Georgia State University
ScholarWorks @ Georgia State University

GPL Reports
Georgia Policy Labs

10-2020

Engagement with Career and Technical Education in Tennessee High Schools: Interim Report

Ge Wu
University of Tennessee, Gwu11@vols.utk.edu

Celeste Carruthers
University of Tennessee, Knoxville, carruthers@utk.edu

Career & Technical Education Policy Exchange

Georgia Policy Labs

Engagement with Career and Technical Education in Tennessee High Schools:

Interim Report

October 2020

Ge Wu
University of Tennessee

Celeste K. Carruthers
University of Tennessee

Contents

HIGHLIGHTS

- Throughout much of the United States, career and technical education (CTE) is offered as one or more elective sequences within comprehensive high schools.
- We know very little about why students select into CTE in such systems, or more generally, whether the labor market affects students' choice of coursework in high school.
- We test whether changes in the local labor market align with and affect course enrollments in three "in-demand" CTE career clusters in Tennessee: advanced manufacturing, information technology, and health science.
- We find evidence of roughly proportionate alignment between changes in advanced manufacturing CTE course-taking and changes in local manufacturing employment in recent years.
- Instrumental variable estimates, however, suggest that this is not necessarily due to students responding to local employment dynamics.
- We do not detect evidence of alignment, causal or otherwise, for health science or information technology CTE.

BACKGROUND

In the United States, the introduction of occupation-specific vocational education into public schools grew out of the early 20th-century industrial revolution, a resulting movement away from apprenticeships, and the expansion of free public high schools (Carruthers & Jepsen, 2020). Technical high schools proliferated in some parts of the country, notably the Northeast, while other areas incorporated vocational learning into comprehensive high schools. The latter, more integrated model is common throughout Tennessee to this day. The state has very few schools dedicated exclusively to technical education, but almost all high schools offer some form of what came to be called career and technical education (CTE).[1]

There is a longstanding tension about the purpose and effects of career and technical education in public schools. Practical learning in up-to-date occupational skills may help graduates move seamlessly into well-paying work (Kemple & Willner, 2008) but at the potential risk of crowding out general skills that transfer between occupations and survive technological change. Hanushek et al. (2017) find evidence of such a tradeoff, manifested as a flatter age-earnings profile among vocationally-educated individuals across 11 countries. Nevertheless, there is a persistent call among both economists and policymakers for formal, public technical education in skills that are aligned with the labor market needs (Cullen et al., 2013; Gonzales & Gong, 2019; Scott & Thompson, 2019).

The degree of alignment between local labor markets and CTE enrollment and the effect of local labor market shocks on CTE enrollment in aligned fields is the focus of this study. Like most states, Tennessee's CTE programs of study are currently organized into 16 career clusters, spanning almost all occupations in

[1] The nationwide semantic shift from "vocational" education to "career and technical" education in the 1990s was in response to a negative stigma attached to vocational programs.

the modern economy.[2] We focus on three occupation groups that have been identified as "in-demand" by Tennessee's economic development agency (Scott & Thompson, 2019): Information Technology, Production, and Healthcare. These fields have direct correspondence to three career clusters offered by K-12 schools—information technology, advanced manufacturing, and health science—and to occupation classifications for which we can observe annual, metro-level employment and wage estimates from the Bureau of Labor Statistics (BLS). Table 1 illustrates our mapping between CTE career clusters and occupations.

Table 1. Mapping between Career Clusters and Occupations

TDOE Career Cluster	BLS Occupation
Advanced Manufacturing	Production Occupations
Information Technology	Computer and Mathematical Occupations
Health Sciences	Healthcare Practitioner and Technical Occupations, Healthcare Support Occupations

RESEARCH QUESTIONS

1) Are course enrollments aligned with changes in the area labor market?
2) Are course enrollments affected by changes in the area labor market?

RELATED RESEARCH

There is a large body of research describing how students are affected by particular kinds of academic high school coursework (see, among others, Altonji, 1992; Rose & Betts, 2004; Attewell & Domina, 2008; Long et al., 2009; Long et al., 2012), as well as a smaller but growing literature on the later effects of CTE coursework (Mane, 1999; Kreisman & Stange, 2020) or enrollment in a dedicated technical high school (Dougherty et al., 2019; Hemelt & Lenard, 2019). The literature is relatively quiet on *why* students choose particular courses in high school. Filling this gap will inform models of how individuals with different skills interact with the labor market after school,[3] as well as the study of CTE in settings like Tennessee, where endogenous sorting into CTE and into particular clusters complicates causal inferences about the link between CTE and later student outcomes. In this study, we investigate whether shocks to local labor markets affect student investment in related fields—a question with economic and practical importance for policymakers and practitioners who value alignment between workforce and education sectors.

