Who Takes High-Earning CTE Pathways?*

Celeste K. Carruthers† — University of Tennessee
Shaun Dougherty — Boston College
Thomas Goldring — Georgia Policy Labs
Daniel Kreisman — Georgia State University
Roddy Theobald — CALDER
Carly Urban — Montana State University
Jesús Villero — University of Pennsylvania

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Wage gaps across demographic groups in the U.S. labor market are well documented. A key question is the degree to which group-based sorting into high- versus low-paying occupations reflects underlying preferences, versus structural barriers or prior educational experiences. High school Career and Technical Education (CTE) programs offer insight into the preference side of this question, since CTE pathways are largely open-access and allow students to explore a career field without committing to it. We study CTE enrollment patterns across four states and one large metro area to assess if potential pay in students' CTE fields foreshadows longstanding inequities in the labor market. We find that women concentrate in fields linked to jobs with 7–20% lower pay, a range that includes the actual U.S. gender pay gap. We also find disparities in potential pay by race, ethnicity, family income, and disability identification, although these are much smaller and less consistent across locations than the gender gap.

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†Corresponding author: carruthers@utk.edu

1 Overview

Career and Technical Education (CTE) is now a mainstay of the U.S. high school curriculum with students taking more CTE courses on average than any other subject except for English and math (Kreisman & Stange, 2020). CTE courses are organized and sequenced into dozens of multi-course programs that collectively align with nearly all occupations and industries in the modern economy. In Tennessee, for example, Coding I, Coding II, and Computer Science are part of the Coding program of study, which builds skills and knowledge needed for jobs in programming, software development, and computer systems analysis. This program is part of a broad Information Technology career cluster, one of 16 career clusters in a national framework.[1] CTE programs are designed to provide both a bridge to well-paying jobs for non-college bound students, and a head start on more advanced career training for those who seek a college degree.

Enrolling in a technical program can increase the likelihood that a student will graduate from high school or attend college (Hemelt et al., 2019), and improve employment and earnings after school (Brunner et al., 2023; Kemple & Willner, 2008). Kreisman and Stange (2020) likewise find that students who engage more deeply with a CTE program by taking advanced classes in a sequence have higher earnings as adults. Returns to *any* high school CTE differ by field of study, however (Dahl et al., 2023; Ecton & Dougherty, 2023), and males tend to realize a larger payoff from CTE coursework (Bertrand et al., 2021; Brunner et al., 2023; Hemelt et al., 2019; Kemple & Willner, 2008). Mixed results across CTE fields and by gender motivate more scrutiny of who enrolls in CTE and their access to, and take-up of, different CTE fields. In addition, the growing CTE literature underscores the value of studying multiple policy contexts at once since systems and results often vary from one place to another (Kamin, 2023; Kim et al., 2021).

Whether students take any CTE, and which pathway and how many courses they take, are choices that typically come at the expense of other electives. Those choices may have consequences for future earnings, just as in the case of a later set of decisions about college major (Altonji et al., 2016; Arcidiacono, 2004; Zafar, 2013). For example, occupations aligned with the Information Technology cluster pay about twice as much as

[1] For the cohorts we study, the 16 career clusters in the national framework were as follows: Agriculture, Food, & Natural Resources; Architecture & Construction; Arts, A/V Technology, & Communications; Business Management & Administration; Education & Training; Finance; Government & Public Administration; Health Science; Hospitality & Tourism; Human Services; Information Technology; Law, Public Safety, Corrections, & Security; Manufacturing; Marketing; Science, Technology, Engineering, & Mathematics (STEM); and Transportation, Distribution, & Logistics. These 16 were re-organized into 14 clusters in 2024, which would not have affected the cohorts we study. Additional details are at https://careertech.org/career-clusters.

jobs aligned with Hospitality, even without a college degree. Focusing on Massachusetts, Ecton and Dougherty (2023) show that earnings and post-secondary outcomes differ significantly across CTE concentration areas in the years immediately following high school, that women were over-represented in clusters with stronger college pipelines (Health and Education, for example), and that men were over-represented in clusters leading to higher employment and earnings after high school (Construction, Transportation, Manufacturing). Jacob and Ricks (2023) show that women were less likely to engage with high-wage CTE programs in Michigan, and they also report sorting by income and race across schools with different levels of access to CTE.

Aside from the Massachusetts and Michigan studies, we have little understanding of how students sort across CTE fields, or what role schools might play in access to higher-paying CTE fields. It is also unclear if the gender patterns shown in these single-state studies are part of a nationwide pattern. Data limitations have obscured the full picture on these questions, since nationwide survey data such as that used by Kreisman and Stange (2020) cannot account for the role of school offerings, and single-state studies reflect specific contexts and are limited to the first several years after high school. Most states do not have the necessary linkages between K-12, post-secondary, and workforce data to track student earnings after high school or college (Clark, 2022). And while states with robust "P-20W" data systems can accurately capture early-to-mid career outcomes for students who left high school many years ago, this may miss the mark for more recent cohorts and constantly evolving CTE systems.

We surmount these barriers and add to the research literature on CTE choices by studying the universe of public high school students across six cohorts in five states: Massachusetts, Tennessee, Washington state, Montana, and the Atlanta metro region—over 330,000 CTE concentrators in all. We generate prospective measures of potential earnings arising from each of the 16 CTE career clusters by attaching those clusters to average pay in aligned occupations. This allows us to observe which students take CTE coursework leading to potentially high- or low-paying work over the lifecycle. Our findings complement retrospective analyzes that link students' actual post-high school earnings to their CTE pathways using state administrative data or nationally representative surveys (Carruthers & Attridge, 2019; Carruthers et al., 2022; Ecton & Dougherty, 2023; Kreisman & Stange, 2020). These prospective earnings are available for all states, represent all ages and career stages, and absorb any college premium that we might miss by studying early-career earnings in state administrative data. Administrative data is key to our analysis, however, because observing the universe of high school students across several cohorts allows us to control for school-level access to different CTE clusters. By conducting the same analysis in five diverse settings, we are able to distinguish common themes from idiosyncratic patterns that may be attributable to state-specific factors.

The dominant theme that emerges from five diverse socioeconomic settings across the United States is that female students enroll in CTE coursework that aligns with far lower-paying occupations than their male peers, even relative to males attending the same school. The gender gap in potential earnings ranges from 7–20% across the five locations in our study, a range which includes the actual gender pay gap among U.S. workers. This is mostly driven by large female over-representation in clusters that are also female-dominated in the labor market: Education and Training, Human Services, and Health Services. Compared with potential pay gaps by gender, gaps by race, ethnicity, and family income are considerably smaller and more variable.

Our findings highlight the need to understand student CTE choices better, and in particular, why women and to a lesser extent non-White and economically disadvantaged students are more likely to enroll in lower-paying fields of study. There are limitations to the inferences we can draw from these descriptive results, chief of which is that we do not know if inequities in *potential* earnings will manifest as *actual* pay gaps after high school. Earnings after high school will reflect the causal return to coursework choices more broadly, including the choice of whether to concentrate in CTE at all, effects of other school inputs, college enrollment, and self-selection into particular jobs based on unobservable factors.[2] Nonetheless, these descriptive patterns expand on what others have shown regarding the greater tendency for young men to enroll in STEM in high school and college (Ahimbisibwe et al., 2025; Card & Payne, 2021; Delaney & Devereux, 2019; Dougherty & Harbaugh Macdonald, 2020; Legewie & DiPrete, 2014; Li et al., 2025; Sadler et al., 2012), by showing that there is gender segregation in high school coursework aside from STEM.

Moreover, our results contribute to a robust literature tying gender segregation in the labor market to college major choices and preferences for job amenities and flexibility (Blau & Kahn, 2017; Cortes & Pan, 2018; Goldin, 2014; Wiswall & Zafar, 2018, 2021). Individuals' occupational and college major choices are strongly influenced by prior educational experiences, and high school CTE choices provide a window into the extent to which future wage gaps may be driven by *initial* occupational preferences. CTE pathways are the earliest career-related decisions we can observe, pre-dating college major choices and full-time labor market entry. Our finding that the potential wage gap in high school

[2]Cleanly separating the return to CTE clusters when there are many choices, as is the case here, requires not only an instrument for each CTE cluster, but also knowledge of each student's next preferred option, as in Kirkboen et al.'s (2016) identification of returns to different college majors.

CTE course taking largely mirrors the observed U.S. wage gap suggests that these initial preferences are an important mechanism for explaining future wage gaps.

2 Data

We rely on student-level data describing course-taking, achievement, and demographic records for sequential cohorts in five geographically and economically diverse locations: Massachusetts, Montana, Tennessee, Washington state, and the Atlanta metro region (the Atlanta metro sample is comprised of data from five individual school districts). Each of the four state samples span 2009–2014 ninth grade cohorts, and for Atlanta, we study 2010–2014 cohorts. We limit our analysis in each location to students whom we observe for at least four years of high school, regardless of graduation status. This allows us to observe students who had sufficient time to complete high school and the opportunity to enroll in a CTE program of study.

In total, our sample includes over 1.2 million individual students, with just fewer than 70,000 in each of Atlanta and Montana, and approximately 350,000 in each of Tennessee, Massachusetts, and Washington. These five locations encompass very different economies, from Atlanta's urban business hub, to Montana's agriculture, tourism, and natural resource industries, to manufacturing and logistics in Tennessee, to technology and life sciences in Massachusetts and Washington. Each location has urban and suburban areas, and the four state samples have many rural areas as well. Atlanta's population is majority non-White, whereas the White non-Hispanic population ranges from 64-83% across the four states. Educational attainment varies widely across the five locations as well, from 30-35% with a bachelor's degree or higher in Montana and Tennessee, to 58% in Atlanta.

CTE systems are also very different across the five locations. In Massachusetts, most CTE concentrators are in standalone technical schools, whereas CTE is more integrated into comprehensive high schools in the other four locations. Concentrating in CTE is an elective choice in all five settings, although in Washington, students need to take at least one occupational credit in order to graduate high school. The percent of high school 12th graders who are CTE concentrators varies from 20% in Massachusetts, just under 30% in Washington, to nearly 50% in Montana and Tennessee (Urban et al., 2022).

Each dataset is siloed as data use agreements do not allow us to pool student-level data from multiple locations. In lieu of a pooled analysis, we harmonize measures to be as comparable as possible across sites, and we estimate all analyses separately for each location.

Our goal is to observe which students take CTE courses that lead to potentially higher or lower paying occupations. This requires first constructing the potential earnings associated with each CTE cluster in each location. We do so by merging three sources of information: (1) data on students and their CTE coursework; (2) a crosswalk connecting CTE fields of study to occupations; and (3) a localized measure of earnings for these occupations. We describe the construction of each of these below.

2.1 Identifying CTE Fields

For the purposes of federal reporting, a CTE concentrator is any student who has completed at least two courses in a single CTE program of study. We might like to identify a student's CTE field as the program or programs where they meet the two-course threshold. But states have discretion in applying and adapting the federal definition, and they differ in the number of courses required for concentrator designations as well as the number and type of programs they offer over time. In addition, CTE programs in the same broad career cluster overlap to varying degrees in their content and aligned occupations. With this in mind, we broaden our view of CTE fields beyond the program level and identify the CTE career cluster where a student could potentially call themselves a concentrator. Atlanta, Tennessee, and Washington organized CTE around the 16-cluster national framework for these cohorts. Massachusetts offered 13 of 16, omitting Education & Training, Finance, and Government & Public Administration. Montana had six clusters in total, with two that aggregated several of the others from the standard set.[3]

In Massachusetts and Montana, we associate students with a CTE cluster if they completed two courses in an aligned sequence in that cluster, consistent with those states' concentrator definitions. In Tennessee and Washington, CTE coursework is more integrated with the comprehensive high school curriculum, and students tend to take more CTE courses whether or not they concentrate in a particular field.[4] This leads to more false positive concentrator designations under a two-course rule. Accordingly, we use a three-course rule to associate Tennessee and Washington students with CTE clusters and better identify advanced progression through a CTE program. In Atlanta, we do not directly observe students' concentration status, but instead we observe whether a student

[3]Montana's Family and Consumer Science cluster includes material from Arts, A/V, & Communications; Education & Training; Hospitality & Tourism; and Human Services. Industrial Technology combines Architecture & Construction; Manufacturing; STEM; and Transportation, Distribution, & Logistics.

[4]In Tennessee, many courses can count toward a CTE concentration as well as general education requirements. For example, Statistics can be taken as part of the Accounting pathway in the Finance cluster, and AP Biology can count toward a STEM concentration and/or a required science credit. Washington has a one-credit CTE requirement, and a large number of students sample 1-2 CTE courses without concentrating.

took a final course in one area of CTE, which typically indicates that a student completed the program. Our course-based rules will identify students who invested a similar degree of time in CTE programs across locations, but they will not necessarily identify students who met each location's formal definition of a CTE concentrator. Official concentrations can depend on factors that we do not observe, such as a school being approved to offer a particular CTE program, or a student having taken a specific sequence of courses.

Student-level data from each location allow us to observe individual characteristics such as race, Hispanic ethnicity, gender, disability status, and, in three of the five sites, whether students were ever eligible for free or reduced-price meals. Having access to subsidized meals in school is a proxy for lower family income. We also observe standardized end-of-course test scores in math and English in Atlanta, Tennessee, and Washington, but only math in Massachusetts and neither subject in Montana.

