





The Effects of Health Sciences CTE Concentration

on Educational and Workforce Outcomes in Nebraska

TECHNICAL APPENDIX

nswers

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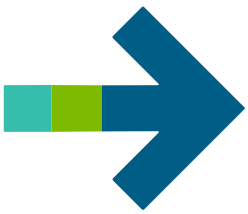










The Nebraska Statewide Workforce & Educational Reporting System, or NSWERS, is a one-of-a-kind research partnership among Nebraska's education and workforce systems designed to create a data-informed decision culture that supports pathways of learning and earning for the people of Nebraska. The NSWERS data system is the most comprehensive education-to-workforce longitudinal information source ever created in Nebraska.

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These provisional results are based on certified NSWERS data as of August 31, 2026. The provisional results in this report may change because of data resubmissions by NSWERS Partners and/or Affiliates. For updated results, please contact support@nswers.org.

Section I. Average Treatment Effect on the Treated (ATT)

The primary estimand used in this study was the Average Treatment Effect on the Treated (ATT). The ATT estimates the average difference in outcomes that Health Sciences CTE concentrators would be expected to experience compared with the expected outcomes had those same students not concentrated in a Health Sciences CTE program. Because this counterfactual outcome cannot be directly observed, it was estimated using propensity score matched comparison students with similar observed baseline characteristics. In the context of this evaluation, the ATT addresses the following question:

> "For students who concentrated in a Health Sciences CTE program, what was the estimated difference in postsecondary education and workforce outcomes compared with what would have been expected had those same students not concentrated in a Health Sciences CTE program?"

Because nonzero (i.e., positive earnings) wage data were incorporated in analyses of wage data, the ATT for wage data represents the estimated average difference in annual wages among matched Health Sciences CTE concentrators *with nonzero observed wages* compared with the wages those same concentrators would have been expected to earn had they not concentrated in Health Sciences CTE. See Section VI for more information.

Several other causal estimands are common in observational studies, each addressing a different set of research questions (Stuart, 2010). The Average Treatment Effect estimates the expected effect if every eligible student in the population concentrated in a Health Sciences CTE program compared to if no students concentrated in the program. In contrast, the ATT estimates the effect among students who actually completed a Health Sciences CTE program of study. Other estimands include (a) the Average Treatment Effect on the Controls, which estimates the

expected effect if non-concentrators had instead completed the program, and (b) the Conditional Average Treatment Effect, which estimates treatment effects within specific subgroups defined by observed characteristics. Because Health Sciences CTE participation is self-selected rather than randomly assigned, and because the primary objective of this evaluation is to estimate the outcomes experienced by students who actually concentrated in a Health Sciences CTE program of study, the ATT was determined to be the most appropriate estimand (Stuart, 2010). This estimand directly addresses the policy-relevant question of how Health Sciences CTE concentration is associated with postsecondary education and workforce outcomes for the students who chose to participate.

The average treatment effect on the treated (ATT) can be defined via Equation 1, where $Y(1)$ and $Y(0)$ denote each student's potential outcomes under Health Sciences CTE concentration and non-concentration, respectively, and $T = 1$ indicates students who concentrated in a Health Sciences CTE program of study. Because only one potential outcome can be observed for each student, the counterfactual outcome was estimated using full matching, weighted outcome models, and G-computation.

$$\text{ATT} = \mathbb{E}[Y(1) - Y(0) \mid T = 1] \quad (1)$$

Section II. Propensity Score Estimation

Because students self-selected into a Health Sciences CTE program and were not randomly assigned, Health Sciences CTE concentrators may differ systematically from non-concentrators in ways that are associated with later educational and workforce outcomes. To reduce bias arising from these pre-existing differences between concentrators and non-concentrators, a quasi-experimental propensity score matching approach was employed. A propensity score represents the estimated probability that a student would concentrate in a Health Sciences CTE program of study conditional on a set of observed baseline characteristics (Rosenbaum & Rubin, 1983). Students with similar propensity scores are expected to have comparable observed characteristics, allowing non-concentrators to serve as an appropriate comparison group for Health Sciences CTE concentrators. The primary goal of propensity score matching is to produce covariate balance between Health Sciences CTE concentrators and non-concentrators, such that the distribution of observed baseline characteristics is approximately equal across groups, as would be expected under a successful randomized experiment. A total of 16 matching covariates were included: cohort year, school district, student gender, student race/ethnicity, chronic absentee classification (i.e., students whose absences accounted for 10 percent or more of the school year), SPED recipients, ELL status, HAL status, cumulative high school grade point average, 11th grade state standardized test score percentiles for science, reading, writing, and math subject tests, an indicator for missing science, reading, writing, and math subject test score percentiles, and American College Testing composite scores (categorized as missing, <20, and ≥20 bins).

Propensity scores were estimated using the MatchIt package in R (Ho et al., 2011), which implements non-parametric matching algorithms to improve covariate balance between treatment

and comparison groups. Propensity scores are defined in Equation 2, where $e(\mathrm{X}_i)$ is the probability that student *i* concentrated in a Health Sciences CTE program of study given the vector of observed baseline covariates X_i.

$$e(\mathrm{X}_i) = P(T_i = 1 \mid \mathrm{X}_i) \tag{2}$$

The logistic model used to estimate propensity scores is formalized in Equation 3. Here, $T_i = 1$ indicates that student *i* concentrated in a Health Sciences CTE program of study, X_{ij} denotes the *j*th observed baseline covariate for student *i*, and $e(\mathrm{X}_i)$ represents the estimated propensity score used for matching.

$$\log\left(\frac{P(T_i=1|\mathbf{X}_i)}{1-P(T_i=1|\mathbf{X}_i)}\right) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} \tag{3}$$

Matching weights generated by the procedure were subsequently incorporated into all outcome analyses to construct a weighted quasi-comparison group that closely resembled Health Sciences CTE concentrators on observed baseline characteristics. The comparison group consisted of students who were eligible to participate in CTE program coursework but elected to not concentrate in a Health Sciences CTE program of study; therefore, these weights allow comparison students to represent the counterfactual outcomes that would have been expected among Health Sciences CTE concentrators had they not concentrated.

Although propensity score matching cannot account for unmeasured confounding, balancing observed baseline characteristics reduces selection bias attributable to measured covariates and improves the plausibility that estimated differences in outcomes reflect differences associated with Health Sciences CTE concentration rather than pre-existing differences between concentrator and non-concentrator students.

Section III. Data Imputation

Assessment percentile scores exhibited missingness due primarily to changes in assessment administration across Health Sciences CTE cohorts. The Nebraska Department of Education transitioned to different statewide assessment instruments beginning with the fourth cohort (2017 graduation year), resulting in incomplete assessment percentile data for a subset of students. Because academic achievement measures were included as baseline covariates in the propensity score model, preserving these observations was necessary to maximize the available analytic sample while maintaining comparability between Health Sciences CTE concentrators and non-concentrators.

Although assessment percentile missingness was concentrated within the fifth cohort because of the statewide assessment transition, this missingness does not influence the estimation of treatment effects for the remaining cohorts. As described later, propensity score estimation techniques ensured that treated and comparison students were matched exclusively within the same graduating cohort. Consequently, imputed assessment values contributed only to the propensity score estimation for students within the affected cohort and did not alter propensity scores, matching weights, or treatment effect estimates for students in other cohorts. This design preserves cohort-specific comparisons while allowing all eligible students to contribute to the overall average treatment effect on the treated.

The amount of covariate data missingness across each cohort is available in Table 1. To treat the large amount of missing assessment score percentiles, percentiles were imputed using a single deterministic regression imputation procedure. Predicted values were generated from a linear regression model using the best linear unbiased prediction conditional on the following observed covariates:

- English Language Learner (ELL) participation
- Special Education (SPED) participation
- High Ability Learner (HAL) participation
- Student gender (male or female)
- Average high school grade point average (GPA)
- Binned ACT composite score

Because assessment percentiles are bounded between 0 and 1, post-hoc truncation was applied to predicted values that fell outside this range. Specifically, predicted values less than 0 were set to 0 and predicted values greater than 1 were set to 1. Imputation was performed using the VIM package in R (Kowarik & Templ, 2016).

Unlike multiple imputation procedures, deterministic regression imputation produces a single predicted value for each missing observation without incorporating stochastic error. This approach was selected because the imputed variables served exclusively as baseline covariates in the propensity score estimation rather than as substantive outcomes of interest. Consequently, the primary objective was to preserve the analytic sample and improve covariate balance rather than to estimate uncertainty attributable to missing data. Although deterministic regression imputation preserves sample size and covariate information, we recognize that imputed values do not contain the same level of individual-specific information as observed scores. Baseline academic readiness for the fifth cohort should be interpreted as being measured with somewhat greater uncertainty than for earlier cohorts.

