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# The Architecture of Expected Wage Gaps: Between- and Within-School Sources of Career Education Inequality

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## Abstract

Using administrative data from Delaware and aggregate occupational wage data from the Bureau of Labor Statistics, this paper examines expected wage inequality in Career and Technical Education (CTE) by analyzing how student demographics relate to selection into programs of study (POS) with different expected wages. Through multilevel mixed-effects modeling, we find substantial gaps in expected wages across student subgroups, with traditionally disadvantaged students selecting into lower-wage pathways. Our decomposition analyses reveal that gender wage gaps primarily stem from within-school factors, while racial and socioeconomic gaps are largely driven by between-school differences. Investigating potential mechanisms, we find that student selection patterns into POS contribute more to these inequalities than schools' program offerings. These results suggest that policy interventions should be tailored by subgroup: addressing within-school practices for gender gaps while focusing on between-school resources and supports for racial and socioeconomic disparities. The findings demonstrate how early career preferences may contribute to eventual wage inequality and highlight opportunities for targeted early intervention.

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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; Killingsworth, 2021). However, wages vary greatly between fields of employment, and even within employment fields, wage disparities persist across genders, races, abilities, and language status (Blau & Klein, 2017; O'Neill & O'Neill, 2006; 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 actual labor market outcomes, such as whether certain demographic groups earn differential wages or work in particular fields (e.g., 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 (e.g., Renzulli et al., 2006; Sloan et al., 2021). The emphasis on college and labor market outcomes is unsurprising, given the close timing of these events. However, we recognize that 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; Nagy et al., 2008; Sadler et al., 2012). 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; Aschbacher et al., 2010; Dick & Rallis, 1991; Wahl & Blackhurst, 2000), 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; Cho-Baker et al., 2021; Evans & Diekman, 2009; Mau & Li, 2018).

We therefore consider it worthwhile to understand how heterogeneous and inequitable preferences for careers form in high school, independently of actual wages earned. This question bears importance partly because it allows for the separation of wage inequities arising from the direct effects of labor market participation (e.g., as arising from discrimination or sector- and firm-specific preferences) and those arising from exposure to careers and training that takes place 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 (e.g., 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 (e.g., Giani, 2019).

The extent to which variability and inequity in wage selection begins to form in high school is therefore an important question, but one not easily answered 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 successfully 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, 2021; Stevens et al., 2019). 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 programs of study. In effect, for each CTE program of study, 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 cluster?
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; National Center for Education Statistics, 2019). Using course data, we identify the CTE program of study that each of these CTE concentrators in the state belong 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 program choice–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 has worked with the Office of Vocational and Adult Education to create a uniform framework, called the National Career Clusters Framework, to guide CTE implementation across the country (Advance CTE, 2023). This Framework puts forth 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) (Advance CTE, 2023; Delaware Department of Education, 2017). 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 enough coursework to specialize in a particular 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., 2014; Reardon, et al., 2019), career aspiration surveys (Signer & Saldana, 2001), and categorical inequalities (Domina, et al., 2017; 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 the mechanisms through which 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.

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. As we apply this framework to our analysis of 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 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. The data also includes CTE course enrollment, academic performance, the high school attended, and concentrator status as identified by LEA. We define concentrator status using course records, determining that a student is a concentrator in CTE POS *j* if the student completed two courses in a given POS with at least one course at or above a level 2 (see Huang et al. (2024) for additional details). We then implement several sample restrictions to assess whether test scores play a key role in determining students' benefits in CTE POS participation. We retain students with 8th-grade English Language Arts (ELA), math, and science scores who graduated from a Delaware public high school and meet the requirements of the Perkins V definition of concentrators. This restriction captures 33,275 students, or about 57% of the original sample.

Second, we use occupational employment and wage statistics from the BLS[1] 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 CIP SOC Crosswalk provided by the National Center for Education Statistics[2]. CIP SOC crosswalk is a dataset that matches the 6-digit 2020 Classification of Instructional Program (CIP) and 2018 Standard Occupational Classification (SOC). If multiple occupational codes are assigned to a POS, we calculate the mean wage of the assigned occupations. In our data, we are able to link 101 POS codes to SOCs out of 185 POSs provided by schools in Delaware, giving us a final analytic sample of 18,329 students, comprising about 31% of the original sample size.

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

[1] Occupational Employment and Wage Statistics: https://www.bls.gov/oes/
[2] CIP SOC Crosswalk: https://nces.ed.gov/ipeds/cipcode/post3.aspx?y=56

in each respective program. We show proportions of student subgroups participating in each career cluster, alongside that career cluster's expected wage. While the statewide sample consists of 51% male and 49% female students, the share of male and female students varies significantly by career cluster. The majority of our students are white (50%), followed by black (18%), Hispanic (16%), and Asian (3%).

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, Cluster 9 has the greatest representation of black students (48%), yet the lowest mean expected wages across all clusters ($32,197). Cluster 17 has the largest representation of Hispanic students (38%) and a moderate expected wage of $79,823. However, Cluster 11 has the greater representation of white and Asian students (62% and 10% respectively), and the highest expected wages across all clusters ($106,194). From this aggregated data flows substantial inequality in expected wages between White and Asian students on the one hand, and Black and Hispanic students on the other. A similar set of results is observable for gender and other groups.

These aggregate data mask variation in expected wages within clusters (i.e., at the POS level) and between schools. For example, in Cluster 1, the expected wage varies across POS from $26,505 to $156,110. These descriptive results, however, lay the groundwork for the quantitative analyses described below.

[Table 1 About Here]

To further illustrate the mechanisms undergirding expected wage inequality, we focus on gender and, in Figure 1, plot the expected wage assigned to a POS against the proportion of females concentrating in that POS for individual schools in the three public districts in the state. The slopes of these lines indicate increases in the expected wage inequality, with positive slopes meaning that more females are represented in high wage POSs. One can see (Figure 1 Panel A) that these slopes are variable between schools within districts and between districts, meaning that a formal analysis decomposing between and within district variance could prove fruitful.

[Figure 1 About Here]

**Methods**

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, $\delta_c$ represents cohort-fixed effects. $\gamma_{ij}$ 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 $\beta_{0j}$ and $\beta_{gj}$. Level 2 equations divide school-specific intercepts and slopes into across-school averages and school-specific parts. $\gamma_{00}$ shows the average of the school means, and $u_{0j}$ indicates the unique intercept for school $j$. Similarly, $\gamma_{g0}$ 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:

$$Y_{ij} = \beta_0 + \beta_1 D_{ij} + \beta_2 p_j + \varepsilon_{ij} \tag{4}$$

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:

$$Wage\ gap\ = \widehat{\beta_1} + \widehat{\beta_2}(\underline{p_j}^f - \underline{p_j}^r) \tag{5}$$

We can rewrite the gap again as follows:

$$Wage\ gap = \ \widehat{\beta_1}[1 - \left(\underline{p_j}^f - \underline{p_j}^r\right)] + (\widehat{\beta_1} + \widehat{\beta_2})(\underline{p_j}^f - \underline{p_j}^r) \tag{6}$$

$\widehat{\beta_1}[1 - \left(\underline{p_j}^f - \underline{p_j}^r\right)]$ is the within school gap, and $\widehat{\beta_2}\left(\underline{p_j}^f - \underline{p_j}^r\right)$ is between school gap. $\widehat{\beta_1}\left(\underline{p_j}^f - \underline{p_j}^r\right)$ is the proportion of the gap which comes from the interaction of between and within school components, making it ambiguous.

