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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Abstract

High school students in Career and Technical Education (CTE) select concentration areas that map to almost every occupation in the modern U.S. economy. Some fields have much higher potential earnings than others. We study CTE enrollment patterns across four states and one large metro area to assess if potential pay arising from 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 evidence of 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 Introduction

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). The range of CTE course offerings has likewise grown dramatically. CTE is organized around dozens of multi-course sequences called "pathways" that fall within 16 broader "career clusters." Interested students can find training for almost any field or occupation in the modern economy, ranging from Agriculture to Nursing to Cyber Security.[1] These CTE programs, re-vamped versions of what was once called "vocational" education, 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.

CTE in the U.S. is no longer a prescriptive track for students. 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 (Kreisman & Stange, 2020). 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 CTE cluster pay about twice as much as jobs aligned with Hospitality, even without a college degree. Yet, we have very little understanding of how students sort across CTE fields, what role schools might play in access to higher-paying CTE fields, and whether sorting by gender, race, and other student characteristics might reinforce post-schooling earnings gaps.

Data limitations have obscured the full picture on these questions. Nationwide surveys cannot account for the role of school offerings, while single-state studies lack broad applicability due to varied labor markets and CTE definitions. We surmount these barriers 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 – 1.2 million students in all. First, we generate measures of potential earnings arising from each of the 16 CTE career clusters by attaching those clusters to pay in aligned occupations. This allows us to then observe which students take CTE coursework leading to potentially high- or low-paying work. Second, by controlling for district and school CTE offerings,

[1]The 16 career clusters in the current national framework are 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. Descriptions and additional details are at https://careertech.org/career-clusters. Some states have state specific clusters, such as Energy in Georgia, or Industrial Technology in Montana.

we ask whether gender, race, income, and other gaps in potential earnings are due to differences in access – for example if higher earning programs are more likely to be offered in wealthy districts – or if group differences persist even within schools.

The dominant theme that emerges is that female students enroll in CTE coursework that aligns with far lower-paying occupations than their male peers. 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. We estimate that if all CTE students went on to earn the median income for jobs aligned with their CTE field that do not require college, the Black-White pay gap would be 1-4% – far smaller than the actual Black-White pay gap. If they instead went on to attain college-level jobs in their field, the Black-White pay gap would be null in two states and no more than 2% in two others. Results are similar when we condition on school fixed effects, suggesting that different levels of access to high-paying pathways across schools is not responsible for the residual variation.

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 each CTE cluster, effects of other school inputs, and self-selection into particular jobs based on unobservable factors.[2] There is reason to believe, however, that gaps in potential earnings foreshadow gaps in actual earnings as adults. Ecton and Dougherty (2023) show that some of the same lower-paying fields we identify lead to lower earnings in the years immediately following high school.

2 Related Research

A recent wave of research has shed more light on the effects of taking CTE coursework on secondary, post-secondary, and labor outcomes (Brunner et al., 2023; Ecton & Dougherty, 2023; Hemelt et al., 2019; Kreisman & Stange, 2020). Mixed results across field, gender,

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

and other student characteristics 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).

In this vein, Carruthers et al. (2021) study three states and one large metro area, finding evidence of wider across-school than within-school gaps in CTE participation by race and ethnicity. We replicate this pattern in results below, which indicates that non-White students in some locations attend schools with less access to CTE, on average, or less take-up of available CTE. Jacob and Ricks (2023) report evidence of gender, race, and family income gaps in CTE participation in Michigan, and they likewise attribute race and income gaps to school-level availability more so than student take-up conditional on availability.[3] By contrast, Carruthers et al. (2021) and Jacob and Ricks (2023) report large within-school gender gaps in CTE participation that are more consistent with differences in CTE preferences than CTE availability for males and females.

Our analysis of student take-up across CTE fields also relates to recent work by Sublett and Griffith (2019) and Carruthers et al. (2024), who study if the distribution of CTE students across clusters aligns with—i.e., is similar to—the distribution of employment across industries and occupations. They find evidence of static alignment, in that a metro area's more popular CTE fields tend to sync with the area's more popular jobs. Carruthers et al. (2024) go on to show that CTE enrollments in general are slow to change following changes in the local labor market.

Given the wide breadth of CTE in the U.S., selecting a CTE field resembles decisions that some students will make later on, when they face choices over postsecondary programs. Our analysis bridges the CTE literature with parallel research describing those choices, which has found that women tend to sort into majors with lower potential earnings (Sloane et al., 2021). Gender differences in major choice have been linked with differences in tastes and non-pecuniary preferences between men and women (Wiswall & Zafar, 2015, 2021; Zafar, 2013), as well as a lack of female role models in male-dominated fields (Porter & Serra, 2020). Considerably less research considers field of study for students still in high school, although for many, high school will be the last of their formal schooling before entering the labor market. In that regard, our results also preface a robust literature on segregation in the labor market by gender (Goldin, 2014) and to a lesser extent race and ethnicity (Del Río & Alonso-Villar, 2015).

[3] This is at odds with historic practice of making vocational education *more* available to immigrant, low-income, and non-White students, at the expense of academic tracks that led to better jobs (Oakes, 1983; Oakes et al., 1992). Today's CTE systems are more *de jure* equitable, and also more *de facto* equitable in some settings that have been studied (Dougherty & Harbaugh Macdonald, 2020; Dougherty & Lombardi, 2016).

3 Data

We rely on student-level data describing course-taking, achievement, and demographic records for sequential ninth grade 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 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.

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.

3.1 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.

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 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.

Table 1 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. Montana has only six clusters in total, with two that aggregate several of the other clusters from the standard set.[5] Of these, 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.

Our detailed student-level data 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 in math in Massachusetts and neither subject in Montana. Summary statistics for students in each location are in Table 2. The male-female gender ratio is similar across all five sites, with Atlanta slightly more female (53%) and Montana slightly more male

[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.

[5]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.

(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).

3.2 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.

3.3 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 meant 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 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.

We merge occupation-level earnings and employment to the typical entry-level education requirement for each occupation, as determined by the BLS. For our main analysis, we omit occupations that typically require a college education and focus on what students might expect to earn absent a college degree in occupations aligned with their CTE cluster. 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 A1 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 $0.5 * earnings_j + 0.5 * earnings_k$.

