Measuring the Economic Returns to Postsecondary Education at Scale

An Analytic Framework and Findings from Texas

May 2026

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This project relies on data managed by the University of Houston Education Research Center. The conclusions of this research do not necessarily reflect the opinion or official position of the University of Houston Education Research Center, the Texas Education Agency, the Texas Higher Education Coordinating Board, the Texas Workforce Commission, or the State of Texas.

Acknowledgements

We are grateful for the contributions of those who made this study possible. We thank Wynn Rosser and David Troutman at the Texas Higher Education Coordinating Board and Jeanette Narvaez and Catherine Horn at the University of Houston Education Research Center (ERC) for their work in helping us access and use ERC data and facilitating our programming efforts. We are indebted to our partners at the Postsecondary Commission for their thought partnership, guidance, and support, including Stig Leschly, Chelsea Pennucci, Jen Dirmeyer, and Joseph Ching. We would also like to acknowledge the Postsecondary Commission's primary donors for this study, the Gates Foundation and the ECMC Foundation. We thank select technical members of the Postsecondary Commission's Advisory Board—Zachary Bleemer, Ben Castleman, Preston Cooper, and Doug Webber—for their expertise, time, and commitment.

We are grateful to the members of the Mathematica study team who performed the data cleaning, programming, and analysis that made this report possible, led by Alma Vigil and including Maria Bartlett, Addison Larson, Nicardo McInnis, Moriah Schwartz, and Sonia Pace. This report was improved by detailed reviews by Brian Gill, editing by Jennifer Brown, and formatting by Sheryl Friedlander.

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Executive Summary

There is growing interest among the public and policymakers in measuring the economic value of postsecondary institutions and programs at scale. However, estimating the impacts of institutions and programs on students' earnings net of costs is challenging. Students' abilities and skills vary widely when entering institutions in ways that likely affect their later earnings. Separating an institution's value added from these differences in students' background characteristics is difficult but critical to ensuring fair comparisons of institutional and program performance.

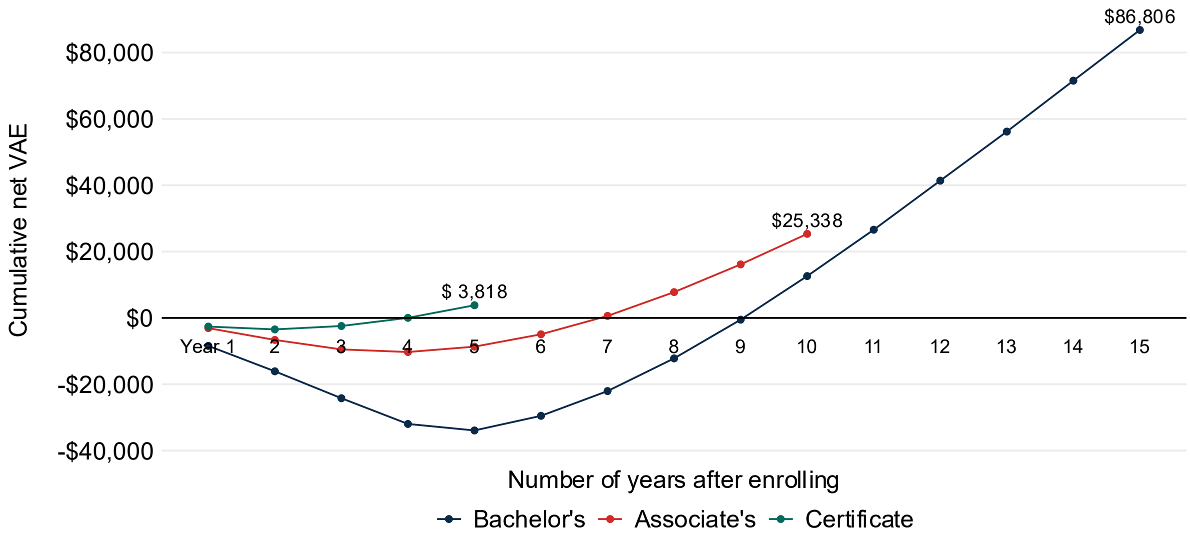
The Postsecondary Commission contracted with Mathematica to design and implement an approach to measuring at scale the economic value that institutions and programs create for students who enroll, relative to what these students would experience if they did not enroll in postsecondary education. Using individual-level administrative data from Texas, the study focuses on students enrolling in-state in two- and four-year public institutions seeking a bachelor's degree, associate's degree, or certificate (which we will refer to broadly as "degree types") between the 2008–09 and 2018–19 academic years.

For each degree type, we estimate the impact of enrolling in an institution or program on students' cumulative earnings after five, 10, or 15 years (depending on whether a student is seeking a certificate, associate's degree, or bachelor's degree, respectively) by comparing students' earnings with those of a matched comparison group of similar individuals who did not enroll in postsecondary education during this follow-up period. The analysis includes all enrollees in an institution or program, regardless of whether they completed their degree. We then subtract the cost of attendance, net of any grant aid and tuition waivers, to calculate cumulative net value-added earnings (hereafter, "cumulative net VAE"). The study uses these cumulative net VAE measures to understand the average economic value of enrolling in different degree types and how this varied across institutions, program of study, and demographic groups. In addition to this report, a companion website publishes our findings, summarizes our methodology and sample, and provides tools to explore and download additional results.

A. Key findings

- **On average, students seeking a bachelor's degree, associate's degree, or certificate from public institutions in Texas experienced positive cumulative net VAE relative to similar students who did not enroll in postsecondary education during the follow-up period.** Students on average earned more than their matched comparison group within the follow-up period, fully recovering their net cost of enrollment, as well as their foregone earnings from enrolling in postsecondary education, after 10 years (bachelor's degree-seeking students), seven years (associate's degree-seeking students), and four years (certificate-seeking students). On average, bachelor's degree-seeking students received a cumulative net VAE of nearly $87,000 after 15 years; associate's degree-seeking students received a cumulative net VAE of over $25,000 after 10 years; and certificate-seeking students received a cumulative net VAE of over $3,800 after five years.

Exhibit ES.1. Cumulative net value-added earnings for all degree types



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 28,614 students who enrolled in bachelor's degree programs in 2008–09; 559,068 students who enrolled in associate's degree programs from 2008–09 through 2013–14; and 67,486 students who enrolled in certificate programs from 2008–09 through 2018–19. Values are student-weighted averages.

- **Although cumulative net VAE varied significantly across institutions, nearly all offered a positive cumulative net VAE to students seeking a bachelor's or associate's degree, and three-quarters offered a positive cumulative net VAE to certificate-seeking students on average.** Cumulative net VAE for bachelor's degree-seeking students 15 years after entry was positive in 27 out of 29 institutions, on average, but ranged widely: from $27,819 for institutions at the 10th percentile to $116,462 for institutions at the 90th percentile. Similarly, 56 out of 57 institutions offered positive cumulative net VAE 10 years after entry, on average, to students seeking an associate's degree. An associate's degree-granting institution at the 10th percentile had cumulative net VAE of $3,858, while an institution at the 90th percentile had cumulative net VAE of $51,857. In contrast, for students seeking certificates, cumulative net VAE after five years was negative in about one-quarter of the 57 institutions. Institutions at the 10th percentile offered a cumulative net VAE of -$7,210 for certificate-seeking students, compared with $16,292 in institutions at the 90th percentile.
- **Across degree types, cumulative net VAE varied significantly depending on students' program of study, with larger cumulative net VAE for STEM (science, technology, engineering, and mathematics) programs, on average.** For bachelor's degree-seeking students, all programs had a positive cumulative net VAE on average, but the highest-earning program (engineering and architecture, with an average cumulative net VAE of $203,435) had much higher cumulative net VAE than the lowest-earning program (liberal arts, with an average cumulative net VAE of $36,177). For associate's degree-seeking students, almost all programs had positive cumulative net VAE, except for personal and culinary services, information technology, and logistics. The spread between the highest and lowest associate's degree programs was also wide (an average of $75,650 for construction trades compared to -$19,541 for logistics). For certificates, only four programs had positive cumulative net

VAE, on average, after five years (construction trades, security and protective services, technical trades, and biology and health), but all others were negative. Across degree types, STEM programs offered higher average returns than non-STEM programs.

- **Across degree types, cumulative net VAE often varied by students' level of high school math achievement, age, and household income.** For bachelor's and associate's degree-seeking students, students with higher math achievement in high school tended to have higher cumulative net VAE. For certificate and associate's degree-seeking students, students who were older at the time of enrolling in postsecondary education tended to have higher cumulative net VAE. Cumulative net VAE varied by household income but only for some degree types. Students from low-income households seeking bachelor's degrees had similar cumulative net VAE as their peers from higher-income households. For students seeking associate's degrees, cumulative net VAE was higher for students from low-income families compared to students from higher-income households, on average. In contrast, among certificate-seeking students, low-income students had higher average cumulative net VAE.
- **Across degree types, students' choice of program of study was related to larger differences in cumulative net VAE than their choice of institution.** Cumulative net VAE varied more across programs within an institution than across institutions overall. As an illustrative example, cumulative net VAE for bachelor's degree-seeking students at an institution in the 90th percentile ranged from $6,519 to $204,697 across programs, a difference of nearly $200,000, while the difference between institutions at the 90th and 10th percentiles overall was only about $89,000. Results from an analysis of variance (ANOVA) show that, for all degree types, students' choice of program explains more of the variation in cumulative net VAE than where they chose to enroll.
- **Across degree types, students' choice of institution was usually related to larger differences in cumulative net VAE than their household income, high school math achievement, or age when they enrolled.** Cumulative net VAE varied more across institutions overall than across household income or age groups within each institution. As an illustrative example, cumulative net VAE for bachelor's degree-seeking students at an institution in the 90th percentile ranged from $116,475 for students from low-income households to $122,307 for students from higher-income households, a difference of under $6,000—much less than the difference between institutions at the 90th and 10th percentiles of about $89,000. For students seeking a bachelor's degree or certificate, cumulative net VAE also varied more across institutions overall than across high school math achievement groups, though this pattern was reversed for students seeking an associate's degree. Overall, the ANOVA results suggest that where a student enrolls tends to matter more for cumulative net VAE than their background.
- **Institutional cohorts in which a higher proportion of students completed a degree had higher cumulative net VAE, on average.** There was a strong, positive relationship between the completion rate of students in an institutional cohort and the cumulative net VAE of that cohort, even after accounting for characteristics of their institution, such as its size and net price. This relationship is consistent across degree types. For example, for every percentage-point increase in the percentage of bachelor's degree-seeking students in a cohort who completed a bachelor's degree (whether at the institution they entered or any other institution during the follow-up period), cumulative net VAE after 15 years was about $2,000 higher, on average.

This study uses a more rigorous approach to estimating the cumulative net VAE that students experience from enrolling in postsecondary institutions at scale than many other approaches currently used by policymakers and practitioners. Although no method that can be implemented at scale can fully account for all differences between students seeking postsecondary degrees and those who do not, the study represents a methodological improvement over simple comparisons that do not adjust extensively for differences in student characteristics and that focus only on graduates rather than entering students.

I. Introduction

Measuring the economic value that postsecondary education provides is critical for helping students make decisions about enrolling, supporting policymakers in setting accountability policy, and informing institutional leaders to drive internal improvement efforts. Although research suggests that college graduates on average enjoy a meaningful earnings premium relative to individuals with only a high school diploma, outcomes can vary significantly for different types of postsecondary institutions and programs of study (Altonji et al. 2012; Andrews et al. 2016). Further, not all students who enroll in postsecondary education complete a degree, and not all graduates earn enough to pay off their investment (Abel and Deitz 2025a, 2025b; National Center for Education Statistics 2022). Amid this uncertainty and the often high cost of pursuing postsecondary education, Americans express broad, bipartisan support for ensuring that postsecondary education provides a financial payoff to students to maintain access to taxpayer funding (Sawyer 2025).

In the past 15 years, several efforts have sought to increase transparency in students' net costs and post-college earnings. At the federal level, the College Scorecard, released in 2013, reports average net costs and median earnings at various points after enrollment or completion for students who received federal financial aid. A growing number of states are also making the earnings of graduates from their public institutions available on their websites. In addition, states and the federal government are increasingly tying institutions' funding or eligibility for financial aid to student outcomes. As of 2020, over 30 states had implemented some form of performance-based funding, holding institutions accountable for outcomes such as completion as part of their funding formulas. Sixteen of these states specifically measure workforce outcomes, such as the earnings of graduates (Whinnery and Keily 2024). Most recently, the One Big Beautiful Bill Act (OBBBA), passed in July 2025, introduced a new accountability standard based on graduates' earnings that postsecondary programs must meet to maintain eligibility for federal loans.

Although these efforts help promote transparency and accountability, conventional approaches to measuring institutions' performance typically examine the outcomes of graduates without accounting for differences in the skills and abilities of individuals who choose to enroll in postsecondary education compared with those who do not. As a result, these measures are unlikely to accurately measure *institutions' contributions* to students' outcomes. The Postsecondary Commission contracted with Mathematica to develop and implement an approach to measuring the economic value associated with enrolling in postsecondary education across institutions and programs of study (hereafter, programs) at scale using appropriate comparison groups to adjust for these differences.

A. Study background

Despite the growing interest in measuring the economic value of institutions and programs, identifying their contribution to students' earnings is inherently challenging. When they initially enroll in postsecondary education, students vary widely in their skills and abilities in ways that likely affect their later earnings. As a result, simply comparing the earnings of individuals who do and do not enroll in a given institution or program will reflect pre-existing differences in their profiles in addition to how much the institution or program contributed to their earnings. For example, students who enroll in more selective institutions or who enroll in a science, technology, engineering, and mathematics (STEM) major tend to have stronger math skills before enrolling in postsecondary education than those who do not and would likely have higher earnings as a result, even if they never enrolled in postsecondary education. Separating an institution's value added from these differences in students' profiles at enrollment is difficult but critical to ensuring fair comparisons of institutional and program performance.

Several studies have used strong research designs to identify the causal impact of institutions or programs on students' earnings. For four-year public institutions that have set minimum grade point average (GPA) or test score requirements for admission, studies have used regression discontinuity designs (Hoekstra 2009; Kirkeboen et al. 2016; Kozakowski 2023; Mountjoy 2026; Smith et al. 2025; Zimmerman 2014) to identify the impact of enrollment on students' earnings. These studies do so by comparing the outcomes of individuals who are just above the cutoff for admission with those just below it, ensuring that both sets of individuals are essentially alike except for their enrollment in the institution. Studies have also used randomized lotteries to estimate the impact of enrolling in a specific program on students' earnings in the rare case where demand for a program exceeds the available seats and a program opts to use a lottery system to determine who to admit (Grosz 2020).

Other studies have used detailed admissions data to estimate the impact of enrolling in specific institutions on students' earnings. These studies control for the set of institutions to which students apply and are admitted or compare students who are and are not admitted from the waitlist (Chetty et al. 2025; Dale and Krueger 2002, 2014; Mountjoy and Hickman 2021). For students entering certificate and associate's degree programs with a substantial employment history, studies have also used fixed effect designs to measure the impact of enrollment on students' earnings. Such studies compare the change in an individual's earnings over time to the change in earnings for those not yet enrolling in postsecondary education over the same period (Jepsen et al. 2014; Minaya and Scott-Clayton 2022).

Although these approaches can credibly identify the impact of an institution or program on students' earnings, they have a few features that make them poorly suited to measuring value at scale. First, these approaches cannot be applied widely to different types of institutions and programs. Most institutions do not have specific GPA or test score thresholds for admission or use admission lotteries, and many students entering U.S. institutions are younger than 20, without substantial employment histories. Second, obtaining detailed admissions data from institutions is difficult to do at scale and can only be used to estimate impacts for institutions that are not open access. Third, these approaches do not always measure impacts for a broad population of students. For example, regression discontinuity designs provide estimates for only a narrow set of students enrolling in four-year colleges—those just barely qualifying for admission—which may be quite different from institutions' impacts on average.

Other simpler approaches have been proposed to measure the economic value of institutions and programs at scale, typically assessing whether institution or program graduates outearn a typical high school graduate without accounting for differences in the characteristics of students who enroll in postsecondary education and those who do not and without assessing the outcomes of students who do not complete a degree.[1] One example is the requirement in OBBBA that in order to be eligible for federal

[1] Examples include the Postsecondary Value Commission's minimum economic return threshold (Dancy et al. 2021); the OBBBA "do no harm" standard (Caldwell et al. 2025); and Texas's Credentials of Value (Cox and Lui 2025).

loans, an undergraduate program must produce graduates who have higher median earnings than the typical high school graduate who does not pursue postsecondary education.[2] Though relatively simple to implement at scale, approaches like this one that do not adjust for differences in the background characteristics of students who pursue postsecondary education or that focus only on degree completers can misstate the value of enrolling in postsecondary education. Also, by comparing postsecondary students' earnings to those of an average individual holding a high school diploma in the same state, these approaches ignore variation in labor markets within states and can disadvantage institutions serving predominantly rural areas, where wages tend to be lower, and advantage those serving urban areas, where wages tend to be higher. Prior studies estimating the economic returns to community colleges and four-year public institutions have found that it is important to adjust for differences in the profiles of students who enroll and those who do not (for example, accounting for where they attended high school and their academic achievement in high school) to reduce bias in the estimates (Cunha and Miller 2014; Kurlaender et al. 2016).

Most of these simpler approaches also rely on the College Scorecard to capture students' post-college earnings and the net cost of postsecondary education. Although it is the most comprehensive public source available for this information, there are important constraints to using these data to measure institutions' value added. Because the College Scorecard reports post-college earnings at a single timepoint, it does not make it possible to measure the opportunity cost of pursuing postsecondary education—that is, the lower earnings students typically have while they are enrolled—or to observe how the economic returns evolve over time.[3] The College Scorecard also only reports earnings for students who receive federal financial aid and who are employed and not enrolled in postsecondary education, which ignores the impacts that enrolling in the institution might have on employment and may not be representative of the typical student enrolling in a given institution.[4] Data on earnings by program of study are also only available for students who complete a degree. Measures of the value of specific programs based on these data ignore the large share of students who begin a program but do not complete it. Among full-time students seeking degrees, one-third of those at four-year colleges and two-thirds at two-year colleges do not actually complete a degree (National Center for Education Statistics 2022).

Although postsecondary institutions provide many nonfinancial benefits to students and society (including improving health outcomes, marriage rates, and civic participation [Dee 2004; Oreopoulos and Salvanes 2011]), policymakers and the public are increasingly interested in ensuring that students do not

[2] The comparison group is based on the median earnings of 24- to 34-year-olds with a high school diploma or equivalent credential who are employed and are not enrolled in postsecondary education. If most students in the institution do not come from the state the institution is located in, the threshold will be based on the earnings of individuals with a high school diploma nationally (Caldwell et al. 2025).

[3] Some approaches have used more sophisticated modeling techniques to estimate opportunity costs and earnings over the lifetime, but they require stronger assumptions and may be sensitive to modeling choices (Cooper 2025; Miller and Akabas 2022).

[4] In addition, College Scorecard cost data are based on first-time, full-time students who pay in-state rates. Because many students enroll part time, come back to college after a pause, or pay out-of-state rates, net cost estimates based on College Scorecard data may not reflect the costs a typical student has paid.

end up saddled with costs they cannot pay off when pursuing a degree. As a result, developing methods that can reliably estimate economic value at scale is critical for improving postsecondary education.

B. Overview of the approach

In this study, we propose an approach to measuring the economic value added of institutions and programs that is more rigorous and comprehensive than simpler approaches currently in use in federal and state policy and that can be implemented at scale. Using individual-level data from Texas, we estimate the impact of enrolling in an institution or program on students' cumulative earnings after five, 10, or 15 years (depending on whether a student is seeking a certificate, associate's, or bachelor's degree, respectively) by comparing students' earnings to the earnings of a matched comparison group of similar individuals who did not enroll in postsecondary education over this period.

For each cohort of students who enroll in an institution (and, within those institutions, for each cohort of students who enroll in a particular program or belong to a particular demographic group), we identify a matched comparison group of individuals who did not enroll in postsecondary education during the follow-up period but have similar earnings potential and likelihood of enrolling in postsecondary education based on their background characteristics. These characteristics include their high school achievement, demographics, prior postsecondary enrollment and completion, and past earnings (for those with work histories), as well as the county where they attended high school to account for their geographic context. The difference in cumulative earnings between the students who enrolled in an institution or program and the cumulative earnings for the matched comparison group over the follow-up period is the cumulative value-added earnings (VAE) of the institutional, programmatic, or demographic cohort in question.

After estimating a cohort's cumulative VAE, we subtract the cohort's average total net cost of attendance, including tuition, fees, and supplies minus any tuition waivers, grants, and scholarships to identify *cumulative net VAE*. Cumulative net VAE provides a measure of how much an institution or program contributed to students' earnings, taking into account students' cost of attendance, including both the direct cost of postsecondary education and the opportunity cost in the form of lower earnings while students are enrolled. This measure is useful for assessing whether enrolling in an institution (or a program) will yield a financial payoff to the student relative to not enrolling in postsecondary education.

Our choice to compare students who enroll in postsecondary education to individuals who do not pursue further postsecondary education (but have similar backgrounds and educational histories) differs from the approach used in most rigorous studies. These studies typically measure the impact of enrolling in a given institution or program compared with enrolling in *other* institutions or programs students otherwise consider. For example, in regression discontinuity designs or lottery designs, many of the individuals who are in the comparison group ultimately enroll elsewhere.

We have chosen to select matched comparison groups from individuals who do not enroll in postsecondary education during the follow-up period for a few reasons. First, policymakers are interested in helping students avoid investments that will not pay off. As such, the more pressing policy question when assessing value is whether enrolling in an institution raises students' earnings sufficiently beyond what they would have earned had they not pursued postsecondary education, rather than whether attending one institution is a better investment than another institution. Second, focusing on whether a given institution raises a student's earnings compared with not enrolling in postsecondary education also ensures that all institutions are held to a consistent standard, which is important for transparency and fairness when designing accountability standards.

Our proposed approach offers the following benefits:

- Uses individual-level administrative data to adjust for the characteristics of students who enroll in postsecondary education, as well as local economic conditions, by comparing these students to individuals with similar characteristics and from the same counties
- Focuses on all students enrolling in a given institution for the first time (including both full- and part-time students and transfer students) regardless of whether they ever complete a degree[5]
- Measures earnings gains starting in the year of entry to incorporate the opportunity cost of foregone earnings—a major component of the cost of postsecondary education—in addition to students' total net cost of attendance, inclusive of financial aid
- Observes earnings over longer and continuous periods, allowing the measures to capture wage gains over time

Although relatively less causally rigorous than some of the approaches used in other research studies (such as randomized lotteries or regression discontinuity designs), our proposed design can be applied at scale to provide a consistent benchmark across many institutions and programs to measure their economic value to students. As a result, these measures can be used to support decision making by families, policymakers, and practitioners as well as to study how the economic value of postsecondary education varies for different types of institutions, programs, and students.

In total, we estimate cumulative net VAE for bachelor's degree-seeking cohorts at 29 institutions, associate's degree-seeking cohorts at 57 institutions, and certificate-seeking cohorts at 57 institutions, spanning both four-year and two-year public colleges in Texas. Because the economic returns to postsecondary education can vary widely depending on a student's chosen program of study, we also estimate cumulative net VAE for programmatic cohorts among bachelor's degree, associate's degree, and certificates at a given institution. Finally, we estimate cumulative net VAE for certain demographic cohorts (based on students' household income, high school math achievement, and age when they enroll) to assess whether cumulative net VAE varied based on students' background characteristics.

After estimating these measures of cumulative net VAE, we analyze the results to explore how institutions and programs contributed to students' earnings outcomes. We describe cumulative net VAE for each degree type—bachelor's, associate's, and certificate—including average cumulative net VAE, variation in cumulative net VAE across institutions, and the average amount of time required for students to break even on their investment. We also describe variation in cumulative net VAE at the program level for each degree type and whether there was more variation in cumulative net VAE across institutions or across programs. This inquiry explores whether decisions about where to enroll or what to major in may be more

[5] Because students incur costs regardless of whether they complete a degree, it is important to include all students enrolling in an institution when assessing an institution's economic returns.

consequential for later earnings outcomes. Within institutions, we examine whether cumulative net VAE varied by select demographic characteristics. Finally, we explore whether select characteristics of the student cohorts (such as their completion rates) and the institutions they enrolled in (such as the level of selectivity) were correlated with the cohorts' cumulative net VAE.

The report proceeds as follows. First, we discuss the approach to calculating cumulative net VAE and the data, sample, and methods used for estimating it. We then describe key findings by degree type. We conclude with a discussion of how the findings fit within the broader literature on postsecondary value added and their potential policy implications. The report also includes a technical appendix that provides greater detail on the data, sample, and methods used to estimate cumulative net VAE; summaries of our analysis sample; sensitivity and robustness checks; and supplemental analyses.

II. Approach to Measuring Cumulative Net VAE

This section provides details about the data, sample, methods, and limitations to our approach to estimating cumulative net VAE. Additional technical details about the data, sample, and methods used in the study appear in Appendix Sections A and B.

A. What data do we use to estimate cumulative net VAE?

We use student-level administrative data from the Texas Education Agency (TEA), the Texas Higher Education Coordinating Board (THECB), and the Texas Workforce Commission (TWC) to identify a sample of high school graduates in Texas (including individuals who do and do not enroll in postsecondary education during the study period) and follow them longitudinally from high school into postsecondary education and the workforce. We supplement this with public data from the Common Core of Data (CCD) and Integrated Postsecondary Education Data System (IPEDS).

1. High school data

The TEA data cover all students who attended public schools in Texas and include information on student age, race, sex, special education status, limited English proficiency status, free- or reduced-price lunch status, standardized test performance, high school attended, attendance, disciplinary actions, course enrollments, and graduation status. We use the TEA data to create a sample of high school graduates from Texas public schools from 2007–08 through 2017–18 with a rich set of background characteristics. We supplement these data with publicly available information from the CCD to identify the county of each high school.

2. Postsecondary data

We merge the sample of high school graduates with data from THECB to track their enrollments in postsecondary institutions in Texas following high school graduation. These data include information on the institutions students enrolled in, as well as their degree types, entry years, programs of study, enrollment length and intensity, and degree attainment. We use National Student Clearinghouse (NSC) data, linked to TEA data and covering high school graduates, to exclude individuals who enrolled in postsecondary education out of state and are thus more likely to be employed out of state, which we cannot observe in the Texas workforce data. We also use student-level administrative data from THECB to capture aid students receive (tuition or fee waivers or exemptions and grants) and whether they are eligible for in-state, in-district, or out-of-state tuition and fees. Finally, we merge in public data from IPEDS to estimate tuition and fees and the cost of books and supplies and capture the characteristics of Texas postsecondary institutions, such as their selectivity and total enrollment.

3. Workforce data

We link the sample of high school graduates with data from the TWC's Unemployment Insurance (UI) data system on quarterly earnings in Texas from 2005 through 2024. Although these data do not cover those who are self-employed, contract workers, or federal workers, they typically cover approximately 90 percent of employed workers in a state (Kornfield and Bloom 1999). We sum quarterly earnings to calculate annual earnings and convert these to 2023 dollars to account for inflation and thus facilitate comparisons across cohorts. One feature of these data is that only non-zero earnings are reported in the system. As a result, unemployment or nonparticipation in the labor force must be inferred. We assume that individuals had zero earnings in quarters in which they do not appear in the Texas UI data, a common approach in the literature using administrative earnings records (see, for example, Andrews et al. 2024; Denning et al. 2019; Minaya and Scott-Clayton 2022), which we interrogate in Appendix Section E.

B. What time frame do we estimate cumulative net VAE for?

We measure cumulative net VAE for a follow-up period of 15 years from entry for bachelor's degree-seeking students, 10 years from entry for associate's degree-seeking students, and five years from entry for those seeking certificates. These follow-up periods vary based on the amount of time required to complete a degree and the cost of each degree. Bachelor's degrees have a higher cost and require more time to complete (four years of full-time enrollment), whereas certificates have the lowest cost and duration (typically one year or less of full-time enrollment).[6] The earnings profile for bachelor's degree holders also tends to grow over an individual's career more than for associate's degree or certificate completers (Tamborini et al. 2015). The follow-up period is therefore longer for bachelor's degree cohorts to capture the longer-term earnings growth for these students.

C. Which individuals do we include in the study?

The study sample consists of students who graduated from a public high school in Texas between 2007–08 and 2017–18. We focus on Texas public high school graduates because the high school data provide a common source of background characteristics for both the students who enrolled in postsecondary education (the focus of the study) and for the individuals in their matched comparison groups who have similar characteristics but did not enroll in postsecondary education during the follow-up period. One implication of this is that we cannot include individuals in the sample who attended a private high school in Texas, were homeschooled, or graduated from high school out of state. The sample begins with the 2007–08 cohort of high school graduates because for earlier cohorts of high school graduates in Texas, there are no data available on whether they enrolled in postsecondary education outside of Texas and we do not want to include individuals in the comparison group with unobserved postsecondary education out of state.

We link this sample of high school graduates to postsecondary data and earnings data through 2023. We use this sample to estimate cumulative net VAE for students entering bachelor's degree programs in the 2008–09 academic year, who we follow for 15 years.[7] In addition, we estimate cumulative net VAE for students entering an associate's degree program from 2008–09 through 2013–14, who we follow for 10 years, and for students entering a certificate program from 2008–09 to 2018–19, who we follow for five years.

Because the sample begins with the 2007–08 cohort of high school graduates, cohorts of students entering degree programs in earlier years, such as 2008–09, are limited to those who went directly from

[6] For students in the study sample who complete the degree they are seeking at their institution, the time to degree completion was about 5 years for bachelor's degrees, 4.25 years for associate's degrees, and 1.5 years for certificates.

[7] We also estimate cumulative net VAE over shorter follow-up periods of 10 to 14 years for students seeking a bachelor's degree in 2009–10 through 2013–14 to explore patterns for additional entering cohorts.

high school to postsecondary education. In comparison, for students who entered postsecondary education in 2018–19, we are able to include students who were as much as 10 years removed from their high school graduation. As a result, for students who entered institutions in 2008–09 and in the few years following, we are limited to studying entering students who recently graduated from high school.

This restriction also constrains the set of postsecondary entry years that can be included for a given degree type, given the different follow-up periods used for each one. For bachelor's degrees, only students who entered postsecondary education in the 2008–09 academic year can be followed for 15 years, given that earnings data go through 2023.[8] For associate's degrees, which have a shorter follow-up period of 10 years, we can include students entering from 2008–09 through 2013–14. For certificates, we include students entering from 2008–09 to 2018–19, as their follow-up period is only five years.

As mentioned previously, because the Texas UI system only tracks earnings for those employed, we assume that individuals had zero earnings in quarters in which they do not appear in the Texas UI data. One risk with this approach is that we may be assuming zero earnings for individuals who were in fact earning wages out of state. To reduce this risk, we limit the sample (for both students who enroll in postsecondary education and individuals in their comparison groups) to individuals who were employed in Texas for at least one quarter in the period after students would have typically earned a degree (six years for bachelor's degrees, three years for associate's degrees, and one-and-a-half years for certificates). This would exclude students who left the state immediately after graduating. We describe additional sample restrictions in Appendix Section A.

D. What groups of students do we estimate cumulative net VAE for?

We estimate cumulative net VAE for three different types of student cohorts who enter an institution in the same academic year.

- **Institutional cohorts** include all students who enrolled at a given institution in a given year pursuing the same type of degree (certificate, associate's, or bachelor's), regardless of whether they went on to complete a degree. Each student is only included in one entry year and degree type at a particular institution, based on when they first enrolled at that institution and the degree they sought at that time. For example, one institutional cohort consists of students enrolling for the first time at a specific institution between 2008–09 and 2013–14 pursuing an associate's degree.[9]
- **Programmatic cohorts** are subsets of institutional cohorts that include all students who pursued a particular program of study (major) within an institutional cohort. Because our approach focuses on estimating the value added of enrolling in a degree program rather than completing a degree, we aim to assign students to their program as early as possible. Assigning programs too late could exclude students who exited early and could inaccurately benefit programs with low completion rates. For those pursuing certificate and associate's degrees, we assign students to their stated program at entry. For those pursuing bachelor's degrees, we focus on the program declared by the end of their

[8] We conduct a set of analyses in the Findings section, as well as Appendix Section D, that examine the degree to which findings for this single entry year generalize to later entry years that we could not observe for the full 15-year follow-up period.

[9] We include students who transferred to this institution from another institution during this period.

second year of study, as this is the time by which most students have declared a major (Cairns 2025). For students no longer enrolled at this point, we use the most recent program. See Appendix Section B.1 for further details on how students are assigned to programs, and Exhibit B.3 on how programs are grouped into 17 categories according to their Classification of Instructional Programs (CIP) code.

- **Demographic cohorts** are subsets of institutional cohorts consisting of students who share a particular background characteristic. Demographic cohorts are constructed based on household income during high school, quartiles of high school math test performance, and age at enrollment (under 20, 20–24, 25 or older).

E. How do we estimate cumulative net VAE?

We estimate cumulative net VAE for every cohort using the following steps:

1. Identify the matched comparison group

We identify a comparison group for each cohort using a statistical method called matching. From the pool of all potential comparison group members who graduated high school in the same year as the students in the cohort but who did not enroll in postsecondary education during the follow-up period, we identify those who best resemble the students in the cohort of interest (also referred to as the treatment group) in terms of their earnings potential and likelihood of enrollment in that cohort. The matching strategy first generates predictions of cumulative earnings and of the probability of postsecondary enrollment using information observed prior to postsecondary enrollment, such as prior earnings, demographic characteristics, and high school academic outcomes. It then identifies a comparison group with similar predicted future earnings and postsecondary enrollment probability based on these background characteristics. Our approach is motivated by several key features:

- We compare students who enrolled in a specific institution with similar individuals who did not enroll in any postsecondary institution during the follow-up period.[10] With this contrast, we might expect that—in particular for more selective institutions—some treatment group members might not have a comparable comparison person, based on at least some of their background characteristics.[11]
- Because nearly 4,000 cohorts require matching, it is not feasible to manually assess the differences between the treatment and matched comparison groups and select matching procedures that result in the best balance (that is, result in only minimal differences between the two groups). Nor can we make assessments involving cohort-specific trade-offs between balance and sample size. Instead, as we describe in detail in Appendix Section B.4, we design an algorithm that selects a comparison group for each cohort in a way that generates strong balance while resolving these trade-offs.

[10] Because there are members of a bachelor's degree program cohort who have already completed an associate's degree, the comparison group donor pool for a bachelor's degree program cohort will also include comparison students who have completed an associate's degree.

[11] If we were to skip the matching step and simply estimate a regression, the information about the counterfactual earnings of such individuals would be based on projections of the regression coefficients for those covariates rather than on earnings of similar individuals. The purpose of performing matching before running a regression is to avoid relying on the accuracy of these projections, a concept often referred to as model dependence (see Ho et al. [2007] for a discussion).

- Our study objectives are to generate VAE measures that are as generalizable to each specific institution as much as possible. To that end, the algorithm is designed to include the highest proportion of each entering class of students as possible in the analysis, subject to the constraint of forming treatment and comparison groups that are sufficiently well balanced on background characteristics.[12]

The algorithm forces exact matches on age bins (younger than 19, 19 and 20, 21 and 22, 23 and 24, 25–29, 30–34, 35–39), county where the student graduated high school, and highest degree previously completed at entry. That is, each student is only matched with comparison group members with the same age, county, and prior degree completed. We exact-match on county because the labor economics literature stresses the importance of controlling for geographic location when evaluating human capital programs (Glazerman et al. 2003). Similarly, because earnings trajectories vary substantially by age and highest degree completed, we require close or exact matches on those variables. If we were to attempt to obtain exact matches on all variables—rather than just these three—we would be unlikely to find matches for most students.[13] Instead, the algorithm seeks balance on a large set of additional background characteristics, on average, without forcing an exact match:

- Demographic characteristics: gender, race, ethnicity, special education status, limited English proficiency status, family low-income status (based mainly on free- or reduced-price lunch status)[14]
- Prior earnings, for older individuals with past work experience[15]
- Standardized test scores in math and English (State of Texas Assessments of Academic Readiness [STAAR] or Texas Assessment of Knowledge and Skills [TAKS], depending on the year)
- Other measures of high school academic engagement and performance: disciplinary actions against the student, their attendance rate, the share of courses and share of core courses they failed, and whether they passed any advanced courses
- The highest degree program they previously enrolled in, if any

Appendix Section B.4 describes our matching and estimation algorithm in detail and provides sample characteristics, summaries of balance, and the proportion of students dropped in matching.

2. Compare earnings during the follow-up period

We use regression to estimate VAE through the end of the follow-up period by comparing the cumulative earnings of students in each cohort and of the individuals in the corresponding matched comparison

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[12] This is subtly different from minimizing mean-square error, a focus of some matching designs (Imai and Ratkovic 2014; Kranker et al. 2021). Also note that not all students in a cohort can be included in the study due to missing data.

[13] This concept is often referred to as the curse of dimensionality.

[14] In addition to students who receive free or reduced-price lunch, Texas's TEA data code students as low-income if their family is eligible for Temporary Assistance for Needy Families or other public assistance.

[15] Studies of human capital programs highlight the importance of controlling for prior earnings when estimating the effects of interventions on future earnings (Heckman et al. 1997, 1998). As explained in further detail in the appendix, in keeping with the prior literature, we do not use prior earnings for individuals younger than 20, as they do not reflect labor market skills or future earnings potential. Instead, we require that everyone in the sample has data on high school test scores, prior earnings (from ages 20 or older), or both.

group, controlling for their background characteristics. This doubly robust approach ensures both groups of individuals are similar. It accounts for differences in background characteristics in two ways: matching to identify an appropriate comparison group in step 1 and statistically adjusting for any small remaining differences between the cohort and its matched comparison group in step 2.

3. Calculate net cost of attendance

In addition to capturing the opportunity cost of enrolling in postsecondary education in the form of foregone earnings, we calculate the total net costs students incur to pay for their education. This calculation is the sum of tuition, fees, and the costs of books and education supplies, minus tuition and fee waivers and exemptions, as well as federal, state, and other grants, for the duration of a student's follow-up period. We account for whether students were eligible for in-state or out-of-state tuition and account for students' enrollment intensity (the number of credits they enroll in, and the number of semesters) to prorate their tuition and fees.

We do not include room and board in net costs, because students generally incur these costs whether they enroll in postsecondary education or not. It is possible that the costs of room and board institutions charge are, in some cases, greater than the costs incurred by students not enrolled in postsecondary education. However, we cannot observe which students live on campus or how on-campus housing costs compare to off-campus housing costs. We thus expect that including on-campus room and board as costs would overstate the true additional cost incurred by students who enroll in postsecondary education (and thus the total net cost of attendance) more than excluding them would understate total net costs, even if the costs students incur for room and board could be measured. For similar reasons, we do not attempt to account for transportation, child care, or other costs that both students and non-students typically incur. However, it is worth noting that our approach can result in low net cost estimates when students receive financial aid that covers more than just the costs of their tuition, fees, books, and education supplies.

We focus only on the costs for the first degree a student pursues at an institution, because this is the only cohort to which a student is assigned. For example, if a student enrolls in a certificate program in fall 2008 and then enrolls in an associate's program in fall 2010 at the same institution, we only assign the student to the certificate cohort in 2008 and therefore also only count the costs of the enrollment for the certificate program. We describe additional details in our net cost calculations in Appendix Section B.1.

4. Subtract net costs from VAE

We subtract the average cumulative net cost of attendance from VAE in each year of the follow-up period to obtain estimates of cumulative net VAE for each cohort.

F. What are the limitations of the approach?

Several limitations of our net VAE measures merit consideration. First, when constructing the matched comparison groups, we cannot adjust for all factors that lead some individuals to enroll in a given institution or program rather than not enroll in any postsecondary education during the follow-up period. As a result, our comparison groups may not fully represent the counterfactual outcome, leading to biased estimates. Second, earnings from some types of employment (such as self-employment or gig work) are not captured in our data. Because individuals with these types of employment may be more or less likely to enroll in postsecondary education, we may mismeasure employment and earnings in ways that differ between the treatment and comparison groups, leading to biased estimates. Third, data limitations restrict the set of students at a given institution that we can examine in our analysis, which means our estimates may not generalize to all students who enroll. Finally, for a given institution or program, a different follow-up period length could lead to different conclusions about the economic returns generated for students. We discuss each of these issues below.