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 "program availability characteristics" and "CTE segregation patterns." These factors map directly onto our analyses of between- versus within-school inequality. Program availability characteristics—measured by the number and average expected wages of POSs offered—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 distribute across available programs even 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, we use the Gini-Simpson diversity index, which measures how students are distributed across POS options within each school. To illustrate how this index captures meaningful variation in student sorting, consider three schools from our sample, each offering 6 POSs in 2017. In the first school, 87% of female students concentrated in a single POS while male enrollment was more evenly distributed, ranging from 2% to 52% across programs. In the second school, we observe the opposite pattern: female enrollment ranged from 14% to 54% across programs, while 88% of male students concentrated in a single POS. The third school showed relatively even gender distribution, with both female and male enrollment ranging from 2% to approximately 50% across programs.

To analyze these patterns systematically, we calculate the Gini-Simpson diversity index for each demographic group (i.e., gender, race/ethnicity, FRPL status, ELL status, and IEP status) and determine the diversity gap between focus and reference groups. The index for group $d$ in school $s$ ( $\lambda_{ds}$) is calculated as follows: $\lambda_{ds} = 1 - \sum_{k, if\ i \in d \in s} p_k$, where $p_k$ indicates the proportion of students in POS $k$. The index equals zero if all students in the school enroll in one POS, and the index equals $1/k$ when all students in the school are equally distributed into $k$ POS. The diversity gap is calculated by subtracting the reference group's index from the focus group's index. A positive gap indicates the focus group is more evenly distributed across POSs than the reference group. In our example schools above, the gender diversity gaps are 0.40, -0.41, and 0.04, respectively, capturing the substantial variation in gender segregation patterns 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 \$2,641.37 (p<0.001; 95% CI \$2,157.99 - \$3,124.75), meaning that males are expected to earn \$2,641.37 more than females. In Panel E, Black students are expected to earn \$2,659.05 less than white students (p<0.001, 95% CI \$2,089.39 - \$3,228.71), and Hispanic students are expected to earn \$4,948.63 less than white students (p<0.001, 95% CI \$4,261.07 - \$5,636.19). For students receiving FRPL, IEPs, ELL services (Panels B—E, respectively), gap magnitudes range from -\$2,338 to -\$7,713.

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[3], 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 \$2,122.91 (p<0.001, 95% CI \$1,677.25 - \$2,568.57), but racial/ethnic expected wage gaps change more dramatically, as Black and Hispanic wage differences are no longer statistically different from zero and are less than 20 percent the size of the total gap. Controlling for between school differences similarly attenuates expected wage gaps for students receiving FRPL, IEPs, and ELL services.

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 (column 3; \$3,515.78; p<0.001, 95% CI \$3,020.81 - \$4,010.75),

[3] In Table A1 we present gap estimates using school fixed effects regressions to show that the random intercept approach yields nearly identical point estimates.

which narrows slightly when including a random intercept (Column 4; p<0,.001, 95% CI $2,241.01 - $3,162.27). Black-White expected wage gaps reverse directionality, meaning that Black students with similar test scores as White students select into career POS with expected wages that are $1,244 greater than White students (p<0.05, 95% CI $652.39 - $1,836.17); including a school-level random intercept has little effect beyond the test score. For Hispanic-White gaps, the gap shrinks by more than half to -$2,032.78 (p<0.001, 95% CI $1,339.16 - $2,726.40) and reduces to $219 after including school-level random intercepts but is no longer statistically significant. Controlling for test scores similarly attenuates expected wage gaps for students receiving FRPL, IEPs, and ELL services, in some cases eliminating the expected wage gap entirely.

*Research Question Two: Within or Between School Factors*

The descriptive evidence from Figure 1 Panel A showing between school differences in the gender composition of different POS, coupled with the attenuating effect of school-level random intercepts on expected wage gaps shown in Table 2, reveals the importance of school-level influences on the generation of expected wage inequality. We investigate the influence of schools as a source of inequality in two ways. First, we modify Equation 2 by including school-specific random slopes, which provide school-specific estimates of the expected wage gap, with and without controlling for test scores. These estimates tell us how much within-school expected wage gaps vary across the state, which are useful because, if there is variation across schools, it suggests school-level factors can contribute to or ameliorate expected wage inequality. Should these school-level expected wage gaps be similar to controls for 8$^{th}$ grade test scores – an important source of student-based selection into career paths – this would provide additional evidence about the importance of schools, which would then implicate school-based policy solutions.

Table 3 presents results from this analysis. Including random slopes greatly attenuates the average difference in expected wage gaps for Black and Hispanic students relative to White students (Table 3, Column 1, Panel E) and increases the imprecision of the gender wage gap, though does not affect the coefficient. Expected wage differences for students qualifying for FRPL, IEPs, or ELL services are less affected. However, our main interest is in the variance of these components, which we transform to standard deviation (SD) units. Here we see confirmation that school-level factors are an important contributor to expected wage inequality: there is substantial variation in the expected wage across schools. For example, the SD of the random slope for gender is $12,509 (also visualized in Figure 1, Panel B), meaning that if expected wage gaps by gender are normally distributed among schools, about 68% of schools have expected wage gaps falling within -$9,220 to $15,798. Though gender has by far the greatest variability, other gaps, especially relative to the average, vary as well. For example, the SD of the random slope for Black-White expected wage gaps is $1,118, meaning that for about 68% of schools the Black-White expected wage gap falls within -$1,702 to $534, and for Hispanic-White expected wage gaps that interval encompasses -$4,087 to $2,169.

The variance in expected wage gaps across schools remains virtually unchanged when controlling for 8th grade test scores. The school-specific random slopes (corresponding to the "shrunken" Empirical Bayes estimate from Equation 3) show correlations of at least 0.99 with and without test score controls for each subgroup comparison. This extremely high correlation indicates that the relative ranking of schools in terms of their wage gaps is preserved—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.

In Table A2, we evaluate the robustness of this correlation by estimating school-specific wage gaps conditional on 8th grade test scores using ordinary least squares regression, coarsened exact matching (CEM; Blackwell et al., 2009) and entropy balancing (Hainmueller & Xu, 2013), separately. These school specific estimates are noisier, and we expect the correlation to the unconditional models to attenuate, but they remain large, ranging between 0.78 to 0.99. Thus, we conclude that school-level variance in the expected wage gaps is largely uncorrelated with 8th grade test scores.

[Table 3 About Here]

Second, we decompose the overall wage gaps into their between and within school components. This decomposition answers a different but related question: how much of the total wage gap between groups stems from differences in the schools they attend (i.e., the between component) versus unequal outcomes within the same schools (i.e., the within component). While the multilevel model shows how wage gaps vary across schools, the decomposition tells us how much this cross-school variation contributes to total inequality relative to within-school processes.

Results are presented in Table 4. For gender, 83% 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. In contrast, for Black-White and Hispanic-White expected wage gaps, 66% and 81% 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 FPRL and ELL services, most of the gap occurs between schools, whereas for students with IEPs, the majority of the gap occurs within schools.

Controlling for test scores (Table 4, Panel B) has no effect for gender gaps, as 85% of the gap remains due to within school factors. For Black-White and Hispanic-White gaps, the between school components continue to contribute to inequality disfavoring Black and Hispanic students – between school segregation and school-level differences negatively affect those expected wage gaps conditional on test scores. However, for Black students, because the gap is now reversed, the within-school component ($2,100) is larger than the total gap ($1,612); this means that if only within-school factors were considered, the gap favoring Black students would be even larger. The negative between-school component (-$776) is partially offsetting this within-school advantage. The pattern is largely the same for Hispanic-White expected wage gaps, though the average gap remains negative: on average, within schools, the gap favors Hispanic students but the between-school component is large and negative.