Table 1

Covariate Data Missingness of Un-matched Sample

	Cohort 1 (2014)	Cohort 2 (2015)	Cohort 3 (2016)	Cohort 4 (2017)	Cohort 5 (2018)
Gender	0	0	0	0	0
Race/ethnicity	0	0	0	0	0
Chronic absenteeism	0.01	0.02	0.04	0.08	0.07
SPED	0	0	0	0	0
ELL	0	0	0	0	0
HAL	0	0	0	0	0
Science percentile	3.85	3.72	3.67	7.06	97.34
Reading percentile	3.84	3.74	3.72	7.12	97.38
Writing percentile	3.85	3.74	3.72	7.12	97.37
Math percentile	3.99	3.98	3.77	7.47	98.31
Average high-school GPA	0.21	0.26	0.21	0.17	0.15
ACT score (binned)	0	0	0	0	0

Notes. Values represent percent missingness. SPED = special education; ELL = English language learner; HAL = high-ability learner; GPA = grade-point average; ACT = American College Testing.

Section IV. Matching Technique

Optimal full matching was performed using propensity scores estimated from the aforementioned logistic regression model as a distance metric (Rosenbaum & Rubin, 1983; Hansen, 2004). To ensure comparisons were made only among students with similar contexts and program availability, exact matching was used on academic year cohort and school district prior to propensity score matching. During this process, the data were partitioned into strata defined by unique combinations of cohort year and school district, and optimal full matching was conducted independently within each stratum. Therefore, matched sets could not include students from different cohort years or school districts. Matching was conducted in the MatchIt R package (Ho et al., 2011).

Within each exact matching stratum, optimal full matching partitioned students into one or more matched subclasses. Unlike nearest-neighbor matching, which often pairs observations one at a time, optimal full matching simultaneously considers all possible matched subclass assignments and chooses the configuration that minimizes the overall within-subclass dissimilarity in propensity scores. This approach generally produces superior covariate balance while retaining substantially more observations than one-to-one matching, which improves the covariate balance and precision of treatment effect estimates (Stuart, 2010).

Students enrolled in school districts that did not offer a Health Sciences CTE program of study during a given cohort year were excluded from the analytic sample because they did not have the opportunity to concentrate in a Health Sciences CTE program. Within each matching stratum, observations for which no acceptable match could be identified were also excluded from subsequent analyses. These restrictions ensured that treatment effect estimation is based on

students with a reasonable opportunity to participate in Health Sciences CTE programming and sufficient overlap in observed baseline characteristics.

Optimal full matching generated propensity score weights that were incorporated into all outcome models. To further improve match quality, a standardized caliper width of 0.20 standard deviations of the propensity score logit was imposed to reduce poor-quality matches and improve covariate balance (Austin, 2011b). This matching procedure retained all successfully matched Health Sciences CTE concentrators while weighting matched non-concentrators to represent the counterfactual outcomes expected of concentrators had they not concentrated in a Health Sciences CTE program.

Because optimal full matching was conducted using a pre-specified caliper, a small number of Health Sciences CTE concentrators (<2%, $n = 79$) were excluded because no sufficiently comparable non-concentrators were available. The exclusion of treated cases has implications for interpretation because the resulting estimand may no longer correspond exactly to the ATT in the original population. If a substantial number of treated cases are excluded, the matched sample may represent a more restricted subset of concentrators, potentially limiting the generalizability of the findings. To assess this possibility, sensitivity analyses compared the distributions of baseline covariates among concentrators before and after matching. Results indicated that the exclusion of unmatched treated cases did not meaningfully alter the covariate distribution of the treated group. Therefore, the matched sample remained highly representative of the original population of Health Sciences CTE concentrators, suggesting that any shift in the target estimand was negligible.

Section V. Matching Quality and Covariate Balance

The propensity score matching procedure was evaluated by assessing covariate balance between Health Sciences CTE concentrators and weighted non-concentrators after matching. Consistent with What Works Clearinghouse standards for quasi-experimental designs (What Works Clearinghouse [WWC], 2022), balance was evaluated via standardized mean differences (SMDs), variance ratios, and empirical cumulative distribution function (eCDF) statistics. Successful covariate balance increases confidence that weighted outcome comparisons estimate the average treatment effect on the treated using groups that are comparable with respect to observed baseline characteristics, though balance on unmeasured covariates cannot be assessed.

The SMDs quantified differences in covariate means between treatment and comparison groups relative to the pooled standard deviation and were unaffected by sample size. Benchmarks for SMDs include $|SMD| \geq 0.10$ (potential imbalance), $|SMD| < 0.10$ (good balance), $|SMD| < 0.05$ (very good balance; Austin, 2009, 2011a; WWC, 2022). Variance ratios compared the dispersion of each covariate between treatment and comparison groups, with values near 1.0 indicating similar variability and values substantially above or below 1.0 suggesting residual distributional imbalance (Stuart, 2010). Finally, eCDF statistics assessed distributional differences beyond the mean, with values closer to zero indicating greater distributional similarity between matched groups.

Following optimal full propensity score matching with exact matching on cohort year and school district, all but one evaluated baseline covariates and covariate-by-covariate interaction interaction satisfied the prespecified balance criteria. SMDs ranged from -0.114 to 0.052, maximum eCDF differences were less than 0.10 (ranging from 0 to 0.024), and variance ratios ranged from 0.903 to 1.048. One interaction term portrayed an SMD value of -0.114 (missing ACT score bin ×

Cohort 5), which slightly exceeded the |0.10| guideline. Overall, the matching procedure successfully balanced the observed baseline characteristics of Health Science CTE concentrators and matched non-concentrators (see Table 2). Covariate balance was assessed using the cobalt package (Greifer, 2025) and is visualized in Figure 1, where the adjusted points show the covariate balance after matching.

We also provide covariate balance information for the full-matched analytic sample used specifically for the wage outcome analysis. Because this analysis only examined individuals with nonzero wages, individuals without positive earnings during the sixth year following high school graduation were excluded from the analysis. Since this restriction to the wage analysis sample altered the composition of the sample, covariate balance checks were repeated for this subset. Satisfactory covariate balance was achieved for this subset following matching (Figure 2, Table 3).