1. Selection into postsecondary education

While our approach to estimating VAE ensures that each treatment cohort and its matched comparison group are similar on key background characteristics (such as high school test scores and prior earnings), our approach may nevertheless fail to account for all possible background differences between the two groups. To the extent that these differences affect whether a student chooses to enroll in postsecondary education and their later earnings, the estimates may be biased.[16] For example, students who choose more selective institutions may have families with stronger career networks, which would help a student secure a higher-paying job regardless of any influence the institution has on their earnings. Because students sort into institutions and majors in ways that are likely positively related to their potential earnings, our estimates may be biased upwards, particularly for more selective institutions and majors, though other limitations could result in bias in other directions, as discussed below.

To partially address concerns about selection bias, we test whether estimating VAE with a methodology that relies less on a matched comparison group leads to different estimates than our main approach. This alternative method, individual fixed effects, cannot serve as our main approach because it requires a history of earnings data that is not available for students who enter postsecondary education directly or soon after high school. Instead, our test focuses on the subset of students who enter postsecondary education at older ages. Estimates of VAE under the alternative model are on average similar or higher than estimates of VAE from matching, easing concerns that our estimates suffer from upward bias. Full details of this sensitivity test are in Appendix Section E.1.

An additional layer of selection could be pertinent in our estimates of net VAE for bachelor's degree programs. Unlike associate's and certificate programs, which assign students to programmatic cohorts based on their program at entry, we assign bachelor's students to programmatic cohorts based on their program at the end of their second year. As a result, a student could enroll in an institution with the intent of pursuing a bachelor's in engineering and could then decide not to declare as an engineering major

[16] In the K–12 context, school and teacher value-added estimates are calculated by controlling for a student's prior-year test scores to isolate the impact of schools and teachers on current-year test scores. Validation studies have found that these estimates capture the causal effects of schools and teachers on student test scores (Chetty et al. 2014; Deming 2014; Kane et al. 2013). However, accounting for all relevant background characteristics to obtain unbiased estimates is more challenging in higher education for a few reasons. First, unlike the K–12 context, in which students are tested annually, there are no annual test scores in postsecondary education and, for outcomes like earnings, there is a larger time gap between the start and end of postsecondary education when labor market impacts can be measured. Second, pre-postsecondary earnings for younger students recently out of high school may not be a good predictor of the student's earnings many years later because it takes time for young workers to find a field. For example, many students in high school or immediately after may work in a short-term job.

after experiencing an introductory course. This student would not be counted as an engineering major in our analysis. These mechanisms—the extent to which a student's program designation could be affected by experiences they have with that program—could vary by program and by institution. Our estimates may thus misstate the economic value of certain programs by not accounting for the sorting of students into or out of programs that occurs in the first two years after they enter postsecondary education.

2. Measuring earnings

The administrative wage records that serve as our source for wages have several limitations that in turn limit the net VAE measures themselves. First, they do not capture earnings from outside of Texas: an individual living in and earning wages in another state appears as having no earnings in Texas.

Second, they exclude earnings from self-employment and "gig work," a growing sector of the economy (Katz and Krueger 2019), as well as other categories (discussed in more detail in Appendix Section A.3). Third, our net VAE estimates do not capture the monetary value of employer-provided benefits, such as health insurance and retirement benefits, which are not observed in the data. These restrictions may be particularly important to the extent that enrolling in postsecondary education affects the likelihood that an individual moves to a different state, earns nonreported (rather than reported) wages, or obtains a job that offers nonwage benefits.

How these restrictions may bias the estimates, however, is unclear. For example, if enrolling in postsecondary education leads to greater inter-state mobility and also decreases the likelihood of earning unreported wages, these effects would be expected to go in opposite directions. We discuss the trade-offs associated with sample restrictions used to address this issue in Appendix Section A.3 and test the sensitivity of our estimates to different decisions in Appendix Section E.2. The magnitude of individual institutions' VAE measures is sensitive to decisions about how to restrict the sample based on the availability of earnings data. This suggests that decisions about how to treat individuals without earnings are pertinent, but the decision generally has uniform effects across institutions.

3. Sample restrictions

Another limitation of this work is that the study cannot include all students who enroll in the estimation of cumulative net VAE. The biggest restriction is that the sample is limited to students who attended a Texas public high school and graduated in 2007–08 or later. As described above, this restriction limits the range of students' age in the analysis sample, especially for earlier entry years. The estimates in this report should be considered most relevant for students who attended public high schools in Texas who are approximately age 18 to 19 when entering postsecondary education for bachelor's degree-seeking cohorts, ages 18 to 24 when entering postsecondary education for associate's degree-seeking cohorts, and ages 18 to 29 for certificate-seeking cohorts. That said, we do not find evidence that cumulative net VAE for later entry years, which include higher proportions of older students at entry, is systematically different from earlier entry years. The proportions of students excluded due to different restrictions are presented in Exhibit A.2.

4. Follow-up period

There are trade-offs involved in selecting follow-up periods over which to track earnings outcomes. We determined the length of the follow-up period for each degree type (15 years from entry for bachelor's degree-seeking students, 10 years from entry for associate's degree-seeking students, and five years from entry for those seeking certificates) based on program length and costs. For example, bachelor's degree programs have a higher cost and require longer to complete (four years of full-time enrollment) compared to associate's degree programs (typically two years of full-time enrollment) or certificate programs (typically one year or less of full-time enrollment). However, longer follow-up periods allow more time for earnings premiums to accrue to help pay off the costs of postsecondary education. Thus, cumulative net VAE would likely increase for all degree types with a longer follow-up period, meaning that negative estimates for institutions, programs, or demographic groups may become positive with longer follow-up periods. This may be particularly pertinent for certificate-seeking students, as certificate-seekers have the largest share of cohorts that did not yet accrue enough VAE to pay off the costs of postsecondary education by the end of the follow-up period. As shown in Exhibit D.2, average *annual* net VAE plateaued for bachelor's degree-seeking cohorts within the follow-up period (around year 12 after entry) but did not yet plateau by the end of the follow-up period for associate's degree and certificates cohorts. This suggests that a longer follow-up period for associate's degree and certificate-seeking cohorts may better capture the longer-term benefits of postsecondary education for these groups. An important trade-off is that the longer follow-up period would also make the estimates less timely for stakeholders.

III. Findings

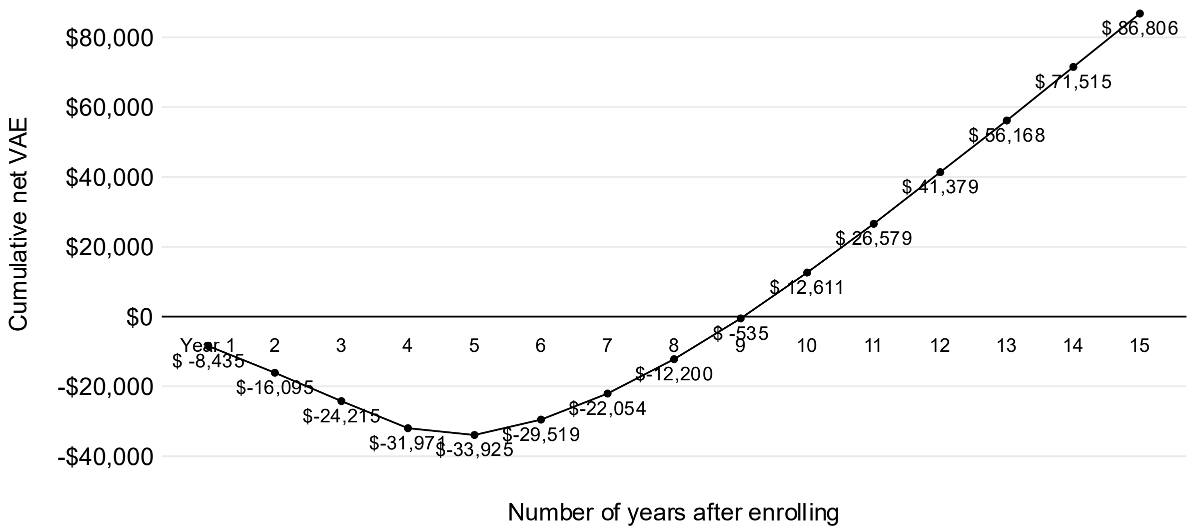
This section presents analyses of our estimates of cumulative net value-added earnings (also referred to as cumulative net VAE) for Texas students enrolling in public institutions in the state. Results are organized by the degree type students pursued (bachelor's, associate's, and certificate), with additional results reported in Appendix Section D.

A. Bachelor's degrees

The average bachelor's degree-seeking student recovered the total costs of enrolling in postsecondary education within 10 years and accumulated a cumulative net VAE of nearly $87,000 after 15 years.

Cumulative net VAE among bachelor's degree-seeking students who enrolled in public institutions in Texas in 2008–09 was initially negative and decreasing during the first five years after enrolling, on average. During this period, students incurred the costs of pursuing postsecondary education and experienced lower earnings from their reduced participation in the labor force compared with similar individuals who did not enroll in postsecondary education during the follow-up period (Exhibit 1). Starting in Year 6, however, cumulative net VAE began to increase, as many students completed a degree and experienced increased earnings. On average, students who enrolled in postsecondary education (regardless of whether they completed a degree) had higher cumulative earnings than the comparison group by Year 8; by Year 10, their cumulative VAE exceeded their total net cost of attendance (Exhibit 2). In other words, on average, students had outearned the comparison group by Year 10 enough to fully recover the total costs of enrolling in postsecondary education. Fifteen years after initial enrollment, the average bachelor's degree-seeking student had a cumulative net VAE of $86,806.

Exhibit 1. Cumulative net value-added earnings for bachelor's degree-seeking students, 2008–09 entry year



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 28,614 students who enrolled in public postsecondary institutions in Texas in 2008–09. Values are student-weighted averages in 2023 dollars.

Exhibit 2. Cumulative earnings, net costs, and value-added earnings for bachelor's degree-seeking students, 2008–09 entry year

Years after enrollment	Cohort cumulative earnings ($)	Comparison group cumulative earnings ($)	Cohort cumulative value-added earnings ($)	Cohort cumulative net cost of attendance ($)	Cohort cumulative net value-added earnings ($)
Year 1	4,348	9,567	-5,220	3,216	-8,435
Year 2	10,909	21,376	-10,467	5,628	-16,095
Year 3	19,700	35,941	-16,241	7,974	-24,215
Year 4	31,993	53,336	-21,342	10,628	-31,971
Year 5	53,180	74,956	-21,776	12,149	-33,925
Year 6	83,892	100,704	-16,812	12,707	-29,519
Year 7	121,445	130,546	-9,101	12,953	-22,054
Year 8	163,575	162,685	890	13,090	-12,200
Year 9	208,854	196,203	12,651	13,186	-535
Year 10	257,509	231,662	25,847	13,236	12,611
Year 11	309,386	269,536	39,850	13,271	26,579
Year 12	362,504	307,831	54,673	13,293	41,379
Year 13	417,092	347,605	69,487	13,319	56,168
Year 14	474,529	389,678	84,852	13,337	71,515
Year 15	533,151	432,996	100,156	13,349	86,806

Source: Authors' calculations using Texas administrative data and IPEDS.

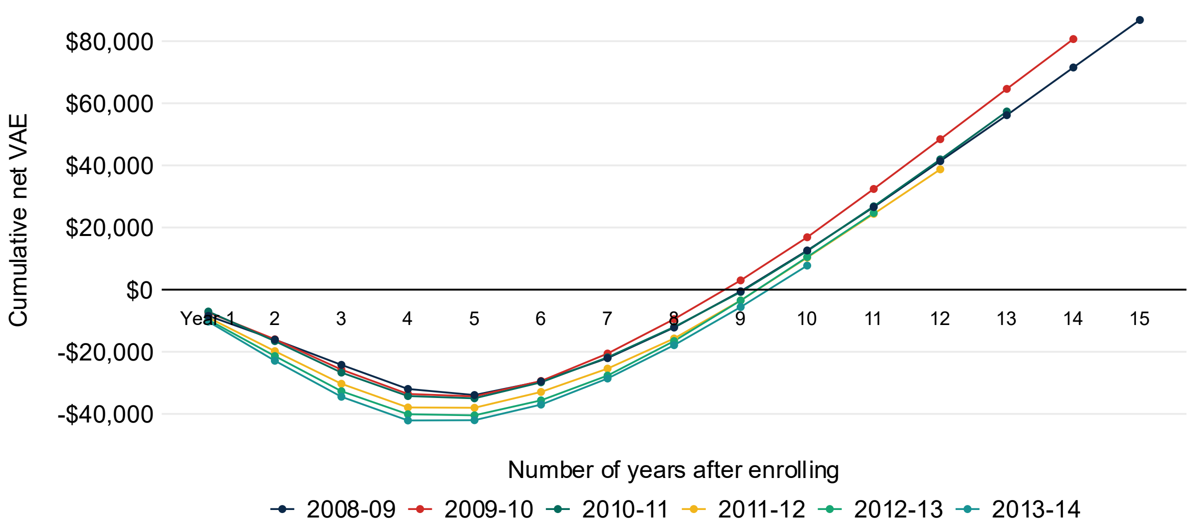
Note: The sample includes 28,614 students who enrolled in public postsecondary institutions in Texas in 2008–09. Values are student-weighted averages in 2023 dollars.

Due to data limitations, the study could follow only the 2008–09 entry cohort of bachelor's degree-seeking students for the full 15-year follow-up period. However, it is possible to study the partial outcomes of cohorts entering in 2009–10 through 2013–14, which can be followed for 10 to 14 years (Exhibit 3). These cohorts had similar trends in average cumulative net VAE to the 2008–09 cohort through the last years they can be observed. For example, bachelor's degree-seeking students in the 2009–10 to 2013–14 entry cohorts on average recovered their net cost of attendance and foregone earnings within 10 years, like those who entered postsecondary education in 2008–09 (Exhibit D.3). Also, when examining outcomes in Year 10 for the 2008–09 to 2013–14 entry cohorts (which is the last year after entry that we can analyze for all cohorts), we find that their average cumulative net VAE was broadly similar, ranging from $7,749 (2013–14 entry cohort) to $16,866 (2009–10 entry cohort). For the 2008–09 entry cohort, the cumulative net VAE in Year 10 was $12,611. The small differences across cohorts may be explained by the fact that more recent cohorts entered postsecondary education in a different, later year and may thus have been exposed to a different postsecondary experience or labor market.[17] Nevertheless, seeking a bachelor's degree led to positive returns after a decade across entry cohorts. These findings are consistent with prior evidence, generated in different postsecondary contexts and using different research methods,

[17] In addition, because of limitations on earlier years of data, more recent cohorts include older students who took time after graduating high school to enroll in postsecondary education.

of positive and meaningful long-run economic returns to pursuing a bachelor's degree (for example, Kozakowski 2023; Mountjoy 2026; Mountjoy and Hickman 2021).[18]

Exhibit 3. Cumulative net value-added earnings for bachelor's degree-seeking students, by entry year (2008–09 to 2013–14)



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 309,213 students who enrolled in public postsecondary institutions in Texas in 2008–09 through 2013–14. Values are student-weighted averages in 2023 dollars.

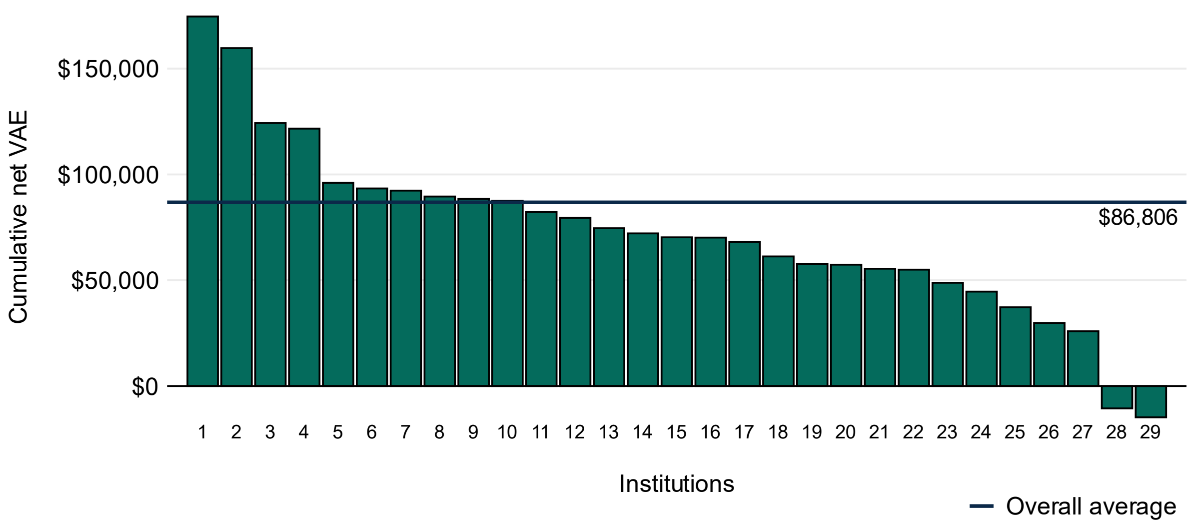
Although cumulative net VAE varied significantly across institutions, all but two of 29 institutions offered a positive cumulative net VAE on average to bachelor's degree-seeking students after 15 years.

Cumulative net VAE for bachelor's degree-seeking students was positive for all but two of 29 institutions after 15 years. However, it varied significantly across institutions, from a low of -$14,803 for students in the lowest-performing institution to a high of $174,632 for students in the highest-performing institution (Exhibit 4). Across institutions, cumulative net VAE was over $88,000 higher for institutions in the top decile of cumulative net VAE compared to the bottom decile. Specifically, an institution at the 90th percentile had cumulative net VAE of $116,462, while an institution at the 10th percentile had cumulative net VAE of $27,819. Another way to interpret how cumulative net VAE varied across institutions is to examine how much institution-level values tended to deviate from the overall average across all institutions. A one standard deviation increase in cumulative net VAE corresponded to an increase of

[18] For example, Mountjoy (2026) uses a regression discontinuity design to estimate an annual earnings premium of $6,700 (in 2015 dollars) eight to 12 years after entry to a Texas public four-year college. This earnings premium is equivalent to about $8,600 in 2023 dollars and is not net of cost of attendance. It is based on students who graduated a Texas high school between 2004 and 2014 and enrolled in a Texas public four-year college but were on the margin of meeting the requirements for admission.

$34,584.[19] This can be roughly thought of as the difference between an average institution and a high-value institution.[20] These results suggest that—despite nearly all institutions providing a positive return—public institutions in Texas varied substantially in their value to students seeking a bachelor's degree.[21]

Exhibit 4. Cumulative net value-added earnings in Year 15 for bachelor's degree-seeking students, by institution, 2008–09 entry year



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 28,614 students who enrolled in public postsecondary institutions in Texas in 2008–09. Values are student-weighted averages in 2023 dollars.

[19] Here and for all degree types, we use an adjusted standard deviation that accounts for the sampling error in each estimate of cumulative net VAE. We perform this adjustment using restricted maximum likelihood estimation, a common approach from the meta-analysis literature (Raudenbush 2009). Percentiles are based on this standard deviation and the assumption that cumulative net VAE follows a normal distribution.

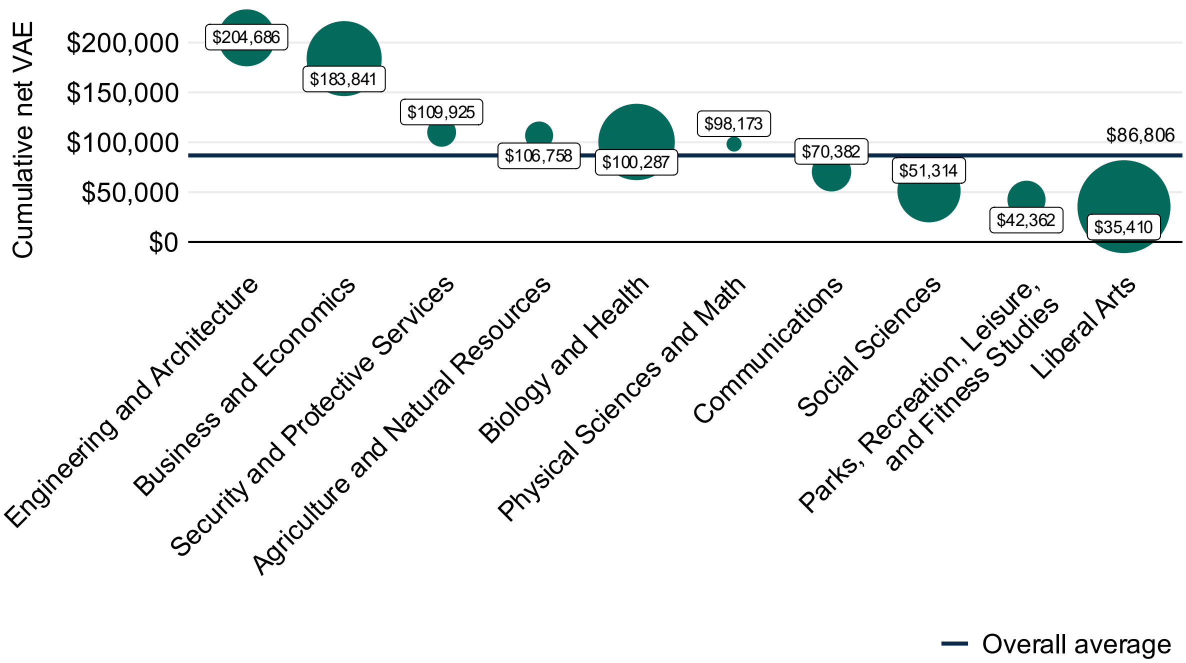
[20] Another study of VAE in Texas also found that they varied across institutions, though it estimated tighter distributions (Mountjoy and Hickman 2021). That study used a different counterfactual, comparing enrolled students to other students admitted to the same set of institutions who did not choose to enroll.

[21] As noted earlier, because students sort into institutions and majors in ways that are likely positively related to their potential earnings, our estimates of cumulative net VAE may be biased upwards, particularly for more selective institutions and programs, though other limitations could result in bias in other directions. Systematic biases for some types of institutions and programs could contribute to the variation in cumulative net VAE observed.

Cumulative net VAE for bachelor's degree-seeking students after 15 years was positive, on average, across all program types but varied by field, with STEM programs offering greater value.

Cumulative net VAE for bachelor's degree-seeking students in 2008–09 varied significantly by program of study, ranging from $204,686 for those who selected a program of study in engineering and architecture to an average of $35,410 for those in liberal arts—the most popular type of program among students in the cohort (Exhibit 5).[22] Engineering and architecture programs include majors such as mechanical engineering, computer engineering, and architectural and building sciences, while liberal arts programs include majors such as English, history, and philosophy.[23, 24]

Exhibit 5. Cumulative net value-added earnings in Year 15 for bachelor's degree-seeking students, by program of study, 2008–09 entry year



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 27,723 students who enrolled in public postsecondary institutions in Texas in 2008–09. Values are student-weighted averages in 2023 dollars. The size of each circle is proportional to the number of cohort students in each program. Differences across programs are statistically significant at the 1 percent level.

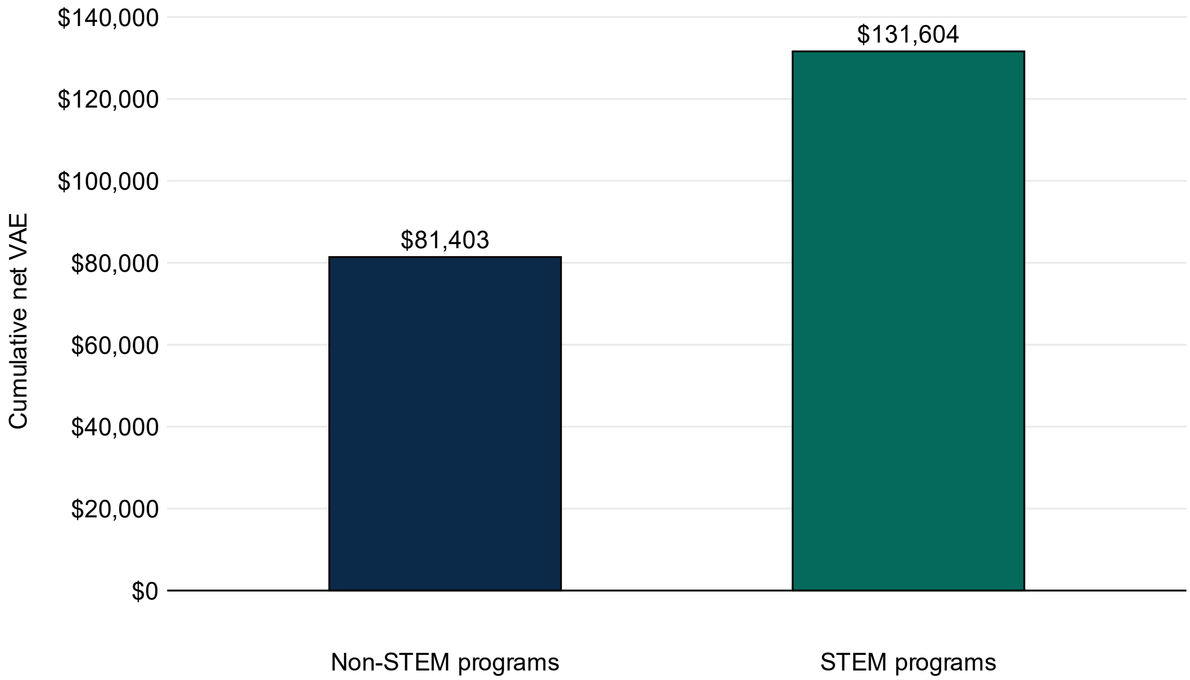
[22] The variation across programs of study in cumulative net VAE was statistically significant.

[23] The study used two-digit and four-digit Classification of Instructional Programs (CIP) codes to group students' program of study into 17 categories for analysis, similar to approaches taken in other research (for example, Andrews et al. 2024). See Appendix Section A for additional details about these classifications. Additionally, we excluded from the analysis undeclared majors and programs with fewer than 200 cohort students across institutions. For students seeking a bachelor's degree, this includes education, information technology, and technical trades programs. We also dropped parks, recreation, leisure, and fitness studies for students seeking a certificate.

[24] To understand whether these results would hold were we able to include bachelor's students from additional entry years, we replicate this analysis for immature bachelor's cohorts, which could be followed for less than 15 years (Appendix Section D). We find a broadly similar ranking of programs when focusing on 10-year cumulative net VAE for bachelor's degree–seeking students in 2008 (Exhibit D.4) and 10-year cumulative net VAE for immature bachelor's cohorts that entered in 2009 through 2013 (Exhibit D.5).

Consistent with these patterns of differences by program type, average cumulative net VAE differed significantly between students enrolled in STEM programs ($131,604) and those in non-STEM programs ($81,403; Exhibit 6).[25] Other research has also found that the economic returns to a bachelor's degree differ substantially by field of study, with STEM degrees showing higher returns.[26]

Exhibit 6. Cumulative net value-added earnings in Year 15 for bachelor's degree-seeking students, by STEM program status, 2008–09 entry year



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes students who enrolled in public postsecondary institutions in Texas in 2008–09. Values are student-weighted averages in 2023 dollars. STEM refers to science, technology, engineering, and mathematics and includes the following programs: agriculture and natural resources, biology and health, engineering and architecture, physical sciences and math, information technology, and technical trades (for associate's and certificate programs). Non-STEM includes all other programs. The difference between program types is statistically significant at the 1 percent level.

[25] STEM refers to science, technology, engineering, and mathematics and includes the following program types: agriculture and natural resources, biology and health, engineering and architecture, physical sciences and math, information technology, and technical trades (for associate's and certificate programs). See Appendix Section B for details on how the study identified and coded programs of study.

[26] For example, using data from Texas, Andrews et al. (2024) find significant variation across fields, with engineering and architecture programs having the highest average returns and liberal arts the lowest average returns among four-year college students. The estimates in Andrews et al. (2024) are based on students who graduated from a Texas high school between 1996 to 2002 and enrolled in a Texas public four-year college. Earnings were measured 16 to 20 years after high school graduation.

Cumulative net VAE for bachelor's degree-seeking students after 15 years varied by students' high school math achievement, with higher-achieving students having higher cumulative net VAE, on average. In contrast, cumulative net VAE did not differ by whether students came from low-income households.

Cumulative net VAE for bachelor's degree-seeking students ranged from $23,766 for those in the lowest quartile of high school math achievement to $111,504 for those in the highest quartile (Exhibit 7), reflecting significant variation by students' level of prior academic achievement.[27] Because students seeking a bachelor's degree tend to have higher test scores than their peers, just 3 percent of this cohort was in the lowest quartile of high school achievement, compared with 44 percent in the highest quartile. Among other reasons, cumulative net VAE may be higher for students with stronger prior math achievement because they are more likely to complete their degree and enter higher-paying fields, such as STEM. Nevertheless, even lower-achieving students had positive cumulative net VAE on average, consistent with past research (for example, Kozakowski 2023; Mountjoy 2026; Smith et al. 2025; Zimmerman 2014).

In contrast, cumulative net VAE did not vary significantly by whether students came from low-income households (Exhibit 7).[28] This finding is consistent with past research showing that the economic returns to enrolling in a four-year college are similar—and sometimes larger—for economically disadvantaged students (Chetty et al. 2020; Zimmerman 2014). Part of our findings could also be explained by students from low-income households having lower net costs because they are eligible for more need-based aid.[29]

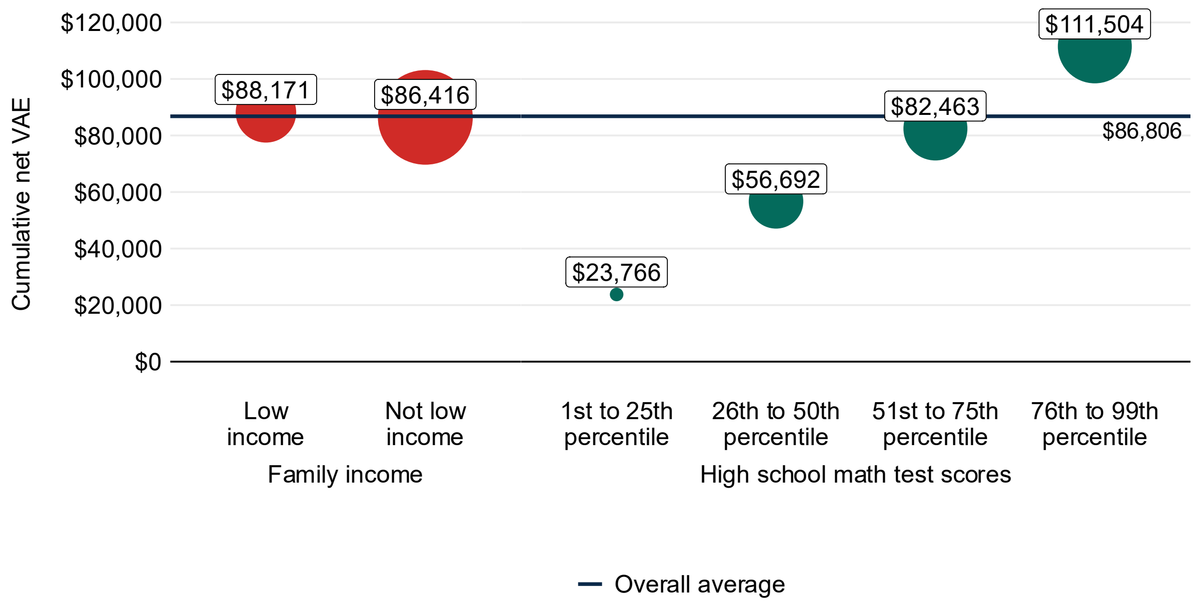
Because of data limitations that restrict the sample to students who graduated high school in 2007–08 or later, we are not able to examine whether cumulative net VAE differed for bachelor's degree- seeking students of different ages at entry, as our cohorts of bachelor's degree-seeking students include only students who enrolled in 2008–09.

[27] Because students who pursue postsecondary education are being compared with other students with similar high school math achievement, this finding reflects that the economic returns to enrolling in postsecondary education are higher for higher-achieving students and not simply that higher-achieving students earn more than those with lower achievement levels.

[28] A student is classified as coming from a low-income family if, in high school, the student received free or reduced-price lunch or their family was eligible for Temporary Assistance for Needy Families or other public assistance.

[29] In Appendix Section D, we examine cumulative net VAE in Year 10 for bachelor's degree–seeking students in entry years 2009–10 through 2013–14 to understand whether results for entry year 2008–09 hold for these later-entry cohorts. We find a similar pattern of cumulative net VAE across high school achievement quartiles and a larger difference in cumulative net VAE across household income groups (Exhibits D.6 and D.7). Students from low-income households had higher cumulative net VAE in Year 10 than students not from low-income households in both the 2008–09 entry year and pooled 2009–10 through 2013–14 entry years, driven by lower average cumulative costs among students from low-income households.

Exhibit 7. Cumulative net value-added earnings in Year 15 for bachelor's degree-seeking students, by demographic group, 2008–09 entry year



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 28,581 students with data on family low-income status and 27,148 students with data on high school math achievement who enrolled in public postsecondary institutions in Texas in 2008–09. Values are student-weighted averages in 2023 dollars. The size of each circle is proportional to the number of cohort students in each demographic group. Differences across groups are statistically significant at the 1 percent level.

Students' choice of program of study was related to larger differences in cumulative net VAE for bachelor's degree-seeking students than their choice of institution.

The previous sections have shown that cumulative net VAE varied across both institutions and programs of study. However, these analyses do not reveal which of these factors is more important for explaining differences in cumulative net VAE. For example, for institutions where more students pursue STEM degrees (which had higher cumulative net VAE, on average, than other programs), it is possible that these institutions had higher cumulative net VAE because more students were in STEM or because the institutions themselves offered higher economic returns to students, regardless of their choice of program. In one extreme case, if what matters for students' earnings outcomes is only their program and not their institution, cumulative net VAE would be the same for a given program type across all institutions. (For example, students in engineering and architecture would have the same cumulative net VAE, on average, regardless of their institution.) At the other end of the spectrum, if what matters for outcomes is only the institution and not the program, cumulative net VAE would be the same for all programs within a given institution, whether a student pursued engineering and architecture or liberal arts.

In practice, students' choice of program of study was related to larger differences in cumulative net VAE than their choice of institution. As Exhibit 8 shows, average cumulative net VAE for bachelor's degree-seeking students in Year 15 varied across both institutions (the yellow lines) and programs within an institution (the green dots), but it varied *more* across programs within an institution than across institutions overall. As an illustrative example, cumulative net VAE within an institution at the 90th percentile ranged from $6,519 to $204,697 across programs, a difference of nearly $200,000. In contrast, the difference in cumulative net VAE between an institution at the 90th percentile and an institution at the 10th percentile was about $89,000.

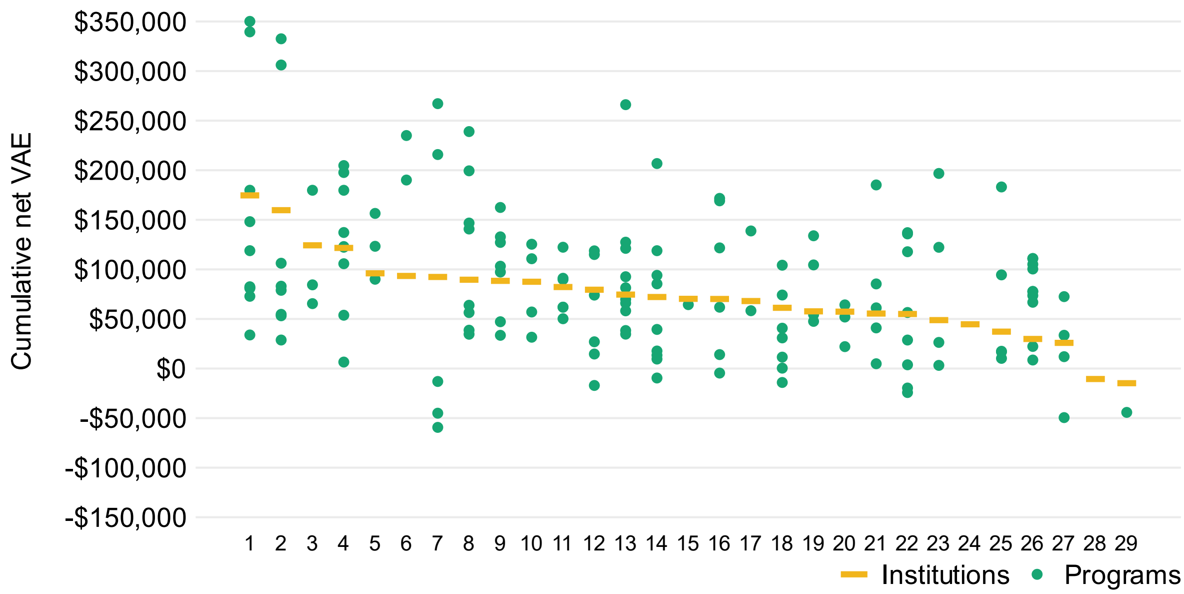
To formally quantify these patterns, we use an analysis of variance (ANOVA), which shows that 35 percent of the variation in cumulative net VAE for bachelor's degree-seeking students was explained by differences across programs within institutions, compared to 20 percent explained by differences across institutions delivering the same program (Appendix D, Exhibit D.15).[30, 31, 32] Both factors were important—that is, some programs tended to have systematically higher (or lower) average cumulative net VAE, no matter which institution they were offered in, and some institutions tended to have systematically higher (or lower) average cumulative net VAE, regardless of which programs of study their students pursued. However, the findings suggest that the choice of program matters more for cumulative net VAE than where students chose to enroll for those seeking a bachelor's degree.

[30] See Appendix Section D.6 for a description of the ANOVA analyses used to generate these estimates.

[31] After accounting for both the institution and program, some portion of the variation in cumulative net VAE for bachelor's degree–seeking students is still unexplained, referred to as the residual. The residual in this case represents differences in cumulative net VAE that are specific to a *particular* combination of institution and program. For example, a health and biology program at a specific institution could perform above or below what we would expect based on its institution or program alone. The value of the residual (43 percent) suggests that a meaningful part of the variation in cumulative net VAE for bachelor's degree–seeking students was explained by specific programs in specific institutions being particularly effective (or not) at providing economic returns to their students. A smaller residual would mean that the average cumulative net VAE for that institution–program combination was very close to what we would expect based on the institution and the program alone, with little unexplained additional difference. See Appendix D for more details.

[32] The matching approach used to estimate cumulative net VAE may not fully account for differences between students who do and do not choose to enroll in a given institution or program, leading to bias in the estimates of cumulative net VAE. To the extent that the approach leads to more bias in the estimates of cumulative net VAE by institutions or programs, this could affect the share of variation that is explained by institutions versus programs. However, it is unclear whether one type of estimates is systematically more biased than the other.

Exhibit 8. Variation in cumulative net value-added earnings in Year 15 for bachelor's degree-seeking students, institutions versus programs



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 29 bachelor's degree-granting institutions. The outcome is Year 15 cumulative net value-added earnings for students enrolling in postsecondary education in 2008–09. Values are student-weighted averages in 2023 dollars.

Students' choice of institution was related to larger differences in cumulative net VAE for bachelor's degree-seeking students than their household income or high school math achievement.

