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Abstract

This study investigates how school-level variation contributes to social stratification even before labor market entry by examining Career and Technical Education (CTE) as a key mechanism for sorting students into pathways with unequal economic returns. Using Delaware administrative data and Bureau of Labor Statistics occupational wage data, we introduce “expected wage” as a measure to quantify inequality in CTE pathways by analyzing how student demographics influence selection into pathways with different expected wages. Multilevel mixed-effects modeling reveals substantial wage gaps across student subgroups, systematically channeling disadvantaged students into lower-wage pathways. Decomposition analyses show gender expected wage gaps stem from within-school factors, while racial and socioeconomic gaps arise from between-school differences. Student segregation into programs contributes more to these inequalities than schools' program offerings. The findings advance our understanding of novel mechanisms for the generation of educational inequality across and within schools.

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Introduction

In the United States, an adult's earned wages directly impact their wellbeing, health, and stability (Chetty et al., 2016). However, wages vary greatly between fields of employment, and even within employment fields, wage disparities persist across genders, races, abilities, and language status (McCall, 2001). An ongoing priority for the country is to embed greater equity in the workplace, as workers of color, workers with disabilities, workers who have immigrated, and workers who identify as non-male genders face wage inequities requiring redress (United States Department of Labor, 2024).

Much research on wage inequities focuses on labor market outcomes, such as whether certain demographic groups earn differential wages or work in particular fields (Bobbitt-Zeher, 2007). Another substantial body of research highlights relationships between college-going behaviors and labor market outcomes, and how these differ between demographic groups (Sloan et al., 2021). The emphasis on college and labor market outcomes is unsurprising, given the close timing of these events. However, these different outcomes likely start much earlier, before the disparities in the labor market become apparent.

Indeed, at least by high school, an individual begins to select coursework and make plans in anticipation of a future career that potentially influences the wages they earn as an adult (Altonji et al., 2012; Card & Payne, 2021). Many high schools have diversified their course offerings to help students prepare for careers, such as introducing advanced placement (AP), international baccalaureate (IB), and career and technical education (CTE) courses. However, a high schooler's course enrollment to support their career aspirations is influenced by external factors, such as the courses available to students and the adults guiding them (Altonji et al., 2012), as well as internal

factors such as their family backgrounds, beliefs about careers and gender norms, sense of self-efficacy, knowledge and skills (Correll, 2001).

Therefore, understanding how heterogeneous and inequitable preferences for careers form in high school is critical, as it helps distinguish wage inequities stemming from labor market participation (e.g., as arising from discrimination or sector- and firm-specific preferences) from those rooted in early career exposure and training in high school. As such, findings from this inquiry could speak to interventions that can apply earlier in an individual's development. Lastly, career-based course offerings (i.e., CTE programs) create a new type of social stratification within schools, distinct from the forms of tracking that have been traditionally studied (Gamoran, 1992). Indeed, as CTE has expanded to encompass multiple professional sectors, there is increasing need to document stratification occurring within CTE programs and the factors associated with this stratification (Giani, 2019).

The extent to which variability and inequity in wage selection begins to form in high school is important but hard to assess due to data limitations. Typically, data on this question have been limited to surveys that ask about students' career aspirations. Holding aside the difficulty of collecting comprehensive and annual survey data on aspirations (e.g., as is collected via the High School Longitudinal Study), aspirations are not necessarily indicative of behavior. In contrast, a CTE career pathway requires completing multiple courses in a specific field of study to become a CTE concentrator. And, because CTE course completion determines a concentration in a career pathway, recurring annual descriptions of this behavior are readily available with student-level administrative data.

CTE courses and students' career pathway concentration therefore provide a different type of social stratification that manifests relatively early in a student's professional career, are

(potentially) substantially unequally distributed, suitable for early policy intervention, and consequential for students' long-run earnings potential, as CTE concentration has been shown in multiple studies to causally increase labor force participation and earnings (Ecton & Dougherty, 2023). Our goal in this study is therefore to quantitatively describe the degree of social stratification within CTE programs of study, focusing on group-level inequality between and within schools.

To do this, we operationalize a concept we call “expected wages,” which are based on the wages assigned to occupational codes from the Bureau of Labor Statistics, which can then be attached to CTE career pathway. In effect, for each CTE career pathway, we can know its expected wage, and these expected wages then form the dependent variable for our analysis.

The research questions guiding this study include:

1. What are the expected wage gaps among student subgroups based on their selected career pathway?
2. How much of these differences in expected wage gaps are due to between versus within school differences?
3. What school-level factors predict variation in expected wage gaps?

Our study context is Delaware, which is a fruitful place to conduct this analysis, as about 90% of students participate in CTE and 60% of Delaware high school graduates are CTE concentrators, as compared to the 49% of students participating in CTE nationally (Association for Career and Technical Education, 2021; Delaware Department of Education, 2023). Using course data, we identify the CTE pathway that each of these CTE concentrators in the state belongs to and link their individual program to aggregate wage data as described above. Our focus is on wage gaps—understood in this context to mean expected wage gaps based on CTE pathway—

between specific groups of students (focusing on differences between gender (coded male or female as recorded by the Delaware Department of Education), race/ethnicity, and economic disadvantage, and the observed factors that are associated with these wage gaps.

Research Context: Career and Technical Education in Delaware

Since 1999, the US Department of Education and the Office of Vocational and Adult Education has developed the National Career Clusters Framework, to guide CTE implementation across the country (Advance CTE, 2023). This Framework outlines 16 “career clusters” that define common knowledge and skills aligned to broad occupational groupings (e.g., Architecture & Construction, Health Science, Hospitality & Tourism) (Advance CTE, 2023; Delaware Department of Education, 2017). Within the career clusters are “career pathways,” or distinct sets of courses that prepare students for a particular career (e.g., Design & Pre-Construction, Health Informatics, Restaurant & Food Services). States are also encouraged to offer “programs of study” (POS) which are specific sequences of courses designed to prepare students for field-specific higher education or the workforce (Delaware Department of Education, 2017). Students are then able to earn the distinction of a “concentrator” upon graduation, meaning they took two courses, one at least at a level two, within a given POS.

In 2018, the Strengthening Career and Technical Education for the 21st Century Act (Perkins V) enabled states to adjust CTE programs to reflect local needs, align with local job markets, and establish definitions for “concentrating” that accurately document processes and outcomes aligned to their CTE programs (ExcelinEd, 2018). Perkins V provided a baseline definition to identify students as concentrators, including any secondary school level student who has completed at least 2 courses in a single CTE POS (Carl D. Perkins Career and Technical Education Act of 2006, 2018). While this definition serves as a basis for state guidance, states are

then able to modify this definition to align with their data collection efforts. In Delaware, a student is considered a concentrator if they participate in two or more sequenced CTE courses within a POS, and Local Education Agencies (LEAs) are responsible for making this distinction for students (Delaware Department of Education, 2020).

Conceptual Framework: Expected Wages as a Measure of Educational Stratification

In the study of social stratification *within* educational processes, researchers have traditionally relied on three primary measures: achievement scores (Reardon, et al., 2019), career aspiration surveys (Signer & Saldana, 2001), and categorical inequalities (Shores, et al., 2020). While each of these measures provides valuable insights, they also have limitations in capturing the full picture of how educational experiences translate to future economic outcomes. To address these limitations and offer a novel perspective on educational stratification, we propose a fourth measure: "expected wages."

The traditional measures, while informative, each present specific challenges. Achievement scores, though indicative of academic performance, are less directly linked to career preferences and potential earnings. Career aspiration surveys reflect student preferences but may not align with actual behaviors or realistic outcomes. Categorical inequalities capture important distinctions in educational experiences, such as enrollment in advanced courses, but often rely on discrete categorizations rather than continuous measures.

Our proposed measure of expected wages combines elements of preference, behavior, and potential economic outcomes, offering several advantages over traditional approaches. First, by using Career and Technical Education (CTE) program enrollment data, it reflects actual student choices rather than just aspirations, providing a behavioral basis for our analysis. Second, it offers a projection of potential earnings, bridging the gap between current educational experiences and

future economic outcomes. This future-oriented approach allows us to examine how early career preferences and educational choices may contribute to wage inequalities.

Unlike categorical inequalities, expected wages offer a continuous scale of potential stratification. This continuous measure provides a more granular view of disparities, allowing for a more detailed analysis of the factors contributing to educational and economic inequalities. Furthermore, the expected wages measure has significant policy relevance, allowing educators and policymakers to assess and address inequalities in real-time, without waiting for long-term labor market outcomes.

The concept of expected wages aligns with the broader understanding of schools as institutions that prepare students for future economic roles. It enables us to examine how early career preferences and educational choices may contribute to wage inequalities, moving beyond simple academic achievement metrics. Additionally, this approach allows us to identify and address stratification within CTE programs, shifting the focus from the traditional CTE versus non-CTE dichotomy to a more nuanced understanding of within-program disparities.

By focusing on expected wages, we can also better understand how educational experiences translate into economic outcomes, offering a more comprehensive view of social stratification in education. This approach provides a more immediate feedback loop for policymakers seeking to reduce inequality in high school settings. It allows for the identification of potential wage gaps early in a student's educational journey, potentially informing interventions or policy changes to address these disparities before they manifest in the labor market. Our specific focus on school-level factors associated with expected wage inequality bolsters this idea.

Recent studies have used expected wages to describe within-school social stratification. Carruthers et al. (2025) construct “potential earnings” for each CTE *cluster* as an employment-

weighted average of local median wages across aligned occupations and show large within-school gender with girls concentrated in lower-paying clusters. Jacob and Ricks (2023) similarly build program-level expected wages to study access and choice; they show gender gaps are driven by preferences, income gaps by supply/access, and race gaps by school-level factors. Relatedly, Carruthers et al. (2024) examine alignment between CTE course-taking and local labor markets and show partial static alignment with limited short-run responsiveness.

Our study advances this literature by shifting the focus from broad career clusters to pathways and by emphasizing the contribution of schools to stratification, rather than only labor-market alignment or program availability. In summary, the introduction of expected wages as a measure of educational stratification offers a novel and potentially powerful tool for researchers and policymakers. By combining elements of student choice, projected economic outcomes, and a continuous scale of measurement, this approach addresses many of the limitations of traditional measures. Applying this framework to CTE programs in Delaware, we anticipate gaining new insights into the formation of wage inequalities and the role of educational institutions in shaping future economic outcomes.

Data

We use two datasets to address our research questions: students' administrative records and aggregate occupational wages from the Bureau of Labor Statistics (BLS). First, the Delaware Department of Education provided the student administrative dataset that we use to construct our sample and act as independent variables. This longitudinal dataset included 57,766 high school students, graduating from 2017 to 2021 (including both CTE concentrators and non-concentrators) alongside information on student demographics (i.e., gender, race/ethnicity) as well as their

participation in special programs, such as Free and reduced-price lunch (FRPL), Individualized Education Programs (IEP) and English Language Learner (ELL) programs.

These data also include CTE course enrollment, academic performance, the high school attended, and concentrator status as identified by LEA. While LEAs identified 30,304 students as concentrators, we refine this definition using course records to more accurately capture concentrator status. Specifically, we classify a student as a concentrator if the student completed two courses in a given pathway with at least one course at or above a level 2 (see Huang et al. (2024) for additional details), yielding 33,275 CTE concentrators. We further limit the sample to Delaware public high school graduates with 8th-grade English Language Arts (ELA) and math scores to assess whether test scores play a key role in determining students' benefits from CTE participation, yielding 29,186 students.

Second, we use occupational employment and wage statistics from the BLS¹ to generate our outcome variable which is the mean expected wage of students selected POS. We link BLS data to DDOE student administrative data using the Delaware Department of Education's crosswalk. Algebraically, we define expected wages for student i as

$$\text{Expected Wages}_i = \frac{1}{|P_i|} \sum_{p \in P_i} \left[\sum_{o \in O_p} \text{MedianWage}_o \left(\frac{\text{Employment}_o}{\sum_{o' \in O_p} \text{Employment}_{o'}} \right) \right],$$

where Expected Wages_i is the employment-weighted average of occupation-level median wages, aggregated first within each pathway (as students can concentrate in multiple pathways) and then across the pathways in which student i concentrated. Let P_i be the set of that student's pathways and $|P_i|$ the number pathways in which student i concentrated. For each pathway $p \in P_i$, let O_p

¹ Occupational Employment and Wage Statistics: <https://www.bls.gov/oes/>

denote the set of SOC occupations linked to p ; index occupations by $o \in O_p$. Let MedianWage_o be the BLS median wage for occupation o in the cohort's graduating year, and Employment_o the corresponding employment count. The denominator $\sum_{o' \in O_p} \text{Employment}_{o'}$ is total employment across occupations in pathway p (o' or "o-prime") is a dummy index used only in the denominator to avoid reusing o . The ratio $\frac{\text{Employment}_o}{\sum_{o' \in O_p} \text{Employment}_{o'}}$ is the employment share of occupation o within pathway p (shares sum to one). The inner sum $\sum_{o \in O_p} \text{MedianWage}_o \left(\frac{\text{Employment}_o}{\sum_{o' \in O_p} \text{Employment}_{o'}} \right)$ yields the employment-weighted mean of median wages for pathway p . The outer average $\frac{1}{|P_i|} \sum_{p \in P_i}$ averages these pathway-level expected wages equally across the student's pathways. Please see Appendix A: Data Appendix for further details on how we constructed this CTE pathway to expected wage link.

Given the country's efforts to improve workplace equity for workers of color, workers with disabilities, non-native English speakers, and workers who identify as non-male genders, we descriptively show several subgroups of interest in Table 1, including male and female students, and white, Black, Hispanic, and Asian students. We additionally provide information comparing students participating in special programs (FRPL, IEP, and ELL) with those who do not participate in each respective program. For visual purposes, we show proportions of student subgroups participating in each career cluster (our analysis is based on linkages to CTE pathways), alongside that career cluster's expected wage. While the statewide sample consists of 51% male and 49% female students, gender representation varies significantly by cluster. For example, the relatively lower expected wage education (C5) career cluster has an 86% female share and the relatively

higher expected wage market (C14) career cluster has a 62% male share. The majority of our students are white (50%), followed by black (18%), Hispanic (16%), and Asian (3%).

Even at the career cluster level of aggregation, an advantage of the descriptive statistics shown in Table 1 is that it is easy to see the sources of expected wage inequality, which stem from two mechanisms: inequality in expected wages by cluster and differential participation in cluster by student group. For example, the hospitality and tourism career cluster (C9) has the greatest representation of Black students (48 percent), with a low mean expected wage of \$28,643. Information technology (C11) has the greatest representation of Asian students (9 percent) and one of the highest expected wages across all clusters (\$90,121). Simple weighted averages from this table ($\bar{w}_g = \frac{\sum_c w_c N_{c,g}}{\sum_c N_{c,g}}$)² show substantial inequality in expected wages between White ($\bar{w}_g = \$59,770$) and Asian ($\bar{w}_g = \$70,859$) students on the one hand, and Black ($\bar{w}_g = \$57,246$) Hispanic ($\bar{w}_g = \$57,210$) students on the other. By far the largest gap is between male ($\bar{w}_g = \$62,721$) and female ($\bar{w}_g = \$54,581$) students, though inequalities are observable for each subgroup.

As we noted earlier, these aggregate data mask variation in expected wages within clusters (i.e., at the pathway level). In addition to between pathway variation within clusters, this table overlooks the significant segregation across pathways that occurs within and between schools, which is the focus of the remainder of this analysis. Nevertheless, these descriptive results lay the groundwork for the quantitative analyses described below.

[Table 1 About Here]

² Weighted averages are computed as $\bar{w}_g = \frac{\sum_c w_c N_{c,g}}{\sum_c N_{c,g}}$, where w_c is the expected wage of career cluster c and $N_{c,g}$ is the number of students in group g enrolled in cluster c .

To further illustrate how gender composition relates to expected wage inequality, Figure 1 plots each school's pathways with female share on the horizontal axis and expected wages on the vertical axis. Each bubble reflects pathway enrollment size, with separate regression lines estimated for three schools. The slopes indicate whether pathways with higher female representation are associated with higher or lower expected wages. In School A (magenta), the slope is strongly negative, showing that pathways with more female students tend to yield lower expected wages. The female-male expected wage gap (estimation methods for this gap are provided below) for this school is -\$48,851. In contrast, School C (blue) exhibits a positive slope, with more female representation in higher wage pathways, with a female-male expected wage gap of \$11,453. School B (green) lies in between, with little relationship overall and an expected wage gap of \$90. These patterns highlight that the link between gender composition and economic returns varies not only across pathways but also sharply across schools, suggesting that a formal decomposition of within- and between-school variation would be a valuable next step.

[Figure 1 About Here]

Methods

Our dependent variable is the student-level measure of expected wages, which links Delaware CTE pathways to BLS occupational wages via the DDOE crosswalk to compute an employment-weighted mean of occupation median wages within each pathway, averaged across the pathways in which a student concentrated. Using this outcome, we estimate subgroup gaps with multilevel mixed-effects models that include cohort fixed effects, allow between-school differences through random intercepts and, in extensions, estimate school-specific gap heterogeneity via random slopes. Models are also estimated with and without 8th-grade test score controls to test whether there is group- and school-selection into expected wage pathways based

on prior achievement. To clarify the mechanisms of inequality, we complement the mixed-effects estimates with a decomposition of total gaps into within- and between-school components following Reardon (2008), which separates disparities due to sorting across schools from those arising inside schools.

