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# Career and Technical Education Alignment Across Five States

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# Abstract

We quantify alignment between high school career and technical education (CTE) and local labor markets across five states: Massachusetts, Michigan, Montana, Tennessee, and Washington. We find that CTE is partially aligned with local labor markets. A 10-percentage-point increase in the share of local jobs most related to a given CTE career cluster is associated with a 3-point increase in CTE concentration in that cluster. Concentrators in business and service fields are more aligned with jobs requiring a college degree, whereas more technical students are more aligned with jobs that do not require college. Women and students from racial or ethnic minority groups are more aligned with college-level jobs than with high-school-level jobs. We find more limited evidence of dynamic, short-term adjustments in CTE after changes in local labor markets. Realignment lags the labor market by two to three years, is less than one-for-one, and is only observed following changes in college-level employment.



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## I. Introduction

Career and Technical Education (CTE) has undergone a dramatic renewal in U.S. high schools over the last two decades. Once considered a vocational track for non-college-bound students, CTE is now interwoven into the fabric of the secondary curriculum with the goal of preparing students for both college and careers. States typically organize CTE programs around "career clusters," and the 16-cluster National Career Cluster Framework[8] that many states have adopted spans almost every occupation one could have, including those requiring a college or advanced degree. This breadth is in response to a perceived skill shortage in middle skill occupations from the perspective of employers (Kochan et al., 2012; Craig, 2019), increasing costs of attending college, and the idea that learning practical, applied, or occupationally relevant skills is valuable for both college-bound and career-bound students. CTE is a big part of modern U.S. education. CTE has bipartisan support at the federal level (Meckler, 2018), its own funding and accountability systems, and its own department in many state and local education agencies. Given its forward-looking employment focus, CTE is often part of the bridge between K-12, college, and the workforce, playing a role in state and local efforts to improve K-12-to-workforce pipelines (Dorn, 2012; Gewertz, 2017). But CTE policy developments have quickly outpaced

[8] The 16 career clusters in the national framework are as follows: Agriculture, Food, & Natural Resources; Architecture & Construction; Arts, A/V Technology, & Communications; Business Management & Administration; Education & Training; Finance; Government & Public Administration; Health Science; Hospitality & Tourism; Human Services; Information Technology; Law, Public Safety, Corrections, & Security; Manufacturing; Marketing; Science, Technology, Engineering, & Mathematics (STEM); and Transportation, Distribution, & Logistics. Descriptions and additional details are at https://careertech.org/career-clusters.

CTE research, especially around the topic of *alignment*, or similarity, between education programs and workforce needs.

Policymakers and economists often call for formal, public technical education in skills that are aligned with labor market needs (Cullen et al., 2013; Gonzales & Gang, 2019; Education Commission of the States, 2019; Tennessee Department of Education, 2019; Scott & Thompson, 2019; State Council of Higher Education for Virginia, 2020), and alignment is also a key priority among chambers of commerce across the country. There is a commonly held belief among policymakers, parents, and students that public schools should educate students in skills and knowledge they can use at work (Klein, 2019). And since most young adults live close to where they attended high school,[9] satisfying this belief would mean providing skills that are in demand by nearby employers.

Scholarly research on alignment lags far behind policy and is largely limited to studies of college students. About one-in-three U.S. high school graduates do not enroll directly in college,[10] and more do not complete a college certificate or degree. For them, high school CTE coursework is a rare opportunity to explore career interests and develop skills that offer a return in the labor market. We study whether a student's CTE coursework resembles the surrounding labor market, which may determine the success of the CTE-to-workforce pipeline. Specifically, we quantify

[9] Sprung-Keyser et al. (2022) find that 58% of 26-year-olds live within 10 miles of where they were at age 16, and 80% live within 100 miles.
[10] U.S. Department of Commerce, Census Bureau, Current Population Survey (CPS), October Supplement, 2010 through 2020. See *Digest of Education Statistics 2021*, table 302.10.

static and dynamic alignment between high school CTE and local labor markets in five states with diverse populations, economies, and CTE systems.

To preview results, we find consistent evidence of partial alignment between the percentage of an area's CTE students who take courses in a particular CTE cluster and the fraction of area jobs aligned with that cluster. A ten percentage-point increase in the share of local jobs related to a CTE career cluster is associated with a 3-point increase in the share of local twelfth-grade CTE students who concentrate in that cluster. CTE concentrators are somewhat more aligned with jobs requiring postsecondary education, although this finding differs by career cluster and student demographics. Women in CTE and students from racial or ethnic minority groups tend to be better aligned with local jobs than men, and they are also more aligned than men with local jobs requiring college. This does not necessarily mean that female and minority CTE students are on track to higher paying jobs after school. In related research, Carruthers et al. (2023) find that—conditional on typical entry-level education requirements—women are more likely to concentrate in lower-paying fields such as human services, hospitality & tourism, education, and health science. This result combined with our findings here suggests that women tend to concentrate in fields where jobs are more plentiful but not necessarily higher paying. We find limited evidence of dynamic, short-term adjustments in CTE alignment, which we quantify as the relationship between an area's employment *growth* in particular fields and *growth* in the number of CTE concentrators in that field. This relationship is consistently positive but statistically imprecise in the very short term. We detect dynamic CTE adjustments 2-3 years after changes in area labor markets, and only for occupations typically following a college education.

These findings deepen a thin area of the CTE research literature and we hope they will spur more studies of CTE-workforce alignment. We leave to future research the question of why certain groups of students are more aligned with local employment, as well as both the short-term and long-term consequences of workforce alignment in CTE programs.

## II. Related Research and Contribution

We start by reviewing the literature on the causal effects of high school CTE on labor market outcomes as well as education-workforce alignment at the postsecondary level. This review is intended to elucidate why CTE may or may not be aligned with local labor markets at the secondary level.

There is a small but growing literature on how CTE coursework affects students, generally showing positive effects on graduation, employment, or earnings in the first several years after high school (Mane, 1999; Dougherty et al., 2019; Hemelt et al., 2019; Kreisman & Stange, 2020). The literature is relatively quiet on *why* students choose particular CTE pathways in high school (or why they choose CTE at all), or why schools offer some CTE pathways but not others. The labor market is a likely candidate for both. For example, Ansel et al. (2022) find that over half of all eighth-grade students from selected middle schools who plan to apply to a Regional Vocational and Technical School in Massachusetts report that future jobs are the most important factor in their high school choice.

After high school, students appear to consider the labor market when deciding whether to enroll in college and whether to major in particular fields (Long et al., 2015; Goulas & Megalokonomou, 2019; Grosz, 2019; Han & Winters, 2019; Liu et al., 2019; Acton, 2021; Blom et al., 2021; Weinstein, 2022). We do not have a clear hypothesis that high school students behave similarly when selecting CTE courses or pathways. The assumption that schools can accommodate student demand for particular fields is less viable for high schools than it is for colleges and universities. High school students have less discretion in choosing their courses, and K-12 schools have less discretion over changing their teaching staff from year-to-year in response to changing demand.

The most closely related literature to our research question is a report by Sublett and Griffith (2019), who quantify the alignment of CTE concentrations and local labor markets, by field, across 215 metropolitan areas in the U.S. using the High School Longitudinal Study of 2009. They find evidence of local alignment, in that "students take more CTE courses in fields that support more local jobs," although overall student participation rates were low in career clusters that synced with the nation's top fields: business, hospitality and tourism, marketing, and manufacturing. Also related are state reports projecting degree completion in specific fields alongside growth in related occupations (e.g., Tennessee Higher Education Commission, 2020).