2.2 Connecting CTE Clusters to Occupations

By design, CTE programs are aligned with specific occupations. We leverage a crosswalk from the Economic Development and Employer Planning System (EDEPS, https://edeps.org) that links CTE clusters and programs to their most related occupations, as defined by the 2010 Standard Occupational Classification (SOC). For example, municipal clerks (#43-4031 in the 2010 SOC) are most aligned with the Government and Public Administration CTE cluster, and agricultural equipment operators (#45-2091) are linked with the Agriculture, Food, and Natural Resource cluster. The EDEPS crosswalk updates a similar 2007 mapping by the U.S. Department of Education, adding new occupation titles from later versions of the SOC.

2.3 Creating Potential Earnings for Each CTE Cluster

We next generate a measure of potential earnings for each cluster. This is not meant to identify what students will earn, nor what they can earn. Rather, it is intended to represent the typical earnings of workers in jobs aligned with their cluster, i.e., what one could reasonably expect to earn with their CTE concentration. We begin by calculating median annual earnings for each state-occupation (or metro-occupation, for Atlanta), using the May Occupational Employment Statistics from the Bureau of Labor Statistics (BLS) for the years 2010–2018, over which time SOC codes are consistent. We translate earnings into real 2018 dollars. This gives us median earnings in each location and year for each occupation. These earnings represent all experience levels, not just the starting pay a student might expect to earn immediately after they leave school, whether they stop with a high school diploma or college credential.

Nonetheless, many occupations are out of reach without a college education. We merge occupation-level earnings and employment to the typical entry-level education requirement for each occupation, as determined by the BLS.[5] For our main analysis, we omit occupations that typically require a college education and focus on potential earnings with no more than a high school diploma. Potential earnings with and without a college degree are highly correlated across CTE clusters, and except where noted, results are not overly dependent on this choice.

Having identified median earnings and total employment at the location-occupation-year level, we then create employment-weighted averages of median wages for all occupations that are aligned with each CTE cluster in each location:

$$\text{Potential Earnings}_{\text{Cluster}=C} \equiv \sum_{\text{Occ} \in C} (\text{Median Earnings Occ}_o) \times \underbrace{\left(\frac{\text{Employment in Occ}_o}{\text{Total Employment in } C} \right)}_{\text{Employment Share}} \tag{1}$$

The right-hand side of Equation 1 takes the average of median earnings of each occupation (o) aligned with cluster C (the first term), weighted by o's share of employment for all occupations aligned with that cluster (the second term). Appendix Table A3 provides an example for occupations associated with the Finance cluster in the Atlanta metro region in 2018. In cases where students concentrated in more than one cluster, we assign proportional shares. For example, if a student concentrated in two clusters j and k, we calculate their potential earnings projections as $0.5 * earnings_j + 0.5 * earnings_k$.

This process reveals that occupations aligned with Information Technology have the highest median earnings without a college degree, although the Arts, A/V, Tech and Communications cluster, along with Government and Public Administration also align with high paying jobs that do not typically require a college degree. Conversely, workers in Hospitality and Tourism, Human Services, and Education and Training earn far less annually than those in other fields. Business, Management and Administration, Marketing, and Health Science are often touted as high-wage fields, but as we show in Appendix Figures A1, A2, and A3, they actually have relatively low earnings potential without a college degree.

[5] BLS's Employment Projections program assigns each detailed occupation a "typical education needed for entry," defined as the education level most workers need to enter the occupation. Assignments are made by BLS economists using both quantitative data (including ACS attainment data, O*NET requirements information, and NCES program-completions data) and input from employers, educators, workers, and professional/trade groups. The listed entry-level education assignment represents the most common path into the occupation, with alternative entry pathways discussed in the narratives of the Occupational Outlook Handbook. See U.S. Bureau of Labor Statistics, *Measures of Education and Training*, August 28, 2025, https://www.bls.gov/emp/documentation/education/tech.htm.

2.4 Analysis Sample

The final analysis sample in each location consists of one observation for each student, the cluster(s) they concentrated in (if any), potential earnings with a high school diploma in that cluster, and additional information such as student demographics and test scores. This allows us to evaluate the potential earnings arising from CTE coursework taken by students with different characteristics.

The Appendix includes summary statistics describing students and potential earnings in greater detail. There, we show that students across the five sites differ widely in their choice of CTE fields (Table A1) and socioeconomic characteristics (Table A2). We additionally find no consistent pattern between cluster popularity and potential earnings; high paying clusters have greater enrollment in some but not all settings (Figure A4).

3 Results

First, we ask whether students sharing certain characteristics—gender, race/ethnicity, family income, or disability identification—are more or less likely to concentrate in clusters that lead to higher-earning occupations. To answer this, for each cluster in a given location, we calculate the share of concentrators in that cluster and location who have select characteristics. For example, consider gender for the 16 CTE clusters in the Atlanta metro region. For each cluster, we calculate the share of all Atlanta concentrators in that cluster who are female. We then plot median potential earnings for each cluster against the percent of concentrators who are female. We compute a summary measure of the relationship between potential earnings and gender shares by fitting a linear slope, weighted by the total number of concentrators in a given location and cluster. We then replicate this analysis by race and ethnicity, free- and reduced-price lunch status, and disability status. Results are illustrated in Figures 1–4.

3.1 Gender

In Figure 1, our most striking finding is that female CTE students consistently concentrate in fields with lower expected pay after high school. There is a steep negative relationship between clusters' potential earnings and the percent of concentrators who are women, and this is consistent across the five sites we study. Focusing on Atlanta, for example, roughly 40% of students in the metro area's Information Technology cluster are female, and earnings without college in Atlanta-area Information Technology jobs are just over $50,000. On the other hand, approximately 65% of concentrators in Human Services are female, with potential earnings of just over $25,000. The clear negative relationship indicates that female students are enrolling in CTE clusters with far lower potential earnings than their male counterparts.

This pattern is consistent across all states, and is largely driven by the same clusters. In all locations, female students are more likely to concentrate in Health Science, Human Services, Hospitality and Tourism, and Education, all of which are tied to occupations that tend to pay less than other fields without a college education. As we discuss in Section 3.4, we find a smaller but nonetheless significant amount of gender inequality in potential college-level wages. Females' over-representation in Health Science would narrow the gap on its own, but this is offset to a degree by increases to potential college-level earnings for males, who tend to be better represented in Information Technology, STEM, and Finance.

3.2 Race/Ethnicity, Family Income, and Disability Status

We then repeat this same exercise for race and ethnicity (Figure 2), free or reduced-price meal status (Figure 3), and disability status (Figure 4). For race and ethnicity, because the five locations have different racial and ethnic compositions, focusing on any one group often leaves insufficiently large sample sizes in other states. We harmonize race/ethnicity subgroups to the extent possible across locations by comparing potential earnings with the percent of non-White or Hispanic students in each cluster. We acknowledge the limitation of this decision and note that in location-specific regression analyses to follow, we are able to control for richer measures of each area's racial and ethnic composition.

In Atlanta and Massachusetts, clusters with more non-White or Hispanic students tend to have lower potential earnings (Figure 2). In both locations, concentrators in high-paying Information Technology are less likely to be non-White or Hispanic, whereas concentrators in lower-paying Human Services and Hospitality and Tourism are more likely to be non-White or Hispanic. The relationship is also negative in Tennessee and Montana, but not as pronounced. Concentrators in Washington state noticeably depart from this pattern, in that Washington's non-White concentrators are better represented in higher-paying fields like STEM, Architecture and Construction, and Government. The positive relationship in Washington is driven primarily by Asian students, who are the second-largest group of non-White students in the state. We return to these relationships in more detail in regression analyses to follow.

We demonstrate a similar pattern when we compare potential earnings with the share of a cluster's concentrators who are eligible for free or reduced-price meals (FRPM), a proxy for low family income. Across the three locations where we observe FRPM status (Atlanta, Massachusetts, and Washington), Figure 3 shows that clusters with more students who were ever FRPM-eligible concentrate in fields that typically earn less after high school, especially in Atlanta and Massachusetts.

Turning finally to disability status, in Figure 4 we show that Atlanta's lower-earning clusters tend to have more students with identified disabilities. The relationship is also negative in Washington but much more muted than in Atlanta. By contrast, Montana's Industrial Technology cluster has one of the state's highest disability rates and is also aligned with higher-paying jobs, on average. There is very little relationship between earnings and disability status in Massachusetts or Tennessee.

3.3 Regression Analysis

While Figures 1–4 demonstrate average, unconditional relationships between demographic characteristics and CTE clusters aligned with high- and low-earning occupations, they do little to tell us if these relationships reflect differences in access to high-paying clusters. For example, we observe a negative relationship in three locations between the share of students in a cluster who were ever FRPM eligible and median earnings among workers in occupations aligned with that cluster. Could this be because schools with high FRPM eligible populations offer fewer courses in high-earning pathways, or does this relationship hold even when students face the same set of course options within schools? The latter possibility was one concern of school counselors who were surveyed by Ansel et al. (2022).

The question of access across schools versus take-up within schools is particularly important for states like Massachusetts, where CTE is concentrated in "wall-to-wall" technical schools. More generally, we might expect concentrators to be more evenly distributed across clusters in places like Atlanta, Tennessee, and Washington, where CTE programs are diffused more widely across all public high schools and where a larger percentage of students concentrate in CTE. Montana has a high concentration rate as well, but with a limited menu of CTE programs in the state's six-cluster aggregation.

To explore these possibilities, we estimate regression models that relate potential earnings to student characteristics illustrated in Figures 1–4 as well as additional controls for student achievement and school fixed effects. Our regression specification, estimated separately for each location, takes the following form:

$$y_{its} = \alpha + X_{it}\beta + \tau_t + \phi_s + \epsilon_{its} \tag{2}$$

Equation 2 describes student i in ninth-grade cohort t, who attended high school s. The outcome y represents log potential earnings aligned with the student's cluster or clusters, calculated by Equation 1. As in Figures 1–4, our main analysis focuses on potential earnings with a high school diploma. With notable exceptions described below, our conclusions are very similar when y represents potential earnings with a college education. We estimate potential earnings where y is measured in inflation-adjusted and logged 2018 dollars, so $\hat{\beta}$ quantifies differences in potential earnings in percentage terms. The vector X is a set of descriptive characteristics for each student, including gender, race and ethnicity, disability, FRPM eligibility status, and math and English Language Arts test scores. Across models, we control for cohort fixed effects (τ_t) and school fixed effects (ϕ_s), which allows us to compare differences in potential earnings for students who faced the same CTE course offerings.

Table 1 reports Equation 2 results. Our headline result is that women typically concentrate in lower-paying CTE clusters. Female students in Atlanta and Washington concentrate in clusters with aligned occupations that have 9-10% lower expected earnings. In Tennessee, Montana, and Massachusetts, differences in earnings are larger: 15% in Tennessee, 18% in Massachusetts, and 20% in Montana. In annual wage or salary terms, these equate to between $3,600 and $7,500 lower expected earnings for women. We reiterate that these are potential and not actual gender pay gaps arising from differences in how males and females choose CTE fields. If CTE concentrators went directly to work in occupations aligned with their cluster and received the median annual earnings for that cluster, results indicate that females would earn between 9 and 20 percent less than their male peers who graduated from the same high school. This range includes the 18% unconditional gender pay gap in median earnings among U.S. workers over the last 20 years (Aragão, 2023), suggesting that labor market segregation begins early, even in vocational oriented fields.

Turning to race and ethnicity, we find relatively small gaps in potential earnings between White and non-White CTE students. "Other" race/ethnicity students have a wide diversity of backgrounds across locations, and their potential pay relative to White students ranges from 1% less (a statistically insignificant difference) to 5% more. Black students concentrate in clusters with around 1-4% lower earnings than White students, and Hispanic students similarly have 0-4% lower potential earnings. Unlike the gender gap in potential pay, the 0-4% scale of Black-White and Hispanic-White gaps is considerably smaller than actual race and ethnicity pay gaps in the U.S., which currently measure 19% for Black workers and 24% for Hispanic workers (Bureau of Labor Statistics, 2023).

In the three locations where we observe FRPM status, estimates in Table 1 suggest that lower-income students concentrate in CTE fields with a similar level of potential earnings as non-FRPM students, or at most 2% less than non-FRPM students. Differences across students with and without disability identifications are also inconsistent across locations, ranging from parity in Tennessee to a 4% shortfall for disabled students in Atlanta. Although 4% is small compared to the gender gap, it is nonetheless larger than Atlanta's Black-White and Hispanic-White gaps. Finally, we find that students with higher math and English achievement enroll in clusters that lead to higher earnings, by 1-2% with a high school diploma.

3.4 Potential Earnings with a College Education

Gender gaps in potential earnings are primarily driven by female over-representation in Education and Training, Health Science, Hospitality and Tourism, Marketing, and Human Services (or in Montana, Family and Consumer Science), which are lower-paying fields for workers without a college education. For Health Science and Marketing, there is a wide gap between earnings with a high school diploma versus a college degree (shown in the Appendix, Figure A2), and it is possible that women who concentrate in these CTE fields are looking ahead to higher-paying pathways that include college. But it is not *a priori* clear that females would reach parity in potential college-level pay, since males tend to be better represented in fields with particularly high pay after college, such as STEM and Information Technology.

