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 nearly 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. Despite for-profits' higher graduation rates, a within-individual design shows that their degrees yield long-run returns comparable to those of CCs. 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 students earn higher returns from CCs, partly due to the option value of academic and four-year pathways. To better understand mechanisms, I assemble new program-level data on course requirements. For-profit programs require significantly less academic coursework, helping rationalize their comparative advantage for academically weaker students. 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 find the subsidy expansion is self-financing and generates substantial earnings gains.

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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 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 first estimating the productivity of for-profit and public programs for students of differing academic skills. To do so, I draw on administrative records from Texas, supplemented with national survey and transcript data and a newly assembled dataset of degree requirements. Identifying the relative effects of for-profit and public colleges is difficult because students self-select into colleges based on their pre-college skills and their expected gains from each sector. In addition, college choice and program choice

[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.

are intertwined, since for-profits specialize in short vocational programs, while CCs bundle vocational training with academic and transfer options. Naive comparisons might therefore confound sector effects with differences in program composition and student sorting. I overcome these challenges using administrative records covering the near-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 exhibit little remaining association with predetermined student characteristics including high-school test scores, providing support for the conditional independence assumption. I find that for-profits raise long-run rates of completion in any credential by 32 percentage points, while reducing Bachelor's attainment by 13 percentage points — consistent with CCs' stronger transfer pathways.

Average effects mask substantial heterogeneity. Pre-college skills are much more predictive of graduation in the public sector. The for-profit completion premium is therefore largest among less academically prepared students, who disproportionately sort into the for-profit sector. Meanwhile, CCs' advantage in Bachelor's attainment is concentrated among higher-skill students, for whom public enrollment raises Bachelor's attainment by 17 percentage points, compared to just 4 points among lower-skill students. These patterns are indicative of academic match effects, as lower-skill students gain more in terms of overall graduation while losing less in terms of four-year option value when they enroll in for-profits. Academic skill heterogeneity also suggests that for-profits may raise graduation rates through less academically intensive degree pathways.

To explore this potential mechanism, I assemble a new program-level dataset of course requirements for more than a thousand vocational programs in Texas. I show that for-profit programs require substantially less academic coursework even in the same fields of study and degree levels. In addition, for-profits shift marginal students into shorter programs with fewer academic requirements. Returning to the distance-IV design, I find that the programs chosen by students on the for-profit/public margin require nearly 20 fewer academic credits at for-profits than at CCs (3 versus 23). And this is before accounting for CCs' remedial requirements. While for-profits rarely require remedial courses, I find that 62% of marginal students face remedial math requirements in the public sector, which can further delay degree

progression. Finally, academic requirements also appear to drive graduation outcomes: the for-profit completion premium is largest in programs where public colleges require relatively more academic coursework.

To better understand how these academic requirements might impact degree progression, I next turn to transcript records. I find that students on the for-profit margin earn average GPAs of just 2.0 out of 4.0 when they enroll in public colleges, near the threshold for academic probation. Their poor performance is driven by academic courses, in which marginal students earn average community-college GPAs of just 1.77. These results suggest that CCs' more extensive academic requirements do pose substantial challenges for marginal students. National transcript data show the same patterns and further reveal that for-profit students with observably similar academic backgrounds earn significantly higher grades than their CC peers. More than a third of this GPA premium can be explained by their narrower vocational course-taking. These differences in curriculum and academic performance rationalize both the for-profit completion premium and the match effects in degree production.

The same features that make for-profit programs easier to complete may also make them less valuable. To understand the implications for college returns, I estimate ex-ante returns to enrollment, accounting for how college choice affects program choice and degree attainment. Direct IV estimates suggest parity between for-profit and CC returns, with substantial heterogeneity across academic skills, but are too imprecise to draw firm conclusions. To improve precision, I augment the distance-IV estimates of marginal students' program choices and degree attainment with a second design that identifies ex-post returns using earnings changes around college enrollment among older students. I develop an alternative estimator that combines these two designs by expressing ex-ante returns as probability-weighted averages of the ex-post returns to different schooling sequences. Individual fixed-effects models of earnings show substantial ex-post 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. The resulting ex-ante return estimates reveal sizeable match effects: relative to CC enrollment, for-profits yield up to \$700 more in long-run quarterly earnings among the academically weakest students, but approximately \$500 less among the strongest students on the academic CC margin. These differences reflect weaker students' elevated dropout risk at CCs, as well as the greater option value of CCs' academic and transfer pathways for stronger students.

To compare the efficiency of for-profit and public degree production technologies, I next estimate the private and social costs of schooling. Combining college-level expenditure and tuition data with administrative enrollment records, I return to the IV design to estimate expected lifetime schooling costs for students on the for-profit/public margin. Although for-

profits incur higher expenditures per enrolled year, their students spend less time in college, resulting in lower total resource costs. Combining these costs with estimates of gross returns, I calculate the net present value of enrollment in each sector across the skill distribution. On average, for-profits generate approximately $26,000 higher net social returns and $9,000 higher net private returns, despite their substantially higher tuition. And among the lowest-skill students, net social returns are positive in both sectors, but about $60,000 higher at for-profits.

These results suggest that community colleges could better serve low-skill, vocation-oriented students by offering programs in the mold of for-profit tracks. While changes in public pathways are a promising avenue for reform, such policy counterfactuals are challenging to quantify since for-profits are effectively the sole provider of these more attainable programs in my setting, leaving no public analogue from which to estimate counterfactual demand and returns. Instead, I consider a closely related policy lever: expanding subsidies for the attainable vocational tracks which are at present housed in the for-profit sector. This policy counterfactual is particularly natural given that existing subsidies strongly favor community colleges, even though for-profits generate comparable — and for some, higher — net returns.[2]

In particular, I estimate the marginal value of public funds (MVPF) associated with a universal voucher applicable toward tuition at two-year for-profit colleges. This requires estimating the potential returns and counterfactual choices among compliers under a for-profit tuition reduction. To do so, I first estimate a college demand model featuring heterogeneous preferences for college sectors, tuition costs, and distance to college. Estimates show that students shifted into for-profits come about equally from non-enrollment and CCs, but primarily from the bottom of the skill distribution — those most likely to benefit from for-profit enrollment. The voucher's efficacy also depends on the extent to which for-profits capitalize the voucher into tuition. Here, I combine the demand model estimates with the first-order conditions from a standard model of price competition to identify these pass-through rates. The model implies that most for-profits reduce tuition in response to the voucher, amplifying the voucher's enrollment effects.[3] As these pass-through estimates rely on a particular model of competition, I also show robustness to much higher rates of tuition capitalization.

Finally, I estimate the voucher's welfare effects by combining the implied substitution

[2]Still, public provision of attainable vocational tracks remains an attractive alternative with its own advantages. Investments in public technical centers narrowly focused on vocational training would represent another way of expanding access to the same kinds of attainable vocational pathways and could in principle generate similar gains, depending on the details of implementation.

[3]This result, known as "overshifting," arises from the estimated curvature of demand; the expansion in for-profit demand is accompanied by higher price sensitivity among marginal enrollees, reducing optimal markups (Weyl and Fabinger 2013).

patterns from the demand model with earlier estimates of expected returns on each complier margin. I find that the voucher's direct cost is more than fully offset by savings from substitution out of already-subsidized CCs and by increased tax revenues, making the voucher self-financing and yielding an infinite MVPF. This result holds even if for-profits capitalize as much as 45% of the voucher into tuition. On the benefits side, each dollar of direct subsidy cost generates more than five dollars in additional earnings, concentrated among those with lower pre-college skills. Even if all of these earnings gains are offset by non-pecuniary costs of schooling and work, the MVPF remains above one for tuition capitalization rates of up to 65% — well above my estimates, which lie near zero. Expanding access to short, attainable vocational pathways through private provision therefore 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 perform worse on 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). These differences partly reflect the fact that for-profits must cover their costs through tuition revenues, while community colleges use their considerable state support to charge much lower tuition rates.[4]

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*a*) find that for-profits in Missouri somewhat outperform community colleges in gross returns.[5] These studies provide important evidence on returns for students selecting into particular sectors and programs. I target a different estimand: relative returns for students on the for-profit/public margin. Under selection on gains, comparing average returns among students selecting into different sectors does not generally identify relative returns for any common population.[6] Another reason standard return estimates may not identify relative returns is that they commonly hold program choice fixed. I find that students induced to

[4]Like community colleges, however, for-profit colleges are eligible for federal grant and loan aid.

[5]Other within-person estimates of for-profit returns include Cellini and Chaudhary (2014), Liu and Belfield (2020), and Jepsen et al. (2025*b*), who find conflicting results.

[6]The matched comparison in Cellini and Turner (2019), for instance, can identify relative returns provided that sorting gains are fully captured by the matching variables.

switch sectors also switch their programs of study, so within-program comparisons exclude an important channel through which college choice shapes returns.[7]

The few studies using instruments for enrollment are better positioned to identify relative returns among marginal students, but existing estimates remain imprecise (Liu and Belfield 2014; Armona, Chakrabarti and Lovenheim 2022). In addition, with multiple enrollment alternatives, standard TSLS estimators do not isolate returns on a particular margin without strong restrictions on sorting or treatment-effect heterogeneity (Hastings, Neilson and Zimmerman 2013; 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 (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, using a rich measure of pre-college skill. 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.

I also contribute to the literature on degree attainment at two-year colleges. 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

[7]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.

and Luetmer 2021; Armona, Chakrabarti and Lovenheim 2022).[8] 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 novel degree-requirement data and transcript records to highlight curricular differences as a likely mechanism.[9]

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 (Person, 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

[8] 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.

[9] 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).

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.

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 and the landscape of two-year colleges in the US. 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.[10] For within-individual earnings regressions, I use an auxiliary sample of older students who initially enroll in college from

[10]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.

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 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 (Cellini and Goldin 2014). 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. I further characterize the colleges included in the Texas analysis sample in Appendix B. There I also describe how Texas' two-year college sector compares to the rest of the US. Overall, Texas is a large and broadly representative market, and the key differences between public and for-profit colleges — in terms of graduation rates, tuition and spending, and program offerings — largely mirror those observed nationally.

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 from program catalogs, 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 completions, respectively. Appendix E 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 in the four-year sector. 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).

Two-year colleges are also the primary vehicle for vocational training in the United States.[11] 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.

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

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

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.[12]

Table 1: Two-Year College Characteristics

	Public	For-profit
Share of new enrollees	80%	17%
Average net tuition	$714	$9,407
Expects Bachelor's degree	77%	38%
Enrolled in vocational program	62%	99%
Enrolled in certificate program	11%	82%
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 program enrollment and expectations of ever earning a Bachelor's degree or higher come from the national BPS data.

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. Consistent with this broader institutional mission, 77% of CC students expect to eventually earn a Bachelor's degree, compared to just 38% of for-profit students. 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, for-profit students overwhelmingly pursue short, vocational programs: 99% enroll in vocational fields and 82% begin in certificate programs, compared with 62% and 11% of CC students, respectively (Table 1). 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. As a result, for-profit enrollment entails greater specialization at entry, making it less attractive to students who are uncertain of their intended program.

[12]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 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.

Yet for-profits' narrower offerings lend themselves to more streamlined curricula centered on vocation-relevant material, while public vocational programs often require academic courses. To illustrate this, Figure 1 presents the modal degree pathways for the for-profit and community-college versions of a common program: the Associate's degree in automobile technology.[13] The public and for-profit versions of this program share much core content in common, typically requiring coursework in vehicle systems, shop class where students practice automobile repair and maintenance, and often an internship with a local employer.

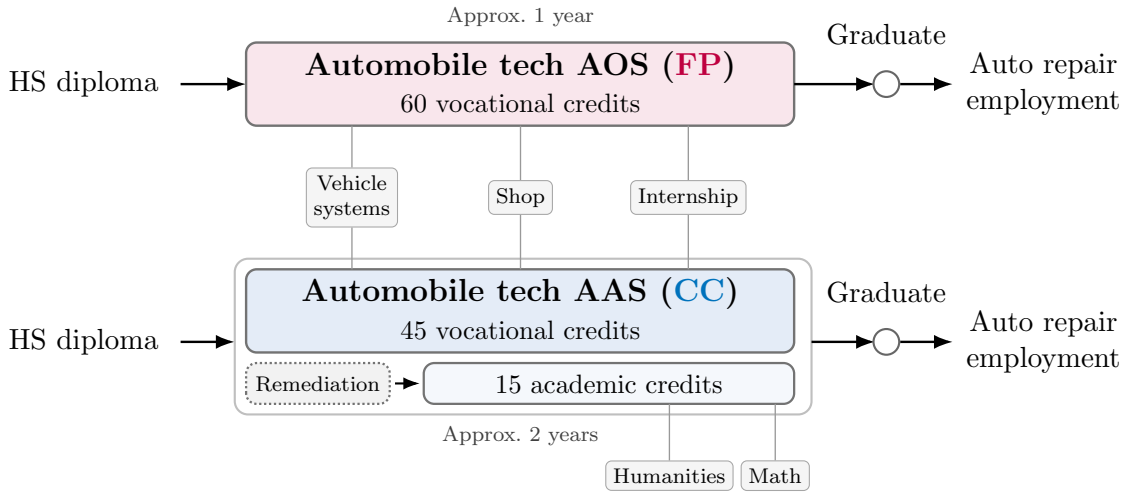


Figure 1: Modal Degree Pathways in Automobile Technology Programs

Beyond this vocational core, the public versions of this degree program also require substantial academic coursework not required in for-profit programs. Students not achieving proficiency on placement exams will be required to first enroll in remedial courses, which can span math, reading, and writing, including up to three sequential math courses in some cases. None of these remedial courses contribute to the degree's credit requirements.[14] This is followed by 15 credits in academic courses including college-level math, speech, and humanities subjects. These courses are generally not required at for-profits. In addition, for-profit degree programs are commonly conducted on accelerated timelines: the for-profit degree in automobile technology usually takes just one year to complete, compared to two years at community colleges even among those enrolling full-time.[15] Graduates may then

[13] In Texas, the community-college version of this program is called an Associate of Applied Science (AAS) degree, while the for-profit version is called an Associate of Occupational Studies (AOS) degree.

[14] 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.

[15] Differences in enrollment intensity can further shorten students' time to completion at for-profits: about 90% of for-profit students enroll full-time, compared with less than half of community-college students. Haygood (2026) shows that this difference partly reflects sector effects on enrollment intensity.

seek a voluntary certification in automobile repair before entering employment. Though automobile technology is a particularly stark example, in Section 4.1 I will use the newly collected degree-requirement data to show that these differences in academic intensity are a more general feature of public and for-profit degree pathways.

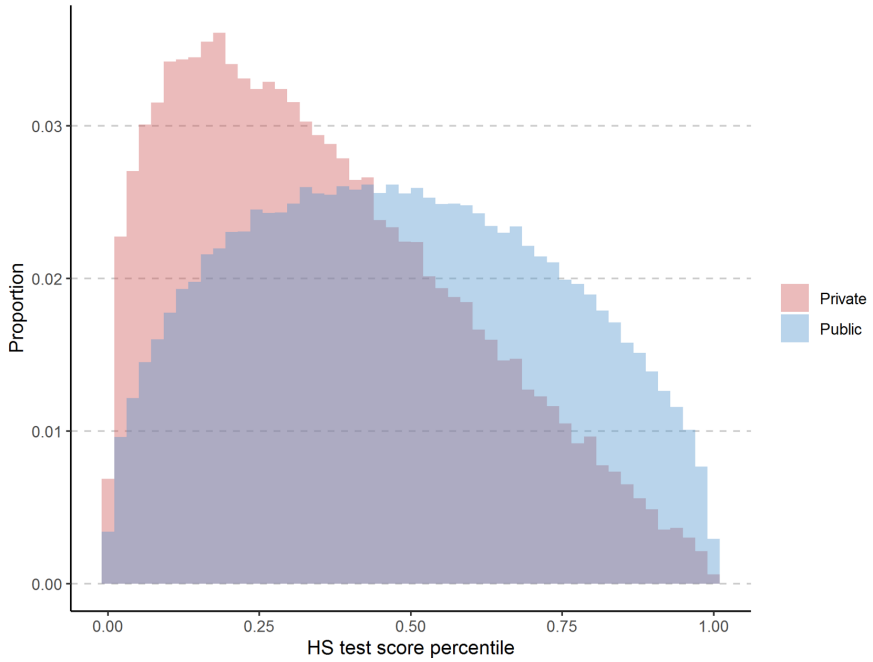


Figure 2: Distributions of Pre-College Skills

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.