Figure 1 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 example, while Information Technology has the highest median earnings in occupations that do not typically require a college degree, the Arts, A/V, Tech and Communications cluster, along with Government and Public Administration also have very high earnings. 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 Figure 1, they actually have relatively low earnings potential without a college degree.

Figure 2, which depicts potential earnings by entry-level education requirement and pooled over all states and years, adds further context.[6] For example, workers in college-level Business, Marketing, and Health Science occupations in fact have very high earnings. 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.

The final analysis sample in each location consists of one observation for each student, the cluster(s) he or she concentrated in (if any), potential earnings with a high school

[6]Figure A1 in the Appendix replicates Figure 2 separately for each state

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.

4 Results

The merits of a multi-site analysis are evident in Figure 3, where we assess if clusters with higher potential earnings enroll more students. Figure 3 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).

Next, 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 demographic, race/ethnicity, income, or disability 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 4–7.

4.1 Gender

In Figure 4, we show that female CTE students tend to concentrate in fields with lower expected pay after high school. The horizontal axis of each figure measures the share of concentrators who are female in each cluster and location, and the vertical axis measures median earnings without college in aligned occupations. We find 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 lower-earning occupations. Recalling Figure 2, these fields tend to pay less than other fields without a college education. As we discuss below and show in the Appendix, 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.

4.2 Race/Ethnicity, Family Income, and Disability Status

We then repeat this same exercise for race and ethnicity (Figure 5), free or reduced-price meal status (Figure 6), and disability status (Figure 7). 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. To give one example, while Black students constitute the majority of concentrators and students in Atlanta, Black students represent a small share of all students in Montana, Washington, and Massachusetts. 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.

Figure 5 shows the relationship between the share of non-White or Hispanic concentrators in each cluster (horizontal axes) and that cluster's potential earnings (vertical axes). In Atlanta and Massachusetts, the relationship is steep and negative, in that clusters with more non-White or Hispanic students tend to have lower potential earnings. 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 very 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 6 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 7 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.

4.3 Regression Analysis

We next move beyond raw comparisons across clusters to individual-level regression analyses. While Figures 4–7 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).

To explore these possibilities, we estimate regression models that predict potential earnings as a function of student characteristics illustrated in Figures 4–7 as well as additional controls for student achievement and school or district fixed effects. Our regression specification, estimated separately for each location, takes the following form:

$$y_i = \alpha + X_i\beta + \tau_{t(i)} \left[+ \delta_{d(i)}\right] \left[+ \phi_{s(i)}\right] + \epsilon_i \tag{2}$$

Equation 2 describes student i in ninth-grade cohort t, who attended high school s. The outcome y_i represents either a binary indicator that student i was a CTE concentrator, or the potential earnings aligned with the student's cluster or clusters. As in Figures 4–7, our main analysis focuses on potential earnings with a high school diploma—–with notable exceptions described below and shown in the Appendix, our conclusions are very similar when y represents potential earnings with a college education. We estimate potential earnings where y is measured in real 2018 dollars and log (real) dollars, the latter of which shows differences in potential earnings in percentage terms. The vector X_i is a set of descriptive characteristics for each student, including gender, race and ethnicity, disability, FRPM eligibility status (where observed), and math and English Language Arts test scores. The parameter τ_t is a cohort fixed effect. Across models, we control for either district (δ_d) or school $\left(\phi_s\right)$ fixed effects. In models with district fixed effects, 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 within schools, netting out school averages.[7] The latter of these (school fixed effects models) allows us to compare differences in either CTE concentration rates or potential earnings for students who faced the same CTE course offerings.

Before estimating regressions where potential earnings (or log potential earnings) are the outcome, we first estimate Equation 2 for the likelihood of concentrating in CTE at all. This provides 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 subsequent results for potential earnings. Results are in Table 3, Columns (1) and (2). 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,

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

which is consistent with a lack of systematic relationship between gender and school characteristics.

Differences in concentration by race and/or ethnicity demonstrate no clear pattern across states. For example, we see conflicting patterns in Atlanta and Tennessee, the two locations with the highest shares of Black students. In the Column (2) model with school fixed effects, we find that Atlanta's Black students are 3.5 percentage points more likely to concentrate in CTE than White students who attend the same school. Yet in Tennessee, Black student concentration rates are very close to those of White students, at just over one percentage point less. Race and ethnicity have little relationship with CTE concentration in Massachusetts, whereas Montana's American Indian and Alaskan Native students are 6 percentage points less likely than White peers to concentrate in CTE. Washington's Black, Hispanic, and other non-White students are 3-4 percentage points less likely to be CTE concentrators than White students, both across and within schools.

Comparing results in columns (1) and (2) in each of Table 3a-3e 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 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 subsequent results 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 3 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.

Columns (3)–(5) of Tables 3a-e show results for potential earnings. Our headline result is that women typically concentrate in lower-paying CTE clusters. In the column (4) model with school fixed effects, for example, we show that 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 10 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.

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 (Figure 2). For Health Science and Marketing, there is a wide gap between earnings with a high school diploma versus a college degree, 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. Appendix Table A2 replicates our Equation (2) results, but with potential college-level pay as the dependent variable y_i. Consistent with a long line of research showing that education explains some degree of gender pay differentials (Goldin, 2014), we find a narrower gap between potential male and female earnings with college, measuring 7-12% rather than 9-20%. Our takeaway inference is that gender gaps in potential pay are large and consistent across locations, particularly among students who do not plan to go on to college.

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 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). Note also that while school fixed effects attenuate racial differences in CTE concentration rates in some locations (particularly Atlanta), they have little impact if any on racial differences in potential earnings conditional on becoming a concentrator. Both within and across schools, and in terms of potential earnings with and without college, we find that Black, Hispanic, and (in Montana) American Indian and Alaska Native students tend to have equivalent or modestly lower expected earnings based solely on their CTE cluster.

In the three locations where we observe FRPM status, estimates in Table 3 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 small and 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, and as shown in Appendix Table A2, 2-3% with a college education.

5 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 females are more likely to concentrate in CTE clusters that are aligned with lower-paying occupations than their male peers. 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 generally 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, socioeconomically disadvantaged 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 two important caveats. The first is that our analysis is descriptive and does not show that existing CTE programs are exacerbating inequalities between different subgroups of students. 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.