Table 2 reports Equation 2 regression results when we define y as equal to employment-weighted expected earnings in aligned occupations that typically require a college education. We construct y using Equation 1, as in the main analysis, but for occupations requiring college at the entry level and their median earnings in each location. Results for college-level potential earnings are broadly in agreement with our conclusions for potential wage gaps in terms of high school-level earnings. The gender gap in aligned college-level earnings is smaller, 7-12% in Table 2 rather than 9-20% in Table 1, but nonetheless larger and more consistent across locations than potential earnings gaps by race, ethnicity, income, disability identification, or achievement. The gender gap in potential earnings would narrow further if we accounted for women's higher rate of college attendance. Across the five locations, 18-20 year-old women were 1-6 percentage points more likely to be in college than 18-20 year-old men.[6] Even with 100% college graduation rates, this is not a large enough difference in potential access to college-level jobs to close the gender gap estimates shown in Table 1 and Table 2. Our takeaway inference is that gender gaps in

[6] Authors' calculations using the 2010 - 2018 American Community Survey (Ruggles et al., 2025), limited to high school graduates age 18-20. We assume that each respondent attended high school where they lived one year prior to being surveyed.

potential pay are large and consistent across locations, particularly among students who do not plan to go on to college.

These findings are consistent with what Imberman et al. (2025) report for post-college earnings by gender and race/ethnicity in Texas. They likewise find that gender gaps in earnings are substantially larger than race/ethnicity gaps, and that differences in college major choice explain less of the latter than the former. In the college-educated population more generally, women tend to have bachelor's degrees that are associated with lower median pay than men, while non-White and Hispanic workers have equal-to-higher potential pay than White workers, based on degree field.[7] One potential explanation for narrower race/ethnicity gaps than gender gaps in potential earnings is the possibility that the gender gap is narrower or reversed for some race/ethnicity groups. In extended results for three of the five locations, we find that the gender gap in potential earnings is indeed somewhat larger for White non-Hispanic students than for non-White and/or Hispanic students. While the differences are statistically significant in all three locations, they are subjectively small, measuring 1.1 log points or less.

Our multi-state research design allows us to look across Tables 1 - 2, and across samples within each table, to identify themes that may be related to cross-state differences in CTE systems. One consistent pattern is that Washington tends to exhibit the narrowest gap in potential pay, by gender, race, ethnicity, income, and achievement. Notably, this is also the setting where all students have to at least minimally engage in CTE to satisfy a graduation requirement. This may have led to more evenness in cluster choices for those who went on to concentrate. By contrast, Massachusetts, Montana, and Tennessee exhibit the widest within-school gaps in potential earnings by gender and race, although CTE is more of an elective pathway in these settings. Massachusetts, with whole-school models that may be the most choice-dependent of the five, exhibits the largest gender gap in potential earnings without college and the second-largest behind Tennessee in terms of college-level earnings. When students have more choice over their CTE options (or when they have to exert more choice), we find that they tend to group into clusters with more of the same gender, and that these choices correlate with earnings potential.

[7] Authors' calculations using 2010-2018 American Community Survey data (Ruggles et al., 2025). For college-educated individuals in the workforce, we compute potential earnings as equal to the median wage and salary income by bachelor's degree field/major. Women have 9-13% lower potential earnings than men in the five locations we study, whereas Black, Hispanic, and other non-White workers have statistically equivalent or higher potential earnings than White workers. We also find that field-of-degree fixed effects explain 14–35% of the gender gap in wage and salary income across the five locations, but explain little to none of the gaps by race and ethnicity.

4 Discussion and Conclusion

Our major takeaway from this analysis is that, across five very different economic and educational settings across the U.S., students enroll in CTE fields in ways that foreshadow pay inequalities in the labor market. Most prominently, we find that women are more likely to concentrate in CTE clusters that are aligned with lower-paying occupations than their male peers, suggesting that gender-based occupational sorting begins at the earliest point students make career-related choices, well before college or labor market entry. These sorting patterns are consistent with women generally experiencing a lower or negligible income premium from CTE coursework, as found in experimental and quasi-experimental contexts (Bertrand et al., 2021; Brunner et al., 2023; Kemple & Willner, 2008), as well as gender differences in preferences over post-secondary fields of study (Ahimbisibwe et al., 2025). We also find that Black, Hispanic, lower-income, and disabled students tend to concentrate in CTE clusters with lower potential earnings, but by a much smaller 0-4% magnitude compared with 7-20% gender gaps. These conclusions are robust to controls for student achievement and school fixed effects, suggesting that academic ability and school-level availability are not the dominant reason why women and, to a lesser extent, non-White, lower income, or disabled students concentrate in lower-paying CTE fields. A primary policy conclusion from this analysis, then, is that the opportunity and outcome gaps between different subgroups of K-12 students may depend in part on how they sort into different CTE fields.

This policy conclusion comes with three important caveats. The first is that our analysis is descriptive and does not identify the causal effect of particular CTE fields or CTE more broadly over a student's next best available option. We do not observe counterfactual potential earnings arising from the courses these students would have taken in the absence of existing CTE programs. High school students have time constraints and evaluate their CTE options alongside other academic and elective courses. Enrolling in a high-paying CTE field may nevertheless reduce potential earnings by crowding out even more promising options. On the other hand, it is possible that CTE programs—despite the inequities in CTE concentration rates documented here—have helped close opportunity and outcome gaps in these states and districts. Results here suggest that at the very least, were students to undertake careers aligned with their CTE programs, we would expect meaningful and disproportionate earnings gaps, especially between men and women. Based on CTE fields alone, concentrators could approach or exceed the U.S. gender gap in earnings.

Second, we determine potential earnings from the cluster where a student concentrated, but this could be more tailored to account for the program within a cluster that a student followed, as well as sampling and mixing 1 - 2 CTE courses without concentrating. This is a fruitful direction for future research.

The final caveat is that a student's decision to concentrate in a specific CTE cluster is likely a result of personal, family, teacher, community, and school influences, none of which we are able to disentangle in this analysis. Our main takeaway across five K-12 settings is that women and men choose very different CTE pathways, but our observational data on course-taking do not allow us to unpack why this is the case. A large literature on gender gaps in STEM education offers several candidate explanations. These include different family expectations for men than for women (Attanasio & Kaufmann, 2014), stereotying from teachers (Carlana, 2019), errors in estimation of relative performance (Owen, 2023), and avoidance of certain fields in anticipation of discrimination (Exley et al., 2024; Lepage et al., 2025). Perhaps most importantly, young men and women simply have very different preferences over fields of study and potential occupations (Ahimbisibwe et al., 2025; Zafar, 2013). Our findings add to this vein of research by showing that students appear to exercise those preferences in high school, at essentially their first opportunity to engage in career preparation at school.

As such, the specific mechanisms for reducing inequalities in CTE cluster participation are unclear, and efforts to reduce gender gaps in high-paying fields may do very little to change deep-rooted student preferences. The consistency of gender gaps across five diverse settings—unlike race/ethnicity, income, and disability gaps—suggests this is not addressable through local policy or practice alone and requires understanding deeper preference formation processes. That said, there seems to be little downside to states and districts better publicizing potential earnings within different CTE clusters to students, teachers, families, and communities, tracking the sorting of specific subgroups of students to specific CTE clusters to address potential inequities in real time, and working directly with schools to ensure equitable access to all CTE programs in their school. In doing so, districts and states may be able to address inequities in CTE participation and help forestall longstanding income inequality in the labor market.

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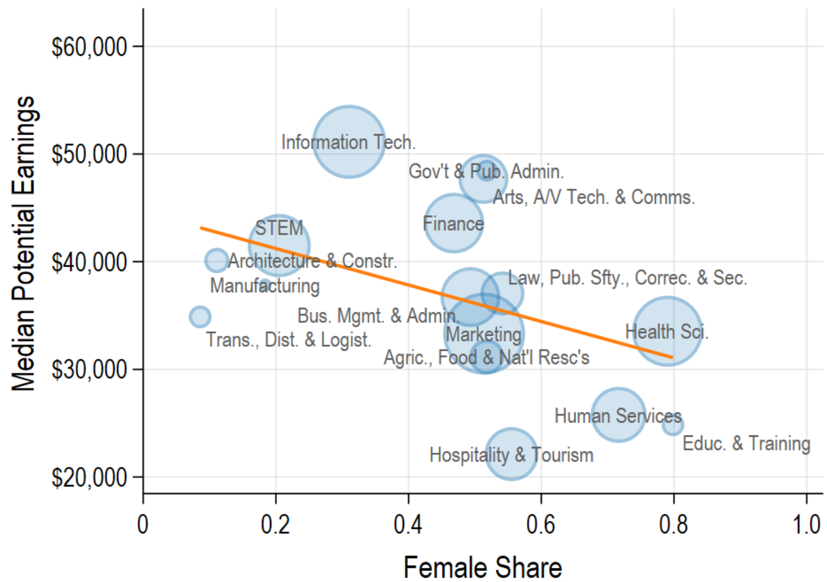
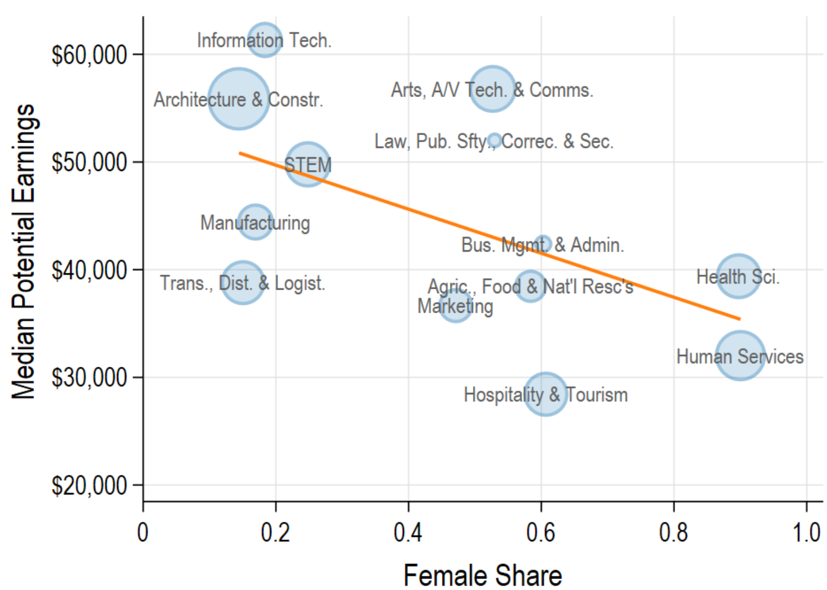
Tables and Figures

Figure 1. Potential Earnings by Share of Concentrators Who Are Female

(a) Atlanta Metro Area



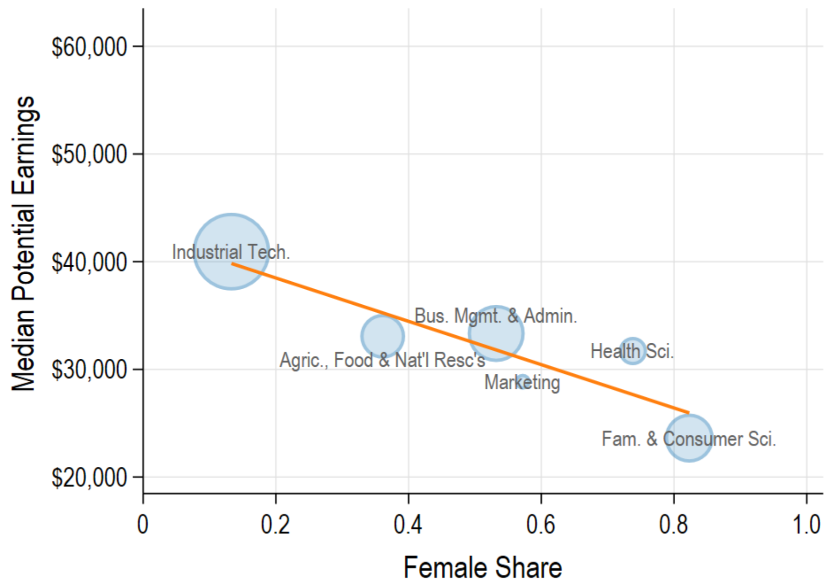
(b) Massachusetts



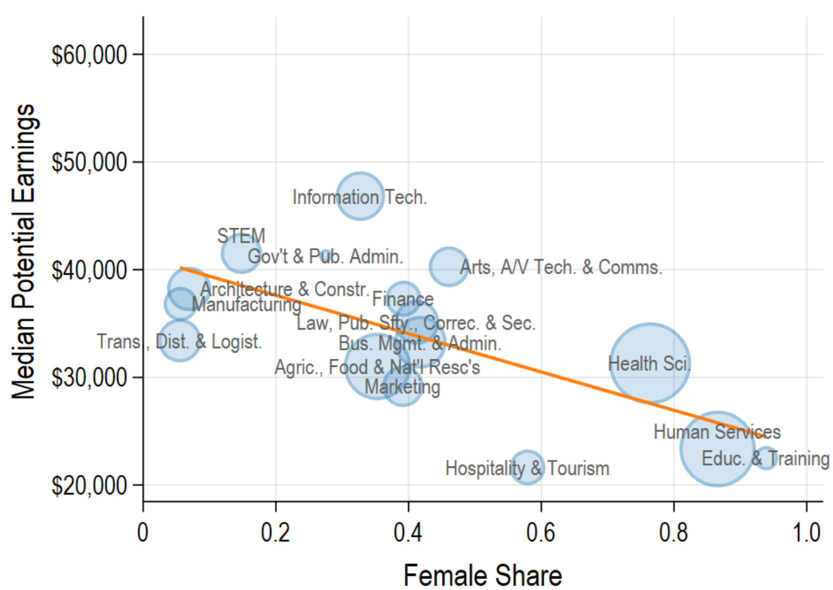
Notes. The figures plot potential earnings (weighted average median earnings) by the share of concentrators in each cluster who are female. Earnings are in inflation-adjusted 2018 dollars. Marker size is in proportion to total cluster enrollment. Data are pooled over all years.