[Table 4 About Here]

There is an apparent 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. How can this be? First, recall that the expected wage gap decomposition is based on between school segregation; differences in the assignment of student groups across schools is a necessary feature of between school inequality. For gender, there is little segregation, as most schools are roughly equally composed of male and female students. Second, the random slopes model captures variation in gender wage gaps that arises from school-specific contextual factors, such as differences in school culture, resources, or teacher practices, which may affect how male and female students experience schooling differently within each school, even if the overall gender composition across schools is similar.

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

We identify school-level differences as mechanisms for expected wage inequality. These differences come from two sources, either variation in within-school practices that cause variation in school-specific expected wage inequality or average differences across schools in expected wages that drive expected wage inequality because of segregation. Our final research question seeks to identify potential mechanisms for this school-level variation. We consider program availability characteristics and CTE segregation patterns as two potential factors.

Of the hypotheses considered, only CTE segregation is a consistent predictor of expected wage inequality. As mentioned above, CTE POS segregation is measured using the Gini-Simpson diversity index, which captures how concentrated a focal group (e.g., male students) is across POS in a school compared to a reference group (e.g., female students). In Table 5, we see that on average, for all subgroups, the diversity index gap positively predicts group-level expected wage differences. For example, in schools where females are more concentrated in singular POS compared to male students (i.e., when male diversity is greater than female diversity across POS), the male-female expected wage gap grows. Specifically, for students attending a school where the male diversity index is 1-unit higher in the diversity index than it is for male students, male students concentrated in POS with expected wages that are $23,911 greater than female students. A one-unit change is about 5.56 SD of variation, so this corresponds to about $4,304 in expected wage differences for a 1 SD change in the diversity gap. These magnitudes and statistical significance are strikingly similar across all subgroups.

Conversely, when the number of POS offered increases or when the average expected wage increases, there is no consistent pattern (signs change across subgroup comparison) and coefficients are often not statistically distinguishable from zero. For gender, when the average expected wage gap increases by $1.00, the gender wage gap increases by $0.20; no other gaps are affected by this variable. For the number of pathways offered, expected wage gaps for gender and race/ethnicity do not vary. FRPL and IEP expected wage gaps narrow with additional pathways, whereas ELL expected wage gaps increase.

We run an alternative model that interacts the number of POS offered in the schools with the diversity gap within schools. The results (Table A3) show that the increase in the number of POS options raises the expected earnings of Black and low-income students when these students are more widely spread across POSs offered in school. In Table A4, we include the mean expected wage of all POSs in the school, and the results suggest that its association with expected wage gap is marginal. This again confirms that the schools' program availability characteristics is not consistently associated with the expected wage gap between student subgroups and that what seems to drive cross-school variation in expected wage inequality is the segregation of students in CTE programs of study.

[Table 5 About Here]

**Policy Applications**

These results lend themselves to potential policy actions. Importantly, our findings allow us to tailor interventions for group-specific inequalities distinguishing between within-school inequality and those inequalities that occur across schools.

For example, for gender-based inequalities, which our study shows primarily manifest within schools with substantial school variation in gender-based expected wages, interventions should focus on school-specific practices. Schools could implement targeted professional development programs for teachers and counselors to address unconscious biases in advising students about CTE pathways (Threeton, 2007). Additionally, school-level mentorship programs pairing female students with successful women in high-wage CTE fields could be highly effective, particularly as complementary literature demonstrates that adult guidance and anticipated pay drives student's career anticipations (Aschbacher et al., 2010; Dick & Rallis, 1991; Wahl & Blackhurst, 2000. Marketing strategies challenging gender stereotypes in various CTE pathways could also be developed and implemented at the school level (LaCosse, 2020; Rainey, et al., 2018). These within-school interventions are crucial because our results indicate significant variation in gender gaps across schools, suggesting that some schools have practices that successfully mitigate these gaps while others do not.

In contrast, our study reveals that racial and socioeconomic inequalities are largely driven by between-school differences, requiring a different approach. These school-level disparities mean that racial/ethnic and socioeconomic segregation will continue to generate inequality in expected wages unless schools serving minoritized and low-income students can offer POS of equal value. Policymakers could address this by improving the quality of CTE programs in schools where Black, Hispanic, and economically disadvantaged students are concentrated. While Delaware's school choice system could theoretically help students access higher-wage programs at other schools, Jacob and Ricks (2023) find that geographic distance between high-quality CTE programs and students' homes reduces program uptake, limiting school choice's effectiveness in addressing between-school inequalities.

Notably, we do not see systematic evidence that the availability of specific high wage pathways explains between school variability in expected wage gaps; rather, the group-level diversity across POS more consistently and strongly moderates selection into higher expected wage POS. What this means for policy is less clear, though it suggests school culture may be a factor, causing disadvantaged students to focus on just one or two POS as opposed to encouraging student groups to identify those POS most suited to their own earnings potential.

To support these targeted interventions, we have provided a framework that allows for the feasible generation of a statewide data system that tracks CTE concentrators into their expected wages. This data-driven approach would allow for the identification of schools with successful practices in reducing specific gaps, facilitating knowledge sharing across the state.

**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., 2021; Ecton & Dougherty, 2021; 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 POS 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. Our analysis on POS diversity suggests that within-school segregation in POS selection drives the wage gap, while school-level offerings of CTE programs of study do not moderate expected wage 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 POSs 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 limited POS options. 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 POS 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.

## References

Advance CTE. (2023). Advancing the framework. https://careertech.org/what-we-do/career-clusters/advancing-the-framework/

Altonji, J. G., Blom, E., & Meghir, C. (2012). Heterogeneity in human capital investments: High school curriculum, college major, and careers. Annual Review of Economics, 4(1), 185-223.

Aschbacher, P. R., Li, E., & Roth, E. J. (2010). Is science me? High school students' identities, participation and aspirations in science, engineering, and medicine. Journal of Research in Science Teaching, 47(5), 564-582.

Association for Career and Technical Education. (2021, May). 2019-20 national CTE enrollment data now available. CTE Policy Watch. https://ctepolicywatch.acteonline.org/2021/05/2019-20-national-cte-enrollment-data-now-available.html

Blackwell, M., Iacus, S., King, G., & Porro, G. (2009). cem: Coarsened exact matching in Stata. The Stata Journal, 9(4), 524-546.

Blau, F. D., & Kahn, L. M. (2017). The gender wage gap: Extent, trends, and explanations. Journal of Economic Literature, 55(3), 789-865.

Bobbitt-Zeher, D. (2007). The gender income gap and the role of education. Sociology of Education, 80(1), 1-22.

Brunner, E. J., Dougherty, S. M., & Ross, S. L. (2023). The effects of career and technical education: Evidence from the Connecticut technical high school system. *Review of Economics and Statistics*, *105*(4), 867-882.

Card, D., & Payne, A. A. (2021). High school choices and the gender gap in STEM. Economic Inquiry, 59(1), 9-28.

Carl D. Perkins Career and Technical Education Act of 2006, Pub. L. No. 115-224, 132 Stat. 1433 (2018).

Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., Bergeron, A., & Cutler, D. (2016). The association between income and life expectancy in the United States, 2001-2014. JAMA, 315(16), 1750-1766.

Cho-Baker, S., Olivera-Aguilar, M., & Fishtein, D. (2021). Using latent class analysis to link career and technical education in adolescence and work and school transitions in young adulthood. Career and Technical Education Research, 46(2), 59-79.

Correll, S. J. (2001). Gender and the career choice process: The role of biased self-assessments. American Journal of Sociology, 106(6), 1691-1730.