We add to existing research in two ways. First, we quantify CTE-to-workforce alignment among recent cohorts of students. Sublett and Griffith (2019) find evidence of alignment in a static sense for a nationally representative sample of the 2013 twelfth-grade cohort, meaning that at a point in time, areas with more concentrated employment in particular sectors tended to have more concentrated student enrollment in affiliated clusters. We examine the same relationship for several recent twelfth-grade cohorts in five states, up to and including the class of 2019. In addition, we quantify whether *changes* in employment are correlated with *changes* in affiliated

CTE course-taking and course offerings. Quantifying dynamic alignment helps us determine if CTE moves in sync with the labor market.

We emphasize that our analyses of static and dynamic alignment are descriptive. Both are symptomatic of a causal relationship between labor markets and schools, which could be driven by student demand for and completion of aligned coursework, or by school systems' responses to local labor markets. The causal direction may run from schools to the workforce as well, if employers locate, expand, or design their operations around the number of area high school graduates with skills in particular fields. But the relationship between local CTE and workforce depth in an area and field could also be driven by outside influences on both sectors, and we do not make causal claims about our findings. In addition, we leave the consequences of aligned or misaligned CTE programs to future research. Perfect alignment with the local labor market, in either a static or dynamic sense, is not necessarily good for students in the long term if the skills they acquire in CTE are rigid and unadaptable to changing technologies and evolving local economies.

## III. Data

Our goal is to quantify the correlation between employment and the total number of aligned CTE concentrators in a labor market. In order to do so, we rely on five states' administrative education data systems for CTE concentrator counts and the Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics (OEWS) series for estimates of total employment by occupation. In order to marry these two data sources, we define local labor market boundaries and use a crosswalk that links occupations to their most relevant CTE career cluster. We describe each of these four inputs in turn.

*Local Labor Markets*

We define local labor markets to be metropolitan statistical areas (MSAs) and nonmetropolitan areas as defined by the U.S. Office of Management and Budget, the U.S. Census Bureau, and the BLS for its May 2021 OEWS release.[11] An MSA is a core urban area with a population of at least 50,000 people, plus surrounding communities with social and economic connections to the core. MSAs can cross state lines, such as the Memphis MSA which includes nine counties in Tennessee, Arkansas, and Mississippi. Counties that are not in an MSA can be grouped into nonmetropolitan areas, such as the 13-county Southwest Montana nonmetropolitan area. Metropolitan area definitions have changed over time,[12] and many nonmetropolitan areas were consolidated beginning with the 2018 OEWS.[13] For consistency, we assign counties to their May 2021 MSA or nonmetropolitan area for all years.[14]

Nonmetropolitan areas describe proximate rural counties in some cases, but they can cover very broad areas and stretch the definition of a local labor market past its logical boundary. The East-Central Montana nonmetropolitan area, for example, spans 32 counties and runs more than 450

[11] https://www.bls.gov/oes/current/msa_def.htm
[12] https://www.census.gov/geographies/reference-files/time-series/demo/metro-micro/historical-delineation-files.html
[13] https://www.bls.gov/oes/areas_2018.htm
[14] One exception is the Wall Walla, WA MSA, which was introduced as a new MSA in 2013. We assign this two-county MSA to its previous MSA (Kennewick-Richland) and combine Walla Walla OEWS figures with Kennewick-Richland figures for all years.

miles east to west. Massachusetts has just one nonmetropolitan area, covering every non-MSA township in the state, from Williamstown in the northwest to Nantucket Island in the southeast. The OEWS has the most detailed annual level of employment estimates for nonmetropolitan areas that we know of, and we keep nonmetropolitan areas in the main analysis sample so that more rural students are represented. As shown below, results are similar when we focus on MSAs and exclude nonmetropolitan areas.

*Cluster-to-Occupation Crosswalk*

We group BLS occupation codes within their most relevant CTE career cluster using a crosswalk developed by the Economic Development and Employer Planning System (EDEPS). The EDEPS crosswalk assigns one of the 16 major career clusters to all non-military occupations listed in the 2018 version of the Standard Occupational Classification (SOC) coding system, which we merge with 2010 SOCs to cover earlier years of OEWS data. We also merge this crosswalk with BLS-determined typical entry-level educational requirements for each occupation.[15] Pest control jobs, for example, are grouped with the Agriculture, Food, and Natural Resources cluster in the EDEPS crosswalk, and workers with this occupation typically have at least a high school diploma or its equivalent. Petroleum engineers are grouped with the Science, Technology, Engineering, & Mathematics cluster, and workers with this occupation typically have at least a bachelor's degree.

[15] https://www.bls.gov/oes/additional.htm

*Occupational Employment Estimates*

We describe local employment in each occupation, aggregated to the career cluster level via the EDEPS crosswalk, using publicly available information from the BLS on employment at the place-by-year-by-occupation level. The OEWS series reports estimated employment volume and earnings for detailed occupations with SOC codes. OEWS data, published annually and available for MSAs and nonmetropolitan areas, are the result of BLS surveys to a rotating sample of over one million firms who report to state unemployment insurance (UI) systems. Necessarily, estimates exclude occupations that are not covered by UI, such as self-employment.

We draw on the 2010–2019 May OEWS for results to follow. Comparing OEWS employment statistics for the same area over time is vital for describing alignment with area CTE (especially dynamic alignment), but this is challenging for several reasons.[16] The BLS has periodically changed the set of detailed occupations listed in the OEWS, shifting from SOC 2010 to 2018 in phases and making other ad hoc consolidations and separations of occupation titles. We reduce the practical effect of these changes by aggregating several hundred occupations into 16 career clusters. In addition, we use the 2010 or 2018 SOC where appropriate and reconcile the two using a BLS crosswalk connecting the two systems.[17] We assign any remaining OEWS occupation codes not found in the EDEPS crosswalk to a career cluster based on related job titles or previous codes for the same job title. Other major changes in the OEWS either predate or

[16] https://www.bls.gov/oes/oes_ques.htm
[17] https://www.bls.gov/soc/2018/crosswalks.htm

post-date the OEWS data we use in this analysis, such as a change to the survey reference period in 2002, or COVID-19-era challenges in survey collection for 2020 and 2021.

*Administrative Education Data*

We have research-practice partnerships with education agencies in Massachusetts, Michigan, Montana, Tennessee, and Washington. Through these partnerships, we have access to student-level, longitudinal data on high school enrollment, course-taking, and CTE career clusters. Administrative data cover the universe of public high school students in each state and span several recent cohorts. Our data agreements do not permit us to pool individual-level data from multiple sites, so the analyses described in the next section rely on student counts that have been aggregated to the year-by-metro level.

We limit each state sample to twelfth-grade students observed at least four years across grades 9-12, and we assign concentrator status to any student with at least two (three, in Tennessee and Washington) courses in a CTE cluster.[18] Our concentrator designation is best thought of as a flag for a student's potential CTE concentration in a particular cluster. The two-course or three-course rule we use is consistent with federal *Perkins V* guidance but will differ from official concentrator designations in each state. A formal CTE concentration depends on criteria that we do not always observe in the data, such as a student having taken a specific sequence of courses,

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[18] In Tennessee, CTE courses include many introductory and general-education courses that may be taken outside of a CTE concentration. Statistics is in the Accounting program of study within the Finance cluster, for example. The three-course assignment rule allows us to more accurately identify CTE concentrators in Tennessee. In addition, Tennessee students in these cohorts needed three courses in a CTE program of study to attain concentrator status. The state moved to a two-course designation following the 2018 reauthorization of the Perkins Act.

or a student's school being approved to offer a particular CTE program of study. We allow students to be flagged as potential concentrators in more than one cluster.