Figure 1

Love Plot of Covariate Balance

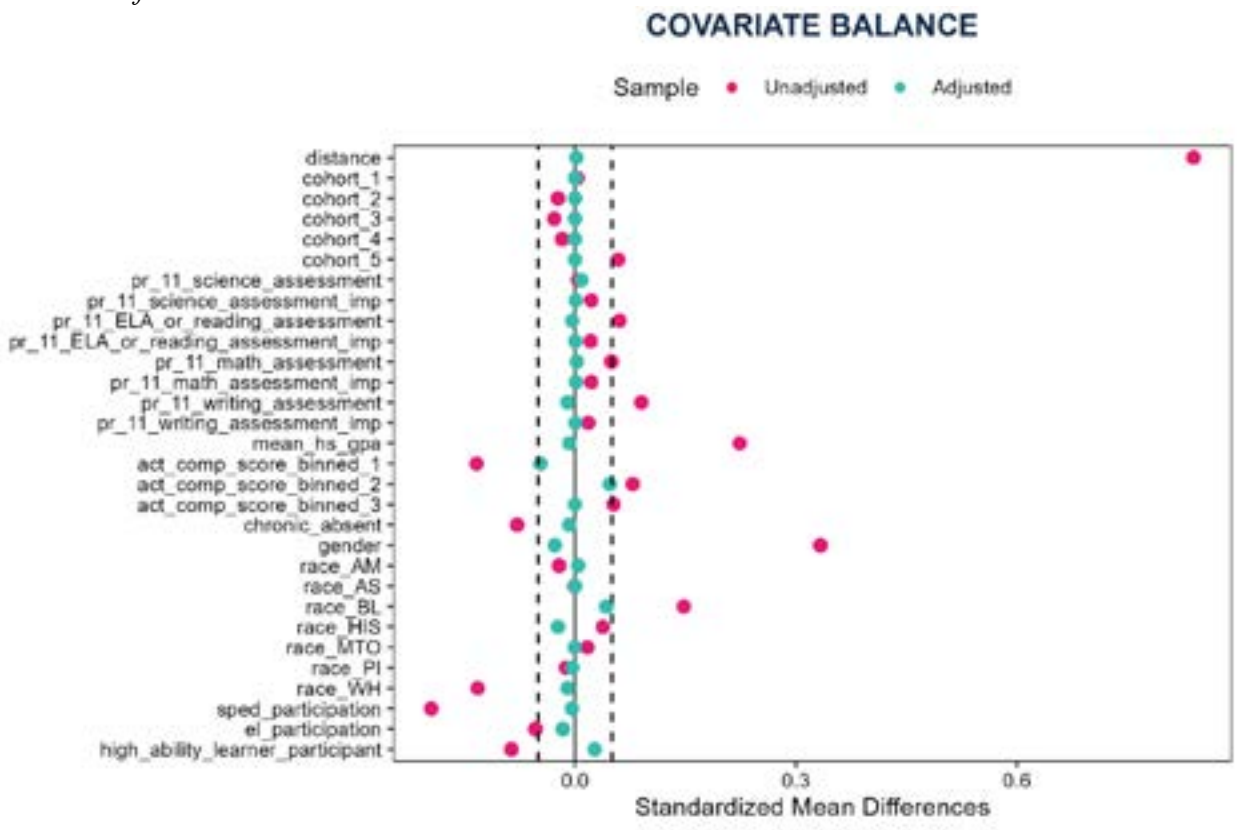

Table 2

Full-Matching Covariate Balance Statistics

Variable	Means Treated	Means Control	Std. Mean Difference	Variance Ratio	eCDF Mean	eCDF Max	Std. Pair Distance
Distance	0.165	0.164	0.002	0.997	0.001	0.004	0.026
Cohort 1	0.182	0.182	0.000	-	0.000	0.000	0.000
Cohort 2	0.179	0.179	0.000	-	0.000	0.000	0.000
Cohort 3	0.186	0.186	0.000	-	0.000	0.000	0.000
Cohort 4	0.199	0.199	0.000	-	0.000	0.000	0.000
Cohort 5	0.254	0.254	0.000	-	0.000	0.000	0.000
11th Grade Science Percentile	0.493	0.491	0.008	0.944	0.006	0.019	1.069
11th Grade Science Percentile Imputed Value	0.263	0.263	0.001	-	0.000	0.000	0.156
11th Grade Reading Percentile	0.513	0.514	-0.004	0.937	0.007	0.021	1.062
11th Grade Reading Percentile Imputed Value	0.263	0.263	0.000	-	0.000	0.000	0.156
11th Grade Math Percentile	0.508	0.508	0.002	0.958	0.005	0.013	0.988
11th Grade Math Percentile Imputed Value	0.263	0.263	0.001	-	0.000	0.000	0.157
11th Grade Writing Percentile	0.470	0.472	-0.010	0.919	0.010	0.024	0.955
11th Grade Writing Percentile Imputed Value	0.265	0.265	0.000	-	0.000	0.000	0.151
Mean High-School GPA	3.055	3.061	-0.008	1.033	0.003	0.008	0.868
ACT Score (binned)							
Missing (1)	0.309	0.330	-0.047	-	0.022	0.022	0.397
<20 (2)	0.312	0.290	0.047	-	0.022	0.022	0.726
≥20 (3)	0.380	0.380	0.000	-	0.000	0.000	0.686
Chronic Absentee							
No (0)	0.846	0.843	0.008	-	0.003	0.003	0.726
Yes (1)	0.154	0.157	-0.008	-	0.003	0.003	0.726
Student Gender							
Female	0.663	0.676	-0.028	-	0.013	0.013	0.686
Male	0.337	0.324	0.028	-	0.013	0.013	0.686
Race/Ethnicity							

American Indian or Alaska Native	0.003	0.003	0.004	-	0.000	0.000	0.140
Asian	0.026	0.026	0.000	-	0.000	0.000	0.278
Black or African American	0.117	0.103	0.043	-	0.014	0.014	0.456
Hispanic	0.171	0.180	-0.023	-	0.009	0.009	0.569
More than one race/ethnicity	0.112	0.113	-0.001	-	0.000	0.000	0.593
Native Hawaiian or Pacific Islander	0.001	0.001	-0.004	-	0.000	0.000	0.068
White	0.570	0.575	-0.010	-	0.005	0.005	0.780
Special Education Participation							
No (0)	0.932	0.931	0.004	-	0.001	0.001	0.717
Yes (1)	0.068	0.069	-0.004	-	0.001	0.001	0.717
English Language Learner Participation							
No (0)	0.978	0.976	0.017	-	0.002	0.002	0.333
Yes (1)	0.022	0.024	-0.017	-	0.002	0.002	0.333
High Ability Learner Participation							
No (0)	0.765	0.777	-0.027	-	0.011	0.011	0.767
Yes (1)	0.235	0.223	0.027	-	0.011	0.011	0.767
Cohort 1 by Gender (Female)	0.120	0.118	0.008	-	0.002	0.002	0.198
Cohort 2 by Gender (Female)	0.115	0.118	-0.011	-	0.004	0.004	0.204
Cohort 3 by Gender (Female)	0.124	0.126	-0.005	-	0.001	0.001	0.213
Cohort 4 by Gender (Female)	0.130	0.137	-0.019	-	0.006	0.006	0.210
Cohort 5 by Gender (Female)	0.174	0.178	-0.011	-	0.004	0.004	0.137
Cohort 1 by Gender (Male)	0.062	0.065	-0.010	-	0.002	0.002	0.269
Cohort 2 by Gender (Male)	0.064	0.061	0.015	-	0.004	0.004	0.267
Cohort 3 by Gender (Male)	0.062	0.060	0.006	-	0.001	0.001	0.294
Cohort 4 by Gender (Male)	0.068	0.062	0.025	-	0.006	0.006	0.282
Cohort 5 by Gender (Male)	0.080	0.076	0.015	-	0.004	0.004	0.193
Cohort 1 by Race (American Indian or Alaska Native)	0.001	0.001	0.010	-	0.000	0.000	0.044
Cohort 2 by Race (American Indian or Alaska Native)	0.000	0.000	0.001	-	0.000	0.000	0.044
Cohort 3 by Race (American Indian or Alaska Native)	0.001	0.000	0.004	-	0.000	0.000	0.041
Cohort 4 by Race (American Indian or Alaska Native)	0.000	0.001	-0.014	-	0.000	0.000	0.045
Cohort 5 by Race (American Indian or Alaska Native)	0.001	0.001	0.002	-	0.000	0.000	0.126
Cohort 1 by Race (Asian)	0.004	0.003	0.005	-	0.000	0.000	0.126

Cohort 2 by Race (Asian)	0.003	0.004	-0.013	-	0.001	0.001	0.112
Cohort 3 by Race (Asian)	0.007	0.004	0.029	-	0.002	0.002	0.110
Cohort 4 by Race (Asian)	0.005	0.006	-0.009	-	0.001	0.001	0.149
Cohort 5 by Race (Asian)	0.007	0.008	-0.014	-	0.001	0.001	0.125
Cohort 1 by Race (Black or African American)	0.022	0.021	0.013	-	0.002	0.002	0.130
Cohort 2 by Race (Black or African American)	0.019	0.017	0.014	-	0.002	0.002	0.338
Cohort 3 by Race (Black or African American)	0.020	0.020	0.000	-	0.000	0.000	0.204
Cohort 4 by Race (Black or African American)	0.022	0.019	0.020	-	0.003	0.003	0.200
Cohort 5 by Race (Black or African American)	0.032	0.025	0.039	-	0.007	0.007	0.127
Cohort 1 by Race (Hispanic)	0.027	0.028	-0.003	-	0.001	0.001	0.206
Cohort 2 by Race (Hispanic)	0.033	0.030	0.017	-	0.003	0.003	0.216
Cohort 3 by Race (Hispanic)	0.038	0.035	0.017	-	0.003	0.003	0.232
Cohort 4 by Race (Hispanic)	0.033	0.040	-0.042	-	0.007	0.007	0.258
Cohort 5 by Race (Hispanic)	0.041	0.048	-0.036	-	0.007	0.007	0.264
Cohort 1 by Race (More than one race/ethnicity)	0.014	0.018	-0.033	-	0.004	0.004	0.255
Cohort 2 by Race (More than one race/ethnicity)	0.022	0.020	0.017	-	0.002	0.002	0.248
Cohort 3 by Race (More than one race/ethnicity)	0.019	0.020	-0.010	-	0.001	0.001	0.211
Cohort 4 by Race (More than one race/ethnicity)	0.026	0.024	0.013	-	0.002	0.002	0.257
Cohort 5 by Race (More than one race/ethnicity)	0.031	0.030	0.004	-	0.001	0.001	0.292
Cohort 1 by Race (Native Hawaiian or Pacific Islander)	0.000	0.000	0.010	-	0.000	0.000	0.016
Cohort 2 by Race (Native Hawaiian or Pacific Islander)	0.000	0.000	0.009	-	0.000	0.000	0.022
Cohort 3 by Race (Native Hawaiian or Pacific Islander)	0.000	0.000	0.001	-	0.000	0.000	0.056
Cohort 4 by Race (Native Hawaiian or Pacific Islander)	0.000	0.000	-0.010	-	0.000	0.000	0.012
Cohort 5 by Race (Native Hawaiian or Pacific Islander)	0.000	0.000	-0.021	-	0.000	0.000	0.017
Cohort 1 by Race (White)	0.114	0.112	0.006	-	0.002	0.002	0.193
Cohort 2 by Race (White)	0.100	0.107	-0.022	-	0.007	0.007	0.271
Cohort 3 by Race (White)	0.102	0.106	-0.015	-	0.004	0.004	0.245
Cohort 4 by Race (White)	0.112	0.108	0.011	-	0.003	0.003	0.259
Cohort 5 by Race (White)	0.142	0.141	0.003	-	0.001	0.001	0.248
Cohort 1 by No English Language Learner Status	0.179	0.178	0.000	-	0.000	0.000	0.019
Cohort 2 by No English Language Learner Status	0.175	0.174	0.002	-	0.001	0.001	0.022
Cohort 3 by No English Language Learner Status	0.181	0.182	-0.001	-	0.000	0.000	0.035