Delaware Department of Education. (2017). CTE programs of study policies and procedures. https://education.delaware.gov/wp-content/uploads/2019/04/2017_08_de_cte_pos_policyandprocedures.pdf

Delaware Department of Education. (2020). Career & technical education fiscal and accountability policies and procedures. https://education.delaware.gov/wp-content/uploads/2021/10/CTE_21_Fiscal_Accountability_Policies_Procedures.pdf

Delaware Department of Education. (2023). Career and technical education in Delaware, quick facts, funding and performance. https://www.doe.k12.de.us/cms/lib/DE01922744/Centricity/Domain/170/CTE%20in%20DE%20Overview_.pdf

Dick, T. P., & Rallis, S. F. (1991). Factors and influences on high school students' career choices. Journal for Research in Mathematics Education, 22(4), 281-292.

Domina, T., Penner, A., & Penner, E. (2017). Categorical inequality: Schools as sorting machines. Annual Review of Sociology, 43(1), 311-330.

Dougherty, S. M. (2018). The effect of career and technical education on human capital accumulation: Causal evidence from Massachusetts. Education Finance and Policy, 13(2), 119-148.

Ecton, W. G., & Dougherty, S. M. (2021). Heterogeneity in high school career and technical education outcomes (EdWorkingPaper No. 21-492). Annenberg Institute at Brown University. https://doi.org/10.26300/4jwf-wb39

ExcelinEd. (2018). Perkins V reauthorization: Opportunities and challenges for states. https://careertech.org/resource/perkins-v-reauthorization-opportunities-challenges-and-risks-for-states/

Evans, C. D., & Diekman, A. B. (2009). On motivated role selection: Gender beliefs, distant goals, and career interest. Psychology of Women Quarterly, 33(2), 235-249.

Fryer Jr, R. G., & Levitt, S. D. (2004). Understanding the black-white test score gap in the first two years of school. Review of Economics and Statistics, 86(2), 447-464.

Gamoran, A. (1992). The variable effects of high school tracking. American Sociological Review, 57(6), 812-828.

Giani, M. S. (2019). Does vocational still imply tracking? Examining the evolution of career and technical education curricular policy in Texas. Educational Policy, 33(7), 1002-1046.

Hainmueller, J., & Xu, Y. (2013). ebalance: A Stata package for entropy balancing. Journal of Statistical Software, 54(7), 1-18.

Hanushek, E. A., & Rivkin, S. G. (2006). School quality and the Black-White achievement gap (Working Paper No. w12651). National Bureau of Economic Research.

Hemelt, S. W., Lenard, M. A., & Paeplow, C. G. (2019). Building bridges to life after high school: Contemporary career academies and student outcomes. Economics of Education Review, 68, 161-178.

Huang, Y., Lee, H., Lentz, A., & Shores, K. A. (2023). Misclassification of career and technical education concentrators: Analysis and policy recommendations (EdWorkingPaper: 23-889). Annenberg Institute at Brown University. https://doi.org/10.26300/esab-m159

Jacob, B. A., & Ricks, M. D. (2023). Why choose career technical education? Disentangling student preferences from program availability (Working Paper No. w31756). National Bureau of Economic Research.

Killingsworth, M. A. (2021). Experienced well-being rises with income, even above $75,000 per year. Proceedings of the National Academy of Sciences, 118(4), Article e2016976118.

LaCosse, J., Canning, E. A., Bowman, N. A., Murphy, M. C., & Logel, C. (2020). A social-belonging intervention improves STEM outcomes for students who speak English as a second language. Science Advances, 6(40), Article eabb6543.

Mau, W. C. J., & Li, J. (2018). Factors influencing STEM career aspirations of underrepresented high school students. The Career Development Quarterly, 66(3), 246-258.

McCall, L. (2001). Sources of racial wage inequality in metropolitan labor markets: Racial, ethnic, and gender differences. American Sociological Review, 66(4), 520-541.

Nagy, G., Garrett, J., Trautwein, U., Cortina, K. S., Baumert, J., & Eccles, J. S. (2008). Gendered high school course selection as a precursor of gendered careers: The mediating role of self-concept and intrinsic value. In H. M. G. Watt & J. S. Eccles (Eds.), Gender and occupational outcomes: Longitudinal assessments of individual, social, and cultural influences (pp. 115-143). American Psychological Association.

National Center for Education Statistics. (2019). Enrollment in elementary, secondary, and degree-granting postsecondary institutions, by level and control of institution, enrollment level, and attendance status and sex of student: Selected years, fall 1990 through fall 2028. https://nces.ed.gov/programs/digest/d18/tables/dt18_105.20.asp

O'Neill, J. E., & O'Neill, D. M. (2006). What do wage differentials tell about labor market discrimination? In S. W. Polachek, C. Chiswick, & H. Rapoport (Eds.), The economics of immigration and social diversity (pp. 293-357). Emerald Group Publishing.

Page, L. C., Murnane, R. J., & Willett, J. B. (2008). Trends in the Black-White achievement gap: Clarifying the meaning of within-and between-school achievement gaps (Working Paper No. w14213). National Bureau of Economic Research.

Rainey, K., Dancy, M., Mickelson, R., Stearns, E., & Moller, S. (2018). Race and gender differences in how sense of belonging influences decisions to major in STEM. International Journal of STEM Education, 5, Article 10.

Reardon, S. F. (2008). Thirteen ways of looking at the black-white test score gap (Working Paper). Stanford Institute for Research on Education Policy & Practice.

Reardon, S. F., Robinson-Cimpian, J. P., & Weathers, E. S. (2014). Patterns and trends in racial/ethnic and socioeconomic academic achievement gaps. In H. F. Ladd & M. E. Goertz (Eds.), Handbook of research in education finance and policy (pp. 491-509). Routledge.

Reardon, S. F., Kalogrides, D., & Shores, K. (2019). The geography of racial/ethnic test score gaps. American Journal of Sociology, 124(4), 1164-1221.

Renzulli, L. A., Grant, L., & Kathuria, S. (2006). Race, gender, and the wage gap: Comparing faculty salaries in predominately White and historically Black colleges and universities. Gender & Society, 20(4), 491-510.

Sadler, P. M., Sonnert, G., Hazari, Z., & Tai, R. (2012). Stability and volatility of STEM career interest in high school: A gender study. Science Education, 96(3), 411-427.

Signer, B., & Saldana, D. (2001). Educational and career aspirations of high school students and race, gender, class differences. Race, Gender & Class, 8(1), 22-34.

Shores, K., Kim, H. E., & Still, M. (2020). Categorical inequality in Black and White: Linking disproportionality across multiple educational outcomes. American Educational Research Journal, 57(5), 2089-2131.