Figure 1, continued. Potential Earnings by Share of Concentrators Who Are Female

(c) Montana



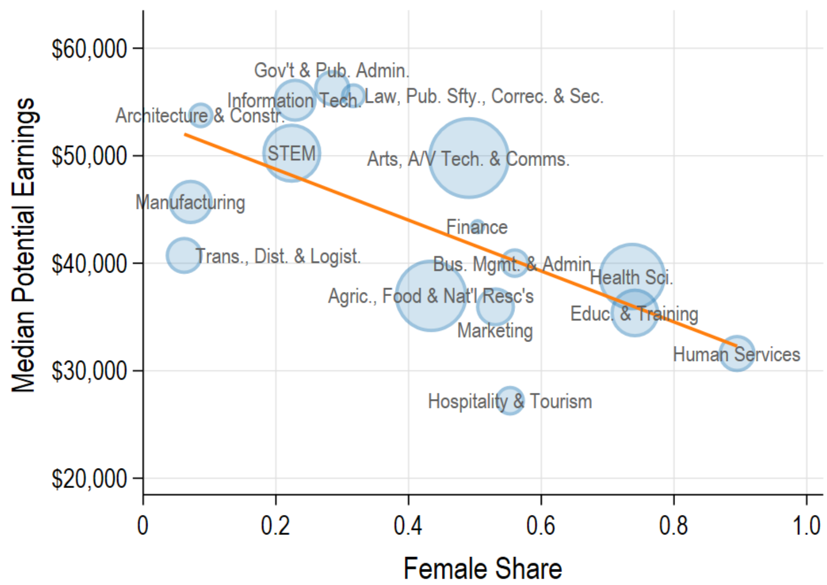
(d) Tennessee



Notes. The figures plot potential earnings (weighted average median earnings) by the share of concentrators in each cluster who are female. Earnings are in inflation-adjusted 2018 dollars. Marker size is in proportion to total cluster enrollment. Data are pooled over all years.

Figure 1, continued. Potential Earnings by Share of Concentrators Who Are Female

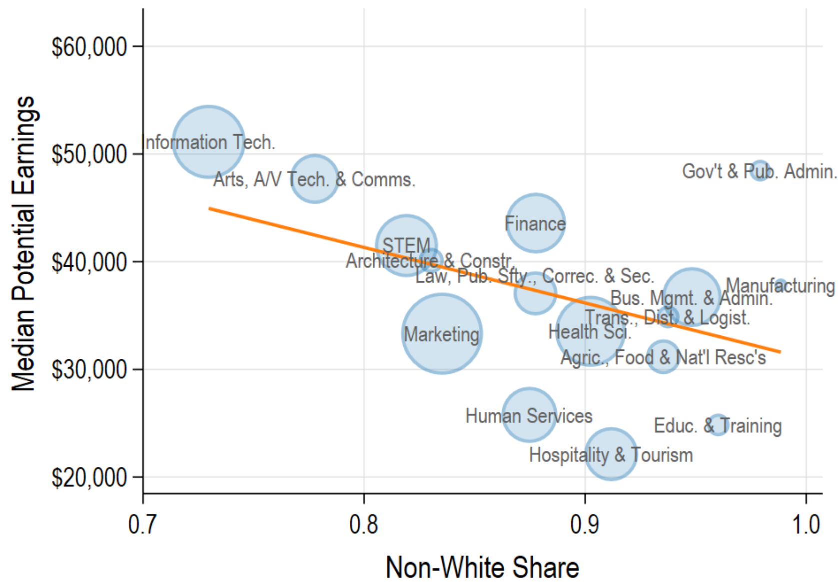
(e) Washington



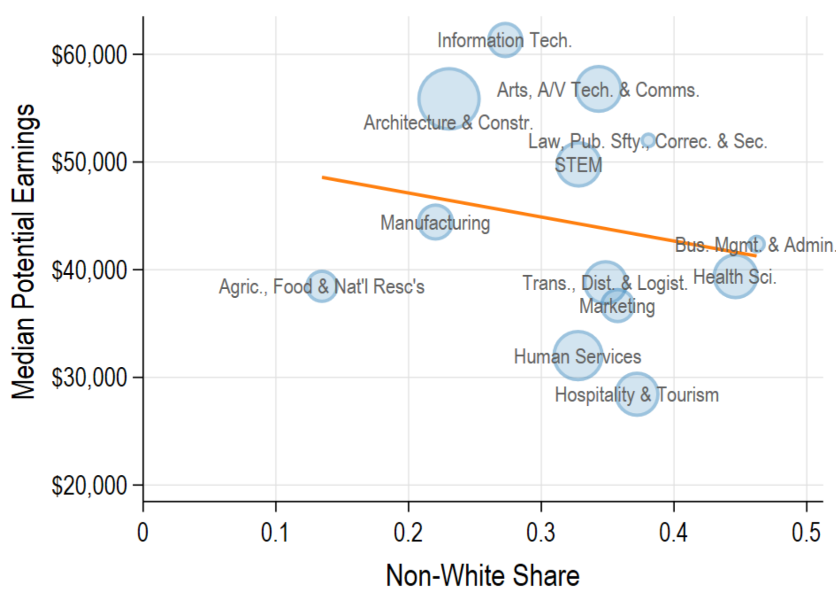
Notes. The figures plot potential earnings (weighted average median earnings) by the share of concentrators in each cluster who are female. Earnings are in inflation-adjusted 2018 dollars. Marker size is in proportion to total cluster enrollment. Data are pooled over all years.

Figure 2. Potential Earnings by Share of Concentrators Who Are Non−White

(a) Atlanta Metro Area



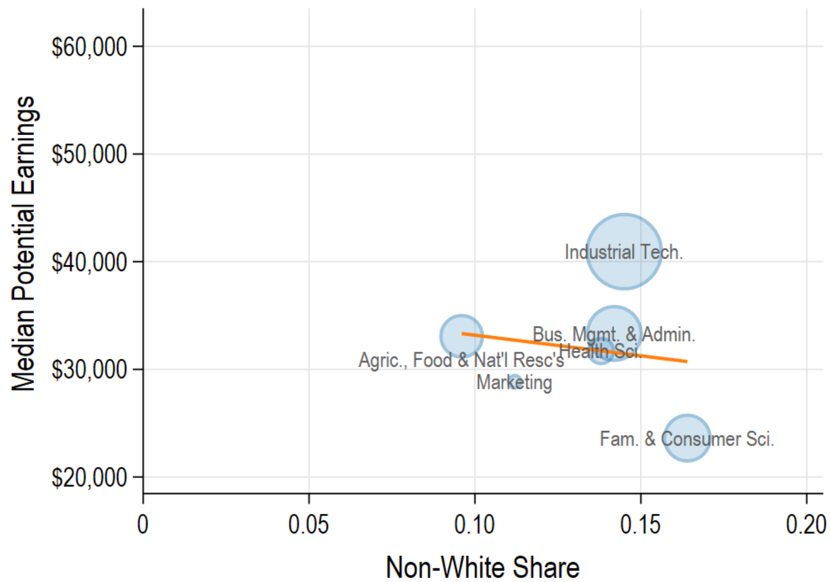
(b) Massachusetts



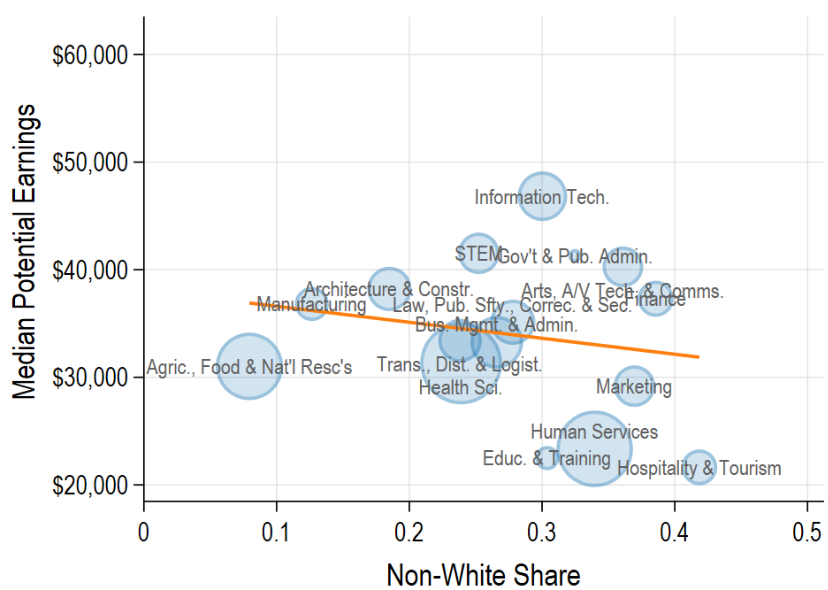
Notes. The figures plot potential earnings (weighted average median earnings) by the share of concentrators in each cluster who are non−White. Earnings are in inflation-adjusted 2018 dollars. Marker size is in proportion to total cluster enrollment. Data are pooled over all years.

Figure 2, continued. Potential Earnings by Share of Concentrators Who Are Non−White

(c) Montana



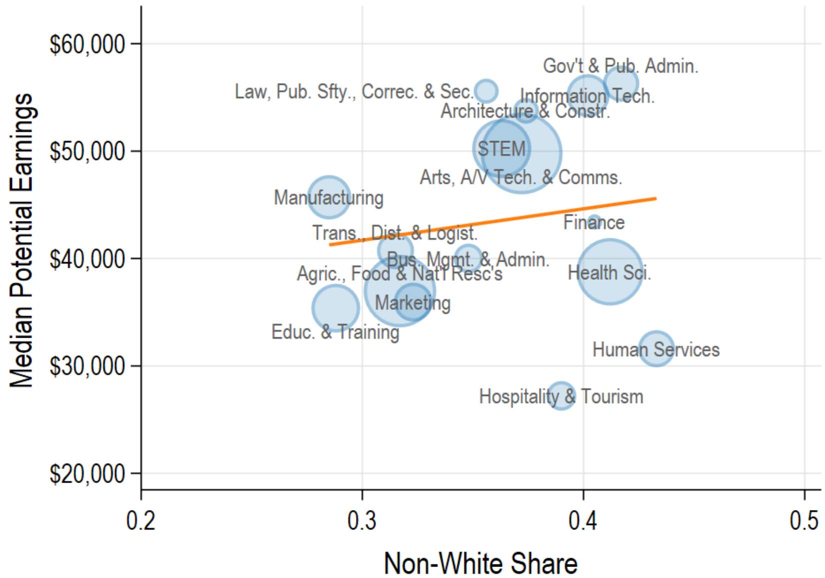
(d) Tennessee



Notes. The figures plot potential earnings (weighted average median earnings) by the share of concentrators in each cluster who are non−White. Earnings are in inflation-adjusted 2018 dollars. Marker size is in proportion to total cluster enrollment. Data are pooled over all years.

Figure 2, continued. Potential Earnings by Share of Concentrators Who Are Non−White

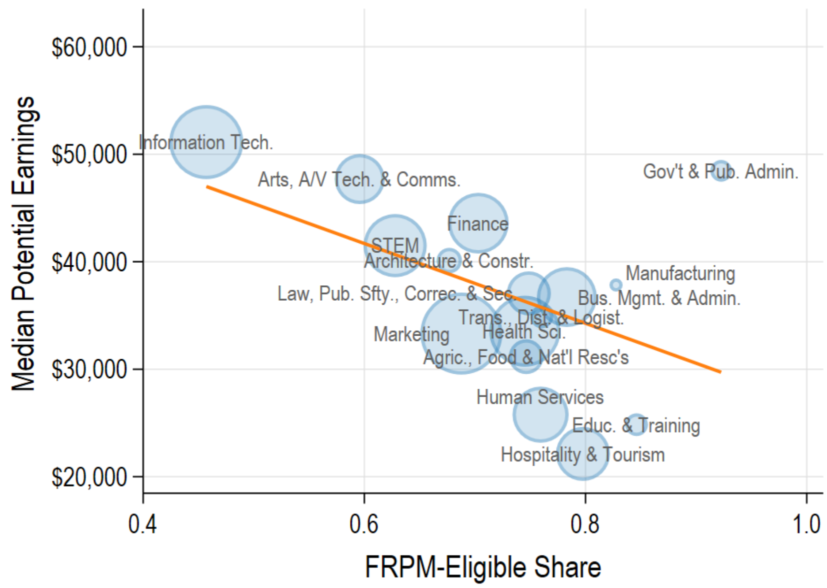
(e) Washington



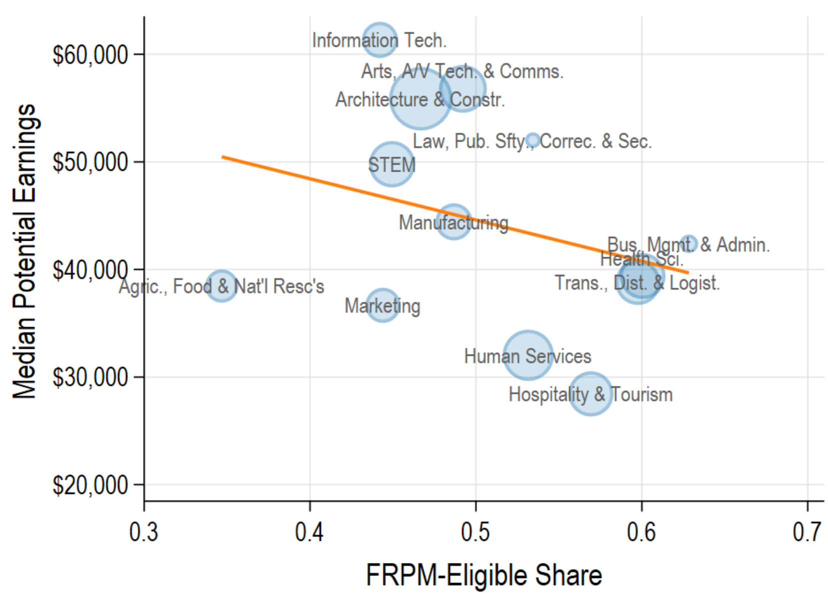
Notes. The figures plot potential earnings (weighted average median earnings) by the share of concentrators in each cluster who are non−White. Earnings are in inflation-adjusted 2018 dollars. Marker size is in proportion to total cluster enrollment. Data are pooled over all years.