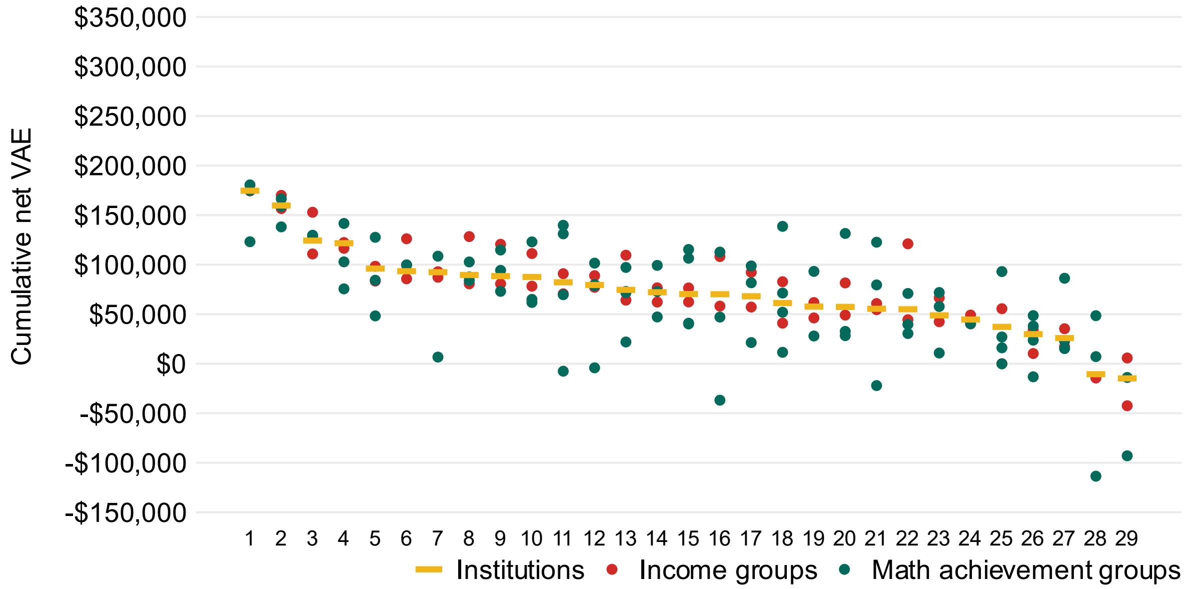
As shown previously, cumulative net VAE varied for bachelor's degree-seeking students with different levels of high school math achievement but not for students with different levels of household income. As with students' choice of program of study, however, students' background characteristics can be related to which institution they attend. For example, institutions that enroll students with higher levels of high school math achievement could have higher cumulative net VAE because they offer higher economic returns to students, regardless of their prior math achievement levels, or because students with higher math achievement have higher cumulative net VAE in general, regardless of which institution they attend. To understand which of these factors matters more, we repeat the ANOVA twice, focusing on how much of the variation in cumulative net VAE is explained by students' household income or high school math achievement (rather than program) compared to their institution.

In practice, students' choice of institution was related to much larger differences in cumulative net VAE than their household income or high school math achievement. Exhibit 9 shows how average cumulative net VAE varied across institutions overall (the yellow lines) and by demographic groups within each institution (the red dots show household income groups and the green dots show high school math achievement groups). In contrast to the distribution of cumulative net VAE across programs in Exhibit 8, differences in cumulative net VAE across household income and high school math achievement groups were much smaller, and indeed smaller than differences across institutions. Below we discuss the results of the ANOVA separately for household income and math achievement groups.

Cumulative net VAE varied much more across institutions overall than across household income levels within an institution. As an illustrative example, average cumulative net VAE for bachelor's degree-seeking students in an institution at the 90th percentile ranged from $116,475 for students from low-income households to $122,307 for students from higher-income households, a difference under $6,000. In contrast, the difference between an institution at the 90th percentile and an institution at the 10th percentile was about $89,000. Consistent with these patterns, the ANOVA results show that 85 percent of the variation in cumulative net VAE for bachelor's degree-seeking students was explained by differences across institutions among students of the same household income level, compared to 4 percent explained by differences across students with different household income levels within a given institution (Appendix D, Exhibit D.15).

Students' choice of institution was also related to larger differences in cumulative net VAE for bachelor's degree-seeking students than their high school math achievement. Though average cumulative net VAE varied more across math achievement levels than across household income levels at a given institution (Exhibit 9), it varied much more across institutions overall. Differences across institutions among students with similar math achievement explain much more of the variation in cumulative net VAE (51 percent) than differences across math achievement levels within a given institution (13 percent; Appendix D, Exhibit D.15). These findings suggest that where a student seeking a bachelor's degree chose to enroll matters far more for cumulative net VAE than either their household income or prior academic achievement.

Exhibit 9. Variation in cumulative net value-added earnings in Year 15 for bachelor's degree-seeking students, institutions versus demographic groups



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 29 bachelor's degree-granting institutions. The outcome is Year 15 cumulative net value-added earnings for students enrolling in postsecondary education in 2008–09. Values are student-weighted averages in 2023 dollars.

Institutional cohorts of bachelor's degree-seeking students in which a higher proportion of students complete a bachelor's degree had higher cumulative net VAE, on average, even after accounting for characteristics of their institution, such as selectivity and price.

As noted earlier, cumulative net VAE for bachelor's degree-seeking students tended to vary substantially across institutions. Understanding which characteristics of the student cohorts and the institutions they enrolled in were correlated with cumulative net VAE can inform policymakers and families. For example, if institutions with higher levels of selectivity—defined as those with higher standardized test scores among entering students[33]—have higher cumulative net VAE, expanding access to those institutions (especially for students from lower-income households) could be an important lever for improving economic mobility. We examine the following institution-wide and cohort-level characteristics: institutions' selectivity level, net price,[34] the number of undergraduate students enrolled in the institution, the percentage of students at the institution who received Pell Grants, and the proportion of students in a

[33] The study used selectivity categories reported in IPEDS from the Carnegie classification system, which uses the standardized test scores of incoming students to group institutions as more selective, selective, or inclusive.

[34] Average net price is reported by IPEDS and refers to the average annual cost of attendance (tuition, fees, room, and board) minus grant and scholarship aid, calculated for first-time, full-time undergraduate students who receive Title IV federal financial aid. It is distinct from cohort students' net costs, which are estimated by the study and are used to calculate cumulative net VAE.

cohort who completed their intended degree during the follow-up period at the institution in question or any other public institution in Texas (Exhibit D.12, column 1).

There was a strong, positive relationship between cumulative net VAE for a given cohort of bachelor's degree-seeking students and the percentage of students in that cohort who completed a bachelor's degree during the follow-up period at the institution or any other public institution in Texas (Exhibit 10).[35] This relationship remained large and statistically significant even after holding constant the characteristics of the institution. For every percentage-point increase in the percentage of students in a cohort who completed a bachelor's degree, cumulative net VAE after 15 years was about $2,000 higher on average (Exhibit D.12, column 4).

A positive relationship between a cohort's degree-completion rate and average cumulative net VAE may be expected, as students who complete a degree tend to earn greater economic returns to postsecondary education compared with students who enroll but do not complete a degree (Oreopoulos and Petronijevic 2013). This relationship may also be reflective of an institution's quality. For example, institutions that offer stronger academic and career supports may help more students complete a degree while also helping their students successfully transition into the labor market. At the same time, this relationship could reflect the characteristics of the students in the cohort, as higher-achieving students tend to have higher rates of degree completion.[36] Regardless of the underlying reasons, these results suggest that degree completion is an important predictor of cumulative net VAE. On average across institutions, 61 percent of bachelor's degree-seeking students in the study completed a bachelor's degree at a Texas institution during the follow-up period.

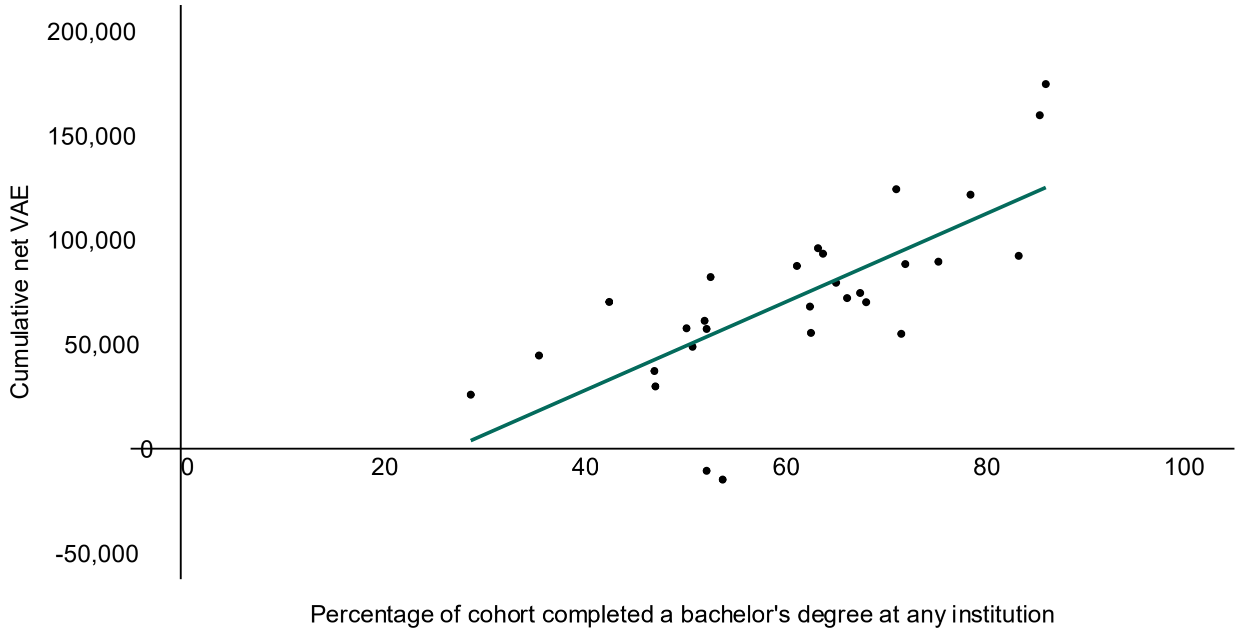
Although the institutional characteristics we examined also exhibited a positive relationship to cumulative net VAE for bachelor's degree-seeking students, these characteristics tend to be correlated with each other. For instance, more selective institutions typically have higher degree-completion rates, higher net prices, and lower shares of Pell Grant recipients. Once we hold all other factors constant, the relationships with cumulative net VAE weaken (Exhibit D.12, columns 2–5). As one example, cohorts of bachelor's

[35] The study measured degree completion rates in four ways to capture nuances related to this key outcome. One is the institution-wide "150 percent graduation rate" reported in IPEDS, which is the percentage of first-time, full-time, degree–seeking students who earned their intended degree at the same institution within 150 percent time of the normal time to completion. Two is the percentage of students in a cohort that we studied who completed any degree at a public institution in Texas within the study's follow-up period. Three is the percentage of students in a cohort that we studied who completed their intended degree (for example, a bachelor's degree for bachelor's cohorts) at any public institution in Texas during this period. And four is the percentage of students in a cohort that we studied who completed their intended degree at the same institution during this period. Bachelor's degree–seeking students are less likely to complete a different degree type than students seeking an associate's degree or certificate (Exhibit D.10). Thus, these measures are all strongly correlated, with correlation coefficients of 0.86 or above for bachelor's degrees (Exhibit D.11). Not all these degree completion rates exhibit a statistically significant relationship with cumulative net VAE for bachelor's degrees (Exhibit D.12), though all show a consistently positive relationship. As noted above, this analysis has a small sample size and therefore limited statistical power to detect relationships where they exist.

[36] Research in Texas by Mountjoy and Hickman (2021) suggests that it is not only the composition of students that matters, however. That study found that institutions with higher VAE tended to have not only higher raw completion rates (which reflect the background characteristics of students who enroll) but also higher *value added* on bachelor's degree completion, which reflects institutional quality after accounting for the characteristics of enrolled students. That study also found that selectivity was a poor predictor of VAE and therefore may not be a good proxy for institutional quality.

degree-seeking students at more selective institutions on average had cumulative net VAE that was nearly $100,000 higher after 15 years compared with institutions considered to be the least selective type of institution. But after holding constant an institution's average net price, size, share of Pell Grant recipients, and the percentage of cohort students completing a bachelor's degree, the difference in average cumulative net VAE between cohorts at more selective and inclusive institutions decreased by more than half to about $40,000 and was no longer statistically significant.[37]

Exhibit 10. Relationship between cumulative net value-added earnings in Year 15 for cohorts of bachelor's degree-seeking students and the percentage of the cohort that completed a bachelor's degree at any institution



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 29 institutions. The outcome is Year 15 cumulative net value-added earnings in 2023 dollars for bachelor's degree-seeking students enrolling in postsecondary education in 2008–09. Values are student-weighted averages.

B. Associate's degrees

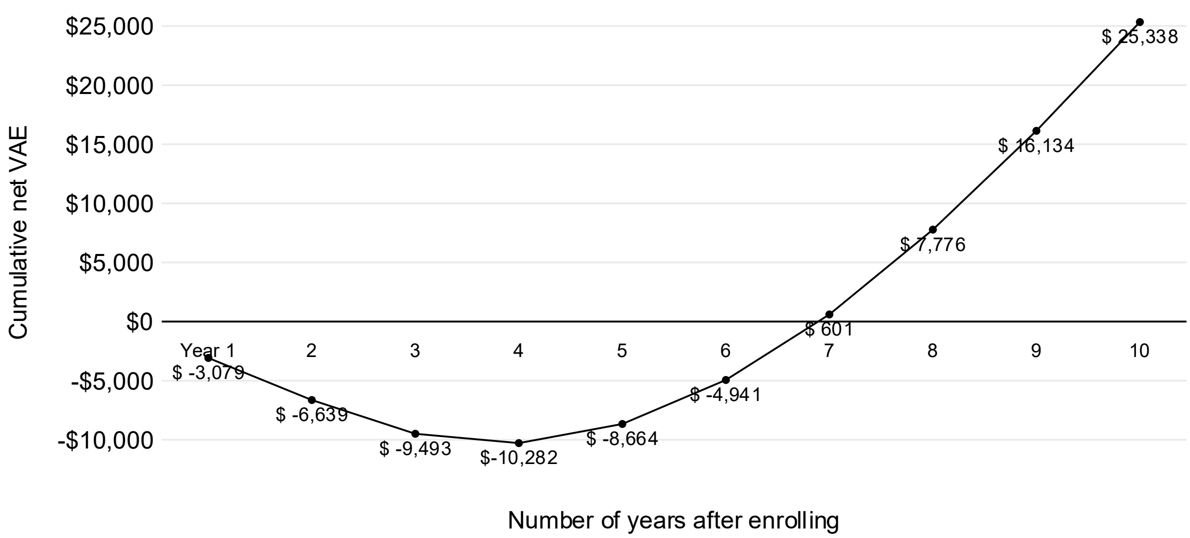
The average associate's degree-seeking student recovered the total costs of enrolling in postsecondary education within seven years and accumulated a cumulative net VAE of over $25,000 after 10 years.

Cumulative net VAE among associate's degree-seeking students who enrolled in public institutions in Texas between 2008–09 and 2013–14 was initially negative and decreasing during the first four years after enrolling, on average (Exhibit 11). Starting in Year 5, however, cumulative net VAE began to increase, as more students completed a degree (either directly with an associate's degree or after transferring to a four-year college) and increased their earnings. By Year 7, these students' cumulative VAE exceeded their

[37] Because this analysis has a limited sample size (in this case, 29 bachelor's degree–granting institutions), we report results that are statistically significant at the 10 percent level or higher but suggest caution in interpreting results.

total net cost of attendance, on average (Exhibit 12). Ten years after initial enrollment, the average associate's degree-seeking student had a cumulative net VAE of $25,338.

Exhibit 11. Cumulative net value-added earnings for associate's degree-seeking students, 2008–09 to 2013–14 entry years



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 559,068 students who enrolled in public postsecondary institutions in Texas in 2008–09 through 2013–14. Values are student-weighted averages in 2023 dollars.

Exhibit 12. Cumulative earnings, net costs, and value-added earnings for associate's degree-seeking students, 2008–09 to 2013–14 entry years

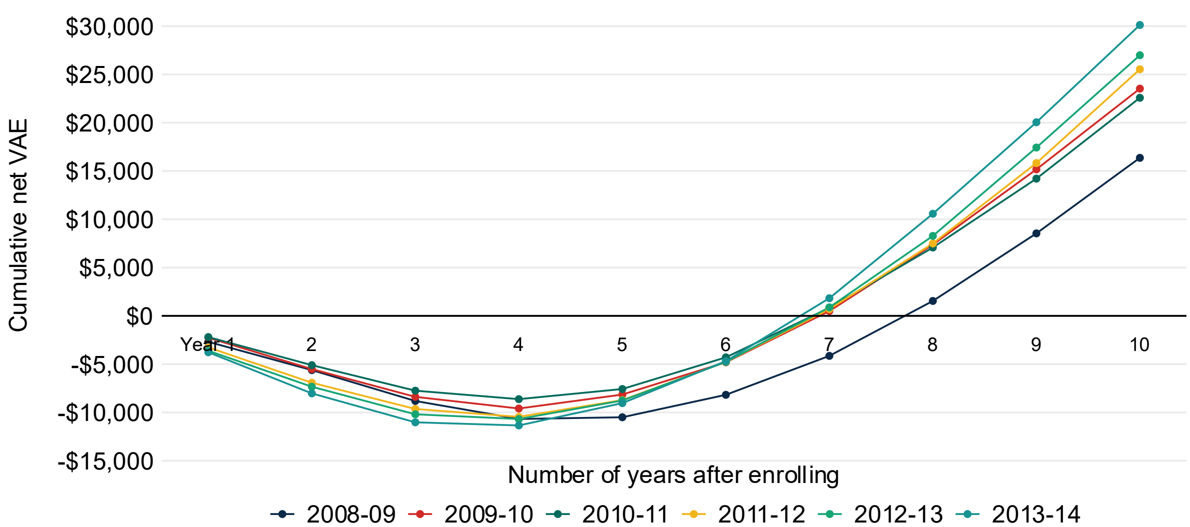
Years after enrollment	Cohort cumulative earnings ($)	Comparison group cumulative earnings ($)	Cohort cumulative value-added earnings ($)	Cohort cumulative net cost of attendance ($)	Cohort cumulative net value-added earnings ($)
Year 1	9,196	11,577	-2,380	698	-3,079
Year 2	22,123	27,529	-5,406	1,233	-6,639
Year 3	39,083	46,984	-7,901	1,591	-9,493
Year 4	60,879	69,342	-8,463	1,819	-10,282
Year 5	87,563	94,262	-6,699	1,965	-8,664
Year 6	118,718	121,598	-2,880	2,061	-4,941
Year 7	153,298	150,572	2,726	2,125	601
Year 8	190,773	180,828	9,946	2,169	7,776
Year 9	230,900	212,566	18,334	2,200	16,134
Year 10	273,207	245,649	27,559	2,221	25,338

Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 559,068 students enrolling in postsecondary education in 2008–09 through 2013–14. Values are student-weighted averages in 2023 dollars.

Some differences in cumulative net VAE are present across entry cohorts (Exhibit 13). Compared with later cohorts, students in the 2008–09 entry cohort on average took one more year to recover their net cost of attendance and foregone earnings (eight years, instead of seven years for students who enrolled after 2008–09). By Year 10, cumulative net VAE ranged from an average of $16,364 for the 2008–09 entry cohort to an average of $30,121 for the 2013 entry cohort, with later cohorts receiving higher cumulative net VAE than earlier cohorts. These differences across entry cohorts could be explained in part by the different timing of when students enrolled and entered the labor market (for example, due to changes in economic conditions, such as the demand for workers with associate's degrees over time). These differences could also be explained by the fact that, due to limitations of the data available in earlier years, recent cohorts include more older students and older students had higher cumulative net VAE, on average (Exhibit 17). Even across entry cohorts, however, the findings are consistent with prior evidence documenting positive long-run economic returns to pursuing an associate's degree in different postsecondary contexts and using different methods (for example, Grosz 2020; Jepsen et al. 2014; Melguizo and Dowd 2015; Minaya and Scott-Clayton 2022).

Exhibit 13. Cumulative net value-added earnings for associate's degree-seeking students, by entry year (2008–09 to 2013–14)



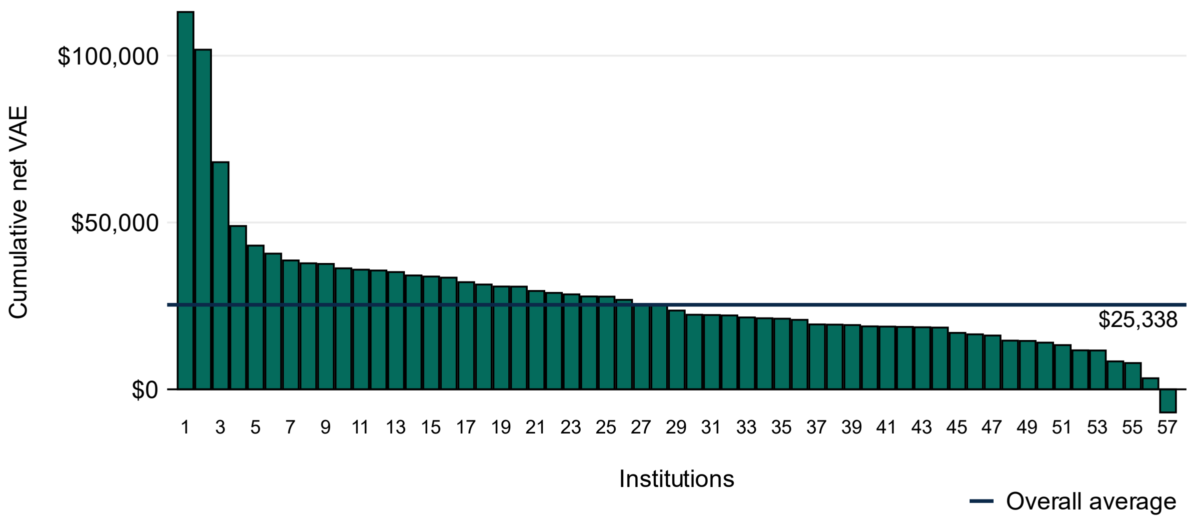
Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 558,926 students who enrolled in public postsecondary institutions in Texas in 2008–09 through 2013–14. Values are student-weighted averages in 2023 dollars.

Although cumulative net VAE varied significantly across institutions, all but one of 57 institutions offered a positive cumulative net VAE to associate's degree-seeking students after 10 years.

Cumulative net VAE for the average associate's degree-seeking student was positive for all but one of 57 institutions after 10 years, though it varied significantly across institutions, from a low of -$6,934 for students in the lowest-performing institution to a high of $113,101 for students in the highest-performing institution (Exhibit 14).[38] Across institutions, cumulative net VAE 10 years after students enrolled in an associate's degree was $48,000 higher for institutions in the top decile of cumulative net VAE compared with the bottom decile. Specifically, an institution at the 90th percentile had cumulative net VAE of $51,857, while an institution at the 10th percentile had cumulative net VAE of $3,858. At the same time, over half of institutions had cumulative net VAE between $20,000 and $40,000, a much narrower range compared with the full range of values. Put differently, a 1 standard deviation increase in an institution's cumulative net VAE after 10 years corresponded to an increase of $18,727. These results suggest that public institutions in Texas offer different value to students seeking an associate's degree, but especially so for a handful of institutions at the tail ends of the distribution.

Exhibit 14. Cumulative net value-added earnings in Year 10 for associate's degree-seeking students, by institution, 2008–09 to 2013–14 entry years



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 558,926 students who enrolled in public postsecondary institutions in Texas in 2008–09 through 2013–14. Values are student-weighted averages in 2023 dollars.

Cumulative net VAE for associate's degree-seeking students after 10 years varied across program types, with some programs having negative cumulative net VAE and STEM programs offering greater value, on average.

After 10 years, cumulative net VAE for associate's degree-seeking students varied significantly, ranging from $72,912 for those who selected a program in construction trades to -$15,401 for those in logistics, which trains students to work in transportation and materials moving (Exhibit 15).[39] Both program types were relatively uncommon among associate's students. Among more popular programs, technical trades

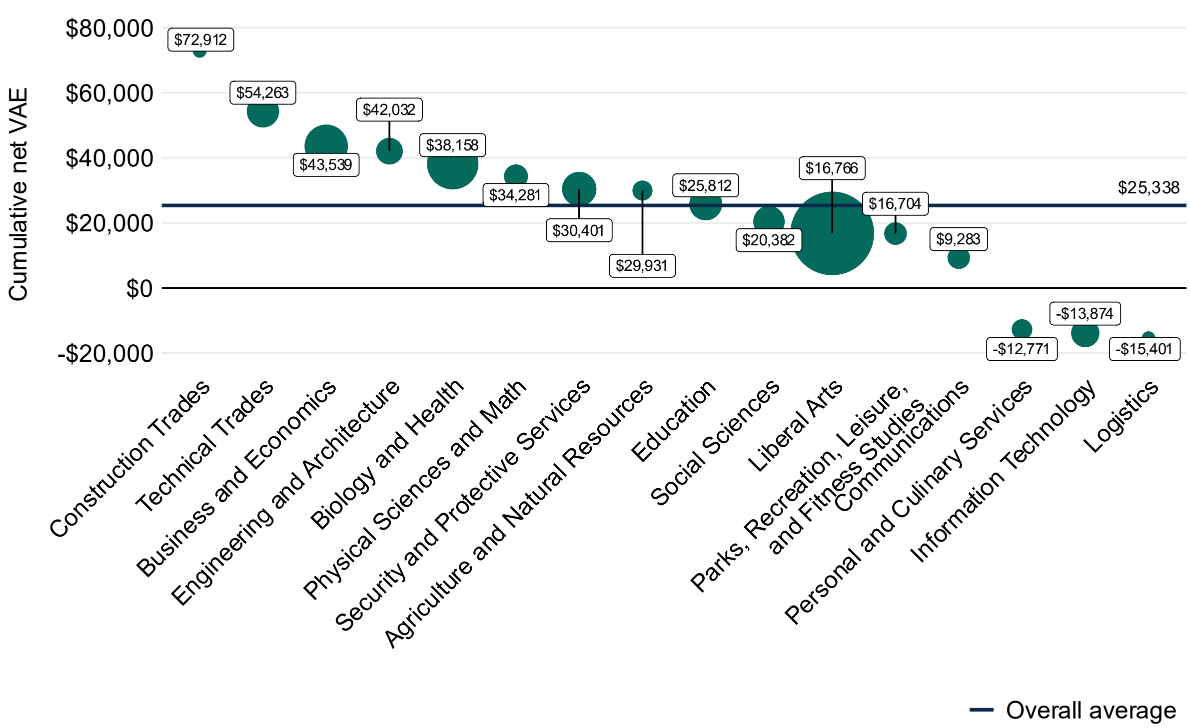
[38] The positive slope of the cumulative net VAE line across years in Exhibit 11 suggests that associate's degree–seeking students will continue to see growing cumulative net VAE over time. Therefore, institutions (or programs) that had negative net cumulative VAE in Year 10 may eventually have a positive cumulative net VAE at some point.

[39] The variation across programs of study in average cumulative net VAE was statistically significant.

(which train students to be technicians in fields like automotive, engineering, and manufacturing technology) offered a high cumulative net VAE of over $54,000, while information technology and personal and culinary services had negative cumulative net VAE, on average.

Across programs, cumulative net VAE for associate's degree-seeking students differed significantly between STEM programs ($35,627) and non-STEM programs ($21,269; Exhibit 16). It is worth noting that the STEM classification does not always map neatly onto shorter programs that are skills-focused and occupationally oriented, which can include technical fields—such as construction trades—that are not classified as STEM.[40] In addition, some popular non-STEM programs (such as liberal arts) may be more common among students seeking transfer to a four-year degree, though not all of them may ultimately do so. Other research has found that the economic returns to associate's degrees differ substantially by field of study, with career-oriented programs (and those in the health fields specifically) often showing higher returns than academically focused ones (for example, Andrews et al. 2024; Jepsen et al. 2023; Stevens et al. 2019).

Exhibit 15. Cumulative net value-added earnings in Year 10 for associate's degree-seeking students, by program of study, 2008–09 to 2013–14 entry years

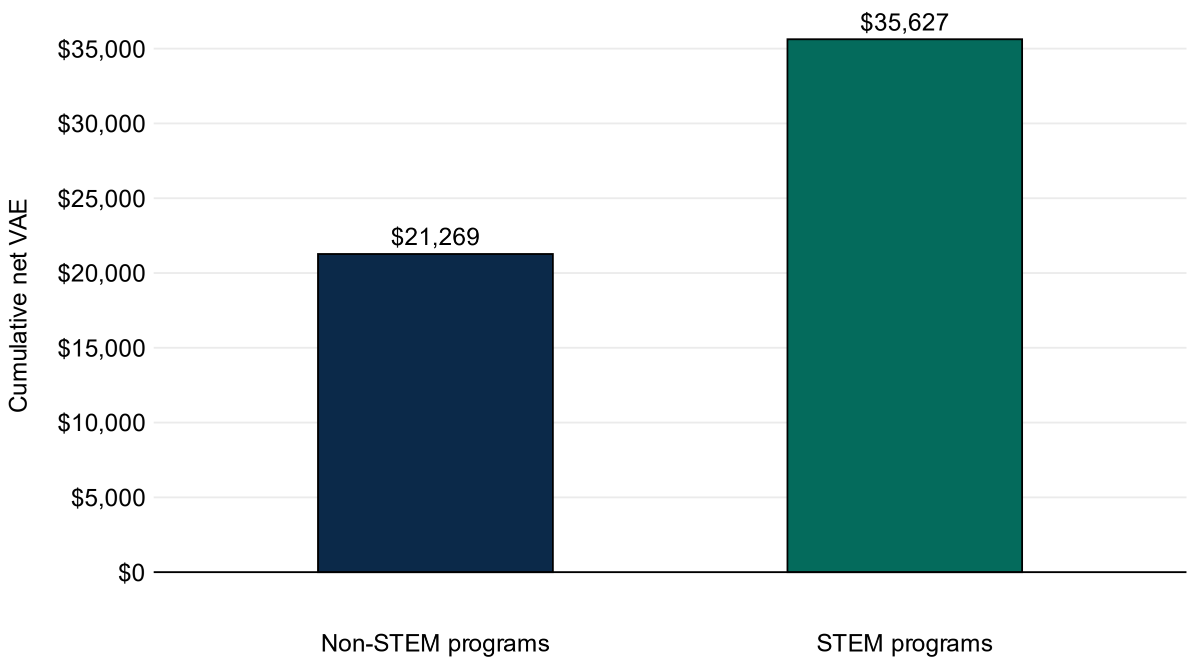


Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 537,658 students who enrolled in public postsecondary institutions in Texas in 2008–09 through 2013–14. Values are student-weighted averages in 2023 dollars. The size of each circle is proportional to the number of cohort students in each program. Differences across programs are statistically significant at the 1 percent level.

[40] Programs were classified as STEM using the U.S. Department of Homeland Security STEM Designated Degree Program List.

Exhibit 16. Cumulative net value-added earnings in Year 10 for associate's degree-seeking students, by STEM program status, 2008–09 to 2013–14 entry years



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 537,658 students who enrolled in public postsecondary institutions in Texas in 2008–09 through 2013–14. Values are student-weighted averages in 2023 dollars. STEM refers to science, technology, engineering, and mathematics and includes the following programs: agriculture and natural resources, biology and health, engineering and architecture, physical sciences and math, information technology, and technical trades (for associate's and certificate programs). Non-STEM includes all other programs. The difference between program types is statistically significant at the 1 percent level.

Average cumulative net VAE for associate's degree-seeking students after 10 years varied by students' household income, high school math achievement, and age, with higher household income, higher achievement, and older age linked with higher cumulative net VAE on average.

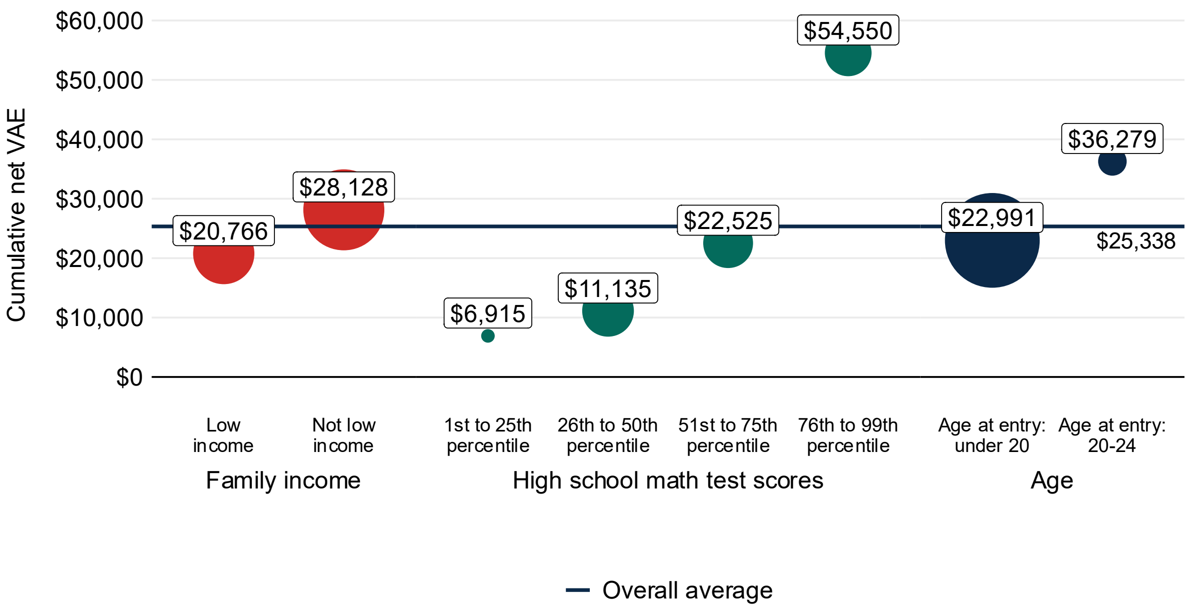
Cumulative net VAE after 10 years differed by students' household income for associate's degree-seeking students. Compared with their peers from higher-income households, students from low-income households had lower average cumulative net VAE ($20,766 versus $28,128; Exhibit 17). Although students from low-income households generally tend to have lower net cost of attendance, this difference is likely smaller among associate's degree-seeking students than among those seeking bachelor's degrees given the lower cost of an associate's degree. In addition, associate's degree-seeking students from low-income households may face greater barriers than their peers from higher-income households to transferring to a four-year college or completing a degree (which leads to greater economic returns down the line).[41]

[41] Although this is also true for bachelor's degree–seeking students, four-year colleges tend to be more selective and better resourced than two-year colleges. Thus, any differences in academic preparation and support by household income may be more significant among associate's degree–seeking students than among those seeking a bachelor's degree.

Cumulative net VAE ranged from an average of $6,915 for those in the lowest quartile of high school math achievement to an average of $54,550 for those in the highest quartile (Exhibit 17). Fourteen percent of students were in the lowest quartile of high school achievement, compared with 26 percent in the highest quartile. Cumulative net VAE may be higher for students with stronger prior academic achievement because they are more likely to complete their degree, transfer to a four-year college, or enter higher-paying fields. Nevertheless, even associate's degree-seeking students with lower math achievement had positive cumulative net VAE on average.

Age at entry was also related to cumulative net VAE for associate's degree-seeking students, with students who were older at the time of enrolling in postsecondary education having higher cumulative net VAE, on average. Students who were younger than 20 when they entered postsecondary education had cumulative net VAE of $22,991, on average, compared with $36,279 among those ages 20 to 24 (Exhibit 17). One potential explanation for why older students may earn higher returns from seeking an associate's degree is if their prior work experience allows them to translate their education into higher-paying jobs. For example, they may select a program that is in demand by employers and builds on their past work experience.

Exhibit 17. Cumulative net value-added earnings in Year 10 for associate's degree-seeking students, by demographic group, 2008–09 to 2013–14 entry years



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample included 559,068 students with data on family low-income status, 558,963 students with data on high school math achievement, and 558,963 students with data on age at entry who enrolled in public postsecondary institutions in 2008–09 through 2013–14. Values are student-weighted averages in 2023 dollars. The size of each circle is proportional to the number of cohort students in each demographic group. Differences across groups are statistically significant at the 1 percent level.

Students' choice of program of study was related to larger differences in cumulative net VAE for associate's degree-seeking students than their choice of institution.

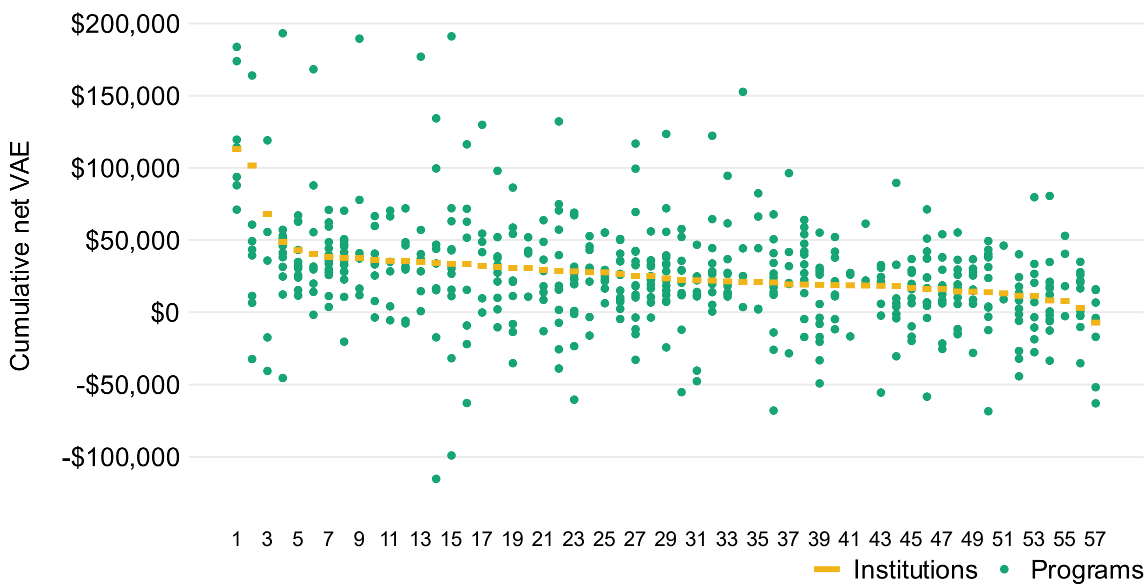
The previous sections have shown that average cumulative net VAE varied across both institutions and programs of study, though not which of these two factors matters more for associate's degree-seeking students. Exhibit 18 shows that average cumulative net VAE for associate's degree-seeking students varied across both institutions (the yellow lines) and programs within an institution (the green dots), but varied *more* across programs within an institution than across institutions overall. As an illustrative example, cumulative net VAE within an institution at the 90th percentile ranged from -$40,559 to $119,087 across programs, a difference of nearly $160,000. In contrast, the difference in cumulative net VAE between an institution at the 90th percentile and an institution at the 10th percentile was about $48,000.

Consistent with the patterns in Exhibit 18, the ANOVA results show that 30 percent of the variation in cumulative net VAE is explained by differences across programs within institutions, compared to 20 percent explained by differences across institutions delivering the same program (Appendix D, Exhibit D.16).[42, 43] Some programs tended to have systematically higher (or lower) average cumulative net VAE, no matter which institution they were offered at, and some institutions tended to have systematically higher (or lower) average cumulative net VAE, regardless of which programs of study their students pursued. Although both factors are important, the findings suggest that the choice of program matters more for cumulative net VAE than where students chose to enroll for those seeking an associate's degree.

[42] After accounting for both the institution and program, 45 percent of the variation in cumulative net VAE for associate's degree–seeking students was still unexplained. This residual value suggests that a meaningful part of the variation in cumulative net VAE for these students was explained by specific programs in specific institutions being particularly effective (or not) at providing economic returns to their students, above and beyond what the program or institution alone would predict, on average.

[43] The matching approach used to estimate cumulative net VAE may not fully account for differences between students who do and do not choose to enroll in a given institution or program, leading to bias in the estimates of cumulative net VAE. To the extent that the approach leads to more bias in the estimates of cumulative net VAE by institutions or programs, this could affect the share of variation that is explained by institutions versus programs. However, it is unclear whether one type of estimates is systematically more biased than the other.

Exhibit 18. Variation in cumulative net value-added earnings in Year 10 for associate's degree-seeking students, institutions versus programs



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 57 associate's degree-granting institutions. The outcome is Year 10 cumulative net value-added earnings for students enrolling in postsecondary education in 2008–09 through 2013–14. Values are student-weighted averages in 2023 dollars.

Students' choice of institution was related to larger differences in cumulative net VAE for associate's degree-seeking students than their household income or age at entry—but not their high school math achievement.

To understand whether the choice of institution matters more than students' background characteristics for explaining differences in cumulative net VAE for associate's degree-seeking students, we repeat the ANOVA focusing on how much of the variation in cumulative net VAE was explained by students' household income, high school math achievement, or age when they enrolled, separately, compared to their institution.