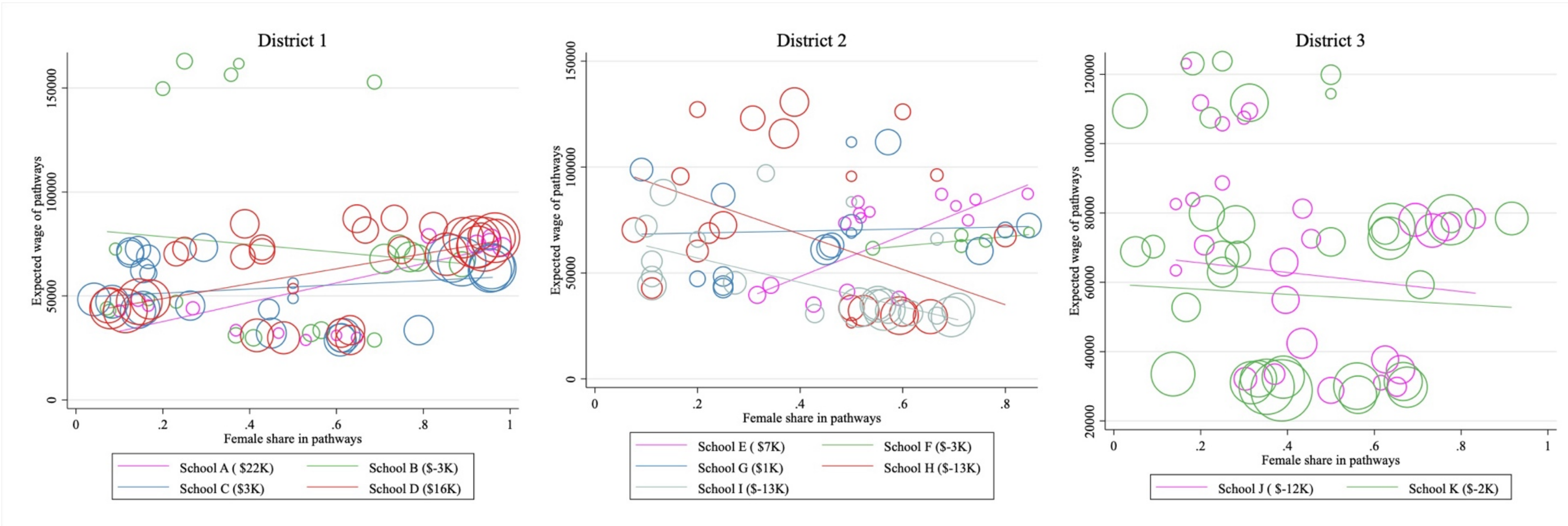
Sloane, C. M., Hurst, E. G., & Black, D. A. (2021). College majors, occupations, and the gender wage gap. Journal of Economic Perspectives, 35(4), 223-248.

Stevens, A. H., Kurlaender, M., & Grosz, M. (2019). Career technical education and labor market outcomes: Evidence from California community colleges. Journal of Human Resources, 54(4), 986-1036.

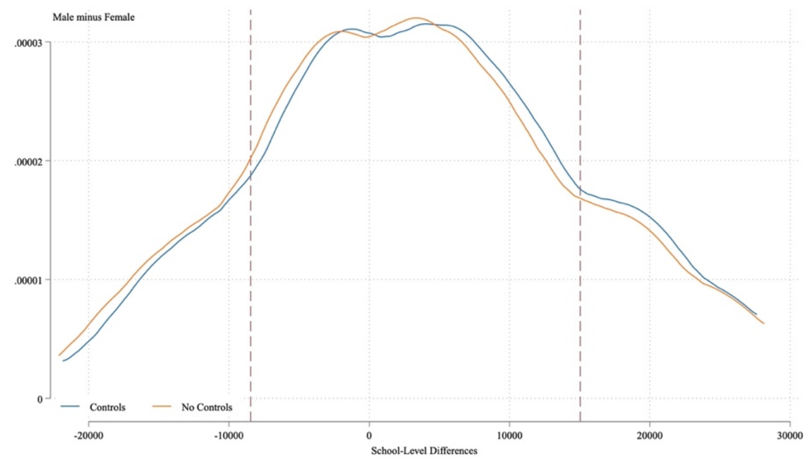
Threeton, M. D. (2007). The Carl D. Perkins Career and Technical Education (CTE) Act of 2006 and the roles and responsibilities of CTE teachers and faculty members. Journal of Industrial Teacher Education, 44(1), 66-82.

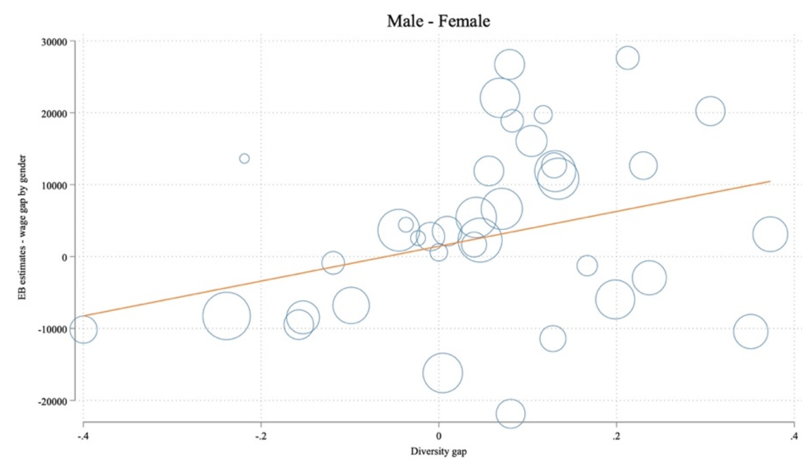
U.S. Department of Labor. (2024). Department of Labor equity action plan. https://www.dol.gov/sites/dolgov/files/general/equity/DOL-Equity-Action-Plan.pdf

Wahl, K. H., & Blackhurst, A. (2000). Factors affecting the occupational and educational aspirations of children and adolescents. Professional School Counseling, 3(5), 367-374.




Panel A: Gender wage gap and female proportion in pathways offered




Panel B. Distribution of School-specific gender wage gap

Panel : Gender wage gap and diversity gap (male – female)

Figure 1: Gender wage gap distribution and female concentration in CTE pathways

Notes: Panel A shows the expected gender wage gaps and female proportions in POSs offered in schools from three public school districts in our dataset for 2017 – 2021 graduating cohort, anonymized here as District 1, District 2, and District C. All school names have also been anonymized. Panel B is the distribution of the school-specific gender wage gap. The yellow line shows the estimated gender gap without test score adjustment and the blue line shows the gap with test score adjustment. Panel C shows the estimated gender gap at each school and the diversity gap which is calculated by subtracting the diversity index for females from the male diversity index. The scatterplot is weighted by using inverse variance weighting.

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

| | State Total | C 1 | C 2 | C 3 | C 4 | C 5 | C 6 | C 8 | C 9 | C 10 | C 11 | C 13 | C 14 | C 15 | C 16 | C 17 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean expected wages | $63 K | $39 K | $72 K | $68 K | $142 K | $78 K | $82 K | $74 K | $32 K | $98 K | $106 K | $61 K | $124 K | $103 K | $45 K | $80 K |
| Student enrollment | 18,329 | 5,073 | 706 | 1,201 | 433 | 473 | 483 | 3,333 | 2,594 | 35 | 156 | 108 | 701 | 1,868 | 907 | 258 |
| Male | 9,344 | 53% | 84% | 52% | 51% | 14% | 67% | 19% | 51% | 17% | 87% | 89% | 63% | 72% | 86% | 17% |
| (Female) | 8,985 | 47% | 16% | 48% | 49% | 86% | 33% | 81% | 49% | 83% | 13% | 11% | 37% | 28% | 14% | 83% |
| FRPL | 6,477 | 35% | 26% | 38% | 24% | 40% | 33% | 36% | 46% | 57% | 19% | 39% | 35% | 20% | 39% | 54% |
| (non-FRPL) | 11,852 | 65% | 74% | 62% | 76% | 60% | 67% | 64% | 54% | 43% | 81% | 61% | 65% | 80% | 61% | 46% |
| IEP | 2,172 | 13% | 13% | 15% | 8% | 12% | 11% | 15% | 12% | 3% | 13% | 19% | 10% | 11% | 20% | 31% |
| (non-IEP) | 16,157 | 87% | 87% | 85% | 92% | 87% | 89% | 85% | 88% | 97% | 87% | 81% | 90% | 89% | 80% | 69% |
| ELL | 2,472 | 13% | 10% | 15% | 13% | 13% | 5% | 7% | 16% | 3% | 4% | 9% | 12% | 7% | 21% | 9% |
| (non ELL) | 15,857 | 87% | 90% | 85% | 87% | 86% | 95% | 93% | 84% | 97% | 96% | 91% | 88% | 93% | 79% | 91% |
| White | 9,171 | 61% | 57% | 45% | 52% | 56% | 48% | 44% | 32% | 46% | 62% | 43% | 47% | 62% | 46% | 22% |
| Black | 5,105 | 18% | 20% | 27% | 31% | 29% | 32% | 32% | 48% | 43% | 20% | 27% | 35% | 18% | 25% | 36% |
| Hispanic | 2,990 | 15% | 17% | 19% | 12% | 12% | 12% | 19% | 16% | 6% | 6% | 24% | 11% | 11% | 27% | 38% |
| Asian | 559 | 3% | 4% | 4% | 3% | 1% | 6% | 3% | 1% | 0% | 10% | 2% | 4% | 6% | 1% | 2% |
| Other race | 504 | 3% | 2% | 4% | 2% | 3% | 3% | 2% | 2% | 6% | 3% | 5% | 2% | 3% | 1% | 2% |