Figure 3. Potential Earnings by Share of Concentrators Who Receive Free or Reduced−Price Meals

(a) Atlanta Metro Area



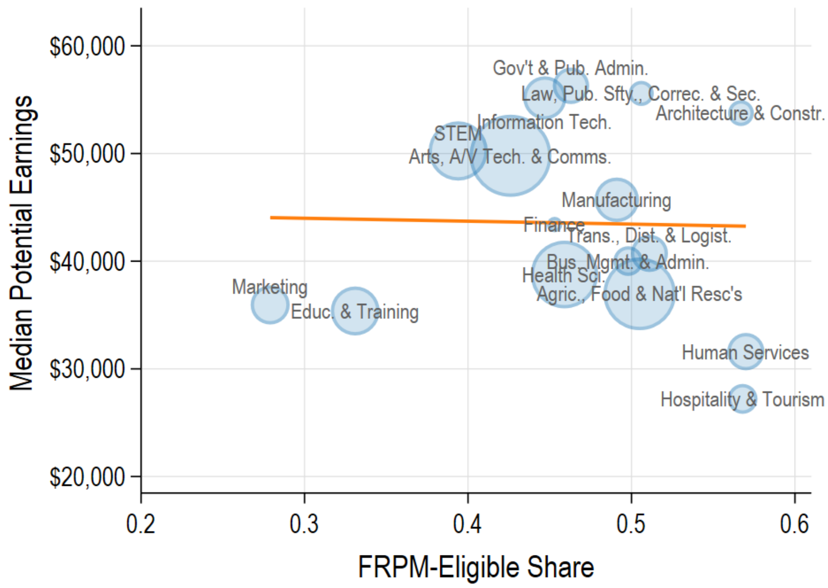
(b) Massachusetts



Notes. The figures plot potential earnings (weighted average median earnings) by the share of concentrators in each cluster who receive free or reduced−price meals. Earnings are in inflation-adjusted 2018 dollars. Marker size is in proportion to total cluster enrollment. Data are pooled over all years.

Figure 3, continued. Potential Earnings by Share of Concentrators Who Receive Free or Reduced−Price Meals

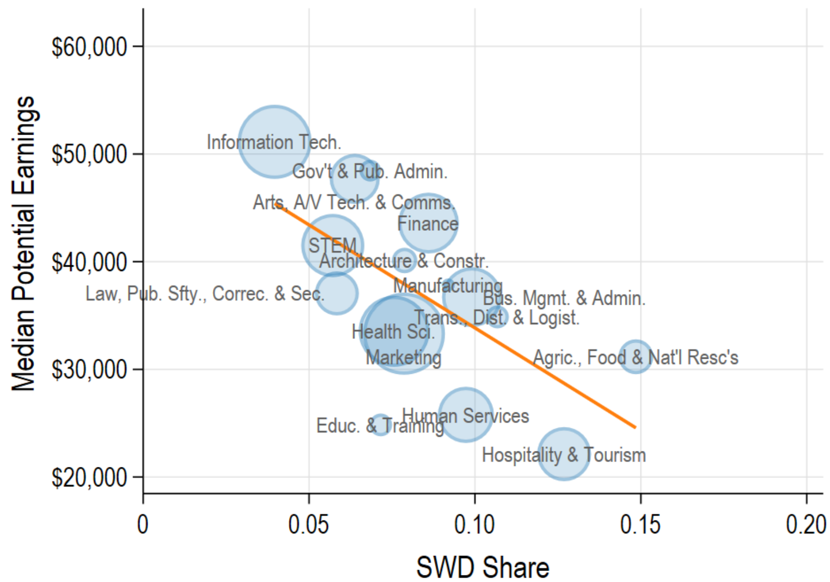
(c) Washington



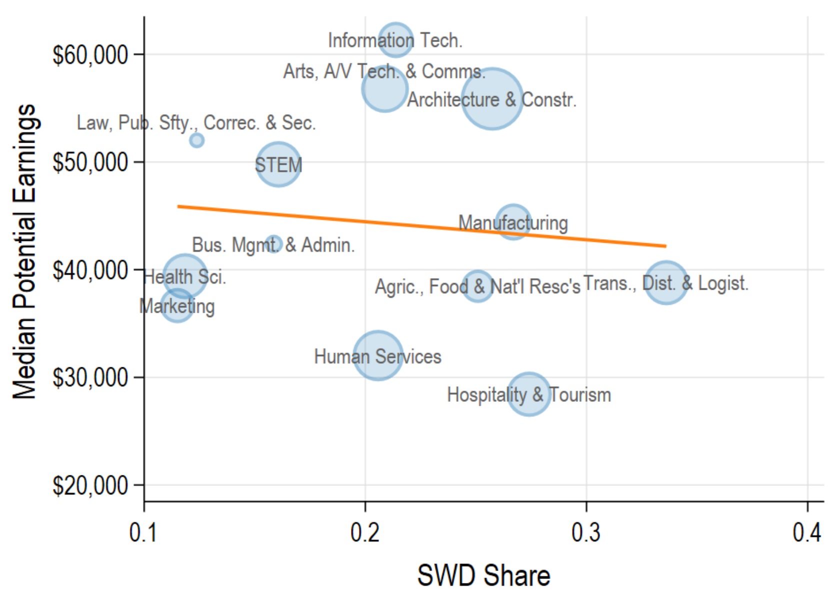
Notes. The figures plot potential earnings (weighted average median earnings) by the share of concentrators in each cluster who receive free or reduced−price meals. Earnings are in inflation-adjusted 2018 dollars. Marker size is in proportion to total cluster enrollment. Data are pooled over all years.

Figure 4. Potential Earnings by Share of Concentrators With an Identified Disability

(a) Atlanta Metro Area



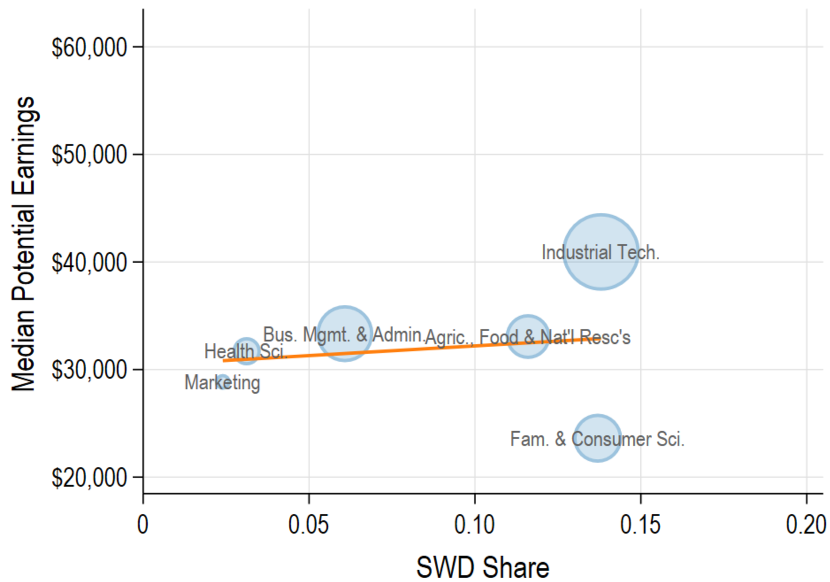
(b) Massachusetts



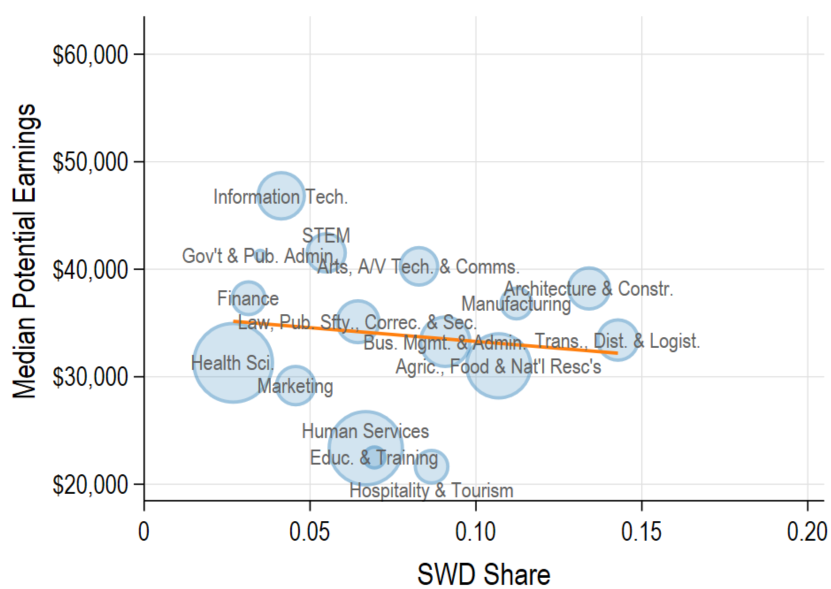
Notes. The figures plot potential earnings (weighted average median earnings) by the share of concentrators in each cluster who have an identified disability. Earnings are in inflation-adjusted 2018 dollars. Marker size is in proportion to total cluster enrollment. Data are pooled over all years.

Figure 4, continued. Potential Earnings by Share of Concentrators With an Identified Disability

(c) Montana



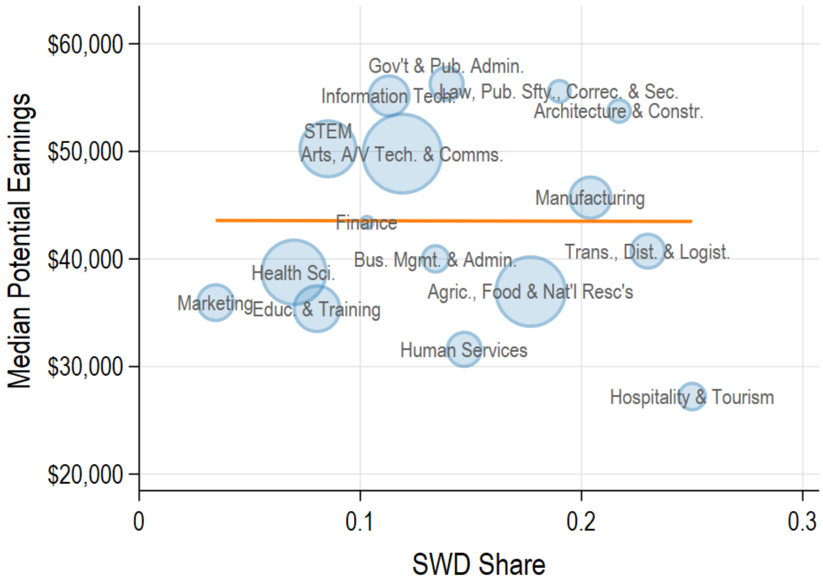
(d) Tennessee



Notes. The figures plot potential earnings (weighted average median earnings) by the share of concentrators in each cluster who have an identified disability. Earnings are in inflation-adjusted 2018 dollars. Marker size is in proportion to total cluster enrollment. Data are pooled over all years.

Figure 4, continued. Potential Earnings by Share of Concentrators With an Identified Disability

(a) Washington



Notes. The figures plot potential earnings (weighted average median earnings) by the share of concentrators in each cluster who have an identified disability. Earnings are in inflation-adjusted 2018 dollars. Marker size is in proportion to total cluster enrollment. Data are pooled over all years.