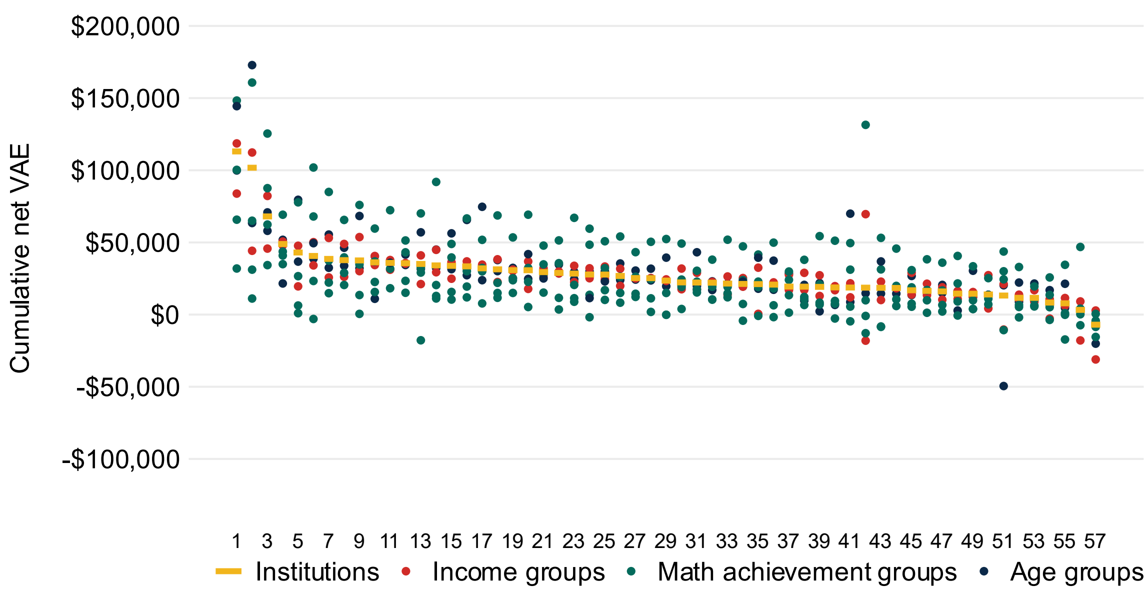
In practice, students' choice of institution was related to much larger differences in cumulative net VAE than their household income or age at entry, but not their high school math achievement. Exhibit 19 shows how average cumulative net VAE varied across institutions overall and by demographic groups within each institution. In contrast to the distribution of cumulative net VAE across programs in Exhibit 18, differences in cumulative net VAE across household income and age at entry groups within an institution were much smaller than differences across institutions overall, though cumulative net VAE tended to vary more across high school math achievement groups within an institution than across institutions.

The choice of institution was related to larger differences in cumulative net VAE for associate's degree-seeking students than their household income. The ANOVA results show that 72 percent of the variation in cumulative net VAE for associate's degree-seeking students was explained by differences across institutions among students of the same household income level, compared to approximately 0 percent explained by differences across students with different household income levels within a given institution (Appendix D, Exhibit D.16).

The choice of institution was also related to larger differences in cumulative net VAE for associate's degree-seeking students than their age at entry. Differences across institutions among students of a similar age at entry explain much more of the variation (74 percent) than differences across age groups within a given institution (3 percent; Appendix D, Exhibit D.16). In other words, students at different ages within an institution tended to have similar cumulative net VAE. The differences in average cumulative net VAE across age groups were mostly due to older students being more likely to enroll in institutions with higher cumulative net VAE compared to younger students. These findings suggest that where a student seeking an associate's degree chose to enroll matters far more for cumulative net VAE than either their household income or age when they enrolled.

In contrast, students' high school math achievement was related to larger differences in cumulative net VAE for associate's degree-seeking students than their choice of institution. Differences across math achievement levels within a given institution explain more of the variation (40 percent) than differences across institutions for students with similar high school math achievement (32 percent; Appendix D, Exhibit D.16). Taken together, the findings suggest that prior academic achievement matters more than choice of institution for associate's degree-seeking students but that both play an important role in explaining differences in cumulative net VAE compared to household income or age at entry.

Exhibit 19. Variation in cumulative net value-added earnings in Year 10 for associate's degree-seeking students, institutions versus demographic groups



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 57 associate's degree-granting institutions. The outcome is Year 10 cumulative net value-added earnings for students enrolling in postsecondary education in 2008–09 through 2013–14. Values are student-weighted averages in 2023 dollars.

Institutional cohorts of associate's degree-seeking students in which more students completed any degree had higher cumulative net VAE, on average, even after accounting for characteristics of their institution, such as size and price.

As noted earlier, cumulative net VAE for associate's degree-seeking students tended to vary substantially across institutions. Some key institutional characteristics may help explain these differences, such as an institution's average net price, the number of undergraduate students enrolled, and the percentage of students who received Pell Grants. Cohort characteristics may also help explain these differences, such as the percentage of students in the cohort who completed any degree, either at the institution in question or at another Texas public institution, during the follow-up period.

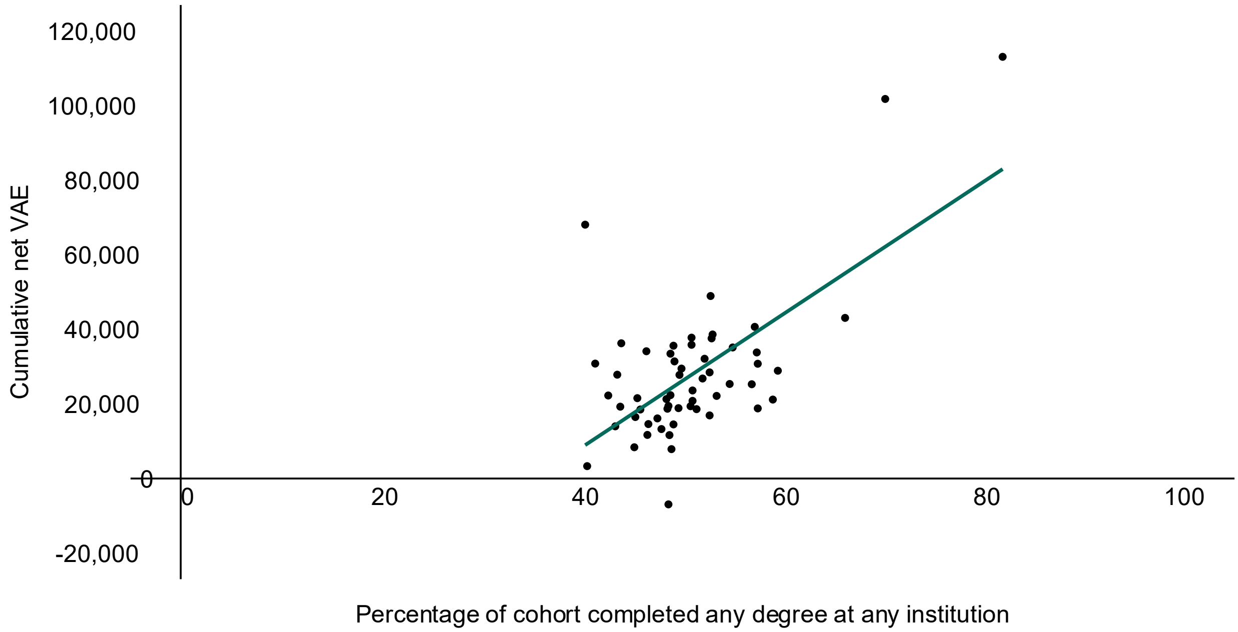
We focus on completion of any degree (and not just the intended associate's degree) because a meaningful share of associate's degree-seeking students transfer to a four-year college without completing an associate's degree and go on to complete a bachelor's degree,[44] which typically offers higher economic returns. Across institutions, 24 percent of cohort students seeking an associate's degree completed an associate's degree during the follow-up period and 51 percent completed any type of degree (including an associate's degree),[45] on average (Exhibit D.10). We do not examine institutional selectivity in this analysis because all associate's degree-granting institutions are considered inclusive in IPEDS.

The percentage of students in the cohort who completed any degree type at any institution during the follow-up period was positively correlated with the cumulative net VAE of that cohort, even after accounting for the characteristics of their institution (Exhibit 20). Specifically, cumulative net VAE was $1,681 higher, on average, for every percentage-point increase in the proportion of students in the cohort who completed a degree (Exhibit D.13, column 3). Net price, size, and the percentage of students who received Pell Grants were not consistently related to cumulative net VAE for associate's degree-seeking students.

[44] In Texas, 35 percent of students in community colleges transfer to a four-year college, with 54 percent of those who transfer going on to complete a bachelor's degree (Miller 2025).

[45] These 51 percent of students include students who obtained a certificate or bachelor's degree but not an associate's degree as well as those who obtained more than one type of credential.

Exhibit 20. Relationship between cumulative net value-added earnings in Year 10 for cohorts of associate's degree-seeking students and the percentage of the cohort that completed any degree at any institution



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 57 institutions. The outcome is Year 10 cumulative net value-added earnings in 2023 dollars for associate's degree-seeking students enrolling in postsecondary education in 2008–09 through 2013–14. Values are student-weighted averages.

Of note, the share of cohort students who completed an associate's degree specifically (rather than any degree) was not related to cumulative net VAE for students seeking an associate's degree (Exhibit D.13, columns 4 and 5).[46] These findings are consistent with the important role of transfers to four-year colleges in the community college context.

C. Certificates

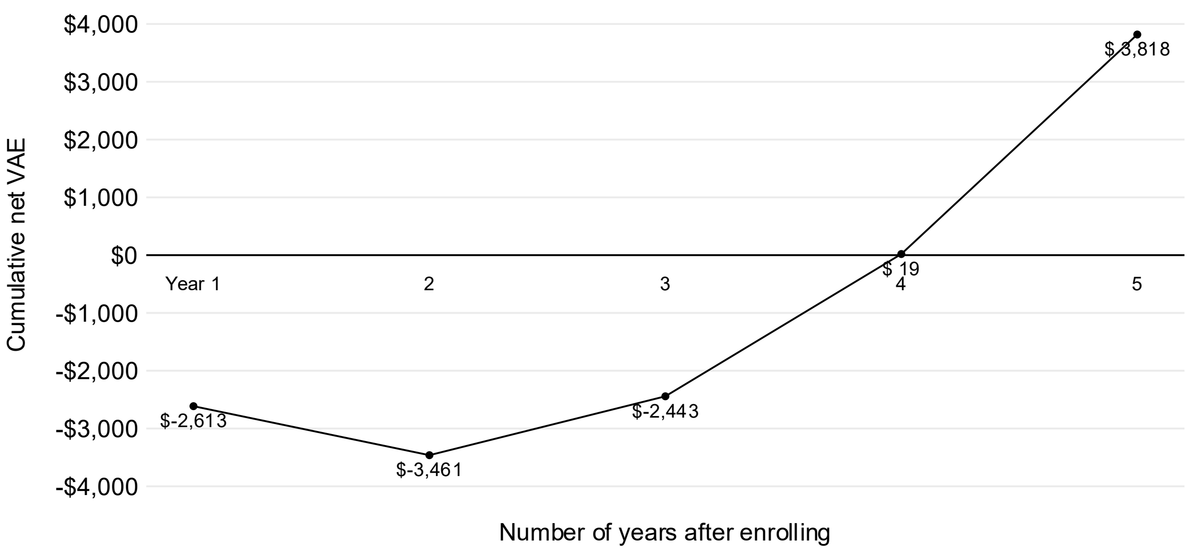
On average, certificate-seeking students recovered the total costs of enrolling in postsecondary education within four years and accumulated a cumulative net VAE of over $3,800 after five years.

Cumulative net VAE for the cohort of certificate-seeking students enrolling in postsecondary education in 2008–09 through 2018–19 was initially negative and decreasing during the first two years after enrolling, on average (Exhibit 21). Starting in Year 3, cumulative net VAE began to increase, as more students who had enrolled in a certificate program completed a credential and entered the labor force. By Year 4, these students' cumulative VAE just exceeded the total net cost of attendance, which were almost $1,000 on average (Exhibit 22). By Year 5, the average certificate-seeking student had a cumulative net VAE of $3,818. They were also outearning comparison group students, receiving average annual earnings of

[46] In addition, the 150 percent graduation rate reported in IPEDS only counts full-time students who complete an associate's degree or certificate, depending on which degree type they sought when they first enrolled. It does not account for students who transfer and go on to complete a degree elsewhere. Therefore, this measure may not necessarily be related to cumulative net VAE for students seeking associate's degrees.

$30,475 compared to $26,629. Although the study's follow-up period for certificate-seeking students is shorter than for other degree types, the positive slope of their average cumulative net VAE starting in Year 2 suggests that their earnings gains may continue to grow beyond the five-year follow-up period, as with students seeking bachelor's and associate's degrees.

Exhibit 21. Cumulative net value-added earnings for certificate-seeking students, 2008–09 to 2018–19 entry years



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 67,486 students who enrolled in public postsecondary institutions in Texas in 2008–09 through 2018–19. Values are student-weighted averages in 2023 dollars.

Exhibit 22. Cumulative earnings, net costs, and value-added earnings for certificate-seeking students, 2008–09 to 2018–19 entry years

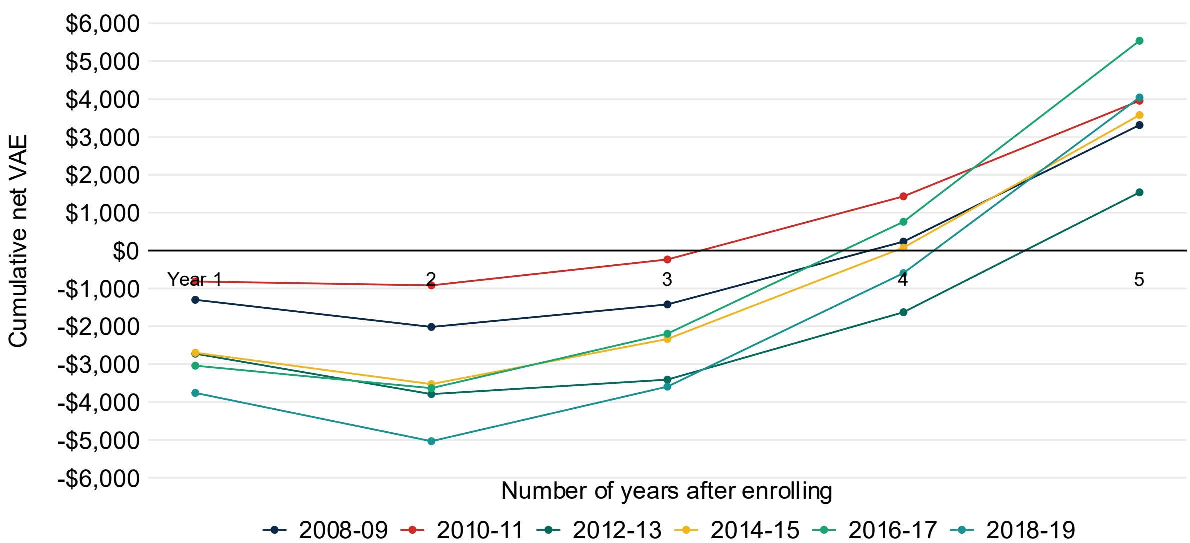
Years after enrollment	Cohort cumulative earnings ($)	Comparison group cumulative earnings ($)	Cohort cumulative value-added earnings ($)	Cohort cumulative net cost of attendance ($)	Cohort cumulative net value-added earnings ($)
Year 1	13,097	15,280	-2,183	431	-2,613
Year 2	32,027	34,739	-2,713	749	-3,461
Year 3	55,259	56,794	-1,534	908	-2,443
Year 4	82,238	81,223	1,015	996	19
Year 5	112,713	107,852	4,862	1,044	3,818

Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 67,486 students who enrolled in public postsecondary institutions in Texas in 2008–09 through 2018–19. Values are student-weighted averages in 2023 dollars.

Cumulative net VAE varied across entry cohorts, though there is no clear pattern across time. Exhibit 23 shows average cumulative net VAE over time for every other entry cohort, starting with 2008–09 and ending with 2018–19.[47] About half of the entry cohorts took one more year to recover the net costs of pursuing a certificate program (five years, instead of four, on average). By Year 5, cumulative net VAE ranged from an average of $1,192 for the 2017-18 entry cohort to an average of $5,538 for the 2016-17 entry cohort. As noted earlier, differences across entry cohorts could be explained by the different timing of when students enrolled and entered the labor market or by the fact that more recent cohorts include more older students due to limitations of the data available in earlier years. Even across entry cohorts, however, the findings demonstrate a positive cumulative net VAE. Prior evidence has also found positive, though small, economic returns to certificate programs in different contexts or using different methods, though returns tend to vary significantly across fields of study, student demographic groups, and states (for example, Jepsen et al. 2014; Minaya and Scott-Clayton 2022; and Xu and Trimble 2016).

Exhibit 23. Cumulative net value-added earnings for certificate-seeking students, by entry year, 2008–09 to 2018–19



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 67,486 students who enrolled in public postsecondary institutions in Texas in 2008–09 through 2018–19 (results are only shown for every other entry year). Values are student-weighted averages in 2023 dollars.

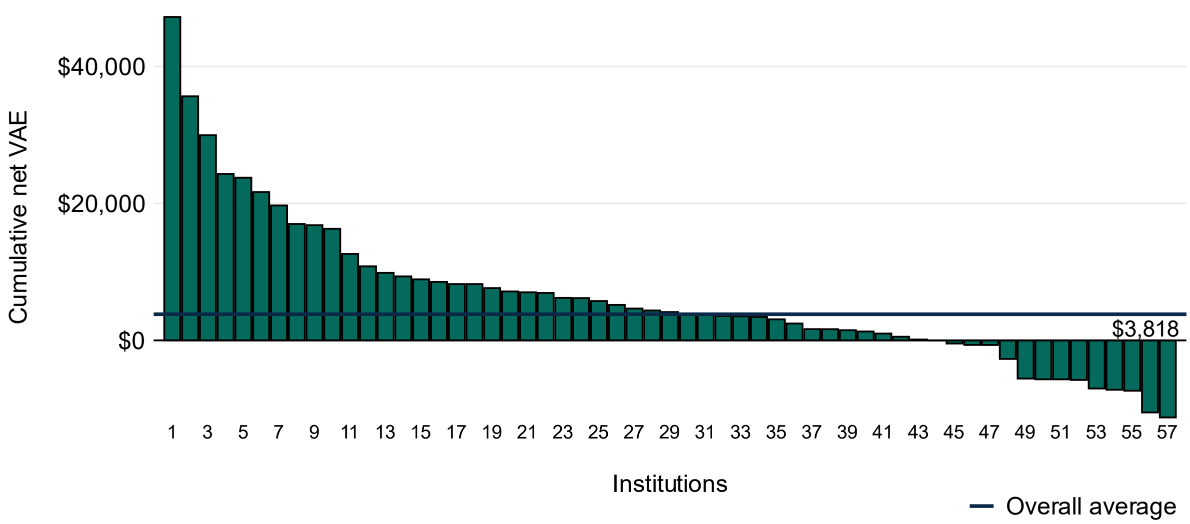
Although cumulative net VAE varied significantly across institutions, most of the 57 institutions offered a positive cumulative net VAE to certificate-seeking students after five years.

Cumulative net VAE for certificate-seeking students was positive for 43 of 57 institutions after five years, though it varied significantly across institutions, from a low of -$11,257 to a high of $47,231 (Exhibit 24). Cumulative net VAE was $23,502 higher for institutions in the top decile of cumulative net VAE compared with the bottom decile. Specifically, an institution at the 90th percentile had cumulative net VAE of $16,292, while an institution at the 10th percentile had cumulative net VAE of -$7,210. Put differently, a 1

[47] We do not graph all entry cohorts for readability of the figure.

standard deviation increase in an institution's cumulative net VAE after five years corresponded to an increase of $9,674. These results suggest that public institutions in Texas offer different value to students seeking a certificate, especially at the tail ends of the distribution. In fact, the bottom 25 percent of institutions all had negative cumulative net VAE after five years, on average. As noted previously, the positive slope of the cumulative net VAE line across years (Exhibit 20) suggests that cumulative net VAE for certificate–seeking students will continue to grow over time and that institutions (or programs) that had negative cumulative net VAE in Year 5 may eventually have a positive cumulative net VAE. However, past research suggests that the economic returns to certificates may be flat over time (Minaya and Scott-Clayton 2022) or may even fade after a few years, in the case of very short programs (Darolia et al. 2025).

Exhibit 24. Cumulative net value-added earnings in Year 5 for certificate-seeking students, by institution, 2008–09 to 2018–19 entry years



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 67,486 students who enrolled in public postsecondary institutions in Texas in 2008–09 through 2018–19. Values are student-weighted averages in 2023 dollars.

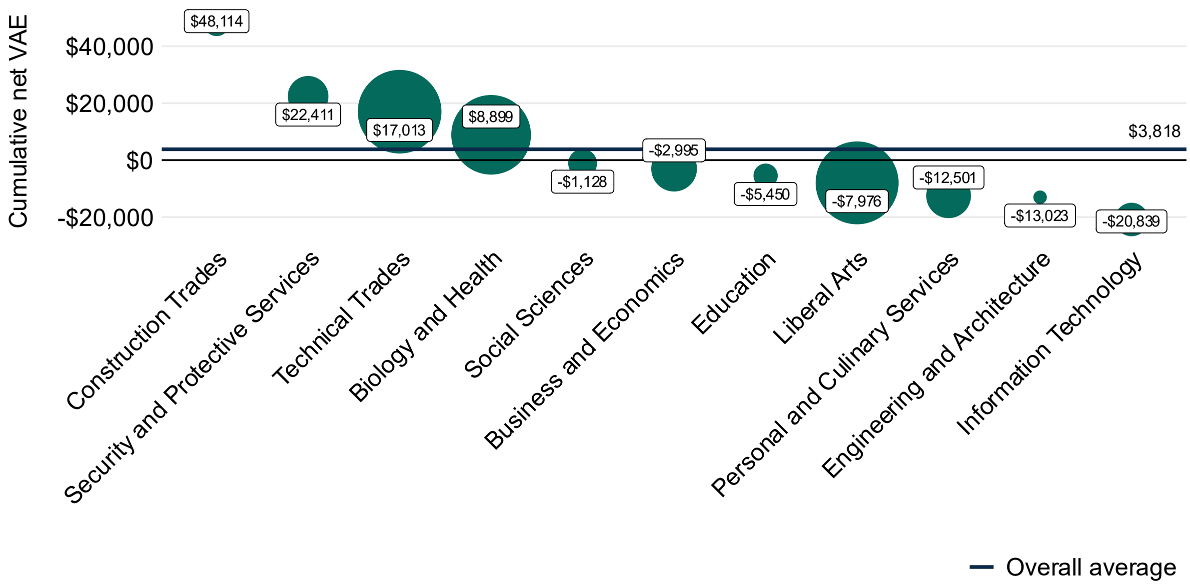
Cumulative net VAE for certificate-seeking students varied across program types, with several programs having negative cumulative net VAE and STEM programs offering greater value, on average.

For certificate-seeking students, cumulative net VAE after five years varied significantly across programs, ranging from an average of $48,114 for those enrolling in construction trades to an average of -$20,839 for those in information technology, which trains students for entry-level roles in communications, media, computing, and information technology support (Exhibit 25).[48] In addition to information technology, many other program types had negative cumulative net VAE after five years. Only four out of 11 program

[48] The variation across programs of study in average cumulative net VAE was statistically.

types (construction trades, security and protective services, technical trades, and biology and health) had positive cumulative net VAE, on average.

Exhibit 25. Cumulative net value-added earnings in Year 5 for certificate-seeking students, by program of study, 2008–09 to 2018–19 entry years



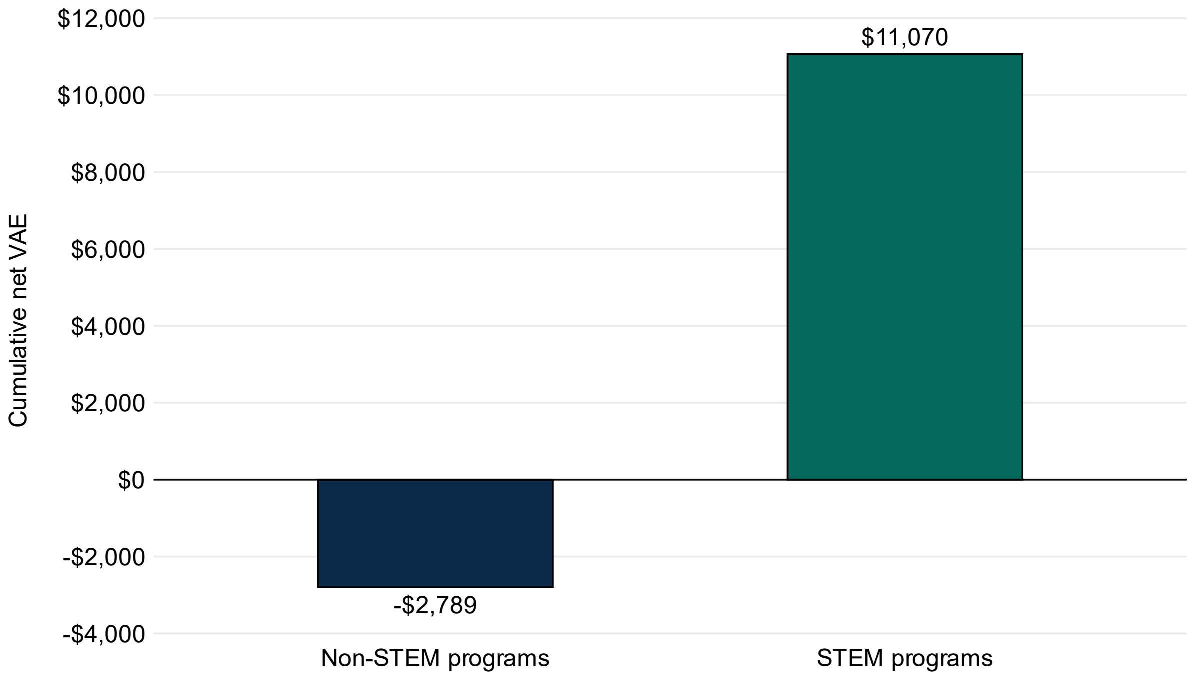
Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 53,534 students who enrolled in public postsecondary institutions in Texas in 2008–09 through 2018–19. Values are student-weighted averages in 2023 dollars. The size of each circle is proportional to the number of cohort students in each program. Differences across programs are statistically significant at the 1 percent level.

Consistent with these patterns, cumulative net VAE differed significantly between students enrolled in STEM programs ($11,070) and those in non-STEM programs (-$2,789; Exhibit 26). As noted earlier, some technical fields—such as construction trades—are not classified as STEM. In addition, even within STEM programs, cumulative net VAE can vary widely. For example, engineering and architecture and information technology programs are considered STEM but had negative cumulative net VAE for students seeking a certificate. Because certificates are much shorter than other degree types (typically requiring 12 to 30 credits, compared with 60 credits for associate's and 120 credits for bachelor's degrees), some STEM certificates may not offer the same skills premium associated with longer STEM degrees.

Other research has also found that the economic returns to certificates differ substantially by field of study—and even within a given field of study, which can encompass multiple types of programs with varying job prospects—with many certificate programs yielding negative returns (for example, Dadgar and Trimble 2014; Jepsen et al. 2014; Xu and Trimble 2016).

Exhibit 26. Cumulative net value-added earnings in Year 5 for certificate-seeking students, by STEM program status, 2008–09 to 2018–19 entry years



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 53,534 students who enrolled in public postsecondary institutions in Texas in 2008–09 through 2018–19. Values are student-weighted averages in 2023 dollars. STEM refers to science, technology, engineering, and mathematics and includes the following programs: agriculture and natural resources, biology and health, engineering and architecture, physical sciences and math, information technology, and technical trades (for associate's and certificate programs). Non-STEM includes all other programs. The difference between program types is statistically significant at the 1 percent level.

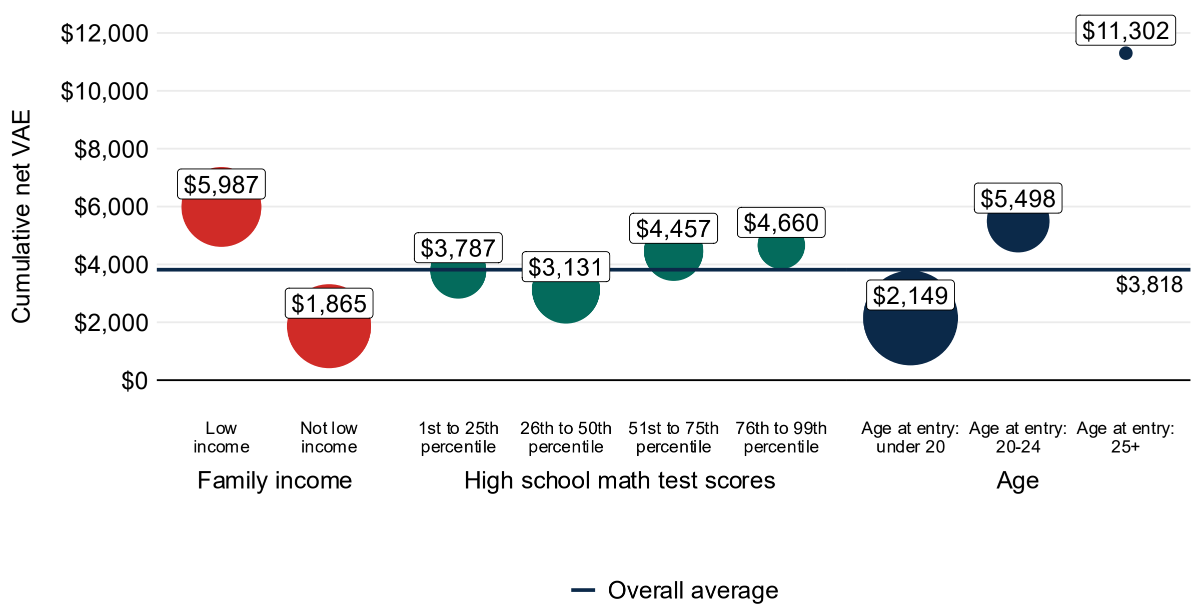
Cumulative net VAE for certificate-seeking students varied by students' household income and age but not by their high school math achievement, with students from low-income households and older students having higher cumulative net VAE on average.

Certificate-seeking students from low-income households had higher cumulative net VAE after five years, on average. This is in contrast with other degree types, in which students from low-income households had either similar or lower returns, on average, compared to their peers from higher-income households. Students from low-income households had an average cumulative net VAE of $5,987, compared with $1,865 for their peers from higher-income households (Exhibit 27). As noted earlier, compared to students from higher-income households, low-income students tend to have lower net costs. In addition, they may benefit more from pursuing a certificate if it allows them to gain access to higher-paying job opportunities that otherwise would be unavailable to them.

Cumulative net VAE for certificate-seeking students varied relatively little for students with differing levels of high school math achievement—from an average of $3,131 for those in the second quartile to an average of $4,660 for those in the top quartile (Exhibit 27). Nearly one-quarter (23 percent) of certificate-seeking cohort students were in the lowest quartile of high school achievement, compared with 15 percent in the highest quartile. Although higher math achievement may help some students translate their education into higher-earning programs and jobs, overall the differences in cumulative net VAE across achievement levels are small for students seeking a certificate, and even students with lower math achievement had positive cumulative net VAE on average.

Age at entry was also related to cumulative net VAE for certificate-seeking students, with students who were older at the time of enrolling having higher cumulative net VAE, on average. Although they make up only 2 percent of cohort students seeking a certificate, those who were 25 and older when they enrolled had significantly higher cumulative net VAE on average ($11,302 compared with $5,498 for students ages 20 to 24 and $2,149 for students younger than 20; Exhibit 27).[49] As noted for students seeking an associate's degree, one reason why older students may earn higher returns from seeking a certificate is if their prior work experience allows them to translate their education into higher-paying jobs than similarly experienced peers who do not pursue postsecondary education.

Exhibit 27. Cumulative net value-added earnings in Year 5 for certificate-seeking students, by demographic group, 2008–09 to 2018–19 entry years



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 67,440 students with data on family low-income status, 61,289 students with data on high school math achievement, and 66,463 students with data on age at entry who enrolled in public postsecondary institutions in 2008–09 through 2018–19. Values are student-weighted averages in 2023 dollars. The size of each circle is proportional to the number of cohort students in each demographic group. Differences across groups are statistically significant at the 1 percent level.

[49] Because of data limitations, the study was only able to include certificate–seeking students who were ages 18 to 29 when they enrolled.

Students' choice of program of study was related to much larger differences in cumulative net VAE for certificate-seeking students than their choice of institution.

The previous sections have shown that cumulative net VAE varied across both institutions and programs of study, though not which of these two factors matters more for certificate-seeking students. Exhibit 28 shows that cumulative net VAE for certificate-seeking students in Year 5 varied more across programs within an institution than across institutions overall. As an illustrative example, cumulative net VAE within an institution at the 90th percentile ranged from -$20,076 to $27,292 across programs, a difference of over $47,000. In contrast, the difference in cumulative net VAE between an institution at the 90th percentile and an institution at the 10th percentile was about $24,000.

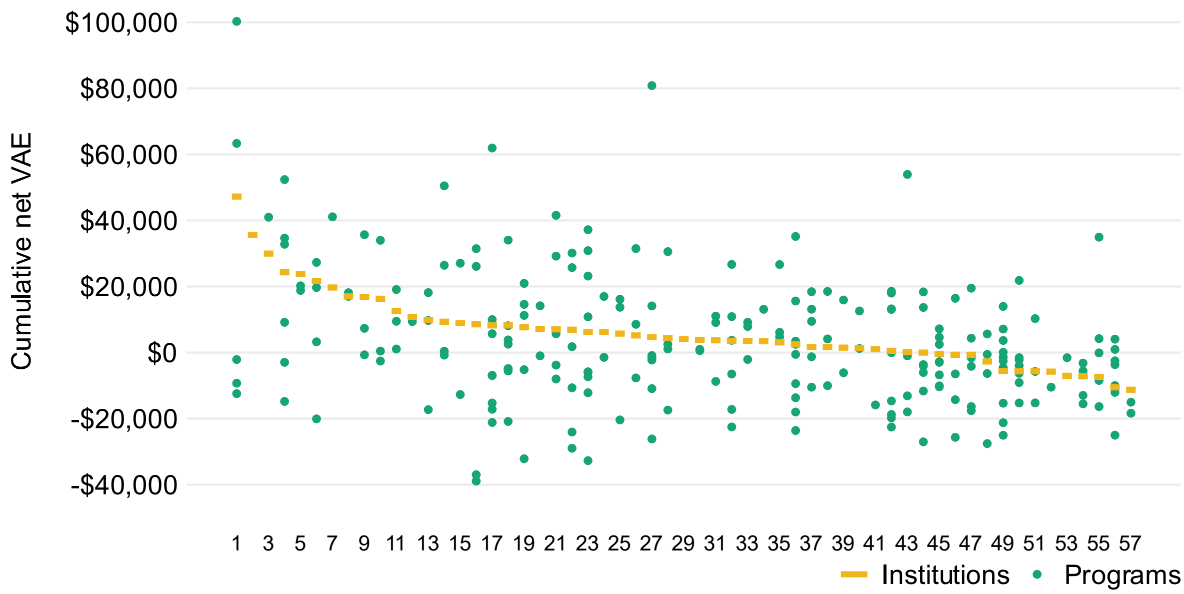
Consistent with the patterns in Exhibit 28, the ANOVA results show that 43 percent of the variation in cumulative net VAE for certificate-seeking students was explained by differences across programs within institutions, compared to 13 percent explained by differences across institutions delivering the same program (Appendix D, Exhibit D.17). [50, 51] The findings suggest that the choice of program matters much more for cumulative net VAE for certificate-seeking students than where they chose to enroll, consistent with research documenting substantial variation in the economic returns to certificates across fields.[52]

[50] After accounting for both the institution and program, 45 percent of the variation in cumulative net VAE for associate's degree–seeking students was still unexplained. This residual value suggests that a meaningful part of the variation in cumulative net VAE for these students is explained by specific programs in specific institutions being particularly effective (or not) at providing economic returns to their students, above and beyond what the program or institution alone would predict, on average.

[51] The matching approach used to estimate cumulative net VAE may not fully account for differences between students who do and do not choose to enroll in a given institution or program, leading to bias in the estimates of cumulative net VAE. To the extent that the approach leads to more bias in the estimates of cumulative net VAE by institutions or programs, this could affect the share of variation that is explained by institutions versus programs. However, it is unclear whether one type of estimates is systematically more biased than the other.

[52] After accounting for both the institution and program, 36 percent of the variation in cumulative net VAE for certificate–seeking students was still unexplained. This residual value suggests that a meaningful part of the variation in cumulative net VAE for these students is explained by specific programs in specific institutions being particularly effective (or not) at providing economic returns to their students.

Exhibit 28. Variation in cumulative net value-added earnings in Year 5 for certificate-seeking students, institutions versus programs



Source: Authors' calculations using Texas administrative data and IPEDS.

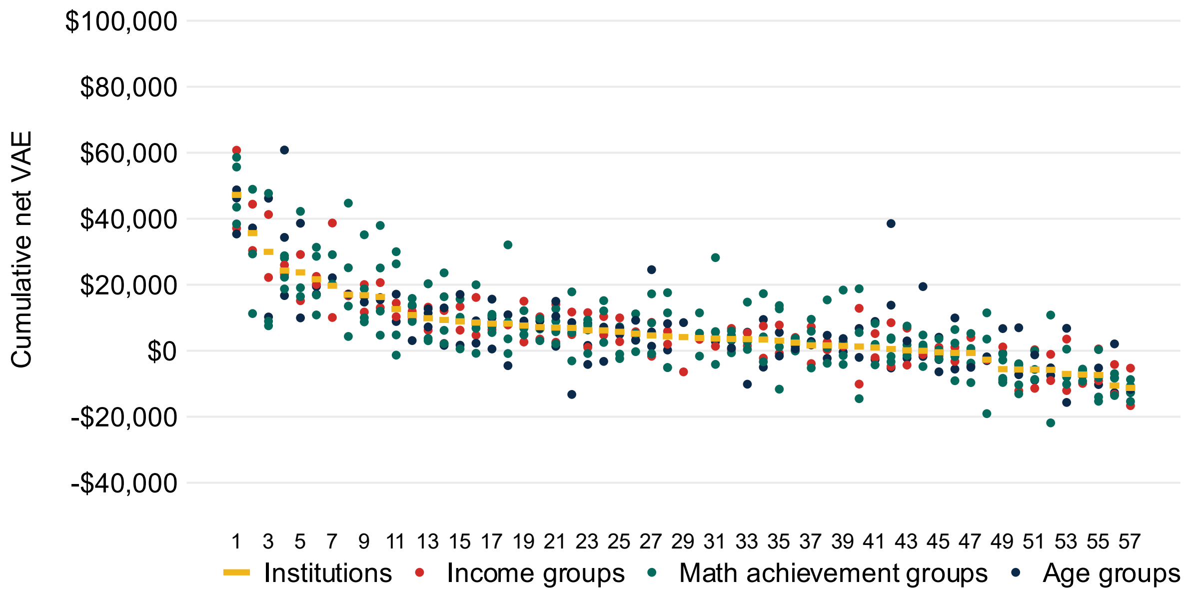
Note: The sample includes 57 certificate-granting institutions. The outcome is Year 5 cumulative net value-added earnings for students enrolling in postsecondary education in 2008–09 through 2018–19. Values are student-weighted averages in 2023 dollars.

Students' choice of institution was related to larger differences in cumulative net VAE for certificate-seeking students than their household income, high school math achievement, or age at entry.

To understand whether the choice of institution matters more than students' background characteristics for explaining differences in cumulative net VAE for certificate-seeking students, we repeat the ANOVA focusing on how much of the variation in cumulative net VAE is explained by students' household income, high school math achievement, or age when they enroll, separately, compared to their institution.