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 compelling 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).[16] 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-

[16]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.

school test score percentiles, which is uniform in the population of high-school graduates.[17] 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 non-enrollment.[18]

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 sub-baccalaureate colleges, IPEDS data show that 62.8% of for-profit students graduate from their initial college within 150% of normal time, compared with just 33.5% of CC students (Table 1). Transfer is more common at CCs, however, and IPEDS does not track the subsequent degree attainment of transfer students. To account for these differences, I next turn to individual-level data from the nationally representative BPS survey, which tracks attainment across institutions.

Given that for-profits offer almost exclusively vocational programs, mostly at the certificate level, I restrict the sample to students intending a vocational major and split the sample by initial degree intention. Similar to the analysis in Deming, Goldin and Katz (2012), Table 2 presents both raw and covariate-adjusted completion-rate gaps, controlling for pre-college measures of academic preparation, socioeconomic background, and other demographics.[19] These comparisons remain descriptive; I account for unobserved heterogeneity in Section 4.

Graduation rates are substantially higher at for-profits even within degree levels. Since for-profit students have weaker academic preparedness and come from more disadvantaged backgrounds, controlling for student characteristics inflates the completion-rate gap. Among Associate's students, only 40.4% of public students graduate within 6 years, compared to a covariate-adjusted 61.6% of for-profit students. Graduation rates for public Certificate students are higher, at 51% within 6 years, but Certificate programs make up a very small

[17] 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.

[18] 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.

[19] 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)
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)

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.

share of public enrollment. Even there, for-profit students remain 12.5 percentage points more likely to graduate.

The composition of degrees earned and the timing of completion also differ substantially by sector. Among Associate's students, 12.1% of public students attain a Bachelor's degree within 6 years, compared with a covariate-adjusted 6.7% of for-profit students. Yet for-profit Associate's graduates complete their degrees much faster, spending roughly half as

much time in school (Table 2). Figure 3 illustrates these differences in completion timing. Appendix Figures A10 and A11 show that these national patterns closely resemble those in the Texas administrative data.

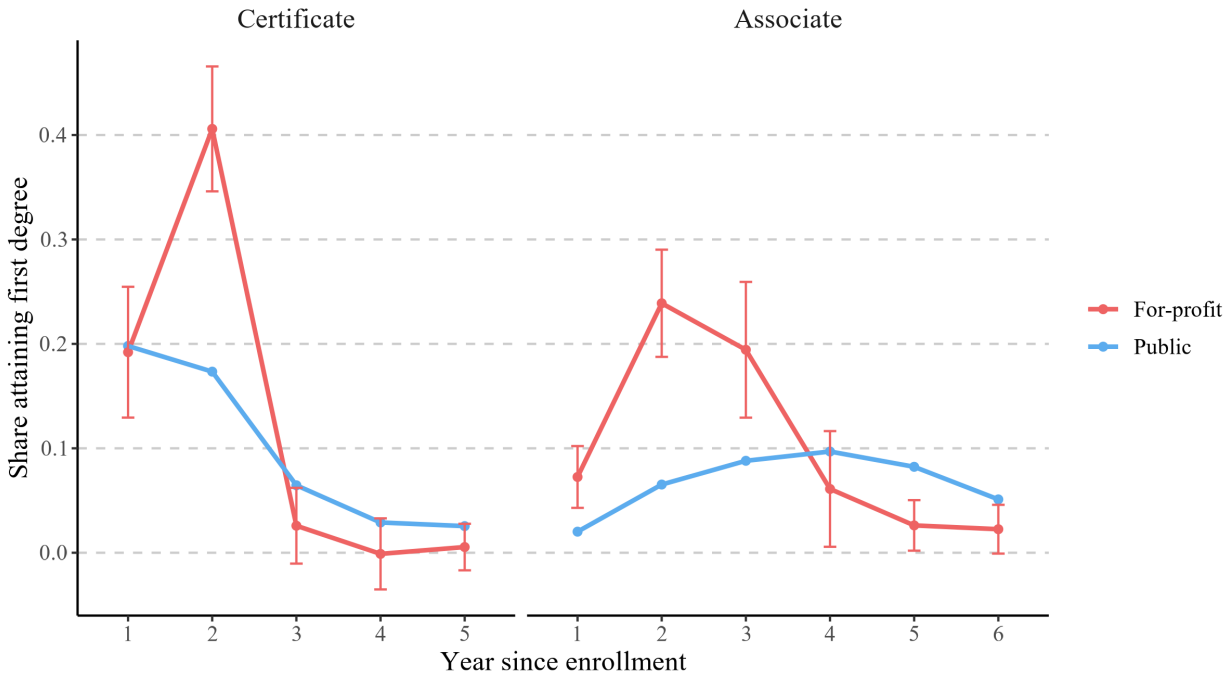


Figure 3: Flow Graduation Rates by Degree Program and Sector

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 covariate-adjusted 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 are the same as in Table 2. Error bars represent 90% confidence intervals.

Finally, to evaluate whether differences in program composition can explain these gaps I turn to the Texas administrative records, which record enrollment in even more granular programs of study. Even within narrowly defined fields of study, for-profit graduation rates substantially exceed public graduation rates 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 students should face particularly low graduation prospects at CCs, and graduation rates should be more sensitive to academic skills in the public sector. To evaluate this prediction, I link college attainment outcomes to measures of students' pre-college

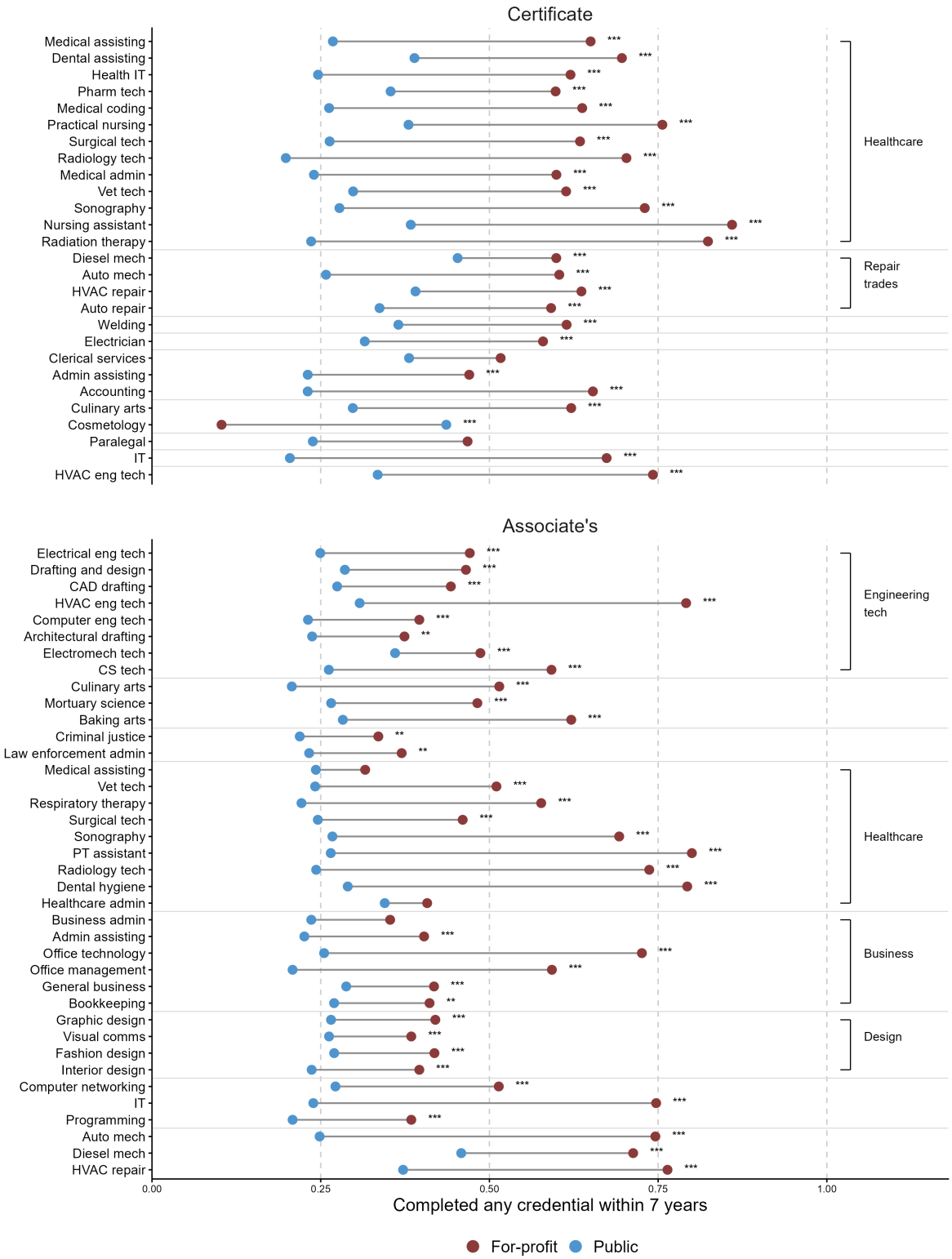


Figure 4: Completion Rates by Program of Study

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.

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.

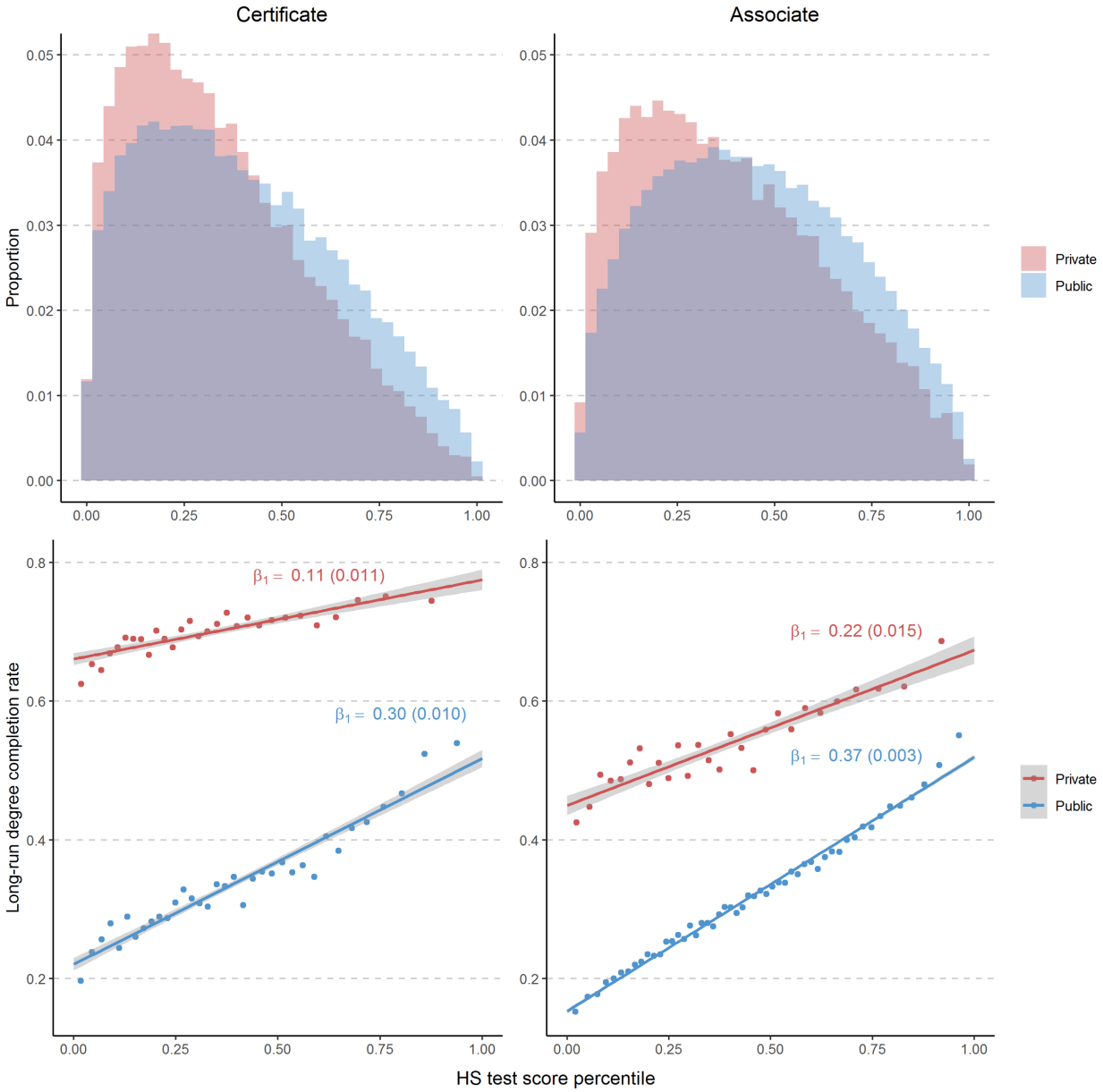


Figure 5: Graduation Rates by Pre-College Academic Skills

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.

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 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 A6).

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.[20] For instance, students may gain skills or learn about their preferences during their first spell, improving their success rate in their next.

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

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 C 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 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.[21]

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

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 $j \neq k$, $j \geq 1$, $k \geq 1$,*

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

Proof. 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.

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

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.[22] 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 predetermined 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,

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

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

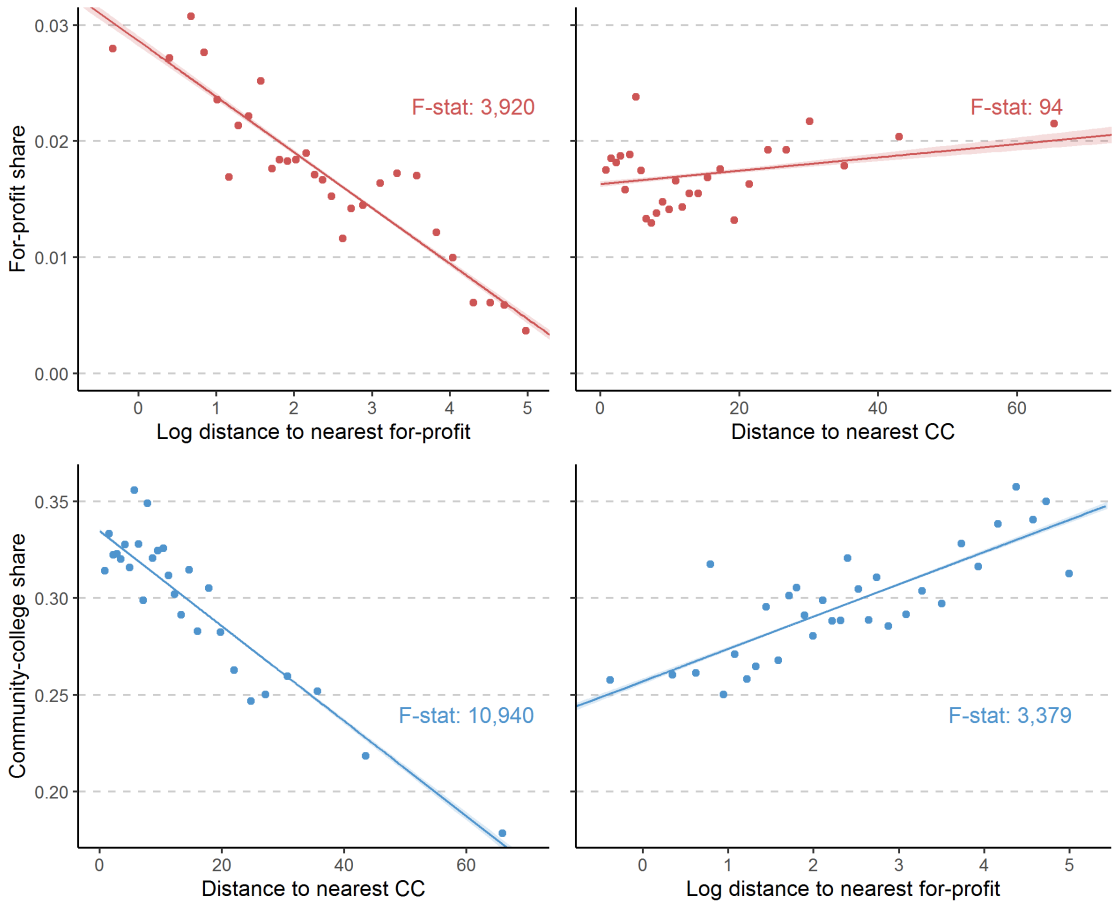


Figure 6: First-Stage Relationships

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 predetermined student characteristics including gender, ethnicity, FRPL as a proxy for socioeconomic status, and the HS test score percentile as a proxy for academic ability.[23] 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

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

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 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 A12). 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 HS test score percentiles among 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.

