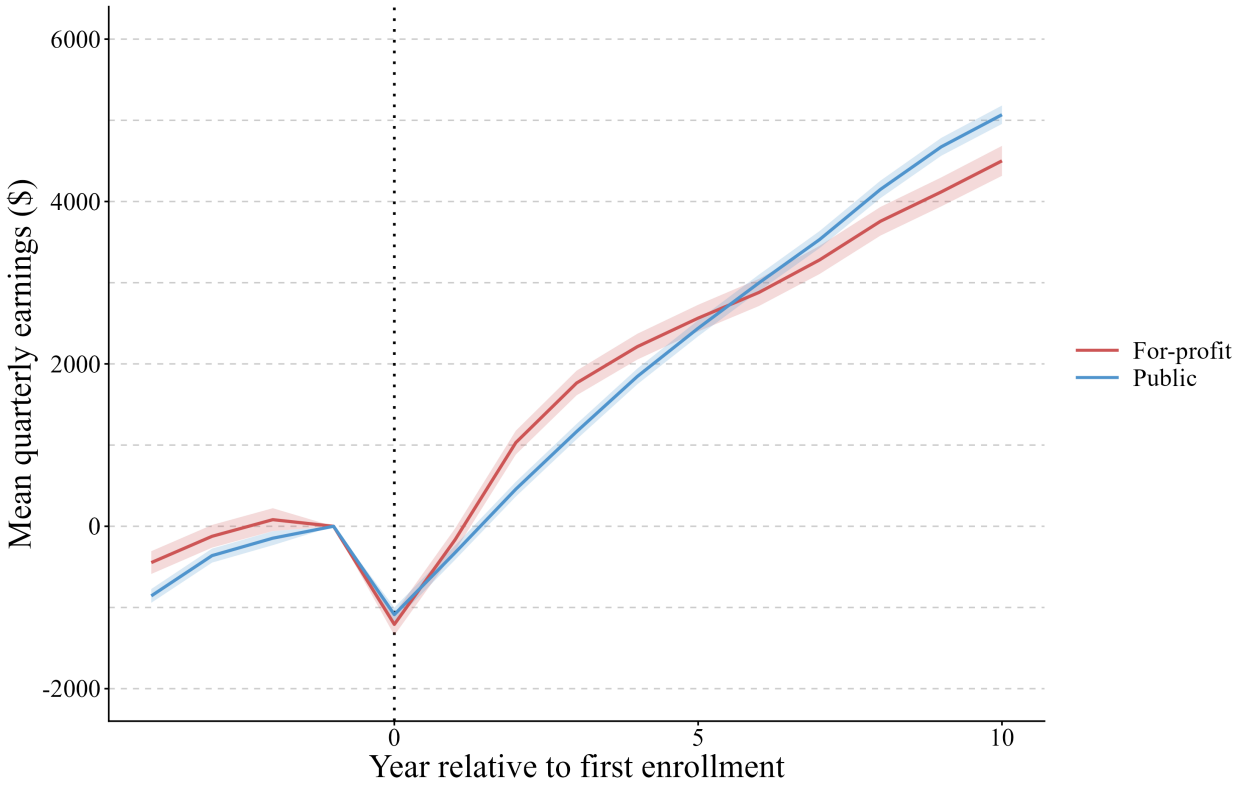


Figure A10: Raw Earnings Profiles of Associate's Degree-Seekers

Notes: See notes for Figure 11. Earnings profiles of eventual graduates and dropouts are pooled within initial enrollment sectors.

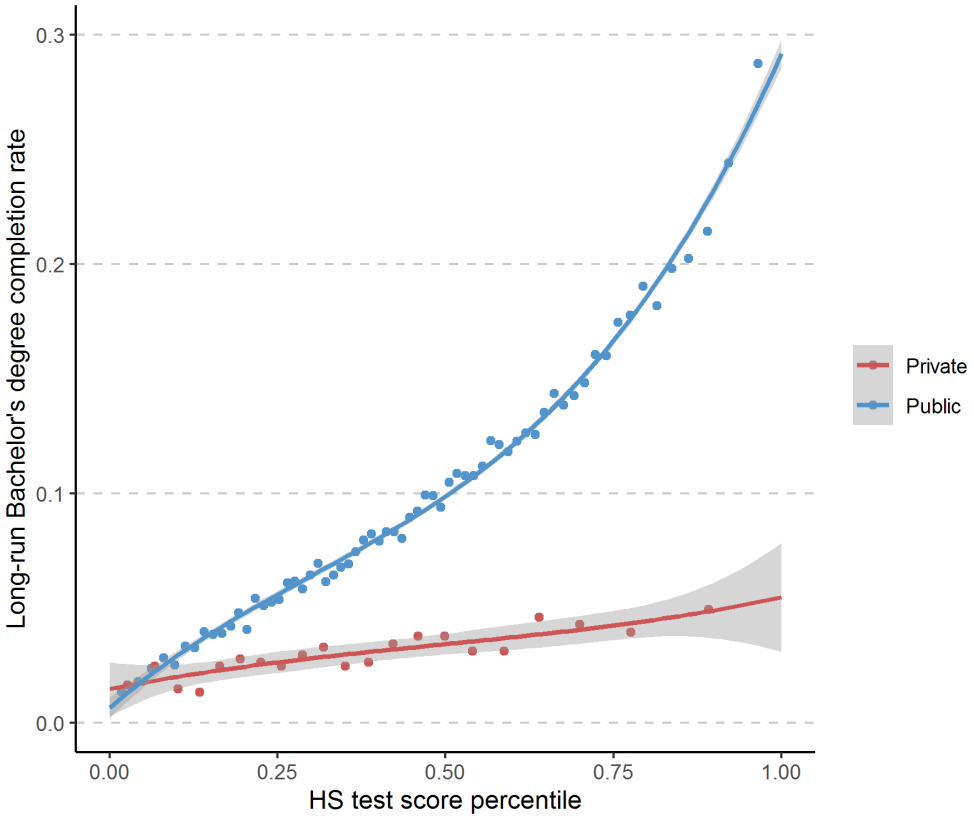


Figure A11: Bachelor's Completion Rates by Pre-College Academic Ability

Notes: Sample includes all Texas public HS students who enroll in a two-year for-profit or community college intending an Associate's degree from 2005-2012. The HS test score percentile is taken from statewide 9th- and 10th-grade tests in math and reading, which are converted to within-cohort percentile ranks. The long-run degree completion rate is the share of students completing a Bachelor's degree from any college within 7 years of first enrollment.