Finally, to explain cross-school variation in expected wage inequality, we use with four plausible predictors that are also available in our data, related to the number of quality of pathways offered across schools and the composition and segregation of students into pathways across schools. These four school-level predictors are (i) program availability (number of CTE pathways offered), (ii) mean expected wage of pathway offered, (iii) the relative subgroup share of students in CTE, which is defined as the ratio of the proportion of the reference group (e.g., males) students to the proportion of focal group (e.g., female) students in the pathway, and (iv) subgroup segregation across pathways within a school, measured using one of the following segregation indices: dissimilarity, Gini, isolation, Theil's information theory, and relative diversity. The first two predictors capture aspects of program offerings and quality, and the latter two predictors capture aspects of differential program participation.

These two approaches to understanding how schools contribute to expected wage inequality answer different questions and, used together, give a fuller picture of inequality. The Reardon-style decomposition partitions the average subgroup gap in expected wages into between-school and within-school components, providing an additive accounting of school-based inequality but not how much the within-school gap varies across schools or why. The mixed-effects models, by contrast, estimate school-specific intercepts and subgroup wage gaps while shrinking each school's estimates toward the overall mean given each school's reliability. This approach balances information from individual schools with information from the full sample,

reducing noise for smaller schools and yielding both the average within-school gap and the distribution of school-level variation. These school-specific gaps can then be related to program characteristics and CTE segregation. The two frameworks also anchor each other: the decomposition's within-school component corresponds to the enrollment-weighted mean of school-specific gaps, and the mixed-effects model adds the missing second moment by quantifying their variance. Prior work typically reports only the decomposition (e.g., Quinn, 2015); our contribution is to pair it with random-slope estimates so that we can measure not just the average within-school gap but also its heterogeneity across schools, which is central for diagnosing mechanisms and targeting policy. Specific estimation procedures for each research question follow below.

To answer RQ1, which aims to estimate the expected wage gap between student subgroups, we employed a multilevel mixed-effects model that accommodates both fixed and random effects. Our analysis begins with an examination of the relationship between students' CTE expected wages and their demographic backgrounds. The multilevel mixed-effects model can be written as follows:

$$\text{Level 1: } Y_{ij} = \beta_{0j} + \beta_{gj}D_{ij} + X_{ij} + \delta_c + \gamma_{ij} \quad (1)$$

$$\text{Level 2: } \beta_{0j} = \gamma_{00} + u_{0j} \quad (2)$$

$$\text{Level 2: } \beta_{gj} = \gamma_{g0} + u_{gj} \quad (3)$$

Here, Y_{ij} denotes the outcomes of interests, mean of expected wage from the POS-connected occupations. D_{ij} is a binary variable showing the main explanatory variable of our interests, which includes students' gender, race/ethnicity, FRPL, ELL, and IEP status. Because we are interested in inequalities between specific groups of students – for example, between Black and White students – we estimate these models sequentially at the subgroup-type level. Specifically, we

estimate models for (i) gender, (ii) race/ethnicity, (iii) economic disadvantage, (iv) ELL status, and (v) IEP status. Estimating at the subgroup-type level allows us to provide the true difference in expected wages and not the conditional differences (e.g., conditional on economic disadvantage). X_{ij} controls for student's 8th grade test scores, which are included in separate models, δ_c represents cohort-fixed effects. γ_{ij} is the error term.

One benefit of the multilevel mixed-effects model is that it allows for random intercepts and random coefficients for the explanatory variables of our choice to observe school-specific variations in the correlations we are interested in. These relationships are shown through β_{0j} and β_{gj} . Level 2 equations divide school-specific intercepts and slopes into across-school averages and school-specific parts. γ_{00} shows the average of the school means, and u_{0j} indicates the unique intercept for school j . Similarly, γ_{g0} is the average difference in expected wages (e.g., male vs female expected wage) for the entire sample while u_{gj} denotes the school-specific difference in expected wages between the focal group (e.g., male students) and the reference group (e.g., female students).

Next, we use Reardon's (2008) gap decomposition strategy to identify how much of the estimated wage gap is due to between versus within school differences. Reardon (2008) combines two decomposition strategies proposed by Fryer and Levitt (2004, henceforth FL) and Hanushek and Rivkin (2006, henceforth HR). Reardon (2008) shows that the Black and White gap (in his case achievement and in our case the expected wage) can be divided into three parts: the unambiguous between-school gap, the unambiguous within-school gap, and an ambiguous portion. To decompose the expected wage gap between the focus group (male, black, Hispanic, ELL, FRPL, and IEP students) and the reference group (female, white, non-ELL, non-FRPL, and non-

IEP students), we use the model from Reardon (2008). First, we estimate the following regression to measure the focus-reference group expected wage gap:

$$Y_{ij} = \beta_0 + \beta_1 D_{ij} + \beta_2 p_j + \varepsilon_{ij} \quad (4)$$

where D_{ij} is a binary variable indicating student i 's demographics in school j , and p_j is the proportion of students in school j who falls into our focus group. From this model, we estimate the average focus-reference group expected wage gap as follows:

$$Wage\ gap = \widehat{\beta}_1 + \widehat{\beta}_2(\underline{p}_j^f - \underline{p}_j^r) \quad (5)$$

We can rewrite the gap again as follows:

$$Wage\ gap = \widehat{\beta}_1[1 - (\underline{p}_j^f - \underline{p}_j^r)] + (\widehat{\beta}_1 + \widehat{\beta}_2)(\underline{p}_j^f - \underline{p}_j^r) \quad (6)$$

$\widehat{\beta}_1[1 - (\underline{p}_j^f - \underline{p}_j^r)]$ is the within-school gap, and $\widehat{\beta}_2(\underline{p}_j^f - \underline{p}_j^r)$ is between-school gap.

$\widehat{\beta}_1(\underline{p}_j^f - \underline{p}_j^r)$ is the proportion of the gap which comes from the interaction of between- and within-school components, making it ambiguous. To conduct the decomposition adjusting for student-level test scores, we obtained $\widehat{\beta}_1$ and $\widehat{\beta}_2$ by estimating Equation (4) including 8th grade ELA and math scores as covariates. We then used these estimates, along with the difference in the proportion of students in the focus and reference groups $(\underline{p}_j^f - \underline{p}_j^r)$, to decompose the total expected wage gap into within-school and between-school components.

Finally, to answer RQ3, which investigates the school-level factors driving school-specific variation in the expected wage gap, we first categorize school-level factors into "CTE opportunity characteristics" and "CTE segregation patterns." These factors map directly onto our analyses of between- versus within-school inequality. CTE opportunity characteristics are measured by the number and average expected wages of POSs offered and could explain between-school gaps if

certain schools systematically offer fewer or lower-wage programs. Meanwhile, CTE segregation patterns speak to within-school inequality by examining how different student groups either differentially participate in CTE programs or are distributed across available programs within the same school. For program availability characteristics, we consider the number of POSs offered in the school and the mean expected wage of all POSs in the school. These metrics show the diversity of POS offerings within each school and indicate the extent to which higher-wage programs are accessible to students.

For CTE segregation, our first measure is relative participation in CTE in school s , $RP_s = \frac{\phi_s^G}{\phi_s^R}$, where G is the focus group (e.g., female), R is the reference group (e.g., male), and ϕ is the percent of students in group G or R that are CTE concentrators in school s . Relative participation less than one indicates that participation rates for the focal group are lower than participation rates for the reference group. Our second measure is subgroup segregation between CTE pathways in school s . Our preferred representation of this is the Dissimilarity index, measured as $D_s = \frac{1}{2} \sum_{p=1}^{P_s} \left| \frac{n_{sp}^G}{\sum_p n_{sp}^G} - \frac{n_{sp}^R}{\sum_p n_{sp}^R} \right|$, where p indexes pathways and n indicates counts of CTE concentrators in group G or R . Larger values indicate greater segregation of G and R across pathways. For robustness, we also include other measures of segregation in Tables C2-C5 in the Online Appendix; results are nearly unchanged.

Given Equations (1) through (3), these CTE opportunity and segregation variables can be entered as interaction terms. Holding the Levels 2 and 3 equations as fixed, we can modify Equation (1) as follows:

$$\text{Level 1: } Y_{ij} = \beta_{0j} + \beta_{gj}D_{ij} + X_{ij} + \mathbf{Z}_{sj} + \beta_{gj}^z(D_{ij} \times \mathbf{Z}_{sj}) + \delta_c + \gamma_{ij} \quad (5)$$

where \mathbf{Z}_{sj} , where s indexes schools, is a vector comprising one of the four CTE opportunity/segregation variables and the interaction of D_{ij} and \mathbf{Z}_{sj} indicates how much the expected wage gap changes as CTE opportunity/segregation increases across schools.

Results

Research Question One: Magnitude and Distribution of Inequality

We start by estimating unconditional wage gaps, which describe average inequality in expected wages for the state. We implement these models pairwise to avoid controlling for subgroup characteristics that might attenuate true group-specific differences (e.g., estimating Black-White expected wage differences controlling for economic disadvantage). The adjusted pairwise difference in wages between male and female students (Table 2, Column 1, Panel A) is -\$10,823.59 ($p < 0.001$), meaning that linked occupational wages to CTE pathways for males exceed those for females by more than \$10,000 – these gaps are by far the largest we observe. In Panel E, Black students concentrate in pathways with expected wages that are -\$4,032.48 less than white students ($p < 0.001$), and Hispanic students expected wages are -\$5,051.60 less than white students ($p < 0.001$). For students receiving FRPL, IEPs, ELL services (Panels B—E, respectively), gap magnitudes range from -\$7,651.44 to -\$2,221.49.

In Column 2, we incorporate a random intercept in the model; doing so allows us to test whether the average wage varies among schools and provides estimates comparable to fixed effects models, yielding expected wage inequalities roughly interpretable to the average within school expected wage gap. Controlling for between school variation in average wages changes gap magnitudes. For gender, the gap narrows only slightly to -\$10,438.22 ($p < 0.001$), but Black and Hispanic expected wage gaps shrink more dramatically, by 68% (-\$1,310.74; $p < 0.01$) and 78% (-

\$1,132.08; $p < 0.05$), respectively. Controlling for between school differences attenuates expected wage gaps for students receiving FRPL, IEPs, and ELL services by comparable amounts—30% to more than 100%, depending on the subgroup. These results point to the importance of cross-school differences in the formation of expected wages, a result we explore more deeply below.

Continuing with the mixed effects framework, in Columns 3 and 4, we run the same models as shown in Columns 1 and 2 but control for 8th grade test scores. The influence of test scores on expected wage gaps is mixed. Gender gaps remain roughly the same $-\$11,395.45$ ($p < 0.001$; column 3) and $-\$10,797.55$ ($p < 0.001$; column 4). Black-White expected wage gaps are no longer distinguishable from zero and are close to zero in magnitude ($-\$127.01$) and, on average within schools, reverse sign to be $\$858.38$, meaning on average within schools among similarly achieving students, Black students have greater expected wages than White students, though this result is not distinguishable from zero difference in expected wage gaps. For Hispanic-White gaps, the gap shrinks by more than half when controlling for test scores but not school-level random intercepts to $-\$2,175.43$ ($p < 0.001$) and reduces to $\$94.48$ when including both test scores and random intercepts, favoring Hispanic students but not statistically significantly different from zero. Controlling for test scores similarly attenuates expected wage gaps for students receiving IEPs or ELL services, making the gaps no longer distinguishable from zero, and for low-income students the gap is reduced by 40% ($-\$4,603.20$; $p < 0.001$) with test scores alone and 70% ($-\$2,310.75$; $p < 0.001$) with test scores and school-level random intercepts.

[Table 2 About Here]

Research Question Two: Within or Between School Factors

Figure 1 documents sharp between-school differences in gender sorting across pathways, and Table 2 shows that adding school-level random intercepts attenuates average expected-wage gaps,

which indicates that schools matter for inequality. To quantify how much they matter, we extend Equation 2 to include school-specific random slopes for the subgroup indicator and summarize the distribution of within-school gaps by its mean and standard deviation. We then re-estimate the model with 8th-grade test scores to adjust for selection on prior achievement. Comparing these unadjusted and adjusted estimates informs our understanding of the contributors to expected wage inequality. First, a lower mean gap after adjustment implies that pre-existing achievement differences explain part of the disparity. Second, a reduction in the variance of the random slopes implies that selection also explains cross-school heterogeneity in gaps. Third, the correlation between school-specific gaps before and after adjustment reveals the persistence of school effects. Even if the mean and variance shrink, a high correlation and stable rank ordering of schools indicate a school-based contribution, whereas a weak correlation would point to school-based sorting correlated with pre-existing achievement as the primary mechanism.

Table 3 presents results from this analysis. Re-estimating Equation 2 with school-specific random slopes leaves the mean gaps very close to the random-intercept estimates in Table 2 (columns 2 and 4), but with larger standard errors and, crucially, it reveals how much those gaps vary across schools. For example, the no test score control female gap is $-\$11,330$ (Table 3, column 1) and $-\$11,640$ with test score controls (column 2) in the random-slope model versus $-\$10,438$ and $-\$10,798$ in the random-intercept model. Similarly for Black-White and Hispanic-White gaps and other subgroups of students receiving educational services, models with random slopes have a limited influence on the magnitude of the expected wage gap, though standard errors consistently increase.

The new information is the dispersion of school-specific gaps (SD of random slopes): $\$12,985.44$ for gender gaps, $\$4,733.85$ for Black-White gaps, $\$3,671.51$ for Hispanic-White gaps,

\$4,913.37 for SWD gaps, \$5,706.20 for low-income gaps, and \$3,393.63 for ELL gaps. Within the context of random slopes, just as with the random intercepts models, adding 8th-grade test scores leaves the female and ELL gaps essentially unchanged, but it attenuates low-income and race/ethnicity gaps and nearly eliminates the SPED gap.

Most notably for understanding the contribution of school-level factors, adding 8th-grade test scores leaves the cross-school variance of the within-school gaps essentially unchanged. As illustrated in Figure 2, which shows kernel density plots for the gender expected wage gap with and without test scores using school-specific OLS estimates from the models in Table 2, we see visually that the variation in these school-specific estimates is largely unchanged. Regression-based approaches show that this pattern generalizes to each subgroup comparison. Specifically, the SD of the school-specific gender gap moves only from \$12,985 to \$12,773 (−1.6%); Black–White \$4,734 to \$4,553 (−3.8%); Hispanic–White \$3,672 to \$3,473 (−5.4%); low-income is \$5,706 to \$5,715 (+0.2%). Cross-school variation shrinks most notably, albeit still modestly, for students receiving special education (\$4,913 to \$4,302; −12.5%) and ELL (\$3,394 to \$3,078; −9.3%) services. In short, conditioning on prior achievement attenuates some mean gaps but does not materially reduce the dispersion of school-specific gaps, indicating that cross-school heterogeneity in expected-wage inequality is not primarily a function of selection on test scores and is consistent with school-level mechanisms.

[Table 3 About Here]

Further corroboration of the school-driven hypothesis can be seen in Table 4, which correlates the unconditional (no test score adjustment) and conditional school-level gap estimates for each subgroup. The school-specific random slopes of expected gap estimates with and without test score controls (corresponding to the "shrunken" Empirical Bayes estimate from Equation 3)

show correlations of at least 0.98 for each subgroup comparison. This extremely high correlation indicates that the relative ranking of schools in terms of their expected wage gaps is preserved regardless of prior student-level achievement; for example, if School A had a larger wage gap than School B before controlling for test scores, it still does after controlling for them. This persistence in the ordering of schools suggests that wage gaps between demographic groups at the school level are not primarily driven by differences in student academic preparation, but rather by school-level factors that generate these inequalities.

We evaluate the robustness of these correlations by estimating school-specific wage gaps conditional on 8th grade test scores via three different estimation approaches: ordinary least squares regression, coarsened exact matching (CEM; Blackwell et al., 2009) and entropy balancing (Hainmueller & Xu, 2013), separately. In practice, we estimate a single regression for each school in our data, regressing expected wages against subgroup indicators and 8th grade test scores, controlling for test scores via these three different approaches. These school specific estimates are noisier, and therefore we expect the correlation to the unconditional models to attenuate, but they remain large, ranging between 0.63 to 0.99. Thus, we conclude that school-level variance in the expected wage gaps is largely uncorrelated with 8th grade test scores.

[Table 4 About Here]

The random-slope models show substantial cross-school dispersion in subgroup gaps, and the ordering of this dispersion changes little when we control for 8th-grade test scores. We then decompose overall expected wage gaps into between- and within-school components. This decomposition answers a related question: how much of the total gap arises from differences in the schools students attend (between) versus unequal outcomes among students within the same schools (within). While the multilevel model quantifies how gaps vary across schools and how

stable that variance is to test-score controls, the decomposition quantifies how much that cross-school variation contributes to total inequality relative to within-school processes. In effect, the decomposition tests a segregation mechanism: if subgroups are sorted into schools with systematically higher or lower mean expected-wages, the between-school component will be large; if not, the gap is driven primarily by within-school placement and course-taking patterns.

Results are presented in Table 5. For gender, 97% of the expected wage gap occurs within schools. This result corresponds to results discussed above, with school-level variation in the expected wage gap being exceptionally high between male and female students and random intercepts models (Table 2 column 2) having little impact on the overall gap. In contrast, for Black-White and Hispanic-White expected wage gaps, 59% and 85% of the variation occurs between schools, respectively, meaning that most of the expected wage gap for racial/ethnic inequality is due to differences among schools in average expected wage offerings and the segregation of Black and Hispanic students into those schools. This result was foreshadowed when we showed that including a school-specific random intercept, controlling for average differences in expected wages between schools, greatly attenuated the gap for Black and Hispanic students. For students receiving ELL services, most of the gap occurs between schools (132%), whereas for students with FRPL services and IEPs, the majority of the gap occurs within schools (49% and 74%, respectively). In general, the ambiguous portion of the gap, which cannot cleanly be attributed to between or within school factors, is trivial.