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 C, 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

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.

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, but characterizing the contribution of different mechanisms to the for-profit completion premium is empirically challenging. Here I present evidence that academic barriers may contribute to the for-profit completion premium, focusing on differences in curricular requirements and students' performance in academic coursework.[24]

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 E. 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

[24]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).

waiver.[25]

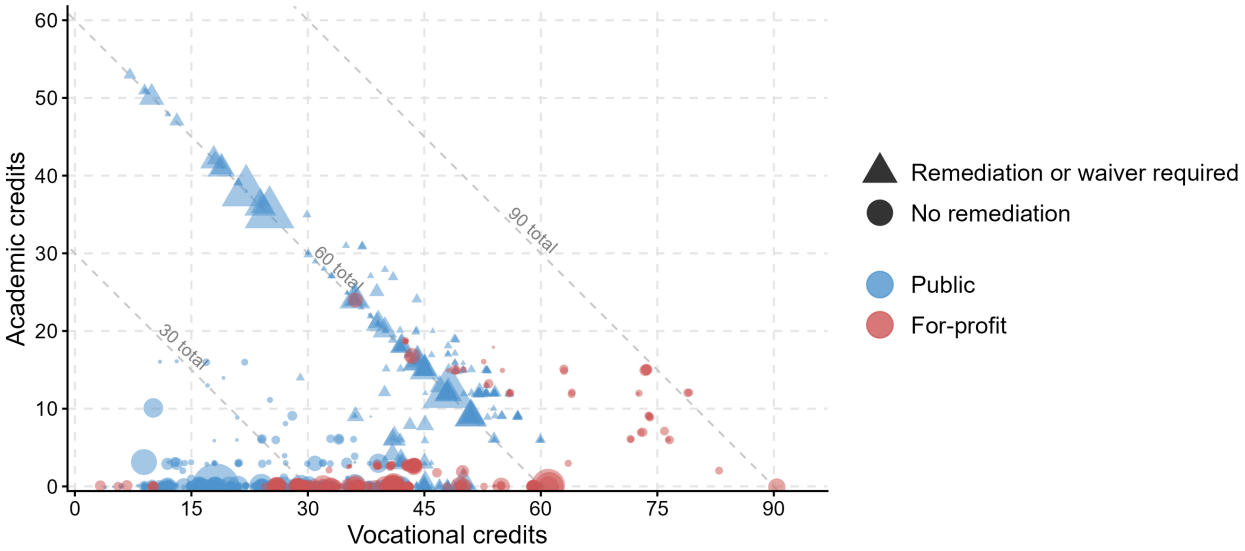


Figure 7: Program Credit Requirements

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.

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

Table 6: Degree Requirements at Two-Year College Programs

	For-profit	Public	
	(1)	(2)	(3)
Panel A: Certificate programs			
Total credits	38.9	28.2	31.9
Academic credits	0.4	0.8	1.7
Academic share of credits (%)	0.8	2.4	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.

Requirements Faced by Marginal Students The comparisons in Table 6 hold degree level fixed, but for-profits also shift many marginal students into the certificate programs featuring less academic content (Table 5). To account for these effects, I return to the distance-IV design.[26] Table 7 shows that the programs chosen by students on the for-profit/public margin require an average of 22.8 academic credits at CCs, compared with just 3.4 at for-profits. Consistent with for-profits' higher certificate shares, marginal students also face lower total credit requirements. Still, the academic *share* of required credits in students' initially chosen programs is 34.7 percentage points higher at CCs.

Performance in Academic Coursework To understand whether these additional academic requirements impede degree progression, I next estimate how students on 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

[26]Requirements are unobserved for approximately 10% of vocational students; in these cases, I impute the average requirements of the associated sector × degree level × two-digit CIP field. Students enrolling in academic programs, for whom I do not collect program-level degree requirements, are assigned total credits of 30 and 60 in certificate and Associate's programs, respectively, fully in academic subjects. Thus, the figures in Table 7 partly reflect my finding that approximately 30% of marginal students would enroll in academic programs at CCs. However, I show in Appendix Table A9 that these gaps in academic credit requirements shrink only modestly when restricting attention to students enrolling in vocational programs.

Table 7: Program Requirements on FP/CC Margin

	Total credits	Academic credits	Academic share of credits (%)
FP	45.1	3.4	5.9
	(1.6)	(0.9)	(1.6)
CC	57.4	22.8	40.7
	(0.33)	(1.3)	(2.2)
Difference	−12.3	−19.4	−34.7
	(1.7)	(1.6)	(2.7)

Notes: Mean program requirements in the initially chosen programs of marginal students in each sector, estimated using the distance-IV design. Academic credits include required general-education and other non-vocational coursework. Heteroskedasticity-robust standard errors in parentheses.

transcripts, the mean CC potential outcomes of students on the for-profit/public margin are still identified using the distance-IV variation.[27] 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 8 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 can limit degree progression by reducing the continuation value of enrollment and causing students to spend additional time retaking courses.

In addition, CC students who do not meet academic placement requirements must enroll in developmental courses in math, English, and/or writing before progressing to their college-level academic course requirements. 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 D presents additional transcript evidence for marginal students.

Graduation Rates by Academic Intensity Marginal students face much larger aca-

[27] 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.

Table 8: 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.

demic burdens in public programs. To understand how these differences relate to graduation outcomes, I next ask whether the for-profit completion premium is larger in programs where CCs require relatively more academic coursework. 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.

Finally, Appendix F shows that these same patterns emerge in national transcript data. There, I observe both public and for-profit GPAs. Controlling for a rich set of pre-college characteristics, I show that for-profit GPAs are 0.47 points higher than public GPAs (s.e. 0.10) in vocational Associate's programs. As in the Texas data, this gap is driven by substantially lower performance in academic courses. In a Oaxaca-Blinder decomposition, I show that more than one third of the overall GPA gap can be explained by reduced academic course-taking at for-profits, further evidence that CCs' academic requirements create performance challenges among less academically oriented students.

These differences in vocational program curricula and academic performance 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

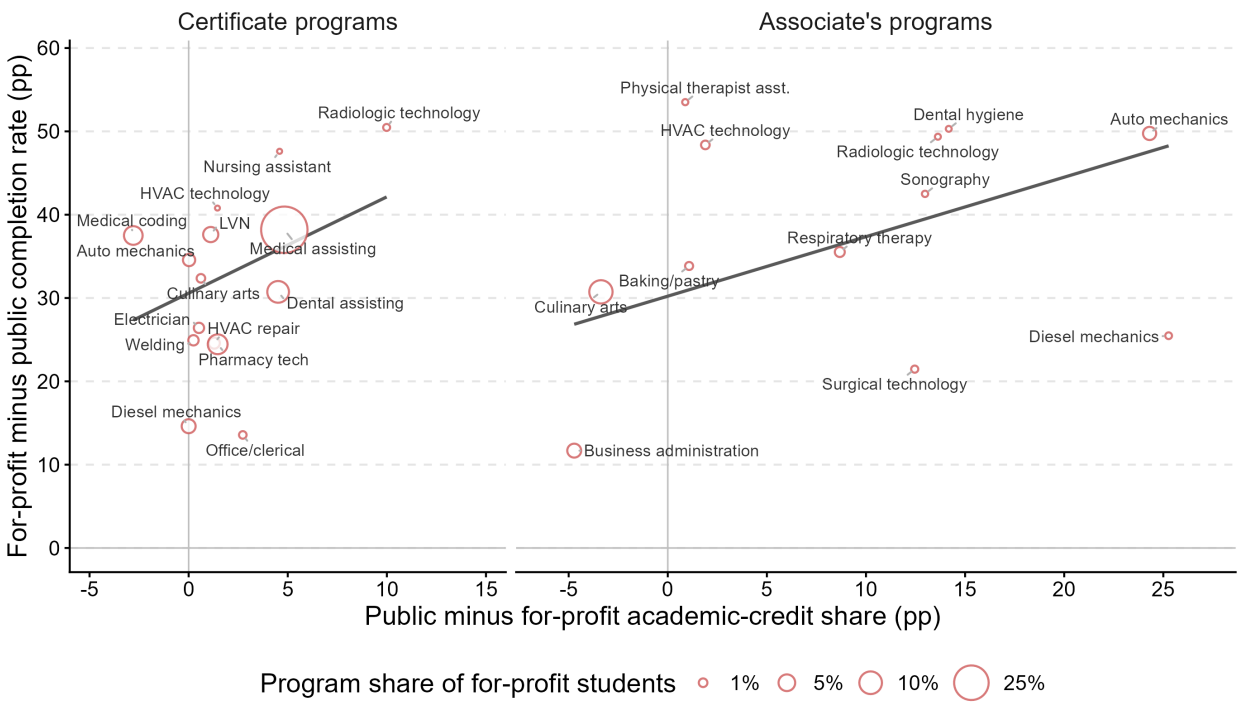


Figure 8: Completion-Rate Gaps versus Academic Requirements by Program

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.

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).

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, leaving the implications for expected returns 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 9 reports the degree-completion effects from before alongside earnings effects, measured in quarterly earnings at age 27–28. I find 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].

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).[28] Conditional on controls, F-statistics in these split samples remain larger than 32 in all cases. First, Table 10 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

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

Table 9: Mean Potential Outcomes and Sector Effects on FP/CC Margin

	Completion of ≤ 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.

by 17 percentage points among high-skill students. The option value of four-year transfer is therefore uniquely relevant for high-skill students.

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 $971 more in quarterly earnings when they enroll in for-profits. Still, these comparisons suffer from statistical imprecision and cannot be distinguished from zero at conventional significance levels. The difference in the relative return to for-profit enrollment across high- and low-skill students ($-\$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

Table 10: Mean Potential Outcomes and Sector Effects by Academic Skill

	Completion of ≤ 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.

$Y_i^{j\ell g}$ 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 $\Delta Y_i^{j\ell g}$,

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

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*a*), 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.[29] This 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.[30] To begin with, I focus on students enrolling in vocational Associate's programs since this is the program set with greatest overlap.

Figure 9 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 A13 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:

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

[29] For example, 70% of marginal students enroll in vocational programs at CCs, compared to just 37% of all CC students. Yet for-profits further raise vocational program enrollment and shift students from Associate's into certificate programs.

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

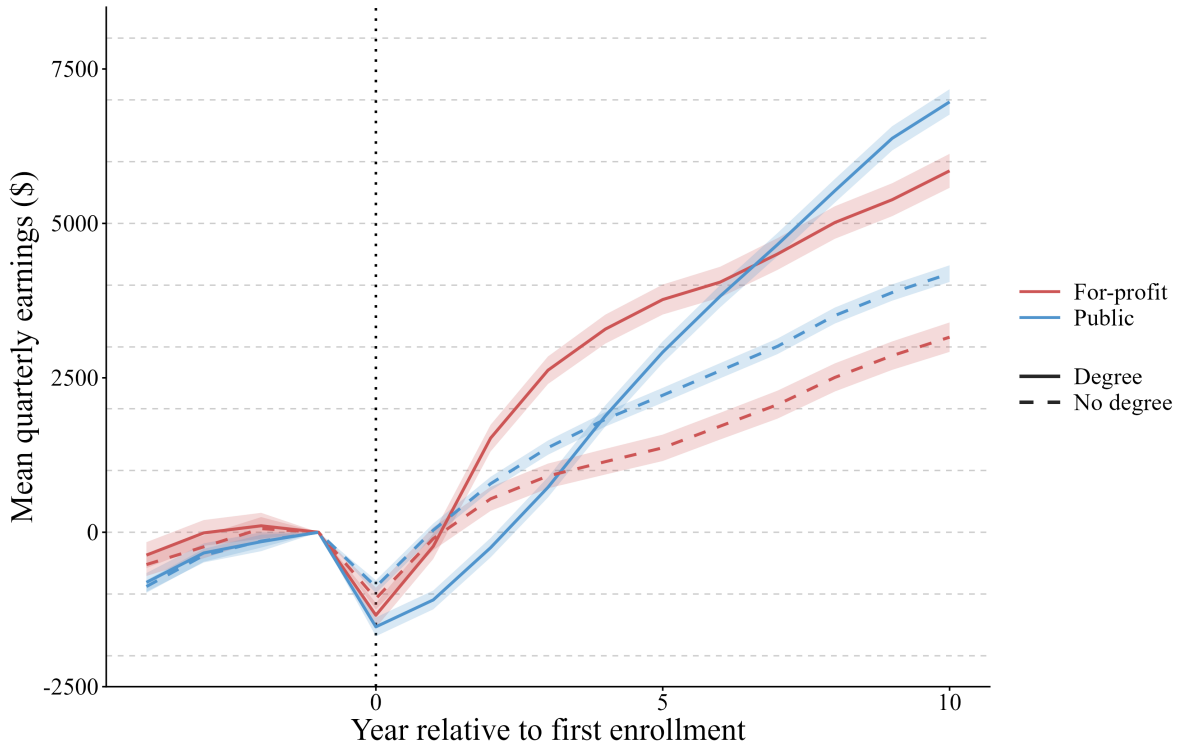


Figure 9: Raw Earnings Profiles of Associate's Degree-Seekers

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 2003–2012 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.

where I fix $\tau_{-2,c} = 0$,[31] and T_i indicates the year of first enrollment. This specification compares 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 $\theta_i t$.[32] 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 9).

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

[31] An Ashenfelter's dip appears in the three to four quarters before enrollment. I treat this as a transitory employment shock occurring in the year before enrollment and therefore fix $\tau_{-2,c} = 0$ rather than $\tau_{-1,c} = 0$.