Table 1: How Student Characteristics Relate to Potential Earnings with a High School Diploma

	Atlanta	Massachusetts	Montana	Tennessee	Washington
Female	−0.100***	−0.176***	−0.199***	−0.147***	−0.090**
	(0.002)	(0.006)	(0.009)	(0.001)	(0.001)
AIAN			−0.008		
			(0.005)		
Black	−0.013**	−0.035***		−0.023***	−0.018**
	(0.005)	(0.005)		(0.002)	(0.004)
Hispanic	−0.024***	−0.036***	−0.012**	−0.009***	−0.001
	(0.006)	(0.005)	(0.005)	(0.002)	(0.002)
Other race	0.046***	−0.008	−0.012**	−0.005	0.008**
	(0.005)	(0.005)	(0.005)	(0.003)	(0.002)
FRPM	−0.020***	−0.015***			−0.002
	(0.003)	(0.003)			(0.001)
Disability	−0.037***	−0.008**	−0.014***	0.002	−0.006**
	(0.005)	(0.003)	(0.005)	(0.002)	(0.002)
Math score	0.024***	0.021***		0.012***	0.009**
	(0.002)	(0.002)		(0.001)	(0.001)
ELA score	0.006**			0.011***	0.005**
	(0.002)			(0.001)	(0.001)
Students	32,663	60,230	22,985	154,405	60,170

Notes. The table reports regression estimates from Equation 2. The analysis sample is limited to concentrators and the dependent variable is log potential earnings with a high school diploma in occupations aligned with a student's CTE cluster. Earnings are in inflation-adjusted 2018 dollars. AIAN is American Indian or Alaskan Native. Black, White, AIAN, and another race are non−Hispanic. FRPM is free or reduced−price meals, a proxy measure for economic disadvantage. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 2: How Student Characteristics Relate to Potential College-Level Earnings

	Atlanta	Massachusetts	Montana	Tennessee	Washington
Female	−0.069***	−0.105***	−0.089***	−0.118***	−0.068**
	(0.002)	(0.007)	(0.009)	(0.001)	(0.001)
AIAN			−0.002		
			(0.005)		
Black	−0.012**	0.008		−0.019***	−0.003
	(0.004)	(0.008)		(0.002)	(0.004)
Hispanic	−0.020***	−0.002		−0.007***	0.012**
	(0.005)	(0.004)		(0.002)	(0.002)
Other race	0.017***	0.020***	0.002	0.006*	0.001
	(0.005)	(0.005)	(0.004)	(0.003)	(0.002)
FRPM	−0.014***	−0.006***			−0.003*
	(0.003)	(0.002)			(0.002)
Disability	−0.028***	−0.017***	−0.032***	−0.011***	−0.016**
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Math score	0.018***	0.027***		0.019***	0.017**
	(0.002)	(0.002)		(0.001)	(0.001)
ELA score	0.004*			0.014***	0.002
	(0.002)			(0.001)	(0.001)
Students	32,663	60,230	22,985	154,405	60,170

Notes. The table reports regression estimates from Equation 2. The analysis sample is limited to concentrators and the dependent variable is log potential earnings with a college education in occupations aligned with a student's CTE cluster. Earnings are in inflation-adjusted 2018 dollars. Student variables are listed at left. AIAN is American Indian or Alaskan Native. FRPM is free or reduced−price meals, a proxy measure for economic disadvantage. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Appendix

Descriptive Statistics: Students

Table A1 summarizes how concentrators are allocated across clusters in each site. Atlanta, Massachusetts, Montana, Tennessee, and Washington have very different populations and economies, and that diversity may help to explain why there is little agreement in cluster popularity across locations. If we collect the top three clusters from Atlanta, Massachusetts, Tennessee, and Washington, we end up with nine distinct clusters, more than half of the total 16. Only Health Science and Human Services are in more than one area's top three. Among Montana's six clusters, Industrial Technology (not to be confused with the Information Technology cluster in other states) is by far the most popular, with 43% of all potential concentrators in that state.

Summary statistics for students in each location are in Table A2. The male-female gender ratio is similar across all five sites, with Atlanta slightly more female (53%) and Montana slightly more male (52%). Atlanta has the largest share of Black students (62%). Montana has the highest percent of White, non-Hispanic students (84%) but also the highest percent of American Indian/Alaska Native students (10%). Free or reduced-price lunch eligibility is observed in three of the five locations, ranging from 24% in Massachusetts to 44% in Washington to 62% in Atlanta. The share of students with an identified disability ranges from 8% (Atlanta and Washington) to 17% (Massachusetts).

Descriptive Statistics: Potential Earnings

Table A3 demonstrates how we compute potential earnings for each CTE cluster, location, and year, taking Finance in Atlanta in 2018 as an example. All occupations aligned with Finance CTE programs are listed at left. For occupations that typically require a high school diploma or less at the entry level, Column (1) lists the share of total Finance employment in that occupation, and Column (2) lists median wages of workers with that occupation. The average employment-weighted median wage for the Finance cluster in Atlanta in 2018 is the sum of the product of each employment share of occupations in that cluster and the median wage for that occupation. For example, 16% of employment in occupations aligned to the Finance cluster are in Bill and Account Collectors, who have median earnings of $37,980. So, we calculate $0.16 * 37{,}980$ and so on for all jobs in that cluster where the weights sum to 1 (see Equation 1 in the main text and below). We call this employment-weighted average a cluster's potential earnings with a high school diploma.

$$\text{Potential Earnings}_{\text{Cluster}=C} = \sum_{\text{Occ}\in C} (\text{Median Earnings Occ}_o) \times \underbrace{\left(\frac{\text{Employment in Occ}_o}{\text{Total Employment in } C}\right)}_{\text{Employment Share}} \tag{A1}$$

The right-hand side of Equation A1 takes the average median earnings of each occupation (o) aligned with cluster C (the first term), weighted by that occupation's share of employment for all occupations aligned with that cluster (the second term). We do this separately for occupations that typically do not require college as an entry requirement for employment, and again for those that do. Table 1 in the main text reports findings for high school-level potential earnings, and results for college-level potential earnings are in Table 2 and discussed below.

Figure A1 plots potential earnings by cluster and year pooled over all five locations (except for Industrial Technology and Family and Consumer Sciences, which are unique to Montana). This figure highlights differences in what workers earn in occupations not typically requiring a college degree aligned with each cluster. For almost all clusters, potential earnings dipped in the years following the Great Recession and began to climb after 2014. There is wide variance in potential earnings across CTE fields. High school-level jobs in Information Technology pay more than two times as much as high school-level jobs aligned with CTE coursework in Hospitality and Tourism, or in Family and Consumer Science. For the latter two fields, potential earnings of $25,000 match the 2018 federal poverty limit for a family of four.

Figure A2 adds further context with illustrations of potential earnings by entry-level education requirement, pooled over all states and years. For example, workers in Business, Marketing, and Health Science occupations have a large income premium with a college degree. This highlights a challenge in how the value of CTE fields is conveyed to students. It would be misleading to claim that completing a pathway in Health Sciences would lead, on its own, to occupations that pay more than $50,000 per year. Rather, it is more accurate to say that health-aligned occupations typically pay just under $40,000 without a college degree, while college-level jobs in health typically pay more than $80,000. And pathways to some of those highest-paying Health occupations may prioritize advanced high school science as much or more than Health Science CTE.

Figure A3 depicts weighted-average potential earnings by cluster, education, and location, replicating the pooled, across-location version in Figure A2. As in the pooled figure, we see that higher-earning clusters with a high school diploma also tend to be higher-earning with a college degree, although there is variation across and within states. One notable exception is Government and Public Administration (one of the least popular clusters in the locations where it is offered), which has a relatively small college premium and tends to be a higher-earning cluster for workers with no more than a high school education.

The merits of a multi-site analysis are evident in Figure A4, where we assess if clusters with higher potential earnings enroll more students. Figure A4 plots each cluster's potential earnings against the share of all CTE concentrators in that cluster. The pattern is inconsistent across locations, an important observation that we would miss if our analysis was limited to one state or district. In Atlanta, Massachusetts, and Washington, there is either no relationship, or a weakly positive relationship, between a CTE cluster's potential earnings and the share of concentrators enrolled in that cluster. The relationship is consistently negative in Tennessee, where lower-wage Health Science and Human Services clusters enroll a large percentage of CTE concentrators. Only in Montana is the cluster with the highest potential earnings also the most popular (Industrial Technology, which combines Architecture & Construction, Manufacturing, STEM, and Transportation, Distribution, & Logistics).

Supplementary Regression Results

Tables A4a - A4e report regression results from alternate specifications of our main analysis:

$$y_{it} = \alpha + X_{it}\beta + \tau_t \left[+ \delta_{d(i)}\right] \left[+ \phi_{s(i)}\right] + \epsilon_{it} \tag{A2}$$

Each column of each table reports regression results for a particular specification and location. The outcome y_{it} is a binary indicator that student i in ninth-grade cohort t is a CTE concentrator in Columns (1) - (2); log potential earnings in Columns (3) - (4); and the level of potential earnings in Column (5). Sub-sections to follow review results for each of these three outcomes (Tables A4a - A4e), as well as for log potential earnings with a college education (Table 2).

As in the main analysis, X represents student characteristics listed in the leftmost column of each table. In models with district fixed effects (δ_d), results for β quantify how y differs for students with different demographic, FRPM, or disability characteristics but enrolled in the same district. When we replace district fixed effects with school fixed effects, the comparison is across students attending the same school, who presumably have access to the same CTE programs.[8] In the main text, Table 1 reports Equation 2 and A2 results with school fixed effects (ϕ_s). These estimates are repeated in Tables A4a - A4e, Column (4).

Equation A2 with $y = \mathbf{1}$(CTE concentrator)

Equation A2 estimates of the likelihood of concentrating in CTE at all provide us with an understanding of how student characteristics correlate with the decision to become a concentrator, and how selection into CTE might play a role in our results for potential earnings.

In all locations other than Tennessee, we find that females are significantly less likely to concentrate in CTE than males. The difference is large in Montana (13.5 percentage points) and ranges from 2-5 percentage points in Massachusetts (2.5 percentage points), Washington (2.3 percentage points) and Atlanta (5 percentage points). Comparing Column (1) with district fixed effects to Column (2) with school fixed effects, we find that the magnitude of the gender gap in CTE concentration is similar across and within schools, which is consistent with a lack of systematic relationship between gender and school characteristics.

Comparing results in Columns (1) and (2) in each of Tables A4a - A4e makes clear that school-level contributions to race disparities in CTE uptake vary widely by context, consistent with results from Carruthers et al. (2021). In Atlanta, race and ethnicity gaps in CTE concentration are meaningfully attenuated when school fixed effects are included. This means that when comparing students across schools, Black students, e.g., are 11.5 percentage pionts more likely to concentrate in CTE than are White students. Within schools that gap falls to 3.5 percentage points. In Massachusetts and Tennessee, little gap exists either within or across schools (less than one percentage point for Black students, and three percentage points for Hispanic students). In Washington, the gap is identical within and across schools. This provides additional evidence that observing a single context would draw an incomplete picture.

Turning to CTE concentration rates by FRPM status, we find that lower-income students are at most 1 percentage point less likely to concentrate in CTE, relative to FRPM-ineligible peers in the same schools.

Student achievement is less of a factor in predicting CTE concentration than gender, race, ethnicity, or disability (again, depending on the location). Students who score higher on standardized Math or English exams tend to be less likely to concentrate in

[8] Results are similar if we modify the specification to include interactions between district and cohort, or between school and cohort.

CTE compared with peers in their schools, but only by 1-2 percentage points per standard deviation increase in test scores (and in Atlanta, higher math achievement is associated with more CTE concentration).

These participation differences are important to take into account in interpreting our findings for potential earnings. For example, consider a policy intended to increase the number of CTE concentrators, possibly by adding CTE course-taking requirements to state curricula. If male and female, or White and non-White, students induced into CTE by the policy concentrated in clusters in similar proportions to those in our data, we would not expect potential earnings gaps to change. If, instead, new females in CTE were more attracted to clusters with high (or low) potential earnings, the gender gaps depicted in Figure 1 of the main paper would narrow (or widen). In general, CTE expansion policies should take into account not simply that students would take more CTE, but which CTE clusters and pathways they choose as well.

Equation A2 with y = high school-level potential earnings

Columns (3) - (5) of Tables A4a - A4e allow us to determine if the unadjusted gaps depicted in Figures 1 - 4 are driven to some extent by how students sort across schools with different levels of access to high paying CTE pathways. In some locations, White non-Hispanic students tend to enroll in CTE clusters aligned with higher paying jobs, and lower-income students tend to enroll in clusters aligned with lower paying jobs. This may be partly due to non-White and lower-income students having a greater tendency to attend schools that do not offer high-paying CTE pathways.

Different specifications of Equation A2 examine this possibility by controlling separately for district fixed effects (Column (3)) or school fixed effects (Columns (4) and (5)). District and school fixed effects condition the unadjusted Figure 1 - 4 trends on, respectively, district and school offerings of different CTE clusters. If non-White, lower income, disabled, or lower achieving students had less access to high paying CTE clusters at their school, we would see Equation A2 coefficients attenuate from Column (3) to Column (4). Looking across Tables A4a - A4e, however, estimated gaps in potential earnings by race, ethnicity, income, disability, and achievement change very little when we narrow the comparison from within-district to within-school. Black students, for example, concentrate in clusters tied to 0-4% lower earnings than non-Black students in their district, as well as non-Black students in their school.