We sum the number of concentrators in each metro/nonmetro area, cohort, and cluster, suppressing counts less than ten (that is, leaving those counts missing in the multi-state sample). We also compute separate sums for the number of female, male, and Black/Hispanic/Native American concentrators in each area, cohort, and cluster, again suppressing counts less than ten. We omit any suppressed metro-cohort-cluster cells from the analysis, and we show that the general pattern of results is not sensitive to their inclusion with small-cell imputations.

Finally, for each metro-cohort-cluster cell, we merge concentrator counts to OEWS estimates for total employment, employment in jobs where a high school entry-level education is typical, and employment in jobs where a college education (including some college without a degree and non-degree certificates) is typical. We merge each twelfth-grade cohort's fall year to that year's May OEWS estimate so that the labor market data are measured as of one year prior to the traditional spring graduation. For example, the 2019-2020 cohort in a metro area is linked to the May 2019 OEWS employment estimates for that area.

Table 1 describes the combined education-employment sample. We observe 7-10 cohorts of twelfth-grade students across the multi-state sample, up to and including the 2019-2020 cohort. There are 6-19 metro/nonmetro areas and 6-16 CTE clusters in each state. Tennessee and Washington follow the 16-cluster National Career Cluster Framework. Michigan does as well but also has a seventeenth cluster for Energy. We group Energy concentrators with Architecture & Construction concentrators in Michigan based on the state curriculum for the Energy program and the clusters where affiliated jobs (e.g., line workers and pipefitters) are grouped in the EDEPS crosswalk.

We observe nine clusters for Massachusetts, one of which is a consolidation of four clusters in the national framework. Business Management & Administration, Finance, Human Services, and Marketing are grouped into "Business and Consumer Services" in Massachusetts. In order for the employment data to match the consolidated cluster, we aggregate OEWS estimates for employment in those fields to the same supercluster for Massachusetts. We do not observe concentrator counts for four of the nationally standardized clusters in Massachusetts, and we treat those omissions in the same way that we treat small-cell suppressions. Rather than correlate zero Government & Public Administration concentrators with a non-zero number of Government & Public Administration jobs in the state, we omit that cluster from the Massachusetts subset of the sample. This tends to overstate alignment in results to follow, but as we show, our conclusions are very similar with and without imputations that account for these omissions.

Montana, the smallest and most rural state in the sample, has just six clusters, although each of these can be harmonized with the national framework. Montana's Family & Consumer Sciences cluster groups together Arts, A/V Technology, & Communications, Education & Training, Hospitality & Tourism, and Human Services. The state's Industrial Technology cluster combines Architecture & Construction, Manufacturing, STEM, and Transportation, Distribution, & Logistics. In the Montana OEWS data, we follow suit and aggregate employment totals to the appropriate cluster.

The last two rows of Table 1 give a sense of scale between CTE concentrator counts and local employment in aligned occupations. For every 100 workers in a metro-year-cluster combination, there are 1-2 potential twelfth-grade CTE concentrators in the same metro, year, and cluster.

## IV. Static Alignment

As a starting point, Figure 1 plots the number of CTE concentrators in a metro, cluster, and year against total employment in the same metro, cluster, and year. Both statistics are expressed in logs to minimize the influence of a small number of very large metropolitan areas, and scatter points represent average values from 100 evenly sized bins. There are 6,692 metro-year-cluster cells depicted in Figure 1. The quadratic fit implies that at the mean, an additional 1,000 local workers in a particular cluster is associated with 6.5 more local concentrators in the same cluster.

This is evidence of alignment between CTE and the local workforce, but much of the pattern in Figure 1 is driven by differences in metro size. Larger metro areas may have more students participating in all kinds of programs, CTE or otherwise. Nevertheless, Figure 1 refutes misalignment in scale between area workforces and CTE programs.

Figure 2 depicts proportional alignment overall and by typical entry-level education. The horizontal axis of Panel A measures the percentage of total area employment in a given year and metro area that is accounted for by employment in a particular cluster. The vertical axis measures the percent of all potential $12^{th}$ grade concentrators in that same area and year, who are concentrating in that same cluster. Panel A shows that in areas where a cluster accounted for a larger percent of area employment, the share of concentrators in that field was also larger. For example, in the Detroit, MI metro area, just 0.5% of 2017 employment was in Agriculture, Food,

& Natural Resources, versus 17.2% in Business Management & Administration. Among 2017-2018 CTE concentrators in the Detroit area, 1.5% were in Agriculture, Food, & Natural Resources whereas 8.7% were in Business Management & Administration. In the Kingsport, TN metro area (which crosses the state line into Bristol, VA), 1.5% of 2018 employment was in STEM and 11.6% was in Health Science. Among CTE concentrators on the Tennessee side of the metro area, 6.3% were in STEM and 17.0% were in Health Science.

We estimate the slope of the fitted line between concentration shares ($CS_{mtc}$), i.e., the percent of potential concentrators in metro area *m*, year/cohort *t*, who were in CTE cluster *c*, and employment shares ($ES_{mtc}$) using the following simple regression model, which we later adapt to quantify dynamic alignment:

$$CS_{mtc} = \alpha + ES_{mtc}\beta + e_{mtc} \qquad (1)$$

In our preferred, baseline specification of Equation (1), we omit metro-year-clusters with suppressed or unavailable concentrator counts, and we weight estimates by total area employment to account for statistical noise arising from small-city fluctuations in employment and concentrator counts. We estimate slope coefficients $\hat{\beta}$ as well as standard errors for $\hat{\beta}$ that allow errors ($e_{mtc}$) to be correlated within metro areas.

Note that $\hat{\beta}$ estimates focus on the relationship between a cluster's employment share and the share of concentrators in a given cluster. This omits a different margin of alignment between CTE and the local workforce: the relationship between a cluster's employment share and the percent of *all* area 12$^{\text{th}}$ graders who were potential CTE concentrators in any cluster. It is possible that some clusters correspond with larger CTE programs. Nevertheless, we estimate alignment with concentrator shares rather than cohort shares to separate the question of CTE alignment from the question of size and scope of CTE in an area. In results not shown, we find that defining $CS_{mtc}$ to be a cluster's share among all 12th graders does not change the sign, significance, or relative magnitude of results to follow, although $\hat{\beta}$ estimates are mechanically smaller by a factor of about one potential concentrator per two 12th graders.

Looking across the whole sample, we estimate the slope of the fitted line in Panel A to be $\hat{\beta} =$ 0.292 and statistically significant. This suggests that if we compare two metro-year-clusters with a 10-percentage-point difference in the share of area employment—City A with 12% of area employment in Health Science to City B with 2%, for example—we would expect about 3% more of City A's concentrators to be in Health Science.

The rest of Figure 2 divides total employment into jobs where entry-level workers typically have a high school diploma or less (Panel B), and jobs where entry-level workers typically have some college or a postsecondary credential (Panel C). That is, we define $ES_{mtc}$ in Equation (1) as equal to the percent of area employment in HS-level jobs aligned with cluster $c$ (Panel B) or the percent of area jobs aligned with college-level jobs (Panel C). The slope between CTE concentration shares and area employment shares is positive for high school-level and college-level jobs, evidence of some degree of proportional alignment for both college and career destinations after high school. The slope is steeper in Panel C ($\hat{\beta}$ = 0.570) than in Panel B ($\hat{\beta}$ = 0.278), suggesting that concentrators are more proportionately aligned with college-level local jobs than with high school-level local jobs.

Table 2 reports Equation (1) estimates for $\hat{\beta}$ under our baseline specification (repeating the $\hat{\beta}$ = 0.292 result visualized in Figure 2, panel A) and under different sample and weighting approaches. In Column 2 we add all suppressed and unavailable metro-year-clusters to the sample, imputing five concentrators where the cluster was not offered or where true number was suppressed for being less than ten. The Column 3 model excludes these imputed cells as well as all nonmetro areas, which as noted in Section II, are sometimes much more spread out than commuting areas. The Column 4 model returns to the baseline sample but does not weight estimates by metro size. Finally, the Column 5 model weights by the inverse of BLS-provided standard error estimates for each employment figure. Results are very similar across the five approaches, with our preferred $\hat{\beta}$ = 0.292 proportional alignment estimate at the midpoint.