Cohort 4 by No English Language Learner Status	0.194	0.194	-0.001	-	0.000	0.000	0.025
Cohort 5 by No English Language Learner Status	0.249	0.247	0.005	-	0.002	0.002	0.022
Cohort 1 by English Language Learner Status	0.004	0.004	-0.003	-	0.000	0.000	0.116
Cohort 2 by English Language Learner Status	0.004	0.004	-0.012	-	0.001	0.001	0.136
Cohort 3 by English Language Learner Status	0.005	0.005	0.005	-	0.000	0.000	0.190
Cohort 4 by English Language Learner Status	0.005	0.004	0.005	-	0.000	0.000	0.150
Cohort 5 by English Language Learner Status	0.005	0.007	-0.031	-	0.002	0.002	0.143
Cohort 1 by No Special Education Participation	0.169	0.171	-0.004	-	0.002	0.002	0.066
Cohort 2 by No Special Education Participation	0.167	0.166	0.005	-	0.002	0.002	0.138
Cohort 3 by No Special Education Participation	0.171	0.173	-0.006	-	0.002	0.002	0.095
Cohort 4 by No Special Education Participation	0.187	0.185	0.007	-	0.003	0.003	0.072
Cohort 5 by No Special Education Participation	0.237	0.236	0.001	-	0.001	0.001	0.093
Cohort 1 by Special Education Participation	0.013	0.012	0.015	-	0.002	0.002	0.216
Cohort 2 by Special Education Participation	0.011	0.013	-0.018	-	0.002	0.002	0.489
Cohort 3 by Special Education Participation	0.015	0.013	0.020	-	0.002	0.002	0.293
Cohort 4 by Special Education Participation	0.011	0.014	-0.026	-	0.003	0.003	0.271
Cohort 5 by Special Education Participation	0.017	0.018	-0.004	-	0.001	0.001	0.308
Cohort 1 by No High Ability Learner Participation	0.150	0.150	0.002	-	0.001	0.001	0.159
Cohort 2 by No High Ability Learner Participation	0.146	0.144	0.008	-	0.003	0.003	0.167
Cohort 3 by No High Ability Learner Participation	0.145	0.144	0.004	-	0.001	0.001	0.156
Cohort 4 by No High Ability Learner Participation	0.146	0.152	-0.017	-	0.006	0.006	0.235
Cohort 5 by No High Ability Learner Participation	0.177	0.187	-0.026	-	0.010	0.010	0.185
Cohort 1 by High Ability Learner Participation	0.032	0.033	-0.004	-	0.001	0.001	0.321
Cohort 2 by High Ability Learner Participation	0.032	0.035	-0.016	-	0.003	0.003	0.336
Cohort 3 by High Ability Learner Participation	0.041	0.042	-0.007	-	0.001	0.001	0.276
Cohort 4 by High Ability Learner Participation	0.052	0.046	0.027	-	0.006	0.006	0.377
Cohort 5 by High Ability Learner Participation	0.077	0.067	0.038	-	0.010	0.010	0.265
Cohort 1 by Mean High-School GPA	0.546	0.551	-0.005	0.982	0.002	0.008	0.089
Cohort 2 by Mean High-School GPA	0.539	0.547	-0.006	0.976	0.003	0.008	0.107
Cohort 3 by Mean High-School GPA	0.573	0.571	0.001	1.004	0.001	0.004	0.096
Cohort 4 by Mean High-School GPA	0.613	0.611	0.002	1.007	0.002	0.006	0.098
Cohort 5 by Mean High-School GPA	0.785	0.781	0.003	1.016	0.004	0.010	0.096

Cohort 1 by ACT Score (Missing)	0.038	0.042	-0.019	-	0.004	0.004	0.199
Cohort 2 by ACT Score (Missing)	0.034	0.039	-0.030	-	0.005	0.005	0.267
Cohort 3 by ACT Score (Missing)	0.039	0.043	-0.023	-	0.004	0.004	0.256
Cohort 4 by ACT Score (Missing)	0.192	0.192	0.000	-	0.000	0.000	0.077
Cohort 5 by ACT Score (Missing)	0.005	0.014	-0.114	-	0.008	0.008	0.239
Cohort 1 by ACT Score (<20)	0.059	0.054	0.023	-	0.005	0.005	0.323
Cohort 2 by ACT Score (<20)	0.066	0.055	0.041	-	0.010	0.010	0.318
Cohort 3 by ACT Score (<20)	0.059	0.054	0.019	-	0.004	0.004	0.307
Cohort 4 by ACT Score (<20)	0.004	0.005	-0.017	-	0.001	0.001	0.199
Cohort 5 by ACT Score (<20)	0.124	0.122	0.009	-	0.003	0.003	0.295
Cohort 1 by ACT Score (≥20)	0.085	0.087	-0.007	-	0.002	0.002	0.257
Cohort 2 by ACT Score (≥20)	0.079	0.084	-0.017	-	0.005	0.005	0.292
Cohort 3 by ACT Score (≥20)	0.089	0.089	0.000	-	0.000	0.000	0.246
Cohort 4 by ACT Score (≥20)	0.003	0.002	0.018	-	0.001	0.001	0.404
Cohort 5 by ACT Score (≥20)	0.124	0.119	0.017	-	0.006	0.006	0.277
Cohort 1 by Chronic Absent (No)	0.154	0.157	-0.008	-	0.003	0.003	0.130
Cohort 2 by Chronic Absent (No)	0.149	0.153	-0.009	-	0.003	0.003	0.158
Cohort 3 by Chronic Absent (No)	0.158	0.156	0.006	-	0.002	0.002	0.142
Cohort 4 by Chronic Absent (No)	0.169	0.167	0.006	-	0.002	0.002	0.121
Cohort 5 by Chronic Absent (No)	0.216	0.211	0.011	-	0.005	0.005	0.148
Cohort 1 by Chronic Absent (Yes)	0.029	0.026	0.017	-	0.003	0.003	0.282
Cohort 2 by Chronic Absent (Yes)	0.029	0.026	0.019	-	0.003	0.003	0.336
Cohort 3 by Chronic Absent (Yes)	0.029	0.031	-0.013	-	0.002	0.002	0.312
Cohort 4 by Chronic Absent (Yes)	0.029	0.031	-0.013	-	0.002	0.002	0.270
Cohort 5 by Chronic Absent (Yes)	0.038	0.043	-0.024	-	0.005	0.005	0.318
Cohort 1 by 11th Grade Science Percentile	0.089	0.089	-0.001	0.994	0.001	0.003	0.238
Cohort 2 by 11th Grade Science Percentile	0.085	0.088	-0.016	0.922	0.004	0.009	0.257
Cohort 3 by 11th Grade Science Percentile	0.091	0.091	-0.003	0.973	0.001	0.005	0.249
Cohort 4 by 11th Grade Science Percentile	0.098	0.095	0.010	1.004	0.005	0.009	0.266
Cohort 5 by 11th Grade Science Percentile	0.131	0.127	0.017	1.046	0.005	0.011	0.201
Cohort 1 by 11th Grade Reading Percentile	0.092	0.093	-0.003	0.989	0.001	0.004	0.242
Cohort 2 by 11th Grade Reading Percentile	0.088	0.092	-0.018	0.907	0.003	0.011	0.246

Cohort 3 by 11th Grade Reading Percentile	0.095	0.096	-0.003	0.963	0.002	0.007	0.240
Cohort 4 by 11th Grade Reading Percentile	0.102	0.101	0.000	0.983	0.002	0.005	0.253
Cohort 5 by 11th Grade Reading Percentile	0.135	0.131	0.016	1.048	0.005	0.010	0.182
Cohort 1 by 11th Grade Math Percentile	0.090	0.091	-0.004	0.985	0.002	0.006	0.211
Cohort 2 by 11th Grade Math Percentile	0.087	0.090	-0.012	0.933	0.003	0.010	0.248
Cohort 3 by 11th Grade Math Percentile	0.093	0.095	-0.010	0.952	0.002	0.007	0.218
Cohort 4 by 11th Grade Math Percentile	0.101	0.099	0.010	1.016	0.004	0.006	0.245
Cohort 5 by 11th Grade Math Percentile	0.136	0.132	0.015	1.047	0.005	0.011	0.191
Cohort 1 by 11th Grade Writing Percentile	0.085	0.086	-0.005	0.967	0.003	0.005	0.236
Cohort 2 by 11th Grade Writing Percentile	0.082	0.086	-0.018	0.903	0.005	0.010	0.238
Cohort 3 by 11th Grade Writing Percentile	0.087	0.087	0.000	0.977	0.001	0.008	0.238
Cohort 4 by 11th Grade Writing Percentile	0.093	0.093	-0.002	0.961	0.003	0.007	0.253
Cohort 5 by 11th Grade Writing Percentile	0.124	0.121	0.012	1.035	0.004	0.012	0.132

Notes. Std. = standardized; eCDF = empirical cumulative distribution functions; variance ratios were not estimated for non-continuous variables.