For certificate-seeking students, the choice of institution was related to much larger differences in cumulative net VAE than their household income, high school math achievement, or age at entry. Exhibit 29 shows how cumulative net VAE for certificate-seeking students in Year 5 varies across institutions overall and by demographic groups within each institution. In contrast to the distribution of cumulative net VAE across programs in Exhibit 28, differences in cumulative net VAE across demographic groups within an institution are much smaller than differences across institutions overall. The ANOVA results reflect this pattern as well: 83 percent, 67 percent, and 70 percent of the variation in cumulative net VAE is explained by differences across institutions among students in the same household income level, high school math achievement level, and age at entry, respectively (Appendix D, Exhibit D.17). In contrast, 3 percent, 6 percent, and 3 percent of the variation is explained by differences across household income levels, math achievement levels, and age at entry, respectively, within the same institution. These findings suggest that where a student seeking a certificate chose to enroll matters far more for cumulative net VAE than their household income, high school math achievement, or age when they enrolled.

Exhibit 29. Variation in cumulative net value-added earnings in Year 5 for certificate-seeking students, institutions versus demographic groups



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 57 certificate-granting institutions. The outcome is Year 5 cumulative net value-added earnings for students enrolling in postsecondary education in 2008–09 through 2018–19. Values are student-weighted averages in 2023 dollars.

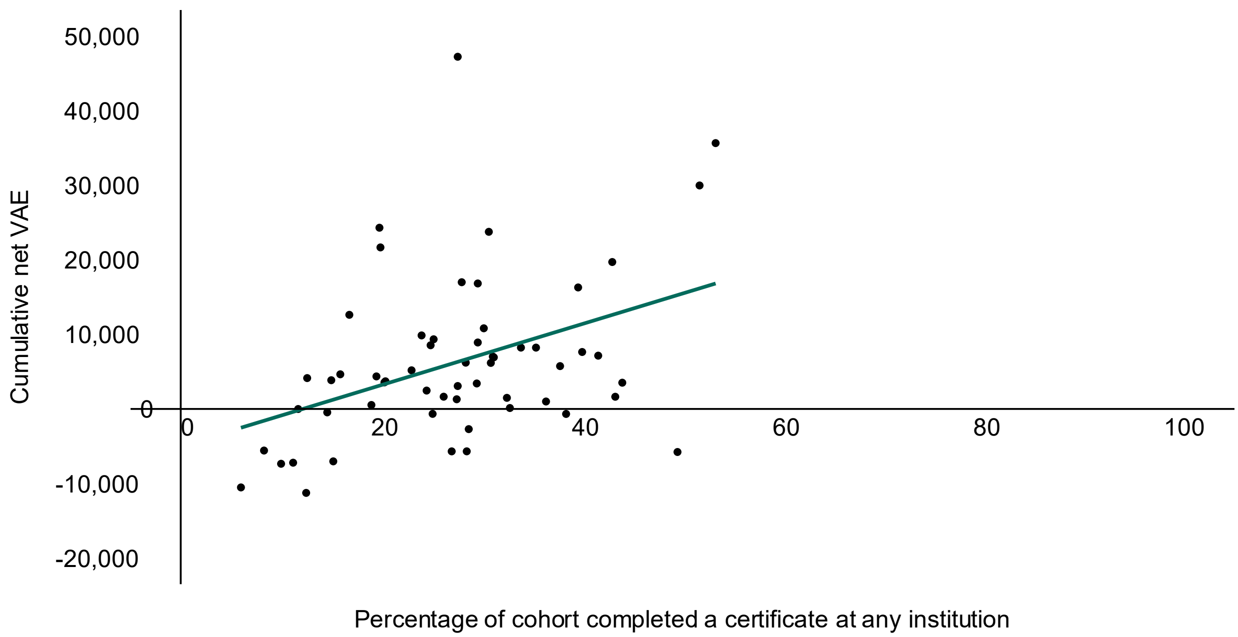
Institutional cohorts of certificate-seeking students in which a higher proportion of students completed a certificate had higher cumulative net VAE, on average, even after accounting for characteristics of their institution, such as size and price.

As noted earlier, cumulative net VAE for certificate-seeking students tended to vary substantially across institutional cohorts. To explore factors that may explain these differences, we examine an institution's average net price, the number of undergraduate students enrolled in the institution, the percentage of students at the institution who received Pell Grants, and the percentage of cohort students who completed a certificate at the institution in question or any other public institution in Texas during the follow-up period. We do not examine institutional selectivity in this analysis because all certificate-granting institutions are considered inclusive in IPEDS. We focus on completion of a certificate because, while some students who obtain certificates go on to "stack" credentials, transfer to another type of degree before completing a certificate is not typically a goal for students seeking a certificate. Across institutions, 27 percent of certificate-seeking cohort students completed a certificate program during the follow-up period, and 40 percent completed any degree (Exhibit D.10).

The percentage of cohort students who completed a certificate during the follow-up period at any institution was positively correlated with cumulative net VAE (Exhibit 30). Even after accounting for institutional characteristics, for every percentage-point increase in the proportion of certificate-seeking students in the cohort who completed a certificate, cumulative net VAE after five years was $353 higher, on average (Exhibit D.14, column 4).[53] Past research has shown the substantial variation in economic returns to certificates by field of study decreases after accounting for students' completion status (Zeidenberg et al. 2015). This finding suggests that completion rates may be an important factor for students selecting a certificate program and for institutions focused on providing better value to students.

An institution's net price, number of undergraduate students enrolled, and percentage of students who received Pell Grants were not related to cumulative net VAE for certificate-seeking students after accounting for the other characteristics examined (Exhibit D.14, column 4). [54]

Exhibit 30. Relationship between cumulative net value-added earnings in Year 5 for cohorts of certificate-seeking students and the percentage of the cohort that completed a certificate at any institution



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 57 institutions. The outcome is Year 5 cumulative net value-added earnings in 2023 dollars for certificate-seeking students enrolling in postsecondary education in 2008–09 through 2018–19. Values are student-weighted averages.

[53] This relationship was very similar when measuring the proportion of the cohort completing a certificate at the same institution, as certificate–seeking students were much less likely to transfer institutions than other degree–seeking students. Only 2 percent of cohort students seeking a certificate went on to complete a certificate at another institution (Exhibit D.14, column 5). In contrast, there was not a statistically significant relationship between the proportion of the cohort completing any degree (not just a certificate) and cumulative net VAE for certificate–seeking students (Exhibit D.14, column 3). If certificate–seeking students go on to pursue a longer degree type, they may initially reduce their labor force participation and take longer than five years to observe positive earnings gains.

[54] It is also worth noting that the institutional characteristics we examine explain much less of the variation in cumulative net VAE across institutions for students seeking certificates compared with associate's and bachelor's degrees, as evidenced by the lower adjusted R^2 values from these regressions (Exhibit D.14).

IV. Implications

This study contributes to the evidence on the economic value of postsecondary education using rich, linked administrative data and quasi-experimental matching methods. We estimate the net value added on earnings of public postsecondary institutions and programs in Texas by comparing the observed earnings of students who enroll in a given institution or program with the earnings of a matched group of similar individuals who did not pursue postsecondary education during the follow-up period. This approach, which accounts for both direct cost of attendance and the opportunity cost of foregone earnings, is designed to capture the causal contribution of postsecondary enrollment to students' earnings over time.

On average, students who pursued certificates, associate's degrees, or bachelor's degrees at public institutions in Texas experienced positive cumulative net VAE across degree types. This analysis was limited to public institutions in Texas. Prior research suggests that returns are more variable—and more frequently negative—among private nonprofit and for-profit institutions, particularly for lower-earning programs of study (Cellini and Turner 2019). As a result, the positive average returns documented here should not be interpreted as representative of the full postsecondary sector in Texas or nationally.

These averages also mask substantial variation by degree type, institution, program of study, and the characteristics of the student cohorts. Although most institutions offered positive cumulative net VAE for bachelor's and associate's degree-seeking students, about one-quarter of institutions had negative cumulative net VAE for certificate-seeking students. Across students seeking all degree types—but especially among those seeking certificates—differences in cumulative net VAE were driven more by choice of program of study than by choice of institution. In addition, students' background characteristics when they entered postsecondary education, such as their age or household income, tended to be much less predictive of differences in cumulative net VAE than which institution they attended. Finally, cumulative net VAE was higher, on average, for cohorts of students with higher rates of degree completion. These findings align with a large body of research using rigorous methods to estimate the economic returns to higher education and underscore that although postsecondary education generates positive returns for many students, outcomes are not uniform. State and federal policymakers and institutional leaders can use measures of cumulative net VAE to identify areas for improvement.

Our estimates differ conceptually and empirically from simpler approaches to measuring the economic returns to higher education. Our approach aims to isolate the value added of institutions and programs by accounting for differences in student characteristics and local labor markets and incorporating the opportunity cost of foregone earnings—a major component of the true cost of postsecondary education. The study features comprehensive measures of net tuition costs inclusive of financial aid, long follow-up periods to track earnings, and the inclusion of students who do not complete a degree. This approach thus provides a more complete picture of postsecondary value and can serve as a framework for future research and for accountability metrics and policy, especially given the growing interest in measuring postsecondary value for use in high-stakes accountability settings. For example, under OBBBA, an undergraduate program's eligibility for federal student aid will be determined by whether the median earnings of graduates four years after program completion meet or exceed the median earnings of high school graduates ages 25 to 34.[55] Some states are also seeking to use this metric to determine funding allocations and program approval (Akers 2026; Cooper 2026).

We find that cumulative net VAE estimates can differ dramatically depending on whether we control for student characteristics at entry (Appendix Section D), demonstrating the importance of making these adjustments to more rigorously estimate students' counterfactual earnings. Simpler approaches that do not account for differences between students in the cohort and those in the comparison group may generate biased results, and in particular overstate the economic returns to higher education because students who enroll tend to have higher earnings potential to begin with. This may have implications for accountability measures like the ones employed under OBBBA and in state postsecondary systems.

This study contributes to ongoing questions about how to reliably measure postsecondary value at scale and illustrates both the promise and the limits of using more rigorous approaches. The methods used here represent an improvement over simpler alternatives, but they rely on Texas' unusually rich state longitudinal data system linking students' K–12 records, postsecondary enrollment, financial aid, and earnings. Texas's data infrastructure made this analysis possible, and it may be challenging to replicate it in states with less advanced data systems. It is not possible to implement this study using federal data.

Several avenues for future work emerge from this analysis. First, the study in Texas would benefit from being expanded to include more recent cohorts of students, particularly for bachelor's degree-seeking students. Additional analyses could provide important insights. For example, additional work is needed to better understand the trajectory of students' earnings gains and whether—and at what point—their long-term outcomes can be reliably predicted, particularly for certificate-seeking students. Additional work is also needed to understand how sensitive the program results are to categorizing students into programs of study at different time points (entry, midway, and graduation) and to explore to what extent the aggregated program categories used in the analyses may mask important variation within categories. Future work should also explore how outcomes vary for additional groups of students, including students who did not complete their degree and students who qualify for special education in high school. In addition, future research should examine whether simpler models—for example, accounting for fewer background student characteristics—can approximate these estimates without introducing substantial bias, enabling state and federal policymakers, who often rely on less rich data than is available in Texas, to implement methods like ours. Future work can also assess and characterize the error associated with cumulative net VAE estimates and develop ways to communicate the level of confidence of those estimates to inform appropriate interpretation and action.

[55] For institutions with more than 50 percent in-state students, the comparison will be with high school graduates in the same state as the institution. Otherwise, the comparison will be with high school graduates nationally.

Expanding this study to states other than Texas would help assess the generalizability of the findings and demonstrate whether the approach can be applied using different state data infrastructures, though not all state systems are comprehensive enough to support this methodology. In addition, even with a rich state longitudinal data system like Texas's, access to more comprehensive earnings data—through tax records, the National Directory of New Hires, or multi-state UI wage sharing—would improve measurement of earnings outcomes and allow measures to include a higher proportion of students. Finally, extending this approach to private nonprofit and for-profit institutions remains an important challenge given the more limited availability of longitudinal data in state systems on the millions of students who attend these institutions.

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Technical Appendix

This appendix provides additional technical details about the data, sample, and methods used to estimate cumulative net value-added earnings (VAE) and to answer each research question in the report. Section A describes the data and sample used in the study. Section B outlines the process for estimating cumulative net VAE, including a description of the matching algorithm, the regressions used to estimate VAE, and the approach to calculating cumulative net VAE. Section C describes the approaches used to analyze the cumulative net VAE estimates and address research questions of interest. Section D presents supplementary exhibits. Section E presents sensitivity analyses.

A. Data and sample

We use student-level administrative data from the Texas Education Agency (TEA), the Texas Higher Education Coordinating Board (THECB), and the Texas Workforce Commission (TWC) to identify a sample of high school graduates in Texas and follow them longitudinally from high school into postsecondary education and the workforce. We use these data to track students' earnings and postsecondary education costs over time to estimate earnings gains and net costs from attending Texas postsecondary institutions.

1. High school data

The TEA data cover all students who attended public schools in Texas and include information on student age, race, sex, special education status, limited English proficiency status, free- or reduced-price lunch status, standardized test performance, high school attended, attendance, disciplinary actions, course enrollments, and graduation status. We use the TEA data to create a sample of high school graduates from Texas public schools from 2007–08 through 2017–18. For state assessment data, we focus on math and English scores and use either the State of Texas Assessments of Academic Readiness (STAAR) or Texas Assessment of Knowledge and Skills (TAKS), depending on which was in use during a student's graduation year.[56] To facilitate comparison across test types, we standardize student scale scores for each test type and subject using the state mean and standard deviation for each test annually. We also use course enrollment data to calculate the share of core courses a student failed in high school and the number of advanced courses a student passed in core subjects. We supplement this with data from the National Center for Education Statistics' Common Core of Data (CCD) to identify the county of each student's high school.

2. Postsecondary data

We merge the sample of high school graduates with data from THECB and the National Student Clearinghouse (NSC) to track students' postsecondary enrollments following high school graduation. From THECB, we use detailed administrative data from Texas postsecondary institutions from 2008–09 to 2022–23 that includes each semester a student was enrolled and whether they earned a degree. These

[56] For STAAR, we use the Algebra I test (typically taken in 9th grade) for the math score and English II test (typically taken in 10th grade) for the English score. When TAKS is used, we use the 9th-grade math test and 10th-grade reading test. If students take these tests multiple times, we use the first test.

data cover community, technical, and four-year colleges in the state. [57] THECB also include data on the type of degree a student was seeking and their program of study (major).[58] We supplemented THECB data with data from NSC, which allow us to identify whether a student enrolled in or completed a degree from a postsecondary institution outside of Texas.[59]

We use THECB and NSC data to determine which students enrolled in postsecondary education following high school graduation and to identify cohorts of students who enroll in Texas public institutions. We also use these data to determine what degrees students are seeking, what programs they are in, and whether they ultimately complete a degree.

Last, we merge in public data from the Integrated Postsecondary Education Data System (IPEDS) to describe characteristics of Texas institutions, such as their selectivity and total enrollment. We use these data to describe the institutions included in the analyses and to examine the relationship between cumulative net VAE and institution characteristics.

3. Workforce data

Additionally, we link the sample of high school graduates with data from TWC on quarterly earnings for eligible earners in Texas from 2005–06 through 2023–24. We use these earnings data from the period after a cohort enrolls in postsecondary education to measure earnings outcomes, and we use data from the period before a cohort enrolls in postsecondary education to match older cohort members (age 20 or older) to comparison group members with similar earnings and employment histories.

We sum quarterly earnings to make annual earnings and convert these to 2023 dollars to facilitate comparisons across cohorts. We also winsorize earnings at the 99th percentile to reduce the influence of extreme values that are often found in earnings data.[60] We create multiple annual earnings measures so that for each postsecondary enrollee we can choose an annual measure that is indexed relative to the first semester within a school year that a student enrolls in a postsecondary institution. For example, if a student first enrolls in an institution in fall of the 2008–09 school year, their Year 1 earnings post-entry is defined as the sum of earnings from Quarter 4 of 2008 through Quarter 3 of 2009. Exhibit A.1 provides additional examples of how Year 1 post-entry would be calculated for students in a 2008–09 institutional cohort based on the first semester they enroll. This approach ensures that for any postsecondary enrollees the post-entry period always starts in the first full quarter after a student has enrolled and that the pre-

[57] THECB collects data on all postsecondary institutions located in Texas, including private institutions, with the exception of those offering degrees only in religious disciplines or operating on military land. We focus on public institutions as they report admissions data which allow us to observe the degree a student sought. In future work we will explore the feasibility of including private institutions in our analysis.

[58] For four-year public colleges, we used admissions data to determine the type of degree a student sought (for example, bachelor's, master's). For community and technical colleges, administrative records collected each semester indicated whether a student was seeking an associate's degree or certificate.

[59] We examined whether estimates that ignored information on whether a Texas high school graduate enrolled in postsecondary education out of state were substantially biased—as compared to estimates that use this information to exclude individuals from the comparison group—and found that they were.

[60] We winsorize earnings by setting any earnings higher than the 99th percentile to be equal to the 99th percentile value. We follow prior research that applies the same winsorizing approach to the Texas data to estimate earnings outcomes following postsecondary enrollment (Mountjoy 2022).

entry period captures an individual's employment history in the quarters right before they enroll in postsecondary education, regardless of whether they first enroll in a fall, spring, or summer semester.

Exhibit A.1. Calculating earnings based on when a student begins (example: 2008–09 year)

First semester enrolled	Calendar quarters used to identify total earnings in Year 1 post-entry	Calendar quarters used to identify total earnings in Year 1 pre-entry
Fall	Q4 2008 through Q3 2009	Q4 2007 through Q3 2008
Spring	Q1 2009 through Q4 2009	Q1 2008 through Q4 2008
Summer	Q3 2009 through Q2 2010	Q3 2008 through Q2 2009

One limitation of the TWC data is that they exclude workers who are not included in Texas's Unemployment Insurance (UI) system, including federal workers and self-employed individuals such as those who work as contractors in the "gig" economy.[61] As a result, it is not possible to distinguish between individuals who were not employed and those who were engaged in employment that is not covered by Texas UI data collection, such as those who worked outside Texas or those who were self-employed. In addition, the data only report on non-zero earnings, and therefore instances of unemployment or nonparticipation in the labor force are not explicitly coded in the data and must be inferred.

To measure the VAE of postsecondary enrollment, it is important to capture the effects of enrolling in postsecondary education on employment as well as on earnings for those who are employed. To do so, we assume that individuals had zero earnings in quarters in which they do not appear in the TWC data, a common approach in the literature using administrative earnings records (see, for example, Andrews et al. 2024; Denning and Jones 2019; Minaya and Scott-Clayton 2022). One risk with this approach is that pursuing postsecondary education may cause some students to move out of state at higher rates. Students might have some earnings in Texas from part-time or summer employment while enrolled and then appear to have zero earnings after completing their enrollment. If these workers appear to have zero earnings because their earnings are not captured in Texas's UI system, this could introduce bias to the estimates. To reduce this risk of bias, we limit the sample to individuals who were employed in Texas at least once in the period after we expect their postsecondary enrollment to have concluded. We define the expected enrollment period as 150 percent of the full-time program length: six years for bachelor's degree programs, three years for associate's degree programs, and one-and-a-half years for certificate programs. It is important to note that this also removes individuals who were not attached to the labor force (and had zero earnings) over a long period. However, we believe that restricting the sample in this way strikes a reasonable balance between potential errors.[62] We also test the sensitivity of our findings to this exclusion, as described in Appendix Section E.2.

The primary earnings outcome of interest is cumulative earnings over a set period of time after a student enrolls in an institution, which we call the "follow-up" period. The follow-up period varies depending on the type of degree a student is seeking: five years for a certificate, 10 for an associate's, and 15 for a

[61] For details, see https://www.twc.texas.gov/programs/unemployment-tax/determine-tax-account or https://www.bls.gov/cew/publications/employment-and-wages-annual-averages/current/home.htm#exclusions.

[62] See Belfield and Bailey (2017) for a review of other papers that use state administrative earnings data to estimate returns to education and that apply the same restriction to missing earnings data.

bachelor's. The length of the follow-up period is based on the amount of time and cost to complete the degree and the typical earnings profile for individuals with different education levels. The average elapsed time between enrollment and completion of the degree sought in the original institution is about 5 years for bachelor's degrees, 4.25 years for associate's degrees, and 1.5 years for certificates in our sample. Prior research shows that the earnings profile of bachelor's degree holders exhibits longer-term growth than that of other college enrollees (Tamborini et al. 2015). Motivated by this finding, we analyze a longer follow-up period for bachelor's degrees to capture their longer-term earnings growth.

4. Cost data

To measure the annual net cost of attendance in a postsecondary institution, we use student-level administrative data from Texas to capture aid students receive (tuition or fee waivers or exemptions and grants) and institution-level data from IPEDS to estimate tuition and fees and the cost of books and supplies. We calculate annual net cost of attendance in the following way:

$$Net\ cost = Tuition + Fees + Books\ and\ Supplies - Tuition\ or\ fee\ waivers\ or\ exemptions - Grants$$

We do not include the costs of housing or transportation, which are costs that could be incurred regardless of whether an individual was enrolled in postsecondary education. Because we are focused on estimating cumulative net VAE for students seeking specific degree types at each institution, we focus on the first degree type a student pursues at an institution and do not include the costs of subsequent degrees a student might pursue at an institution. For example, if a student enrolls in a certificate program in fall 2008 and then enrolls in an associate's program in fall 2010, we do not count the costs of the enrollment in the associate's program as part of the costs of the certificate program.

THECB data include student-level data from the Financial Aid Database System on tuition waivers or exemptions and all other forms of institutional, state, or federal financial aid provided to a student for each institution they enroll in annually. IPEDS includes data on tuition and fees for in-state, in-district, and out-of-state students, as well as the cost of books and supplies on average.[63] We use THECB enrollment data to determine whether a student is eligible for in-state, in-district, or out-of-state tuition and fees and apply the appropriate cost for each student. One limitation of the IPEDS data is that they are only reported for students enrolled full time. To estimate the costs of tuition and fees and books and supplies for students who are enrolled less than full time, we use student-level data to calculate each student's enrollment intensity based on the total semester credit hours they are enrolled for in the fall and spring terms. We then create an annual enrollment intensity and scale the costs of tuition, fees, books, and supplies to account for each student's enrollment intensity. We then subtract any aid a student has received in the form of tuition or fee waivers or exemptions and grants to get a net annual cost for each student. Once all annual costs have been estimated, we convert costs to 2023 dollars to facilitate comparisons over time and calculate a total cumulative cost over the follow-up period through the last year of the study (2022–23).

Another cost we incorporate is the foregone earnings that a student experienced while enrolled. These costs are measured implicitly by summing cumulative earnings from the point in time when students

[63] Some states, such as Texas, have community college districts within the state that offer lower tuition rates for students residing in those districts.

enrolled and began to incur lost wages because of their education commitments. By comparing students' earnings during this period to the earnings of individuals who were not enrolled in postsecondary education, we capture the opportunity costs that students incur from enrolling.

5. Sample

The sample consists of graduates from Texas public high schools from 2007–08 through 2017–18. We start with 2007–08, as this is the first year that out-of-state postsecondary enrollment data from NSC are available for high school graduates.[64] The sample is limited in a few important ways:

a. **Student records must have a valid Social Security number (SSN).** A valid SSN is needed to link student records to earnings in the TWC file, a key outcome variable in the analysis.

b. **A student must not have attended an institution outside of Texas.** We exclude any students from the sample who attended an out-of-state postsecondary institution. These students likely have earnings outside of Texas that are not observable in the TWC data.

c. **Student records must have the following data fields for matching:**

   – **Age.** Age is an important matching variable to ensure that we compare individuals' earnings outcomes at similar stages of life.

   – **For individuals younger than age 20 in the entry year, high school test scores.** For students younger than 20 in the entry year, we require test score data from standardized tests. For individuals aged 20 and older at the entry year, we match on prior earnings and, when available, test scores but do not require test score data for inclusion in the analysis. For students younger than 20, we do not use earnings for matching because earnings and employment at this age are less predictive of later earnings. Instead, we require this group to have test score data from standardized tests.

d. **Students must have some non-zero earnings during the follow-up period after we expect enrollment to have concluded.** As described in the section on earnings data, we do not include individuals in the sample for matching if they had no earnings reported for the portion of the follow-up period during which we expect members of the cohort who enrolled in postsecondary education to have completed their degree and entered the workforce (after 150 percent of degree time). For bachelor's degrees, this period is Years 7 through 15, for associate's degrees Years 4 through 10, and for certificates Years 2 through 5.

We summarize the total sample size of enrolled students in institutional cohorts before and after applying these requirements for each degree type and entry year (Exhibit A.2).[65] The restrictions are applied sequentially moving from left to right in the table below, so the same student could not be excluded by multiple restrictions. The starting sample in the table includes all individuals who enrolled in Texas public

[64] Using data from earlier high school graduation cohorts that are not covered by the NSC data would result in comparison groups that include students who were pursuing higher education outside of Texas. If the institutions they attended had positive value added and they returned to Texas to work, this would cause the counterfactual earnings to be too high, and bias estimates of cumulative net VAE downwards.

[65] We are not able to report on the number of students excluded due to lacking a valid SSN due to issues linking these individuals to institutions.

institutions of higher education at the degree level and during the entry years noted. The first two restrictions select those students who graduated from a Texas public high school from 2007–08 to 2017–18. A large share of enrolled students across degree types and entry years could not be linked to a Texas public high school. This could be because they attended high school outside of Texas or because they attended high school in Texas prior to the 2001–02 school year, which is the earliest year available before we apply the restriction that students must have graduated since 2007–08. Another large share of exclusions come from the requirement that students graduated from a Texas high school since 2007–08. This requirement is most restrictive in the 2008–09 entry year, as it only allows for one year of high school graduates in the enrollment pool.

Once we have narrowed the sample of students to include those who graduated from a Texas public high school since 2007–08, additional restrictions have smaller impacts on the final sample. Relatively few students are excluded due to missing data. The share of students excluded due to out-of-state enrollment during the follow-up period is relatively higher for associate's degree programs, possibly reflecting the high rate of student transfers from associate's programs to four-year colleges in general, even if most of those transfers occur within the state. The earnings requirement excludes a higher share of students seeking bachelor's degrees, nearly 3 percent, possibly because these students are more likely to work outside Texas after completing their degree. Of 2,098,901 students entering Texas public institutions of higher education during the sample period, 750,491 (36 percent) were eligible for matching. If we only consider the students who enrolled after graduating from a Texas public high school since 2007–08, the share who were eligible for matching was 84 percent.

Exhibit A.2. Exclusions of students enrolled in Texas institutions of higher education due to sample requirements

Institutional cohorts	Number of institutions	Total number of students before restrictions	Share excluded due to no TX high school match	Share HS graduates excluded due to no NSC data prior to 2008	Share excluded due to missing matching variables	Share excluded due to out-of-state enrollment	Share excluded due to no reported earnings	Number of students eligible for matching
Bachelor's 2008–09	29	128,885	35.3%	24.6%	1.0%	1.5%	2.9%	44,718
Associate's 2008–09	57	273,309	46.6%	21.7%	1.6%	2.0%	1.3%	73,402
Associate's 2009–10	57	304,168	47.7%	14.0%	1.8%	4.0%	1.4%	94,853
Associate's 2010–11	57	307,624	46.4%	10.7%	1.1%	4.5%	1.7%	109,343
Associate's 2011–12	57	291,195	44.6%	7.9%	1.0%	4.8%	1.9%	115,817
Associate's 2012–13	57	272,591	43.7%	6.6%	1.1%	4.7%	2.2%	113,742
Associate's 2013–14	57	273,963	40.9%	5.1%	1.1%	4.4%	2.6%	125,768
Certificate 2008–09	52	22,239	63.7%	17.2%	2.4%	0.6%	0.8%	3,384
Certificate 2009–10	53	25,613	65.1%	13.3%	2.3%	1.1%	0.9%	4,411
Certificate 2010–11	55	24,409	62.6%	11.9%	0.8%	1.6%	1.2%	5,359
Certificate 2011–12	55	23,391	60.1%	10.2%	<1%	1.8%	1.3%	6,115
Certificate 2012–13	54	22,388	60.3%	9.1%	<1%	1.7%	1.4%	6,060
Certificate 2013–14	56	24,027	58.4%	7.3%	0.5%	1.6%	1.7%	7,328

Institutional cohorts	Number of institutions	Total number of students before restrictions	Share excluded due to no TX high school match	Share HS graduates excluded due to no NSC data prior to 2008	Share excluded due to missing matching variables	Share excluded due to out-of-state enrollment	Share excluded due to no reported earnings	Number of students eligible for matching
Certificate 2014–15	57	22,220	55.0%	7.3%	1.0%	1.7%	2.0%	7,349
Certificate 2015–16	57	21,851	51.2%	6.1%	1.8%	2.5%	2.0%	7,963
Certificate 2016–17	57	22,042	47.5%	5.2%	1.9%	3.3%	2.2%	8,800
Certificate 2017–18	57	19,565	46.4%	4.3%	1.4%	3.9%	2.5%	8,095
Certificate 2018–19	56	19,421	46.8%	4.0%	1.5%	3.8%	2.8%	7,984

Source: Authors' calculations using Texas administrative data.

B. Estimating cumulative net VAE

We use the sample to estimate the cumulative net VAE of cohorts of students enrolling in public institutions in Texas. This section provides more information about the cohorts we examine, the methods used to identify a matched comparison group for each cohort, and the approach to estimating cumulative net VAE for each cohort.

1. Defining cohorts

We estimate the value added of enrolling in an institution for three different types of student cohorts who enter an institution in the same academic year:

- **Institutional cohorts** include all individuals who enrolled at a given institution in the same academic year pursuing the same type of degree (certificate, associate's, or bachelor's).
- **Programmatic cohorts** are subsets of institutional cohorts that include all individuals who pursued a particular program of study (major).
- **Demographic cohorts** are subsets of institutional cohorts consisting of students who share a particular background characteristic.

a. Institutional cohorts

An institutional cohort includes all individuals who enrolled at a given institution during the academic year (from the fall semester to the final summer semester) for the first time seeking the same type of degree (certificate, associate's, or bachelor's). We assign students to cohorts based on the first academic year that they initially enrolled at an institution. Students are counted as enrolled if they are enrolled on census day, which is the 12th class day for the fall and spring semesters and the 4th class day for each of the summer semesters. An individual student could be included in institutional cohorts at multiple institutions provided they met the enrollment criteria for all. However, a student can only be included in one institutional cohort within a given institution. If a student first enrolled in a certificate program and subsequently enrolled in an associate's degree program at the same institution, we would not be able to disentangle the impact of the associate's degree from that of the certificate, as the second degree is endogenous to the first. Instead, we estimate the intent-to-treat impact on earnings of the first enrollment. This implicitly includes the impact of any subsequent degrees at the same institution.[66]

We estimate the earnings impact of enrollment in an institution for all cohorts for which we can observe earnings over the full follow-up period, which we refer to as "mature" cohorts. Exhibit B.1 shows all these cohorts, grouped by degree type and entry year, and their associated follow-up period. The last column reports the expected age range of the students we can include in the sample for each cohort, given that the sample is limited to students who have graduated from high school in 2007–08 or later. For example, the cohort entering certificate programs in 2008–09 could only include students who graduated high school in 2007–08. Assuming a typical student graduates high school at age 18, this implies that the 2008–09 cohort enrolled in certificate programs was typically 18 to 19 years old when they first enrolled.

Exhibit B.1. Mature cohorts for analysis

Degree type	Outcome	Cohort	Follow-up period	Expected age range of cohort at entry
Certificate	Cumulative net VAE over 5 years	2008–09	2008–2013	<19 in 2008
		2009–10	2009–2014	<20 in 2009
		2010–11	2010–2015	<21 in 2010
		2011–12	2011–2016	<22 in 2011
		2012–13	2012–2017	<23 in 2012
		2013–14	2013–2018	<24 in 2013
		2014–15	2014–2019	<25 in 2014
		2015–16	2015–2020	<26 in 2015
		2016–17	2016–2021	<27 in 2016
		2017–18	2017–2022	<28 in 2017
		2018–19	2018–2023	<29 in 2018
Associate's	Cumulative net VAE over 10 years	2008–09	2008–2018	<19 in 2008
		2009–10	2009–2019	<20 in 2009
		2010–11	2010–2020	<21 in 2010
		2011–12	2011–2021	<22 in 2011
		2012–13	2012–2022	<23 in 2012
		2013–14	2013–2023	<24 in 2013
Bachelor's	Cumulative net VAE over 15 years	2008–09	2008–2023	<19 in 2008

We also report results for immature bachelor's degree cohorts that enrolled from 2009–10 to 2013–14 and for which we observe 10 to 14 years of follow-up earnings. Specifically, we compare cumulative net VAE estimates across the mature and immature cohorts to examine whether patterns are similar between the immature and mature cohorts through the years that can be observed for both groups. This is useful for identifying whether more recent cohorts follow similar trends as older cohorts.

[66] A small number of students initially enroll in multiple degree types, such as a certificate and associate's degree, in their first term at an institution. In these cases, we assign students to the highest degree type they are pursuing.

Exhibit B.2 describes the average characteristics of the students included in the mature institutional cohorts for bachelor's degrees, associate's degrees, and certificates. Students seeking bachelor's degrees had higher high school test scores, on average, than students seeking associate's degrees, and students seeking associate's degrees had higher test scores than students seeking certificates.[67] Bachelor's degree-seeking students, compared with associate's degree-seeking students (and associate's students compared with certificate students), also appear less likely to be from low-income backgrounds, had fewer years with a suspension in high school, had higher rates of high school attendance, and were more likely to pass advanced courses. Associate's degree- and certificate-seeking students were more likely than bachelor's students to have previously enrolled in a postsecondary degree program. This is expected because the bachelor's cohort is limited to students who only recently graduated from high school.

Recall that we do not use pre-enrollment earnings before a student reached 20 years old. For pre-enrollment earnings accrued before a student turned 20, we re-code earnings values to zero.[68] We report the share of cohorts with recoded pre-enrollment earnings based on their age at entry. Very few students in the bachelor's cohorts were old enough to report pre-enrollment earnings, resulting in these variables being masked due to small sample size. A small share of students included in the associate's and certificate cohorts were old enough to report pre-enrollment earnings, which tended to be higher, at just under $20,000 per year, for those who enrolled in certificate programs compared to those who enrolled in associate's degree programs.

Exhibit B.2. Average characteristics of mature institutional cohort members, by degree type

Characteristics	Bachelor's cohorts (2008–09)	Associate's cohorts (2008–09 to 2013–14)	Certificate cohorts (2008–09 to 2018–19)
Female	53%	53%	46%
Race/ethnicity			
White	52%	42%	39%
Black	17%	13%	12%
Hispanic	27%	40%	45%
Asian	*	3%	2%
All other	*	1%	2%
High school characteristics			
Standardized math score	0.58	0.20	-0.07
Standardized English score	0.45	0.15	-0.09
Missing standardized math score	3%	5%	8%
Missing standardized English score	2%	4%	6%
Special education	1%	6%	12%
Limited English proficiency	<1%	1%	3%
Low-income background	26%	38%	47%
Number of years with a suspension	0.45	0.67	0.76

[67] All comparisons are based on visual inspection of the table by the authors and not tests of statistical significance.

[68] We account for this recoding in estimating VAE by matching on and controlling for indicators of whether each baseline earnings measure was recoded.

Characteristics	Bachelor's cohorts (2008–09)	Associate's cohorts (2008–09 to 2013–14)	Certificate cohorts (2008–09 to 2018–19)
Average attendance rate	97%	95%	95%
Share of core courses failed	3%	5%	7%
Share of all courses failed	2%	5%	6%
Passed advanced courses	90%	81%	77%
Previous enrollment			
Previously enrolled in 4-year institution	5%	17%	13%
Previously enrolled in 2-year institution	28%	32%	33%
Previously enrolled in less-than-2-year institution	*	<1%	<1%
Previously earned bachelor's degree	*	<1%	*
Previously earned associate's degree	*	0%	2%
Previously earned a certificate	*	<1%	<1%
Average earnings			
One year prior to entry	*	$13,290	$19,556
One year prior to entry recoded due to age < 21	*	93%	80%
Two years prior to entry	*	$12,697	$19,439
Two years prior to entry recoded due to age < 22	*	97%	86%
Three years prior to entry	*	$11,560	$18,369
Three years prior to entry recoded due to age < 23	*	99%	91%
Number of students	28,614	559,068	67,486
Number of institutions	29	57	57

Source: Authors' calculations using Texas administrative data.

Note: This table presents the average characteristics of the students included in the bachelor's degree, associate's degree, and certificate institutional cohorts when enrolling in an institution. Table cells marked with an asterisk were masked due to small sample sizes. All dollar values are in 2023 dollars.

b. Programmatic cohorts

A programmatic cohort includes all individuals who registered in a given program of study and degree type and who entered an institution in a given academic year. Programmatic cohorts are subsets of institutional cohorts.

Because we seek to estimate the value added of *enrolling* in a degree program (rather than the value added of *completing* a degree in a specific program), we had to choose a point in time that best captures a student's intended program. For bachelor's degrees in particular, students tend to change programs year to year, settling on their intended program after some time in their studies. Assigning programs too early could mean program assignment is not representative of the student's ultimate degree. However, assigning programs too late could also be unrepresentative and could exclude students who did not complete their studies. If some programs demonstrate better completion rates than others in ways that could affect value added, this should be reflected in programmatic cohort estimates.

To balance these trade-offs, we assign bachelor's degree program cohorts based on their second semester of their second year after enrolling. For students who were no longer enrolled by this point, we use the most recent program a student was enrolled in. For certificate and associate's degree program cohorts, we assign programs based on the program at entry, as program switching is not common in these degree types. Students can be in multiple programmatic cohorts if they have multiple majors.

We aggregate programs using two-digit and four-digit Classification of Instructional Programs (CIP) codes into 17 distinct programmatic cohorts: agriculture and natural resources, communications, information technology, engineering and architecture, liberal arts, biology and health, physical sciences and math, social sciences (excluding economics), business and economics, education, and vocational majors, including personal and culinary services, security and protective services, logistics, construction trades, technical trades, and parks and recreation (Exhibit B.3). We also include a category for students who are undeclared, which could be a student's major if they leave an institution before completing a degree. Education majors are restricted to two-year institutions only in Texas. This approach is similar to the approach outlined in Andrews et al. (2024) with the exception that we further disaggregate vocational majors to provide greater detail for certificates and remove any programs that are only offered for graduate degrees.

We further aggregate program categories into STEM and non-STEM in our analysis. STEM refers to science, technology, engineering, and mathematics. Programs were classified as STEM using the U.S. Department of Homeland Security STEM Designated Degree Program List. The following programs were classified as STEM: agriculture and natural resources, biology and health, engineering and architecture, physical sciences and math, information technology, and technical trades (for associate's and certificate programs). Non-STEM includes all other programs. Although STEM classifications tend to be intuitive for bachelor's and associate's degree programs, the STEM classification does not always map neatly onto certificate programs. Certificate programs are skills-focused and occupationally oriented and include technical fields, such as construction trades, that are not classified as STEM.