Figure 3 depicts proportional alignment for two broad groups of CTE clusters, and for three demographic subgroups of students. For Panel A-B results, we estimate Equation (1) for two subsamples of metro-area-cluster cells. The Panel A sample focuses on 6 technical and/or applied clusters: Agriculture, Food, & Natural Resources; Architecture & Construction; Law, Public Safety, Corrections, & Security; Manufacturing; STEM; and Transportation, Distribution, & Logistics. For Panel B, we focus on the remaining 10 clusters of business, service, and other fields. We chose this particular division to be in agreement with Massachusetts and Montana cluster consolidations, and because these two superclusters have different education levels in the workforce. Jobs in the technical and applied supercluster tend to have lower entry-level education—36.9% are college-level jobs versus 57.4% in the business, service, and other occupation supercluster.[19] Panels A-B as well as Equation (1) regression results in panel titles point to a similar degree of proportional alignment for both superclusters.

Panels C-E of Figure 3 depict proportional alignment for demographic subgroups: females, males, and racial and ethnic minority students. To generate these figures and subgroup regression results, we first compute the total number of concentrators meeting each demographic criteria in a given metro and cohort, and then the share of each demographic subgroup of concentrators who were in a particular cluster in that metro and cohort. Using Equation (1), we then associate each subgroup's concentration shares with aligned employment shares in their metro and cohort. For example, Panel C reports Equation (1) estimates when $CS_{mtc}$ is equal to the share of female CTE concentrators in metro *m*, cohort *t*, who are in cluster *c*.

Results indicate that females and racial/ethnic minority students are notably more aligned than males. Returning to an earlier example, if City A has 12% of area employment in Health Science and City B has 2%, female concentrators in City A would be 4.3% more likely to concentrate in Health Science than in City B, on average, Black, Hispanic, or Native American concentrators would be 3.3% more likely, whereas males would be just 1.9% more likely. Omitting metro-year-clusters with missing or suppressed concentrator counts may overstate proportional alignment for all three demographic groups, because total concentrator counts are more likely to fall under the 10-student threshold when we divide state-specific samples into demographic subsets. In results not shown, we find that results for proportional alignment by demographic

[19] STEM is a big exception to this pattern, with no HS-level jobs. In Montana, STEM is part of Industrial Technology along with most of the other fields in our technical/applied supercluster.

subsets are very similar if we assume that suppressed metro-year-cluster-demographic cells had 5 concentrators.

Table 3 reports Equation (1) proportional alignment results by supercluster and entry-level education. For comparison, Figure 2 findings for overall alignment and alignment with HS-level and college-level jobs are repeated in the first block of results ("All Clusters"). Turning to the technical/applied supercluster and the middle block of results, we find that concentrators in these fields are more aligned with HS-level jobs than with college-level jobs. In fact, concentrator shares in these fields do not significantly rise with college-level employment shares in aligned occupations. By contrast, concentrators in the more college-oriented supercluster spanning business, service, and other occupations (third block of Table 3 results) are much more aligned with college-level jobs in the area than with HS-level jobs. The $\hat{\beta} = 0.544$ result in that block means that concentrator shares in that supercluster grow at about half the rate of employment shares in related, college-level occupations.

Table 4 results explore demographic trends from Figure 3 in more detail, breaking out proportional alignment by demographic subgroup and entry-level education. Findings reported in the first block of results indicate that females are proportionately one-for-one aligned with local college-level jobs. The $\hat{\beta} = 1.08$ estimate suggests that the allocation of females across CTE fields very closely resembles the allocation of local college-level jobs across CTE fields. Males are somewhat more aligned with HS-level jobs than college-level jobs, but the difference is not as stark as for females. Finally, Black, Hispanic, and Native American students are notably more aligned with college-level jobs than with HS-level jobs. Carruthers et al. (2023) find that females and racial/ethnic minority students also tend to concentrate in lower-paying fields, both in terms of the college-level and HS-level wage. Females, for example, are more likely to concentrate in Education & Training, Human Services, and Health Science, where typical wages and salaries are lower than in STEM, Information Technology, and Transportation, Distribution, & Logistics. Collective findings across these two studies suggests that females and racial/ethnic minorities tend to concentrate where jobs are more plentiful—particularly jobs requiring college—but where pay is lower, conditional on educational attainment.

## V. Dynamic Alignment

The extent of CTE-workforce alignment at a point in time is interesting regardless of the causal channels connecting one to the other. Results discussed so far indicate that there is a significant degree of similarity, in proportion and scale, between CTE student concentrations and area employment. But the industrial and occupational makeup of a place changes over time, and it is unclear if CTE students and their schools undergo similar shifts, away from declining fields or toward growing fields.

Figure 4 depicts our first look at dynamic alignment across these five states, plotting the 3-year change in each area's total concentrators in a given field (vertical axis, in log scale) against the 3-year change in each area's total employment in that field (horizontal axis, in log scale). In order to smooth out noise from year-to-year fluctuations in concentrator counts and employment, the beginning and end of each 3-year period are computed as the average of the current and prior year. Most points in the figure fall in the top-right quadrant, meaning that growing employment in a field is associated with a growing number of concentrators in that field. The slope of the fitted line indicates that for each 10% increase in a field's employment level in an area, concentrators in that field grow by about 1%.

Figure 5 plots 3-year changes in concentrator shares by field against 3-year changes in employment shares. There is no significant relationship between the two. Results in the previous section consistently pointed to proportional alignment at a given point in time, but Figure 5 shows that CTE concentrators' proportional alignment does not shift simultaneously with the area labor market.

Even though the 3-year windows depicted in Figure 4-5 would have accounted for most of a student's time in high school, it is possible that student and school responses to area changes in the workforce take time to manifest as changes in concentrator counts or shares. CTE program and cluster offerings go through district and state approval processes that would hinder an immediate realignment with the area workforce, and knowledge about labor market changes might not be immediately apparent. Even with perfect insight into local labor market dynamics and the ability to adjust course offerings in real time, students and schools might prudently wait to judge if employment shifts are going to be long-lasting. In order to examine dynamic alignment in more detail, we estimate the following:

$$C_{mtc} = E_{mkc}\gamma + \alpha_t + \alpha_{mc} + e_{mtc}, \quad (2)$$

Where $C_{mtc}$ is the log of concentrator counts in metro area *m*, year *t*, and cluster *c*, $E_{mkc}$ is the log of total employment in area *m*, a particular year $k \leq t$, and cluster *c*, $\alpha_t$ is a year fixed effect, and $\alpha_{mc}$ is a metro-by-cluster fixed effect. As in Figure 4, we measure log employment at time *k* as a rolling two-year average. With $\alpha_t$ and $\alpha_{mc}$ in the model, the dynamic alignment parameter $\hat{\gamma}$

quantifies the elasticity between $C_{mtc}$ and $E_{mkc}$ in a typical area and cluster, or the degree to which within-area, over-time changes in cluster employment are associated with within-area, over-time changes in concentrators. We are not as concerned about the effects of scale alone—bigger areas having more concentrators regardless of field, as in Figure 1—because $\alpha_{mc}$ controls for factors like typical area size.