As we observed previously, when we condition on 8th-grade test scores (Table 2, columns 3 and 4; Table 3 column 2) the total expected wage gaps shrink for several groups. When the total gap is small, the within versus between shares become unstable and often reflect offsetting components, so interpretation should focus on dollar levels. In this decomposition the between-

school component is the part of the gap that arises because the two groups (with similar test scores) are distributed across schools with different average expected wages. The within-school component is the average difference between the groups (with similar test scores) within the same school. In levels, the female–male gap is $-\$11,395$, almost entirely within ($-\$10,992$) with a tiny between piece ($-\$236$). For Black–White, the total gap is essentially zero ($+\$119$) offset by a positive within school gap of $\$1,064$ and a negative between school gap of $\$1,094$. For Hispanic–White, the total gap is negative still, at $-\$2,050$, with the between school component dominating at $-\$2,642$ dominating and the within school component partially offsetting at $\$512$. For low-income expected wage gaps, the total is $-\$4,603$, split roughly half within ($-\$2,104$) and half between ($-\$2,345$). For SWDs, the total is essentially zero ($-\$67$) because a within advantage ($+\$381$) offsets a between disadvantage ($-\$450$). ELL shows the same structure: total $-\$752$ with within $+\$1,095$ offset by between $-\$1,922$. The ambiguous component is small in all cases.

[Table 5 About Here]

There may seem a tension in the results presented above, as we observe large between-school variation in school-specific gender gaps, but the between-school component of the gender-expected wage gap is trivial. However, there is no contradiction in observing large between-school variation in school-specific gender gaps while the between-school component of the mean gender gap is trivial. The Reardon-style decomposition attributes between-school inequality to segregation across schools; for gender there is little segregation because most schools enroll similar shares of boys and girls, so the between component is near zero. By contrast, the random-slope model captures within-school heterogeneity in the gender gap arising from school contexts—culture, offerings, counseling, resources—even when overall gender composition is balanced. This

differs for groups that are more unevenly distributed across schools (e.g., low-income, Hispanic, ELL), where the between component is then meaningful.

A second tension concerns how test-score adjustment affects the role of schools in expected-wage inequality. For the Black-White comparison, conditioning on 8th-grade scores nearly eliminates the mean gap and moves the decomposition from mostly between schools (59%) to almost entirely within schools. This shift occurs because Black-White segregation among students with similar test scores is not correlated with variation in school mean expected wages. However, the decomposition still shows an important school contribution. Even among similarly achieving Black and White students, a sizable within-school expected-wage gap remains (about \$1,064). Further, the dispersion of school-specific within-school gaps is nearly unchanged (Table 3, column 2), and the rank ordering of schools by those gaps before and after adjustment is highly stable ($\rho \geq 0.80$; Table 4). In short, conditioning on test scores explains the average cross-school component through ability-linked composition, yet schools continue to differ in how similarly prepared students are placed and steered within schools.

Lastly, the evidence weighs against student preferences as the primary driver of expected-wage inequality. First, if preferences were dominant, conditioning on 8th-grade test scores (a proxy for accumulated opportunity) would not erase the average Black–White gap; it would persist after adjustment. Instead, controlling for unequal opportunity eliminates the Black-White gap entirely. Second, if preferences drove expected wage inequality, then the cross-school pattern of within-school gaps should not remain stable: holding ability constant should reduce both the mean and the variance of school-specific gaps and reshuffle which schools look most unequal. Instead, test-score adjustment collapses the mean racial gap—consistent with achievement-linked sorting and unequal prior opportunity—yet the dispersion of within-school gaps is essentially unchanged and

school rankings of those gaps remain highly correlated. The failure to reshuffle, even after conditioning on ability, points to school processes (program availability, counseling/placement, scheduling) rather than preferences, and motivates our next step, which is to identify which school features predict cross-school variation in within-school expected-wage gaps.

Research Question Three: Predictors of School-Level Gaps in Wage Inequality

The results above showed small or vanishing between-school contributions once we condition on test scores but persistent cross-school dispersion in within-school gaps. Thus, we treat schools as important contributors to inequality and ask which school features predict larger (or smaller) within-school expected-wage gaps. We focus on two mechanisms aligned with our prior discussion: (i) opportunity structure, captured by program availability (number of POS/pathways and the mean expected wage of a school's offerings), and (ii) within-school sorting, captured by the relative share of subgroups concentrating in a CTE pathway and CTE segregation measures (i.e., the dissimilarity index). These factors map directly onto the channels identified by the mixed-effects and decomposition results: opportunity structure speaks to what schools make available; segregation speaks to how students are distributed across those offerings within schools.³

Of the hypotheses considered, CTE pathway availability and relative CTE participation are associated with smaller female-male and White-Black expected wage gaps, and subgroup segregation across CTE pathways is associated with larger female-male and FRPL gaps (Table 6). For pathway availability, each additional CTE pathway offered is associated with a \$328.41 smaller female-male gap ($p < 0.05$; \$2,578.35 per 1 SD of offerings) and a \$304.46 smaller Black-White gap ($p < 0.01$; \$2,390.32 per 1 SD). For relative participation, a one-unit increase in the

³ In reporting results, to conserve space, we focus on female-male, low income-non-low income, and Black-White expected wage gaps. For other subgroups (ELL, SWD, Hispanic, and Asian students), none of the interaction terms were statistically significant at conventional levels.

Black-White representation ratio is associated with an \$8,863.37 smaller Black-White gap ($p < 0.01$; \$1,444.73 per 1 SD); the gender model shows no reliable association. For segregation, a one-unit increase in the dissimilarity index is associated with a \$34,149.68 larger male advantage in the female model ($p < 0.001$; \$4,961.95 per 1 SD) and a \$16,562.69 larger non-FRPL advantage in the FRPL model ($p < 0.01$; \$1,301.83 per 1 SD). Interactions with the school's mean pathway wage are indistinguishable from zero in all models, consistent with no differential moderation of gaps by average pathway wage levels. For ELL and SWD students these predictors are not associated with expected wage gap variation. We run alternative specifications with alternative measures of CTE pathway segregation (Tables C2—C5) and the results are nearly entirely unaffected. Figure 3 visualizes these relationships by plotting the school-level gender expected wage gap against five alternative measures of gender segregation. Consistent with the regression results, all indices yield a clear negative association. Schools showing stronger gender segregation across CTE pathways show systematically larger wage gaps that disadvantage female students, underscoring the robustness of the pattern across different measurement approaches.

[Table 6 About Here]

[Figure 3 About Here]

Conclusion

CTE programs offer several benefits, including greater high school graduation rates, improved labor market participation, and increased earnings. However, there is substantial variation in these outcomes across different student subgroups (Brunner et al., 2023; Ecton & Dougherty, 2023; Dougherty, 2018; Hemelt et al., 2019). Using administrative data from the Delaware Department of Education and occupation employment and wage statistics from the Bureau of Labor Statistics, we estimate the expected wage gap between student subgroups.

Our estimation confirms that significant expected wage gaps exist across student subgroups. Female, Black, Hispanic, low-income, IEP participants, and ELL students are more likely to enroll in CTE pathways with lower expected wages, and these wage gaps vary substantially between schools. For gender, within-school factors contribute more to the wage gap between female and male students, while between-school factors are more significant for Black-White and Hispanic-White gaps.

Despite the importance of identifying the sources of wage gaps among CTE concentrators, limitations remain. First, we were unable to determine why students, especially disadvantaged ones, are concentrated in specific CTE pathways instead of pursuing a broader range of options. For instance, our data does not capture the influence of peer networks or peer effects, which may drive disadvantaged students toward pathways with weaker labor market outcomes. Second, the results may not be generalizable (e.g., Jacob & Ricks, 2023 emphasize school choice mechanisms as drivers of inequality). Third, we lack detailed qualitative information about the factors influencing students' decisions to concentrate in different pathways and how those factors may differ across schools and by subgroup. Further exploration to collect alternative hypotheses, coupled with testable interventions, would allow policymakers to more carefully design policies to ensure more equitable engagement with the rich CTE offerings currently available to students.

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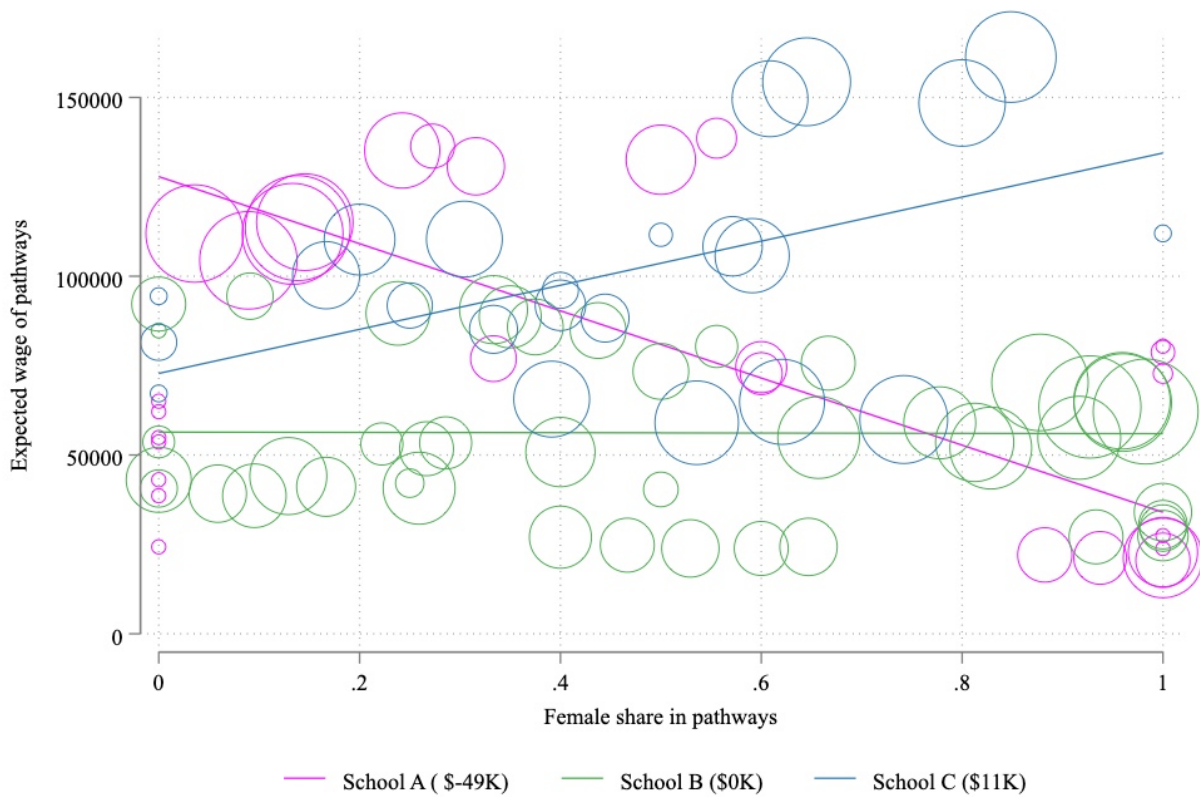


Figure 1. Expected Pathway Wages vs Female Share for Selected Schools.

Each circle represents a pathway, weighted by student enrollment. The line show the school-specific relationship between the expected wage of a pathway and its share of female concentrators. The three schools were selected to illustrate heterogeneity and represent cases with a large negative (School A), near-zero (School B), and positive (School C) school-level gender gap, as estimated by our multilevel model.

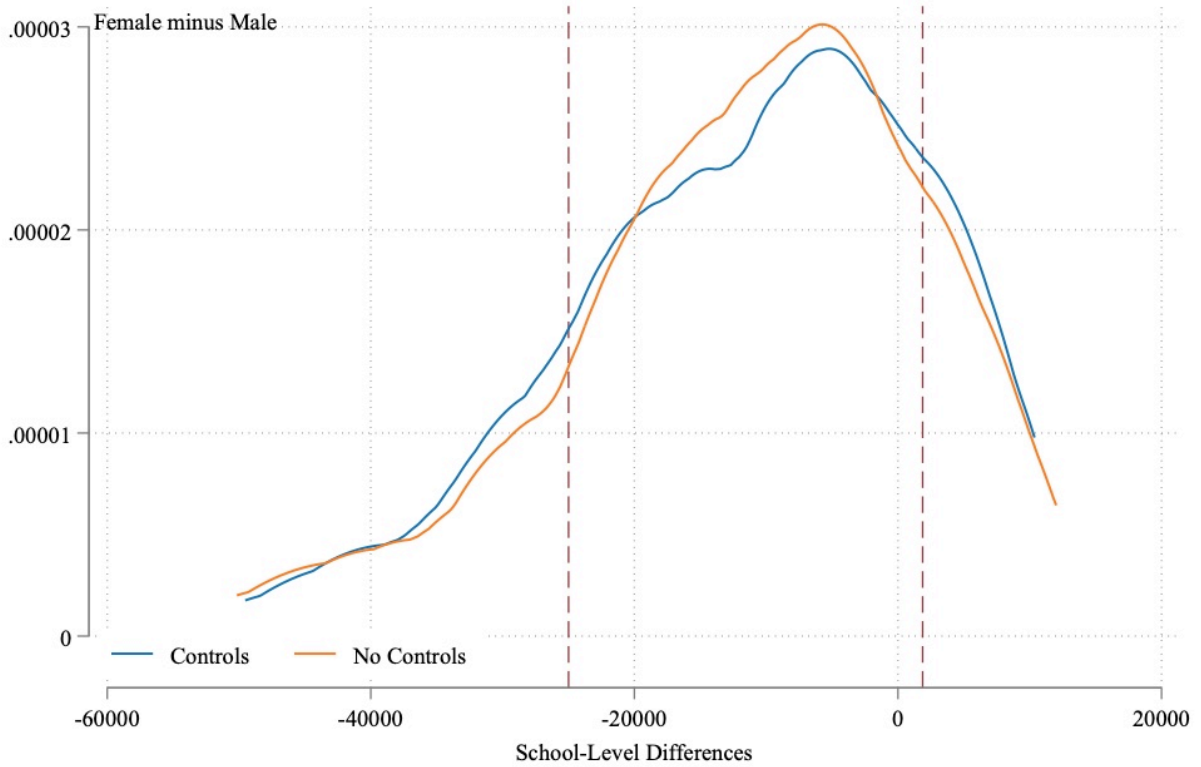


Figure 2. Distribution of School-level Gender Gaps.

The plot shows the kernel density distribution of school-level gender gaps (OLS). The “Control” line represents estimates from a model controlling students’ 8th-grade test scores, while “No Controls” line is from a model without these controls. The dashed vertical lines represent one standard deviation from the mean of the unconditional distribution.

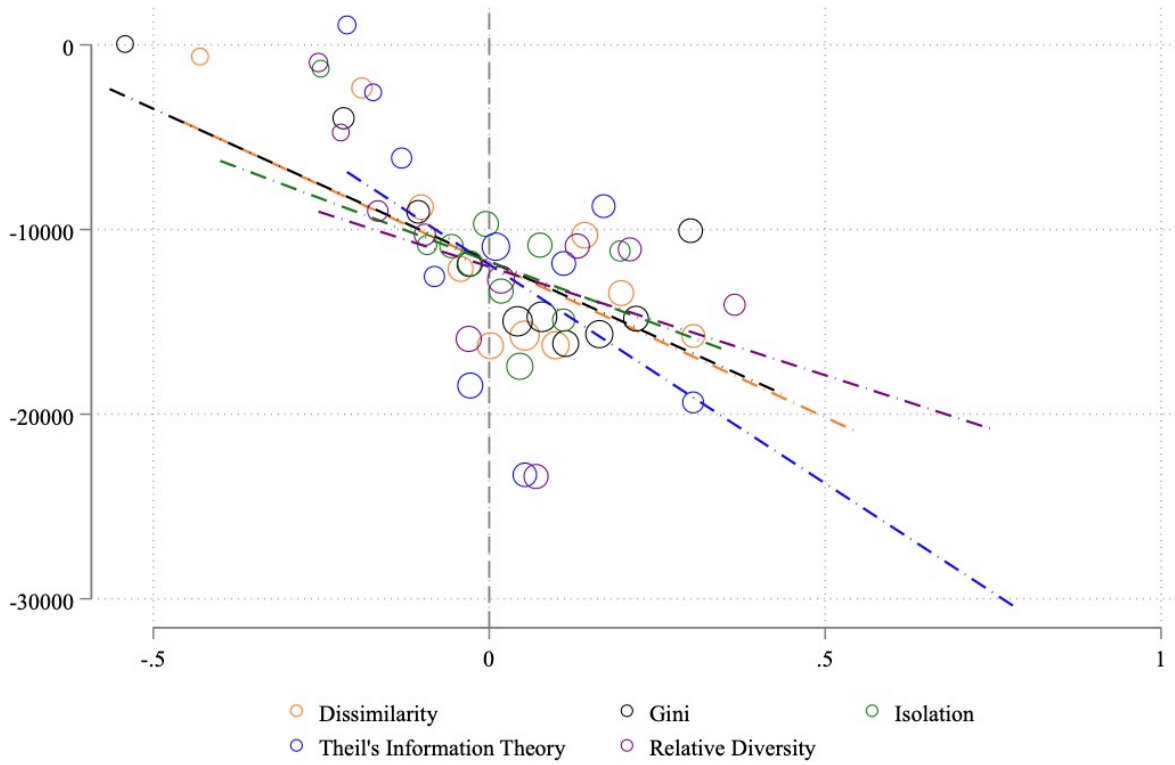


Figure 3. School-level Gender Gaps by Various Segregation Indices.