Notes: Expected wages are obtained from the occupational wage of the U.S. Department of Labor using occupational code assigned to pathways. Dollars rounded to thousands place for space. 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, 13: Manufacturing, 14: Marketing, 15: STEM, 16: Automotive Technology, 17: Career Exploration

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 | 2641.37*** | 2122.91*** | 3515.78*** | 2701.64*** |
| | (483.38) | (445.66) | (494.97) | (460.63) |
| ***Panel B: FRPL*** | | | | |
| Expected wage | -7265.84*** | -3196.75*** | -4240.37*** | -1726.60*** |
| | (503.31) | (481.36) | (516.78) | (488.43) |
| ***Panel C: IEP*** | | | | |
| Expected wage | -7712.89*** | -5145.40*** | -658.17 | -894.82 |
| | (745.99) | (684.83) | (796.69) | (737.04) |
| ***Panel D: ELL*** | | | | |
| Expected wage | -2337.69*** | 857.15 | -722.20 | 1187.32 |
| | (708.41) | (666.07) | (702.51) | (664.23) |
| ***Panel E: Race/Ethnicity*** | | | | |
| Expected wage (Black) | -2659.05*** | -451.54 | 1244.28** | 1545.64*** |
| | (569.66) | (549.44) | (591.89) | (563.76) |
| Expected wage (Hispanic) | -4948.63*** | -918.45 | -2032.78*** | 219.17 |
| | (687.56) | (658.97) | (693.62) | (662.25) |
| Expected wage (Asian) | 10917.61*** | 6231.74*** | 8298.79*** | 4851.58*** |
| | (1420.72) | (1309.87) | (1405.98) | (1304.00) |
| Expected wage (Other race) | -2098.40 | 357.38 | -1003.35 | 919.28 |
| | (1491.94) | (1367.59) | (1470.59) | (1357.86) |
| N | 18329 | 18329 | 18329 | 18329 |

Notes: Expected wages are obtained from 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 mean of the occupational wage of assigned occupations. Each panel shows results from separate multilevel mixed-effects regressions for male vs female, FRPL vs non-FRPL, IEPvs non-IEP, ELL vs non-ELL and white vs other race/ethnicity groups. Column (3) and (4) control for 8th grade English, Math and Science test scores. All models are controlled for cohort-fixed effects and standard errors are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1)

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 | 3289.30 | 3902.66* |
| | (2133.69) | (2114.32) |
| SD of Random Slope | 12509.34 | 12370.59 |
| ***Panel B: FRPL*** | | |
| Expected wage | -3200.22*** | -1652.37 |
| | (1021.28) | (1042.25) |
| SD of Random Slope | 5119.13 | 5239.2 |
| ***Panel C: IEP*** | | |
| Expected wage | -4751.73*** | -557.59 |
| | (1283.97) | (1262.11) |
| SD of Random Slope | 6055.14 | 5689.43 |
| ***Panel D: ELL*** | | |
| Expected wage | 1061.24 | 1424.59 |
| | (861.05) | (872.24) |
| SD of Random Slope | 2794.76 | 2909.91 |
| ***Panel E: Race/Ethnicity*** | | |
| Black: Expected wage | -584.14 | 1494.54 |
| | (1117.76) | (1110.13) |
| SD of Random Slope | 5524.93 | 5422.92 |
| Hispanic: Expected wage | -959.19 | 183.33 |
| | (897.27) | (892.76) |
| SD of Random Slope | 3128.31 | 3074.89 |
| Asian: Expected wage | 7498.66*** | 6264.87** |
| | (2481.50) | (2446.58) |
| SD of Random Slope | 29548.98 | 29320.44 |
| Other: Expected wage | 385.98 | 942.34 |
| | (1363.36) | (1353.66) |
| SD of Random Slope | 5484.74 | 5380.63 |
| N | 18329 | 18329 |

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. 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 English, Math, and Science 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. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$)

Table 4. Decomposing expected wage gap among concentrators (w/ test scores)

| Group | (1)<br>Total gap | (2)<br>Within school | (3)<br>Between-school | (4)<br>Ambiguous |
|---|---|---|---|---|
| Panel A: Wage gap decomposition **without** test score adjustment | | | | |
| Male - Female | 2641.37 | 2187.22 | 301.27 | 71.50 |
| (%) | | 83% | 11% | 3% |
| FRPL – non-FRPL | -7265.84 | -2769.03 | -3878.81 | -270.11 |
| (%) | | 38% | 53% | 4% |
| IEP – non-IEP | -7712.89 | -4941.72 | -2122.81 | -108.11 |
| (%) | | 64% | 28% | 1% |
| ELL – non-ELL | -2337.70 | 956.20 | -3624.07 | 84.69 |
| (%) | | -41% | 155% | -4% |
| Black - White | -2642.95 | -526.90 | -1742.30 | -76.65 |
| (%) | | 20% | 66% | 3% |
| Hispanic - White | -4979.18 | -592.05 | -4050.05 | -105.80 |
| (%) | | 12% | 81% | 2% |
| Asian - White | 10976.08 | 5203.39 | 4564.18 | 229.77 |
| (%) | | 47% | 42% | 2% |
| Panel B: Wage gap decomposition **with** test score adjustment | | | | |
| Male - Female | 3515.78 | 2983.92 | 409.25 | 122.61 |
| (%) | | 85% | 12% | 3% |
| FRPL – non-FRPL | -4240.37 | -1469.86 | -2654.02 | -116.49 |
| (%) | | 35% | 63% | 3% |
| IEP – non-IEP | -658.17 | 219.13 | -879.78 | 2.48 |
| (%) | | -33% | 134% | 0% |
| ELL – non-ELL | -722.20 | 1468.39 | -2302.69 | 112.10 |
| (%) | | -203% | 319% | -16% |
| Black - White | 1611.88 | 2100.03 | -776.40 | 288.26 |
| (%) | | 130% | -48% | 18% |
| Hispanic - White | -1882.75 | 686.03 | -2680.35 | 111.57 |
| (%) | | -36% | 142% | -6% |
| Asian - White | 8136.98 | 3563.92 | 4394.17 | 178.89 |
| (%) | | 44% | 54% | 2% |

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). Within-school gap indicates that the proportion of the wage gap is attributable to the within-school factors, and between school gap represents the proportion of the wage gap that can be explained by between-school factors. Ambiguous gap represents the proportion of gap where Fryer and Levitt (2004) attribute within school gap while Hanushek and Rivkin (2006) attribute to the between school gap.