Table A1: Career Clusters and the Share of CTE Concentrators, by Area

	ATL	MA	MT	TN	WA
Any CTE Concentration	0.48	0.18	0.35	0.41	0.17
Conditional on Any CTE Concentration					
Agriculture, Food & Natural Resources	0.03	0.04	0.13	0.12	0.16
Architecture & Construction	0.01	0.19		0.05	0.02
Arts, A/V Technology & Communications	0.06	0.10		0.04	0.20
Business Management & Administration	0.09	0.01	0.22	0.07	0.02
Education & Training	0.01			0.01	0.07
Finance	0.09			0.03	<0.01
Government & Public Administration	0.01			<0.01	0.03
Health Science	0.12	0.09	0.05	0.19	0.14
Hospitality & Tourism	0.07	0.09		0.03	0.02
Human Services	0.07	0.12		0.16	0.04
Information Technology	0.13	0.05		0.06	0.05
Law, Public Safety, Corrections & Security	0.04	0.01		0.05	0.01
Manufacturing	<0.01	0.06		0.03	0.05
Marketing	0.17	0.05	0.01	0.04	0.04
Science, Technology, Engineering & Mathematics	0.10	0.09		0.04	0.10
Transportation, Distribution & Logistics	0.01	0.09		0.05	0.04
Family & Consumer Sciences			0.16		
Industrial Technology			0.43		

Notes. The table shows the share of potential CTE concentrators within each career cluster, by location. The locations include the Atlanta metro area (ATL), Massachusetts (MA), Montana (MT), Tennessee (TN), and Washington state (WA). The Family & Consumer Sciences and Industrial Technology clusters are specific to Montana.

Table A2: Student Summary Statistics, by Area

Student Characteristic	ATL	MA	MT	TN	WA
Female	0.53	0.50	0.48	0.49	0.49
Black	0.61	0.09		0.24	0.04
White	0.21	0.69	0.84	0.67	0.60
Hispanic	0.08	0.14		0.06	0.18
AIAN			0.10		
Another race	0.10	0.08	0.05	0.03	0.18
FRPM−eligible	0.62	0.24			0.44
Identified disability	0.08	0.17	0.10	0.08	0.12
Observations	68,330	336,985	65,079	376,807	365,125

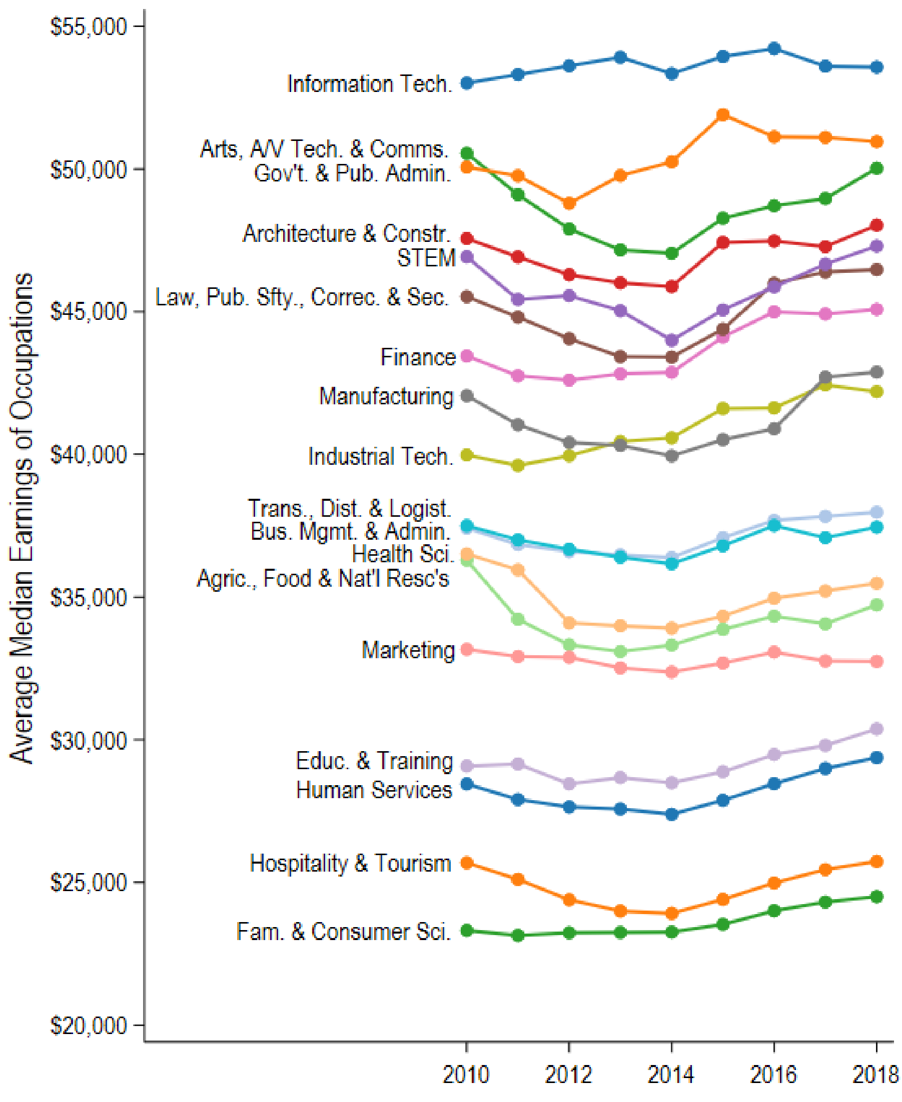
Notes. The table describes the share of students with each characteristic listed at left, by location. The locations include the Atlanta metro area (ATL), Massachusetts (MA), Montana (MT), Tennessee (TN), and Washington state (WA). AIAN is American Indian or Alaskan Native. Black, White, AIAN, and another race are non−Hispanic. FRPM is free or reduced−price meals, a proxy measure for economic disadvantage.

Table A3: Earnings in Occupations Aligned with the Finance Cluster

	Less than college req.		College+ req.	
	(1)	(2)	(3)	(4)
Occupation	Emp. %	Median $	Emp. %	Median $
Credit Authorizers, Checkers, and Clerks	1%	30,310		
Financial Clerks, All Other	1%	49,820		
Insurance Appraisers, Auto Damage	1%	60,040		
Brokerage Clerks	2%	46,580		
Tax Preparers	4%	40,330		
Loan Interviewers and Clerks	7%	39,270		
Claims Adjusters, Examiners, and Investigators	15%	64,510		
Tellers	15%	31,820		
Bill and Account Collectors	16%	37,980		
Insurance Sales Agents	18%	45,060		
Insurance Claims and Policy Processing Clerks	21%	44,240		
Actuaries			1%	111,630
Budget Analysts			2%	67,780
Credit Analysts			2%	64,060
Financial Specialists, All Other			5%	75,650
Personal Financial Advisors			5%	99,390
Loan Officers			6%	60,920
Insurance Underwriters			7%	75,810
Financial Analysts			8%	77,060
Securities, Commodities, and Fin. Svcs. Agents			9%	55,330
Financial Managers			19%	135,190
Accountants and Auditors			37%	71,790
Weighted Average Earnings		44,113		84,450

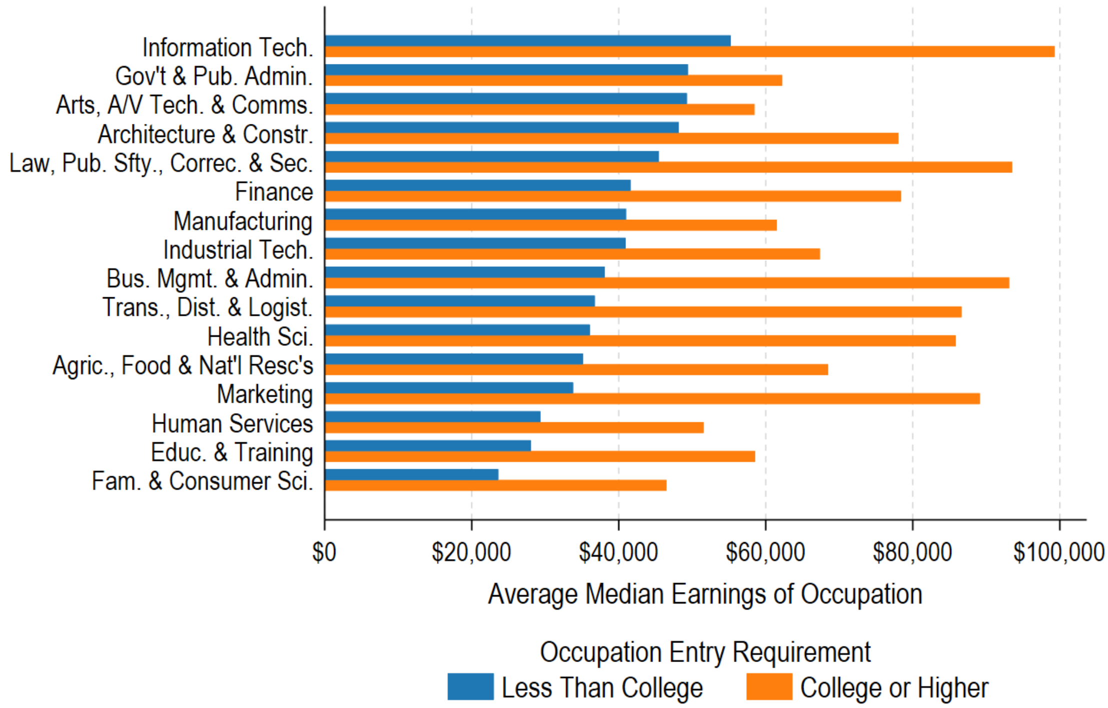
Notes. The table illustrates how potential earnings are computed for each cluster, location, and year, taking Finance in Atlanta in 2018 as an example. Columns (1) and (2) respectively list employment shares and median Atlanta earnings for each occupation requiring no more than a high school diploma at the entry level, and Columns (3) and (4) list employment shares and median earnings for occupations requiring a college degree. Earnings are in inflation-adjusted 2018 dollars.

Figure A1. Median Earnings for Occupations With No College Entry Requirement, by Career Cluster



Notes. The figure plots trends over time in median earnings for occupations aligned with the career clusters listed at left. Earnings are in inflation-adjusted 2018 dollars.

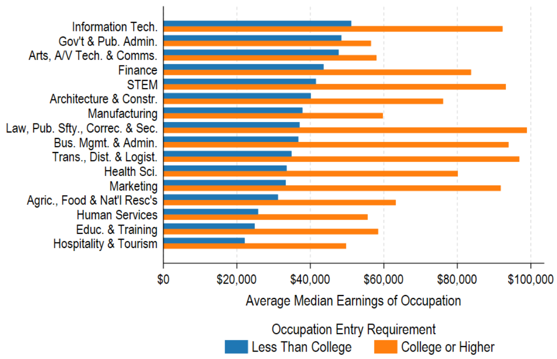
Figure A2. Median Earnings by Career Cluster



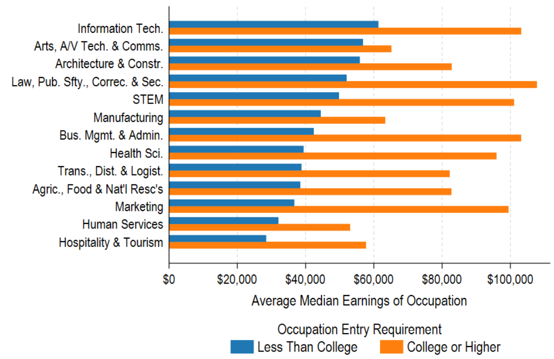
Notes. The figure plots weighted average median earnings of occupations aligned with each cluster, by level of typical entry–level education. Earnings are in inflation-adjusted 2018 dollars. Data are pooled over all years.