[32] 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.[33] I assume that, conditional on X_i and the program-attainment path a student would realize under sector j, residual heterogeneity in ex-post

[33] 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 10 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.[34] 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-

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

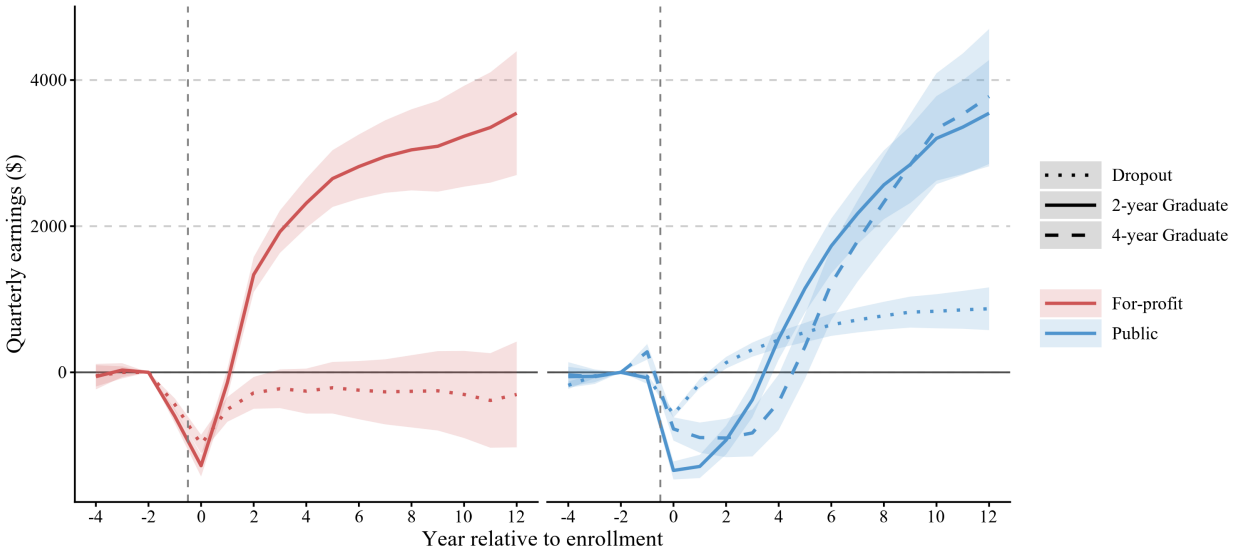


Figure 10: Gross Ex-Post Returns

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, age at entry, and enrollment year. 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,[35] 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 J for details.

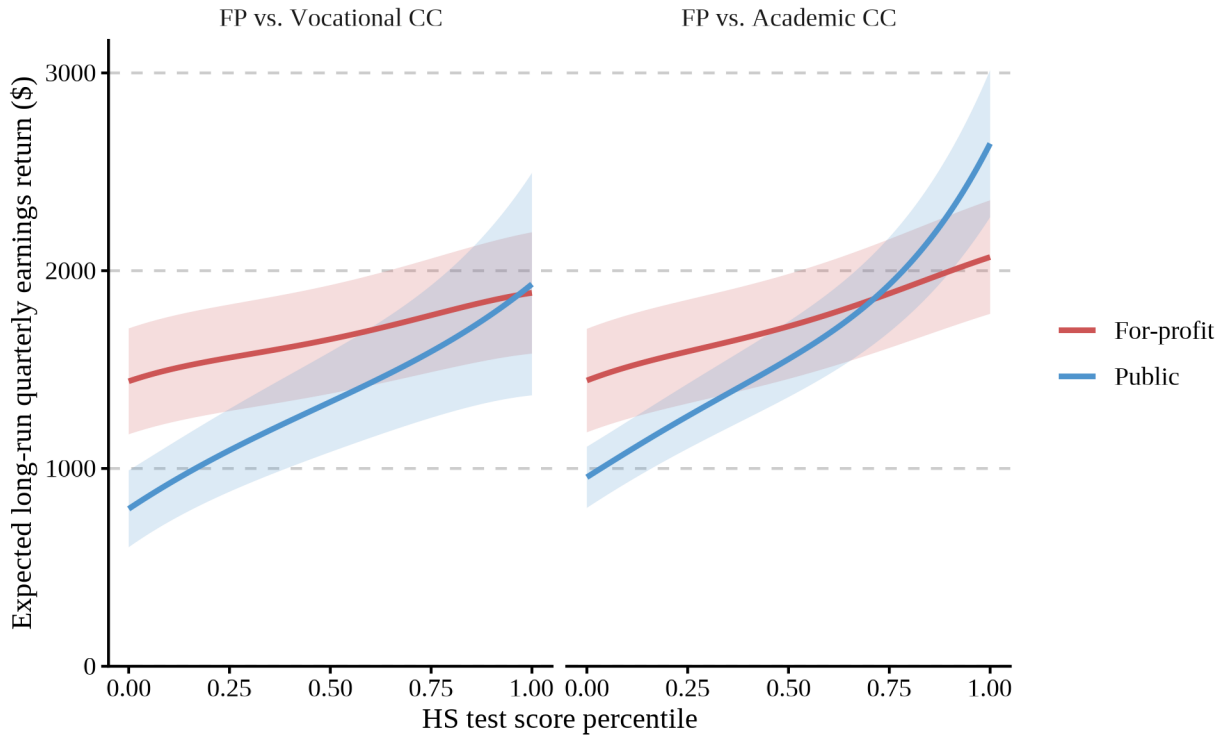


Figure 11: Ex-Ante Returns by Academic Ability

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 $\bar{\rho}^j(A) \equiv$

[35] 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.

$\mathbb{E}_{X|D_i=\text{FP},A}\left[\rho^j(A,X)\right]$.[36] Figure 11 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 long-run gross earnings effects, which do not account for the costs of schooling. 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 college-level revenue and expenditure data from IPEDS with administrative enrollment records to construct individual-level estimates of tuition and college expenditures. These costs include all observed subsequent enrollment spells in both two-year and four-year colleges. I then use the distance-IV design from before to estimate the expected present value of schooling costs among students on the for-profit/public margin. I measure private costs using after-grant tuition and fees, and social costs using total college expenditures.[37]

[36] Given the limited sample size of students who earn Bachelor's degrees after beginning at a two-year for-profit, I pool four-year graduates across sectors when estimating the ex-post return to Bachelor's attainment.

[37] The ideal cost measure would capture all resources devoted to students' education, including both instructional and non-instructional inputs. I consider both total expenditures and a narrower definition restricting spending to instruction, academic support, student services, and institutional support. Net return estimates are not particularly sensitive to this choice. Another limitation is that college-level expenditures may not accurately reflect costs in individual degree programs. 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 offering exclusively vocational programs and show that they spend nearly the same amount per student as traditional CCs (Appendix Table A11), suggesting that program composition is not driving relative expenditure estimates. Hoxby (2018) discusses these and related issues with estimating higher education productivity in greater depth.

I next calculate the expected net present value of enrollment for students (using tuition) and for society (using college expenditures).[38] 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 opportunity costs of enrollment through reduced in-school labor supply. For each initial sector j, let T_{it}^j denote after-grant tuition and C_{it}^j denote college expenditures. Assuming an average tax rate of $\tau = 0.20$, expected net returns are given by

$$\mathbb{E}[\text{PDV}_j^{social}] = \sum_{t=0}^{T} \delta^t \Big(\mathbb{E}[Y_{it}^j - Y_{it}^0] - \mathbb{E}[C_{it}^j] \Big)$$
$$\mathbb{E}[\text{PDV}_j^{private}] = \sum_{t=0}^{T} \delta^t \Big((1-\tau)\mathbb{E}[Y_{it}^j - Y_{it}^0] - \mathbb{E}[T_{it}^j] \Big).$$

Setting $T = 35$ and $\delta = 0.98$, I present social and private PDVs in Table 11. These calculations continue to use gross return estimates reweighted to match the for-profit demographic distribution, combined with the distance-IV estimates of costs, program choice, and attainment among marginal students. I find large social and private returns to both public and for-profit enrollment, ranging from $91,000 to $125,000 in present value. The net social return to for-profit enrollment is about $26,000 larger than that of CC enrollment. This difference reflects both higher gross earnings returns and lower resource costs: although for-profits spend more per enrolled year, their students spend substantially less time in college, reducing total expected expenditures by about $3,400. However, private costs are much greater at for-profits due in part to public tuition subsidies. The difference in private returns is therefore narrower, but for-profits still yield average returns about $9,400 higher.

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 approximately $50,000 in net social returns enrolling in CCs and $112,000 at for-profits. Thus, for-profits' degree production technology is particularly efficient among academically weak students.

[38] 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.

Table 11: Expected Net Returns by Initial Sector

	For-Profit	Public	Difference
Panel A: Social returns			
Gross earnings returns	142,340	120,142	22,198
Resource costs	17,015	20,461	−3,446
Net PDV	125,325	99,681	25,644
Panel B: Private returns			
After-tax earnings returns	113,872	96,114	17,758
Tuition costs	13,100	4,733	8,367
Net PDV	100,772	91,381	9,391

Notes: Gross returns combine estimates of ex-post earnings effects with distance-IV estimates of program-choice and attainment probabilities. Costs are estimated for students on the FP/CC margin using the distance-IV design. Social costs represent total college expenditures; private costs represent after-grant tuition and fees. All dollar values are measured in 2025 dollars and discounted using $\delta = 0.98$. Private earnings returns are net of an average tax rate of $\tau = 0.20$.

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.[39] Appendix H 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.[40] 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

[39]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.

[40]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.

value added of unobserved potential entrants would be difficult without significant structural 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 H, 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 may raise the pass-through rate. 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 I, 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).[41] Overshifting is a common finding in empirical studies of pass-through that exploit variation in taxes, subsidies, and input costs across a range of other imperfectly competitive markets (Besley and Rosen 1999; Miller, Osborne and Sheu 2017; Pless and van Benthem 2019; Conlon and Rao 2020; Gehrsitz, Saffer and Grossman 2021). This result, while still reliant on a particular model of competition, provides additional evidence for κ near zero. Still, I will consider robustness to alternative pass-through rates.

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

$$\text{WTP}(\phi, \kappa, \omega_\pi) = \overbrace{s^0_{\text{FP}}(1-\kappa)}^{\text{Direct transfer}} + \phi \sum\nolimits_{k \in \{0,\text{CC},4\}} \overbrace{s_{\text{FP}\leftarrow k}\left[(1-\tau)\Delta\rho_k - (t_{\text{FP}} - t_k)\right]}^{\text{Income gains on margin } k} + \overbrace{\omega_\pi \Delta\pi}^{\text{FP profits}}$$

The MVPF is then defined as

$$\text{MVPF}(\phi, \kappa, \omega_\pi) = \begin{cases} \dfrac{\text{WTP}(\phi, \kappa, \omega_\pi)}{\text{NGC}(\kappa)}, & \text{if NGC}(\kappa) > 0 \\ \infty, & \text{if NGC}(\kappa) \leq 0 \text{ and WTP}(\phi, \kappa, \omega_\pi) > 0 \end{cases}$$

reflecting that policies with negative net costs are self-financing and are therefore assigned an infinite MVPF (Hendren and Sprung-Keyser 2020). 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

[41] 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.

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 (a two-year for-profit, a vocational CC program, an academic CC program, or a four-year college). College utilities are

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

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 mean tuition sensitivity $\bar{\alpha}_t$ 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 sensitivity. 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 I elaborates further the identification result and the particular inequality constraints used to identify bounds on the tuition coefficient. 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 12. 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.

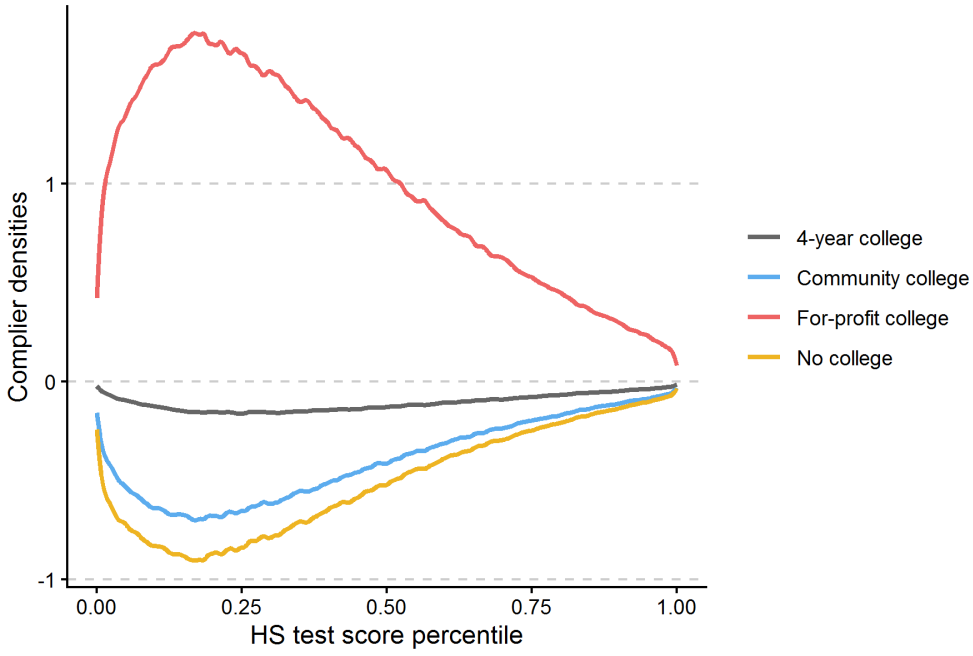


Figure 12: Complier Distributions under a For-Profit Subsidy

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

Distribution of Private Returns To understand who benefits from the subsidy, I next

estimate changes in the net present value of higher education across the skill distribution by combining demand-model estimates with expected return estimates on each margin. This quantity corresponds to the WTP expression derived above, evaluated at $\phi = 1$, $\kappa = 0$, and $\omega_\pi = 0$, but now conditioning all enrollment shares and complier distributions on the HS test score percentile. It measures both the direct tuition savings to existing for-profit students and changes in expected after-tax earnings net of private tuition costs among students induced to switch sectors.

The change in expected gross returns on margin k 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. To estimate skill-specific returns, I condition these complier distributions on A. I estimate gross return functions $\rho^k(A)$ 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 × gender — with the completion-rate and program-choice schedules estimated using distance IVs (Appendix J). I also estimate the difference in expected private tuition costs $t_{\text{FP}} - t_k$ using distance IVs.[42] I assume an average marginal tax rate of $\tau = 0.20$ and an annual discount factor of 0.98.

Figure 13 plots the resulting change in expected net private benefits corresponding to a dollar of direct government expenditure on the subsidy, averaging across all HS graduates of a given test score percentile. I find that low-skill students earn the bulk of the for-profit subsidy's pecuniary benefits, both because they are more likely to shift their enrollment, and because they earn larger relative returns to for-profit enrollment when they do. The for-profit subsidy therefore tends to reduce inequality in college returns.

Estimating the MVPF To estimate the MVPF of the for-profit subsidy, I next supplement these WTP estimates with estimates of the change in government costs of schooling Δf_k on each complier margin, again identified using the distance-IV design.[43] Throughout, I conservatively assign zero welfare weight to changes in for-profit profits, $\omega_\pi = 0$.

Figure 14 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

[42] For the non-enrollment margin, distance-IV designs are insufficiently powered. There I use the same expressions, but substitute completion-rate schedules, program-choice probabilities, and costs based on selection-on-observables estimates.

[43] As before, I must rely on selection-on-observables estimates of expected costs for the non-enrollment margin.