The second 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 (including, critically, access to particular clusters in schools). As such, the specific mechanisms for reducing inequalities in CTE cluster participation are unclear. 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

Table 1: Career Clusters and the Share of CTE Concentrators, by Area

Cluster	ATL	MA	MT	TN	WA
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 2: 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 student characteristics, 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 3a: How Student Characteristics Relate to CTE Concentration and Potential Earnings - 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 2 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 nominal potential earnings with a high school diploma in occupations aligned with a student's CTE cluster. Student variables are listed at left. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 3b: How Student Characteristics Relate to CTE Concentration and Potential Earnings - 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 2 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 nominal potential earnings with a high school diploma in occupations aligned with a student's CTE cluster. Student variables are listed at left. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 3c: How Student Characteristics Relate to CTE Concentration and Potential Earnings - 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 2 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 nominal potential earnings with a high school diploma in occupations aligned with a student's CTE cluster. Student variables are listed at left. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 3d: How Student Characteristics Relate to CTE Concentration and Potential Earnings - 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

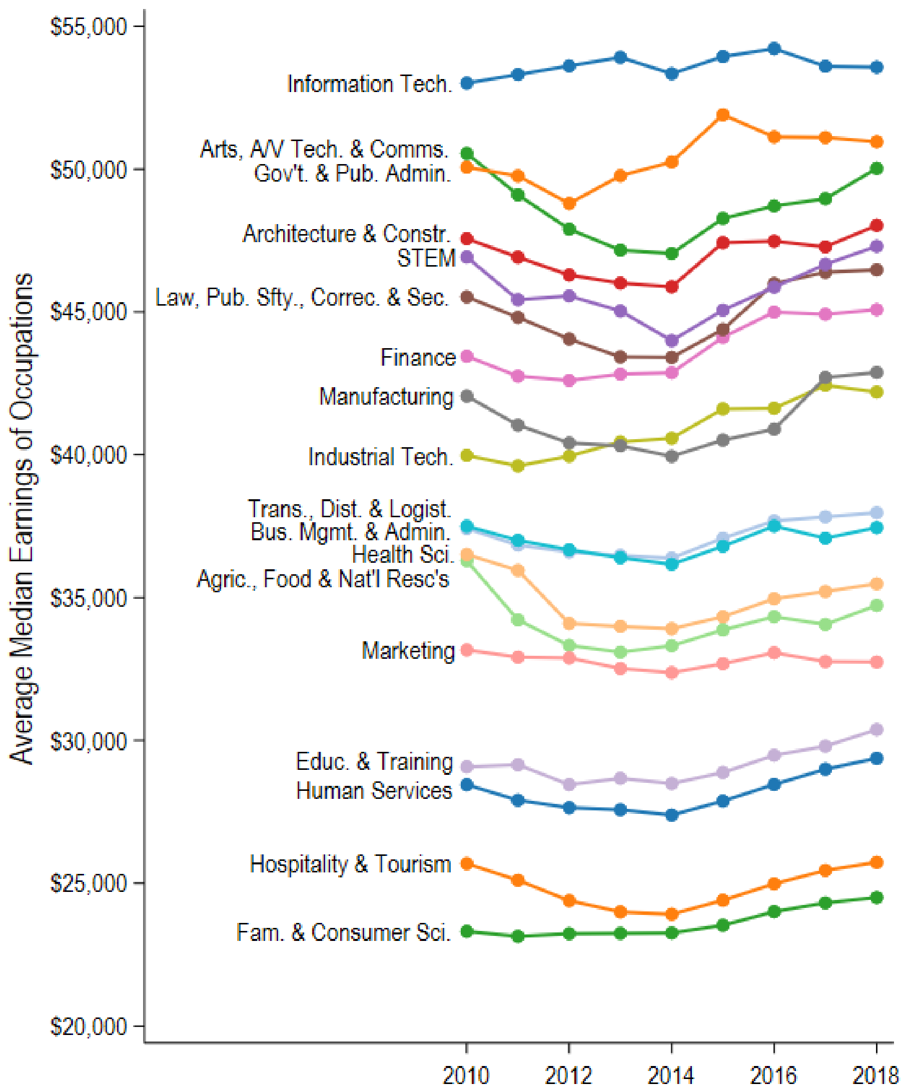
Notes. The table reports results from Equation 2 regression estimates. The dependent variable in Columns 1 and 2 is whether or not a student concentrated in a CTE cluster. The analysis sample is limited to concentrators in Columns 3–5, where the dependent variable is log or nominal potential earnings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

Table 3e: How Student Characteristics Relate to CTE Concentration and Potential Earnings - 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)
FRPL	−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

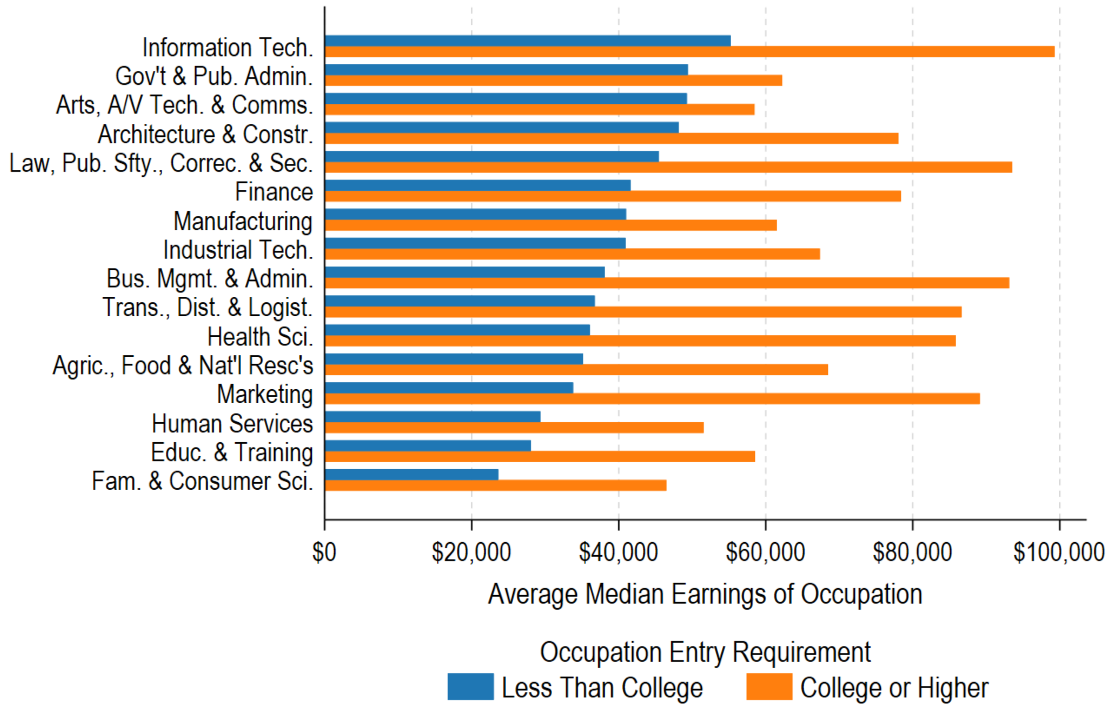
Notes. The table reports results from Equation 2 regression estimates. The dependent variable in Columns 1 and 2 is whether or not a student concentrated in a CTE cluster. The analysis sample is limited to concentrators in Columns 3–5, where the dependent variable is log or nominal potential earnings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