Figure A3. Median Earnings by State and Occupation Entry Requirement

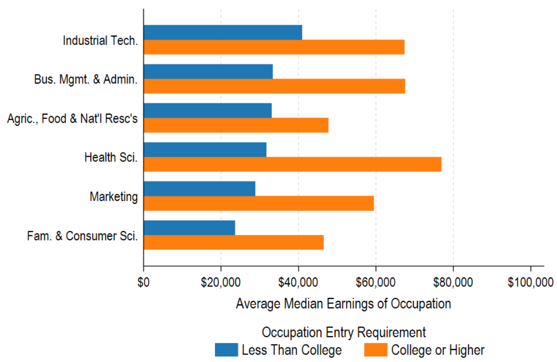
(a) Atlanta Metro Area



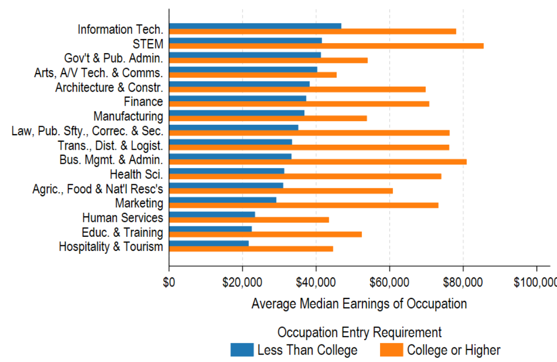
(b) Massachusetts



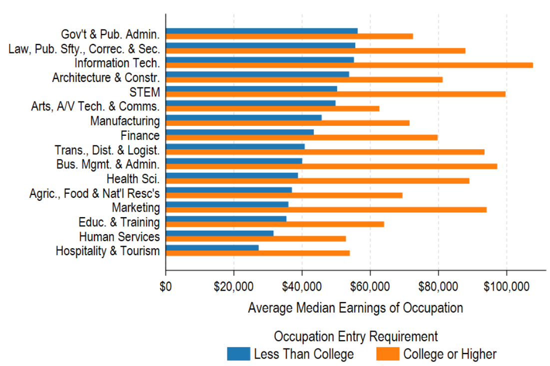
(c) Montana



(d) Tennessee

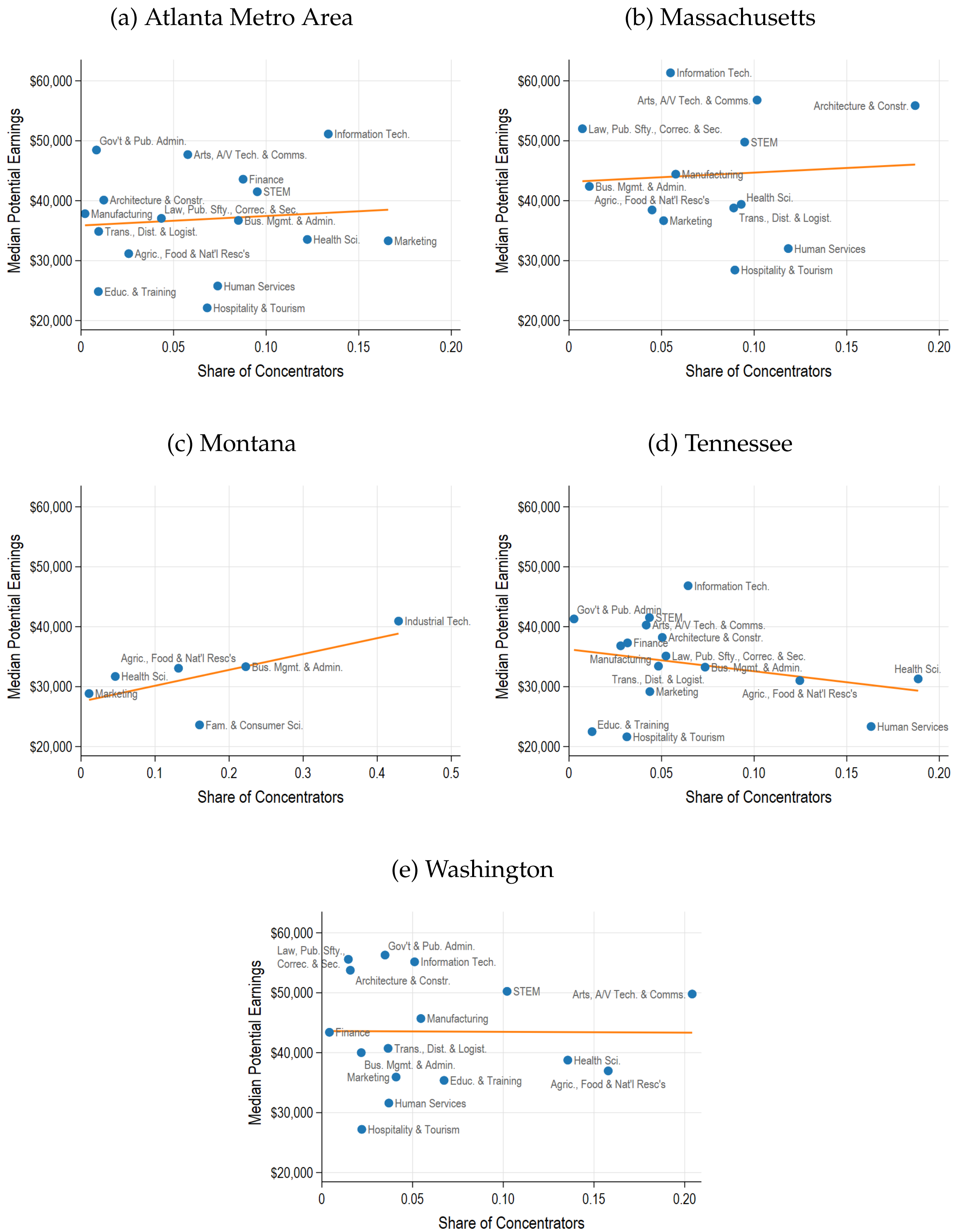


(e) Washington



Notes. The figure plots weighted average median earnings of all occupations aligned with each cluster, by state and level of typical entry−level education. Earnings are in inflation-adjusted 2018 dollars. Data are pooled over all years.

Figure A4. Potential Earnings by Share of All Concentrators



Notes. The figures plot potential earnings (weighted average median earnings) by the share of all concentrators in each state who are in each cluster. Earnings are in inflation-adjusted 2018 dollars. Data are pooled over all years.

Table A4a: How Student Characteristics Relate to CTE Concentration and Potential Earnings with a High School Diploma - Atlanta

	Ever Concentrator		Potential Earnings (Logged)		Potential Earnings ($)
	(1)	(2)	(3)	(4)	(5)
Female	−0.051***	−0.054***	−0.105***	−0.100***	−3,594.2***
	(0.004)	(0.004)	(0.002)	(0.002)	(83.6)
Black	0.115***	0.035***	−0.015***	−0.013**	−349.1*
	(0.006)	(0.007)	(0.004)	(0.005)	(170.7)
Hispanic	0.032***	0.013	−0.013*	−0.024***	−695.8***
	(0.008)	(0.009)	(0.006)	(0.006)	(210.6)
Other race	0.061***	0.026***	0.061***	0.046***	1,963.7***
	(0.007)	(0.008)	(0.005)	(0.005)	(183.7)
FRPM	0.027***	−0.003	−0.035***	−0.020***	−753.4***
	(0.005)	(0.005)	(0.003)	(0.003)	(115.6)
Disability	−0.056***	−0.056***	−0.037***	−0.037***	−1,324.0***
	(0.007)	(0.007)	(0.005)	(0.005)	(165.0)
Math score	0.014***	0.020***	0.032***	0.024***	972.9***
	(0.003)	(0.003)	(0.002)	(0.002)	(69.0)
ELA score	−0.011***	−0.008**	0.007***	0.006**	205.9**
	(0.003)	(0.003)	(0.002)	(0.002)	(66.8)
School FE		x		x	x
District FE	x		x		
Cohort FE	x	x	x	x	x
Students	68,330	68,330	32,663	32,663	32,663

Notes. The table reports results from Equation A2 regression estimates. The dependent variable in Columns 1 and 2 is whether or not a student concentrated in a CTE cluster. The analysis sample is limited to concentrators in Columns 3–5, where the dependent variable is log or level potential earnings with a high school diploma in occupations aligned with a student's CTE cluster. Earnings are in inflation-adjusted 2018 dollars. Student variables are listed at left. FRPM is free or reduced−price meals, a proxy measure for economic disadvantage. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A4b: How Student Characteristics Relate to CTE Concentration and Potential Earnings with a High School Diploma - Massachusetts

	Ever Concentrator		Potential Earnings (Logged)		Potential Earnings ($)
	(1)	(2)	(3)	(4)	(5)
Female	−0.025***	−0.024***	−0.177***	−0.176***	−7,508***
	(0.004)	(0.004)	(0.006)	(0.006)	(266.6)
Black	−0.006	−0.004	−0.038***	−0.035***	−1,546***
	(0.006)	(0.004)	(0.005)	(0.005)	(212.9)
Hispanic	0.003	−0.007**	−0.037***	−0.036***	−1,590***
	(0.009)	(0.003)	(0.005)	(0.005)	(213.1)
Other race	−0.018**	−0.005	−0.009*	−0.008	−367.4
	(0.009)	(0.004)	(0.005)	(0.005)	(243.8)
FRPM	−0.002	−0.008***	−0.015***	−0.015***	−625.9***
	(0.004)	(0.003)	(0.003)	(0.003)	(119.4)
Disability	−0.031***	−0.021***	−0.008**	−0.008**	−285.7**
	(0.007)	(0.004)	(0.003)	(0.003)	(142.7)
Math score	−0.018***	−0.013***	0.022***	0.021***	884.6***
	(0.003)	(0.002)	(0.002)	(0.002)	(83.43)
School FE		x		x	x
District FE	x		x		
Cohort FE	x	x	x	x	x
Students	336,985	336,985	60,230	60,230	60,230

Notes. The table reports results from Equation A2 regression estimates. The dependent variable in Columns 1 and 2 is whether or not a student concentrated in a CTE cluster. The analysis sample is limited to concentrators in Columns 3–5, where the dependent variable is log or level potential earnings with a high school diploma in occupations aligned with a student's CTE cluster. Earnings are in inflation-adjusted 2018 dollars. Student variables are listed at left. FRPM is free or reduced−price meals, a proxy measure for economic disadvantage. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A4c: How Student Characteristics Relate to CTE Concentration and Potential Earnings with a High School Diploma - Montana

	Ever Concentrator		Potential Earnings (Logged)		Potential Earnings ($)
	(1)	(2)	(3)	(4)	(5)
Female	−0.135***	−0.135***	−0.199***	−0.199***	−6,467.1***
	(0.013)	(0.011)	(0.010)	(0.009)	(297.7)
AIAN	−0.062***	−0.060***	−0.008	−0.008	−221.9
	(0.013)	(0.016)	(0.005)	(0.005)	(166.5)
Other race	−0.033***	−0.033***	−0.012***	−0.012**	−369.3**
	(0.009)	(0.010)	(0.004)	(0.005)	(151.8)
Disability	−0.002	−0.003	−0.014**	−0.014***	−301.9*
	(0.012)	(0.012)	(0.006)	(0.005)	(175.7)
School FE		x		x	x
District FE	x		x		
Cohort FE	x	x	x	x	x
Students	65,069	65,069	22,985	22,985	22,985

Notes. The table reports results from Equation A2 regression estimates. The dependent variable in Columns 1 and 2 is whether or not a student concentrated in a CTE cluster. The analysis sample is limited to concentrators in Columns 3–5, where the dependent variable is log or level potential earnings with a high school diploma in occupations aligned with a student's CTE cluster. Earnings are in inflation-adjusted 2018 dollars. Student variables are listed at left. AIAN is American Indian or Alaskan Native. FRPM is free or reduced−price meals, a proxy measure for economic disadvantage. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A4d: How Student Characteristics Relate to CTE Concentration and Potential Earnings with a High School Diploma - Tennessee

	Ever Concentrator		Potential Earnings (Logged)		Potential Earnings ($)
	(1)	(2)	(3)	(4)	(5)
Female	0.007***	0.007***	−0.149***	−0.147***	−4,670***
	(0.002)	(0.002)	(0.001)	(0.001)	(29.8)
Black	−0.014***	−0.011***	−0.024***	−0.023***	−635.1***
	(0.003)	(0.003)	(0.002)	(0.002)	(53.6)
Hispanic	0.031***	0.004	−0.011***	−0.009***	−204.4***
	(0.004)	(0.004)	(0.002)	(0.002)	(68.8)
Other race	−0.049***	−0.040***	0.001	−0.005	−109.9
	(0.005)	(0.005)	(0.003)	(0.003)	(96)
Disability	−0.048***	−0.041***	0.002	0.002	108.4*
	(0.004)	(0.004)	(0.002)	(0.002)	(61.7)
Math score	−0.004***	−0.001	0.012***	0.012***	353.4***
	(0.001)	(0.001)	(0.001)	(0.001)	(23.6)
ELA score	−0.034***	−0.022***	0.012***	0.011***	361.4***
	(0.001)	(0.001)	(0.001)	(0.001)	(25.8)
School FE		x		x	x
District FE	x		x		
Cohort FE	x	x	x	x	x
Students	376,807	376,807	154,405	154,405	154,405

Notes. The table reports results from Equation A2 regression estimates. The dependent variable in Columns 1 and 2 is whether or not a student concentrated in a CTE cluster. The analysis sample is limited to concentrators in Columns 3–5, where the dependent variable is log or level potential earnings with a high school diploma in occupations aligned with a student's CTE cluster. Earnings are in inflation-adjusted 2018 dollars. Student variables are listed at left. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A4e: How Student Characteristics Relate to CTE Concentration and Potential Earnings with a High School Diploma - Washington

	Ever Concentrator		Potential Earnings (Logged)		Potential Earnings ($)
	(1)	(2)	(3)	(4)	(5)
Female	−0.023**	−0.023**	−0.093**	−0.090**	−3,856.6**
	(0.001)	(0.001)	(0.001)	(0.001)	(56.6)
Black	−0.044**	−0.042**	−0.016**	−0.018**	−718.9**
	(0.003)	(0.003)	(0.004)	(0.004)	(164.5)
Hispanic	−0.026**	−0.026**	−0.001	−0.001	−27.6
	(0.002)	(0.002)	(0.002)	(0.002)	(86.2)
Other race	−0.029**	−0.029**	0.009**	0.008**	373.3**
	(0.002)	(0.002)	(0.002)	(0.002)	(84.0)
FRPM	−0.011**	−0.012**	−0.003*	−0.002	−48.6
	(0.001)	(0.001)	(0.001)	(0.001)	(62.7)
Disability	0.000	−0.002	−0.005*	−0.006**	−191.3*
	(0.002)	(0.002)	(0.002)	(0.002)	(91.1)
Math score	−0.010**	−0.011**	0.010**	0.009**	386.5**
	(0.001)	(0.001)	(0.001)	(0.001)	(44.7)
ELA score	−0.008**	−0.009**	0.005**	0.005**	194.8**
	(0.001)	(0.001)	(0.001)	(0.001)	(43.1)
School FE		x		x	x
District FE	x		x		
Cohort FE	x	x	x	x	x
Students	365,125	365,125	60,170	60,170	60,170

Notes. The table reports results from Equation A2 regression estimates. The dependent variable in Columns 1 and 2 is whether or not a student concentrated in a CTE cluster. The analysis sample is limited to concentrators in Columns 3–5, where the dependent variable is log or level potential earnings with a high school diploma in occupations aligned with a student's CTE cluster. Earnings are in inflation-adjusted 2018 dollars. Student variables are listed at left. FRPM is free or reduced−price meals, a proxy measure for economic disadvantage. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.