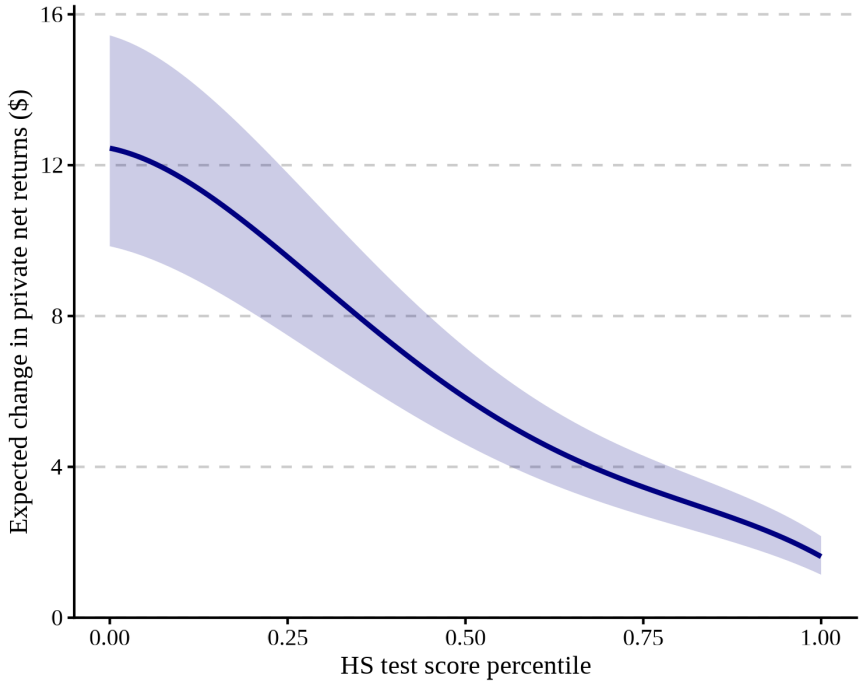


Figure 13: Change in Private Net Returns under a For-Profit Subsidy

Notes: Change in the expected present value of earnings net of private tuition costs, averaging over all HS graduates, in response to a for-profit subsidy costing $1 in direct government expenditure. Ribbon represents a 95% pointwise confidence band.

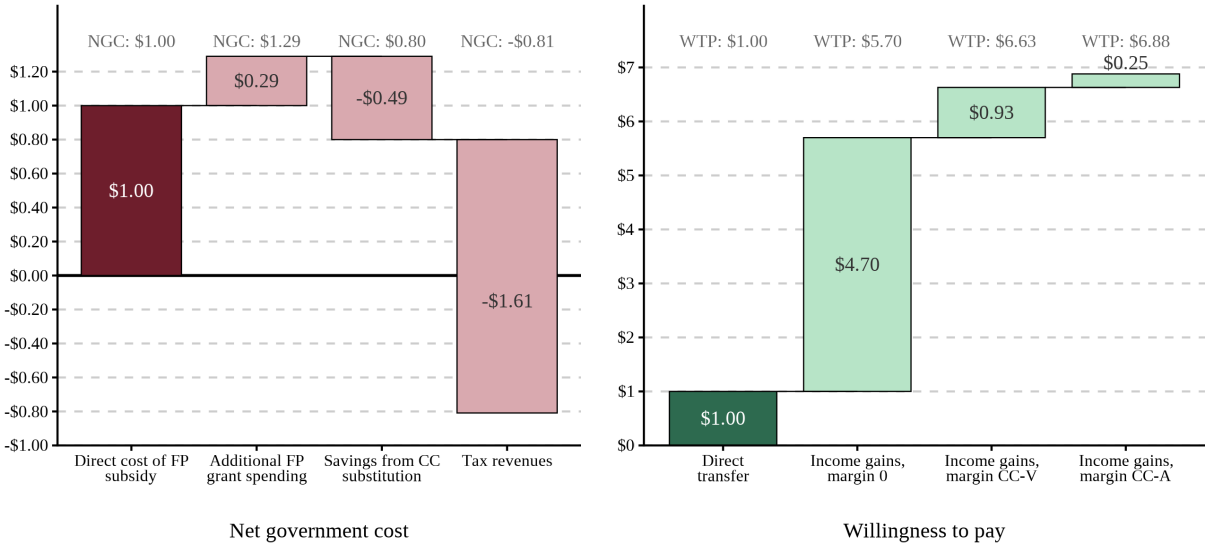


Figure 14: Costs and Benefits of a For-Profit Subsidy

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).

recoups $0.49 from substitution away from subsidized public options and another $1.61 from future tax revenues. Incorporating the behavioral effects of the subsidy therefore pushes the net government cost well below zero, implying a fiscal *gain* of $0.81 per dollar of direct costs. The for-profit subsidy is therefore self-financing. 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.

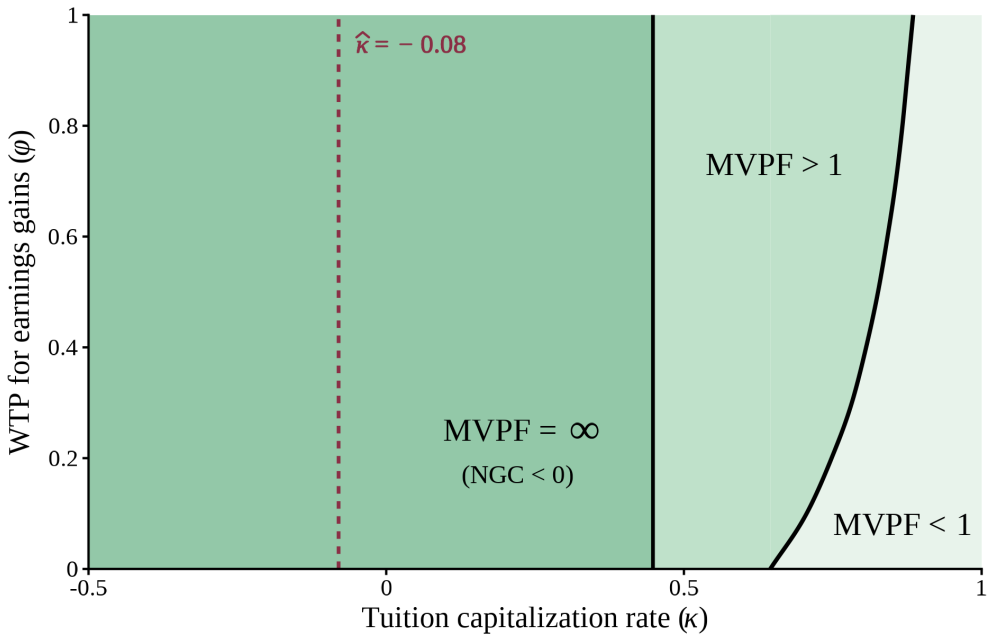


Figure 15: MVPF of a For-Profit Subsidy

Notes: MVPF of a for-profit tuition subsidy, for different values of pass-through κ and WTP for earnings gains ϕ. Valuation of firm profits ω_π fixed to zero. $\hat{\kappa}$ is the estimated average pass-through rate under a Bertrand competition model.

Since net government costs are negative, the MVPF of the subsidy is infinite in the benchmark with perfectly elastic long-run supply — even if students value none of the earnings gains ($\phi = 0$). The 95% confidence interval on net government costs in this scenario is $[-1.18, -0.44]$. Even assuming 50% pass-through, the MVPF remains robust, at 36.54 (95% CI $[15.40, \infty]$) assuming full WTP ($\phi = 1$) and 5.31 (95% CI $[1.85, \infty]$) under zero WTP for earnings gains ($\phi = 0$). The subsidy remains self-financing for pass-through rates of up to 45%, as shown in Figure 15. Only when the bulk of the subsidy is capitalized into tuition and the planner assigns no value to firm profits does the MVPF fall below 1 (Figure 15). These large MVPFs owe primarily to added tax revenues among students newly

induced into college. However, even assuming no earnings gains among these students still yields MVPFs of at least 2.17 when $\kappa = 0$.

Looking across a variety of public programs designed to improve the labor-market outcomes of young adults, MVPF estimates of even just 2 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 tradeoff 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 large fiscal savings: the subsidy expansion is self-financing under plausible values of tuition pass-through. These subsidies would also generate significant earnings gains, even among those diverted from community colleges. And the resulting earnings gains accrue primarily to lower-skill students, 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 College-Level Characteristics

Here I present college-level descriptive statistics for the Texas colleges underlying the main analysis and then compare the Texas two-year college sector to the rest of the US. The Texas analysis sample contains enrollment and graduation records for all public colleges in the state, but coverage is incomplete for the for-profit sector. The administrative records do contain nearly all two-year for-profit colleges but only a subset of less-than-two-year for-profits. Table A1 shows that the Texas analysis sample covers 96% of all two-year for-profit enrollment in the state from 2003–2014, along with 29% of less-than-two-year for-profit enrollment. Two-year, mostly degree-granting for-profits are therefore overrepresented in the analysis sample relative to the IPEDS universe.[44] At the college level, the analysis sample covers 93 of the 104 two-year for-profits in the state, as well as 56 of the 274 less-than-two-year for-profits.

Those less-than-two-year for-profits for which we do observe administrative records differ primarily in terms of program specialization: those in the analysis sample award 77% of credentials in healthcare, compared to 54% in the wider sector, and they award no cosmetology credentials, compared to 27% in the wider less-than-two-year universe. This lack of cosmetology programs is the key distinction between the for-profits in my administrative sample and the wider for-profit sector. Since public colleges offer few cosmetology programs, this part of the for-profit sector is not particularly relevant for understanding relative returns — to the extent that students do not tend to substitute between cosmetology and other vocational programs.[45]

Next I evaluate how Texas compares to the rest of the US. Table A2 shows that Texas two-year for-profits resemble the national for-profit sector quite closely. Importantly, they have nearly identical graduation and transfer rates. While Texas for-profits are somewhat larger, they are similar in full-time share. The primary observable difference is that the Texas for-profits award a larger share of credentials in shorter programs, those of one year or less in advertised duration. For-profits in Texas and the wider US enroll a very small share of their students in fully online programs. They enroll students of similar demographic backgrounds, with the exception that Texas features much larger Hispanic shares. And on financial characteristics, Texas for-profits are highly similar to for-profits nationally.

I compare Texas community colleges to the rest of the US in Table A3. Texas CCs are somewhat larger on average, and they have somewhat lower full-time enrollment shares.

[44] The IPEDS universe is itself limited to colleges which participate in federal financial aid. Cellini and Goldin (2014) show that many very small for-profit schools operate without access to this federal aid, and these are also excluded from my analysis sample. These schools are almost entirely non-degree-granting and specialize in shorter programs, often of just a few weeks in length.

[45] Armona and Cao (2024) find that for-profit cosmetology programs yield substantially lower returns than the rest of the sector.

Table A1: Composition and Coverage of the Texas For-Profit Analysis Sample

	Two-year		Less-than-two-year	
	Sample	Texas universe	Sample	Texas universe
Total annual enrollment	46,718	48,717	16,002	55,419
Share of Texas enrollment covered	95.9%	100.0%	28.9%	100.0%
Number of institutions	93	104	56	274
Share of Texas institutions covered	89.4%	100.0%	20.4%	100.0%
Share of completions				
Health professions	64.6%	63.1%	77.1%	53.7%
Cosmetology/barbering	0.3%	0.4%	0.0%	27.0%
$<$ 1-year certificate	30.9%	30.8%	44.3%	43.8%

Notes: Statistics correspond to 2003–2014 IPEDS enrollment and completions data for Texas for-profits classified as two-year or less-than-two-year. Within degree-granting two-year colleges, enrollment coverage is 98.5%.

IPEDS defines transfer students as those who have not graduated from the original college, making graduates and transfer students disjoint groups. While the samples feature similar total shares of students graduating from the original college or transferring within 150% of normal time, Texas CCs appear to be more transfer-oriented. This difference may reflect the fact that Texas CCs certify students in the "Core Curriculum," which is a block of 42-48 SCH, just shy of the 60 SCH typically required for the Associate's degree. Completing the Core Curriculum allows students to transfer their general-education requirements as a block to another Texas public institution without first earning an Associate's degree, potentially contributing to Texas's relatively high rate of transfer before degree receipt. Texas CCs award credentials of similar levels, though awarding relatively fewer strictly less-than-one-year certificates. And on financial metrics, Texas CCs are quite representative, though their total revenues and spending are modestly lower.

Finally, I compare program-of-study distributions. Figure A1 shows that Texas two-year colleges are largely representative of the US in their fields of study. Community colleges in particular are quite similar. The primary distinction is that two-year for-profits in Texas award relatively more credentials in healthcare fields and virtually no credentials in cosmetology. Note that the share of students *enrolled* in academic CC programs like liberal arts and general studies is higher than indicated by degree completions, since students in academic majors are more likely to transfer to four-year colleges and not show up in community-college completion records.

On the whole, Texas is a large and broadly representative subset of the US two-year college sector. The key sector differences in terms of graduation-rate patterns, tuition and

spending, and program mix are all similar, suggesting that the key factors driving returns in Texas may be shared across other US markets. The two primary caveats are that Texas CC students are much more likely to transfer before graduating — though combined rates of transfer or graduation are similar — and that Texas two-year for-profits specialize more heavily in the shorter certificate programs.

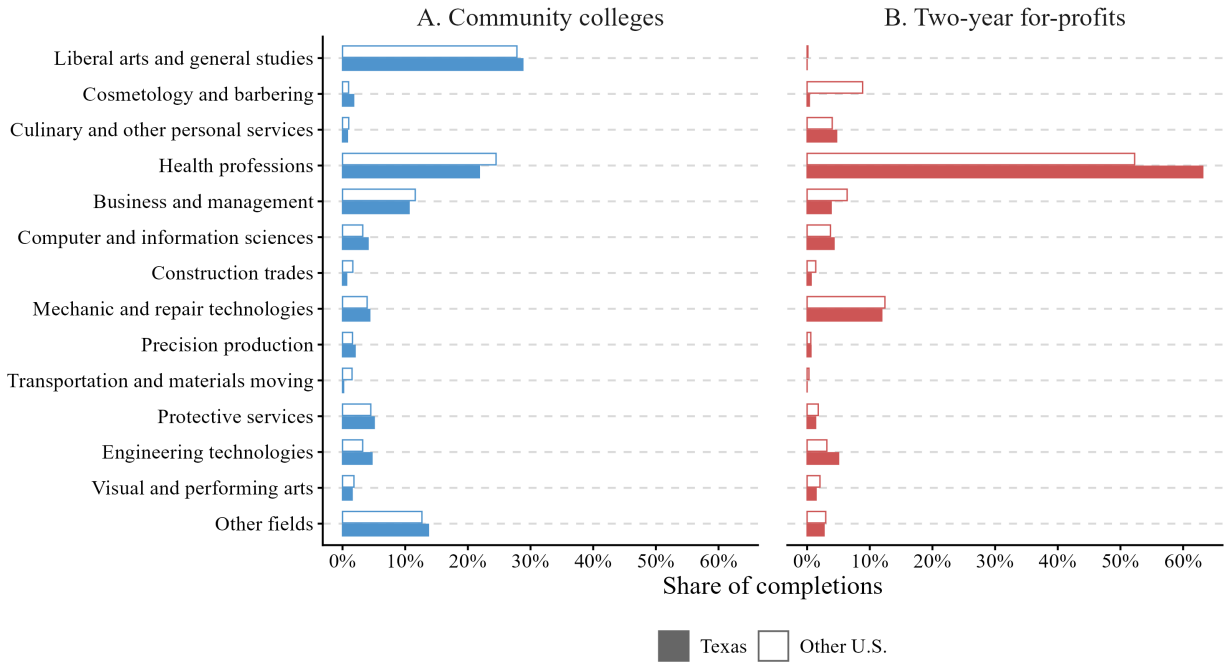


Figure A1: Program-of-Study Distributions

Notes: Data from 2003–2014 IPEDS completion records. Community colleges include all primarily sub-baccalaureate public institutions; for-profits include degree- and non-degree-granting two-year institutions.