Figure 2

Love Plot of Covariate Balance for the Wage Analysis Sample

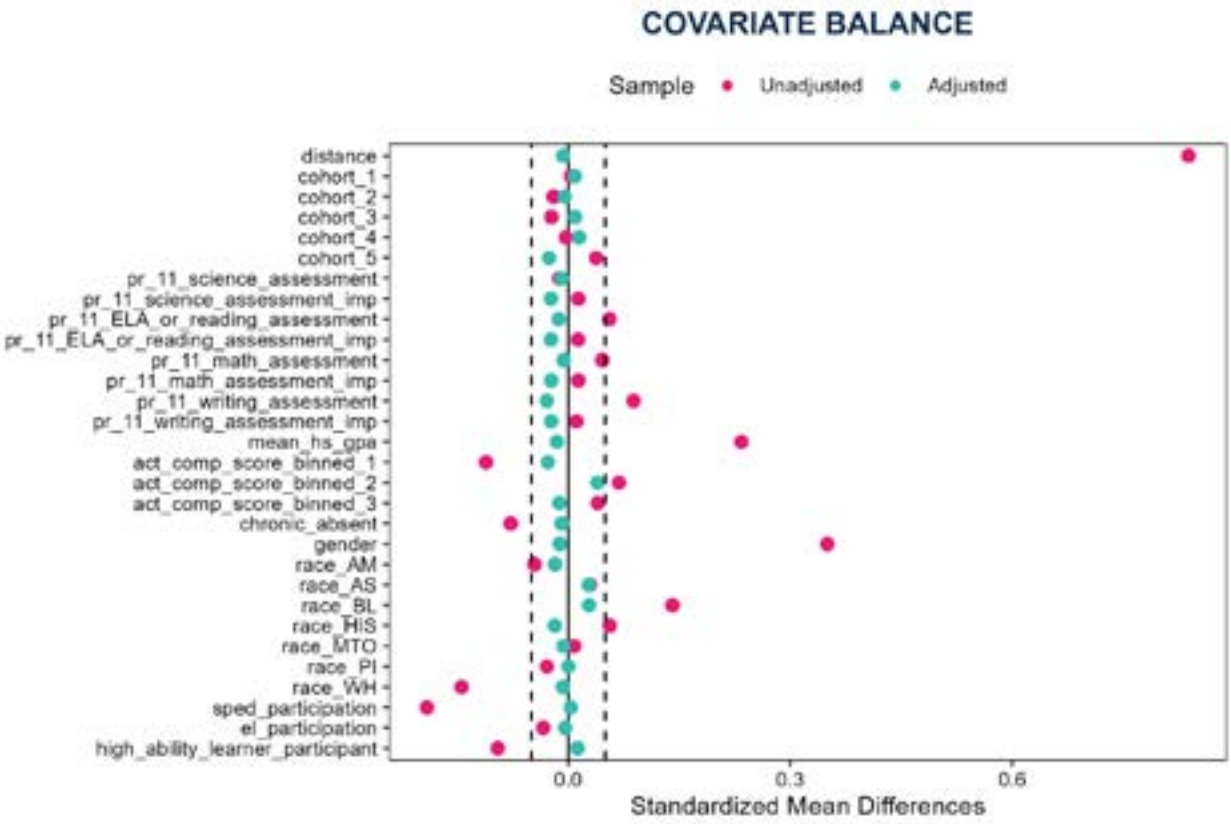

Table 3

Full-Matching Covariate Balance Statistics for the Wage Analysis Sample

Variable	Means Treated	Means Control	Std. Means Diff.	Variance Ratio	ECDF max
Distance	0.166	0.166	-0.007	0.975	0.009
Cohort 1	0.182	0.179	0.009	-	0.003
Cohort 2	0.181	0.183	-0.005	-	0.002
Cohort 3	0.188	0.184	0.009	-	0.004
Cohort 4	0.201	0.195	0.015	-	0.006
Cohort 5	0.248	0.259	-0.026	-	0.011
11th Grade Science Percentile	0.477	0.479	-0.009	0.943	0.017
11th Grade Science Percentile Imputed Value	0.256	0.266	-0.023	-	0.01
11th Grade Reading Percentile	0.5	0.503	-0.013	0.945	0.019
11th Grade Reading Percentile Imputed Value	0.256	0.266	-0.023	-	0.01
11th Grade Math Percentile	0.495	0.497	-0.006	0.952	0.017
11th Grade Math Percentile Imputed Value	0.256	0.266	-0.023	-	0.01
11th Grade Writing Percentile	0.461	0.468	-0.029	0.911	0.029
11th Grade Writing Percentile Imputed Value	0.258	0.268	-0.023	-	0.01
Mean High-School GPA	3.028	3.039	-0.015	1.014	0.015
ACT Score (binned)					
Missing (1)	0.309	0.322	-0.027	-	0.013
<20 (2)	0.329	0.31	0.039	-	0.018
>=20 (3)	0.362	0.368	-0.012	-	0.006
Race/Ethnicity					
American Indian or Alaska Native	0.002	0.002	-0.018	-	0.001
Asian	0.025	0.021	0.028	-	0.004
Black or African American	0.114	0.105	0.028	-	0.009
Hispanic	0.182	0.189	-0.018	-	0.007

More than one race/ethnicity	0.112	0.114	-0.007	-	0.002
Native Hawaiian or Pacific Islander	0	0	0	-	0
White	0.565	0.568	-0.007	-	0.004
Student Gender					
Male	0.326	0.32	0.011	-	0.005
Female	0.674	0.68	-0.011	-	0.005
Chronic Absentee					
No (0)	0.847	0.844	0.009	-	0.003
Yes (1)	0.153	0.156	-0.009	-	0.003
Special Education Participation					
No (0)	0.931	0.932	-0.003	-	0.001
Yes (1)	0.069	0.068	0.003	-	0.001
English Language Learner Participation					
No (0)	0.98	0.98	0.004	-	0.001
Yes (1)	0.02	0.02	-0.004	-	0.001
High Ability Learner Participation					
No (0)	0.783	0.788	-0.013	-	0.005
Yes (1)	0.217	0.212	0.013	-	0.005
Cohort 1 by Gender (Male)	0.063	0.062	0.005	-	0.001
Cohort 2 by Gender (Male)	0.06	0.062	-0.008	-	0.002
Cohort 3 by Gender (Male)	0.06	0.059	0.002	-	0.001
Cohort 4 by Gender (Male)	0.067	0.062	0.019	-	0.005
Cohort 5 by Gender (Male)	0.076	0.075	0.004	-	0.001
Cohort 1 by Gender (Female)	0.119	0.117	0.007	-	0.002
Cohort 2 by Gender (Female)	0.121	0.121	0.001	-	0
Cohort 3 by Gender (Female)	0.128	0.125	0.009	-	0.003
Cohort 4 by Gender (Female)	0.135	0.133	0.004	-	0.001
Cohort 5 by Gender (Female)	0.172	0.184	-0.032	-	0.012
Cohort 1 by Race (American Indian or Alaska Native)	0	0	-0.015	-	0
Cohort 2 by Race (American Indian or Alaska Native)	0	0	-0.007	-	0
Cohort 3 by Race (American Indian or Alaska Native)	0	0	-0.001	-	0

Cohort 4 by Race (American Indian or Alaska Native)	0	0	-0.016	-	0
Cohort 5 by Race (American Indian or Alaska Native)	0.001	0.001	0.002	-	0
Cohort 1 by Race (Asian)	0.004	0.003	0.013	-	0.001
Cohort 2 by Race (Asian)	0.003	0.004	-0.007	-	0
Cohort 3 by Race (Asian)	0.006	0.004	0.033	-	0.003
Cohort 4 by Race (Asian)	0.006	0.004	0.021	-	0.002
Cohort 5 by Race (Asian)	0.007	0.007	-0.003	-	0
Cohort 1 by Race (Black or African American)	0.024	0.021	0.018	-	0.003
Cohort 2 by Race (Black or African American)	0.018	0.017	0.009	-	0.001
Cohort 3 by Race (Black or African American)	0.019	0.021	-0.014	-	0.002
Cohort 4 by Race (Black or African American)	0.022	0.019	0.017	-	0.003
Cohort 5 by Race (Black or African American)	0.031	0.026	0.025	-	0.004
Cohort 1 by Race (Hispanic)	0.027	0.027	0.001	-	0
Cohort 2 by Race (Hispanic)	0.035	0.032	0.015	-	0.003
Cohort 3 by Race (Hispanic)	0.041	0.037	0.022	-	0.004
Cohort 4 by Race (Hispanic)	0.036	0.042	-0.035	-	0.007
Cohort 5 by Race (Hispanic)	0.043	0.051	-0.039	-	0.008
Cohort 1 by Race (More than one race/ethnicity)	0.015	0.019	-0.037	-	0.004
Cohort 2 by Race (More than one race/ethnicity)	0.022	0.021	0.008	-	0.001
Cohort 3 by Race (More than one race/ethnicity)	0.018	0.02	-0.008	-	0.001
Cohort 4 by Race (More than one race/ethnicity)	0.026	0.024	0.011	-	0.002
Cohort 5 by Race (More than one race/ethnicity)	0.032	0.031	0.004	-	0.001
Cohort 1 by Race (Native Hawaiian or Pacific Islander)	0	0	-0.002	-	0
Cohort 2 by Race (Native Hawaiian or Pacific Islander)	0	0	-0.001	-	0
Cohort 3 by Race (Native Hawaiian or Pacific Islander)	0	0	0.009	-	0
Cohort 4 by Race (Native Hawaiian or Pacific Islander)	0	0	-0.006	-	0
Cohort 5 by Race (Native Hawaiian or Pacific Islander)	0	0	-0.004	-	0
Cohort 1 by Race (White)	0.112	0.108	0.014	-	0.004
Cohort 2 by Race (White)	0.103	0.11	-0.021	-	0.006
Cohort 3 by Race (White)	0.102	0.103	-0.002	-	0.001
Cohort 4 by Race (White)	0.112	0.105	0.023	-	0.007