Table 5. Multilevel mixed effects model with school-level characteristics

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Male | Black | FRPL | ELL | IEP |
| Group = 1 | 2572.09*** | 1325.21** | -1494.28*** | 542.86 | -573.76 |
| | (463.94) | (538.90) | (502.40) | (685.62) | (759.43) |
| Mean expected wage of pathways (offered by school) | 0.14*** | 0.28*** | 0.25*** | 0.27*** | 0.26*** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| Diversity gap (Group 1 - Group 0) | -7847.63*** | 1907.12 | 9333.91** | 1999.73 | 10499.18*** |
| | (2984.87) | (2891.13) | (3891.75) | (2029.56) | (2417.86) |
| Number of pathways offered | -223.12** | -274.63** | -224.49** | -189.72* | -191.43* |
| | (108.38) | (107.97) | (107.40) | (105.44) | (105.22) |
| Group=1 X Mean expected wage of pathways (offered by school) | 0.20*** | -0.03 | -0.01 | -0.06 | 0.07 |
| | (0.04) | (0.05) | (0.05) | (0.06) | (0.06) |
| Group = 1 X Diversity gap (Group=1 - Group0) | 23911.42*** | 30768.64*** | 36469.52*** | 21307.16*** | 26262.89*** |
| | (2459.80) | (4521.68) | (6241.92) | (5668.95) | (6078.20) |
| Group = 1 X Number of pathways offered | 81.73 | 34.16 | -145.33** | 150.37* | -191.78** |
| | (58.99) | (66.94) | (64.51) | (81.90) | (92.68) |
| Constant | 63337.19*** | 64122.03*** | 64061.42*** | 64562.85*** | 65080.57*** |
| | (3402.22) | (3186.07) | (3115.42) | (3346.17) | (3326.51) |
| Random Effects Std. Dev. (group) | 20352.30*** | 19164.82*** | 18808.12*** | 20050.78*** | 19922.98*** |
| | (2538.00) | (2382.63) | (2334.78) | (2505.15) | (2492.41) |
| Residual Std. Dev. | 29322.37*** | 29423.47*** | 29405.14*** | 29460.53*** | 29453.71*** |
| | (153.35) | (153.97) | (153.83) | (154.42) | (154.36) |
| N | 18323 | 18303 | 18314 | 18241 | 18246 |

Notes: Each column shows the expected wage gap between male vs female, black vs white, FRPL vs non-FRPL, ELL vs non-ELL and IEP vs non-IEP student groups. The mean expected wage of pathways follows the definition of Table 1. Number of pathways offered represents the number of pathways offered by the school that the student attended. The diversity gap is calculated by subtracting the diversity indices of the reference group from that of the focus group. Standard Deviations of the Diversity gap of each group are - Male - Female (0.18), Black - White (0.12), FRPL (0.08), IEP (0.12), and ELL (0.14). (*** p<0.01, ** p<0.05, * p<0.1)

**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:

$$Y_{ij} = \beta_0 + \beta_1 D_{ij} + X_{ij} + \epsilon_{ij} \qquad \text{(A1)}$$

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. $\epsilon_{ij}$ is student-specific standard errors. We are interested in estimating $\beta_1$, 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 ($j$):

$$Y_i = \beta_0 + \beta_1 D_i + \epsilon_i \qquad \text{(A2)}$$

$Y_i$ 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 (A2) since CEM already controls for the covariates when creating strata. This regression is weighted using the CEM weights. Again, we are interested in measuring $\beta_1$, 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:

$$Y_i = \beta_0 + \beta_1 D_i + \epsilon_i \qquad \text{(A3)}$$

This model equation is equivalent to Equation (A2). 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 (A1) – (A3), we compared these results with our main analysis. Firstly, we obtained the correlation coefficients of the estimated $\beta_1$s from our main model (1) and alternative methods (A1 – A3). 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 A2, 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.

Table A1: Regression results from fixed-effects model

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | w/o test score | | w/ test score | |
| | Cohort FE | Cohort & School FE | Cohort FE | Cohort & School FE |
| ***Panel A: Male*** | | | | |
| Expected wage | 2641.37*** | 2118.91*** | 3515.78*** | 2698.17*** |
| | (483.46) | (445.77) | (495.09) | (460.78) |
| ***Panel B: Low-income*** | | | | |
| Expected wage | -7265.84*** | -3171.93*** | -4240.37*** | -1708.33*** |
| | (503.39) | (481.51) | (516.91) | (488.58) |
| ***Panel C: Special ED*** | | | | |
| Expected wage | -7712.89*** | -5124.00*** | -658.17 | -880.43 |
| | (746.11) | (685.03) | (796.89) | (737.37) |
| ***Panel D: ELL*** | | | | |
| Expected wage | -2337.69*** | 867.50 | -722.20 | 1193.18* |
| | (708.53) | (666.22) | (702.69) | (664.43) |
| ***Panel E: Race/Ethnicity*** | | | | |
| Expected wage (Black) | -2659.05*** | -430.58 | 1244.28** | 1558.05*** |
| | (569.80) | (549.71) | (592.09) | (564.04) |
| Expected wage (Hispanic) | -4948.63*** | -896.87 | -2032.78*** | 233.46 |
| | (687.73) | (659.21) | (693.85) | (662.52) |
| Expected wage (Asian) | 10917.61*** | 6206.60*** | 8298.79*** | 4829.66*** |
| | (1421.07) | (1310.21) | (1406.44) | (1304.44) |
| Expected wage (Other race) | -2098.40 | 355.74 | -1003.35 | 915.24 |
| | (1492.31) | (1367.90) | (1471.08) | (1358.26) |
| N | 18329 | 18329 | 18329 | 18329 |

Notes: Expected wages are obtained from 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 mean of the occupational wage of assigned occupations. Each panel shows results from separate multilevel mixed-effects regressions for male vs female, low-income vs non low-income, special ED vs non special ED, ELL vs non ELL and white vs other race/ethnicity groups. Column (3) and (4) control for 8th grade English, Math and Science test scores. All models are controlled for cohort-fixed effects and standard errors are in parentheses. (*** p<0.01, ** p<0.05, * p<0.1)

Table A2: Correlation & SD of Anticipated Wage Gaps (weighted coefficients)

| Group | **Gender** | **Black** | **Hispanic** | **Asian** | **FRPL** | **IEP** | **ELL** |
|---|---|---|---|---|---|---|---|
| *Panel A: Correlations of Anticipated Wage Gaps between Unadjusted Random Effects and Alternative Models* | | | | | | | |
| Mixed (w/ test score) | 0.999 | 0.992 | 0.988 | 0.997 | 0.991 | 0.996 | 0.989 |
| OLS (w/o test score) | 0.997 | 0.984 | 0.853 | 0.948 | 0.864 | 0.936 | 0.843 |
| OLS (w/ test score) | 0.991 | 0.903 | 0.838 | 0.920 | 0.813 | 0.811 | 0.867 |
| CEM | 0.988 | 0.853 | 0.776 | 0.850 | 0.829 | 0.825 | 0.793 |
| EBALANCE | 0.991 | 0.890 | 0.879 | 0.931 | 0.915 | 0.848 | 0.881 |
| *Panel B: Standard Deviation of Random Effects or School-Specific Anticipated Wage Gaps* | | | | | | | |
| Mixed (w/o test score) | 11812 | 4616 | 1841 | 10280 | 3927 | 4759 | 1564 |
| Mixed (w/ test score) | 11717 | 4558 | 1811 | 10104 | 4040 | 4398 | 1700 |
| OLS (w/o test score) | 6247 | 5710 | 2624 | 8657 | 3053 | 3824 | 2633 |
| OLS (w/ test score) | 6659 | 5480 | 2461 | 7813 | 2517 | 2776 | 2735 |
| CEM | 3486 | 2802 | 1754 | 1287 | 1625 | 2021 | 1379 |
| EBALANCE | 11541 | 4537 | 3773 | 4976 | 3264 | 5007 | 3683 |
| N | 36 | 35 | 36 | 31 | 37 | 35 | 36 |