Table A2: Two-Year For-Profit College Characteristics

	Texas	Other US
Panel A: Core characteristics		
Annual FTE enrollment	732	526
Full-time share	92.4%	89.3%
Graduated $\leq$ 150% of normal time	60.8%	61.1%
Transferred	0.4%	0.7%
Graduated or transferred	61.2%	61.8%
Panel B: Program characteristics		
# program offerings	5.9	8.3
# two-digit CIP offerings	2.5	2.8
Share of completions		
$<$ 1-year certificate	30.8%	22.7%
1-year certificate	42.6%	35.3%
2-year certificate	6.8%	10.0%
Associate's	19.8%	32.0%
Vocational major	98.6%	97.7%
Fully online enrollment	2.0%	5.8%
Continuous enrollment window	23.4%	32.5%
Panel C: Student characteristics		
Women	60.1%	64.5%
Black	21.8%	23.9%
Hispanic	35.9%	16.2%
White	23.9%	42.7%
Age $\geq$ 25	47.2%	48.9%
Panel D: Financial characteristics, per FTE		
Tuition minus all grants	\$10,941	\$10,150
Implicit subsidy	\$4,109	\$5,003
Total revenue	\$16,014	\$17,018
Total spending	\$14,094	\$15,153
Instructional spending	\$4,413	\$4,794
Services and support spending	\$8,093	\$8,190
Number of colleges	104	1,431

Notes: Statistics represent enrollment-weighted averages, calculated for 2003–2014 IPEDS data for two-year for-profit colleges. Annual FTE enrollment, however, is not enrollment-weighted, and variables denoted under "Share of completions" are weighted by completions. Fully online enrollment is only measured in 2012–14. All monetary amounts measured in 2025 dollars. Implicit subsidies to for-profits are simply government grants, which include Pell, other federal, and state/local student grants. Services and support spending includes expenditures on academic support, student services, and institutional support.

Table A3: Community College Characteristics

	Texas	Other US
Panel A: Core characteristics		
Annual FTE enrollment	6,533	4,310
Full-time share	33.8%	39.9%
Graduated $\leq$ 150% of normal time	12.8%	21.7%
Transferred	24.1%	17.6%
Graduated or transferred	36.9%	39.3%
Panel B: Program characteristics		
# program offerings	74.7	63.0
# two-digit CIP offerings	18.7	16.6
Share of completions		
$<$ 1-year certificate	13.1%	23.1%
1-year certificate	21.7%	13.5%
2-year certificate	0.6%	0.8%
Associate's	64.6%	62.6%
Vocational major	64.4%	66.2%
Fully online enrollment	12.3%	10.0%
Continuous enrollment window	0.0%	0.1%
Panel C: Student characteristics		
Women	57.2%	56.6%
Black	14.2%	13.6%
Hispanic	30.4%	14.2%
White	44.4%	56.0%
Age $\geq$ 25	35.6%	40.9%
Panel D: Financial characteristics, per FTE		
Tuition minus all grants	\$499	\$1,146
Implicit subsidy	\$9,092	\$10,164
Total revenue	\$14,842	\$16,907
Total spending	\$13,858	\$15,895
Instructional spending	\$5,727	\$6,553
Services and support spending	\$4,201	\$5,056
Number of colleges	66	1,096

Notes: Statistics represent enrollment-weighted averages, calculated for 2003–2014 IPEDS data for primarily sub-baccalaureate public colleges. Annual FTE enrollment is not enrollment-weighted, and variables denoted under "Share of completions" are weighted by completions. Fully online enrollment is only measured in 2012–14. All monetary amounts measured in 2025 dollars. For public colleges, implicit subsidies are defined as spending on instruction and academic, student, and institutional support, plus government grants, minus gross tuition revenues. Services and support spending includes expenditures on academic support, student services, and institutional support.

C 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 $\to$ 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 $\to$ 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 $\to$ 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 A4 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 A4: 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 A5 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 A12).

Table A5: 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.

D 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 A6 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, students on the for-profit margin 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%.[46] 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.

[46] Note that this differs from the 37% reported in Table 9 because transcript data is only available beginning in 2011, and the sample therefore differs.

Table A6: 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.

E 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 A7).

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 A7: 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.[47] Prerequisite courses, and whether they count toward the credit total, are also documented separately. Remedial requirements are excluded, as these largely follow a statewide schedule.[48] 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

[47] 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.

[48] 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 1,078 programs representing 86.1% of completions in the sampling frame. It covers 90.8% of for-profit programs and 95.4% of for-profit completions, together with 69.9% of public programs and 83.3% of public completions.

Sample Statistics Table A8 presents average program requirements at two-year for-profit and public colleges in Texas. Semester-credit requirements are available for programs representing 95.4% of for-profit completions and 83.3% of public-college completions. To account for differential missingness across fields of study, I calculate each sector's completion-weighted means within six-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 six-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 2.4% of public requirements, rising to 4.9% 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 12.4%, 3.8%, and 8.9%. 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 A8: Degree Requirements at Two-Year College Programs

	For-profit	Public	
	(1)	(2)	(3)
Panel A: Certificate programs			
Total credits	38.9	28.2	31.9
Academic credits, conservative	0.4	0.8	1.7
Academic share, conservative (%)	0.8	2.4	4.9
Academic credits, broad	5.3	1.2	3.1
Academic share, broad (%)	12.4	3.8	8.9
Number of programs	136	486	486
Share of completions (%)	95.3	84.1	84.1
Panel B: Associate's programs			
Total credits	69.1	61.3	61.3
Academic credits, conservative	6.4	19.2	15.2
Academic share, conservative (%)	9.1	31.3	24.8
Academic credits, broad	9.0	23.7	17.9
Academic share, broad (%)	12.4	38.7	28.9
Number of programs	51	405	405
Share of completions (%)	95.7	82.2	82.2
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 six-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 24.8%. Under the broader definition, the corresponding shares are 38.7%, 12.4%, and 28.9%. 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.

Program Requirements within Vocational Majors I next evaluate how much of the differences in marginal students' academic requirements, described in Table 7, owe to CC students' greater likelihood of enrolling in fully academic programs. Table A9 presents the same specifications as in Table 7, but dropping students who initially enroll in academic programs. Since vocational major choice is endogenous, contrasting these potential outcomes does not generally identify treatment effects conditional on vocational major choice. Rather, these outcomes describe the requirements faced by students on the FP/CC margin who self-select into vocational majors. This subsample of vocational students comprises 70% of those enrolling in CCs and 99% of those enrolling in for-profits. Even within vocational programs, marginal CC students face substantially greater academic coursework, averaging 12.4 additional academic credits and 21.1 percentage points greater academic credit shares.

Table A9: Program Requirements on FP/CC Margin (Vocational Only)

	Total credits	Academic credits	Academic share of credits (%)
FP	42.6	3.3	5.1
	(2.3)	(0.9)	(1.4)
CC	58.9	15.8	26.2
	(0.4)	(0.4)	(0.7)
Difference	−16.3	−12.4	−21.1
	(2.4)	(1.6)	(1.7)

Notes: Mean program requirements in the initially chosen programs of marginal students in each sector, estimated using the distance-IV design. Sample excludes students enrolling in academic programs, who make up approximately 30% of marginal students who enroll in CCs. Academic credits include required general-education and other non-vocational coursework. Heteroskedasticity-robust standard errors in parentheses.

F Additional Evidence on Academic Barriers

Public colleges impose heightened academic requirements which appear quite costly for students on the margin of for-profit enrollment. To further understand how students perform in *for-profit* coursework, I 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 instead 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. I first document differences in course-taking and then compare academic performance across sectors, before decomposing the overall for-profit GPA premium into differences in curriculum and within-subject grades.

Curricular Differences For-profit students take a substantially narrower set of courses than observably similar public-college students, consistent with the evidence from Section 4.1 on differences in degree requirements. Figure A2 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.[49]

Course-taking patterns also differ in breadth, as public-college students are more likely to take courses outside their major. Figure A2 also plots the share of students taking each of several subjects, restricting in each case to students who are not majoring in the given

[49] 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).

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 do not offer academic coursework in these subjects, given that they almost exclusively offer a handful of vocational majors.

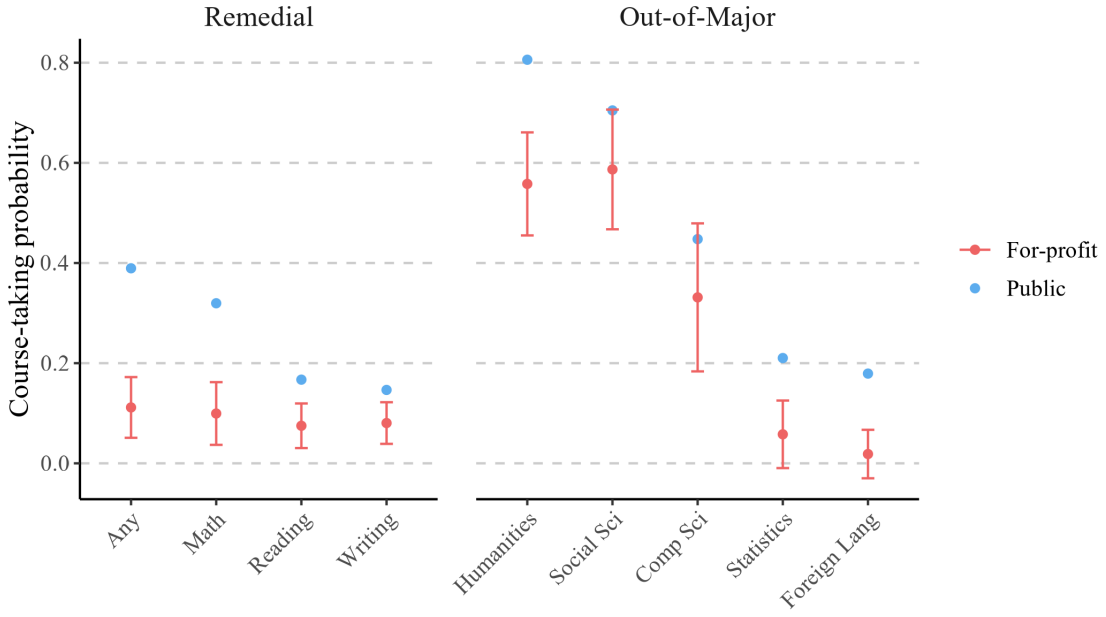


Figure A2: Remedial and Out-of-Major Course-Taking

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.

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.[50] For-profit course-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

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

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 distinguish grading standards from student learning, I 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 in academic achievement (value added) and the college's subjective grading standards.

Table A10 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 A10 also shows that this gap falls to 0.16 within CTE courses (among students majoring in a CTE field).

The BPS data also record performance in academic and vocational (CTE) coursework. Figure A3 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 A3 shows that public students take substantially larger shares of their credits in the academic courses where they struggle most.

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 grades.

Decomposing GPA Differences: Curriculum vs. Within-Subject Grades Let the

Table A10: Grade Differences 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.

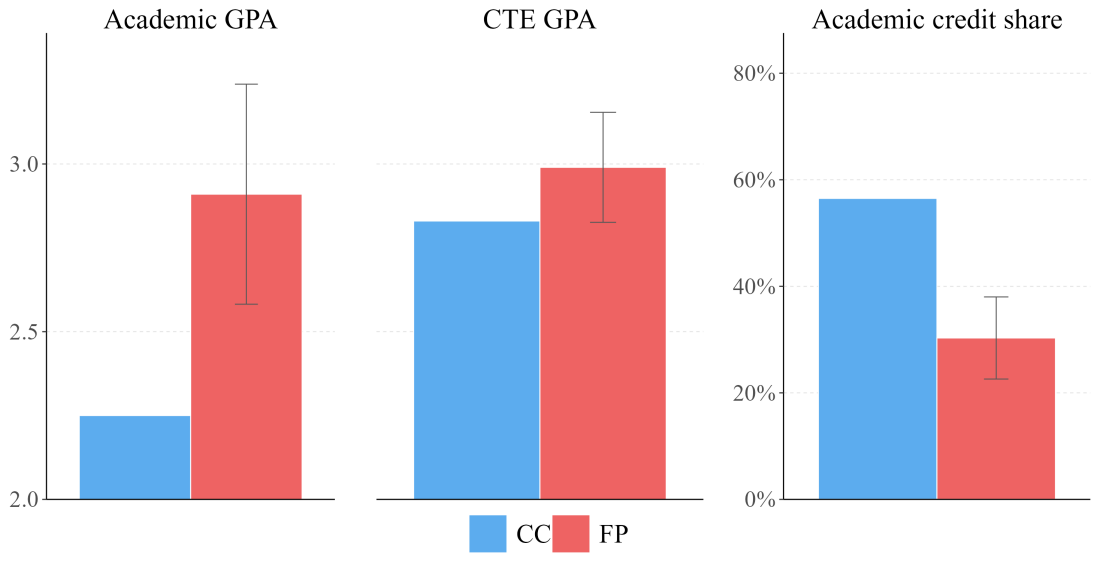


Figure A3: Course Composition and GPAs among CTE Students

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

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 covariate-adjusted 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. Figure A4 summarizes these three components.

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 A5 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 patterns suggest that for-profit students both anticipate greater academic success and earn higher grades than their CC peers. Awareness of weaker academic requirements at entry may also influence student sorting, particularly among academically under-prepared students.

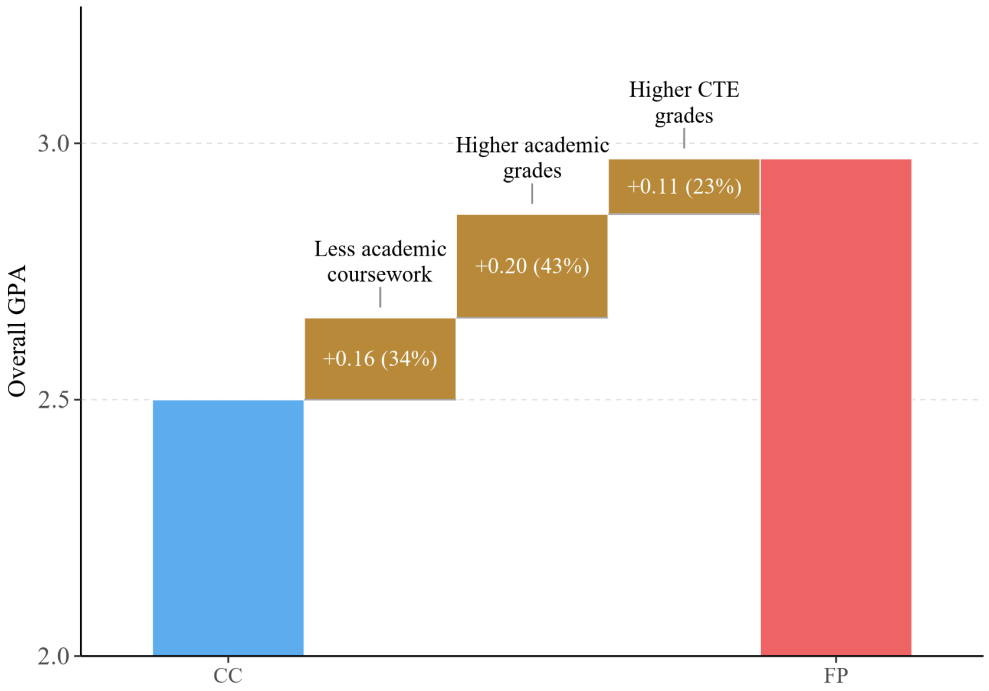


Figure A4: Oaxaca-Blinder Decomposition

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.