The plot shows the relationship between the school-level gender wage gap and five different measures of gender segregation. Each segregation index is centered on its mean to compare indices with different scales.

Table 1. Mean expected wages and student enrollment by career cluster

	C1	C2	C3	C4	C5	C6	C8	C9	C10	C11	C12	C13	C14	C15	C16
Mean expected wages	37.5K	57.9K	51.2K	116.2K	61.1K	86.5K	65.2K	28.6K	24.2K	90.1K	52.9K	66.2K	126.7K	106.7K	41.5K
Student enrollment	5,238	2,314	2,242	1,022	490	1,115	3,803	2,761	1,963	1,115	433	149	814	1,947	949
Female	47%	11%	44%	45%	86%	39%	80%	49%	94%	26%	74%	12%	38%	28%	14%
(Male)	53%	89%	56%	55%	14%	61%	20%	51%	6%	74%	26%	88%	62%	72%	86%
Low-income	36%	33%	36%	29%	40%	34%	36%	47%	42%	27%	39%	36%	38%	21%	40%
(non low-income)	64%	67%	64%	71%	60%	66%	64%	53%	58%	73%	61%	64%	62%	79%	60%
Special ED	14%	15%	13%	14%	13%	6%	7%	17%	12%	10%	6%	12%	14%	8%	20%
(non special ED)	86%	85%	87%	86%	87%	94%	93%	83%	88%	90%	94%	88%	86%	92%	80%
ELL	13%	15%	15%	8%	12%	13%	16%	12%	11%	13%	10%	15%	11%	12%	20%
(non ELL)	87%	85%	85%	92%	88%	87%	84%	88%	89%	87%	90%	85%	89%	88%	80%
White	61%	52%	47%	53%	55%	44%	44%	32%	46%	52%	35%	45%	44%	61%	46%
Black	18%	26%	27%	31%	30%	34%	32%	48%	36%	25%	47%	28%	37%	18%	25%
Hispanic	15%	19%	19%	12%	12%	12%	19%	16%	15%	12%	14%	22%	13%	12%	28%
Asian	3%	2%	4%	2%	1%	7%	3%	1%	1%	9%	1%	1%	4%	6%	1%
Other race	3%	1%	3%	2%	2%	2%	2%	2%	2%	2%	2%	3%	2%	3%	1%

Notes: Expected wages are obtained from the occupational wage of the U.S. Department of Labor using occupational code assigned to pathways. If more than one occupational codes are assigned to a pathway, we use the mean of the occupational wage of assigned occupations. Mean expected wages are calculated based on the number of students in pathways and mean occupational wages assigned to each cluster. Columns refer to the following career clusters:

1: Agriculture science, 2: Architecture, 3: Communication, Arts, & A/V Technology, 4: Business 5: Education, 6: Finance, 8: Health Science, 9: Hospitality & Tourism, 10: Early Childhood & Cosmetology, 11: Information Technology, 12: Public Safety, 13: Manufacturing, 14: Marketing, 15: STEM, 16: Automotive Technology

Table 2: Regression results from multilevel mixed-effects models

	(1)	(2)	(3)	(4)
	w/o test score		w/ test score	
	Mixed	Mixed (Random intercept)	Mixed	Mixed (Random intercept)
Panel A: Male				
Expected wage	-10,823.59*** (394.20)	-10,438.22*** (357.73)	-11,395.45*** (392.53)	-10,797.55*** (359.31)
Panel B: FRPL				
Expected wage	-7,651.44*** (413.64)	-3,893.88*** (393.18)	-4,603.20*** (421.40)	-2,310.75*** (395.78)
Panel C: IEP				
Expected wage	-7,100.04*** (609.99)	-4,981.25*** (556.70)	-67.00 (649.30)	-359.46 (596.79)
Panel D: ELL				
Expected wage	-2,221.49*** (585.10)	621.23 (546.97)	-752.06 (577.16)	875.73 (542.23)
Panel E: Race/Ethnicity				
Expected wage (Black)	-4,032.48*** (464.15)	-1,310.74** (447.90)	-127.01 (476.85)	858.38 (453.38)
Expected wage (Hispanic)	-5,051.60*** (567.31)	-1,132.08* (541.39)	-2,175.43*** (567.84)	94.48 (539.03)
Expected wage (Asian)	14,469.36*** (1170.08)	9,222.16*** (1078.75)	11,411.64*** (1157.82)	7,384.50*** (1071.51)
Expected wage (Other race)	-1,289.32 (1321.27)	105.54 (1206.88)	-332.21 (1301.78)	756.69 (1195.38)
N	26,841	26,841	26,841	26,841

Notes: Each panel shows results from separate multilevel mixed-effects regressions for male vs female, FRPL vs non-FRPL, IEP vs non-IEP, ELL vs non-ELL and white vs other race/ethnicity groups. Column (3) and (4) control for 8th grade Math and ELA test scores. All models control for cohort-fixed effects and standard errors are in parentheses. (***) $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 3: Regression results from multilevel mixed-effects model

	(1)	(2)
	Mixed + Random coefficient (w/o test score)	Mixed + Random coefficient (w/ test score)
Panel A: Male		
Expected wage	-11,329.59*** (2,179.16)	-11,640.35*** (2,144.84)
SD of Random Slope	12,985.44	12,772.53
Panel B: FRPL		
Expected wage	-4,000.95*** (1,061.63)	-2,225.84* (1,064.01)
SD of Random Slope	5,706.2	5,715.11
Panel C: IEP		
Expected wage	-4,786.28*** (1,043.57)	-187.47 (982.33)
SD of Random Slope	4,913.37	4,301.52
Panel D: ELL		
Expected wage	737.38 (842.53)	988.18 (799.10)
SD of Random Slope	3,393.63	3,078.08
Panel E: Race/Ethnicity		
Black: Expected wage	-1,716.91 (952.40)	619.16 (929.01)
SD of Random Slope	4,733.85	4,553.44
Hispanic: Expected wage	-825.65 (878.76)	416.28 (850.75)
SD of Random Slope	3,671.54	3,472.58
Asian: Expected wage	9,195.64*** (1,990.12)	7,689.76*** (1,979.65)
SD of Random Slope	9,009.45	8,976.83
Other: Expected wage	78.18 (1,205.17)	720.89 (1,193.71)
SD of Random Slope	0.01	0.03
N	26,841	26,841

Notes: Each panel shows results from separate multilevel mixed-effects regressions for male vs female, FRPL vs non-FRPL, IEP vs non-IEP, ELL vs non-ELL, and white vs other race/ethnicity groups. Column (2) controls for 8th grade Math and ELA test scores. All models are controlled for cohort-fixed effects. Standard errors are in parentheses and standard deviations of random effects are presented under standard errors. (***) $p < 0.001$, ** $p < 0.01$, * $p < 0.05$)

Table 4: Correlation & SD of Anticipated Wage Gaps (weighted coefficients)

Group	Gender	Black	Hispanic	Asian	Low-income	Sped ED	ELL
<i>Panel A: Correlations of Anticipated Wage Gaps between Unadjusted Random Effects and Alternative Models</i>							
Mixed (w/ test score)	0.999	0.983	0.986	0.996	0.986	0.992	0.982
OLS (w/o test score)	0.992	0.943	0.886	0.945	0.968	0.949	0.911
OLS (w/ test score)	0.988	0.813	0.827	0.902	0.930	0.703	0.914
CEM	0.989	0.827	0.630	0.771	0.886	0.641	0.845
EBALANCE	0.990	0.808	0.883	0.889	0.944	0.730	0.926
<i>Panel B: Standard Deviation of Random Effects or School-Specific Anticipated Wage Gaps</i>							
Mixed (w/o test score)	11,742	3,655	2,488	8,292	4,330	3,780	2,241
Mixed (w/ test score)	11,596	3,524	2,316	8,284	4,279	3,174	1,979
OLS (w/o test score)	9,789	3,793	4,089	9,124	3,862	4,701	3,897
OLS (w/ test score)	10,007	3,718	3,684	8,176	3,001	3,548	3,535
CEM	9,862	3,216	2,797	6,378	3,054	3,278	3,543
EBALANCE	9,872	3,593	3,405	5,894	3,065	3,899	3,253
N	37	37	37	33	37	36	37

Notes: Panel A shows correlation coefficients of expected wage gaps between the test-score unadjusted random effects model and alternative models. CEM represents the coarsened exact matching method and EBALANCE represents the entropy balancing method. Correlation coefficients are obtained using inverse variance weighting. Panel B shows the standard deviation of random effects or school-specific anticipated wage gaps estimated from multilevel mixed-effects models and the alternative models presented.

Table 5. Decomposing expected wage gap among concentrators

Group	(1) Total gap	(2) Within school	(3) Between-school	(4) Ambiguous
Panel A: Wage gap decomposition without test score adjustment				
Male - Female	-10,784.94	-10,478.26	-171.78	-134.89
(%)		97%	2%	1%
FRPL – non-FRPL	-7,075.21	-3,472.10	-3,314.73	-288.38
(%)		49%	47%	4%
IEP – non-IEP	-6,532.06	-4,835.71	-1,623.04	-73.31
(%)		74%	25%	1%
ELL – non-ELL	-2,503.30	737.49	-3,300.57	59.78
(%)		-29%	132%	-2%
Black - White	-3,806.25	-1,350.89	-2,239.92	-215.43
(%)		35%	59%	6%
Hispanic - White	-5,106.77	-634.01	-4,355.61	-117.15
(%)		12%	85%	2%
Asian - White	13,107.48	7,918.83	4,830.74	357.91
(%)		60%	37%	3%
Panel B: Wage gap decomposition with test score adjustment				
Male - Female	-11,395.45	-10,992.00	-236.36	-167.09
(%)		96%	2%	1%
FRPL – non-FRPL	-4,603.21	-2,104.23	-2,344.92	-154.05
(%)		46%	51%	3%
IEP – non-IEP	-67.00	380.98	-450.12	2.14
(%)		-569%	672%	-3%
ELL – non-ELL	-752.06	1,094.81	-1,921.96	75.10
(%)		-146%	256%	-10%
Black - White	119.24	1,064.10	-1,094.40	149.53
(%)		892%	-918%	125%
Hispanic - White	-2,049.82	511.72	-2,641.64	80.09
(%)		-25%	129%	-4%
Asian - White	10,933.36	5,750.59	4,874.05	308.72
(%)		53%	45%	3%

Notes: The wage gap decomposition follows the methods in Reardon (2008), where the student achievement gap is attributed to three parts: within-school, between-school, and ambiguous gap, based on Fryer and Levitt (2004) and Hanushek and Rivkin (2006).

Table 6. Multilevel Mixed-Effects Models with School Characteristics (Dissimilarity)

	(1)	(2)	(3)
	Female	FRPL	Black
Group = 1	-13284.99*** (2180.50)	-1988.37 (1114.99)	353.13 (1014.23)
Mean expected wage of pathways (offered by school)	0.36*** (0.04)	0.38*** (0.04)	0.32*** (0.04)
Segregation Index	19632.00*** (3852.28)	5755.68 (3764.70)	5071.13 (3790.63)
Number of pathways offered	-249.49* (105.71)	-121.18 (93.91)	-180.67 (109.00)
Relative Participation	6085.89* (2741.15)	-2359.13 (2183.01)	-2971.06 (1940.54)
Group = 1 X Mean expected wage of pathways	0.01 (0.05)	-0.06 (0.05)	0.08 (0.06)
Group = 1 X Segregation Index	-34149.68*** (5225.61)	-16562.69** (6265.82)	-4169.37 (5602.19)
Group = 1 X Number of pathways offered	328.41* (139.87)	73.68 (114.05)	304.46** (112.94)
Group = 1 X Relative Participation	-6212.53 (3753.47)	2420.09 (4058.33)	8863.37** (3238.56)
_cons	64834.02*** (2840.67)	59071.10*** (2515.05)	58201.68*** (2759.43)
Random Effects Std. Dev. (group)	12795.01	6012.82	5116.05
Residual Std. Dev.	17090.11	15130.39	16558.93
N	26782	26780	20926

Notes: Each column presents results from a separate multilevel mixed-effects model estimating the expected wage gap between a focus group and a reference group (Column 1: Female vs. Male; Column 2: Free-Reduced Priced Lunch (FRPL) vs. non-FRPL; Column 3: Special Education vs. non-Special Education; Column 4: ELL vs. non-ELL; Column 5: Black vs. White). The "Group = 1" variable represents the main effect for the focus group (e.g., Female). School-level predictor variables are defined as follows. "Mean expected wage of pathways" is the average expected wage of all CTE pathways offered by the school. The "Segregation Index" used in this main table is the Dissimilarity Index; results using four alternative indices are presented in Online Appendix. "Number of pathways offered" is the total count of CTE pathways available at the school. "Relative Participation" is the school-level ratio of female-to-male CTE concentrators; a value greater than 1 indicates higher participation by female students. The remaining rows show the interaction terms between the group indicator and these continuous school-level variables. All models control for students' 8th-grade ELA and math test scores and include cohort fixed effects. Standard errors are in parentheses. (***) $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Online Appendix for “*The Architecture of Expected Wage Gaps: Between- and Within School Source of Career Education Inequality*”

Hojung Lee
Kenneth A. Shores
Arielle Lentz

Appendix A: Data Appendix

Merge between DDOE pathway – BLS SOC

In practice, every measure of “expected wages” requires a crosswalk from an education taxonomy (clusters, pathways, CIP codes) to an occupation taxonomy (SOC codes with BLS wages). Two decisions are relevant. The first is the crosswalk itself. These crosswalks are inherently many-to-many: a single program can plausibly lead to several occupations and an occupation can map back to multiple programs. Researchers typically choose among three “off-the-shelf” options: (i) a coarse cluster-to-SOC mapping (e.g., USED 2007, EDEPS; e.g., Carruthers, et al., 2025), (ii) a program of study-to-SOC mapping maintained by NCES/BLS (CIP2020–SOC2018), or (iii) state-specific program-to-SOC files created for Perkins accountability. Like Michigan (Jacobs and Ricks, 2023), Delaware falls squarely in the third category. The Delaware Department of Education (DDOE) maintains its own pathway system and a hand-built crosswalk from those pathways to SOC 2010 codes, as the DDOE pathway/CIP labels do not match NCES CIP codes one-for-one.⁴ We therefore use the DDOE crosswalk as the authoritative bridge between programs and occupations.

The second decision is about the level of aggregation (or granularity) of the student’s CTE program to link to the BLS: career cluster, pathway, or program of study. Career clusters are broad industry groupings (for example, Health Science, IT) that map cleanly to SOC codes using national “off-the-shelf” crosswalks, which aids comparability across states but collapses meaningful within-career cluster heterogeneity. Pathways are sub-cluster course sequences defined by states; they align more closely with

⁴ Since DDOE pathways are mapped to SOC based on 2010 occupation codes, we backwards converted current BLS codes to their 2010 values using the BLS 2010 to 2018 SOC crosswalk. Crosswalks from the 2010 SOC to the 2018 SOC: <https://www.bls.gov/soc/2018/crosswalks.htm>

what students actually study and thus better capture expected wage variability. Programs of Study (POS) are the most granular, often tied to local course sequences or CIPs; they maximize fidelity to student choices but exacerbate sparse cells, unstable estimates, and crosswalk maintenance burdens as states update catalogs and federal taxonomies evolve. In practice, Delaware offered only the pathway to SOC crosswalk, ruling out a POS-SOC linking.

We opted not to aggregate to the career cluster for three related reasons. First, aggregating only trivially increased our sample size (146 additional students can be merged to clusters instead of pathways) but resulted in much coarser wage measures. For example, career clusters link to an average of 33.1 SOC codes, while pathways link to an average of 7.6 SOC codes, meaning that each career cluster aggregates about 4.3 times as many occupational codes as pathways. Second, the expected wage of a career cluster is not very well aligned with the expected wage of a pathway. For example, the correlation between student-level expected wages using the career cluster vs pathway merge was just 0.658. Third, aggregating to career clusters discards within cluster/cross pathway variation, as shown in Figure C1. The figure shows box plots presenting pathway-level wage distributions weighted by local labor force size, with red dots showing cluster-level weighted means. In this plot, expected wages vary widely across pathways within the same cluster; the standard deviations of pathway-level wages within clusters ranges from \$7,035 to \$45,638. Additional details about the crosswalk are available in Online Appendix D: Delaware CTE – BLS SOC Crosswalk Dictionary.

Figure C1 About Here

Appendix B: Technical Appendix - Model Sensitivity Check

To ensure that our multilevel mixed-effects model results are robust to model selection or selection of covariate balancing methods, we employed multiple alternative approaches and compared the results from these alternative methods with our main results. Specifically, we used Ordinary Least Squares (OLS), Coarsened Exact Matching (CEM, Blackwell et al., 2009), and Entropic Balancing (ebalance) methods (Hainmueller & Xu, 2013).