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 A3. Multilevel mixed effects model with school-level characteristics

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Mean Expected Wages | Male | Black | FRPL | ELL | IEP |
| Group = 1 | 2693.22*** | 1140.05** | -1502.08*** | 503.30 | -623.53 |
| | (468.37) | (542.31) | (502.19) | (685.27) | (769.90) |
| Mean expected wage of pathways (offered by school) | 0.14*** | 0.31*** | 0.24*** | 0.23*** | 0.29*** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| Diversity gap (Group 1 - Group 0) | -8081.34*** | 1850.34 | 251.83 | 970.81 | 10441.14*** |
| | (3041.13) | (2947.75) | (4833.36) | (2038.96) | (2506.08) |
| Number of pathways offered | -215.92** | -287.95*** | -214.03* | -115.43 | -250.43** |
| | (109.19) | (109.78) | (111.02) | (108.49) | (105.76) |
| Diversity gap (Group 1 - Group 0) X Number of pathways offered | -16.13 | -1348.91** | -1532.79** | -1297.07*** | 1533.53*** |
| | (432.68) | (591.92) | (660.63) | (453.38) | (393.42) |
| Group=1 X Mean expected wage of pathways (offered by school) | 0.19*** | -0.05 | -0.01 | -0.07 | 0.06 |
| | (0.04) | (0.05) | (0.05) | (0.06) | (0.06) |
| Group = 1 X Diversity gap (Group=1 - Group0) | 22775.87*** | 29734.63*** | 47167.07*** | 21738.41*** | 26459.62*** |
| | (2539.96) | (4556.39) | (6748.08) | (5705.12) | (6141.97) |
| Group = 1 X Number of pathways offered | 89.90 | 40.10 | -149.24** | 115.07 | -194.53** |
| | (59.18) | (66.96) | (64.50) | (104.48) | (92.65) |
| Group = 1 X Diversity gap (Group 1 - Group 0) X Number of pathways offered | -770.99* | 2476.38*** | 3370.49*** | 594.29 | 647.88 |
| | (432.89) | (842.45) | (924.54) | (1049.45) | (1126.96) |
| Diversity gap (Group 1 - Group 0) X Mean expected wage of pathways (offered by school) | -0.20 | 0.22 | 0.14 | 0.68*** | 1.07*** |
| | (0.16) | (0.23) | (0.26) | (0.20) | (0.20) |
| _cons | 63428.98*** | 64071.28*** | 63993.01*** | 64329.26*** | 64745.59*** |
| | (3404.16) | (3077.74) | (3039.23) | (3448.58) | (3289.74) |
| Random Effects Std. Dev. (group) | 20341.96*** | 18465.55*** | 18309.48*** | 20674.78*** | 19692.61*** |
| | (2544.40) | (2339.41) | (2319.48) | (2585.23) | (2465.58) |
| Residual Std. Dev. | 29318.16*** | 29415.48*** | 29392.78*** | 29438.86*** | 29427.30*** |
| | (153.33) | (153.93) | (153.77) | (154.31) | (154.22) |
| N | 18323 | 18303 | 18314 | 18241 | 18246 |

Notes: Each column shows the expected wage gap between male vs female, black vs white, FRPL vs non-FRPL, ELL vs non-ELL and IEP vs non-IEP student groups. The mean expected wage of pathways follows the definition of Table 1. Number of pathways offered represents the number of pathways offered by the school that the student attended. The diversity gap is calculated by subtracting the diversity indices of the reference group from that of the focus group. Standard Deviations of the Diversity gap of each group are - Male - Female (0.18), Black - White (0.12), FRPL (0.08), IEP (0.12), and ELL (0.14). (*** p<0.01, ** p<0.05, * p<0.1)

Table A4. Multilevel mixed effects model with school-level characteristics

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Mean Expected Wages | Male | Black | FRPL | ELL | IEP |
| Group = 1 | 2612.15*** | 1162.12** | -1492.71*** | 667.82 | -671.94 |
| | (469.86) | (544.53) | (502.96) | (694.46) | (770.48) |
| Mean expected wage of pathways (offered by school) | 0.17*** | 0.31*** | 0.25*** | 0.26*** | 0.26*** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| Diversity gap (Group 1 - Group 0) | -7754.38** | 1507.03 | 292.36 | 1517.01 | 11751.09*** |
| | (3057.28) | (2906.98) | (4808.03) | (2033.94) | (2501.47) |
| Number of pathways offered | -231.59** | -268.33** | -211.75* | -103.73 | -217.47** |
| | (108.39) | (108.78) | (110.91) | (108.21) | (105.65) |
| Diversity gap (Group 1 - Group 0) X Number of pathways offered | 167.73 | -1843.00*** | -1709.01*** | -1579.50*** | 730.41** |
| | (436.30) | (584.53) | (548.35) | (444.80) | (364.59) |
| Number of pathways offered X Mean expected wage of pathways (offered by school) | 0.00 | -0.01* | -0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Group=1 X Mean expected wage of pathways (offered by school) | 0.16*** | -0.04 | -0.00 | -0.05 | 0.07 |
| | (0.04) | (0.05) | (0.05) | (0.06) | (0.06) |
| Group = 1 X Diversity gap (Group=1 - Group0) | 21818.71*** | 29926.13*** | 47056.02*** | 21494.21*** | 26149.29*** |
| | (2592.28) | (4563.44) | (6742.23) | (5706.94) | (6146.76) |
| Group = 1 X Number of pathways offered | 102.94* | 37.54 | -151.58** | 124.94 | -198.14** |
| | (59.47) | (67.16) | (64.91) | (105.11) | (92.92) |
| Group = 1 X Diversity gap (Group 1 - Group 0) X Number of pathways offered | -1049.34** | 2476.62*** | 3384.62*** | 671.35 | 783.49 |
| | (460.15) | (844.50) | (934.95) | (1051.85) | (1138.04) |
| Group1 X Number of pathways offered X Mean expected wage of pathways (offered by school) | -0.01* | 0.00 | 0.00 | 0.01 | -0.01 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| _cons | 63300.53*** | 63941.15*** | 63948.93*** | 64103.82*** | 64917.74*** |
| | (3335.92) | (2959.76) | (2987.93) | (3323.93) | (3289.11) |
| Random Effects Std. Dev. (group) | 19907.48*** | 17724.39*** | 17983.24*** | 19889.05*** | 19672.79*** |
| | (2555.34) | (2314.16) | (2323.58) | (2561.86) | (2542.06) |
| Residual Std. Dev. | 29316.68*** | 29416.26*** | 29393.40*** | 29448.81*** | 29448.93*** |
| | (153.33) | (153.94) | (153.78) | (154.37) | (154.35) |
| N | 18323 | 18303 | 18314 | 18241 | 18246 |

Notes: Each column shows the expected wage gap between male vs female, black vs white, FRPL vs non-FRPL, ELL vs non-ELL and IEP vs non-IEP student groups. The mean expected wage of pathways follows the definition of Table 1. Number of pathways offered represents the number of pathways offered by the school that the student attended. The diversity gap is calculated by subtracting the diversity indices of the reference group from that of the focus group. Standard Deviations of the Diversity gap of each group are - Male - Female (0.18), Black - White (0.12), FRPL (0.08), IEP (0.12), and ELL (0.14). (*** p<0.01, ** p<0.05, * p<0.1)