Exhibit B.3. Program categories used in the study

Program categories	Specific program	CIP code
Agriculture and natural resources	Agriculture, Agriculture Operations, and Related Sciences	01, 02
	Natural Resources and Conservation	03
Communications	Communication, Journalism, and Related Programs	09
Information technology	Communications Technologies/Technicians and Support Services	10
	Computer and Information Sciences and Support Services	11
Engineering and architecture	Architecture and Related Services	04
	Engineering	14

Program categories	Specific program	CIP code
Liberal arts	Area, Ethnic, Cultural, and Gender Studies	05
	Foreign Languages, Literatures, and Linguistics	16
	English Language and Literature/Letters	23
	Liberal Arts and Sciences, General Studies and Humanities	24
	Library Science	25
	Multi/Interdisciplinary Studies	30
	Philosophy and Religious Studies	38
	Theology and Religious Vocations	39
	Visual and Performing Arts	50
	History	45.08, 54
Biology and health	Biological and Biomedical Sciences	26
	Health Professions and Related Clinical Sciences	51
	Dietitian Assistant	20.0404
Physical sciences and math	Physical Sciences	40
	Mathematics and Statistics	27
Social sciences	Family and Consumer Sciences/Human Sciences	19, 19.10, 19.1001
	Legal Professions and Studies	22
	Psychology	42
	Public Administration and Social Service Professions	44
	Social Sciences, General	45.01
	Anthropology	45.02
	Archaeology	45.03
	Criminology	45.04
	Demography and Population Studies	45.05
	Geography and Cartography	45.07
	International Relations and Affairs	45.09
	Political Science and Government	45.10
	Sociology	45.11
	Urban Studies/Affairs	45.12
	Sociology and Anthropology	45.13
	Rural Sociology	45.14
	Social Sciences, Other	45.99
	Vocational Home Economics	13.1308
	Vocational Home Economics	20
Business and economics	Business, Management, Marketing, and Related Support Services	52, 08
	Economics	45.06
Education	Education	13

Program categories	Specific program	CIP code
Personal and culinary services	Personal and Culinary Services	12
	Institutional Food Workers	20.0401
	Restaurant, Culinary, and Catering Management/Manager	20.0405
Security and protective services	Security and Protective Services	43
Logistics	Transportation and Materials Moving	49
Construction trades	Construction Trades	46
Technical trades	Engineering Technologies/Technicians	15
	Military Technologies	29
	Science Technologies/Technicians	41
	Mechanic and Repair Technologies/Technicians	47
	Precision Production	48
Parks, recreation, leisure, and fitness studies	Parks, Recreation, Leisure, and Fitness Studies	31
Undeclared	Undeclared	99, 24.0199

c. *Demographic cohorts*

Demographic cohorts include all individuals who enrolled at a given institution for a given degree type during the academic year for the first time and share a similar characteristic. Demographic cohorts, like programmatic cohorts, are subsets of institutional cohorts. We examined demographic cohorts organized based on age at enrollment (under 20, 20–24, 25 or older), household income during high school (determined by free- or reduced-price lunch status), and quartiles of performance on the high school math test. Quartiles are defined relative to the state distribution of students who took the test in a given year in high school.

2. Cohort sample sizes

Some cohorts are small, particularly for the programmatic and student demographic cohorts. Because small samples produce imprecise estimates of cumulative net VAE, we only produce estimates for cohorts with at least 50 individuals.[69] To further avoid drawing conclusions based on small samples, we also exclude programs or student demographic groups from analyses if they did not have at least 200 students enrolled across all institutions. This additional requirement resulted in excluding the information technology program for bachelor’s degree-seeking students and the parks, recreation, and leisure program for certificate-seeking students. In addition, we also pool cohorts across years to increase the precision of the estimates. For example, for institutional cohorts for associate’s degrees, we estimate cumulative net VAE for all the associate’s degree cohorts from 2008–09 to 2013–14 together to increase the sample size. In the report, we focus on reporting results for these pooled estimates to maximize precision, but certain analyses rely on estimates for cohorts of students from a single entry year.

Exhibit B.4 shows the number of pooled mature institutional, programmatic, and demographic cohorts included in the report for each degree type and provides summary statistics about the distribution of

[69] This rule applies whether we estimate cumulative net VAE for a single entry year for a cohort or pool across multiple entry years for a cohort.

sample sizes for each group of cohorts.[70] Our sample covers 29 institutions offering bachelor's degree programs, 57 institutions offering associate's degree programs, and 57 institutions offering certificate programs (hereafter, bachelor's institutions, associate's institutions, and certificate institutions). The number of students, on average, in each institutional cohort was 987 for bachelor's institutions, 9,808 for associate's institutions, and 1,184 students for certificate institutions. The larger number of students in associate's degree cohorts reflects a large number of annual entrants in the typical institution (whereas certificate programs tend to have small annual enrollments), as well as pooling across several entry years. Programmatic and demographic cohorts tend to be a fraction of the size of institutional cohorts. As can be seen by comparing the number of demographic cohorts across different subgroups, many institutions do not meet the sample size requirement of 50 students when broken into smaller subgroups. For example, only eight bachelor's institutions had a sufficient number of students in the bottom quartile of baseline math achievement to allow us to generate estimates for the related demographic cohort.

Exhibit B.4. Summary of sample sizes for mature institutional, programmatic, and demographic cohorts

Cohorts	Number of cohorts	Average sample size	Range of sample sizes	10th percentile of sample sizes	90th percentile of sample sizes
Institutional cohorts					
Bachelor's cohorts (2008–09)	29	987	129–2,573	224	2,287
Associate's cohorts (2008–09 to 2013–14)	57	9,808	404–46,940	1,547	27,212
Certificate cohorts (2008–09 to 2018–19)	57	1,184	127–5,742	261	3,016
Programmatic cohorts					
Bachelor's cohorts (2008–09)	151	203	50–1,218	57	417
Associate's cohorts (2008–09 to 2013–14)	541	1,067	50–36,049	73	2,331
Certificate cohorts (2008–09 to 2018–19)	230	236	51–3,048	62	432
Demographic cohorts					
Bachelor's cohorts (2008–09)					
Age at entry: Younger than 20	29	986	127–2,573	224	2,286
Low income	28	268	52–891	59	502
Not low income	29	727	59–2,074	95	1,937
Quartile of math test performance: 0 to 25th percentile	8	92	67–147	67	147
Quartile of math test performance: 26th to 50th percentile	27	219	53–529	71	424
Quartile of math test performance: 51st to 75th percentile	28	305	51–879	64	703
Quartile of math test performance: 76th to 100th percentile	26	460	50–1,523	86	1,167

[70] We also generate cumulative net VAE estimates for immature bachelor's degree cohorts, which are separated by entry year due to differences in the follow-up period. These include 160 institutional cohorts, 1,014 programmatic cohorts, and 1,897 demographic cohorts.

Cohorts	Number of cohorts	Average sample size	Range of sample sizes	10th percentile of sample sizes	90th percentile of sample sizes
Associate's cohorts (2008–09 to 2013–14)					
Age at entry: Younger than 20	57	8,258	369–38,859	1,376	24,418
Age at entry: 20–24	56	1,576	60–8,077	266	4,909
Low income	57	3,707	166–20,564	555	10,519
Not low income	57	6,101	238–27,981	1,088	17,555
Quartile of math test performance: 0 to 25th percentile	57	1,312	71–6,640	215	3,419
Quartile of math test performance: 26th to 50th percentile	57	2,843	159–13,336	496	7,718
Quartile of math test performance: 51st to 75th percentile	57	2,699	106–12,496	482	7,739
Quartile of math test performance: 76th to 100th percentile	57	2,471	62–12,249	348	8,740
Certificate cohorts (2008–09 to 2018–19)					
Age at entry: Younger than 20	57	822	75–4,272	172	2,072
Age at entry: 20–24	54	336	50–1,363	100	829
Age at entry: 25 and older	15	99	50–195	50	187
Low income	56	567	79–3,246	118	1,542
Not low income	57	626	57–3,180	142	1,599
Quartile of math test performance: 0 to 25th percentile	56	249	53–1,489	65	653
Quartile of math test performance: 26th to 50th percentile	56	392	73–2,000	93	1,001
Quartile of math test performance: 51st to 75th percentile	54	296	51–1,395	81	734
Quartile of math test performance: 76th to 100th percentile	41	229	51–1,437	61	528

Source: Authors' calculations using Texas administrative data.

Note: Sample sizes refer to the number of students who enrolled in public postsecondary institutions in Texas and were included in the matched sample.

3. Comparison groups

For every cohort, we construct a comparison group that we use to estimate the impacts of enrollment on earnings. The comparison group donor pool consists of individuals who meet all the requirements laid out in Section A.5 and who did not enroll in a postsecondary institution during the follow-up period for the cohort of interest. As described in Section B.4, we exact-match cohort members to comparison group members with the same level of prior postsecondary education attainment at the time of enrollment. Therefore, some comparison group members enrolled in postsecondary education *before* the follow-up period.

We select comparison group members from this pool with the goal of identifying members who are as similar as possible to individuals in the treatment cohort. An individual may be included in the comparison group for multiple cohorts. For example, an individual could be in the comparison group for the institutional cohort Texas State Technical College (TSTC) 2008 (enrolled in TSTC for the first time in 2008) and in the comparison group for the institutional cohort TSTC 2009 or for another institutional, programmatic, or demographic cohort. Moreover, a comparison group member may later be a member of a cohort. For example, if an individual worked for five years after high school without enrolling in postsecondary education, they would be eligible for the comparison group of certificate cohorts, which have a follow-up period of five years. If they then pursued a degree after those five years, they would be included in the appropriate treatment cohort for that degree.

4. Matching algorithm

The design of our matching algorithm is shaped by three key motivations. The first is the guidance that the end goal of matching is to achieve balance on characteristics that are determined prior to treatment (known as pre-treatment covariates), as laid out by Ho et al. (2007) and elsewhere. As Ho et al. (2007) argue, this is subtly distinct from the objective of achieving balance on the propensity score, which on its own does not address selection concerns but is a means to achieving balance on pre-treatment covariates. Second, it is designed to maximize external validity by including the largest possible treatment group, subject to the constraint of achieving strong balance. This is distinct from a mean-squared error criterion, which does not necessarily maximize the treatment group sample. Finally, the algorithm is fully automated and does not require a researcher to assess balance statistics, a necessary constraint given the task of identifying matched treatment and comparison groups for more than 4,000 separate contrasts.

Our overall VAE estimation approach includes two high-level steps: (1) forming closely matched treatment and comparison groups and (2) using a regression to estimate VAE on the matched sample, controlling for pre-treatment covariates. The first step can be thought of as aiding the second: matching greatly reduces the model dependence of the VAE regression (Ho et al. 2007). Alternatively, the VAE estimation step can be thought of as removing the influence of any imbalance leftover after the matching step. In the next sections we describe the propensity score and the prognostic score, which are key tools in our approach; lay out the matching algorithm; and describe the VAE regression.

a. Matching on the propensity score and prognostic score

We use both the propensity score and the prognostic score as our key matching variables, following Leacy and Stuart (2014). The propensity score measures the likelihood that an individual enters the treatment group conditional on observable characteristics. Matching on the propensity score therefore allows us to account for selection into the treatment group on a large number of covariates using a single variable, making it a popular method in non-experimental research (Stuart 2010). Because the propensity score is so commonly used in non-experimental causal inference, we focus attention here on motivating and describing the prognostic score, which is used rarely. We first describe the prognostic score as a balance measure and describe how it might be applied with one (or a few) treatment groups, in which we could manually examine the balance generated by different matching approaches.

The prognostic score, introduced by Hansen (2008), is the predicted outcome of each person in the sample, based on a regression estimated using only the comparison group (or, more optimally as discussed below, a holdout sample of the comparison group). The prognostic score has strong features as a balance measure: (1) like the propensity score (as well as other measures), it resolves the "curse of dimensionality" (Rosenbaum and Rubin 1983) and (2) it weights covariates based on the strength of their relationship with the outcome. Put differently, instead of examining balance on every individual covariate and needing to decide whether we would prefer to sacrifice balance on covariate X_1 to obtain greater balance on covariate X_2 (and so on), we can simply assess overall balance on a single construct, the prognostic score. Doing so resolves the trade-off described here by seeking greater balance on a variable in proportion to its relationship with the outcome. (In addition to Hansen [2008], Stuart et al. [2013] explicitly applies the prognostic score as a balance measure.) This is, again, especially important in our application, where some covariates have stronger associations with cumulative earnings than others. As such, we would be satisfied with sacrificing some imbalance on a more minor covariate to achieve stronger balance on others.

If we had one treatment group, we could perform matching using a number of different strategies—relying on the propensity score—and use the prognostic score to determine the approach that led to the best balance. Even then, we could not simply select the approach that led to the best balance, because we may prefer an approach that provided slightly worse balance if it also resulted in a larger matched treatment group. In any case, because we have many treatment groups, we require a design in which an algorithm selects a treatment and comparison group without human involvement.

b. Using the prognostic score directly in matching

Rather than using the prognostic score as only a balance measure, our design uses it as one of two central matching scores. Our design formally selects an analytic sample with the largest possible treatment group subject to being at or below a certain threshold of imbalance on the propensity and prognostic scores. In addition, the algorithm only allows estimation if the matched treatment group sample size is at least 50. (Matching directly on the prognostic score has been proposed and found to perform well in simulation studies by Zhao [2004] and Leacy and Stuart [2013] and has been applied in an empirical study by He et al. [2020]). We then use a regression with pre-treatment covariates on the matched sample that is expected to remove bias from the remaining imbalance on observed characteristics. We describe the specific steps of our approach below.

c. Matching design steps

We perform the first four steps described here separately by entry year and degree type. All steps are performed using individuals in the treatment and comparison groups who have met the sample restrictions described in the previous section. The degree type determines the specific outcome in the VAE estimation (cumulative earnings over 15, 10, or five years) and thus also in the prognostic score estimation. By conducting these steps separately by entry year, we also ensure that the set of calendar years used are the same for each person.

1. **Create a holdout sample.** We use random sampling to select a 5 percent holdout sample from only the comparison group donor pool. In cases where the comparison group donor pool has fewer than 100,000 students, we select a 10 percent holdout sample.
2. **Estimate the prognostic score** using the holdout sample with a regression of cumulative earnings on pre-enrollment characteristics and county of high school fixed effects.[71]
3. **Generate prognostic score variable.** Use the coefficients from the regression in Step 2 to generate the prognostic score for everyone in the comparison group donor pool and all applicable cohorts (treatment groups).
4. **Exclude the holdout sample** from the steps that follow.

We note here the importance of using a holdout sample to estimate the prognostic score. Hansen (2004) points out that, unlike the propensity score, a potential disadvantage of using the prognostic score directly in matching is that it can introduce bias if the prognostic score is overfit. Using a holdout sample, however, eliminates the risk of an overfit prognostic score. We also note that a single prognostic score is generated for all individuals in a specific degree type and entry year.

We perform the next set of steps separately for each cohort-entry year. More precisely, for an institutional cohort, we limit the data to treatment group members in a given institution-degree-entry year and all eligible comparison group donors. For programmatic cohorts, we limit to a given institution-degree-program-entry year and all eligible comparison group donors.

5. **Perform exact matching.** We first perform an exact match on age category, highest degree received as of the entry year, and high school county. That is, we create cells defined by the intersection of these variables and keep only treatment and comparison group members in cells with at least one treatment and one comparison group member. We require exact matches on age and prior education because they are critical variables that are also used to make sample restrictions. Exact matching on the county of the person's high school is useful because these identifiers are less suitable for parametric modeling.
6. **Estimate the propensity score.** Using a logistic regression framework, we regress the treatment indicator, capturing enrollment in the cohort of interest, on the same covariates and county fixed effects used in the prognostic score model. The propensity score is the predicted logit score from this regression and represents the log-odds of enrollment in a cohort conditional on the covariates.

[71] The covariates include wages from one, two, and three years prior to enrollment, indicators for whether prior wages were recoded to zero due to an individual being younger than 20, a cubic polynomial of age, math and reading scores on standardized tests, indicators for missing math or reading scores which were recoded to zero, indicators for race/ethnicity by sex, an indicator for special education status in high school graduation year, an indicator for English language learner status in high school graduation year, an indicator for low-income households as of high school graduation year, the number of high school years in which the student had a disciplinary incident, the average annual attendance rate in high school, the share of high school courses failed, the share of core high school courses failed, an indicator for whether the student passed any advanced courses in high school, and a set of indicators for whether a student previously enrolled in or completed a certificate, associate's, or bachelor's program. The average values of these variables for different cohorts are reported in Exhibit B.2.

7. **Perform cardinality matching.** We use cardinality matching (Zubizarreta 2012) on the propensity score and prognostic score to identify the largest subset of the treatment group that can be matched to a comparison group while achieving an imbalance of both the propensity score and the prognostic score (mean difference) that is no larger than 0.25 standard deviations.[72] This step may result in maintaining the full treatment group.[73]

   We note here that we use cardinality matching only to select the treatment group and not the matched comparison group. That is because the comparison group selected by cardinality matching restricts the comparison group such that each treatment group member has the same number of matches. This would often result in dropping individuals in the comparison group who are equally strong matches as other comparison individuals who are selected, which increases variance without any accompanying reduction in bias (see the discussion in Ho et al. [2007] of exact matching as compared to one-to-one matching, a direct analog).

8. **Limit comparison group to areas of common support.** We select the subset of the comparison group that is within the convex hull of the treatment group selected in Step 6, based on the propensity score and the prognostic score (King and Zeng 2006).

   Note that this amounts to discarding individuals in the comparison group with propensity or prognostic scores above (below) the maximum (minimum) propensity or prognostic score in the selected treatment group, plus or minus a tolerance of 0.1 standard deviations.

9. **Perform full matching.** We conduct full matching (Hansen 2004) on a Mahalanobis distance combining the propensity score and prognostic score, using the treatment group selected in Step 7 and the comparison group selected in Step 8. The Mahalanobis distance measures the distance between a given combination of the propensity score and prognostic score from the joint distribution of scores. This allows us to collapse the two matching variables into a single distance measure that accounts for the covariance between the propensity score and the prognostic score.[74] Full matching in this step will not exclude any observations but generates a set of optimal weights for the comparison group to be used to estimate a treatment-on-the-treated parameter. As described in Hansen (2004), full matching generates an optimal set of subclasses, each of which has at least one treatment member and at least one comparison member, in such a way that minimizes the weighted average within-subclass distance on the matching variable—the Mahalanobis distance in this case. The weights applied to each comparison member are then a simple function of the number of treatment and comparison members in their subclass, such that the sum of the weights across comparison group members within a subclass equals the number of treatment group members in that subclass.

[72] Rubin (1973) suggests that the regressions we propose can sufficiently remove bias induced by baseline differences up to 0.25 standard deviations. This is also the threshold used by systematic review clearinghouses, such as the What Works Clearinghouse (https://ies.ed.gov/ncee/wwc).

[73] We implement cardinality matching using the MatchIt R package ("cardinality" method). We specify the propensity score and prognostic score as the matching variables, the "ATT" estimand, a ratio of 1, the exact match variables specified in Step 5, and a tolerance of 0.25 standardized mean difference. As noted in the main text, we use the treatment group selected by cardinality matching, but we do not limit the comparison group to the subset selected in this step.

[74] Leacy and Stuart (2014) found that full matching on the Mahalanobis distance combining the propensity and prognostic scores performed well in simulations when compared with matching on only the propensity or prognostic score.

Weights are then normalized such that the sum of the weights across all comparison group members is equal to the number of comparison group members.[75]

For each institutional and programmatic cohort, we use this matching algorithm to construct the treatment and comparison groups. For demographic cohorts, we use the comparison group constructed for the relevant institutional cohort and subset to students with the characteristic of interest.[76] For each matching Step 6, 7, and 8, we also specify the exact-match variables from Step 5 within the matching routines.

d. Summary of matching results

Exhibit B.5 summarizes the share of cohort students eligible for matching that we were able to match to similar individuals in the comparison group. The match rate for bachelor's degree-seeking students was relatively lower, at 64 percent compared with 88 percent for associate's and 93 percent for certificate. This is expected given the types of students who enroll in bachelor's programs and the requirements we place on match quality. Bachelor's degree-seeking students had higher average achievement on high school standardized tests than other degree types. For a high-achieving student who enrolled in a bachelor's program with no prior degree, we would need to find similar high-achieving students from their same home county who did not enroll in any institution for 15 years, did not enroll out of state, and had earnings in Texas. This poses a challenge as high achievers are more likely to pursue postsecondary education, resulting in a lower match rate.

Exhibit B.5. Average match rates and total matched sample for institutional cohorts

Institutional cohorts	Number of students eligible for matching	Share of eligible students matched	Total number of students matched
Bachelor's (2008–09)	44,718	64.0%	28,614
Associate's (2008–09 to 2013–14)	632,925	88.3%	559,068
Certificate (2008–09 to 2018–19)	72,848	92.6%	67,486

Source: Authors' calculations using Texas administrative data.

Note: Number of students eligible for matching includes enrolled students who met sample requirements listed in Exhibit A.2. Students could potentially not be matched if there were no eligible comparison students with their same categorical age, prior highest degree earned, and county of their high school; or if there were no comparison students with these attributes and who had sufficiently similar propensity and prognostic scores.

The tables below display the distribution of the standardized mean difference (the difference, divided by the standard deviation for the treatment group) in propensity and prognostic scores across treatment and comparison groups. Exhibits B.6 through B.8 display, for institutional, programmatic, and demographic cohorts, respectively, the average of the absolute value of the standardized mean difference, the proportion with an absolute difference less than 0.05 standard deviations, and the proportion with an

[75] We implement full matching using the MatchIt R package ("full" method). We specify the propensity score and prognostic score as the matching variables, Mahalanobis as the distance metric, the "ATT" estimand, and the exact match variables specified in Step 5.

[76] We describe the reasoning for treating demographic cohorts differently from institutional and programmatic cohorts in subsection 5 below.

absolute difference less than 0.25 standard deviations.[77] Although we focus on the propensity and prognostic scores to make matching tractable, the end goal of matching is to achieve balance on pre-treatment covariates. The tables thus additionally summarize the balance achieved on pre-treatment variables.

We achieve strong balance on the propensity score, the prognostic score, and other pre-treatment variables across degree types for the institutional cohorts (Exhibit B.6). Few institutions exceed an absolute standardized mean difference of 0.25 across measures of race/ethnicity, sex, high school characteristics, prior postsecondary enrollment, and earnings prior to enrollment, and many institutions fall below 0.05 standard deviations on these covariates. We do not report balance on variables that we exact-match on, including age, highest prior degree earned, and county, as we achieve perfect balance on these variables by design.

We similarly observe strong balance for programmatic cohorts (Exhibit B.7), though balance appears to be slightly weaker than for institutional cohorts on some measures, like the propensity score and standardized test scores in the bachelor's cohorts. The average absolute value of standardized mean difference does not exceed 0.25 across the propensity score, prognostic score, and all covariates, and a low share of program-institution cohorts exceed this threshold on any variable.

Demographic cohorts similarly meet the 0.25 standard deviation benchmark for standardized mean differences across covariates, on average, though balance for this cohort type is weaker than for institutional and programmatic types (Exhibit B.8), especially for bachelor's cohorts. This is because we do not explicitly match within each demographic subgroup cohort and instead rely on their institutional matches, which are unlikely to be as closely balanced within a subgroup.

Exhibit B.6. Summary of pre-treatment covariate balance for institutional cohorts

	Bachelor's			Associate's			Certificate		
	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25
Prognostic score	0.012	0.0%	0.0%	0.014	0.0%	0.0%	0.015	0.0%	0.0%
Propensity score	0.136	93.1%	3.5%	0.064	54.4%	0.0%	0.047	36.0%	0.0%
Race/ethnicity and sex									
White female	0.042	34.5%	0.0%	0.073	77.2%	0.0%	0.062	55.1%	0.0%
White male	0.038	21.4%	0.0%	0.033	10.5%	0.0%	0.056	56.2%	0.0%
Black female	0.045	35.7%	0.0%	0.052	42.9%	0.0%	0.065	56.5%	0.0%
Black male	0.056	34.5%	3.5%	0.068	66.1%	0.0%	0.040	23.3%	0.0%
Hispanic female	0.035	24.1%	0.0%	0.048	42.1%	0.0%	0.055	48.0%	0.0%
Hispanic male	0.037	24.1%	0.0%	0.044	31.6%	0.0%	0.056	54.2%	0.0%
Asian female	0.062	43.5%	0.0%	0.033	14.3%	0.0%	0.054	48.6%	0.0%
Asian male	0.052	40.7%	0.0%	0.025	5.9%	0.0%	0.045	36.1%	0.0%

[77] The Department of Education's What Works Clearinghouse sets an upper limit of 0.25 standard deviations balance on pre-treatment variables as a research standard in non-experimental designs that include these variables as regression controls.

	Bachelor's			Associate's			Certificate		
	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25
All other female	0.048	33.3%	0.0%	0.032	13.0%	0.0%	0.046	40.5%	0.0%
All other male	0.037	19.1%	0.0%	0.022	4.3%	0.0%	0.037	27.5%	0.0%
High school characteristics									
Standardized math score	0.067	44.8%	3.5%	0.054	47.4%	0.0%	0.052	44.0%	0.0%
Standardized English score	0.071	48.3%	0.0%	0.082	75.4%	0.0%	0.047	44.0%	0.0%
Missing standardized math score	0.055	72.4%	0.0%	0.026	8.8%	0.0%	0.047	40.0%	0.0%
Missing standardized English score	0.032	13.8%	0.0%	0.033	12.3%	0.0%	0.042	31.9%	0.0%
Special education	0.028	13.8%	0.0%	0.035	21.4%	0.0%	0.050	46.0%	0.0%
Limited English proficiency	0.029	16.7%	0.0%	0.034	21.4%	0.0%	0.037	23.8%	0.0%
Low income	0.034	20.7%	0.0%	0.040	21.1%	0.0%	0.047	42.0%	0.0%
Number of years with a suspension	0.032	13.8%	0.0%	0.030	17.5%	0.0%	0.043	36.0%	0.0%
Average attendance rate	0.038	24.1%	0.0%	0.045	42.1%	0.0%	0.045	28.0%	0.0%
Share of core courses failed	0.051	41.4%	0.0%	0.068	70.2%	0.0%	0.047	30.0%	0.0%
Share of all courses failed	0.049	37.9%	0.0%	0.069	71.9%	0.0%	0.047	32.0%	0.0%
Passed advanced courses	0.037	34.5%	0.0%	0.063	61.4%	0.0%	0.050	48.0%	0.0%
Previous enrollment									
Previously enrolled in bachelor's degree program	0.058	44.8%	3.5%	0.094	94.5%	0.0%	0.061	55.3%	0.0%
Previously enrolled in associate's degree program	0.091	82.8%	0.0%	0.095	84.2%	0.0%	0.059	56.0%	0.0%
Average earnings									
One year prior to entry	n.a.	n.a.	n.a.	0.018	5.4%	0.0%	0.034	14.3%	0.0%
One year prior to entry recoded due to age < 21	n.a.	n.a.	n.a.	0.000	0.0%	0.0%	0.000	0.0%	0.0%
Two years prior to entry	n.a.	n.a.	n.a.	0.021	3.8%	0.0%	0.045	29.8%	0.0%
Two years prior to entry recoded due to age < 22	n.a.	n.a.	n.a.	0.021	3.7%	0.0%	0.024	0.0%	0.0%
Three years prior to entry	n.a.	n.a.	n.a.	0.016	2.0%	0.0%	0.145	31.9%	2.1%
Three years prior to entry recoded due to age < 23	n.a.	n.a.	n.a.	0.000	0.0%	0.0%	0.000	0.0%	0.0%

Source: Authors' calculations using Texas administrative data.

Note: |SMD| signifies the absolute standardized mean difference. Table cells related to prior earnings, which are marked "n.a." (not applicable), could not be reported because students did not have prior earnings in the bachelor's 2008–09 cohort. Similarly, we do not report balance on whether a student previously enrolled in certificate programs, because this variable lacked variation.

Exhibit B.7. Summary of pre-treatment covariate balance for programmatic cohorts

	Bachelor's			Associate's			Certificate		
	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25
Prognostic score	0.020	5.6%	0.0%	0.022	5.7%	0.0%	0.019	0.0%	0.0%
Propensity score	0.213	99.3%	25.2%	0.078	77.4%	0.0%	0.061	67.5%	0.0%
Race/ethnicity and sex									
White female	0.066	55.3%	0.0%	0.075	67.7%	0.3%	0.067	56.8%	0.0%
White male	0.042	35.3%	0.0%	0.050	38.8%	0.6%	0.070	61.5%	0.0%
Black female	0.068	52.0%	0.0%	0.062	50.7%	0.3%	0.065	73.3%	0.0%
Black male	0.099	66.7%	7.1%	0.077	66.6%	0.3%	0.055	50.0%	0.0%
Hispanic female	0.057	41.8%	1.4%	0.062	53.6%	0.6%	0.057	53.8%	0.0%
Hispanic male	0.057	42.6%	1.4%	0.056	49.2%	0.0%	0.061	57.5%	0.0%
Asian female	0.098	69.2%	3.3%	0.048	37.7%	0.0%	0.077	60.9%	0.0%
Asian male	0.084	77.8%	1.1%	0.051	43.4%	0.0%	0.051	43.5%	0.0%
All other female	0.045	33.3%	0.0%	0.043	32.2%	0.0%	0.046	47.8%	0.0%
All other male	0.047	44.0%	0.0%	0.047	33.0%	0.4%	0.054	38.5%	0.0%
High school characteristics									
Standardized math score	0.141	80.4%	17.5%	0.071	66.6%	0.6%	0.063	62.5%	0.0%
Standardized English score	0.123	73.4%	9.1%	0.082	72.3%	0.3%	0.064	60.0%	0.0%
Missing standardized math score	0.054	48.5%	0.0%	0.041	24.8%	0.3%	0.041	22.5%	0.0%
Missing standardized English score	0.043	29.0%	0.0%	0.041	26.4%	0.3%	0.044	30.6%	0.0%
Special education	0.041	29.3%	0.0%	0.046	34.1%	0.3%	0.052	40.0%	0.0%
Limited English proficiency	0.052	27.3%	0.0%	0.041	29.2%	0.0%	0.039	30.6%	0.0%
Low income	0.064	47.6%	0.0%	0.056	48.5%	0.3%	0.052	51.3%	0.0%
Number of years with a suspension	0.059	39.2%	2.1%	0.044	27.4%	0.3%	0.052	32.5%	0.0%
Average attendance rate	0.058	42.0%	2.1%	0.051	39.2%	0.3%	0.048	32.5%	0.0%
Share of core courses failed	0.061	52.4%	0.0%	0.061	53.9%	1.2%	0.053	45.0%	0.0%
Share of all courses failed	0.054	44.8%	0.0%	0.062	52.7%	0.6%	0.053	45.0%	0.0%
Passed advanced courses	0.076	54.3%	3.1%	0.059	55.9%	0.0%	0.052	30.0%	0.0%
Previous enrollment									
Previously enrolled in bachelor's degree program	0.068	50.4%	1.6%	0.091	86.7%	0.0%	0.066	57.9%	0.0%
Previously enrolled in associate's degree program	0.133	81.8%	5.6%	0.087	75.3%	1.2%	0.064	45.0%	0.0%
Average earnings									
One year prior to entry	n.a.	n.a.	n.a.	0.035	15.3%	0.3%	0.036	17.9%	0.0%
One year prior to entry recoded due to age < 21	n.a.	n.a.	n.a.	0.000	0.0%	0.0%	0.000	0.0%	0.0%
Two years prior to entry	n.a.	n.a.	n.a.	0.077	32.6%	3.6%	0.110	34.2%	5.3%

	Bachelor's			Associate's			Certificate		
	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25
Two years prior to entry recoded due to age < 22	n.a.	n.a.	n.a.	0.032	13.6%	0.0%	0.024	2.6%	0.0%
Three years prior to entry	n.a.	n.a.	n.a.	0.084	27.2%	3.5%	0.251	42.1%	2.6%
Three years prior to entry recoded due to age < 23	n.a.	n.a.	n.a.	0.000	0.0%	0.0%	0.000	0.0%	0.0%

Source: Authors' calculations using Texas administrative data.

Note: |SMD| signifies the absolute standardized mean difference. Table cells related to prior earnings, which are marked "n.a." (not applicable), could not be reported because students did not have prior earnings in the bachelor's 2008–09 cohort. Similarly, we do not report balance on whether a student previously enrolled in certificate programs, because this variable lacked variation.

Exhibit B.8. Summary of pre-treatment covariate balance for demographic cohorts

	Bachelor's			Associate's			Certificate		
	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25
Prognostic score	0.052	34.9%	1.1%	0.061	51.6%	0.2%	0.071	63.4%	0.6%
Propensity score	0.161	86.9%	16.6%	0.088	69.1%	2.5%	0.078	72.7%	0.6%
Race/ethnicity and sex									
White female	0.077	54.1%	2.9%	0.093	81.7%	0.5%	0.100	86.0%	3.2%
White male	0.071	45.7%	4.3%	0.074	58.9%	0.5%	0.098	87.3%	0.0%
Black female	0.092	65.6%	3.7%	0.083	70.2%	0.3%	0.091	85.7%	0.8%
Black male	0.084	54.5%	5.4%	0.094	80.6%	1.0%	0.081	71.3%	0.8%
Hispanic female	0.064	48.9%	1.7%	0.083	70.3%	1.4%	0.090	85.4%	1.8%
Hispanic male	0.062	45.1%	0.6%	0.073	66.4%	0.9%	0.093	87.4%	0.6%
Asian female	0.079	65.3%	1.7%	0.054	43.8%	0.9%	0.086	78.4%	0.0%
Asian male	0.077	65.0%	1.5%	0.047	34.4%	0.0%	0.069	63.3%	0.0%
All other female	0.055	33.3%	1.4%	0.048	40.0%	0.6%	0.073	66.7%	0.0%
All other male	0.054	36.0%	2.7%	0.039	25.3%	0.0%	0.065	53.7%	0.0%
High school characteristics									
Standardized math score	0.133	68.0%	16.6%	0.082	74.8%	0.5%	0.093	81.4%	1.7%
Standardized English score	0.138	75.4%	13.7%	0.103	87.0%	2.0%	0.092	83.7%	1.7%
Missing standardized math score	0.061	64.7%	0.0%	0.047	34.1%	0.0%	0.074	74.5%	0.9%
Missing standardized English score	0.061	48.5%	1.2%	0.058	47.8%	0.3%	0.071	74.2%	0.0%
Special education	0.058	49.7%	0.6%	0.065	55.2%	0.5%	0.076	71.9%	0.0%
Limited English proficiency	0.043	26.2%	0.0%	0.053	48.2%	0.0%	0.076	69.7%	1.5%
Low income	0.085	55.9%	5.9%	0.079	67.3%	0.9%	0.084	81.1%	1.8%
Number of years with a suspension	0.070	51.4%	2.3%	0.067	58.8%	0.2%	0.092	80.2%	4.7%
Average attendance rate	0.073	47.4%	4.0%	0.086	74.8%	1.1%	0.102	88.4%	1.7%
Share of core courses failed	0.086	60.0%	5.1%	0.095	79.3%	2.3%	0.113	89.5%	4.7%

	Bachelor's			Associate's			Certificate		
	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25	Avg. |SMD|	Share |SMD| ≥ 0.05	Share |SMD| ≥ 0.25
Share of all courses failed	0.084	58.9%	5.1%	0.096	83.2%	2.5%	0.116	89.0%	4.1%
Passed advanced courses	0.063	50.9%	1.2%	0.081	71.6%	1.8%	0.085	78.0%	0.0%
Previous enrollment									
Previously enrolled in bachelor's degree program	0.087	66.3%	4.2%	0.120	89.5%	5.1%	0.100	88.0%	2.0%
Previously enrolled in associate's degree program	0.120	77.1%	7.4%	0.121	85.9%	7.5%	0.110	88.2%	2.4%
Average earnings									
One year prior to entry	n.a.	n.a.	n.a.	0.066	47.5%	1.3%	0.093	80.2%	1.7%
One year prior to entry recoded due to age < 21	n.a.	n.a.	n.a.	0.064	43.3%	1.3%	0.079	67.5%	0.8%
Two years prior to entry	n.a.	n.a.	n.a.	0.073	41.5%	2.3%	0.090	76.0%	1.0%
Two years prior to entry recoded due to age < 22	n.a.	n.a.	n.a.	0.049	40.6%	0.0%	0.070	65.6%	0.0%
Three years prior to entry	n.a.	n.a.	n.a.	0.069	34.4%	3.9%	0.285	77.3%	4.5%
Three years prior to entry recoded due to age < 23	n.a.	n.a.	n.a.	0.039	24.1%	0.4%	0.062	61.0%	0.0%

Source: Authors' calculations using Texas administrative data.

Note: |SMD| signifies the absolute standardized mean difference. Table cells related to prior earnings, which are marked "n.a." (not applicable), could not be reported because students did not have prior earnings in the bachelor's 2008–09 cohort. Similarly, we do not report balance on whether a student previously enrolled in certificate programs, because this variable lacked variation.

5. Estimating VAE

The main estimates analyzed in this report are pooled across entry years. For example, our institutional VAE estimate for a given institution's associate's degree pools across up to six entry years (2008–09 to 2013–14). To estimate VAE for a cohort that is pooled across entry years, we first "stack" the matched samples corresponding to entry years within each cohort. (Because there is only a single entry year for mature bachelor's cohorts, pooling is not possible.) In other applications (and in some applications in this report), we also generate VAE estimates pertaining to a single entry year.

In the case of a single entry year, we estimate VAE using the following weighted least squares regression, in which we restrict the estimation sample as described in the previous section and apply the weights that result from the full matching routine:

$$Y_i = T_i\delta + X_i\beta + \varepsilon_i$$

where Y_i is the cumulative earnings of individual i through the relevant follow-up period following enrollment, T_i is an indicator for being in the cohort (rather than the comparison group), X_i is a vector of other covariates, and δ represents VAE. We also estimate similar regressions with the same basic structure but using cumulative earnings through each year in the follow-up period.

When pooling cohorts across multiple entry years, we include entry year fixed effects and allow the influence of each covariate in X_i to vary by entry year (via interaction terms). In these pooled regressions, comparison group members may be used more than once because each of an institution's entry year is matched independently. To address this resampling of comparison units, we estimate cluster-robust standard errors at the individual level.

a. Estimating VAE for demographic cohorts

To estimate VAE for demographic cohorts, we use the matched institutional cohort and comparison group. We estimate heterogeneous treatment effects for each demographic cohort through regression analysis, applying the institutional matched weights. That is, for each demographic subgroup type (age, economic disadvantage, and high school test quartile) we estimate the following regression:

$$Y_i = \sum_{s \in \boldsymbol{S}} s_i \, T_i \delta_s + X_i \beta + \varepsilon_i$$

where s_i is an indicator for membership in subgroup s, δ_s is the VAE for subgroup s, and the regression sums over all possible subgroups in the type, $\boldsymbol{S}$. The subgroups enter the regression as main effects in the covariate vector X_i. The regression is augmented as above for cohorts that pool across entry years.

This differs from our approach for programmatic cohorts, for which we carry out the full matching procedure independently for each program of study. This decision is motivated by two factors. First, we consider enrollment in a specific program of study within an institution to be a treatment that is distinct from enrollment in the institution overall. For a unique treatment, it is important to remodel the relationship between observed baseline covariates and selection into treatment through matching. In contrast, demographic cohorts may have distinct treatment effects, but the treatment of interest is the same. Second, carrying out an independent matching procedure for each demographic subgroup may produce deviations from the institutional matching in the sample that is included, the propensity score that is estimated, the matches that are generated, and ultimately the VAE estimates. Cumulatively, these deviations would make comparisons between institutional and demographic VAE challenging to interpret.

6. Calculating cumulative net VAE

We calculate cumulative net VAE for each year during the follow-up period that subtracts the total net cost up to that point from the estimated cumulative VAE. Our primary measure of interest is cumulative net VAE at the end of the follow-up period: five years after enrollment for certificates, 10 years after enrollment for associate's degrees, and 15 years after enrollment for bachelor's degrees.

C. Detailed methods for analyzing patterns in cumulative net VAE measures

We perform descriptive analyses of cumulative net VAE measures to analyze patterns in the returns to postsecondary education in Texas. To summarize a typical student's returns to pursuing a given degree, we take the student-weighted average of cumulative net VAE. That is, each institution receives a weight equal to the number of enrolled students included in the sample for that institution divided by the sum of enrolled students included in the sample across all institutions. For analyses that focus on understanding differences across institutions and analyses that focus on the extent to which cumulative net VAE measures change under alternative analytical approaches (Appendix Section E), the institution is the unit of interest and thus we do not apply student weights.

In summarizing the distribution of cumulative net VAE across institutions, we perform a statistical adjustment to the standard deviation of cumulative net VAE to account for sampling error in each cumulative net VAE estimate. We perform this adjustment using restricted maximum likelihood estimation, a common approach from the meta-analysis literature (Raudenbush 2009). As noted in the main text, institutional percentiles are based on this standard deviation and the assumption that cumulative net VAE follows a normal distribution.

In examining average cumulative net VAE across programs or student characteristics, we conduct tests of whether group-level differences in average cumulative net VAE are statistically significant. Specifically, for each grouping (such as programs) we estimate a student-weighted linear regression with institution-by-subgroup cumulative net VAE on the left-hand side and indicator variables for each subgroup on the right-hand side. We then use the F-statistic from the regression to test the null hypothesis that average cumulative net VAE was equal for all subgroups. A sufficiently large F-statistic leads us to reject the null hypothesis and conclude that differences across subgroups are statistically significant.