First, we used OLS methods to see if our preferred model results deviated significantly from the simplest regression model. The regression model can be written as follows:

$$Y_{ij} = \beta_0 + \beta_1 D_{ij} + X_{ij} + \epsilon_{ij} \quad (\text{B1})$$

Here, Y_{ij} represents the mean expected wages of pathway that student i in school j enrolled in. D_{ij} is binary variables that shows students demographics (gender, race/ethnicity, FRPL status, IEP status, and ELL status). X_{ij} is the vector of covariates, which includes students ELA, math, science test scores and graduating cohort. ϵ_{ij} is student-specific standard errors. We are interested in estimating β_1 , the estimated wage gap between student subgroups (i.e., male vs female, white vs other racial groups).

Next, we use CEM methods to improve covariate balance. Based on matched sets created from CEM, we estimated weighted least square model and compare these results with our main model. CEM is the matching methods that can be useful for improving the match between treatment and control group. Exact matching methods matches treatment and control group observations only when they have the same value in the covariates of the interests. This will create only a small number of matches, especially when covariates of interests are continuous. Instead, CEM coarsens (groups) the data into intervals and generates strata based on the bins created from the coarsened covariates. Observations in the same stratum function as a matched set. In our data, we create matches based on students' 8th grade ELA, math and science test scores and high school graduating cohort. We divide each test subjects into 6 bins and create a bin for each graduating cohort for every public high school in our sample. When strata are generated, the weights are also assigned to the stratum if the stratum is matched. After creating strata and weights, we run the following regression model for each school (j):

$$Y_i = \beta_0 + \beta_1 D_i + \epsilon_i \quad (\text{B2})$$

Y_i is the mean of expected wage from the pathway that student i enrolled in, and D_i represents binary variables of our interests, which includes gender, race/ethnicity, ELL, FRPL, and IEP status. Here, we do not include covariate in Equation (B2) since CEM already controls for the covariates when creating

strata. This regression is weighted using the CEM weights. Again, we are interested in measuring β_1 , the estimated expected wage gap between student subgroups.

Another approach we use to improve covariate balance is entropic balancing (ebalance). Ebalance creates weights that ensure covariate balance between the treatment and control groups by generating weights w_{ij} that minimize entropy distance $\sum_{i \in R, i \in j} w_{ij} \log w_{ij}$ with respect to $\sum_{i \in R, i \in j} w_{ij} x_{ijk} = \sum_{i \in F, i \in j} x_{ijk}, \forall k$ for student i in school j . Here, the subscript F denotes the focus group (male, black or Hispanic, ELL, FRPL and IEP students) and R means reference group (female, white, non-ELL, non-FRPL and non-IEP students). k represents covariate of our interest, which includes 8th grade test scores and high school graduating cohort. Note that in our analysis, we are not looking for causal impacts of a treatment, but estimating the gap estimates between student demographics, so we use focus group and reference group instead of treatment and control groups.

After generating weights from the covariates, we created a weighted dataset for each demographic variable and then ran a simple OLS model with the reweighted datasets. The OLS model for school j can be written as follows:

$$Y_i = \beta_0 + \beta_1 D_i + \epsilon_i \quad (\text{B3})$$

This model equation is equivalent to Equation (B2). However, it differs in estimation, as Equation (A3) is weighted using ebalance weights. The model is also different from Equation (A1) since it does not include covariates since the weighted datasets already controlled covariates by reweighting.

After estimating models (B1) – (B3), we compared these results with our main analysis. Firstly, we obtained the correlation coefficients of the estimated β_1 s from our main model (1) and alternative methods (B1 – B3). The correlation coefficients are presented in Table A1, Panel A. The baseline model is the multilevel mixed-effects model without test score adjustment. For gender, the estimated wage gaps show the highest correlation across models, all above 0.98. The coefficients from the models for Black, Asian, FRPL, and IEP are slightly lower than those for gender. The weakest correlations between the multilevel mixed-effects model and the alternative methods are found in the CEM Hispanic and CEM

ELL groups. However, these correlations are still strong enough to conclude that our multilevel mixed-effects model results are robust to alternative model selection and covariate balancing methods.

Next, we examined the estimated standard deviations of the random effects or the standard deviations of the school-specific estimated wage gaps by methods. These results are presented in Table C1, Panel B. The mixed-effects models and the ebalance method show similar magnitudes of standard deviations of wage gaps, while the OLS models and CEM show much smaller standard deviations. Although the standard deviations from the OLS models and CEMs are smaller, the trends shown by the groups are quite similar. Therefore, our main results are not solely the product of the multilevel model we employed but reflect the actual phenomena of Delaware career technical education.

Appendix C: Additional Tables and Figures

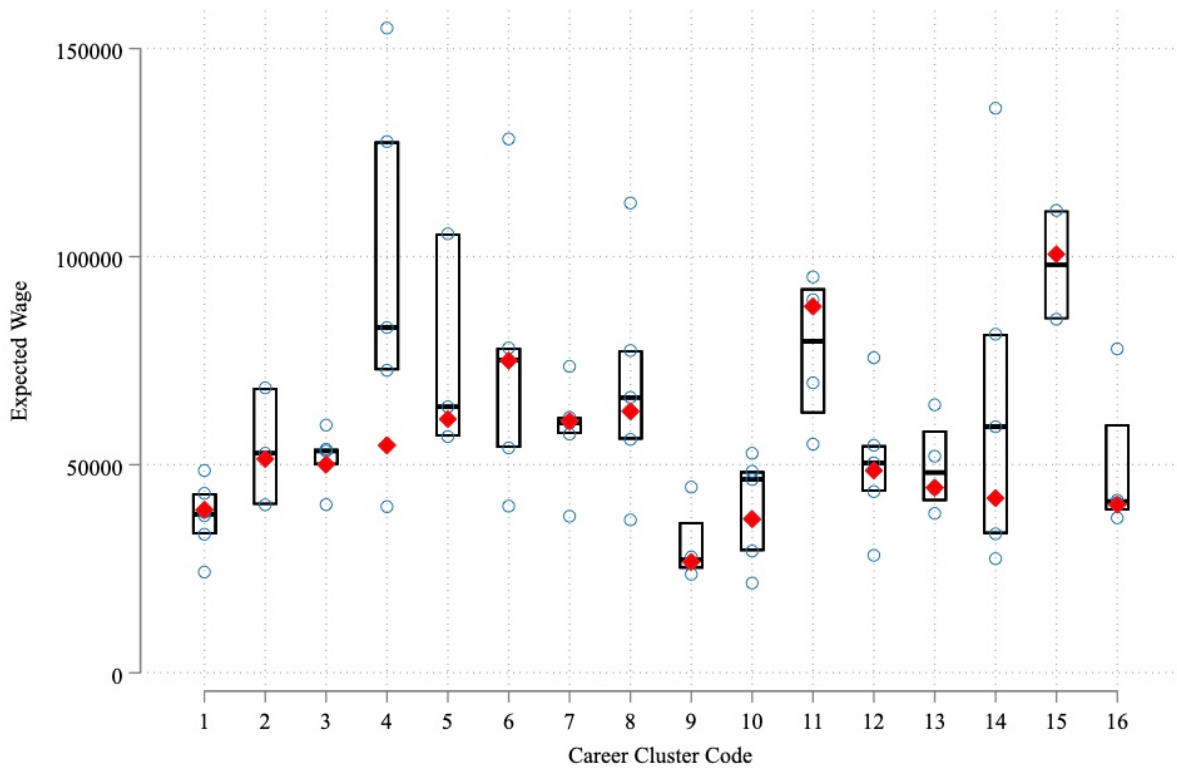


Figure C1. Variation in Expected Wages by Career Cluster and Pathways.

The box plot shows the distribution (median and interquartile range) of expected wages for individual pathways within each career cluster. The red diamond represents the mean expected wage for the career cluster as a whole. While career clusters aggregate an average of 33.1 unique occupations, pathways represent a more granular level of aggregation with an average of 7.6 occupations. In cluster 4, 73% percent of the workers are in pathways where the expected wage is less than or equal to \$72,000. This result makes the mean wage for the career cluster less than the bottom quartile of expected wages among pathways within that cluster and is why the cluster mean falls outside the IQR.

Table C1: Correlation & SD of Anticipated Wage Gaps (unweighted coefficients)

Group	Gender	Black	Hispanic	Asian	FRPL	IEP	ELL
<i>Panel A: Correlations of Anticipated Wage Gaps between Unadjusted Random Effects and Alternative Models</i>							
Mixed (w/ test score)	0.999	0.987	0.988	0.995	0.990	0.993	0.983
OLS (w/o test score)	0.998	0.983	0.892	0.931	0.985	0.949	0.853
OLS (w/ test score)	0.994	0.802	0.829	0.867	0.933	0.710	0.871
CEM	0.994	0.673	0.750	0.708	0.947	0.735	0.460
EBALANCE	0.993	0.797	0.830	0.875	0.929	0.731	0.851
<i>Panel B: Standard Deviation of Random Effects or School-Specific Anticipated Wage Gaps</i>							
Mixed (w/o test score)	13032	3952	2615	7159	5101	3884	2279
Mixed (w/ test score)	12822	3773	2422	7156	5120	3251	1979
OLS (w/o test score)	13609	6396	6842	11420	7097	7207	7096
OLS (w/ test score)	13496	5278	6224	10931	5070	5169	5952
CEM	13734	7348	6983	13957	5368	5759	11903
EBALANCE	13738	5478	6152	10976	5082	5876	6093
N	37	37	37	33	37	36	37

Notes: Panel A shows correlation coefficients of expected wage gaps between the test-score unadjusted random effects model and alternative models. CEM represents the coarsened exact matching method (Blackwell et al., 2009) and EBALANCE represents the entropy balancing method (Hainmueller & Xu, 2013). Correlation coefficients are obtained using inverse variance weighting. Panel B shows the standard deviation of random effects or school-specific anticipated wage gaps estimated from multilevel mixed-effects models and the alternative models presented.

Table C2. Multilevel Mixed-Effects Models with School Characteristics (Gini)

	(1)	(2)	(3)
	Female	FRPL	Black
Group = 1	-13776.62*** (2210.81)	-1986.52 (1127.36)	323.17 (1022.54)
Mean expected wage of pathways (offered by school)	0.36*** (0.04)	0.37*** (0.04)	0.32*** (0.04)
Segregation Index	18028.17*** (3673.31)	4016.90 (3269.99)	6595.20* (3253.76)
Number of pathways offered	-248.56* (106.13)	-128.87 (94.79)	-185.98 (109.49)
Relative Participation	6523.29* (2743.33)	-2325.05 (2183.80)	-3039.21 (1939.61)
Group = 1 X Mean expected wage of pathways	0.01 (0.05)	-0.06 (0.05)	0.08 (0.06)
Group = 1 X Segregation Index	-34055.19*** (4950.56)	-17842.35*** (5234.54)	-4617.76 (4696.54)
Group = 1 X Number of pathways offered	322.23* (140.02)	109.94 (115.83)	309.55** (114.09)
Group = 1 X Relative Participation	-6857.74 (3753.34)	2361.37 (4058.69)	8745.37** (3226.71)
_cons	65023.07*** (2896.16)	59046.29*** (2522.49)	58295.76*** (2803.36)
Random Effects Std. Dev. (group)	12949.38	6091.22	5179.04
Residual Std. Dev.	17417.52	15175.22	16833.01
N	26782	26780	20926

Notes: Each column presents results from a separate multilevel mixed-effects model estimating the expected wage gap between a focus group and a reference group (Column 1: Female vs. Male; Column 2: Free-Reduced Priced Lunch (FRPL) vs. non-FRPL; Column 3: Special Education vs. non-Special Education; Column 4: ELL vs. non-ELL; Column 5: Black vs. White). The "Group = 1" variable represents the main effect for the focus group (e.g., Female). School-level predictor variables are defined as follows. "Mean expected wage of pathways" is the average expected wage of all CTE pathways offered by the school. The "Segregation Index" used in this main table is the Gini Segregation Index. "Number of pathways offered" is the total count of CTE pathways available at the school. "Relative Participation" is the school-level ratio of female-to-male CTE concentrators; a value greater than 1 indicates higher participation by female students. The remaining rows show the interaction terms between the group indicator and these continuous school-level variables. All models control for students' 8th-grade ELA and math test scores and include cohort fixed effects. Standard errors are in parentheses. (***) $p < 0.001$, (**) $p < 0.01$, (*) $p < 0.05$)

Table C3. Multilevel Mixed-Effects Models with School Characteristics (Isolation)

	(1)	(2)	(3)
	Female	FRPL	Black
Group = 1	-12707.12*** (2190.83)	-1798.62 (1140.46)	321.81 (952.75)
Mean expected wage of pathways (offered by school)	0.35*** (0.04)	0.38*** (0.04)	0.32*** (0.04)
Segregation Index	33602.13*** (6020.51)	1218.56 (5139.91)	21030.97*** (4704.09)
Number of pathways offered	-216.89* (105.33)	-145.92 (95.51)	-206.62 (109.20)
Relative Participation	-74.38 (2969.26)	-3144.15 (2270.76)	-5622.06** (2030.03)
Group = 1 X Mean expected wage of pathways	0.02 (0.05)	-0.08 (0.05)	0.07 (0.05)
Group = 1 X Segregation Index	-56667.11*** (8450.79)	-21146.47*** (6373.88)	-11626.88* (4819.78)
Group = 1 X Number of pathways offered	263.01 (139.54)	110.04 (117.30)	355.08** (110.68)
Group = 1 X Relative Participation	3964.52 (4068.72)	5868.08 (4186.15)	9974.48** (3304.95)
_cons	64667.06*** (2809.18)	58954.21*** (2497.80)	58876.71*** (2970.16)
Random Effects Std. Dev. (group)	12913.43	6143	4679.75
Residual Std. Dev.	16911.91	15004.31	17863.98
N	26782	26780	20926

Notes: Each column presents results from a separate multilevel mixed-effects model estimating the expected wage gap between a focus group and a reference group (Column 1: Female vs. Male; Column 2: Free-Reduced Priced Lunch (FRPL) vs. non-FRPL; Column 3: Special Education vs. non-Special Education; Column 4: ELL vs. non-ELL; Column 5: Black vs. White). The "Group = 1" variable represents the main effect for the focus group (e.g., Female). School-level predictor variables are defined as follows. "Mean expected wage of pathways" is the average expected wage of all CTE pathways offered by the school. The "Segregation Index" used in this main table is the Isolation Index. "Number of pathways offered" is the total count of CTE pathways available at the school. "Relative Participation" is the school-level ratio of female-to-male CTE concentrators; a value greater than 1 indicates higher participation by female students. The remaining rows show the interaction terms between the group indicator and these continuous school-level variables. All models control for students' 8th-grade ELA and math test scores and include cohort fixed effects. Standard errors are in parentheses. (***) $p < 0.001$, (**) $p < 0.01$, (*) $p < 0.05$)

Table C4. Multilevel Mixed-Effects Models with School Characteristics (Theil's Information Theory)

	(1)	(2)	(3)
	Female	FRPL	Black
Group = 1	-12832.72*** (2181.73)	-1974.84 (1078.88)	413.85 (998.15)
Mean expected wage of pathways (offered by school)	0.37*** (0.04)	0.39*** (0.04)	0.32*** (0.04)
Segregation Index	13150.47*** (3976.03)	35996.86*** (9321.42)	11620.52 (7411.01)
Number of pathways offered	-227.53* (104.69)	-128.75 (92.94)	-176.68 (108.33)
Relative Participation	5401.86* (2744.63)	-2107.44 (2179.94)	-3396.40 (1964.88)
Group = 1 X Mean expected wage of pathways	-0.00 (0.05)	-0.07 (0.05)	0.08 (0.06)
Group = 1 X Segregation Index	-32965.45*** (5457.76)	-46590.47*** (14038.07)	-1353.63 (10611.07)
Group = 1 X Number of pathways offered	264.45 (139.32)	57.40 (111.27)	298.12** (111.63)
Group = 1 X Relative Participation	-4769.81 (3764.23)	1990.51 (4044.62)	8039.81* (3367.76)
_cons	64350.45*** (2648.85)	59054.42*** (2463.00)	58023.62*** (2743.93)
Random Effects Std. Dev. (group)	12824.98	5784.6	4995.73
Residual Std. Dev.	15906.42	14806.19	16457.46
N	26782	26780	20926

Notes: Each column presents results from a separate multilevel mixed-effects model estimating the expected wage gap between a focus group and a reference group (Column 1: Female vs. Male; Column 2: Free-Reduced Priced Lunch (FRPL) vs. non-FRPL; Column 3: Special Education vs. non-Special Education; Column 4: ELL vs. non-ELL; Column 5: Black vs. White). The "Group = 1" variable represents the main effect for the focus group (e.g., Female). School-level predictor variables are defined as follows. "Mean expected wage of pathways" is the average expected wage of all CTE pathways offered by the school. The "Segregation Index" used in this main table is the Theil's Information Theory Index. "Number of pathways offered" is the total count of CTE pathways available at the school. "Relative Participation" is the school-level ratio of female-to-male CTE concentrators; a value greater than 1 indicates higher participation by female students. The remaining rows show the interaction terms between the group indicator and these continuous school-level variables. All models control for students' 8th-grade ELA and math test scores and include cohort fixed effects. Standard errors are in parentheses. (***) $p < 0.001$, (**) $p < 0.01$, (*) $p < 0.05$)

Table C5. Multilevel Mixed-Effects Models with School Characteristics (Relative Diversity)