Figure 1. Median Earnings for Occupations With No College Entry Requirement, by Career Cluster



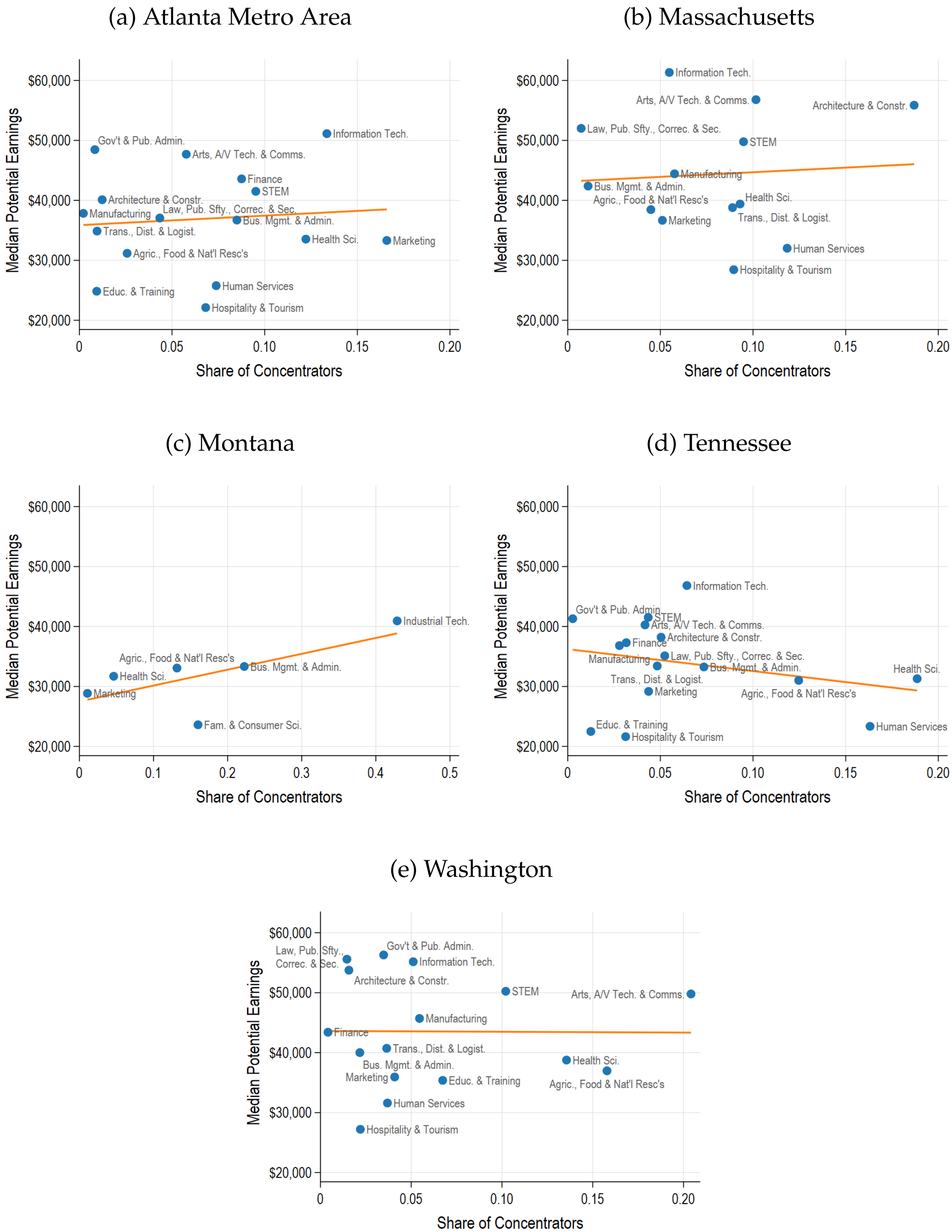
Notes. The figure plots trends over time in median earnings for occupations aligned with the career clusters listed at left.

Figure 2. Median Earnings by Career Cluster



Notes. The figure plots weighted average median earnings of all occupations aligned with each cluster and two levels of typical entry–level education requirement. Data are pooled over all years.