Table 5 reports Equation (2) results for all occupations, HS-level occupations, and college-level occupations, and for different lags of $E_{mkc}$ ranging from 0-4 years prior to a concentrator's 12$^{th}$ grade year. Each coefficient in the table is a $\hat{\gamma}$ estimate from a separate Equation (2) regression. Looking to the first block of results for all occupations, we find that concentrators realign after area employment changes, but to a modest degree that is statistically insignificant for labor force changes 0-1 years prior to 12$^{th}$ grade. If area employment in a cluster increases 10%, for example, we can't say with confidence that the number of aligned concentrators would increase over the next 2 school years, but results indicate that they would increase with weak statistical significance by 1.3% after 2 years and by a more precisely estimated 0.9% after 3.

The middle block of Table 5 results focuses on dynamic alignment with HS-level jobs. Estimates for $\hat{\gamma}$ are very small and statistically insignificant, meaning that growth or decline in HS-level jobs was not followed by similar changes in aligned CTE concentrators. Instead, it appears that lagged dynamic alignment was driven entirely by changes in college-level jobs. If a cluster's college-level jobs increased by 10% in an area, aligned concentrators grew by 0.9 – 1.4% after 2-3 years.

## VI. Conclusions and Limitations

We offer new evidence from five diverse states that CTE systems are somewhat aligned with local labor markets, at least in a static and proportional sense. The distribution of jobs across career clusters in a metro or nonmetro area is significantly correlated with the distribution of 12th grade CTE concentrators across those same career clusters. This static alignment is more pronounced when we focus on jobs where entry-level workers typically have some college education, or when we focus on female or racial/ethnic minority concentrators. Evidence of dynamic alignment is weaker. The size of a cluster's 12th grade CTE cohort adjusts to changes in that cluster's area employment, but by a small degree after 2-3 years. This modest readjustment is only observed following changes in college-level jobs. CTE concentrator populations do not significantly change following changes in area HS-level jobs.

These insights push what we know about CTE-workforce alignment, but only descriptively. We have correlated area employment with aligned CTE populations (and changes therein), but our research design does not permit causal inferences about the responsiveness of CTE students and their schools to local labor markets, or vice versa.

Another self-imposed limitation is that we make no inferences about whether alignment benefits students. Despite wide calls for better alignment, from policymakers, chambers of commerce, and academics, the right level of alignment is unclear. Even if schools could identify in-demand jobs and align CTE programs to suit them very quickly, we do not know if this will serve students well. We cannot foresee if today's in-demand skill will be obsolete in a short time. Graduates with technical skills may move seamlessly into well-paying work (Kemple and Willner, 2008) and help to address the perceived shortage of middle-skill workers. There is a risk, however, that CTE will crowd out general skills that transfer between occupations and survive technological change (Hanushek et al., 2017) or keep up with firms that can move more easily than households. We leave to future research the causes of static and dynamic alignment, which may include student and school responses to area labor markets, and the consequences of CTE-workforce alignment for students in the years after high school.

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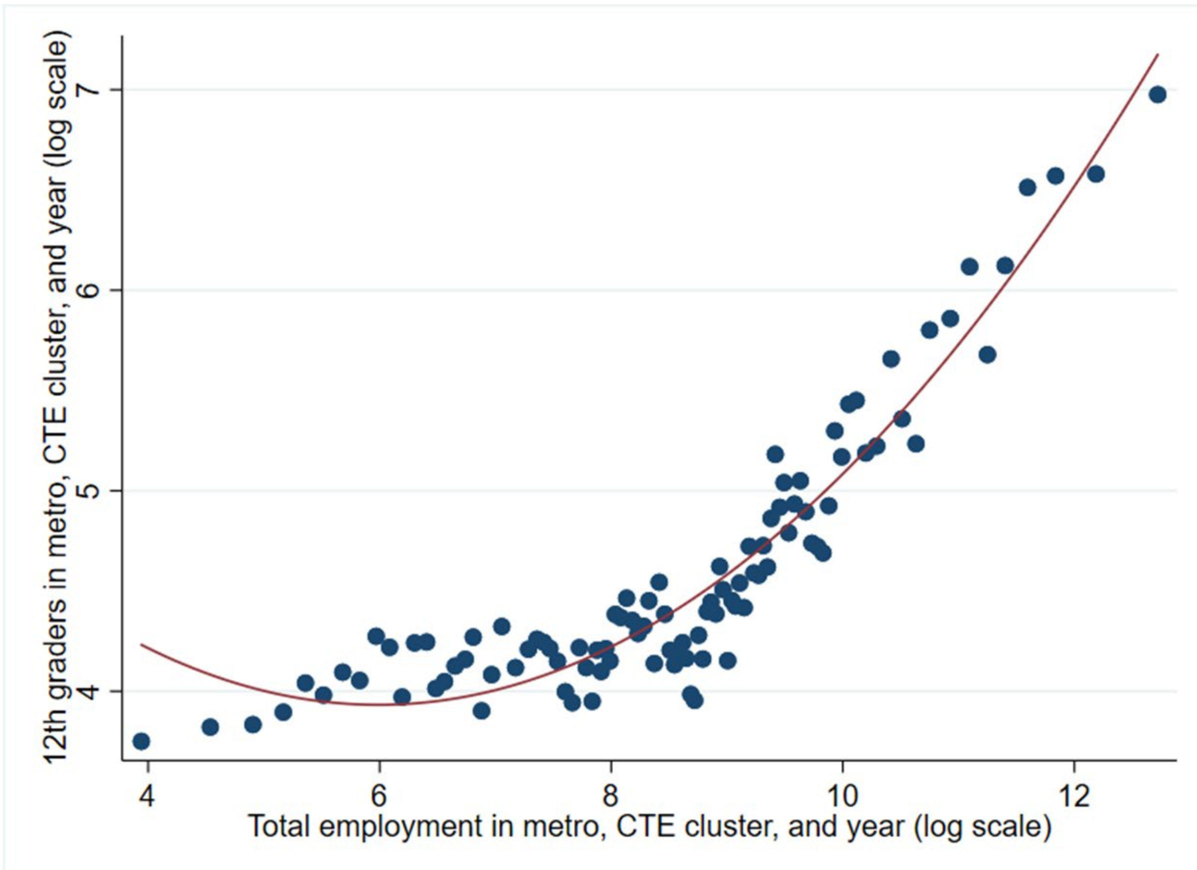
Table 1. Cross-State Sample

| | Massachusetts | Michigan | Montana | Tennessee | Washington |
|---|---|---|---|---|---|
| 12th grade cohorts | 2011-2020 | 2011-2020 | 2012-2020 | 2011-2020 | 2014-2020 |
| Number of CTE clusters | 10 | 16 | 6 | 16 | 16 |
| Number of metro and nonmetro areas | 9 | 19 | 6 | 14 | 14 |
| Average concentrators per cohort-metro-cluster | 428 | 161 | 114 | 255 | 217 |
| Average employment in year-metro-cluster | 40,234 | 15,450 | 11,276 | 13,458 | 19,680 |

*Notes*: The table describes the multi-state sample of CTE concentrator counts, by state-defined cluster, matched to area employment in each cluster's aligned occupations. We define potential concentrators as students with at least two courses in a cluster in Massachusetts, Michigan, and Montana, or at least three courses in a cluster in Tennessee and Washington. We do not apply other criteria used by states for formal concentrator designations, as these vary across states and years and involve additional data that we do not always observe. Cohort refers to the spring of the 12th grade academic year.