	(1)	(2)	(3)
	Female	FRPL	Black
Group = 1	-12939.23*** (2188.99)	-1935.35 (1065.32)	407.25 (1001.73)
Mean expected wage of pathways (offered by school)	0.36*** (0.04)	0.38*** (0.04)	0.32*** (0.04)
Segregation Index	12125.58*** (3467.78)	40924.84*** (7858.11)	4380.68 (5918.51)
Number of pathways offered	-225.07* (104.84)	-127.85 (92.42)	-177.16 (108.32)
Relative Participation	5267.92 (2748.81)	-1654.74 (2181.82)	-3055.26 (1956.64)
Group = 1 X Mean expected wage of pathways	0.01 (0.05)	-0.07 (0.05)	0.08 (0.06)
Group = 1 X Segregation Index	-28509.99*** (4744.55)	-50255.09*** (12713.31)	3172.64 (8551.55)
Group = 1 X Number of pathways offered	262.88 (139.41)	51.54 (110.06)	297.20** (112.18)
Group = 1 X Relative Participation	-4568.09 (3768.27)	1454.28 (4030.71)	8022.27* (3331.24)
_cons	64350.45*** (2648.85)	59054.42*** (2463.00)	58023.62*** (2743.93)
Random Effects Std. Dev. (group)	12858.94	5699.68	5018.29
Residual Std. Dev.	16023.64	14720.9	16357.59
N	26782	26780	20926

Notes: Each column presents results from a separate multilevel mixed-effects model estimating the expected wage gap between a focus group and a reference group (Column 1: Female vs. Male; Column 2: FRPL vs. non-FRPL; Column 3: IEP vs. non-IEP; Column 4: ELL vs. non-ELL; Column 5: Black vs. White). The "Group = 1" variable represents the main effect for the focus group (e.g., Female). School-level predictor variables are defined as follows. "Mean expected wage of pathways" is the average expected wage of all CTE pathways offered by the school. The "Segregation Index" used in this main table is the Relative Diversity Index. "Number of pathways offered" is the total count of CTE pathways available at the school. "Relative Participation" is the school-level ratio of female-to-male CTE concentrators; a value greater than 1 indicates higher participation by female students. The remaining rows show the interaction terms between the group indicator and these continuous school-level variables. All models control for students' 8th-grade ELA and math test scores and include cohort fixed effects. Standard errors are in parentheses. (***) $p < 0.001$, (**) $p < 0.01$, (*) $p < 0.05$

Appendix D: Delaware CTE-BLS SOC crosswalk Dictionary

Table D1. Delaware CTE Pathway - BLS SOC Crosswalk

Pathway	Matched Standard Occupational Classification (SOC) Code
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- 1.01 19-1012;19-4011;45-1011;45-2041
- 1.02 19-1013;19-4021;37-3012;37-3013;45-2092
- 1.03 19-1011;39-2021;45-2021;45-2093
- 1.04 17-2021;45-2091;49-3041
- 1.05 11-9121;19-1023;19-1032;19-4041;19-4093;45-3011;45-3021;45-4011;45-4021;45-4022;45-4023;45-4029
- 1.06 17-2081;17-3025;19-4091;37-2021;47-4041;51-8031;53-7081
- 1.07 11-9013;13-1021;13-1074
- 2.01 13-1051;17-1011;17-1012;17-1022;17-2051;17-3011;17-3022;17-3031;27-1025

11-9021;47-1011;47-2021;47-2022;47-2031;47-2041;47-2042;47-2043;47-2044;47-2051;47-2053;47-2061;47-2071;47-2072;47-2073;47-2081;47-2082;47-2111;47-2121;47-2131;47-2132;47-2141;47-2142;47-2151;47-2152;47-2161;47-2171;47-2181;47-2211;47-2221;47-2231;47-3011;47-3012;47-3013;47-3014;47-3015;47-3016;47-3019;47-4031;47-4091;47-5011;47-5012;47-5013;47-5021;47-5031;47-5041;47-5042;47-5049;47-5051;47-5061;47-5071;47-5081;47-5099;49-9095;49-9096;51-2041;53-7011;53-7021;53-7031;53-7032;53-7033;53-7041
- 2.02
- 2.03 37-1012;37-3011;37-3019;47-2011;47-4021;47-4051;47-4071;47-4099;49-9011;49-9012;49-9021;49-9044;49-9045;49-9051;49-9092;49-9098;51-8021
- 3.01 50-0709;50-0710;50-0711;50-0712;50-0713;50-0799
- 3.02 43-9031;43-9081;51-5111;51-5112;51-5113
- 3.03 27-1011;27-1012;27-1013;27-1014;27-1019;27-1021;27-1022;27-1023;27-1024;27-1027;27-1029
- 3.04 13-1011;27-2011;27-2012;27-2031;27-2032;27-2041;27-2042;27-2099;27-3012;39-3092;39-5091
- 3.05 27-3011;27-3021;27-3022;27-3041;27-3042;27-3043;27-3099;27-4011;27-4012;27-4013;27-4014;27-4021;27-4031;27-4032;27-4099
- 3.06 49-2022;49-9052
- 4.01 11-1011;11-1021;11-9199
- 4.02 11-3021
- 4.03 11-3111;11-3121;11-3131;13-1071;13-1075;13-1141;13-1151
- 4.04 11-3011;11-3051;11-3061;13-1111;13-1121;13-1131;13-1199;15-2031

43-1011;43-2011;43-2021;43-2099;43-3031;43-3051;43-3061;43-4021;43-4051;43-4071;43-4111;43-4121;43-4141;43-4151;43-4161;43-4171;43-4199;43-5041;43-5051;43-5052;43-5053;43-5071;43-5081;43-6011;43-6014;43-9011;43-9021;43-9022;43-9051;43-9061;43-9071;43-9199
- 4.05
- 5.01 11-9031;11-9032;11-9033;11-9039
- 5.02 21-1012;25-4011;25-4012;25-4013;25-4021;25-4031;25-9011;25-9031

- 5.03 25-1011;25-1021;25-1022;25-1031;25-1032;25-1041;25-1042;25-1043;25-1051;25-1052;25-1053;25-1054;25-1061;25-1062;25-1063;25-1064;25-1065;25-1066;25-1067;25-1069;25-1071;25-1072;25-1081;25-1082;25-1111;25-1112;25-1113;25-1121;25-1122;25-1123;25-1124;25-1125;25-1126;25-1191;25-1192;25-1193;25-1194;25-1199;25-2011;25-2012;25-2021;25-2022;25-2023;25-2031;25-2032;25-2051;25-2052;25-2053;25-2054;25-2059;25-3011;25-3021;25-3099;25-9021;25-9041;25-9099;27-2022
- 6.01 13-2052;13-2099;41-3031;43-4011
- 6.02 11-3031;13-2031;13-2051;13-2082
- 6.03 13-2011
- 6.04 13-1031;13-1032;13-2053;15-2011;41-3021;43-9041
- 6.05 13-2041;13-2072;43-3011;43-3071;43-3099;43-4041;43-4131
- 7.01 11-1031;13-1041;13-2061;53-6051
- 7.02 33-9093;55-1011;55-1012;55-1013;55-1014;55-1015;55-1016;55-1017;55-1019;55-2011;55-2012;55-2013;55-3011;55-3012;55-3013;55-3014;55-3015;55-3016;55-3017;55-3018;55-3019
- 7.03 45-0901
- 7.04 19-3051;43-9111
- 7.05 13-2021;13-2081
- 7.06 29-9011;29-9012;45-2011;47-4011
- 7.07 11-9131;11-9161;43-4031;43-4061
- 8.01 29-1011;29-1021;29-1022;29-1023;29-1024;29-1029;29-1031;29-1041;29-1051;29-1061;29-1062;29-1063;29-1064;29-1065;29-1066;29-1067;29-1069;29-1071;29-1081;29-1122;29-1123;29-1124;29-1125;29-1126;29-1127;29-1128;29-1129;29-1131;29-1141;29-1151;29-1161;29-1171;29-1181;29-1199;29-2021;29-2051;29-2052;29-2053;29-2054;29-2055;29-2057;29-2061;29-2081;29-2091;29-2092;29-9091;29-9092;29-9099;31-1011;31-1013;31-1014;31-2011;31-2012;31-2021;31-2022;31-9091;31-9092
- 8.02 19-1041;29-2011;29-2012;29-2031;29-2032;29-2033;29-2034;29-2035;29-2056;29-2099
- 8.03 29-2071;31-9094;43-6013
- 8.04 11-9111;31-1015;31-9093;31-9095;31-9096;31-9097;31-9099
- 8.05 17-2031;19-1042
- 9.01 11-9051;35-1011;35-1012;35-2011;35-2012;35-2013;35-2014;35-2015;35-2019;35-2021;35-3011;35-3021;35-3022;35-3031;35-3041;35-9011;35-9021;35-9031;35-9099;51-3011
- 9.02 11-9081;37-1011;37-2011;37-2012;37-2019;39-6011;39-6012;43-4081
- 9.03 27-3091;39-7011;39-7012;41-3041;43-4181
- 9.04 11-9071;27-2021;27-2023;39-1011;39-1012;39-2011;39-3011;39-3012;39-3019;39-3021;39-3031;39-3091;39-3099;39-9032;41-2012;43-3041

- 10.01 39-9011
- 10.02 19-3031;19-3032;19-3039;21-1011;21-1013;21-1014;21-1015;21-1019;21-1023
- 10.03 11-9151;21-1021;21-1022;21-1029;21-1091;21-1093;21-1094;21-1099;21-2011;21-2021;21-2099
- 10.04 11-9061;31-9011;39-1021;39-3093;39-4011;39-4021;39-4031;39-5011;39-5012;39-5092;39-5093;39-5094;39-9021;39-9031;39-9041;39-9099;51-6011;51-6021;51-6052
- 10.05 13-2071
- 11.01 15-1122;15-1141;15-1142;15-1143;15-1152
- 11.02 15-1151;15-1199
- 11.03 15-1134
- 11.04 15-1121;15-1131;15-1132;15-1133
- 12.01 21-1092;33-1011;33-3012
- 12.02 29-2041;33-1021;33-2011;33-2021;33-2022;43-5031
- 12.03 33-1099;33-3011;33-9031;33-9032;33-9091;33-9092;33-9099
- 12.04 19-4092;33-1012;33-3021;33-3031;33-3041;33-3051;33-3052;33-9011;33-9021
- 12.05 23-1011;23-1012;23-1021;23-1022;23-1023;23-2011;23-2091;23-2093;23-2099;43-6012
- 13.01 51-1011;51-2011;51-2021;51-2022;51-2023;51-2031;51-2091;51-2092;51-2093;51-2099;51-3021;51-3022;51-3023;51-3091;51-3092;51-3093;51-3099;51-4011;51-4012;51-4021;51-4022;51-4023;51-4031;51-4032;51-4033;51-4034;51-4035;51-4041;51-4051;51-4052;51-4061;51-4062;51-4071;51-4072;51-4081;51-4111;51-4121;51-4122;51-4191;51-4192;51-4193;51-4194;51-4199;51-6031;51-6041;51-6042;51-6051;51-6061;51-6062;51-6063;51-6064;51-6091;51-6092;51-6093;51-6099;51-7011;51-7021;51-7031;51-7032;51-7041;51-7042;51-7099;51-8011;51-8012;51-8013;51-8091;51-8092;51-8093;51-8099;51-9011;51-9012;51-9021;51-9022;51-9023;51-9031;51-9032;51-9041;51-9051;51-9071;51-9081;51-9083;51-9111;51-9121;51-9122;51-9123;51-9141;51-9151;51-9191;51-9192;51-9193;51-9194;51-9195;51-9196;51-9197;51-9198;53-7063
- 13.02 13-1023;17-3012;17-3013;17-3019;17-3021;17-3023;17-3024;17-3026;17-3027;17-3029;19-4031;19-4051
- 13.03 49-1011;49-2011;49-2021;49-2092;49-2094;49-2095;49-2097;49-2098;49-3053;49-9031;49-9041;49-9043;49-9061;49-9062;49-9063;49-9064;49-9069;49-9071;49-9081;49-9091;49-9093;49-9094;49-9099;51-9082
- 13.04 43-5061;43-5111;51-9061
- 14.01 11-2011;11-2021;11-2022;11-2031;11-9141
- 14.02 41-1011;41-1012;41-2011;41-2021;41-2022;41-2031;41-3011;41-3099;41-4011;41-4012;41-9011;41-9021;41-9022;41-9031;41-9041;41-9091;41-9099;53-3031
- 14.03 13-1022;27-1026;41-9012
- 14.04 27-3031

- 14.05 13-1161
- 15.01 11-9041;17-2011;17-2041;17-2061;17-2071;17-2072;17-2111;17-2112;17-2121;17-2131;17-2141;17-2151;17-2161;17-2171;17-2199
- 15.02 15-1111;15-2021;15-2041;15-2091;15-2099;19-1021;19-1022;19-1029;19-1031;19-1099;19-2011;19-2012;19-2021;19-2031;19-2032;19-2041;19-2042;19-2043;19-2099;19-3011;19-3022;19-3041;19-3091;19-3092;19-3093;19-3094;19-3099;19-4061;19-4099;17-1021
- 16.01 43-5021;53-1011;53-1021;53-1031;53-2011;53-2012;53-2031;53-3011;53-3021;53-3022;53-3032;53-3033;53-3041;53-3099;53-4011;53-4012;53-4013;53-4021;53-4031;53-4041;53-4099;53-5011;53-5021;53-5022;53-5031;53-6011;53-6061;53-6099;53-7051;53-7062;53-7064;53-7071;53-7072;53-7073;53-7111;53-7121;53-7199
- 16.02 11-3071;13-1081;43-5032
- 16.03 52-0409;52-0410
- 16.04 47-4061;49-2091;49-2093;49-2096;49-3011;49-3021;49-3022;49-3023;49-3031;49-3042;49-3043;49-3051;49-3052;49-3091;49-3092;49-3093;49-9097;53-6031;53-7061
- 16.05 53-2021;53-2022;53-6041
- 16.07 43-3021;43-5011;53-6021

Table D2. Mapping Dictionary of CTE Pathways and SOC Occupations

SOC Code	Title	SOC Code	Title
11-1011	Chief Executives	11-1021	General and Operations Managers
11-1031	Legislators	11-2011	Advertising and Promotions Managers
11-2021	Marketing Managers	11-2022	Sales Managers
11-2031	Public Relations and Fundraising Managers	11-3011	Administrative Services Managers
11-3021	Computer and Information Systems Managers	11-3031	Financial Managers
11-3051	Industrial Production Managers	11-3061	Purchasing Managers
11-3071	Transportation, Storage, and Distribution Managers	11-3111	Compensation and Benefits Managers
11-3121	Human Resources Managers	11-3131	Training and Development Managers
11-9013	Farmers, Ranchers, and Other Agricultural Managers	11-9021	Construction Managers
11-9031	Education Administrators, Preschool and Childcare Center/Program	11-9032	Education Administrators, Elementary and Secondary School
11-9033	Education Administrators, Postsecondary	11-9039	Education Administrators, All Other
11-9041	Architectural and Engineering Managers	11-9051	Food Service Managers
11-9061	Funeral Service Managers	11-9071	Gaming Managers
11-9081	Lodging Managers	11-9111	Medical and Health Services Managers
11-9121	Natural Sciences Managers	11-9131	Postmasters and Mail Superintendents
11-9141	Property, Real Estate, and Community Association Managers	11-9151	Social and Community Service Managers
11-9161	Emergency Management Directors	11-9199	Managers, All Other
13-1011	Agents and Business Managers of Artists, Performers, and Athletes	13-1021	Buyers and Purchasing Agents, Farm Products
13-1022	Wholesale and Retail Buyers, Except Farm Products	13-1023	Purchasing Agents, Except Wholesale, Retail, and Farm Products
13-1031	Claims Adjusters, Examiners, and Investigators	13-1032	Insurance Appraisers, Auto Damage
13-1041	Compliance Officers	13-1051	Cost Estimators
13-1071	Human Resources Specialists	13-1074	Farm Labor Contractors
13-1075	Labor Relations Specialists	13-1081	Logisticians
13-1111	Management Analysts	13-1121	Meeting, Convention, and Event Planners
13-1131	Fundraisers	13-1141	Compensation, Benefits, and Job Analysis Specialists
13-1151	Training and Development Specialists	13-1161	Market Research Analysts and Marketing Specialists
13-1199	Business Operations Specialists, All Other	13-2011	Accountants and Auditors
13-2021	Appraisers and Assessors of Real Estate	13-2031	Budget Analysts
13-2041	Credit Analysts	13-2051	Financial Analysts
13-2052	Personal Financial Advisors	13-2053	Insurance Underwriters
13-2061	Financial Examiners	13-2071	Credit Counselors
13-2072	Loan Officers	13-2081	Tax Examiners and Collectors, and Revenue Agents
13-2082	Tax Preparers	13-2099	Financial Specialists, All Other
15-1111	Computer and Information Research Scientists	15-1121	Computer Systems Analysts
15-1122	Information Security Analysts	15-1131	Computer Programmers
15-1132	Software Developers, Applications	15-1133	Software Developers, Systems Software
15-1134	Web Developers	15-1141	Database Administrators
15-1142	Network and Computer Systems Administrators	15-1143	Computer Network Architects
15-1151	Computer User Support Specialists	15-1152	Computer Network Support Specialists
15-1199	Computer Occupations, All Other	15-2011	Actuaries