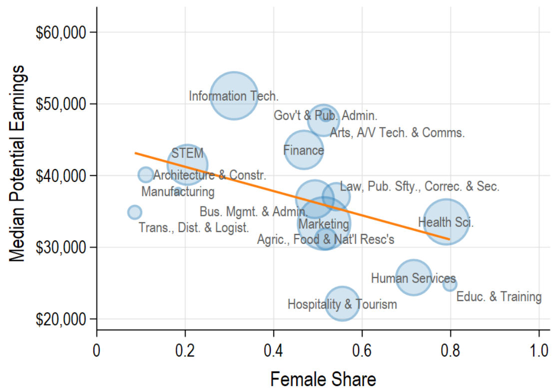
Figure 3. Potential Earnings by Share of All Concentrators



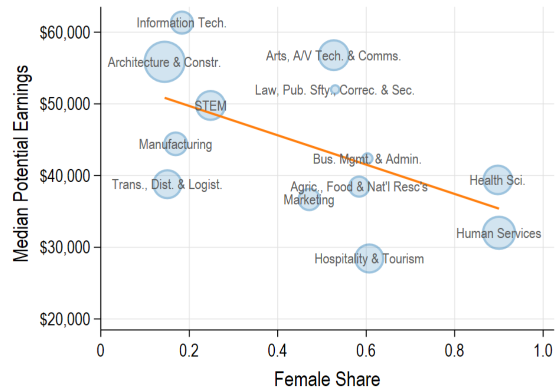
Notes. The figures plot potential earnings (weighted average median earnings) by the share of all concentrators in each state who are in each cluster. Data are pooled over all years.