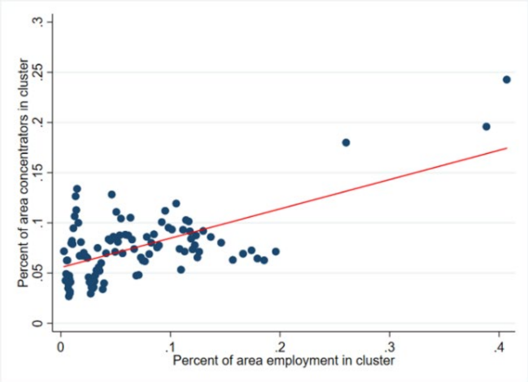
Figure 1. Overall Alignment between CTE Concentrators and Area Employment



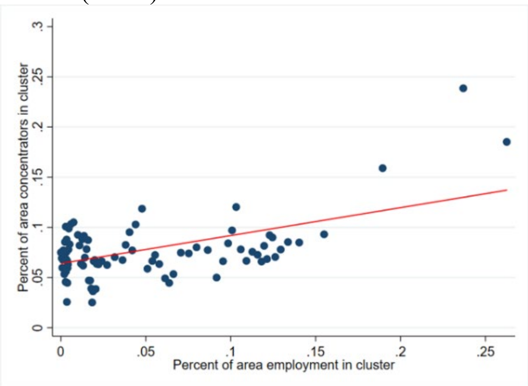

*Notes*: The figure plots the total number of concentrators in a given cluster, metro area, and 12th grade cohort (vertical axis, in log scale) against total employment in aligned occupations in the same area and year (horizontal axis, in log scale), overlaid with a quadratic fit (solid red line). The underlying data are grouped into 100 evenly sized bins. Scatter points represent averages within these bins.

Figure 2. Proportional Alignment between CTE Concentrators and Area Employment

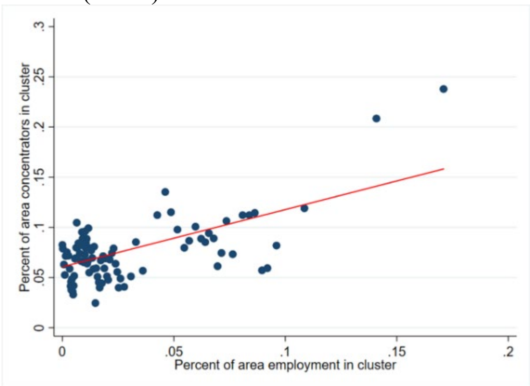
A. Overall proportional alignment
0.292* (0.028)




B. Proportional alignment with HS-level jobs
0.278* (0.041)




C. Proportional alignment with college-level jobs
0.570* (0.061)




*Notes*: Each figure plots the percent of a cohort-metro's total concentrators in a given cluster (vertical axis), against the percent of metro-year total employment in occupations aligned with that cluster (horizontal axis), overlaid with a linear fit weighted by metro size (red line). Panel A depicts proportional alignment with respect to all area occupations. Panel B depicts proportional alignment with respect to jobs where the typical entry-level education is a high school diploma or less. Panel C depicts proportional alignment with jobs where the typical entry-level education is some college or a college credential. The underlying data are grouped into 100 evenly sized bins. Scatter points represent averages within these bins. Equation (1) estimates of $\hat{\beta}$ are shown above each figure, with standard errors in parentheses. * indicates statistical significance at 95% confidence or greater.

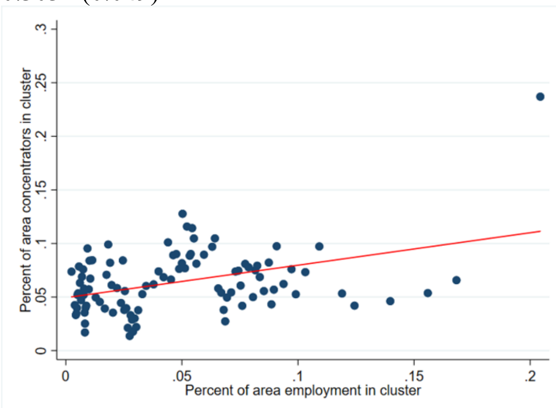
Table 2. Proportional Alignment Estimates: Sensitivity to Weighting, Imputation, and Metro-Only Samples

| | (1) Baseline model | (2) With small-cell imputations | (3) Without nonmetro areas | (4) Unweighted | (5) Weighted by BLS estimation error |
|---|---|---|---|---|---|
| Percent of area employment in aligned occupations | 0.292* | 0.316* | 0.272* | 0.297* | 0.288* |
| | (0.027) | (0.026) | (0.017) | (0.015) | (0.015) |
| Metro-year-clusters | 6,692 | 7,634 | 5,141 | 6,692 | 6,692 |

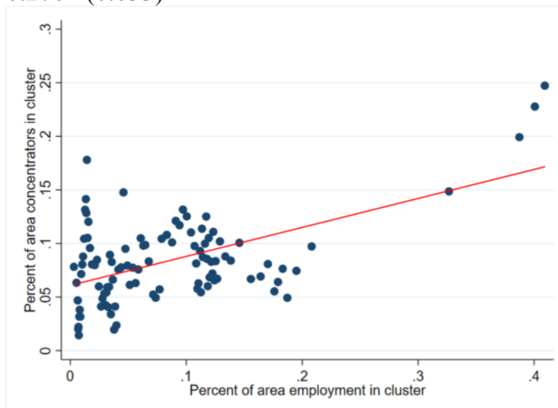
*Notes*: The table reports results from Equation (1) regressions of the proportion of local concentrators in a given cluster against the proportion of local employment in occupations aligned with that cluster. Column 1 is our preferred specification of this regression, with a pooled sample of metro and nonmetro areas, weights for metro size to account for noise arising from small-area fluctuations, and omitting metro-cluster-year cells with fewer than ten concentrators. Columns 2-5 report results for alternative weighting, samples, and suppression rules. The Column 2 result is from a regression where we assume that a metro-year-cluster had 5 concentrators if a cluster was unavailable, or the number of concentrators was suppressed or otherwise missing. The Column 3 result follows our baseline suppression rule but omits nonmetropolitan areas. The Column 4 result is unweighted. Finally the Column 5 result weights by the inverse of BLS-provided estimates of the standard error of employment estimates. Our own standard error estimates, in parentheses below each coefficient, are cluster robust and allow for correlated errors within metro areas. * signifies statistical significance at 95% confidence or greater.

Figure 3. Proportional Alignment by Supercluster, Gender, and Race/Ethnicity

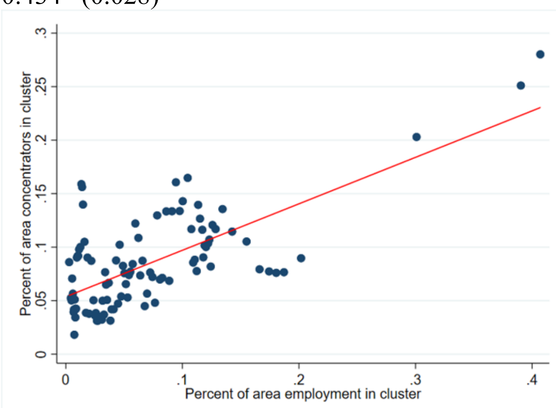
A. Technical and applied clusters
0.303* (0.049)