15-2021	Mathematicians	15-2031	Operations Research Analysts
15-2041	Statisticians	15-2091	Mathematical Technicians
15-2099	Mathematical Science Occupations, All Other	17-1011	Architects, Except Landscape and Naval
17-1012	Landscape Architects	17-1021	Cartographers and Photogrammetrists
17-1022	Surveyors	17-2011	Aerospace Engineers
17-2021	Agricultural Engineers	17-2031	Biomedical Engineers
17-2041	Chemical Engineers	17-2051	Civil Engineers
17-2061	Computer Hardware Engineers	17-2071	Electrical Engineers
17-2072	Electronics Engineers, Except Computer	17-2081	Environmental Engineers
17-2111	Health and Safety Engineers, Except Mining Safety Engineers and Inspectors	17-2112	Industrial Engineers
17-2121	Marine Engineers and Naval Architects	17-2131	Materials Engineers
17-2141	Mechanical Engineers	17-2151	Mining and Geological Engineers, Including Mining Safety Engineers
17-2161	Nuclear Engineers	17-2171	Petroleum Engineers
17-2199	Engineers, All Other	17-3011	Architectural and Civil Drafters
17-3012	Electrical and Electronics Drafters	17-3013	Mechanical Drafters
17-3019	Drafters, All Other	17-3021	Aerospace Engineering and Operations Technicians
17-3022	Civil Engineering Technicians	17-3023	Electrical and Electronics Engineering Technicians
17-3024	Electro-Mechanical Technicians	17-3025	Environmental Engineering Technicians
17-3026	Industrial Engineering Technicians	17-3027	Mechanical Engineering Technicians
17-3029	Engineering Technicians, Except Drafters, All Other	17-3031	Surveying and Mapping Technicians
19-1011	Animal Scientists	19-1012	Food Scientists and Technologists
19-1013	Soil and Plant Scientists	19-1021	Biochemists and Biophysicists
19-1022	Microbiologists	19-1023	Zoologists and Wildlife Biologists
19-1029	Biological Scientists, All Other	19-1031	Conservation Scientists
19-1032	Foresters	19-1041	Epidemiologists
19-1042	Medical Scientists, Except Epidemiologists	19-1099	Life Scientists, All Other
19-2011	Astronomers	19-2012	Physicists
19-2021	Atmospheric and Space Scientists	19-2031	Chemists
19-2032	Materials Scientists	19-2041	Environmental Scientists and Specialists, Including Health
19-2042	Geoscientists, Except Hydrologists and Geographers	19-2043	Hydrologists
19-2099	Physical Scientists, All Other	19-3011	Economists
19-3022	Survey Researchers	19-3031	Clinical, Counseling, and School Psychologists
19-3032	Industrial-Organizational Psychologists	19-3039	Psychologists, All Other
19-3041	Sociologists	19-3051	Urban and Regional Planners
19-3091	Anthropologists and Archeologists	19-3092	Geographers
19-3093	Historians	19-3094	Political Scientists
19-3099	Social Scientists and Related Workers, All Other	19-4011	Agricultural and Food Science Technicians
19-4021	Biological Technicians	19-4031	Chemical Technicians
19-4041	Geological and Petroleum Technicians	19-4051	Nuclear Technicians
19-4061	Social Science Research Assistants	19-4091	Environmental Science and Protection Technicians, Including Health
19-4092	Forensic Science Technicians	19-4093	Forest and Conservation Technicians
19-4099	Life, Physical, and Social Science Technicians, All Other	21-1011	Substance Abuse and Behavioral Disorder Counselors

21-1012	Educational, Guidance, School, and Vocational Counselors	21-1013	Marriage and Family Therapists
21-1014	Mental Health Counselors	21-1015	Rehabilitation Counselors
21-1019	Counselors, All Other	21-1021	Child, Family, and School Social Workers
21-1022	Healthcare Social Workers	21-1023	Mental Health and Substance Abuse Social Workers
21-1029	Social Workers, All Other	21-1091	Health Educators
21-1092	Probation Officers and Correctional Treatment Specialists	21-1093	Social and Human Service Assistants
21-1094	Community Health Workers	21-1099	Community and Social Service Specialists, All Other
21-2011	Clergy	21-2021	Directors, Religious Activities and Education
21-2099	Religious Workers, All Other	23-1011	Lawyers
23-1012	Judicial Law Clerks	23-1021	Administrative Law Judges, Adjudicators, and Hearing Officers
23-1022	Arbitrators, Mediators, and Conciliators	23-1023	Judges, Magistrate Judges, and Magistrates
23-2011	Paralegals and Legal Assistants	23-2091	Court Reporters
23-2093	Title Examiners, Abstractors, and Searchers	23-2099	Legal Support Workers, All Other
25-1011	Business Teachers, Postsecondary	25-1021	Computer Science Teachers, Postsecondary
25-1022	Mathematical Science Teachers, Postsecondary	25-1031	Architecture Teachers, Postsecondary
25-1032	Engineering Teachers, Postsecondary	25-1041	Agricultural Sciences Teachers, Postsecondary
25-1042	Biological Science Teachers, Postsecondary	25-1043	Forestry and Conservation Science Teachers, Postsecondary
25-1051	Atmospheric, Earth, Marine, and Space Sciences Teachers, Postsecondary	25-1052	Chemistry Teachers, Postsecondary
25-1053	Environmental Science Teachers, Postsecondary	25-1054	Physics Teachers, Postsecondary
25-1061	Anthropology and Archeology Teachers, Postsecondary	25-1062	Area, Ethnic, and Cultural Studies Teachers, Postsecondary
25-1063	Economics Teachers, Postsecondary	25-1064	Geography Teachers, Postsecondary
25-1065	Political Science Teachers, Postsecondary	25-1066	Psychology Teachers, Postsecondary
25-1067	Sociology Teachers, Postsecondary	25-1069	Social Sciences Teachers, Postsecondary, All Other
25-1071	Health Specialties Teachers, Postsecondary	25-1072	Nursing Instructors and Teachers, Postsecondary
25-1081	Education Teachers, Postsecondary	25-1082	Library Science Teachers, Postsecondary
25-1111	Criminal Justice and Law Enforcement Teachers, Postsecondary	25-1112	Law Teachers, Postsecondary
25-1113	Social Work Teachers, Postsecondary	25-1121	Art, Drama, and Music Teachers, Postsecondary
25-1122	Communications Teachers, Postsecondary	25-1123	English Language and Literature Teachers, Postsecondary
25-1124	Foreign Language and Literature Teachers, Postsecondary	25-1125	History Teachers, Postsecondary
25-1126	Philosophy and Religion Teachers, Postsecondary	25-1191	Graduate Teaching Assistants
25-1192	Home Economics Teachers, Postsecondary	25-1193	Recreation and Fitness Studies Teachers, Postsecondary
25-1194	Vocational Education Teachers, Postsecondary	25-1199	Postsecondary Teachers, All Other
25-2011	Preschool Teachers, Except Special Education	25-2012	Kindergarten Teachers, Except Special Education
25-2021	Elementary School Teachers, Except Special Education	25-2022	Middle School Teachers, Except Special and Career/Technical Education

25-2023	Career/Technical Education Teachers, Middle School	25-2031	Secondary School Teachers, Except Special and Career/Technical Education
25-2032	Career/Technical Education Teachers, Secondary School	25-2051	Special Education Teachers, Preschool
25-2052	Special Education Teachers, Kindergarten and Elementary School	25-2053	Special Education Teachers, Middle School
25-2054	Special Education Teachers, Secondary School	25-2059	Special Education Teachers, All Other
25-3011	Adult Basic and Secondary Education and Literacy Teachers and Instructors	25-3021	Self-Enrichment Education Teachers
25-3099	Teachers and Instructors, All Other	25-4011	Archivists
25-4012	Curators	25-4013	Museum Technicians and Conservators
25-4021	Librarians	25-4031	Library Technicians
25-9011	Audio-Visual and Multimedia Collections Specialists	25-9021	Farm and Home Management Advisors
25-9031	Instructional Coordinators	25-9041	Teacher Assistants
25-9099	Education, Training, and Library Workers, All Other	27-1011	Art Directors
27-1012	Craft Artists	27-1013	Fine Artists, Including Painters, Sculptors, and Illustrators
27-1014	Multimedia Artists and Animators	27-1019	Artists and Related Workers, All Other
27-1021	Commercial and Industrial Designers	27-1022	Fashion Designers
27-1023	Floral Designers	27-1024	Graphic Designers
27-1025	Interior Designers	27-1026	Merchandise Displayers and Window Trimmers
27-1027	Set and Exhibit Designers	27-1029	Designers, All Other
27-2011	Actors	27-2012	Producers and Directors
27-2021	Athletes and Sports Competitors	27-2022	Coaches and Scouts
27-2023	Umpires, Referees, and Other Sports Officials	27-2031	Dancers
27-2032	Choreographers	27-2041	Music Directors and Composers
27-2042	Musicians and Singers	27-2099	Entertainers and Performers, Sports and Related Workers, All Other
27-3011	Radio and Television Announcers	27-3012	Public Address System and Other Announcers
27-3021	Broadcast News Analysts	27-3022	Reporters and Correspondents
27-3031	Public Relations Specialists	27-3041	Editors
27-3042	Technical Writers	27-3043	Writers and Authors
27-3091	Interpreters and Translators	27-3099	Media and Communication Workers, All Other
27-4011	Audio and Video Equipment Technicians	27-4012	Broadcast Technicians
27-4013	Radio Operators	27-4014	Sound Engineering Technicians
27-4021	Photographers	27-4031	Camera Operators, Television, Video, and Motion Picture
27-4032	Film and Video Editors	27-4099	Media and Communication Equipment Workers, All Other
29-1011	Chiropractors	29-1021	Dentists, General
29-1022	Oral and Maxillofacial Surgeons	29-1023	Orthodontists
29-1024	Prosthodontists	29-1029	Dentists, All Other Specialists
29-1031	Dietitians and Nutritionists	29-1041	Optometrists
29-1051	Pharmacists	29-1061	Anesthesiologists
29-1062	Family and General Practitioners	29-1063	Internists, General
29-1064	Obstetricians and Gynecologists	29-1065	Pediatricians, General
29-1066	Psychiatrists	29-1067	Surgeons
29-1069	Physicians and Surgeons, All Other	29-1071	Physician Assistants
29-1081	Podiatrists	29-1122	Occupational Therapists
29-1123	Physical Therapists	29-1124	Radiation Therapists
29-1125	Recreational Therapists	29-1126	Respiratory Therapists

29-1127	Speech-Language Pathologists	29-1128	Exercise Physiologists
29-1129	Therapists, All Other	29-1131	Veterinarians
29-1141	Registered Nurses	29-1151	Nurse Anesthetists
29-1161	Nurse Midwives	29-1171	Nurse Practitioners
29-1181	Audiologists	29-1199	Health Diagnosing and Treating Practitioners, All Other
29-2011	Medical and Clinical Laboratory Technologists	29-2012	Medical and Clinical Laboratory Technicians
29-2021	Dental Hygienists	29-2031	Cardiovascular Technologists and Technicians
29-2032	Diagnostic Medical Sonographers	29-2033	Nuclear Medicine Technologists
29-2034	Radiologic Technologists	29-2035	Magnetic Resonance Imaging Technologists
29-2041	Emergency Medical Technicians and Paramedics	29-2051	Dietetic Technicians
29-2052	Pharmacy Technicians	29-2053	Psychiatric Technicians
29-2054	Respiratory Therapy Technicians	29-2055	Surgical Technologists
29-2056	Veterinary Technologists and Technicians	29-2057	Ophthalmic Medical Technicians
29-2061	Licensed Practical and Licensed Vocational Nurses	29-2071	Medical Records and Health Information Technicians
29-2081	Opticians, Dispensing	29-2091	Orthotists and Prosthetists
29-2092	Hearing Aid Specialists	29-2099	Health Technologists and Technicians, All Other
29-9011	Occupational Health and Safety Specialists	29-9012	Occupational Health and Safety Technicians
29-9091	Athletic Trainers	29-9092	Genetic Counselors
29-9099	Healthcare Practitioners and Technical Workers, All Other	31-1011	Home Health Aides
31-1013	Psychiatric Aides	31-1014	Nursing Assistants
31-1015	Orderlies	31-2011	Occupational Therapy Assistants
31-2012	Occupational Therapy Aides	31-2021	Physical Therapist Assistants
31-2022	Physical Therapist Aides	31-9011	Massage Therapists
31-9091	Dental Assistants	31-9092	Medical Assistants
31-9093	Medical Equipment Preparers	31-9094	Medical Transcriptionists
31-9095	Pharmacy Aides	31-9096	Veterinary Assistants and Laboratory Animal Caretakers
31-9097	Phlebotomists	31-9099	Healthcare Support Workers, All Other
33-1011	First-Line Supervisors of Correctional Officers	33-1012	First-Line Supervisors of Police and Detectives
33-1021	First-Line Supervisors of Fire Fighting and Prevention Workers	33-1099	First-Line Supervisors of Protective Service Workers, All Other
33-2011	Firefighters	33-2021	Fire Inspectors and Investigators
33-2022	Forest Fire Inspectors and Prevention Specialists	33-3011	Bailiffs
33-3012	Correctional Officers and Jailers	33-3021	Detectives and Criminal Investigators
33-3031	Fish and Game Wardens	33-3041	Parking Enforcement Workers
33-3051	Police and Sheriff's Patrol Officers	33-3052	Transit and Railroad Police
33-9011	Animal Control Workers	33-9021	Private Detectives and Investigators
33-9031	Gaming Surveillance Officers and Gaming Investigators	33-9032	Security Guards
33-9091	Crossing Guards	33-9092	Lifeguards, Ski Patrol, and Other Recreational Protective Service Workers
33-9093	Transportation Security Screeners	33-9099	Protective Service Workers, All Other
35-1011	Chefs and Head Cooks	35-1012	First-Line Supervisors of Food Preparation and Serving Workers
35-2011	Cooks, Fast Food	35-2012	Cooks, Institution and Cafeteria
35-2013	Cooks, Private Household	35-2014	Cooks, Restaurant

35-2015	Cooks, Short Order	35-2019	Cooks, All Other
35-2021	Food Preparation Workers	35-3011	Bartenders
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food	35-3022	Counter Attendants, Cafeteria, Food Concession, and Coffee Shop
35-3031	Waiters and Waitresses	35-3041	Food Servers, Nonrestaurant
35-9011	Dining Room and Cafeteria Attendants and Bartender Helpers	35-9021	Dishwashers
35-9031	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop	35-9099	Food Preparation and Serving Related Workers, All Other
37-1011	First-Line Supervisors of Housekeeping and Janitorial Workers	37-1012	First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	37-2012	Maids and Housekeeping Cleaners
37-2019	Building Cleaning Workers, All Other	37-2021	Pest Control Workers
37-3011	Landscaping and Groundskeeping Workers	37-3012	Pesticide Handlers, Sprayers, and Applicators, Vegetation
37-3013	Tree Trimmers and Pruners	37-3019	Grounds Maintenance Workers, All Other
39-1011	Gaming Supervisors	39-1012	Slot Supervisors
39-1021	First-Line Supervisors of Personal Service Workers	39-2011	Animal Trainers
39-2021	Nonfarm Animal Caretakers	39-3011	Gaming Dealers
39-3012	Gaming and Sports Book Writers and Runners	39-3019	Gaming Service Workers, All Other
39-3021	Motion Picture Projectionists	39-3031	Ushers, Lobby Attendants, and Ticket Takers
39-3091	Amusement and Recreation Attendants	39-3092	Costume Attendants
39-3093	Locker Room, Coatroom, and Dressing Room Attendants	39-3099	Entertainment Attendants and Related Workers, All Other
39-4011	Embalmers	39-4021	Funeral Attendants
39-4031	Morticians, Undertakers, and Funeral Directors	39-5011	Barbers
39-5012	Hairdressers, Hairstylists, and Cosmetologists	39-5091	Makeup Artists, Theatrical and Performance
39-5092	Manicurists and Pedicurists	39-5093	Shampooers
39-5094	Skincare Specialists	39-6011	Baggage Porters and Bellhops
39-6012	Concierges	39-7011	Tour Guides and Escorts
39-7012	Travel Guides	39-9011	Childcare Workers
39-9021	Personal Care Aides	39-9031	Fitness Trainers and Aerobics Instructors
39-9032	Recreation Workers	39-9041	Residential Advisors
39-9099	Personal Care and Service Workers, All Other	41-1011	First-Line Supervisors of Retail Sales Workers
41-1012	First-Line Supervisors of Non-Retail Sales Workers	41-2011	Cashiers
41-2012	Gaming Change Persons and Booth Cashiers	41-2021	Counter and Rental Clerks
41-2022	Parts Salespersons	41-2031	Retail Salespersons
41-3011	Advertising Sales Agents	41-3021	Insurance Sales Agents
41-3031	Securities, Commodities, and Financial Services Sales Agents	41-3041	Travel Agents
41-3099	Sales Representatives, Services, All Other	41-4011	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical & Scientific Products	41-9011	Demonstrators and Product Promoters
41-9012	Models	41-9021	Real Estate Brokers
41-9022	Real Estate Sales Agents	41-9031	Sales Engineers
41-9041	Telemarketers	41-9091	Door-to-Door Sales Workers, News and Street Vendors, and Related Workers