Cohort 5 by Race (White)	0.135	0.143	-0.024	-	0.008
Cohort 1 by Chronic Absent (No)	0.153	0.153	0	-	0
Cohort 2 by Chronic Absent (No)	0.152	0.157	-0.015	-	0.005
Cohort 3 by Chronic Absent (No)	0.161	0.153	0.022	-	0.008
Cohort 4 by Chronic Absent (No)	0.173	0.165	0.022	-	0.008
Cohort 5 by Chronic Absent (No)	0.208	0.216	-0.02	-	0.008
Cohort 1 by Chronic Absent (Yes)	0.029	0.026	0.02	-	0.003
Cohort 2 by Chronic Absent (Yes)	0.029	0.026	0.021	-	0.004
Cohort 3 by Chronic Absent (Yes)	0.027	0.031	-0.027	-	0.004
Cohort 4 by Chronic Absent (Yes)	0.028	0.031	-0.016	-	0.003
Cohort 5 by Chronic Absent (Yes)	0.039	0.042	-0.016	-	0.003
Cohort 1 by English Language Learner Participation (No)	0.178	0.175	0.008	-	0.003
Cohort 2 by English Language Learner Participation (No)	0.178	0.179	-0.002	-	0.001
Cohort 3 by English Language Learner Participation (No)	0.182	0.18	0.006	-	0.002
Cohort 4 by English Language Learner Participation (No)	0.197	0.192	0.012	-	0.005
Cohort 5 by English Language Learner Participation (No)	0.245	0.253	-0.019	-	0.008
Cohort 1 by English Language Learner Participation (Yes)	0.004	0.003	0.008	-	0
Cohort 2 by English Language Learner Participation (Yes)	0.003	0.004	-0.018	-	0.001
Cohort 3 by English Language Learner Participation (Yes)	0.006	0.004	0.019	-	0.001
Cohort 4 by English Language Learner Participation (Yes)	0.004	0.003	0.02	-	0.001
Cohort 5 by English Language Learner Participation (Yes)	0.003	0.006	-0.051	-	0.003
Cohort 1 by Special Education Participation (No)	0.168	0.167	0.002	-	0.001
Cohort 2 by Special Education Participation (No)	0.17	0.17	0	-	0
Cohort 3 by Special Education Participation (No)	0.172	0.171	0.002	-	0.001
Cohort 4 by Special Education Participation (No)	0.189	0.182	0.018	-	0.007
Cohort 5 by Special Education Participation (No)	0.232	0.242	-0.023	-	0.01
Cohort 1 by Special Education Participation (Yes)	0.014	0.012	0.023	-	0.003
Cohort 2 by Special Education Participation (Yes)	0.011	0.013	-0.019	-	0.002
Cohort 3 by Special Education Participation (Yes)	0.016	0.013	0.023	-	0.003
Cohort 4 by Special Education Participation (Yes)	0.012	0.014	-0.011	-	0.001
Cohort 5 by Special Education Participation (Yes)	0.016	0.017	-0.012	-	0.001

Cohort 1 by High Ability Learner Participation (No)	0.153	0.149	0.011	-	0.004
Cohort 2 by High Ability Learner Participation (No)	0.153	0.148	0.014	-	0.005
Cohort 3 by High Ability Learner Participation (No)	0.15	0.146	0.011	-	0.004
Cohort 4 by High Ability Learner Participation (No)	0.152	0.152	0.001	-	0
Cohort 5 by High Ability Learner Participation (No)	0.175	0.194	-0.048	-	0.018
Cohort 1 by High Ability Learner Participation (Yes)	0.03	0.03	-0.002	-	0
Cohort 2 by High Ability Learner Participation (Yes)	0.028	0.035	-0.041	-	0.007
Cohort 3 by High Ability Learner Participation (Yes)	0.038	0.038	-0.001	-	0
Cohort 4 by High Ability Learner Participation (Yes)	0.049	0.044	0.025	-	0.005
Cohort 5 by High Ability Learner Participation (Yes)	0.072	0.065	0.027	-	0.007
Cohort 1 by 11th Grade Science Percentile	0.085	0.085	-0.001	0.984	0.006
Cohort 2 by 11th Grade Science Percentile	0.081	0.089	-0.036	0.864	0.014
Cohort 3 by 11th Grade Science Percentile	0.089	0.087	0.009	0.998	0.01
Cohort 4 by 11th Grade Science Percentile	0.095	0.09	0.023	1.033	0.013
Cohort 5 by 11th Grade Science Percentile	0.126	0.128	-0.007	1.005	0.01
Cohort 1 by 11th Grade Reading Percentile	0.088	0.088	0.001	0.992	0.005
Cohort 2 by 11th Grade Reading Percentile	0.087	0.093	-0.031	0.873	0.015
Cohort 3 by 11th Grade Reading Percentile	0.094	0.092	0.011	0.998	0.009
Cohort 4 by 11th Grade Reading Percentile	0.1	0.097	0.013	1.008	0.01
Cohort 5 by 11th Grade Reading Percentile	0.13	0.132	-0.009	1.009	0.01
Cohort 1 by 11th Grade Math Percentile	0.087	0.087	0.003	0.999	0.006
Cohort 2 by 11th Grade Math Percentile	0.086	0.091	-0.024	0.902	0.01
Cohort 3 by 11th Grade Math Percentile	0.091	0.091	0.004	0.973	0.009
Cohort 4 by 11th Grade Math Percentile	0.1	0.095	0.02	1.035	0.009
Cohort 5 by 11th Grade Math Percentile	0.131	0.134	-0.01	1.003	0.011
Cohort 1 by 11th Grade Writing Percentile	0.082	0.083	-0.005	0.946	0.007
Cohort 2 by 11th Grade Writing Percentile	0.08	0.087	-0.032	0.857	0.014
Cohort 3 by 11th Grade Writing Percentile	0.086	0.085	0.007	0.987	0.009
Cohort 4 by 11th Grade Writing Percentile	0.093	0.09	0.011	0.979	0.013
Cohort 5 by 11th Grade Writing Percentile	0.12	0.123	-0.015	0.997	0.012
Cohort 1 by Mean High-School GPA	0.537	0.533	0.003	0.992	0.007

Cohort 2 by Mean High-School GPA	0.543	0.56	-0.015	0.953	0.011
Cohort 3 by Mean High-School GPA	0.574	0.557	0.014	1.031	0.01
Cohort 4 by Mean High-School GPA	0.617	0.596	0.017	1.035	0.011
Cohort 5 by Mean High-School GPA	0.758	0.793	-0.026	0.974	0.015
Cohort 1 by ACT Score (Missing)	0.038	0.04	-0.008	-	0.002
Cohort 2 by ACT Score (Missing)	0.035	0.04	-0.027	-	0.005
Cohort 3 by ACT Score (Missing)	0.036	0.042	-0.033	-	0.006
Cohort 4 by ACT Score (Missing)	0.195	0.189	0.016	-	0.006
Cohort 5 by ACT Score (Missing)	0.004	0.01	-0.095	-	0.006
Cohort 1 by ACT Score (<20)	0.063	0.057	0.028	-	0.007
Cohort 2 by ACT Score (<20)	0.072	0.059	0.049	-	0.013
Cohort 3 by ACT Score (<20)	0.064	0.058	0.024	-	0.006
Cohort 4 by ACT Score (<20)	0.004	0.005	-0.019	-	0.001
Cohort 5 by ACT Score (<20)	0.126	0.132	-0.017	-	0.006
Cohort 1 by ACT Score (>=20)	0.081	0.083	-0.007	-	0.002
Cohort 2 by ACT Score (>=20)	0.074	0.083	-0.036	-	0.009
Cohort 3 by ACT Score (>=20)	0.088	0.084	0.014	-	0.004
Cohort 4 by ACT Score (>=20)	0.003	0.002	0.015	-	0.001
Cohort 5 by ACT Score (>=20)	0.117	0.117	0.002	-	0.001

Section VI. Generalized Linear Models

Following propensity score matching, generalized linear models (GLMs) were estimated separately for each outcome using the matched analytic sample. Matching weights obtained from the optimal full matching procedure were used as weights in the outcome regression models, which allowed the weighted comparison group to represent the counterfactual outcomes that Health Science CTE concentrators would have been expected had they not concentrated in a Health Science CTE program.