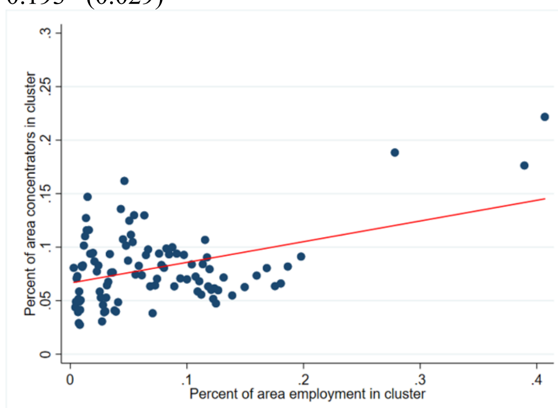

B. Business, service and other clusters
0.270* (0.033)



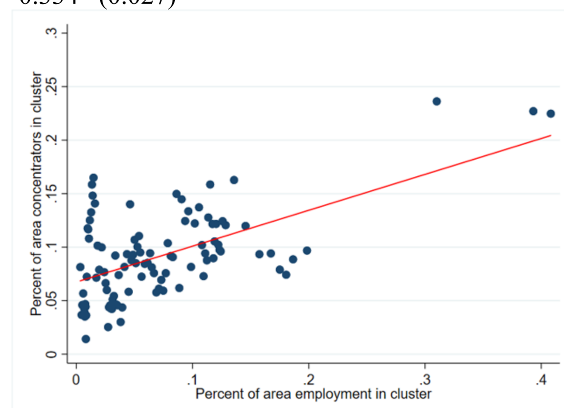

C. Females
0.434* (0.028)




D. Males
0.193* (0.029)




E. Black, Hispanic, or Native American
0.334* (0.027)




*Notes*: Figures depict proportional alignment by cluster division (Panels A and B), gender (Panels C and D), and for racial and ethnic minority students (Panel E). Equation (1) estimates of $\hat{\beta}$ are shown above each figure, with standard errors in parentheses. * indicates statistical significance at 95% confidence or greater.

Table 3. Proportional Alignment by Supercluster and Entry-Level Education

| | (1) | (2) | (3) |
|---|---|---|---|
| | All Clusters | | |
| | Overall proportional alignment | Proportional alignment with HS-level jobs | Proportional alignment with college-level jobs |
| Area employment share | 0.292* | 0.278* | 0.570* |
| | (0.028) | (0.064) | (0.061) |
| Metro-year-clusters | 6,692 | 6,692 | 6,692 |
| | Technical and applied clusters<br>Percent of Occupations with Postsecondary Entry-Level Education: 36.9% | | |
| | Overall proportional alignment | Proportional alignment with HS-level jobs | Proportional alignment with college-level jobs |
| Area employment share | 0.303* | 0.338* | 0.239 |
| | (0.049) | (0.052) | (0.213) |
| Metro-year-clusters | 2,628 | 2,628 | 2,628 |
| | Business, service, and other cluster<br>Percent of Occupations with Postsecondary Entry-Level Education: 57.4% | | |
| | Overall proportional alignment | Proportional alignment with HS-level jobs | Proportional alignment with college-level jobs |
| Area employment share | 0.270* | 0.247* | 0.544* |
| | (0.033) | (0.048) | (0.075) |
| Metro-year-clusters | 4,064 | 4,064 | 4,064 |

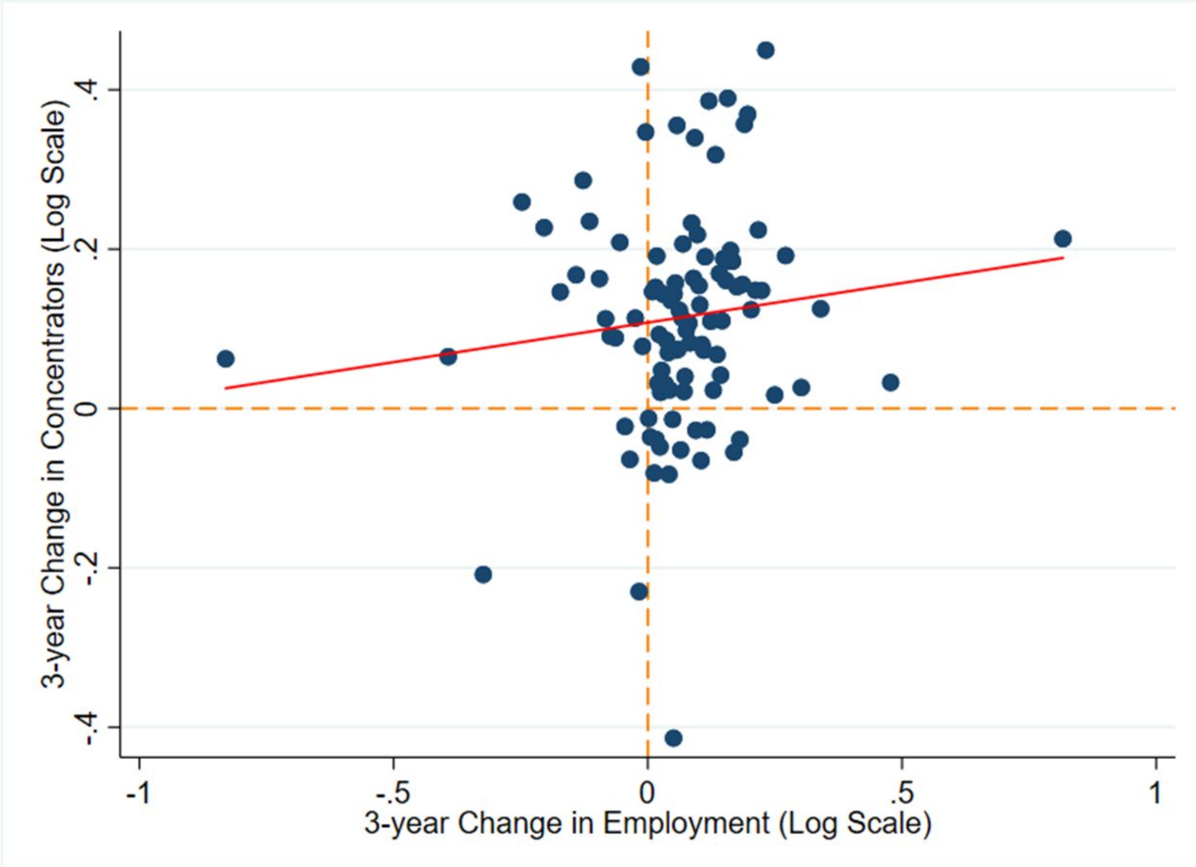
*Notes*: The table reports results from Equation (1) regressions of the proportion of local concentrators in a given cluster against the proportion of local employment in occupations aligned with that cluster. Each model follows the baseline specification described in Table 2. The Column 1 model describes proportional alignment with respect to all area occupations. Column 2 describes proportional alignment with jobs where the typical entry-level education is a high school diploma or less. Columns 3 describes proportional alignment with jobs where the typical entry-level education is some college or a degree. The second and third rows of results are from Equation (1) specifications limited to a subset of clusters. Standard errors, in parentheses below coefficients, allow for correlated errors within metro areas. * signifies statistical significance at 95% confidence or greater.

Table 4. Proportional Alignment by Entry-Level Education and Gender, Race/Ethnicity

| | (1) | (2) | (3) |
|---|---|---|---|
| | Female Concentrators | | |
| | Overall proportional alignment | Proportional alignment with HS-level jobs | Proportional alignment with college-level jobs |
| Percent of area employment in aligned occupations | 0.434* | 0.330* | 1.076* |
| | (0.028) | (0.051) | (0.063) |
| Metro-year-clusters | 5,275 | 5,275 | 5,275 |
| | Male Concentrators | | |
| | Overall proportional alignment | Proportional alignment with HS-level jobs | Proportional alignment with college-level jobs |
| Percent of area employment in aligned occupations | 0.193* | 0.253* | 0.187* |
| | (0.029) | (0.038) | (0.083) |
| Metro-year-clusters | 5,923 | 5,923 | 5,923 |
| | Black, Hispanic, and Native American Concentrators | | |
| | Overall proportional alignment | Proportional alignment with HS-level jobs | Proportional alignment with college-level jobs |
| Percent of area employment in aligned occupations | 0.335* | 0.363* | 0.540* |
| | (0.027) | (0.041) | (0.066) |
| Metro-year-clusters | 3,853 | 3,853 | 3,853 |