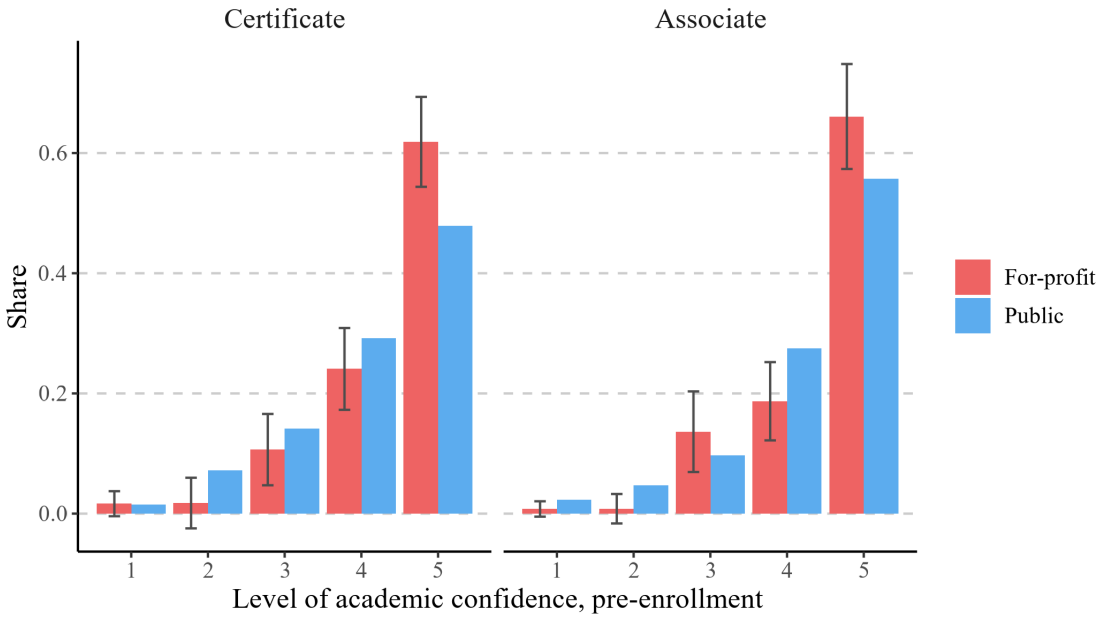


Figure A5: Academic Confidence at Entry

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.

Ability Gradients in the National Data Using the earlier BPS 04/09 survey, Figure A6 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 investment. While prior work has documented that for-profit students report significantly lower satisfaction with their schooling choices, Figure A6 shows that this pattern is concentrated among academically better-prepared students. Academically weaker 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.

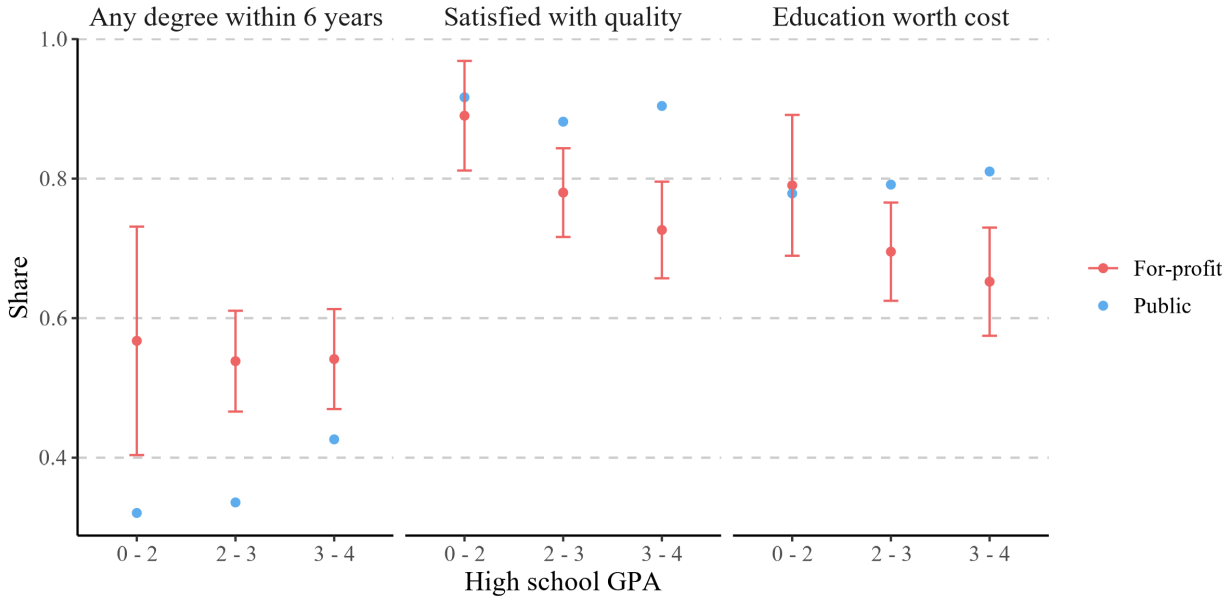


Figure A6: Relative Success by Academic Preparedness

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 covariate-adjusted 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.

G Public Technical Colleges

A small subset of primarily sub-baccalaureate public colleges resembles primarily sub-baccalaureate 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 270 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 A11 documents how these colleges compare to primarily sub-baccalaureate for-profits and traditional public colleges. 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 programs and majors. As for outcomes, graduation rates at both for-profit and technical public colleges are about 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 about 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 net tuition at technical public colleges is much higher than at traditional publics, for-profits are significantly more expensive than both public groups.

Table A11: Two-Year College Characteristics

	For-Profit	Technical Public	Traditional Public
Panel A: Core characteristics			
Annual FTE enrollment	334	256	3,768
Full-time share	84.3%	71.6%	35.7%
Graduated $\leq$ 150% of normal time	66.9%	73.3%	35.5%
Transferred	0.9%	1.8%	15.0%
Graduated or transferred	67.7%	75.2%	50.5%
Panel B: Program characteristics			
# program offerings	3.8	10.0	55.7
# two-digit CIP offerings	1.5	4.2	15.7
Share of completions			
$<$ 1-year certificate	32.9%	31.4%	24.2%
1-year certificate	53.2%	61.6%	16.9%
2-year certificate	4.3%	4.0%	0.5%
Associate's	9.6%	3.0%	58.4%
Vocational major	98.9%	100.0%	64.2%
Fully online enrollment	3.1%	1.3%	28.0%
Continuous enrollment window	60.2%	21.9%	2.0%
Panel C: Flexibility and amenities			
Offers part-time enrollment	48.0%	63.3%	99.7%
Partly online enrollment	12.9%	1.6%	27.4%
Offers online courses	24.8%	11.5%	96.0%
Offers online programs	8.4%	7.4%	78.4%
Offers non-credit remediation	0.6%	18.5%	56.6%
Offers Bachelor's programs	6.0%	0.7%	19.3%
Offers dormitories	0.9%	2.2%	27.4%
Offers meals	0.3%	1.5%	22.5%
Semester calendar	4.3%	8.5%	89.0%
Panel D: Financial characteristics, per FTE			
Tuition minus all grants	\$9,490	\$5,240	\$820
Implicit subsidy	\$4,394	\$15,411	\$16,218
Total revenue	\$16,015	\$24,629	\$26,435
Total spending	\$13,930	\$24,082	\$23,394
Instructional spending	\$5,483	\$13,804	\$8,678
Services and support spending	\$6,414	\$7,097	\$9,046
Number of colleges	1,987	270	1,023

Notes: Unweighted means based on 2023 IPEDS data for primarily sub-baccalaureate institutions. Technical publics are defined as those only offering vocational fields; all other public colleges are defined as traditional community colleges. All monetary amounts measured in 2025 dollars. For public colleges, implicit subsidies are defined as spending on instruction and academic, student, and institutional support, plus government grants, minus gross tuition revenues. Implicit subsidies to for-profits are simply government grants, which include Pell, other federal, and state/local student grants. Services and support spending includes expenditures on academic support, student services, and institutional support.

H 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.

H.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.

H.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.

H.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.

H.4 Illustration

Figure A7 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.

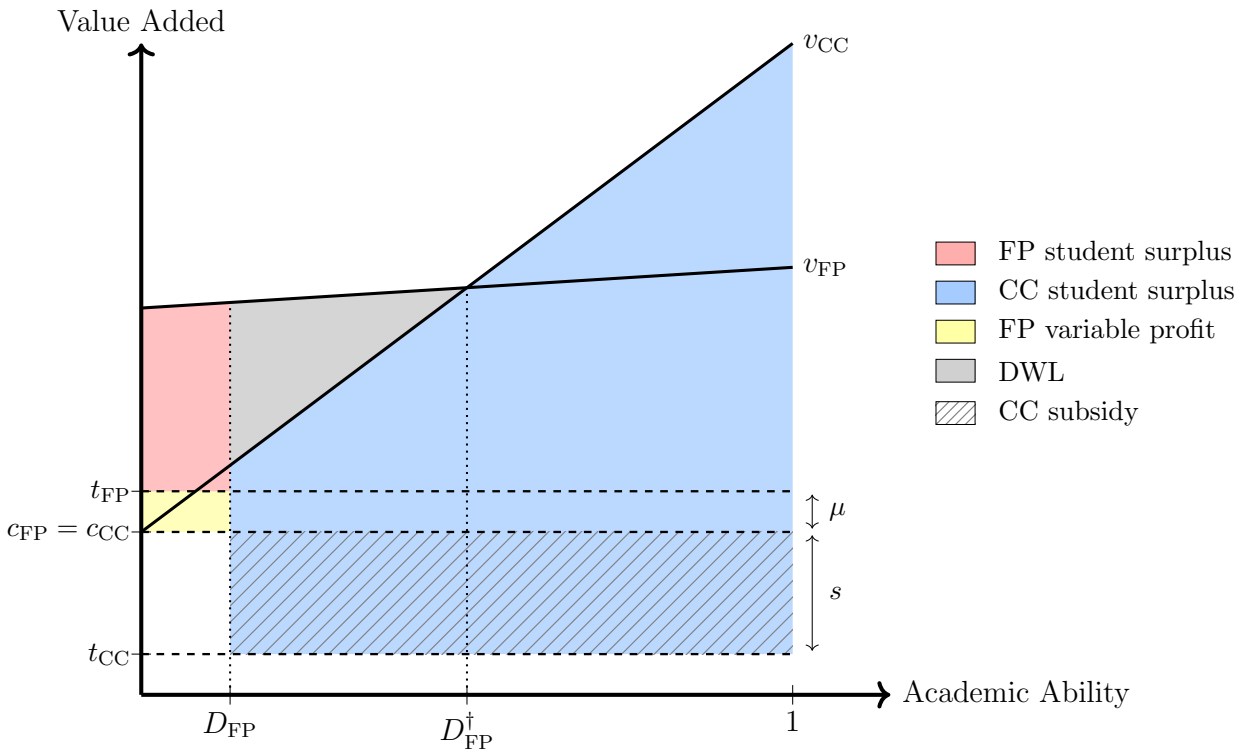


Figure A7: The Decentralized Equilibrium and Efficient Sorting

I Additional Details on MVPF Estimation

Pass-Through Estimation In Section 6 I evaluate the MVPF across a range of subsidy pass-through rates. Here I estimate equilibrium pass-through, using my estimated demand model in conjunction with a Bertrand competition model. 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 $1 < C_j < 2$,[51] college j optimally *reduces* its posted tuition under the subsidy, leading net tuition to fall by more than the subsidy amount. Indeed, my demand 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

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

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.

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.

J 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:

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

where $q_{j\ell}^{j\leftrightarrow k}(x) \equiv \mathbb{P}\{L_i^j = \ell \mid j \leftrightarrow k, X_i = x\}$ and $\mathbb{P}\{G_i^j = g \mid j \leftarrow k \text{ compliers}\}$ are identified by distance IVs. Figure A8 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.

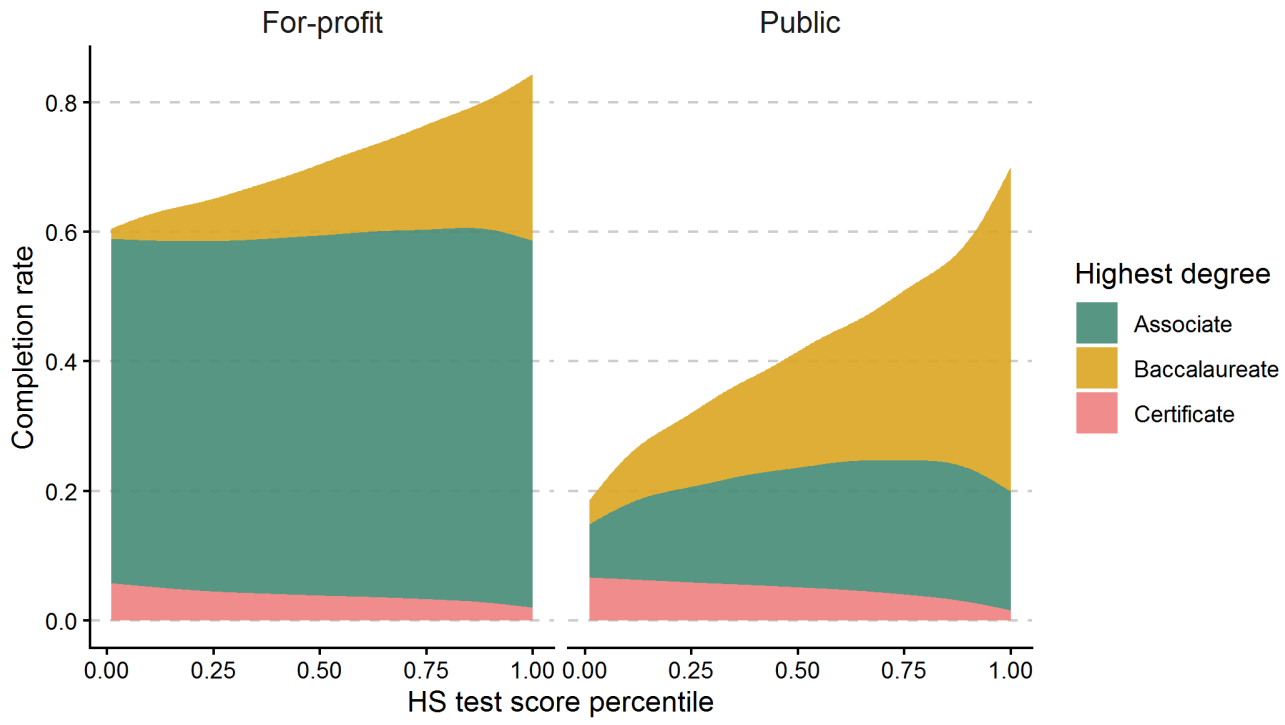


Figure A8: Selection-corrected completion rates by ability (Associate programs)

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.

K Additional Figures and Tables

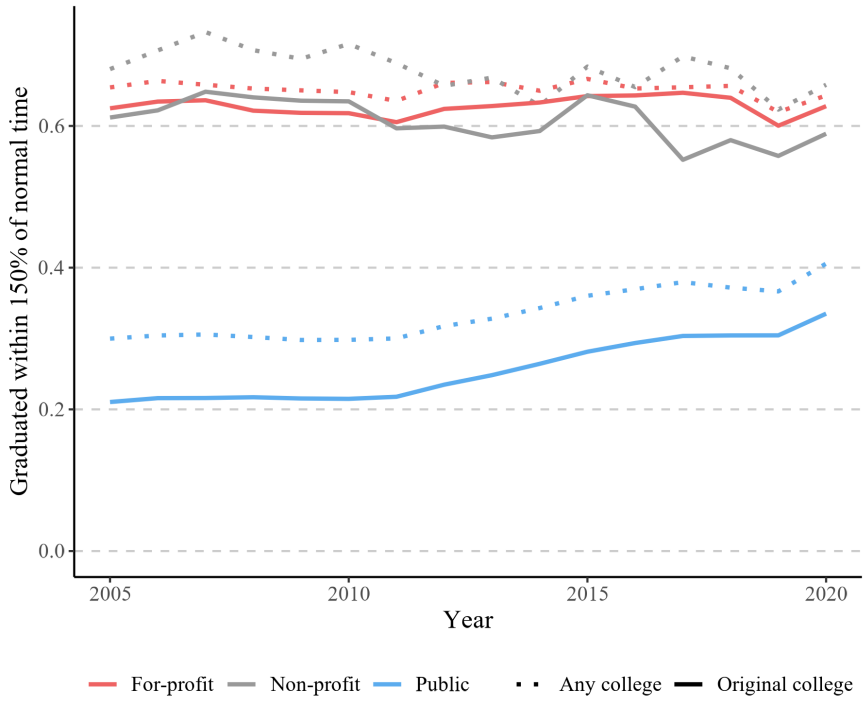


Figure A9: Degree Completion Rates by Sector

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 A12: First Stages, Reduced Forms, and IV Estimates with Student Controls

	Control set	
	Location only	Location and student
Outcome: Long-run completion rate		
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
	(0.014)	(0.014)
Panel B: Reduced forms		
$Y \times D_{CC} \sim Z_{FP}$	0.0057	0.0056
	(0.0004)	(0.0004)
$Y \times D_{FP} \sim Z_{CC}$	0.080	0.085
	(0.011)	(0.011)
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: First stages		
$D_{CC} \sim Z_{FP}$	0.0143	0.0145
	(0.0006)	(0.0006)
$D_{FP} \sim Z_{CC}$	0.117	0.122
	(0.014)	(0.014)
Panel E: Reduced forms		
$Y \times D_{CC} \sim Z_{FP}$	73.0	70.8
	(5.7)	(5.7)
$Y \times D_{FP} \sim Z_{CC}$	543.9	588.8
	(103.9)	(103.8)
Panel F: IV		
Y_{CC}	5,118	4,885
	(310)	(304)
Y_{FP}	4,662	4,823
	(629)	(598)

Notes: Z_{FP} is log distance to the nearest for-profit; Z_{CC} is 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 $\boldsymbol{Z}_{-j}$. Earnings specifications additionally control for the calendar year of earnings observation; first stages therefore differ slightly. The second column adds 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.