To understand how much of the variation in cumulative net VAE is due to differences between institutions versus differences between groups of students within the same institution, we use a statistical technique called two-way analysis of variance (ANOVA). Two-way ANOVA breaks down the total variation in cumulative net VAE into a component explained by institutions, a component explained by subgroups (for example, programs of study), and residual variation that is not explained by either factor. We use separate two-way ANOVAs for each subgroup (program or demographic subgroups).

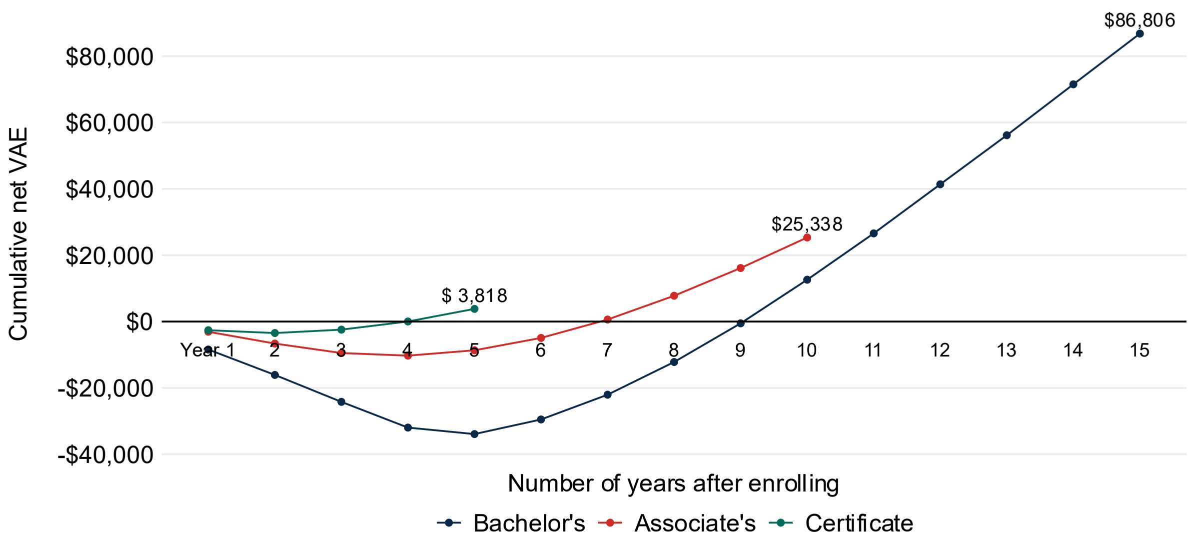
We use linear regression to estimate relationships between cumulative net VAE for a given degree type and institutional or cohort characteristics, such as the selectivity of institutions and completion rates of institutions overall and among study cohorts specifically. We estimate univariate regressions with institutional cumulative net VAE on the left-hand side and the variable measuring the institution or cohort characteristic of interest on the right-hand side. We additionally estimate multivariate regressions that include all characteristics of interest as independent variables. Each multivariate regression includes a single measure of the rate for the cohort's degree completion, and we estimate the regression separately using alternative measures of degree completion.

D. Additional findings

1. Contrasting cumulative net VAE across degree types

Exhibit D.1 combines Exhibits 1, 8, and 15 from the main findings into a single plot. The figure illustrates that, on average, students seeking bachelor's degrees incurred larger costs which took longer to recover than students seeking associate's degrees or certificates. Students seeking certificates experienced the strongest returns by Year 5, and students seeking associate's degrees experienced stronger returns by Year 10 than students seeking bachelor's degrees. However, the trend of each series suggests that this ranking is unlikely to be consistent in the long run as students seeking bachelor's degrees experienced strong earnings gains after Year 10.

Exhibit D.1. Cumulative net value-added earnings for all degree types



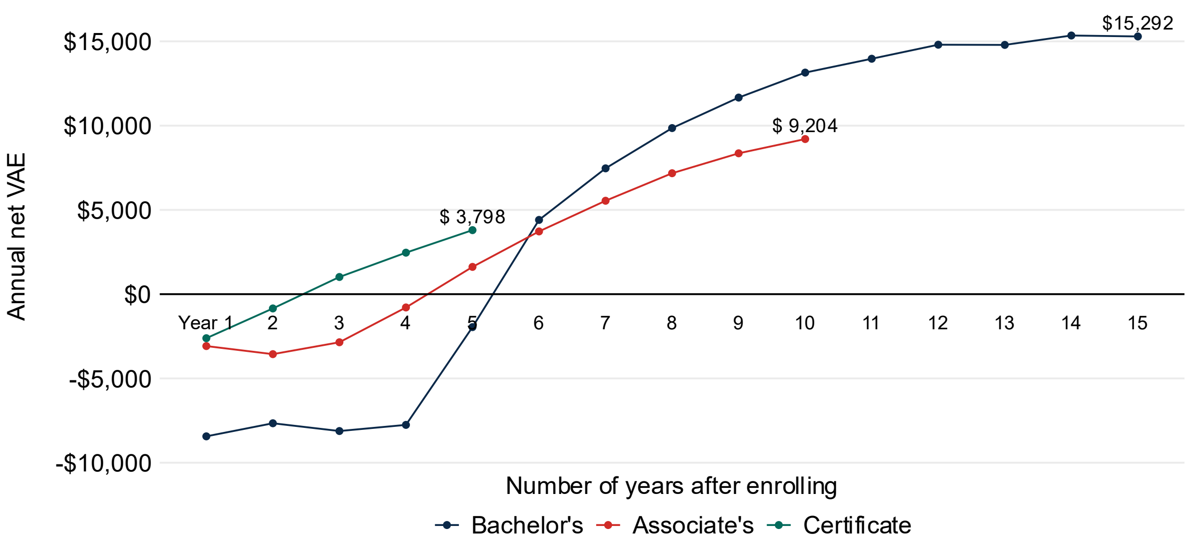
Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 28,614 students who enrolled in bachelor's degree programs in 2008–09; 559,068 students who enrolled in associate's degree programs from 2008–09 through 2013–14; and 67,486 students who enrolled in certificate programs from 2008–09 through 2018–19. Values are student-weighted averages.

2. Estimates of annual (noncumulative) net VAE

We transform the cumulative net VAE estimates into annual estimates by taking the year-to-year difference in cumulative net VAE to illustrate how students' annual returns varied over time. For example, to calculate annual net VAE in Year 15, we subtract the Year 14 cumulative net VAE estimate from the Year 15 cumulative net VAE estimate. Exhibit D.2 plots the (student-weighted) average annual net VAE for students seeking bachelor's degrees, associate's degrees, and certificates. This figure is analogous to Exhibits 1, 8, and 15 in the main text and illustrates the same patterns in a slightly different way. Annual net VAE was negative in the first five years after enrollment for bachelor's degree-seeking students, the first four years after enrollment for associate's degree-seeking students, and the first two years after enrollment for certificate-seeking students. This period of negative annual net VAE aligns with the average time-to-degree in the sample for students who earned the degree sought. For students seeking bachelor's degrees, annual net VAE was level and negative for four years, then increased rapidly from Years 4 to 6, increased at a slower pace from Years 6 through 12, and leveled off in Year 12 around $15,000 per year. Annual net VAE for associate's degree-seeking students began to increase after Year 2 and rose relatively steadily from Years 3 to 10, though at a slower pace than gains from bachelor's programs. Annual net VAE for certificate-seeking students rose steadily over the five-year follow-up period and exceeded that of bachelor's and associate's degree-seeking students during this period.

Exhibit D.2. Annual net value-added earnings for all degree types



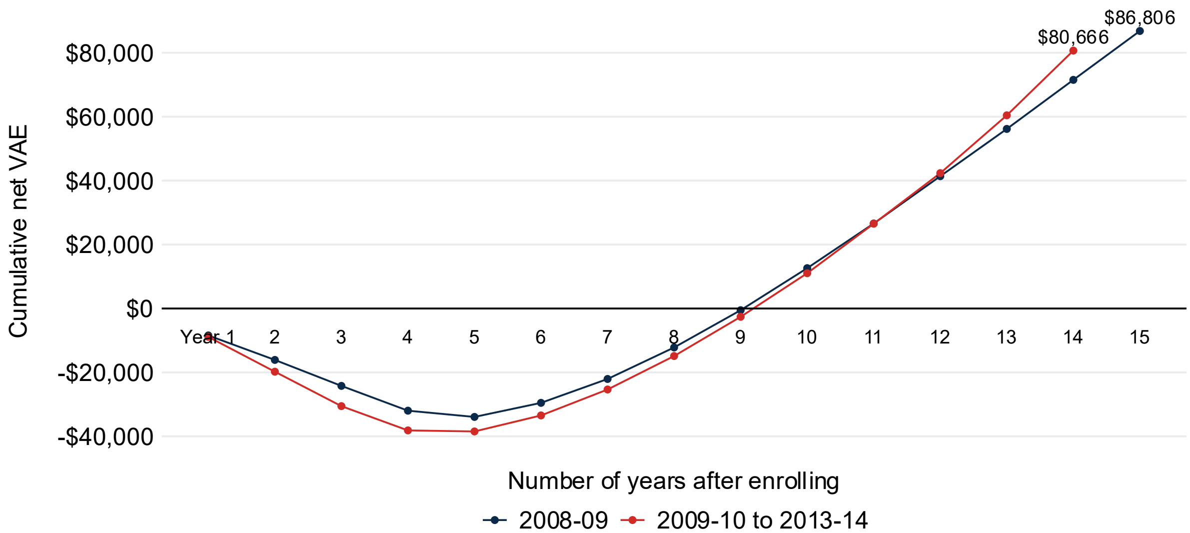
Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 28,614 students who enrolled in bachelor's degree programs in 2008–09; 559,068 students who enrolled in associate's degree programs from 2008–09 through 2013–14; and 67,486 students who enrolled in certificate programs from 2008–09 through 2018–19. Values are student-weighted averages.

3. Comparing mature and immature bachelor's cohorts for programmatic and demographic cohorts

In the Findings section, we showed that average cumulative net VAE was similar across entry years for the mature and immature bachelor's institutional cohorts. This is also the case when we compare the 2008–09 entry year to an average of the 2009–10 through 2013–14 entry years, especially for 10-year cumulative net VAE (Exhibit D.3). In this section, we take this investigation further by examining the extent to which these similarities extend to programmatic and demographic cohorts. We present results for 10-year cumulative net VAE because this could be estimated for the full set of entry years.

Exhibit D.3. Cumulative net value-added earnings for bachelor's degree-seeking students, by cohort maturity



Source: Authors' calculations using Texas administrative data and IPEDS.

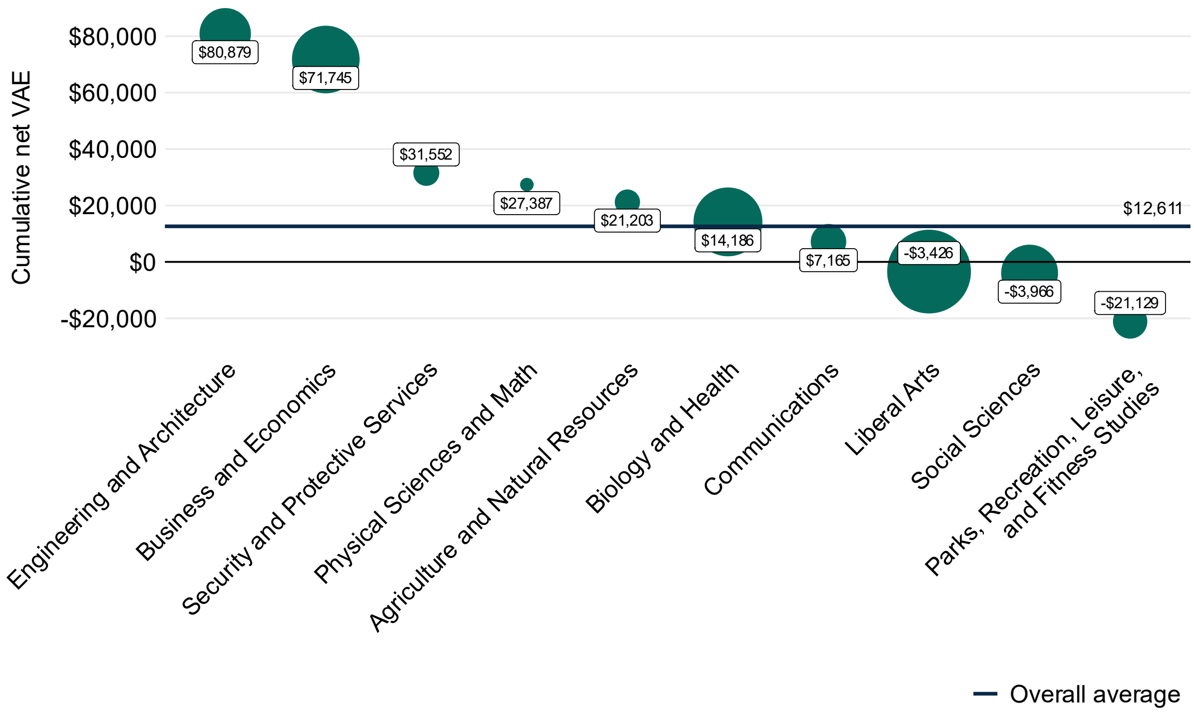
Note: The sample includes 28,614 students who enrolled in bachelor's degrees in 2008–09 and 280,599 students who enrolled in bachelor's degree programs from 2009–10 through 2013–14. Values are student-weighted averages.

a. Programmatic cohort findings

Before making comparisons across the mature and immature cohorts, we first confirm that for students seeking bachelor's degrees in 2008–09 the ranking of programs by 10-year average cumulative net VAE (Exhibit D.4) was similar to the ranking according to 15-year average cumulative net VAE (Exhibit 5). Engineering and architecture programs had the highest returns, on average, according to both measures, followed closely by business and economics programs. Several programs had negative 10-year cumulative net VAE, including liberal arts; social sciences; and parks, recreation, leisure, and fitness studies. Students seeking degrees in these programs recovered costs more slowly, breaking even at some point between 10 and 15 years after enrollment (as we find 15-year returns were positive).

We find that programs with relatively higher 10-year cumulative net VAE for the 2008–09 entering cohort, such as engineering and architecture and business and economics, remained higher in the ranking of programs for the 2009–10 through 2013–14 entering cohorts (Exhibit D.5). Similarly, liberal arts; social sciences; and parks, recreation, leisure, and fitness studies remained in the bottom of the distribution. One exception to this pattern was the physical sciences and math program, which shifted from the upper half of the distribution for the 2008–09 entering cohorts to the lower half for the 2009–10 through 2013–14 cohorts. Enrollment in these programs was small, likely causing more variability in VAE estimates. Overall, patterns in program-specific VAE were broadly consistent across students who sought bachelor's degrees in 2008–09 and those who did so from 2009–10 through 2013–14.

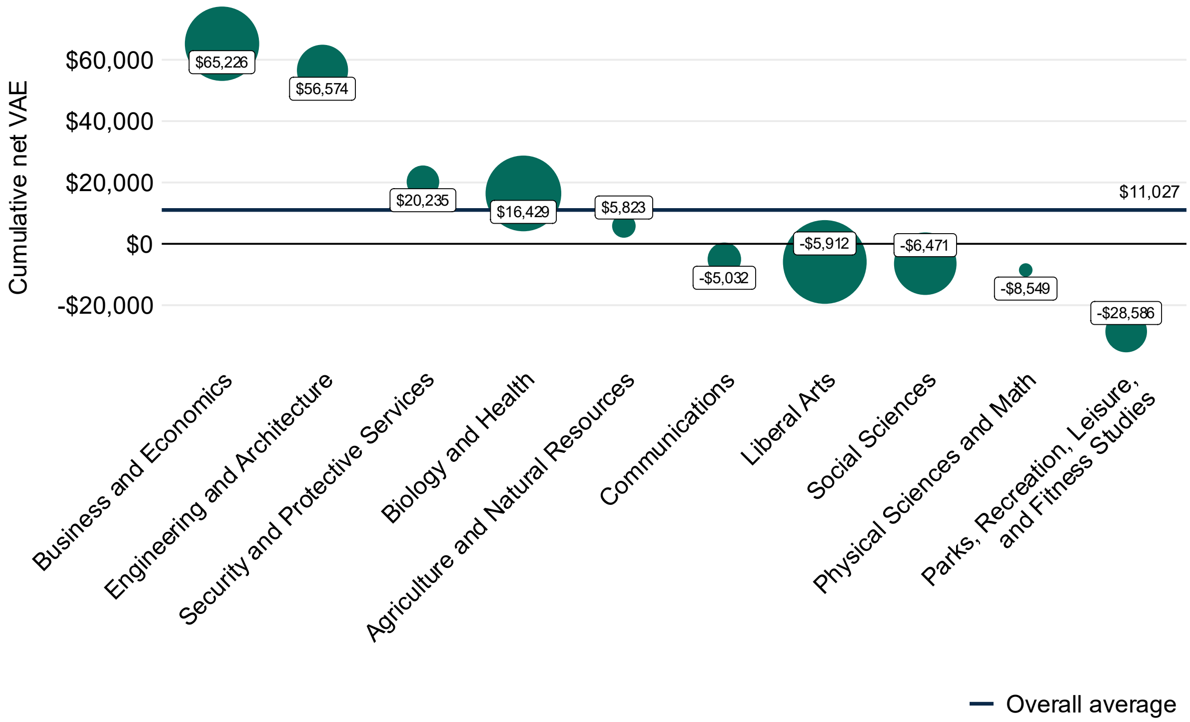
Exhibit D.4. Cumulative net value-added earnings in Year 10 for bachelor's degree-seeking students, by program of study, 2008–09 entry year



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 27,723 students who enrolled in public postsecondary institutions in Texas seeking bachelor's degrees in 2008–09. Values are student-weighted averages in 2023 dollars. The size of each circle is proportional to the number of cohort students in each program. Differences across programs are statistically significant at the 1 percent level.

Exhibit D.5. Cumulative net value-added earnings in Year 10 for bachelor's degree-seeking students, by program of study, 2009–2013 entry years



Source: Authors' calculations using Texas administrative data and IPEDS.

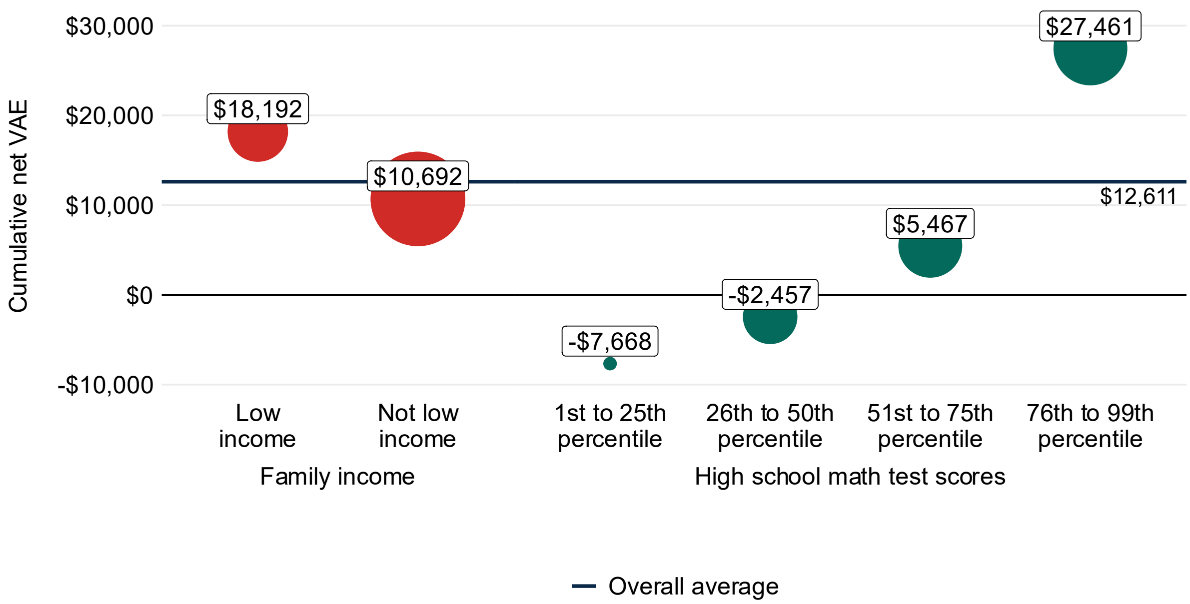
Note: The sample includes 240,933 students who enrolled in public postsecondary institutions in Texas seeking bachelor's degrees from 2009–10 through 2013–14. Values are student-weighted averages in 2023 dollars. The size of each circle is proportional to the number of cohort students in each program. Differences across programs are statistically significant at the 1 percent level. For ease of comparison with Exhibit D.4, we exclude the information technology program from this figure. This program did not exceed the sample size threshold for any 2008–09 entering cohorts.

b. Demographic cohort findings

Before comparing findings across the mature and immature bachelor's demographic cohorts, we first note that average cumulative net VAE was higher for students from low-income households in Year 10 (Exhibit D.6), whereas we found no differences by household income in Year 15 (Exhibit 7). This was due to lower direct costs to enrolling in bachelor's degrees, on average, for students from low-income households. Students who sought bachelor's degrees and who were not from low-income households had higher cumulative VAE from Year 5 to Year 15. In Year 10, lower costs among the students from low-income households outweighed higher VAE among students who were not from low-income households. By Year 15, differences in average costs and VAE balanced out, resulting in similar cumulative net VAE across these groups. We find the same pattern holds across household income groups in Year 10 for students enrolled in the 2009–10 through 2013–14 entry years (Exhibit D.7).

For the cohort of bachelor's degree-seeking students enrolling in postsecondary education in 2008–09, the cumulative net VAE of enrolling after 10 years was lowest for the bottom quartile of high school math achievement and highest for the top quartile of high school math achievement (Exhibit D.6), consistent with 15-year cumulative net VAE (Exhibit 7). The same pattern of variation in 10-year cumulative net VAE by prior academic achievement is observed for students who sought bachelor's degrees from 2009–10 through 2013–14 (Exhibit D.7). Altogether, we find similar results across mature and immature cohorts in Year 10 cumulative net VAE for demographic groups seeking bachelor's degrees.

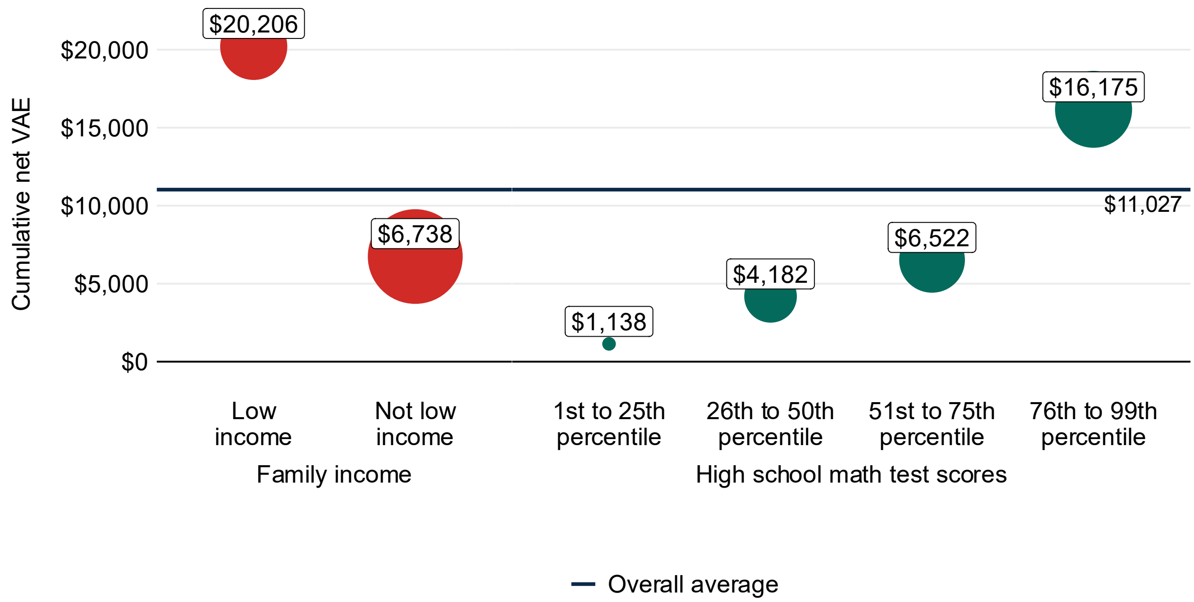
Exhibit D.6. Cumulative net value-added earnings in Year 10 for bachelor's degree-seeking students, by demographic group, 2008–09 entry year



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 28,581 students with data on family low-income status and 27,148 students with data on high school math achievement who enrolled in public postsecondary institutions in Texas in 2008–09. Values are student-weighted averages in 2023 dollars. The size of each circle is proportional to the number of cohort students in each demographic group. Differences across groups are statistically significant at the 1 percent level.

Exhibit D.7. Cumulative net value-added earnings in Year 10 for bachelor's degree-seeking students, by demographic group, 2009–10 to 2013–14 entry years



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 280,344 students with data on family low-income status and 269,223 students with data on high school math achievement who enrolled in public postsecondary institutions in Texas from 2009–10 through 2013–14. Values are student-weighted averages in 2023 dollars. The size of each circle is proportional to the number of cohort students in each demographic group. Differences across groups are statistically significant at the 1 percent level.

4. Quantifying the importance of matching

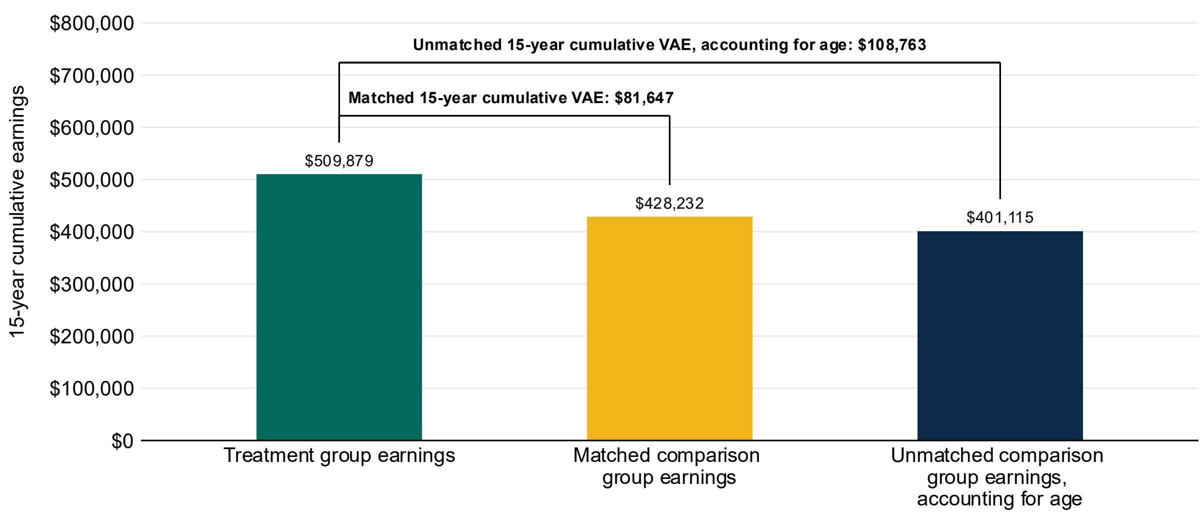
The goal of our matching strategy is to construct a comparison group that represents the counterfactual earnings of the cohorts of interest had they not enrolled in higher education. Without a carefully constructed counterfactual, differences in earnings between the cohort and comparison group could reflect selection bias. Bias is a significant concern in this setting, where characteristics like academic readiness are likely to influence both selection into higher education and later earnings.

To quantify the importance of matching in estimating VAE, we compare our estimates to estimates from a simple comparison that does not involve matching. This exercise is instructive for understanding the role of matching in our analysis and for shedding light on the direction and size of bias in other measures that do not use matched comparison groups. For this exercise, the treatment group includes the same individuals in our matched treatment sample. The comparison group includes untreated individuals who met all sample restrictions and were eligible to be matched (see Appendix Section A.5 for details on sample requirements). Simple measures of the returns to postsecondary education typically make comparisons between individuals of roughly a similar age and include in the comparison group those with no postsecondary education. To mimic these features we account for differences in age across the treatment and comparison groups and exclude individuals from the comparison group who previously earned a postsecondary degree.[78] We refer to this as the unmatched comparison group.

To understand how matching affects VAE estimates at different points in time and for different student profiles, we focus on cohorts that enrolled in 2008–09 and 2013–14. Students who enrolled in 2008–09 did so directly from high school as the sample includes those who graduated since 2007–08. The 2013–14 entry cohort includes some students who are older as well as those who were in the labor force before enrolling.

The differences in matched and unmatched VAE estimates are driven by the choice of comparison group. This is illustrated in Exhibit D.8, which lays out this exercise for bachelor's degree-seeking students who enrolled in 2008. The matched 15-year VAE estimate ($81,647) is the difference between the average treatment group earnings and the average *matched* comparison group earnings. The unmatched 15-year VAE estimate ($108,763) is the difference between the average treatment group earnings and the average *unmatched* comparison group earnings, after accounting for age.

Exhibit D.8. Treatment and comparison group average earnings under matching and no matching, bachelor's degree-seeking students in 2008–09 entry year



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 28,614 students who enrolled in public postsecondary institutions in Texas in 2008–09. The matched 15-year VAE estimate is equal to the difference in the treatment group's average earnings and the matched comparison group's average earnings. The unmatched 15-year VAE estimate is equal to the difference in the treatment group's average earnings and the unmatched comparison group's average earnings. Averages are institution-weighted averages.

[78] Individuals who earned a prior postsecondary degree are included in both the treatment and comparison groups in our matching approach as we exact match on the highest prior degree earned.

Earnings for the unmatched comparison group were lower on average than earnings for the matched comparison group, resulting in higher unmatched VAE for bachelor's degrees (Exhibits D.8 and D.9). This is likely due to individuals with high earnings potential selecting into bachelor's degrees, both in the 2008–09 and 2013–14 entry years. When unaccounted for, this bias results in 15-year VAE estimates that were $27,116 higher in 2008–09 and 10-year VAE estimates that were $23,560 higher in 2013.[79]

We observe a similar pattern for associate's degrees and certificates (Exhibit D.9). For associate's degrees, unmatched VAE estimates were $13,402 higher in the 2008 entry cohort and $7,856 higher in the 2013–14 cohort compared with matched VAE estimates. For certificates, unmatched VAE estimates were $5,980 higher in the 2008–09 entry cohort and $2,325 higher in the 2013–14 cohort compared with matched VAE estimates.

The pattern of results is consistent with a few hypotheses. First, when limiting to students that move directly from high school into postsecondary education (as in the results for the 2008–09 entry year), we find positive selection bias in all degree types. When including both these students and those that enter postsecondary education at older ages (up to age 23 in these data), the reduced upward bias may be the result of a combination of this same positive selection for younger students and negative selection for older students who pursued associate's degrees and certificates. These students may have pursued associate's degrees and certificates in response to a negative experiences in the labor market.

[79] We report 10-year cumulative VAE for the bachelor's 2013 cohort because it could not be followed for the full 15-year period.

Exhibit D.9. Cumulative value-added earnings estimated using matching and no matching, by degree type and entry year

Source: Authors' calculations using Texas administrative data.
Note: The sample includes 28,614 students who enrolled in bachelor's degrees in 2008–09; 67,444 students who enrolled in bachelor's degrees in 2013–14; 50,329 students who enrolled in associate's degrees in 2008–09; 117,569 students who enrolled in associate's degrees in 2013–14; 2,329 students who enrolled in certificates in 2008–09; and 6,312 students who enrolled in certificates in 2013–14. Year 10 VAE is bolded for the bachelor's 2013 cohort to distinguish this outcome from Year 15 VAE for the bachelor's 2008 cohort. Averages are institution-weighted averages.

5. Estimating the relationship between institutional and cohort characteristics and cumulative net VAE

In the Findings section, we described which institution-wide and cohort-level characteristics were related to cumulative net VAE. In this section, we provide additional details about the characteristics used in that exploration (Exhibit D.10), the correlations between degree-completion measures (Exhibit D.11), and the regressions used to estimate these relationships (Exhibits D.12–D.14) for each degree type.

All institutions in our sample enrolling bachelor's degree-seeking students were four-year institutions, and two institutions enrolling certificate-seeking students were also four-year (Exhibit D.10). Around half of bachelor's institutions in the sample were considered selective and 10 percent were considered very selective. Bachelor's institutions had, on average, a higher share of students receiving Pell Grants, greater undergraduate enrollment, and higher net prices, compared with associate's and certificate institutions.[80]

The study measures degree-completion rates in four ways to capture nuances related to this key outcome. The measures include the following:

a. The institution-wide "150 percent graduation rate" reported in IPEDS, which is the percentage of first-time, full-time, degree-seeking students who earned their intended degree at the same institution within 150 percent of the normal time to completion
b. The percentage of students in the study cohort who completed any degree at any public institution in Texas within the study's follow-up period
c. The percentage of students in the study cohort who completed their intended degree (for example, a bachelor's degree for bachelor's cohorts) at any public institution in Texas during this period
d. The percentage of students in the study cohort who completed their intended degree at the same institution during this period

On average, most (69 percent) bachelor's degree-seeking students in study cohorts completed a degree during the follow-up period (Exhibit D.10), and completers typically earned a bachelor's degree at their original institution (47 percent, or 68 percent of those who completed any degree). In contrast, 51 percent of associate's degree-seeking cohort students completed a degree, but only 24 percent completed an associate's degree and only 18 percent did so at their original institution. For certificate seekers, those who completed any degree (40 percent) mostly earned a certificate at their original institution (25 percent, or 63 percent of those who completed any degree). Average rates of degree completion based on the institution-wide "150 percent graduation rate" reported in IPEDS were slightly lower than the cohort rate of completion at the original institution in the degree sought. This is consistent with the more limited period for measuring completion in IPEDS.

[80] Selectivity is based on the Carnegie classification system reported in IPEDS. Net price is defined in IEPDS as the average net price for full-time, first-time degree–seeking undergraduates paying the in-state or in-district tuition rate who received grant or scholarship aid from federal, state, or local governments, or the institution.

Exhibit D.10. Descriptive statistics of institutions

Characteristics	All degree types	Bachelor's	Associate's	Certificate
Four or more years (percent)	21	100	0	2
Selective (percent)	10	52	0	0
More selective (percent)	2	10	0	0
% Pell Grant recipients (average)	29	35	27	28
Total undergraduate enrollment (average)	11,824	14,056	11,015	11,499
Net price (average)	$6,420	$9,774	$5,577	$5,557
% full-time, first-time students who complete program within 150% time (average)	20	39	15	15
% cohort that completed any degree at any institution (average)	50	69	51	40
% cohort that completed degree sought at any institution (average)	33	61	24	27
% cohort that completed degree sought at same institution (average)	26	47	18	25
Number of institutions (N)	143	29	57	57

Source: Texas administrative data and IPEDS.

Note: The table reports means of each characteristic across institutions. The measures of cohort degree completion are based on the matched cohort used to estimate VAE and pooled across entry years and reflect completion within the cohort's follow-up period. All other variables are from IPEDS and are based on the earliest entry year for a given institution.

The extent to which the four measures of degree-completion rates were related varied considerably across degree types. For bachelor's degrees, they were all strongly correlated, with correlation coefficients of 0.86 or above (Exhibit D.11). This is because bachelor's degree-seeking students who completed their degrees typically did so in the same degree program and institution in which they first enrolled. In contrast, associate's degree-seeking students often completed other degree types at other institutions, consistent with the common practice of transferring from two-year associate's programs to four-year bachelor's programs. For certificate-seeking students, there was a strong correlation between the rate of cohort students completing a certificate in the original institution and in any institution, reflecting that those who complete their certificates were likely to do so in their original institution.

Exhibit D.11. Correlations between different measures of degree-completion rates

Measure 1	Measure 2	Correlation coefficients			
		All degree types	Bachelor's	Associate's	Certificate
Percentage of full-time, first-time students who completed program within 150% time	Percentage of cohort that completed any degree at any institution	0.73	0.86	0.14	0.37
Percentage of full-time, first-time students who completed program within 150% time	Percentage of cohort that completed degree sought at any institution	0.83	0.88	0.10	0.46
Percentage of full-time, first-time students who completed program within 150% time	Percentage that completed degree sought at same institution	0.79	0.93	0.08	0.47
Percentage of cohort that completed any degree at any institution	Percentage of cohort that completed degree sought at any institution	0.75	0.99	-0.17	0.61
Percentage of cohort that completed any degree at any institution	Percentage that completed degree sought at same institution	0.63	0.91	-0.36	0.58
Percentage of cohort that completed degree sought at any institution	Percentage that completed degree sought at same institution	0.95	0.93	0.68	0.99
N		143	29	57	57

Source: Texas administrative data and IPEDS. The measures of cohort degree completion are based on the matched cohort used to estimate VAE and pooled across entry years and reflect completion within the cohort's follow-up period. The institution-wide 150 percent graduation rate is from IPEDS and is based on the earliest entry year for a given institution.

To analyze relationships between cumulative net VAE and institutional or cohort characteristics, we estimate both univariate and multivariate regressions with cumulative net VAE as the dependent variable. The unit of analysis is the institution. Exhibits D.12, D.13, and D.14 report coefficients and *p*-values from these regressions for the bachelor's, associate's, and certificate cohorts, respectively. Column 1 of each exhibit reports estimates from univariate regressions between each institutional factor and cumulative net VAE, where each row represents a separate regression. Columns 2 through 5 report estimates from multivariate regressions that include as covariates: institutional selectivity, percentage of Pell Grant recipients at the institution, total undergraduate enrollment at the institution, institution-wide average net price, an IPEDS-based institution completion rate, and one of three cohort-level degree completion measures. Each of columns 2 through 5 represents a separate multivariate regression. Because this analysis has a limited sample size, we report statistical significance at the 10 percent level or higher but suggest caution in interpreting results.

For students seeking bachelor's degrees, institutional cumulative net VAE was negatively correlated with the share of students receiving Pell Grants and positively correlated with selectivity, undergraduate enrollment, net price, and measures of degree completion (column 1 of Exhibit D.12). After controlling for all factors together, the only relationships that were statistically significant were for the percentage of the cohort that completed any degree at any institution within the follow-up period, or the degree sought at any institution within that same period (columns 2–5 of Exhibit D.12). Specifically, a 1 percentage-point higher share of students who completed any degree at any institution was associated with $2,557 higher 15-year cumulative net VAE (column 3 of Exhibit D.12); and a 1 percentage-point increase in the share of students who completed a bachelor's degree at any institution was associated with $2,033 higher 15-year cumulative net VAE (column 4 of Exhibit D.12).

Exhibit D.12. Institutional factors associated with cumulative net VAE, bachelor's degree-seeking students

	(1) Not controlling for any other factors	(2) Controlling for listed factors	(3) Controlling for listed factors	(4) Controlling for listed factors	(5) Controlling for listed factors
Selective institutions (vs. inclusive)	18,351 0.17	-7,056 0.75	-16,596 0.35	-16,117 0.35	-5,464 0.79
More selective institutions (vs. inclusive)	99,658** 0.00	38,174 0.34	40,631 0.18	37,906 0.21	48,739 0.17
Percentage of Pell Grant recipients at institution	-1,948** 0.00	-591 0.43	419 0.55	223 0.76	-347 0.62
Total undergraduate enrollment (100 students)	163* 0.05	-27 0.68	-59 0.23	-57 0.29	-44 0.48
Net price ($100)	731** 0.02	278 0.38	319 0.22	292 0.27	311 0.30
Percentage of full-time students who completed degree sought at same institution, 150% time	1,811** 0.00	925 0.12			
Percentage of cohort that completed any degree at any institution	2,482** 0.00		2,557** 0.01		
Percentage of cohort that completed degree sought at any institution	2,116** 0.00			2,033** 0.01	
Percentage of cohort that completed degree sought at same institution	2,025** 0.00				1,179 0.11
Adjusted R^2	0.410	0.61	0.71	0.70	0.63
Number of institutions	29	29	29	29	29

Source: Texas administrative data and IPEDS.