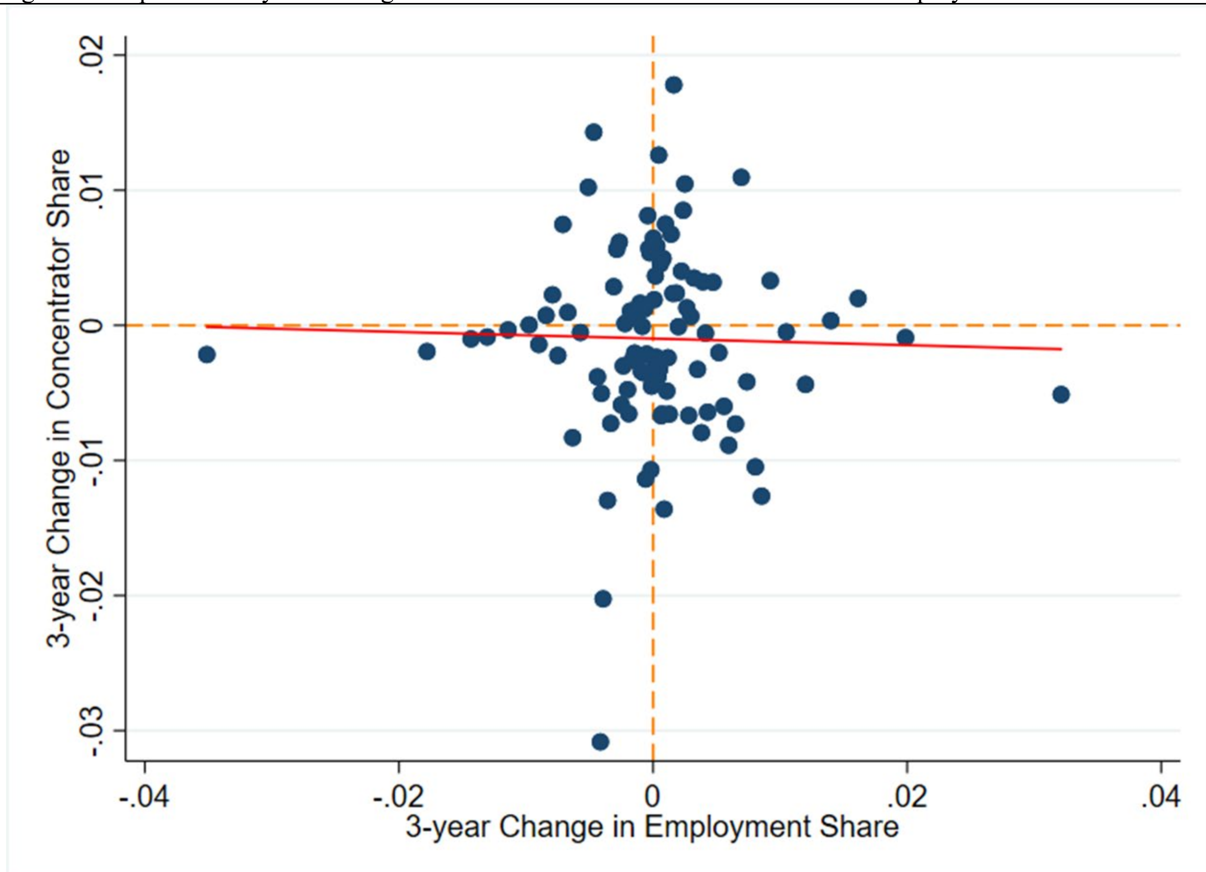
*Notes*: The table reports results from regressions of the proportion of local concentrators in a given cluster against the proportion of local employment in occupations aligned with that cluster. Each model follows the baseline specification described in Table 2, but limited to a demographic subgroup of students. The Column 1 model describes proportional alignment with respect to all area occupations. Column 2 describes proportional alignment with respect to jobs where the typical entry-level education is a high school diploma or less. Columns 3 describes proportional alignment with jobs where the typical entry-level education is some college or a degree. Standard errors, in parentheses below coefficients, allow for correlated errors within metro areas. * signifies statistical significance at 95% confidence or greater.

Figure 4. Overall Dynamic Alignment between CTE Concentrators and Area Employment




*Notes*: The figure plots three-year changes in the rolling average number of concentrators in a given cluster, metro area, and 12th grade cohort (vertical axis, in log scale) against three-year changes in rolling average total employment in aligned occupations in the same area and year (horizontal axis, in log scale), overlaid with a linear fit (solid red line). The underlying data are grouped into 100 evenly sized bins. Scatter points represent averages within these bins.

Figure 5. Proportional Dynamic Alignment between CTE Concentrators and Area Employment




*Notes*: The figure plots the three-year change in the rolling average share of concentrators in a given cluster, metro area, and 12th grade cohort (vertical axis) against the three-year change in rolling average employment shares in aligned occupations in the same area and year (horizontal axis), overlaid with a linear fit (solid red line). The underlying data are grouped into 100 evenly sized bins. Scatter points represent averages within these bins.

Table 5. Dynamic Alignment, by Entry-Level Education and 0-4 Year Lagged Employment

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | All occupations | | | | |
| | 4 years prior | 3 years prior | 2 years prior | 1 year prior | current year |
| Aligned lagged/current area employment | 0.025 | 0.087* | 0.128 | 0.123 | 0.103 |
| | (0.034) | (0.042) | (0.068) | (0.089) | (0.137) |
| | HS-level occupations | | | | |
| | 4 years prior | 3 years prior | 2 years prior | 1 year prior | current year |
| Aligned lagged/current area employment | -0.044 | 0.001 | 0.025 | 0.018 | 0.027 |
| | (0.029) | (0.034) | (0.053) | (0.074) | (0.090) |
| | College-level occupations | | | | |
| | 4 years prior | 3 years prior | 2 years prior | 1 year prior | current year |
| Aligned lagged/current area employment | 0.037 | 0.094* | 0.136* | 0.098 | 0.033 |
| | (0.032) | (0.036) | (0.065) | (0.073) | (0.095) |
| Metro-cluster-years | 3,536 | 4,269 | 5,001 | 5,708 | 6,211 |

*Notes*: The table reports results from Equation (2), i.e., the correlation between lagged or current employment and the number of 12th graders concentrating in aligned fields (both measured in logs). Each reported coefficient is from a separate regression. Controlling for area-by-cluster and year fixed effects, coefficients quantify the extent to which within-area changes in lagged employment in particular fields are associated with within-area changes in the number of concentrators in those fields. Standard errors, in parentheses below coefficients, allow for correlated errors within metro areas. * signifies statistical significance at 95% confidence or greater.

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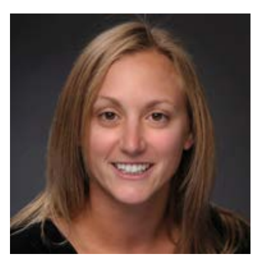

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## About the Georgia Policy Labs

The Georgia Policy Labs is an interdisciplinary research center that drives policy and programmatic decisions that lift children, students, and families—especially those experiencing vulnerabilities. We produce evidence and actionable insights to realize the safety, capability, and economic security of *every* child, young adult, and family in Georgia by leveraging the power of data. We work alongside our school district and state agency partners to magnify their research capabilities and focus on their greatest areas of need. Our work reveals how policies and programs can be modified so that every child, student, and family can thrive.

Housed in the Andrew Young School of Policy Studies at Georgia State University, we have three components: the Metro Atlanta Policy Lab for Education (metro-Atlanta K–12 public education), the Child & Family Policy Lab (supporting children, families, and students through a cross-agency approach), and the Career & Technical Education Policy Exchange (a multi-state consortium exploring high-school based career and technical education).

Learn more at gpl.gsu.edu.