Model specifications varied according to the distributional characteristics of each outcome. Each binary outcome, such as the educational and employment outcomes, was modeled using logistic regression with a binomial distribution and logit link function. This permits the modeling of the conditional probability for each outcome while constraining predicted probabilities to the interval [0, 1].

Annual wage outcomes were estimated among individuals with nonzero observed annual wages (i.e., positive earnings). This approach distinguishes two conceptually distinct labor outcomes: whether an individual had observed employment and, conditional on observed employment, the amount earned. This distinction is important because treating the absence of observed earnings as zero earnings would combine differences in employment with differences in earnings among workers. State UI wage records do not capture all forms of employment or earnings (e.g., some federal employment, military employment, self-employment, and employment occurring outside the state wage-record system); therefore, absence from the UI wage records does not necessarily indicate unemployment. Geographic mobility and other forms of attrition from state UI wage data may result in employed individuals no longer appearing in the state's records. Restricting analyses to individuals with positive earnings reduced the bias in

estimated differences that can arise when relying on UI wage records within a single state because individuals who disappear from a state's UI records are less likely to be incorrectly treated as earning zero income (Foote & Stange, 2026). Thus, wage models were restricted to individuals with observed positive wages to provide an estimate of earnings conditional on observed employment while employment was modeled as a separate outcome.

Wage outcomes were modeled using a Gamma distribution with a log link because they were continuous, strictly positive, and right skewed, with greater variability observed at higher wage levels. The Gamma model is appropriate for outcomes where the conditional variance increases approximately with the square of the conditional mean, which is plausible for wages because the absolute spread of earnings generally increases as expected earnings increase. Although Poisson-type estimators can be used more generally as quasi-likelihood methods for modeling conditional means, the Gamma variance structure was determined to be a better reflection of these data due to the increasing dispersion of observed wages across wage levels. Log-normal and inverse Gaussian models were also considered; however, the Gamma GLM directly modeled the conditional mean wage on the original dollar scale and provided a variance structure that is consistent with the pattern of increased wage variability as expected wages increase. The log link ensured that fitted wage values remained positive and represented covariate effects on a multiplicative scale.

Across all models, modeled parameters were estimated using maximum likelihood, with matching weights incorporated as prior weights. These weights were implemented in models to preserve the balance achieved during propensity score matching by assigning each observation a contribution proportional to its role in the matched subclasses (Austin & Stuart, 2015). The inclusion of these weights in the estimated models allowed the weighted comparison group to

represent the counterfactual outcomes for Health Sciences CTE concentrators. Found in Equation 4, the fitted GLMs served as the outcome models for the subsequent G-computation procedure used to estimate the ATT.

$$g\{\mathbb{E}(Y_i)\} = \beta_0 + \beta_1 T_i + \beta_2 C_i + \sum_{k=1}^{16} \beta_{3k} X_{ik} + \beta_4 (T_i C_i) + \sum_{k=1}^{16} \beta_{5k} (T_i X_{ik}) \qquad (4)$$

Where Y_i represents the outcome for student i, T_i is the Health Sciences CTE concentrator treatment indicator (0 = non-concentrator, 1 = concentrator), C_i is the academic year cohort, X_i is the vector of 16 covariates, and g is the logit link for binary outcomes or log link for annual wage outcomes. The covariate vector contains the same variables used for the aforementioned matching process.

Section VII. G-Computation

Following estimation of the generalized linear models, the ATT was estimated using G-computation, otherwise referred to as regression standardization (Snowden et al., 2011). Rather than interpreting the treatment coefficient directly from the fitted generalized linear model, G-computation uses the model to generate each treated student's potential outcome under both the observed treatment condition and the unobserved counterfactual comparison condition while holding all observed baseline characteristics constant. These individual-level potential outcomes are then averaged across treated students to obtain marginal outcome estimates, with their difference representing the marginal ATT on the outcome scale. Regression adjustment following propensity score full matching can further reduce residual covariate differences and improve the robustness of treatment effect estimates to model misspecification (Stuart, 2010).

Two covariate-adjusted predicted potential outcomes were generated for every Health Sciences CTE concentrator in the matched sample. The first prediction represented the expected outcome under the student's observed treatment condition (i.e., assuming the student concentrated in a Health Sciences CTE program of study). The second prediction represented the expected counterfactual outcome for that same student under the comparison condition (i.e., assuming the student had not concentrated), while all other observed characteristics remained unchanged. Because both predictions were generated for the same individual while holding all observed covariates fixed, their difference represents the estimated causal effect implied by the fitted outcome model after adjustment for measured confounding through propensity score matching and covariate adjustment.

The predicted outcomes under both treatment conditions (concentrating and not concentrating) were then averaged across all Health Sciences CTE concentrators. Because

predictions were averaged only across Health Sciences CTE concentrators, the resulting estimates correspond to the average treatment effect on the treated (ATT) rather than the average treatment effect (ATE). This ATT estimate represented the average expected change attributable to concentrating in a Health Sciences CTE program of study among students who actually concentrated (see Equation 5).

$$\widehat{\mathrm{ATT}} = \frac{1}{N_T}\sum_{i:T_i=1}\left[\hat{Y}_i(1) - \hat{Y}_i(0)\right] \quad (5)$$

Where N_T denotes the number of Health Sciences CTE concentrators in the matched sample, $\hat{Y}_i(1)$ is the predicted outcome for concentrator *i* when the treatment status is set to Health Sciences CTE concentration, and $\hat{Y}_i(0)$ is the predicted outcome for concentrator *i* when the treatment status is set to non-concentration.

For binary outcomes, ATT estimates were expressed as risk differences, representing percentage-point differences in the probability of experiencing the outcome (Equation 6). For annual wage outcomes, ATT estimates were expressed as mean differences in expected annual wages and are reported in inflation-adjusted 2025 U.S. dollars (Equation 7). Generalized linear models were estimated using the stats package, and ATT estimates were obtained via G-computation using the marginaleffects R package (Arel-Bundock et al., 2024). All analyses were conducted in R (version 4.4.2; R Core Team, 2025).

$$\widehat{\mathrm{RD}}_{\mathrm{ATT}} = \hat{P}(Y = 1 \mid T = 1) - \hat{P}(Y = 1 \mid T = 0) \quad (6)$$

$$\widehat{\mathrm{MD}}_{\mathrm{ATT}} = \hat{\mu}_{T=1} - \hat{\mu}_{T=0} \quad (7)$$

Section VIII. Hierarchical Linear Modeling

Students in the analytic sample were naturally clustered within school districts, raising the possibility of estimating hierarchical linear models (HLMs) to account for between-district variation. However, HLMs were not used because the primary objective of this evaluation was to estimate the ATT through within-district comparisons rather than to model variation across districts. School district was incorporated directly into the study design through exact matching, such that propensity score matching was conducted independently within each district-by-cohort stratum. Because of this, all ATT estimates compared Health Sciences CTE concentrators with non-concentrators from the same district and cohort year, controlling for characteristics that were constant within each district-by-cohort matching stratum.

Because district-level differences were addressed through the matching design, the remaining analyses focused on estimating student-level ATT effects rather than partitioning variance across levels of observations (e.g., school, district). Because the ATT is defined by contrasting each treated student's observed treatment condition with their predicted counterfactual outcome, the estimand is a within-student counterfactual comparison rather than an estimate of between-school or between-district differences. An HLM framework may have been used if the objectives included estimating between-district variation in treatment effects, examining school- or district-level predictors of effectiveness, incorporating school- or district-level covariates, or making comparisons across schools or districts. These ideas were not central to this evaluation. Instead, the evaluation estimated a single statewide ATT representing the expected outcomes for students who concentrated in a Health Sciences CTE program of study.

Although HLMs can improve statistical inference by explicitly modeling clustered data or producing cluster-adjusted standard errors, such adjustments were considered a lower priority

in the present study because exact matching on school district substantially reduced district-level confounding prior to outcome analysis, and the large statewide sample yielded highly precise treatment effect estimates. Moreover, incorporating multilevel outcome models within the matched, weighted G-computation framework substantially increases computational complexity and introduces convergence challenges while providing limited additional information relevant to the study's research questions. Accordingly, weighted generalized linear models following exact propensity score matching were determined to provide the most direct and appropriate framework for estimating the ATT.