41-9099	Sales and Related Workers, All Other	43-1011	First-Line Supervisors of Office and Administrative Support Workers
43-2011	Switchboard Operators, Including Answering Service	43-2021	Telephone Operators
43-2099	Communications Equipment Operators, All Other	43-3011	Bill and Account Collectors
43-3021	Billing and Posting Clerks	43-3031	Bookkeeping, Accounting, and Auditing Clerks
43-3041	Gaming Cage Workers	43-3051	Payroll and Timekeeping Clerks
43-3061	Procurement Clerks	43-3071	Tellers
43-3099	Financial Clerks, All Other	43-4011	Brokerage Clerks
43-4021	Correspondence Clerks	43-4031	Court, Municipal, and License Clerks
43-4041	Credit Authorizers, Checkers, and Clerks	43-4051	Customer Service Representatives
43-4061	Eligibility Interviewers, Government Programs	43-4071	File Clerks
43-4081	Hotel, Motel, and Resort Desk Clerks	43-4111	Interviewers, Except Eligibility and Loan
43-4121	Library Assistants, Clerical	43-4131	Loan Interviewers and Clerks
43-4141	New Accounts Clerks	43-4151	Order Clerks
43-4161	Human Resources Assistants, Except Payroll and Timekeeping	43-4171	Receptionists and Information Clerks
43-4181	Reservation and Transportation Ticket Agents and Travel Clerks	43-4199	Information and Record Clerks, All Other
43-5011	Cargo and Freight Agents	43-5021	Couriers and Messengers
43-5031	Police, Fire, and Ambulance Dispatchers	43-5032	Dispatchers, Except Police, Fire, and Ambulance
43-5041	Meter Readers, Utilities	43-5051	Postal Service Clerks
43-5052	Postal Service Mail Carriers	43-5053	Postal Service Mail Sorters, Processors, and Processing Machine Operators
43-5061	Production, Planning, and Expediting Clerks	43-5071	Shipping, Receiving, and Traffic Clerks
43-5081	Stock Clerks and Order Fillers	43-5111	Weighers, Measurers, Checkers, and Samplers, Recordkeeping
43-6011	Executive Secretaries and Executive Administrative Assistants	43-6012	Legal Secretaries
43-6013	Medical Secretaries	43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive
43-9011	Computer Operators	43-9021	Data Entry Keyers
43-9022	Word Processors and Typists	43-9031	Desktop Publishers
43-9041	Insurance Claims and Policy Processing Clerks	43-9051	Mail Clerks and Mail Machine Operators, Except Postal Service
43-9061	Office Clerks, General	43-9071	Office Machine Operators, Except Computer
43-9081	Proofreaders and Copy Markers	43-9111	Statistical Assistants
43-9199	Office and Administrative Support Workers, All Other	45-0901	International Relations and Affairs
45-1011	First-Line Supervisors of Farming, Fishing, and Forestry Workers	45-2011	Agricultural Inspectors
45-2021	Animal Breeders	45-2041	Graders and Sorters, Agricultural Products
45-2091	Agricultural Equipment Operators	45-2092	Farmworkers and Laborers, Crop, Nursery, and Greenhouse
45-2093	Farmworkers, Farm, Ranch, and Aquacultural Animals	45-3011	Fishers and Related Fishing Workers
45-3021	Hunters and Trappers	45-4011	Forest and Conservation Workers
45-4021	Fallers	45-4022	Logging Equipment Operators
45-4023	Log Graders and Scalers	45-4029	Logging Workers, All Other

47-1011	First-Line Supervisors of Construction Trades and Extraction Workers	47-2011	Boilermakers
47-2021	Brickmasons and Blockmasons	47-2022	Stonemasons
47-2031	Carpenters	47-2041	Carpet Installers
47-2042	Floor Layers, Except Carpet, Wood, and Hard Tiles	47-2043	Floor Sanders and Finishers
47-2044	Tile and Marble Setters	47-2051	Cement Masons and Concrete Finishers
47-2053	Terrazzo Workers and Finishers	47-2061	Construction Laborers
47-2071	Paving, Surfacing, and Tamping Equipment Operators	47-2072	Pile-Driver Operators
47-2073	Operating Engineers and Other Construction Equipment Operators	47-2081	Drywall and Ceiling Tile Installers
47-2082	Tapers	47-2111	Electricians
47-2121	Glaziers	47-2131	Insulation Workers, Floor, Ceiling, and Wall
47-2132	Insulation Workers, Mechanical	47-2141	Painters, Construction and Maintenance
47-2142	Paperhangers	47-2151	Pipelayers
47-2152	Plumbers, Pipefitters, and Steamfitters	47-2161	Plasterers and Stucco Masons
47-2171	Reinforcing Iron and Rebar Workers	47-2181	Roofers
47-2211	Sheet Metal Workers	47-2221	Structural Iron and Steel Workers
47-2231	Solar Photovoltaic Installers	47-3011	Helpers--Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters
47-3012	Helpers--Carpenters	47-3013	Helpers--Electricians
47-3014	Helpers--Painters, Paperhangers, Plasterers, and Stucco Masons	47-3015	Helpers--Pipelayers, Plumbers, Pipefitters, and Steamfitters
47-3016	Helpers--Roofers	47-3019	Helpers, Construction Trades, All Other
47-4011	Construction and Building Inspectors	47-4021	Elevator Installers and Repairers
47-4031	Fence Erectors	47-4041	Hazardous Materials Removal Workers
47-4051	Highway Maintenance Workers	47-4061	Rail-Track Laying and Maintenance Equipment Operators
47-4071	Septic Tank Servicers and Sewer Pipe Cleaners	47-4091	Segmental Pavers
47-4099	Construction and Related Workers, All Other	47-5011	Derrick Operators, Oil and Gas
47-5012	Rotary Drill Operators, Oil and Gas	47-5013	Service Unit Operators, Oil, Gas, and Mining
47-5021	Earth Drillers, Except Oil and Gas	47-5031	Explosives Workers, Ordnance Handling Experts, and Blasters
47-5041	Continuous Mining Machine Operators	47-5042	Mine Cutting and Channeling Machine Operators
47-5049	Mining Machine Operators, All Other	47-5051	Rock Splitters, Quarry
47-5061	Roof Bolters, Mining	47-5071	Roustabouts, Oil and Gas
47-5081	Helpers--Extraction Workers	47-5099	Extraction Workers, All Other
49-1011	First-Line Supervisors of Mechanics, Installers, and Repairers	49-2011	Computer, Automated Teller, and Office Machine Repairers
49-2021	Radio, Cellular, and Tower Equipment Installers and Repairs	49-2022	Telecommunications Equipment Installers and Repairers, Except Line Installers
49-2091	Avionics Technicians	49-2092	Electric Motor, Power Tool, and Related Repairers
49-2093	Electrical and Electronics Installers and Repairers, Transportation Equipment	49-2094	Electrical and Electronics Repairers, Commercial and Industrial Equipment
49-2095	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay	49-2096	Electronic Equipment Installers and Repairers, Motor Vehicles
49-2097	Electronic Home Entertainment Equipment Installers and Repairers	49-2098	Security and Fire Alarm Systems Installers
49-3011	Aircraft Mechanics and Service Technicians	49-3021	Automotive Body and Related Repairers

49-3022	Automotive Glass Installers and Repairers	49-3023	Automotive Service Technicians and Mechanics
49-3031	Bus and Truck Mechanics and Diesel Engine Specialists	49-3041	Farm Equipment Mechanics and Service Technicians
49-3042	Mobile Heavy Equipment Mechanics, Except Engines	49-3043	Rail Car Repairers
49-3051	Motorboat Mechanics and Service Technicians	49-3052	Motorcycle Mechanics
49-3053	Outdoor Power Equipment and Other Small Engine Mechanics	49-3091	Bicycle Repairers
49-3092	Recreational Vehicle Service Technicians	49-3093	Tire Repairers and Changers
49-9011	Mechanical Door Repairers	49-9012	Control and Valve Installers and Repairers, Except Mechanical Door
49-9021	Heating, Air Conditioning, and Refrigeration Mechanics and Installers	49-9031	Home Appliance Repairers
49-9041	Industrial Machinery Mechanics	49-9043	Maintenance Workers, Machinery
49-9044	Millwrights	49-9045	Refractory Materials Repairers, Except Brickmasons
49-9051	Electrical Power-Line Installers and Repairers	49-9052	Telecommunications Line Installers and Repairers
49-9061	Camera and Photographic Equipment Repairers	49-9062	Medical Equipment Repairers
49-9063	Musical Instrument Repairers and Tuners	49-9064	Watch Repairers
49-9069	Precision Instrument and Equipment Repairers, All Other	49-9071	Maintenance and Repair Workers, General
49-9081	Wind Turbine Service Technicians	49-9091	Coin, Vending, and Amusement Machine Servicers and Repairers
49-9092	Commercial Divers	49-9093	Fabric Menders, Except Garment
49-9094	Locksmiths and Safe Repairers	49-9095	Manufactured Building and Mobile Home Installers
49-9096	Riggers	49-9097	Signal and Track Switch Repairers
49-9098	Helpers--Installation, Maintenance, and Repair Workers	49-9099	Installation, Maintenance, and Repair Workers, All Other
50-0709	Sculpture	50-0710	Printmaking
50-0711	Ceramic Arts and Ceramics	50-0712	Fiber, Textile and Weaving Arts
50-0713	Metal and Jewelry Arts	50-0799	Fine Arts and Art Studies, Other
51-1011	First-Line Supervisors of Production and Operating Workers	51-2011	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers
51-2021	Coil Winders, Tapers, and Finishers	51-2022	Electrical and Electronic Equipment Assemblers
51-2023	Electromechanical Equipment Assemblers	51-2031	Engine and Other Machine Assemblers
51-2041	Structural Metal Fabricators and Fitters	51-2091	Fiberglass Laminators and Fabricators
51-2092	Team Assemblers	51-2093	Timing Device Assemblers and Adjusters
51-2099	Assemblers and Fabricators, All Other	51-3011	Bakers
51-3021	Butchers and Meat Cutters	51-3022	Meat, Poultry, and Fish Cutters and Trimmers
51-3023	Slaughterers and Meat Packers	51-3091	Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders
51-3092	Food Batchmakers	51-3093	Food Cooking Machine Operators and Tenders
51-3099	Food Processing Workers, All Other	51-4011	Computer-Controlled Machine Tool Operators, Metal and Plastic
51-4012	Computer Numerically Controlled Machine Tool Programmers, Metal and Plastic	51-4021	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic
51-4022	Forging Machine Setters, Operators, and Tenders, Metal and Plastic	51-4023	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic

51-4031	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	51-4032	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51-4033	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	51-4034	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51-4035	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic	51-4041	Machinists
51-4051	Metal-Refining Furnace Operators and Tenders	51-4052	Pourers and Casters, Metal
51-4061	Model Makers, Metal and Plastic	51-4062	Patternmakers, Metal and Plastic
51-4071	Foundry Mold and Coremakers	51-4072	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic
51-4081	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	51-4111	Tool and Die Makers
51-4121	Welders, Cutters, Solderers, and Brazers	51-4122	Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders
51-4191	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic	51-4192	Layout Workers, Metal and Plastic
51-4193	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic	51-4194	Tool Grinders, Filers, and Sharpeners
51-4199	Metal Workers and Plastic Workers, All Other	51-5111	Prepress Technicians and Workers
51-5112	Printing Press Operators	51-5113	Print Binding and Finishing Workers
51-6011	Laundry and Dry-Cleaning Workers	51-6021	Pressers, Textile, Garment, and Related Materials
51-6031	Sewing Machine Operators	51-6041	Shoe and Leather Workers and Repairers
51-6042	Shoe Machine Operators and Tenders	51-6051	Sewers, Hand
51-6052	Tailors, Dressmakers, and Custom Sewers	51-6061	Textile Bleaching and Dyeing Machine Operators and Tenders
51-6062	Textile Cutting Machine Setters, Operators, and Tenders	51-6063	Textile Knitting and Weaving Machine Setters, Operators, and Tenders
51-6064	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	51-6091	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic & Glass Fibers
51-6092	Fabric and Apparel Patternmakers	51-6093	Upholsterers
51-6099	Textile, Apparel, and Furnishings Workers, All Other	51-7011	Cabinetmakers and Bench Carpenters
51-7021	Furniture Finishers	51-7031	Model Makers, Wood
51-7032	Patternmakers, Wood	51-7041	Sawing Machine Setters, Operators, and Tenders, Wood
51-7042	Woodworking Machine Setters, Operators, and Tenders, Except Sawing	51-7099	Woodworkers, All Other
51-8011	Nuclear Power Reactor Operators	51-8012	Power Distributors and Dispatchers
51-8013	Power Plant Operators	51-8021	Stationary Engineers and Boiler Operators
51-8031	Water and Wastewater Treatment Plant and System Operators	51-8091	Chemical Plant and System Operators
51-8092	Gas Plant Operators	51-8093	Petroleum Pump System Operators, Refinery Operators, and Gaugers
51-8099	Plant and System Operators, All Other	51-9011	Chemical Equipment Operators and Tenders
51-9012	Separating, Filtering, Clarifying, Precipitating, & Still Machine Setters, Operators, & Tenders	51-9021	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders
51-9022	Grinding and Polishing Workers, Hand	51-9023	Mixing and Blending Machine Setters, Operators, and Tenders

51-9031	Cutters and Trimmers, Hand	51-9032	Cutting and Slicing Machine Setters, Operators, and Tenders
51-9041	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	51-9051	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers	51-9071	Jewelers and Precious Stone and Metal Workers
51-9081	Dental Laboratory Technicians	51-9082	Medical Appliance Technicians
51-9083	Ophthalmic Laboratory Technicians	51-9111	Packaging and Filling Machine Operators and Tenders
51-9121	Coating, Painting, and Spraying Machine Setters, Operators, and Tenders	51-9122	Painters, Transportation Equipment
51-9123	Painting, Coating, and Decorating Workers	51-9141	Semiconductor Processors
51-9151	Photographic Process Workers and Processing Machine Operators	51-9191	Adhesive Bonding Machine Operators and Tenders
51-9192	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders	51-9193	Cooling and Freezing Equipment Operators and Tenders
51-9194	Etchers and Engravers	51-9195	Molders, Shapers, and Casters, Except Metal and Plastic
51-9196	Paper Goods Machine Setters, Operators, and Tenders	51-9197	Tire Builders
51-9198	Helpers--Production Workers	52-0409	Parts, Warehousing, & Inventory Management Operations
52-0410	Traffic, Customs, & Transportation Clerk/Technician	53-1011	Aircraft Cargo Handling Supervisors
53-1021	First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand	53-1031	First-Line Supervisors of Transportation and Material-Moving Machine & Vehicle Operators
53-2011	Airline Pilots, Copilots, and Flight Engineers	53-2012	Commercial Pilots
53-2021	Air Traffic Controllers	53-2022	Airfield Operations Specialists
53-2031	Flight Attendants	53-3011	Ambulance Drivers and Attendants, Except Emergency Medical Technicians
53-3021	Bus Drivers, Transit and Intercity	53-3022	Bus Drivers, School or Special Client
53-3031	Driver/Sales Workers	53-3032	Heavy and Tractor-Trailer Truck Drivers
53-3033	Light Truck or Delivery Services Drivers	53-3041	Taxi Drivers and Chauffeurs
53-3099	Motor Vehicle Operators, All Other	53-4011	Locomotive Engineers
53-4012	Locomotive Firers	53-4013	Rail Yard Engineers, Dinkey Operators, and Hostlers
53-4021	Railroad Brake, Signal, and Switch Operators	53-4031	Railroad Conductors and Yardmasters
53-4041	Subway and Streetcar Operators	53-4099	Rail Transportation Workers, All Other
53-5011	Sailors and Marine Oilers	53-5021	Captains, Mates, and Pilots of Water Vessels
53-5022	Motorboat Operators	53-5031	Ship Engineers
53-6011	Bridge and Lock Tenders	53-6021	Parking Lot Attendants
53-6031	Automotive and Watercraft Service Attendants	53-6041	Traffic Technicians
53-6051	Transportation Inspectors	53-6061	Transportation Attendants, Except Flight Attendants
53-6099	Transportation Workers, All Other	53-7011	Conveyor Operators and Tenders
53-7021	Crane and Tower Operators	53-7031	Dredge Operators
53-7032	Excavating and Loading Machine and Dragline Operators	53-7033	Loading Machine Operators, Underground Mining
53-7041	Hoist and Winch Operators	53-7051	Industrial Truck and Tractor Operators
53-7061	Cleaners of Vehicles and Equipment	53-7062	Laborers and Freight, Stock, and Material Movers, Hand
53-7063	Machine Feeders and Offbearers	53-7064	Packers and Packagers, Hand

53-7071	Gas Compressor and Gas Pumping Station Operators	53-7072	Pump Operators, Except Wellhead Pumpers
53-7073	Wellhead Pumpers	53-7081	Refuse and Recyclable Material Collectors
53-7111	Mine Shuttle Car Operators	53-7121	Tank Car, Truck, and Ship Loaders
53-7199	Material Moving Workers, All Other	55-1011	Air Crew Officers
55-1012	Aircraft Launch and Recovery Officers	55-1013	Armored Assault Vehicle Officers
55-1014	Artillery and Missile Officers	55-1015	Command and Control Center Officers
55-1016	Infantry Officers	55-1017	Special Forces Officers
55-1019	Military Officer Special and Tactical Operations Leaders, All Other	55-2011	First-Line Supervisors of Air Crew Members
55-2012	First-Line Supervisors of Weapons Specialists/Crew Members	55-2013	First-Line Supervisors of All Other Tactical Operations Specialists
55-3011	Air Crew Members	55-3012	Aircraft Launch and Recovery Specialists
55-3013	Armored Assault Vehicle Crew Members	55-3014	Artillery and Missile Crew Members
55-3015	Command and Control Center Specialists	55-3016	Infantry
55-3017	Radar and Sonar Technicians	55-3018	Special Forces
55-3019	Military Enlisted Tactical Operations & Air/Weapons Specialists & Crew Members, All Other		

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