Figure 4. Potential Earnings by Share of Concentrators Who Are Female

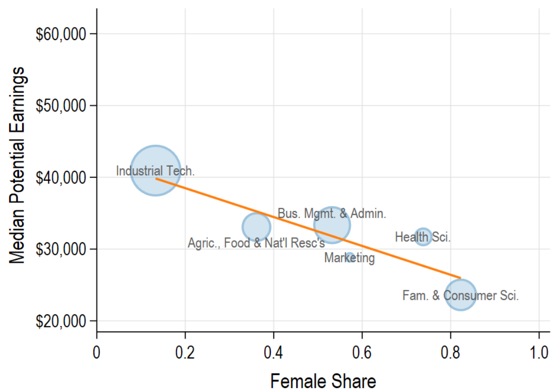
(a) Atlanta Metro Area



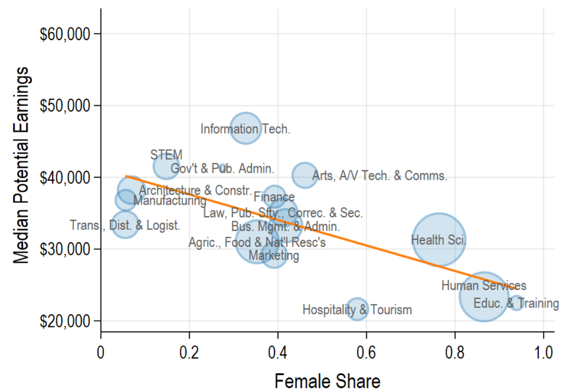
(b) Massachusetts



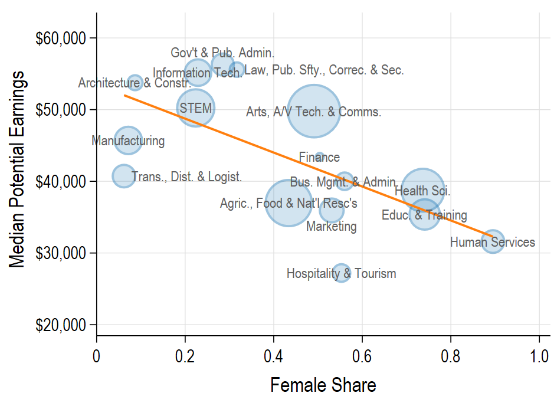
(c) Montana



(d) Tennessee

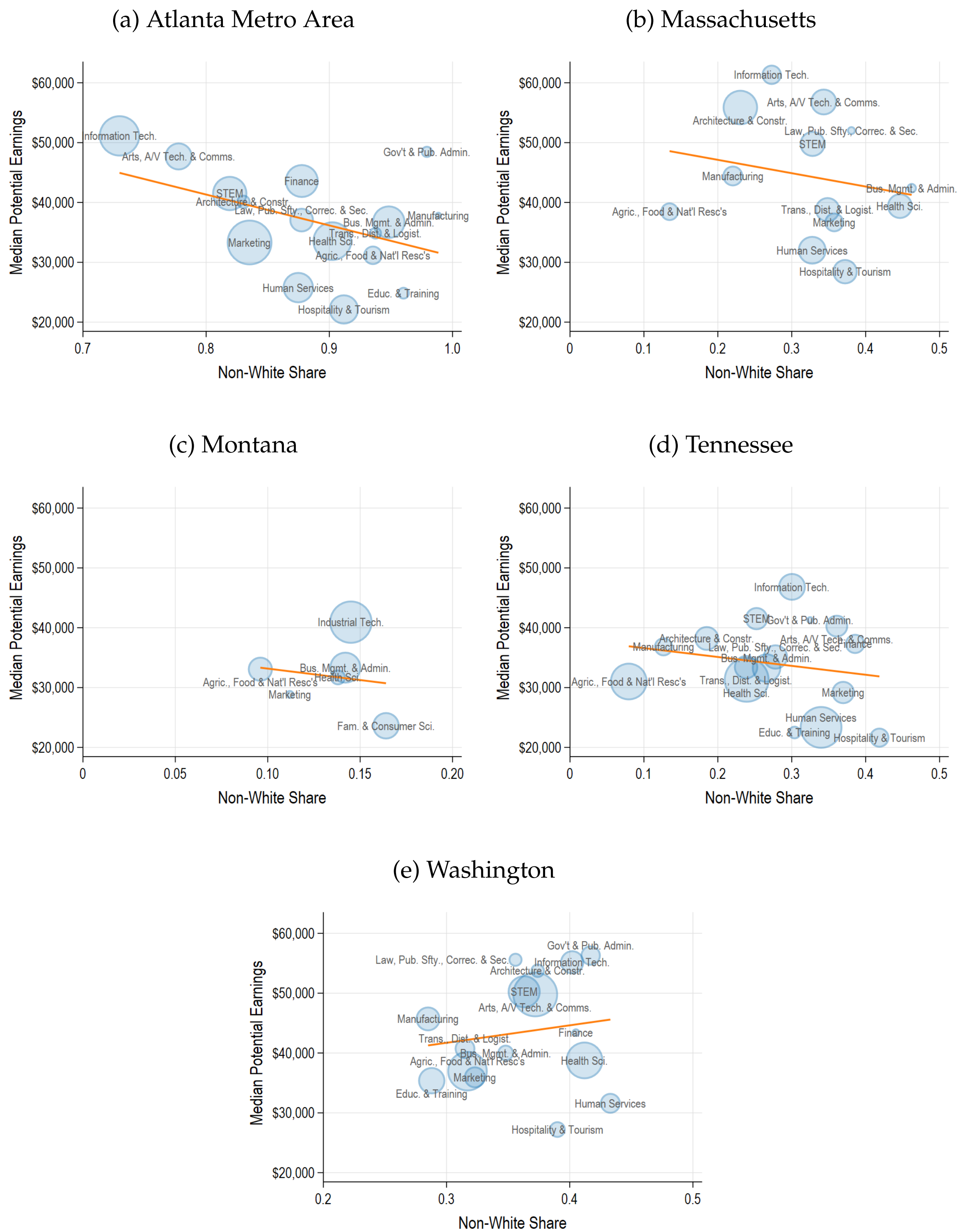


(e) Washington



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

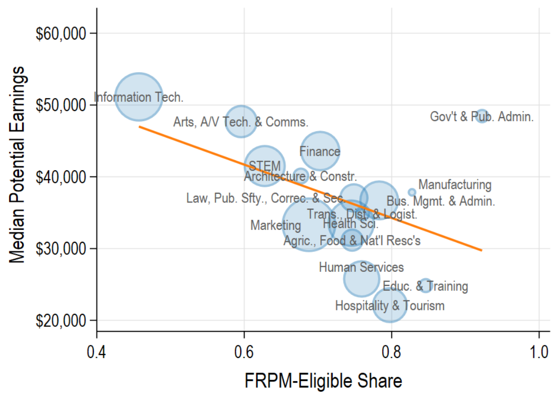
Figure 5. Potential Earnings by Share of Concentrators Who Are Non−White



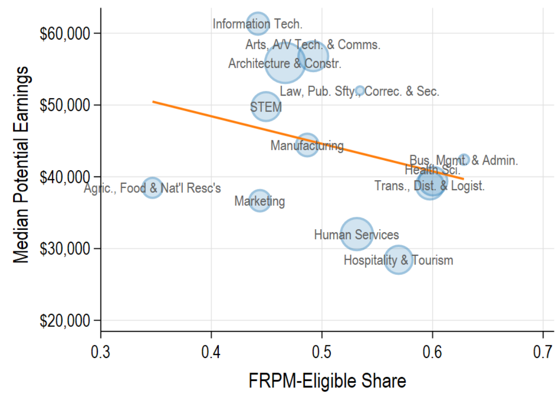
Notes. The figures plot potential earnings (weighted average median earnings) by the share of concentrators in each cluster who are non−White. Marker size is in proportion to total cluster enrollment. Data are pooled over all years.

Figure 6. Potential Earnings by Share of Concentrators Who Receive Free or Reduced–Price Meals