Note: In each cell of the table, the first row is the coefficient and the second is the *p*-value. The outcome of all regressions is the Year 15 cumulative net VAE for each institution, based on the 2008–09 entry cohort, in 2023 dollars. For the univariate regressions in column (1), the adjusted R^2 refers to the average adjusted R^2 across all models. The measures of cohort degree completion are based on the matched cohort used to estimate VAE and pooled across entry years and reflect completion within the cohort's follow-up period. All other variables are from IPEDS and are based on the earliest entry year for a given institution.

* = statistically significant at the 10 percent level; ** = statistically significant at the 5 percent level.

For students seeking associate's degrees, cumulative net VAE was negatively correlated with the share of students receiving Pell Grants and positively correlated with the percentage of the cohort that completed any degree at any institution (column 1 of Exhibit D.13). Other univariate relationships were not statistically significant.[81] After controlling for all other factors, we find that a 1 percentage-point higher rate of any degree completion was associated with $1,681 higher 10-year cumulative net VAE (column 3 of Exhibit D.13). Other relationships between cumulative net VAE and institutional factors (which were statistically significant in columns 2, 4, and 5 of Exhibit D.13) were no longer statistically significant after accounting for the rate of completion of any degree.

Exhibit D.13. Institutional factors associated with cumulative net VAE, associate's degree-seeking students

	(1) Not controlling for any other factors	(2) Controlling for listed factors	(3) Controlling for listed factors	(4) Controlling for listed factors	(5) Controlling for listed factors
Percentage of Pell Grant recipients at institution	-484* 0.07	-565* 0.08	-78 0.60	-493* 0.05	-514* 0.05
Total undergraduate enrollment (100 students)	-22 0.15	-20 0.21	-14 0.24	-40* 0.08	-32* 0.08
Net price ($100)	136 0.28	-31 0.85	73 0.60	48 0.71	-14 0.93
Percentage of full-time students who completed degree sought at same institution, 150% time	584 0.36	508 0.48			
Percentage of cohort that completed any degree at any institution	1,780** 0.00		1,681** 0.00		
Percentage of cohort that completed degree sought at any institution	-755 0.38			-989 0.22	
Percentage of cohort that completed degree sought at same institution	-904 0.29				-820 0.29
Adjusted R^2	0.09	0.16	0.44	0.20	0.18
Number of institutions	57	57	57	57	57

Source: Texas administrative data and IPEDS.

Note: In each cell of the table, the first row is the coefficient and the second is the *p*-value. The outcome of all regressions is the Year 10 cumulative net VAE for each institution, based on the 2008–09 to 2013–14 entry cohorts, in 2023 dollars. For the univariate regressions in column (1), the adjusted R^2 refers to the average adjusted R^2 across all models. The measures of cohort degree completion are based on the matched cohort used to estimate VAE and pooled across entry years and reflect completion within the cohort's follow-up period. All other variables are from IPEDS and are based on the earliest entry year for a given institution.

* = statistically significant at the 10 percent level; ** = statistically significant at the 5 percent level.

[81] We do not estimate the relationship between cumulative net VAE and selectivity for associate's degrees or certificates because there were no selective institutions that enrolled in these degree types.

For students seeking a certificate, cumulative net VAE was negatively correlated with total undergraduate enrollment and positively correlated with measures of degree completion, except the completion rate of certificates at any institution (column 1 of Exhibit D.14). Accounting for all factors together, statistically significant relationships remained between cumulative net VAE and undergraduate enrollment, the percentage of the cohort that completed a certificate at any institution, and the percentage of the cohort that completed a certificate at the original institution. Because these two completion rates were highly correlated (correlation coefficient of 0.99), we will focus on the regression estimated using the latter measure in column 5. We find that total undergraduate enrollment that was higher by 100 students was associated with five-year cumulative net VAE that was $13 lower, and a 1 percentage-point higher rate of certificate completion at the original institution was associated with five-year cumulative net VAE that was $323 higher (column 5 of Exhibit D.14). As discussed in the Findings section, the percentage of the cohort that completed a degree was the only factor consistently related to a cohort's cumulative net VAE, across degree types, when controlling for other factors.

Exhibit D.14. Institutional factors associated with cumulative net VAE, certificate-seeking students

	(1) Not controlling for any other factors	(2) Controlling for listed factors	(3) Controlling for listed factors	(4) Controlling for listed factors	(5) Controlling for listed factors
Percentage of Pell Grant recipients at institution	-94 0.41	-148 0.21	-124 0.26	-78 0.46	-76 0.47
Total undergraduate enrollment (100 students)	-25** 0.00	-21** 0.01	-29** 0.01	-12 0.13	-13* 0.07
Net price ($100)	57 0.27	-2 0.98	22 0.70	53 0.25	61 0.18
Percentage of full-time students who completed degree sought at same institution, 150% time	456* 0.07	341 0.21			
Percentage of cohort that completed any degree at any institution	108 0.69		-92 0.76		
Percentage of cohort that completed degree sought at any institution	409** 0.00			353** 0.04	
Percentage of cohort that completed degree sought at same institution	368** 0.01				323** 0.03
Adjusted R^2	0.07	0.15	0.12	0.21	0.21
Number of institutions	57	57	57	57	57

Source: Texas administrative data and IPEDS.

Note: In each cell of the table, the first row is the coefficient and the second is the *p*-value. The outcome of all regressions is the Year 5 cumulative net VAE for each institution, based on the 2008–09 to 2018–19 entry cohorts, in 2023 dollars. For the univariate regressions in column (1), the adjusted R^2 refers to the average adjusted R^2 across all models. The measures of cohort degree completion are based on the matched cohort used to estimate VAE and pooled across entry years and reflect completion within the cohort's follow-up period. All other variables are from IPEDS and are based on the earliest entry year for a given institution.

* = statistically significant at the 10 percent level; ** = statistically significant at the 5 percent level.

6. Decomposing variation in cumulative net VAE using ANOVA

In this section, we provide the full results of the analysis of variance (ANOVA) exercise discussed in the main findings to decompose cumulative net VAE into differences between institutions versus differences between groups of students within the same institution. For each degree type, we repeat this exercise four times to examine the relative importance to cumulative net VAE of (1) institutions versus programs of study, (2) institutions versus high school math achievement quartiles, (3) institutions versus household income status, and (4) institutions versus age at entry.[82] Each two-way ANOVA uses cumulative net VAE estimates at the institution-by-group level (where a group is either a program or student group). The ANOVA decomposes the variation in these cumulative net VAE measures into a component explained by institutions, a component explained by programs or student groups, and an unexplained component.[83]

a. Bachelor's degree-seeking students

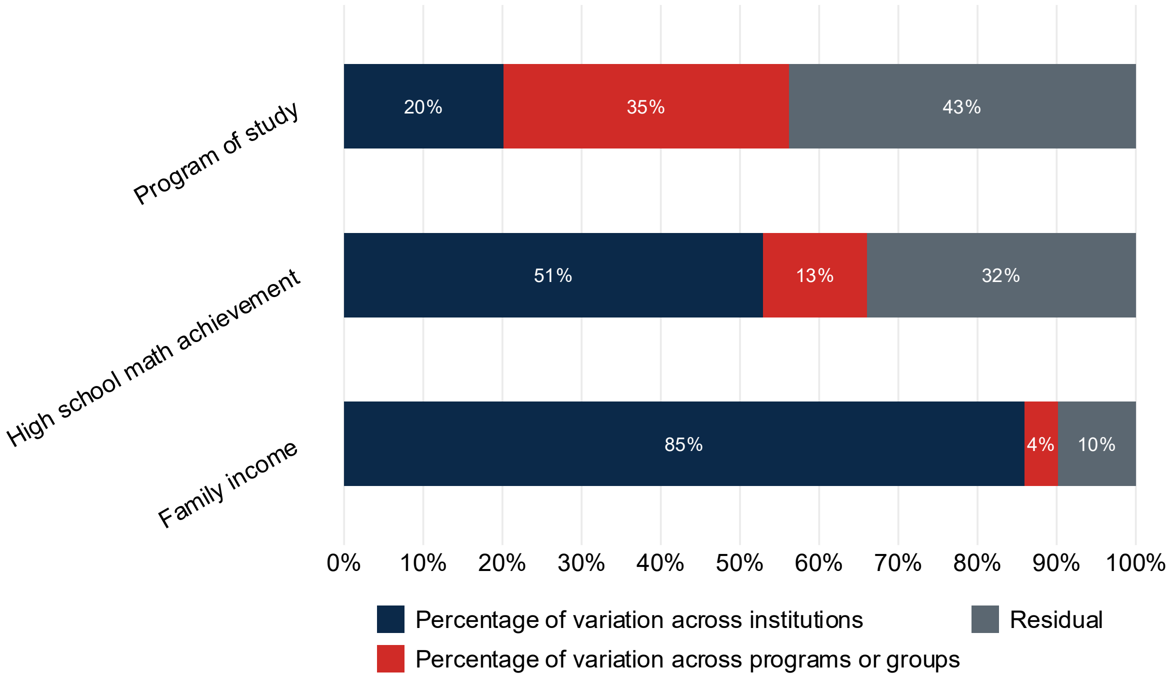
We find that more of the variation in cumulative net VAE for bachelor's degree-seeking students in Year 15 was explained by differences across programs within institutions than across institutions delivering the same program (35 versus 20 percent, Exhibit D.15). The value of the residual (43 percent) suggests that a meaningful part of the variation in cumulative net VAE for bachelor's degree-seeking students was explained by specific programs in specific institutions being particularly effective (or not) at providing economic returns to their students.

When comparing the relative importance of institutions to students' background characteristics, we find differences across institutions among cohort students with similar achievement levels explained much more of the variation in cumulative net VAE (51 percent) than differences across students' math achievement within a given institution (13 percent). Similarly, differences across institutions among cohort students of a similar household income level explained much more of the variation in cumulative net VAE (85 percent) than differences across students' household income level within a given institution (4 percent).

[82] There was only one age grouping (under 20 at entry) that met the sample size threshold for bachelor's degree–seeking students. We therefore do not examine this dimension for the bachelor's degree type.

[83] The share of variation contributed to different components may not sum to 100 percent in practice. To understand why, consider the decomposition exercise for program and institutions. The two-way ANOVA distinguishes the variation in cumulative net VAE explained by institutions, while holding programs constant, and the variation explained by programs, holding institutions constant. What cannot be explained by either is the residual. However, some variation is explained jointly by both programs and institutions. Because the ANOVA attributes to each factor only its incremental contribution conditional on the other, this shared variation is not uniquely assigned to either component. As a result, the reported shares need not sum to 100 percent.

Exhibit D.15. Percentage of variation in cumulative net value-added earnings in Year 15 for bachelor's degree-seeking students, institutions versus groups



Source: Authors' calculations using Texas administrative data and IPEDS.

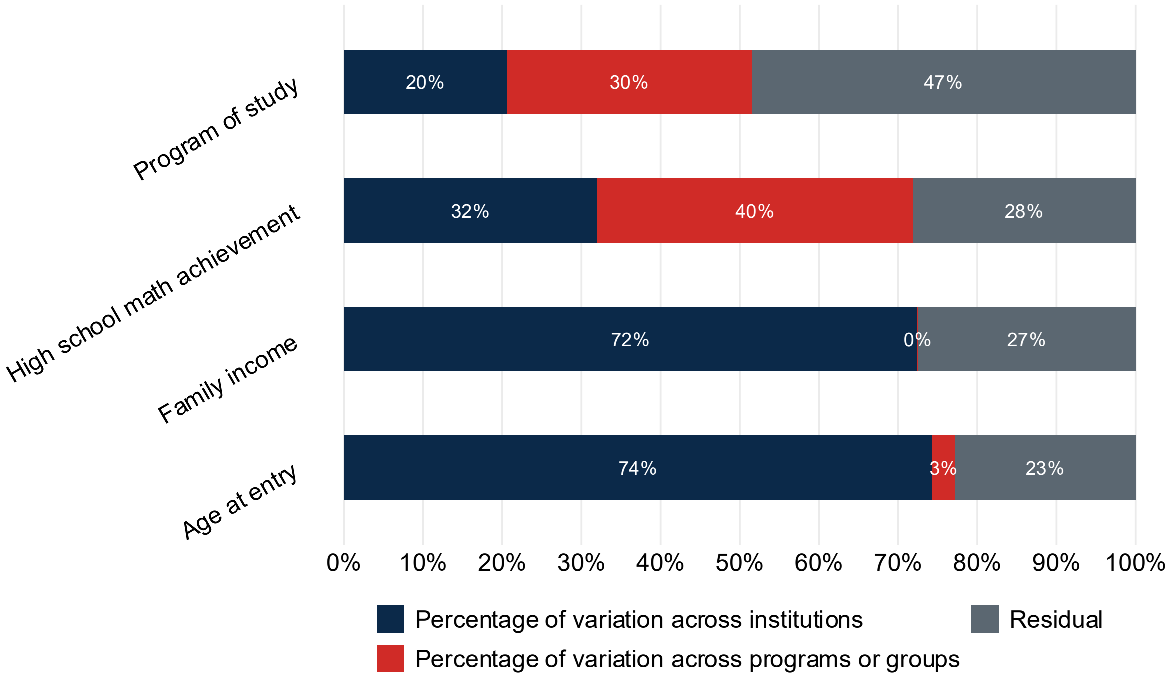
Note: The sample includes 29 bachelor's degree-granting institutions. The outcome is Year 15 cumulative net value-added earnings for students enrolling in postsecondary education in 2008–09.

b. Associate's degree-seeking students

Similar to bachelor's degree-seeking students, we find that more of the variation in cumulative net VAE for associate's degree-seeking students was explained by differences across programs than across institutions (30 versus 20 percent, Exhibit D.16). After accounting for both the institution and program, 45 percent of the variation in cumulative net VAE for associate's degree-seeking students was still unexplained.

Differences across institutions for students with similar math achievement levels explained *less* of the variation in cumulative net VAE (32 percent) than differences in students' math achievement levels within a given institution (40 percent), suggesting that prior math achievement matters more than choice of institution for associate's degree-seeking students. In contrast, within a given institution, differences in students' household income or age at entry explained only a trivial portion of the variation in cumulative net VAE for associate's degree-seeking students (0 percent and 3 percent, respectively).

Exhibit D.16. Percentage of variation in cumulative net value-added earnings in Year 10 for associate's degree-seeking students, institutions versus groups



Source: Authors' calculations using Texas administrative data and IPEDS.

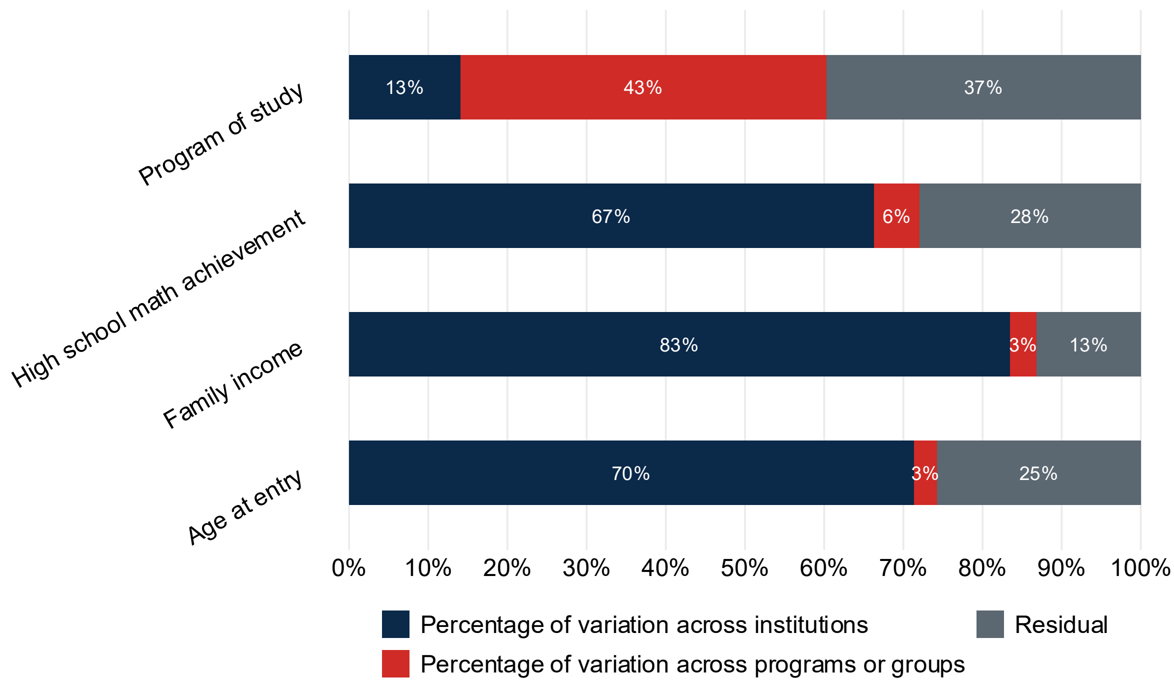
Note: The sample includes 57 associate's degree-granting institutions. The outcome is Year 10 cumulative net value-added earnings for students enrolling in postsecondary education in 2008–09 through 2013–14.

c. *Certificate-seeking students*

We find that much more of the variation in cumulative net VAE for certificate-seeking students in Year 5 was explained by differences across programs within institutions than across institutions delivering the same program (43 versus 13 percent, Exhibit D.17). After accounting for both the institution and program, 36 percent of the variation in cumulative net VAE for certificate-seeking students was still unexplained.

When comparing the relative importance of institutions with students' background characteristics, we find that differences across institutions among cohort students with similar background characteristics explained much more of the variation in cumulative net VAE (67 to 83 percent) than differences within a given institution in students' math achievement (6 percent), household income level (3 percent), or age at entry (3 percent).

Exhibit D.17. Percentage of variation in cumulative net value-added earnings in Year 5 for certificate-seeking students, institutions versus groups



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 57 certificate-granting institutions. The outcome is Year 5 cumulative net value-added earnings for students enrolling in postsecondary education in 2008–09 through 2018–19.

E. Sensitivity checks

To examine how sensitive the VAE estimates are to certain design decisions, we generate the VAE measures under alternative specifications and compare them with our main estimates. We focus on two key design decisions: (1) the core estimation framework under which VAE estimates are generated and (2) restrictions on individuals based on the extent to which they have observed earnings. Because of how computationally intensive it is to estimate many thousands of treatment effects under many different specifications, we limited the sensitivity to only institutional cohorts and to only a randomly selected sample of half of the institution cohorts within each degree type. For both sensitivity checks, we estimate and compare measures of cumulative VAE, and not cumulative *net* VAE, as the two approaches vary in how they measure wages and wage gains but not in how they measure or calculate net costs.

1. Fixed effects model of wage gains

Our main estimation framework involves a matching algorithm complemented by a dynamic, cross-sectional weighted least squares regression in which pre-treatment characteristics and lagged outcomes, where available, are used as covariates. An alternative method used widely in the literature is an individual-fixed effects model, which uses within-person variation in earnings to estimate the treatment effect. This model has strong internal validity because it leverages repeated observations from the same individuals over time to compare each person's earnings before and after the person enrolled in postsecondary education, relative to each person in the comparison group over the same period. Counterfactual earnings are constructed from the person's pattern of earnings prior to enrollment in postsecondary education, thereby not depending on across-individual variation as in our main model.

Because the fixed effects approach requires that we observe earnings prior to postsecondary education enrollment, and because we do not use earnings data for ages under 20, we cannot employ fixed effects as our primary approach. Indeed, because we can only include individuals who graduated from high school in 2007–08 or later and the bachelor's cohorts started postsecondary education in 2008–09, we cannot estimate the fixed effects model for the bachelor's cohorts. We further focus this analysis on cohorts with more recent entry years in order to include a larger share of students who enrolled at older ages. We estimate fixed effects models only for individuals who sought associate's degrees and certificates since 2011–12.

To construct the samples for estimating the fixed effects model, we begin with the set of individuals in the treatment and comparison groups who were matched in our main approach (see Exhibit B.5 for a summary of the proportion of individuals in the treatment group included in the matched sample). We further restrict to years of data in which an individual was age 20 or older, as we do not use earnings measured prior to this. We require that students in the treatment group had at least one year of baseline earnings observed before enrollment, effectively restricting to those age 21 or older at entry. Individuals in the comparison group never enroll, so a similar restriction does not apply to them.

a. Fixed effects model estimation

The fixed effects model is estimated using the following regression:

$$y_{it} = \alpha + age_{it} + \lambda_t + \delta_i + \sum_k \beta_k T_{it}^k + \epsilon_{it}$$

where y_{it} is annual earnings of individual i in year t, age_{it} is a vector of age fixed effects, λ_t are calendar-year fixed effects for each year included in the follow-up period, δ_i are individual fixed effects, and T_{it}^k is an indicator for whether individual i enrolled in the cohort of interest k years ago (as of year t). Under the parallel trends assumption, the parameters β_k estimate the average earnings gain of enrolling in the cohort of interest k years after enrolling, where $k \in \{-3, -2, \ 1, 2, 3 \ldots, K\}$ and K is 5 or 10 for certificates and associate's degree, respectively. The year before enrollment, $k = -1$, is excluded as a reference period, and $k = 1$ denotes the first year of enrollment. To obtain the average cumulative earnings gain k years after enrolling, we sum the estimated coefficients in all periods from $k = 1$ to k. For example, to obtain the cumulative wage gain three years after enrolling, we sum the estimated coefficients β_1, β_2, and β_3.

The parallel trends assumption requires that in the absence of postsecondary enrollment the earnings of cohort members and the comparison group would have followed a parallel trajectory, on average, following enrollment. The parallel trends assumption may be violated due to the existence of an "Ashenfelter dip." This refers to a pattern of sudden earnings declines just before beginning treatment, where treatment may be a response to the negative earnings shock (Ashenfelter 1978). Prior research estimating the earnings gains from two-year college degrees in Ohio found evidence of an Ashenfelter dip leading up to enrollment relative to a comparison group of non-attendees (Minaya and Scott-Clayton

2022). We deploy tests of the parallel trends assumption recommended in the econometrics literature by conducting hypothesis tests on the parameter estimates $\widehat{\beta_k}$ in the periods prior to enrollment (Roth et al. 2023). We restrict the results to those cohorts in which the test indicates the treatment and comparison groups had parallel earnings trends prior to enrollment, providing supporting evidence that the assumption is not violated.

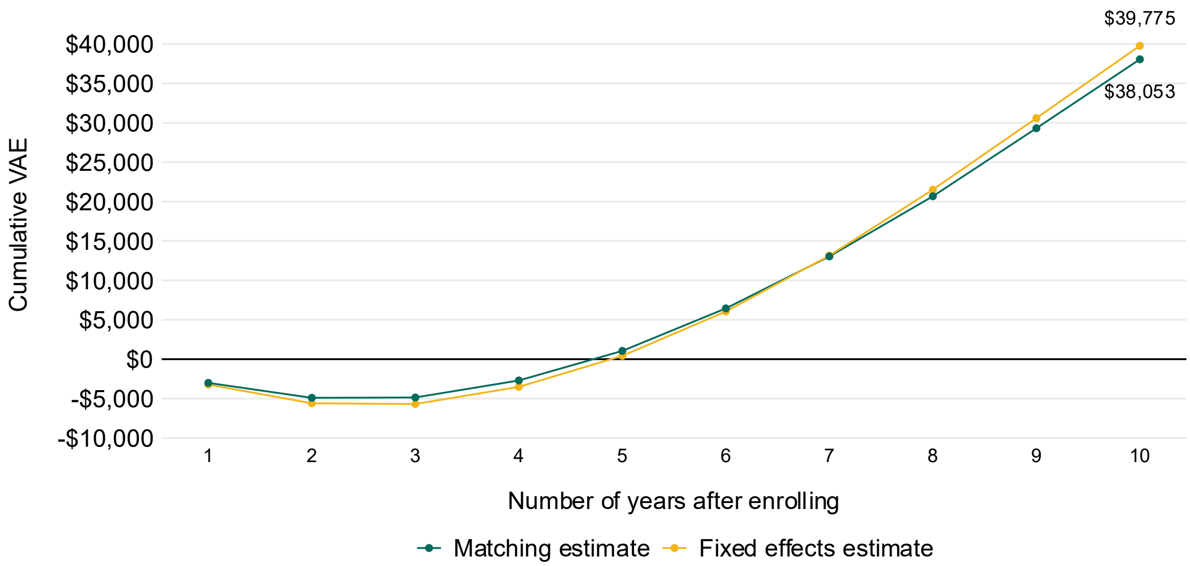
We compare cumulative VAE estimates from the fixed effects model to those generated using our main model for individuals ages 21 and older at the time of enrollment. By restricting the sample to individuals who can be included in both our main model and the person fixed-effects model, we can be confident that any differences are due to differences in estimation approaches rather than sample restrictions.

We generate fixed effects cumulative VAE estimates for 26 associate's institutions (of 29 included in the 50 percent sample for sensitivity analyses) that had 50 or more students ages 21 and older who enrolled between 2011–12 and 2013–14. For 17 of the 26 institutions, we fail to reject the null hypothesis of no parallel trends in the pre-enrollment period, providing support to the parallel trends assumption. We generate fixed effects cumulative VAE estimates for 25 (out of 28 sampled) certificate institutions that had at least 50 students ages 21 and older and enrolled between 2011–12 and 2018–19. Of these, we fail to reject the null of no parallel trends for 17 institutions. We limit our comparison of the fixed effects and main matching estimates to these 17 associate's and 17 certificate institutions.

b. Fixed effects model findings

For associate's degrees, average cumulative VAE estimated using the fixed effects model was similar to that of our main approach throughout the follow-up period (Exhibit E.1). By the end of the follow-up period (Year 10), the difference in average cumulative VAE was $1,722 (5 percent). For most institutions, the fixed effects estimate was within the 95 percent confidence interval of the main estimate, suggesting that the fixed effects estimates are generally consistent with the range of values plausibly supported by the matching approach. However, the correlation between Year 10 cumulative VAE estimated using the two approaches was modest at 0.48.

Exhibit E.1. Fixed effects and matching model estimates of cumulative value-added earnings for associate's institutions, 2011–12 through 2013–14 entry years

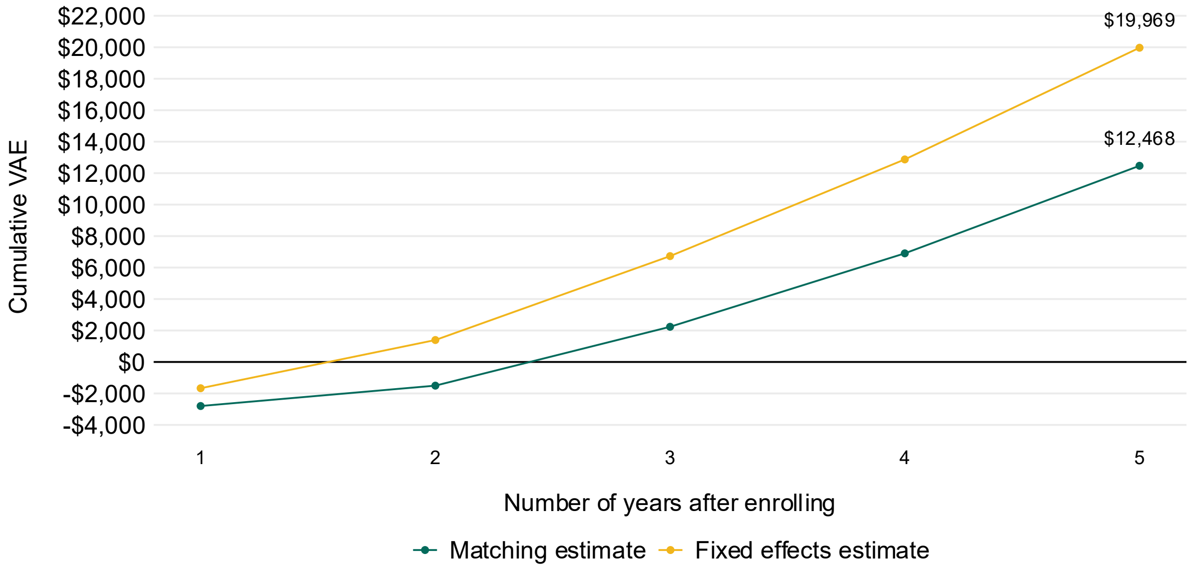


Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 11,912 students ages 21 and over who enrolled in associate's degree programs in the 50 percent random sample of public postsecondary institutions in Texas in 2011–12 through 2013–14. Values are institution-weighted averages in 2023 dollars. Matching estimates are calculated using the same students in the same institutions under our preferred approach.

Average cumulative VAE for certificates was higher when estimated using the fixed effects model compared with the matching model throughout the follow-up period (Exhibit E.2). The difference between the estimates was larger in magnitude than for associate's degrees. By the end of the follow-up period (Year 5), the difference in average cumulative VAE was $7,502 (60 percent). This pattern was quite consistent across institutions, and the correlation between the two estimates in Year 5 was strong at 0.85.

Exhibit E.2. Fixed effects and matching model estimates of cumulative value-added earnings for certificate institutions, 2011–12 through 2018–19 entry years



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 4,115 students ages 21 and older who enrolled in certificate programs in the 50 percent random sample of public postsecondary institutions in Texas in 2011–12 through 2018–19. Values are institution-weighted averages in 2023 dollars. Matching estimates are calculated using the same students in the same institutions under our preferred approach.

To understand why the estimates are sensitive to this model choice, consider that the key difference underlying the matching and fixed effects approaches is in how counterfactual earnings are estimated. The counterfactual in the fixed effects model is each individual's earnings the year before they enrolled, after accounting for earnings variation due to age or the calendar year. The counterfactual in the matching model is the contemporaneous earnings of a comparison group that did not enroll during the follow-up period but had similar characteristics to those who did. A key concern of the matching model—which motivates the use of the fixed effects model—is that we may not be able to fully account for positive selection into higher education on earnings potential (that is, individuals who pursue higher education may have had higher earnings regardless of this choice, perhaps due to greater ambition, skills, or opportunities), which would cause upward bias in our estimates. The fixed effects model, in contrast, could be less susceptible to this bias.

We do not find that our cumulative VAE estimates are inflated relative to fixed effects estimates for associate's degrees, and in fact estimate lower cumulative VAE under matching for certificates. Considering the nature of certificate programs, which are shorter-term, lower-cost, and often focused on occupation-specific skills, an alternative selection explanation is also plausible. Individuals—particularly those who are older—may elect to enroll in a certificate program to fill a gap in their professional skills, to address stagnant wages at their occupational level, or because of an adverse labor event such as a termination. Though we match on up to three years of prior earnings, our approach may nonetheless not sufficiently address these types of negative selection that are based on prior labor market experience, causing downward bias in our estimates. Although we find that naive cumulative VAE estimates that account only for age are higher than matched cumulative VAE for certificates, this may mask some underlying negative selection that matching does not fully address. In other words, the matching estimate may appropriately adjust for positive selection in a way that naive estimators do not, while the fixed effects estimates better accounts for both positive and negative selection.

2. Cumulative VAE under alternative requirements for earnings data

We test the sensitivity of cumulative VAE estimates to the sample restriction that requires cohort members and their matched comparison group to have some non-zero earnings during the years of the follow-up period in which we expect enrollment to have concluded (Years 7 through 15 for the bachelor's cohorts, Years 4 through 10 for the associate's cohorts, and Years 2 through 5 for the certificate cohorts). We implement two alternatives to this restriction:

a. Cohort members and their matched comparison group must have some non-zero earnings during any years of the follow-up period (**less restrictive**)
b. Cohort members and their matched comparison group must have non-zero earnings in at least half of the post-enrollment years during the follow-up period (**more restrictive**)

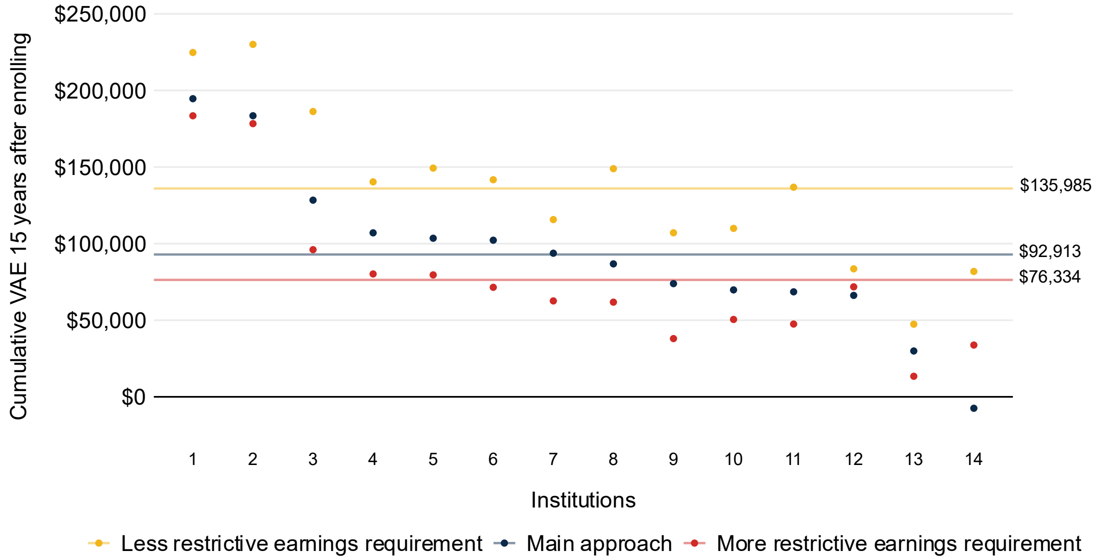
Under both alternative specifications, we continue to treat the absence of observed earnings in a given quarter as having 0 earnings, the same as in our main approach. After repeating our full matching process under each alternative restriction, we reestimate cumulative VAE using our main approach. We compare cumulative VAE under these alternative restrictions to cumulative VAE estimated using our main approach for the 50 percent random sample of institutions.

a. Findings under alternative earnings restrictions

Relative to cumulative VAE estimated using the preferred earnings restriction, institutional cumulative VAE estimates were higher under the less restrictive earnings requirements and lower under the more restrictive earnings requirements for almost every institution (Exhibits E.3–E.5).[84] This was the case for all degree types, and the pattern holds, on average, throughout the follow-up period. At the end of the follow-up period, cumulative VAE in the less restrictive case was $43,072 (46 percent) higher for bachelor's degrees, $11,070 (40 percent) higher for associate's degrees, and $2,452 (32 percent) higher for certificates. In the more restrictive case, cumulative VAE was $16,579 (18 percent) lower for bachelor's degrees, $13,532 (49 percent) lower for associate's degrees, and $2,000 (26 percent) lower for certificates. This pattern is consistent across institutions: for nearly all institutions (12 out of 14 bachelor's, all 29 associate's, and 19 out of 23 certificates), the less restrictive approach generated higher cumulative VAE estimates than the main approach, which generated higher cumulative VAE estimates than the more restrictive approach.

[84] Compared with the full sample of institutions, the 50 percent random sample had average cumulative VAE that was slightly higher for bachelor's degrees and certificates, and similar for associate's degrees (not shown).

Exhibit E.3. Cumulative value-added earnings for bachelor's degree-seeking students under alternative earnings requirements for sample inclusion, 2008–09 entry year



Source: Authors' calculations using Texas administrative data and IPEDS.

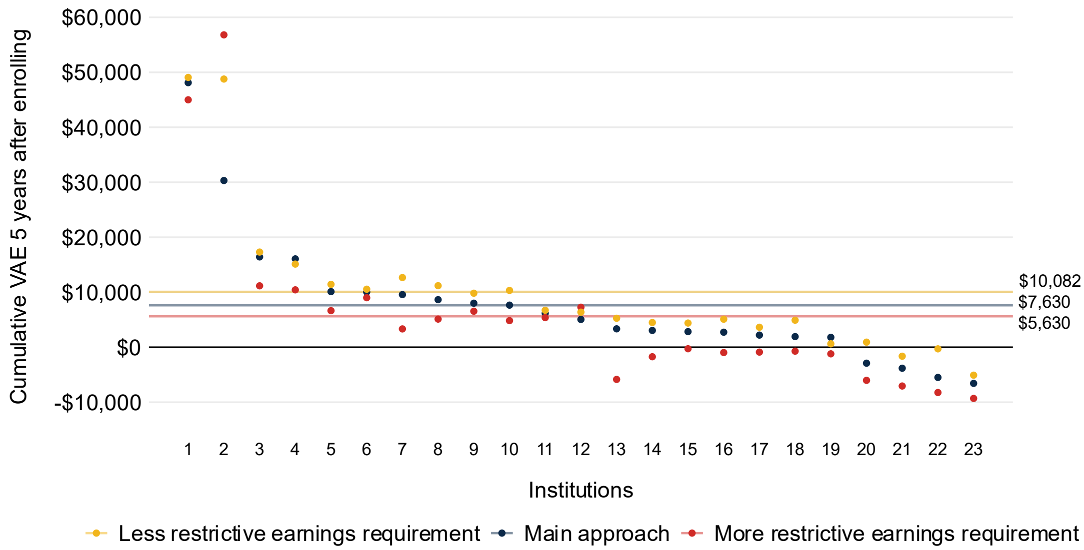
Note: The sample includes 16,268 students under the less restrictive earnings requirement, 14,396 under the main approach, and 11,606 under the more restrictive earnings requirement, all of whom enrolled in bachelor's degree programs in the 50 percent random sample of public postsecondary institutions in Texas in 2008–09. Values are student-weighted averages in 2023 dollars.

Exhibit E.4. Cumulative value-added earnings for associate's degree-seeking students under alternative earnings requirements for sample inclusion, 2008–09 through 2013–14 entry years

Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 310,637 students under the less restrictive earnings requirement, 297,392 under the main approach, and 255,787 under the more restrictive earnings requirement, all of whom enrolled in associate's degree programs in the 50 percent random sample of public postsecondary institutions in Texas in 2008–09 through 2013–14. Values are student-weighted averages in 2023 dollars.

Exhibit E.5. Cumulative value-added earnings for certificate-seeking students under alternative earnings requirements for sample inclusion, 2008–09 through 2018–19 entry years



Source: Authors' calculations using Texas administrative data and IPEDS.

Note: The sample includes 36,357 students under the less restrictive earnings requirement, 36,805 under the main approach, and 33,199 under the more restrictive earnings requirement, all of whom enrolled in certificate programs in the 50 percent random sample of public postsecondary institutions in Texas in 2008–09 through 2018–19. Values are student-weighted averages in 2023 dollars.

There are several potential explanations for the sensitivity of VAE to the earnings requirements. Recall that an individual may not report earnings in the workforce data for four reasons: (1) they were unemployed or not in the labor force, (2) they worked outside of Texas, (3) they worked outside the formal sector, and (4) they worked in uncovered employment in Texas (such as federal or self-employed workers). If enrollment in postsecondary education caused an increase in employment or working in the formal sector, a plausible scenario, then the more restrictive requirement would remove relatively more individuals (with zero observed earnings) from the comparison group, resulting in lower estimated VAE. The reverse is true in the less restrictive case. And, if postsecondary enrollment causes individuals to be more likely to work outside of Texas or become self-employed, then this would result in lower estimated VAE under the less restrictive earnings requirement. Although both of these factors may be at play, the observed pattern suggests that the former dominates the latter.

A final potential explanation relates to the limitations of the NSC data, which we use to determine enrollment in U.S. postsecondary institutions outside of Texas. These data capture out-of-state enrollments that occur within one to two years of high school graduation but would miss out-of-state enrollments after that. Consider an individual with high earnings potential who worked for a year after high school and went on to attend postsecondary education and have earnings outside of Texas. Under the less restrictive earnings requirement, this person would be included in the comparison group and matched to an individual in the treatment group who also had high earnings potential. However, because we could observe neither their enrollment nor their earnings, their inclusion would result in VAE estimates that are too high.

Given the sensitivity of VAE estimates to the earnings restriction, it is important to consider inclusion criteria in a way that attempts to balance the trade-offs between capturing employment effects while limiting the inclusion of individuals whose wages could not be observed. Our choice of inclusion criteria is conceptually motivated by focusing on the period in which we would expect postsecondary completers to accumulate earnings. Although having no observed earnings in this period is a strong indication that earnings could not be observed, we may also inadvertently exclude those not in the labor force or with long-term unemployment spells. The sensitivity analysis shows that these trade-offs can have sizable, though also fairly uniform, impacts on VAE estimates.

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