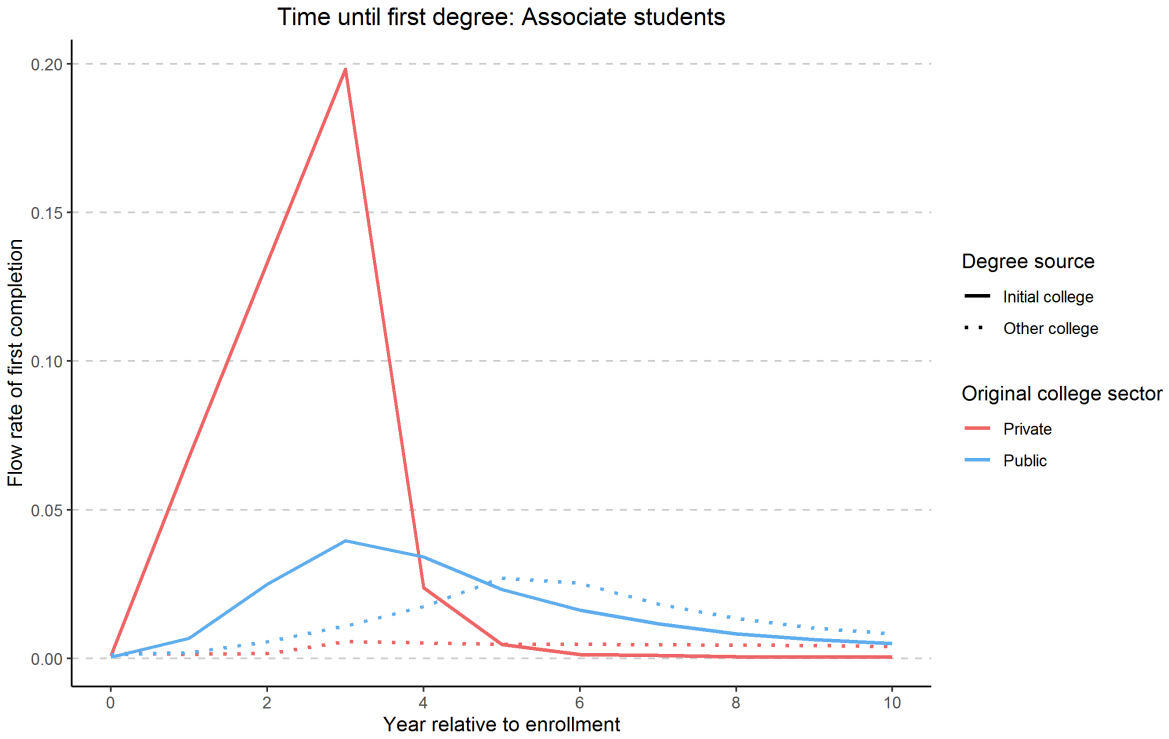


Figure A10: Flow Completion Rates by Initial vs. Transfer School

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.

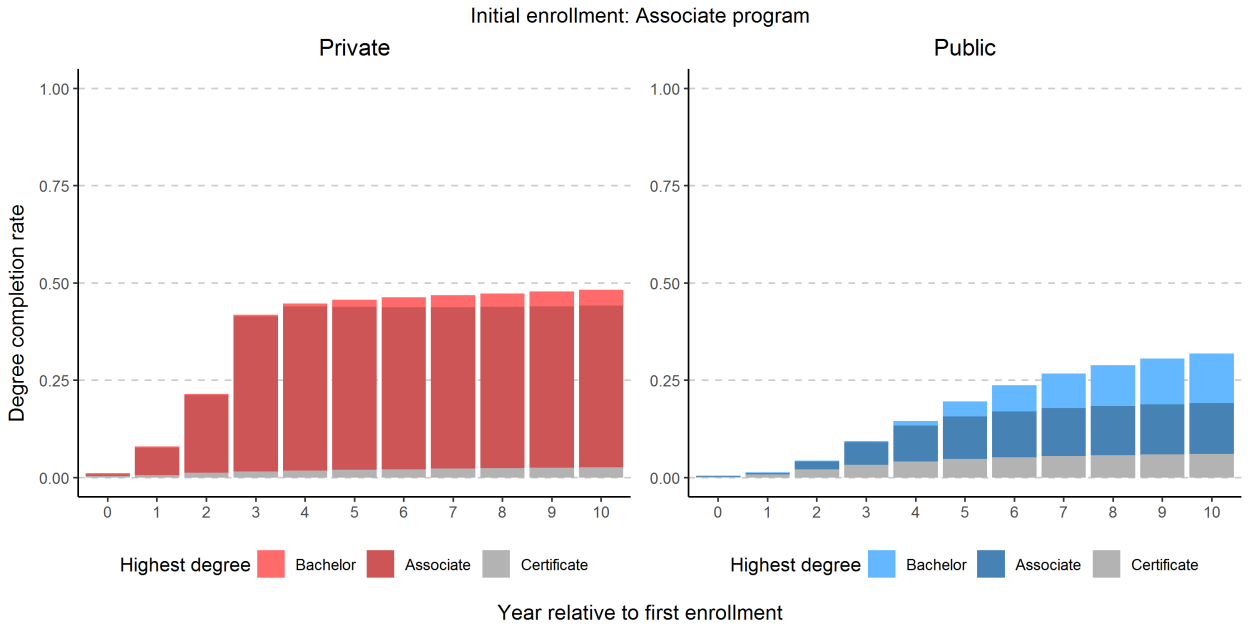


Figure A11: Composition of Degrees Earned among Initially Associate's Students

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.

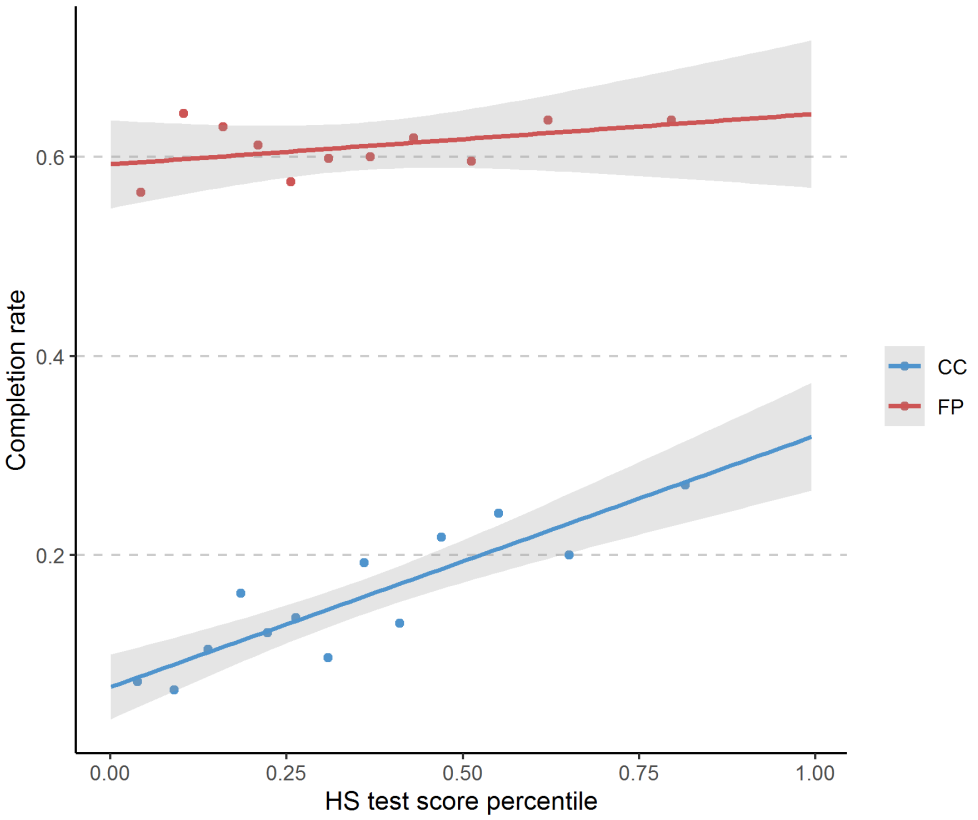


Figure A12: Completion Rates of FP → CC Switchers

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.

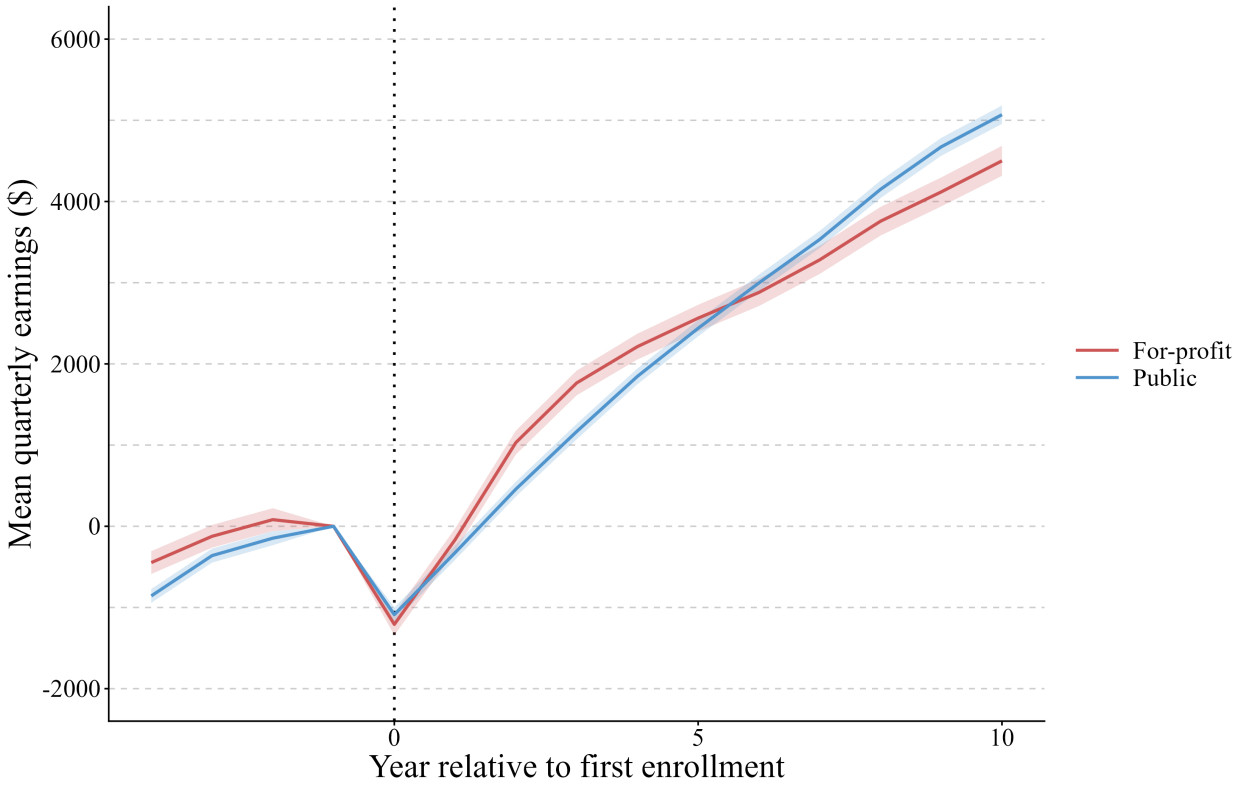


Figure A13: Raw Earnings Profiles of Associate's Degree-Seekers

Notes: See notes for Figure 9. Earnings profiles of eventual graduates and dropouts are pooled within initial enrollment sectors.

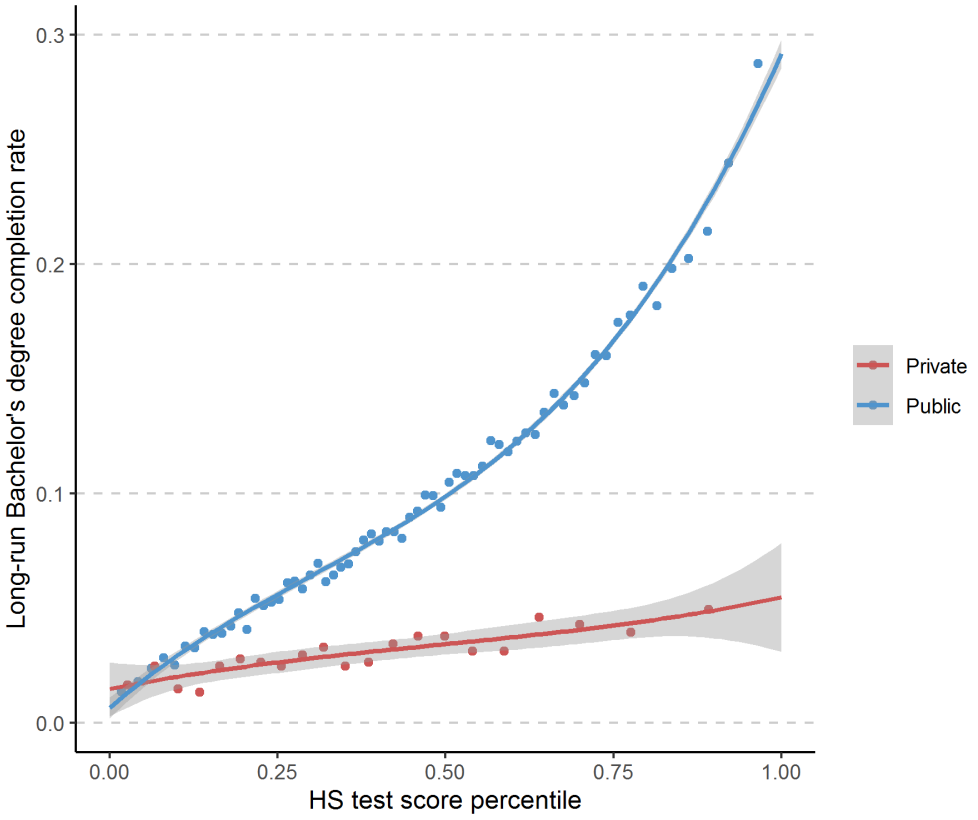


Figure A14: Bachelor's Completion Rates by Pre-College Academic Ability

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.