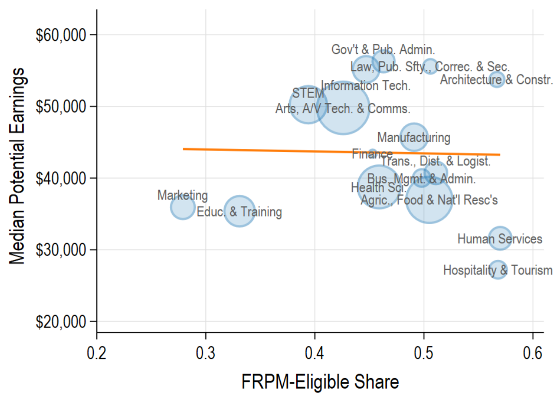
(a) Atlanta Metro Area



(b) Massachusetts

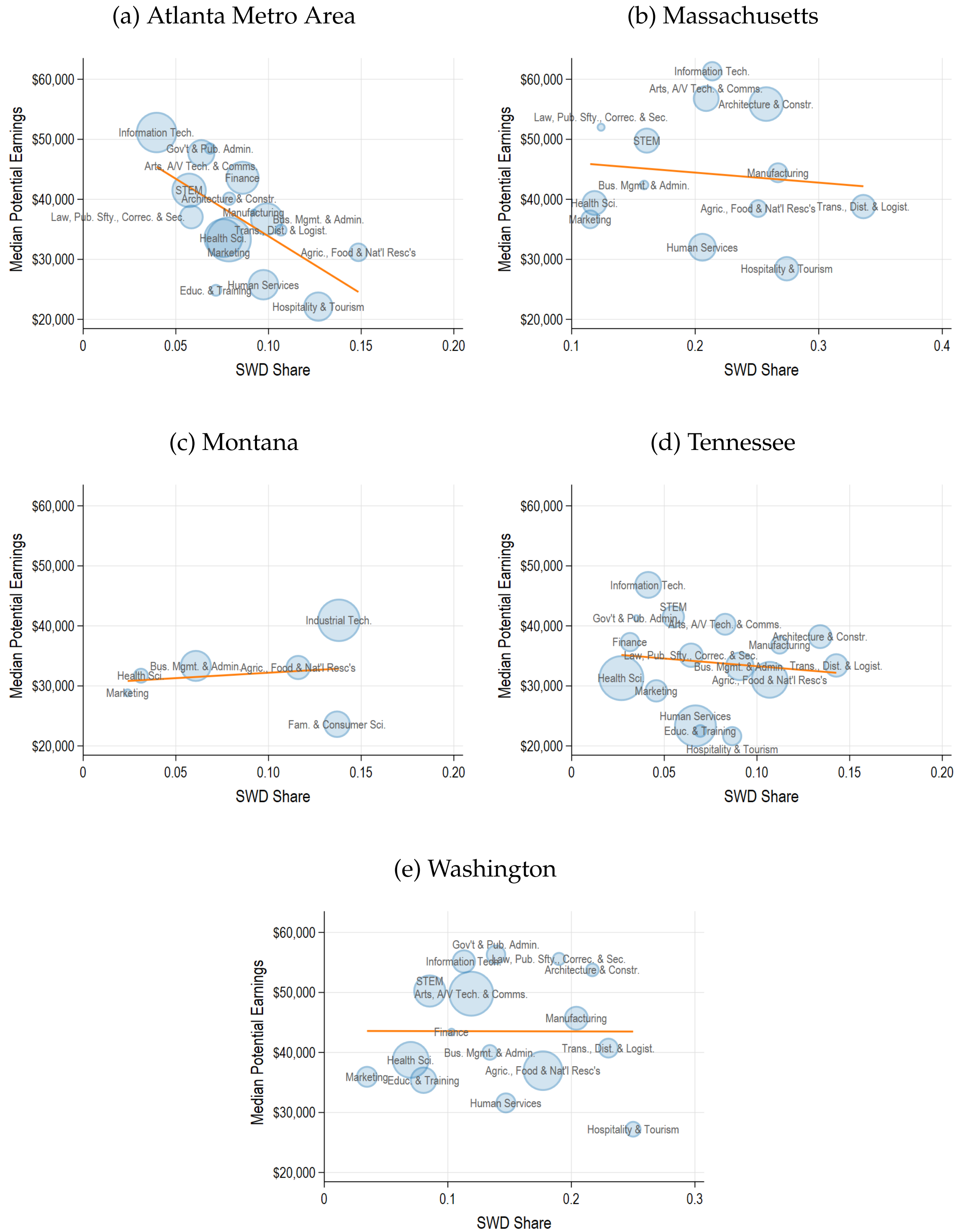


(c) Washington



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. Marker size is in proportion to total cluster enrollment. Data are pooled over all years.

Figure 7. Potential Earnings by Share of Concentrators With an Identified Disability



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

Appendix

Table A1 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.

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

The right-hand side of the equation 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, focusing on the former for Tables 3a–3e results in the main analysis.

Figure A1 depicts weighted-average potential earnings by cluster and location, replicating the pooled, across-location version in Figure 2. 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.

Tables A2a–A2e report Equation 2 regression results when we define y_i as equal to employment-weighted expected earnings in aligned occupations that typically require a college education. We construct y_i using Equation 1, as in the main analysis, but for occupations requiring college at the entry level and their median earnings in each location.

Table A1: 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.

Table A2a: How Student Characteristics Relate to CTE Concentration and College-Level Potential Earnings - Atlanta

	Potential Earnings (Logged)		Potential Earnings ($)
	(1)	(2)	(3)
Female	−0.071***	−0.069***	−5,173.7***
	(0.002)	(0.002)	(153.5)
Black	−0.009*	−0.012**	−829.6**
	(0.004)	(0.004)	(313.3)
Hispanic	−0.021***	−0.020***	−1,340.7***
	(0.005)	(0.005)	(386.4)
Other race	0.025***	0.017***	1,298.3***
	(0.004)	(0.005)	(337.0)
FRPM	−0.015***	−0.014***	−1,040.1***
	(0.003)	(0.003)	(212.0)
Disability	−0.027***	−0.028***	−2,027.3***
	(0.005)	(0.004)	(302.8)
Math score	0.022***	0.018***	1,321.7***
	(0.002)	(0.002)	(126.6)
ELA score	0.004*	0.004*	272.6*
	(0.002)	(0.002)	(122.5)
School FE		x	x
District FE	x		
Cohort FE	x	x	x
Observations	32,663	32,663	32,663

Notes. The table reports regression estimates from Equation 2, where the dependent variable is log or nominal potential earnings with a college education in occupations aligned with a student's CTE cluster. Included explanatory variables are listed at left. The analysis sample is limited to CTE concentrators. FRPM is free or reduced-price meal eligibility and ELA is English Language Arts. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A2b: How Student Characteristics Relate to CTE Concentration and College-Level Potential Earnings - Massachusetts

	Potential Earnings (Logged)		Potential Earnings ($)
	(1)	(2)	(3)
Female	−0.105***	−0.105***	−6,928***
	(0.007)	(0.007)	(556.7)
Black	0.011	0.008	812.2
	(0.007)	(0.008)	(592.7)
Hispanic	−0.004	−0.002	−8.993
	(0.003)	(0.004)	(280.4)
Other race	0.021***	0.020***	1,667***
	(0.005)	(0.005)	(389.0)
FRPM	−0.007***	−0.006***	−510.0***
	(0.002)	(0.002)	(167.5)
Disability	−0.018***	−0.017***	−1,342***
	(0.004)	(0.004)	(307.2)
Math score	0.028***	0.027***	2,135***
	(0.002)	(0.002)	(168.7)
School FE		x	x
District FE	x		
Cohort FE	x	x	x
Observations	60,230	60,230	60,230

Notes. The table reports regression estimates from Equation 2, where the dependent variable is log or nominal potential earnings with a college education in occupations aligned with a student's CTE cluster. Included explanatory variables are listed at left. The analysis sample is limited to CTE concentrators. FRPM is free or reduced-price meal eligibility. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A2c: How Student Characteristics Relate to CTE Concentration and College-Level Potential Earnings - Montana

	Potential Earnings (Logged)		Potential Earnings ($)
	(1)	(2)	(3)
Female	−0.089***	−0.089***	−4,954.8***
	(0.010)	(0.009)	(514.3)
AIAN	−0.002	−0.002	−113.1
	(0.006)	(0.005)	(319.5)
Other race	0.003	0.002	133.6
	(0.004)	(0.004)	(249.2)
Disability	−0.032***	−0.032***	−1,866.3***
	(0.004)	(0.004)	(241.8)
School FE		x	x
District FE	x		
Cohort FE	x	x	x
Observations	22,985	22,985	22,985

Notes. The table reports regression estimates from Equation 2, where the dependent variable is log or nominal potential earnings with a college education in occupations aligned with a student's CTE cluster. Included explanatory variables are listed at left. The analysis sample is limited to CTE concentrators. AIAN is American Indian or Alaska Native. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A2d: How Student Characteristics Relate to CTE Concentration and College-Level Potential Earnings - Tennessee