Section IX. Miscellaneous Analysis Notes

Health Sciences CTE Cohort Definition

Students were assigned to cohort years based on their high school graduation year.

Health Sciences CTE Concentration

Health Sciences CTE concentration was identified using the definition provided by the Nebraska Department of Education ([NDE]; NDE, 2024). Health Sciences CTE enrollment data is collected at the course level. A Health Sciences CTE concentrator is a secondary student who, in grades 9 through 12, earned credit in at least two courses in a single career cluster program at the intermediate or capstone level. Intermediate courses are those that build on the foundational knowledge of introductory courses to further develop the academic, technical, and career readiness skills within the health career field and occupational area. Capstone courses develop the necessary and required academic, technical, and career readiness skills needed for seamless transitions to postsecondary education and employment. Capstone courses often provide opportunities for students to earn postsecondary credit.

School District Eligibility

Only students enrolled in school districts that offered a Health Sciences CTE program of study during the corresponding cohort year were eligible for inclusion in the analytic sample. This was determined by whether a student was observed as having participated in Health Science CTE programming within the school district. Students attending districts without a Health Sciences CTE program during that cohort year were excluded because they did not have the opportunity to receive the treatment of interest (Health Sciences CTE program concentration).

Outcome Specific Analytic Samples

Analytic sample sizes differed across outcomes because each postsecondary or workforce outcome was only observable for students who were eligible to experience that outcome. For example:

- Postsecondary enrollment analyses included only Nebraska public high school graduates.
- Degree attainment analyses included only students who had sufficient follow-up time to complete the credential under evaluation.
- Employment analyses included eligible students with and without observed Nebraska employment. Wage analyses included only students with positive observed Nebraska wages. Wage outcomes were modeled only for cases with positive earnings rather than imputing $0 wages for unobserved individuals since this has been found to reduce biases associated with wage outcomes using single state UI-wage records (Foote & Stange, 2026).

Overall Observed Outcome Descriptive Statistics for the Full Study Population

Outcome	Value
Enrollment in Postsecondary Institution	
One year after high school graduation	69.13%
Two-Year Postsecondary Institution	29.51%
Four-Year Postsecondary Institution	42.79%
Four years after high school graduation	76.61%
Two-Year Postsecondary Institution	45.9%
Four-Year Postsecondary Institution	50.06%
Enrollment in Health Major at Postsecondary Institution	
Overall	11.71%
One year after high school graduation (Overall)	5.89%
Two-Year Postsecondary Institution	2.18%
Four-Year Postsecondary Institution	3.78%
Four years after high school graduation (Overall)	9.57%
Two-Year Postsecondary Institution	4.67%
Four-Year Postsecondary Institution	5.58%
Postsecondary Award Attainment	41.34%

Certificate	4.2%
Associates	10.18%
Bachelors or higher	30.83%
Postsecondary Health-Related Award Attainment	4.8%
Certificate	0.91%
Associates	1.31%
Bachelors or higher	3.08%
Employment in Nebraska	67.68%
Employment in Nebraska Health Industry	13.94%
Annual Wages	$37,479.69

Mean High School GPA

The average cumulative high school GPA is defined as the weighted average GPA across all high school courses. This was used as one indicator of academic achievement for students.

ACT Composite Scores

The percentages of students meeting each ACT composite score category are presented for Health Sciences CTE concentrators and matched non-concentrators. ACT composite score categories represent students' highest recorded ACT composite score during high school and were included as proxy measures of college readiness.

Chronic Absenteeism

Chronic absentee classification was determined based upon whether the student missed 10% or more of school days at any point during grades 9-12. Classification was based on students with available attendance records during the cohort period.

Postsecondary Enrollment

The percentages of students enrolling in postsecondary education are presented separately for any postsecondary institution, two-year institutions, and four-year institutions. Enrollment reflects students' observed enrollment following high school graduation. Enrollment

outcomes were defined cumulatively over the one-year and four-year follow-up periods, such that students were classified as enrolled if they entered the corresponding postsecondary sector at any time during the applicable observation window (e.g., the one- or four-year follow-up period). Therefore, this cumulative definition captures whether students ever enrolled within the specified timeframe rather than whether they were enrolled within the exact observed window year, lending to short-term degrees and students who enrolled but then withdrew before the observation window.

Health-Related Major

The percentages of students that enrolled in a health-related postsecondary major are presented for Health Sciences CTE concentrators and non-concentrators. Health major enrollment was operationalized as enrolling in a health major at any point during the period of observed postsecondary education. Health-related majors were identified using the Classification of Instructional Programs (CIP) code 51 ("Health Professions and Related Clinical Sciences").

Postsecondary Award Attainment

The percentages of students earning postsecondary awards are presented separately for each credential type evaluated in this study. Award attainment was defined as the successful completion of the corresponding postsecondary credential during the analysis window. Because completion of longer-duration credentials requires an extended period of postsecondary education, analyses were restricted to the following award types: certificates, associates, and bachelor's degrees or higher. Health-related awards were identified using the CIP code 51.

Employment Outcomes

The percentages of students who were employed in Nebraska are presented for Health Science CTE concentrators and non-concentrators. The North American Industry Classification

System (NAICS) was used to identify employment in the health industry, where Code 62 designates the "Health Care and Social Assistance" workforce sector. Annual wages are calculated by summing an individual's quarterly wages earned throughout the year across all industries of employment.

Employment outcomes were determined based on Nebraska's Unemployment Insurance (UI) quarterly wage records. Statewide, these UI wage records cover approximately 95-98 percent of employment in Nebraska (NDOL, personal communication). These records do not include individuals whose employers are exempt from paying UI tax, such as federal employees, members of the armed forces, self-employed, proprietors, unpaid family workers, church employees, railroad workers covered by the railroad unemployment insurance system, and students employed at a college or university as part of a financial aid package. Employment outside of Nebraska is also not captured in these data. Student records could be linked to Nebraska UI wage records in circumstances if they had either enrolled at a Nebraska public postsecondary institution or if they were issued a state drivers/motorcycle license or state ID card by Nebraska Department of Motor Vehicles. Rates of successful linkage to Nebraska UI wage records were similar between Health Science CTE concentrators and non-concentrators in this study (98.2 percent and 96.5 percent linkage rates, respectively).

Outcome Interpretation

Observed Outcomes and Differences

For each study outcome, observed differences in educational and workforce-related outcomes are discussed. This section does not attempt to make causal claims nor does it present model results.

Adjusted Differences

The covariate-adjusted estimates correspond to the ATT and therefore the outcome interpretation applies only to students who concentrated in a Health Science CTE program of study. More specifically, the analyses compare concentrators' observed outcomes with their estimated outcomes under the counterfactual scenario in which they had not concentrated in Health Science CTE. Estimates should not be interpreted as the expected effects of expanding Health Science CTE participation to all Nebraska students.

For binary outcomes, covariate-adjusted estimates are depicted as risk differences, representing the estimated percentage-point association between Health Science CTE concentration and the probability of an outcome. In these comparisons, a change in "risk" is attributable to concentrating in Health Science CTE programming. Percentage-point units were used to interpret risk differences, such that a risk difference of 10 percentage points indicates that Health Science CTE concentrators were associated with a 10 percentage point higher probability of achieving the outcome than would be expected had those same students not concentrated in Health Science CTE.

The covariate-adjusted estimates for wage outcomes are measured as mean differences in annual wages. For example, a mean difference of $5,000 in wages conveys that Health Science CTE concentrators earned $5,000 more than what they would have earned if they had not achieved Health Science CTE concentrator status. When interpreting effects, we recommend comparing the overall observed (mean) percentage or income value to the estimated effect to evaluate whether the magnitude of risk difference is meaningfully significant. To assess practical significance, effects are translated into an estimated change in number of postsecondary enrollees, health major enrollees, degrees completed, employees, and differences in average annual wage.

Effect size plots illustrate the magnitude of estimated associations or mean differences, where 95% confidence intervals communicate the variability in differences. An estimate whose confidence interval spans zero is one that is non-significant. For each examined outcome, tables of model results offer the exact size of estimated associations and mean differences alongside other complementary statistical information. To aid interpretation, estimated associations for binary outcomes were also translated into approximate whole-number changes in outcomes by applying the estimated risk difference to the number of Health Science CTE concentrators, yielding the estimated number of additional students expected to achieve each outcome relative to the same students had they not achieved Health Science CTE concentration.

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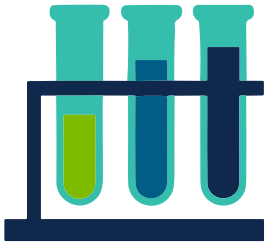


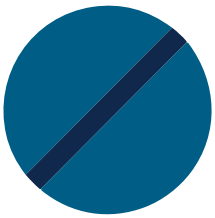
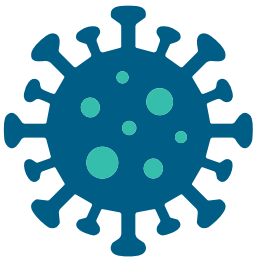









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