	Potential Earnings (Logged)		Potential Earnings ($)
	(1)	(2)	(3)
Female	−0.119***	−0.118***	−7,151***
	(0.001)	(0.001)	(63.8)
Black	−0.023***	−0.019***	−944.1***
	(0.002)	(0.002)	(116.7)
Hispanic	−0.004*	−0.007***	−258.2*
	(0.002)	(0.002)	(149.7)
Other race	0.013***	0.006*	494.7**
	(0.004)	(0.003)	(205.6)
Disability	−0.012***	−0.011***	−679.0***
	(0.002)	(0.002)	(143.2)
Math score	0.019***	0.019***	1,151***
	(0.001)	(0.001)	(51.0)
ELA score	0.015***	0.014***	828.5***
	(0.001)	(0.001)	(55.7)
School FE		x	x
District FE	x		
Cohort FE	x	x	x
Observations	154,405	154,405	154,405

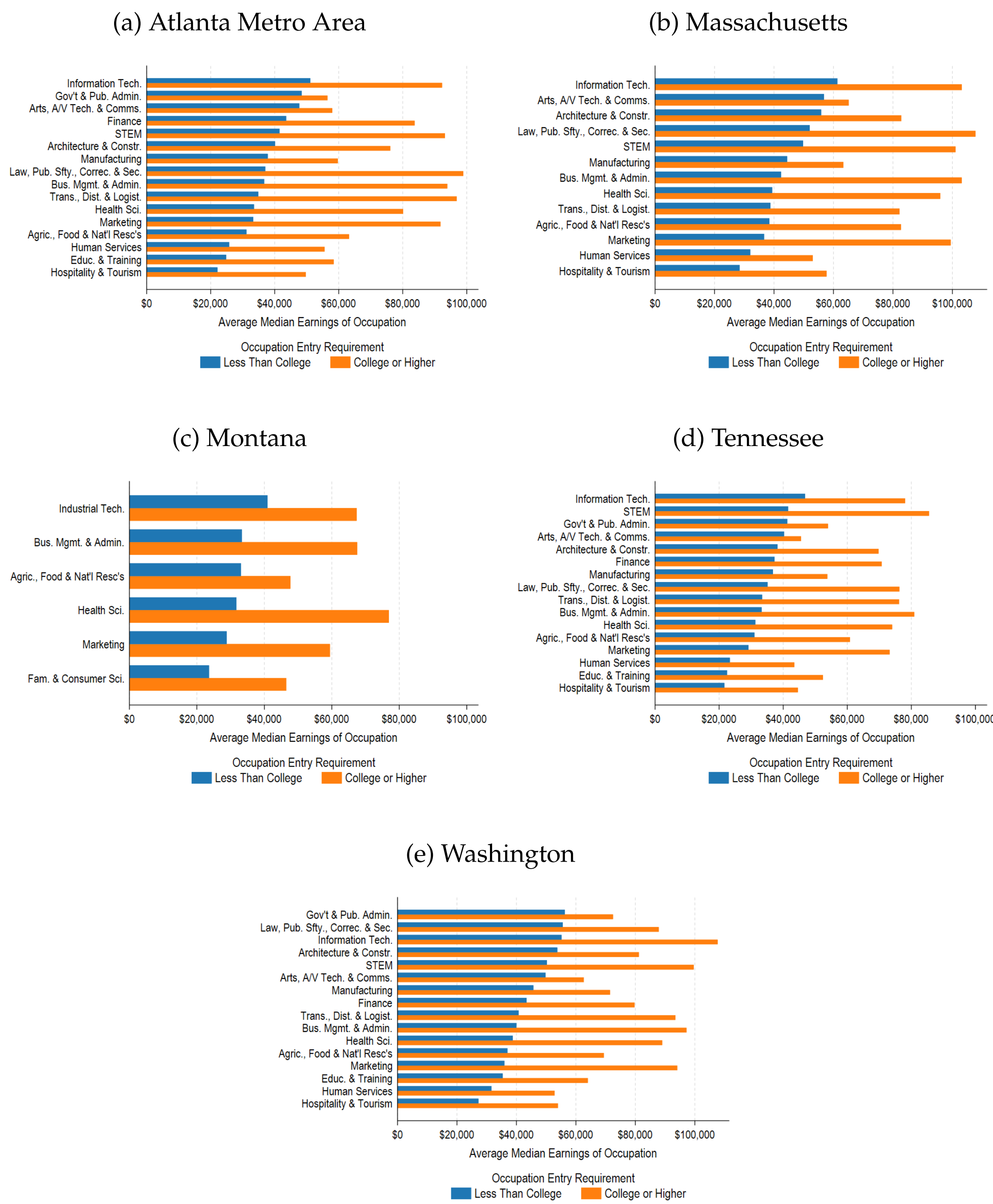
Notes. The table reports regression estimates from Equation 2, where the dependent variable is log or nominal potential earnings with a college education in occupations aligned with a student's CTE cluster. Included explanatory variables are listed at left. The analysis sample is limited to CTE concentrators. ELA is English Language Arts. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A2e: How Student Characteristics Relate to CTE Concentration and College-Level Potential Earnings - Washington

	Potential Earnings (Logged)		Potential Earnings ($)
	(1)	(2)	(3)
Female	−0.071**	−0.068**	−5,286.4**
	(0.002)	(0.001)	(117.1)
Black	0.009*	−0.003	−155.1
	(0.004)	(0.004)	(340.1)
Hispanic	0.012**	0.012**	1,039.5**
	(0.002)	(0.002)	(178.3)
Other race	0.008**	0.001	154.4
	(0.002)	(0.002)	(173.6)
FRPM	0.000	−0.003*	−185.6
	(0.002)	(0.002)	(129.7)
Disability	−0.017**	−0.016**	−1,263.7**
	(0.002)	(0.002)	(188.4)
Math score	0.020**	0.017**	1,411.3**
	(0.001)	(0.001)	(92.3)
ELA score	0.001	0.002	132.3
	(0.001)	(0.001)	(89.2)
School FE		x	x
District FE	x		
Cohort FE	x	x	x
Observations	60,170	60,170	60,170

Notes. The table reports regression estimates from Equation 2, where the dependent variable is log or nominal potential earnings with a college education in occupations aligned with a student's CTE cluster. Included explanatory variables are listed at left. The analysis sample is limited to CTE concentrators. FRPM is free or reduced-price meal eligibility and ELA is English Language Arts. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Figure A1. Median Earnings by State and Occupation Entry Requirement



Notes. The figure plots weighted average median earnings of all occupations aligned with each cluster and typical educational entry requirement by state. Data are pooled over all years.