We may have a murky understanding of why students choose particular high school courses, but researchers have found a causal connection between the labor market and postsecondary study in a variety of national and local contexts (see, for example, Blom et al., 2015; Weinstein, 2017; Goulas &

[2] Tennessee CTE career clusters include Advanced Manufacturing; Agriculture, Food, & Natural Resources; Architecture & Construction; Arts, Audio/Visual Technology, & Communications; Business Management & Administration; Education & Training; Finance; Government & Public Administration; Health Science; Hospitality & Tourism; Human Services; Information Technology; Law, Public Safety, Corrections, & Security; Marketing, Distribution, & Logistics; STEM; and Transportation.
[3] Lazear (2009), for example, takes an individual's skill mix as exogenous upon entry to the labor market.

Megalokonomou, 2019; Han & Winters, 2019; Liu et al., 2019). This vein of research generally indicates that students' decisions to enroll in college or to major in particular fields is influenced by the labor market, although Wiswall and Zafar (2015) find that a large component of student major choice is explained by unobserved and idiosyncratic tastes.

Most related to our study 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 United States 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 are low in career clusters that sync with the nation's top fields: business, hospitality and tourism, marketing, and manufacturing.

We add to this body of work, first, by quantifying the extent of *dynamic alignment* between CTE engagement and the local workforce. Sublett and Griffith (2019) find evidence of alignment in a *static* sense, meaning that at a point in time, areas with more concentrated employment in particular sectors tend to have more concentrated student enrollment in affiliated clusters. Instead, we test whether *changes* in employment are associated with *changes* in affiliated CTE course-taking and course offerings. Estimates of dynamic alignment help us determine if CTE moves in sync with the labor market. Second, we are the first to examine whether dynamic alignment is due to a causal relationship whereby employment growth in a field encourages more students to study that field at the secondary level.

DATA

The Tennessee Department of Education (TDOE) provides student-level data on enrollment, course-taking, achievement, and student demographics. Results reported here are limited to school years 2013-14 through 2016-17. At this time, these are the years for which we can precisely map course codes to CTE career clusters.

The United States BLS provides publicly-accessible data on employment, measured at the area-by-year-by-occupation level. There are 14 areas across Tennessee, including 10 metropolitan areas anchored by one or more cities and four non-metropolitan areas covering more rural parts of the state.

We merge administrative TDOE and BLS data in the state's P-20 longitudinal data system. We match each student's high school to current and recent BLS employment statistics in the surrounding area.

Key variables include

1) Course enrollments: the total count of course enrollment in a given school, year, and cluster;
2) Course offerings: the number of unique courses offered in each school, year, and cluster; and
3) Area employment: total employment in occupations related to a given cluster, measured for each metropolitan or non-metropolitan area around a school and year.

Table 2 summarizes these variables for the academic years 2013-14 through 2016-17. At a glance, trends in enrollments, offerings, and related employment mirror some of the regression results to follow. Advanced manufacturing enrollments and offerings declined and then rose, as did manufacturing employment. But student participation in health science and information technology moved opposite of the labor market. Health science enrollments and offerings rose and then fell, whereas employment in health occupations fell from 2013 to 2014 before rising the following two years. Information technology enrollments and course offerings fell in each year of the panel even through "computing and mathematical" occupations were growing in number.

Table 2. Summary Statistics

	All	2013	2014	2015	2016
Course Participation					
Advanced Manufacturing Enrollments	73	83	68	69	74
Health Science Enrollments	235	231	251	228	229
Information Technology Enrollments	150	167	159	137	137
Course Offerings					
Advanced Manufacturing Course Offerings	2.7	2.7	2.6	2.6	2.8
Health Science Course Offerings	5.4	5.2	5.5	5.2	5.4
Information Technology Course Offerings	3.3	3.7	3.3	3.0	3.3
Area Employment					
Advanced Manufacturing	32,972	30,298	31,861	34,255	35,491
Health Science	37,325	35,909	35,837	38,241	39,340
Information Technology	8,058	7,431	7,671	8,204	8,936
Other Occupations	330,753	308,094	318,611	342,912	353,601
School-by-year Observations	1,644	408	417	412	407

STATISTICAL METHODS AND RESULTS

To address question the first research question, we estimate school-level longitudinal models of the form

$$C_{sgy}^{f} = L_{gt}^{f}\beta^{f} + X_{sgy}\gamma^{f} + \alpha_{s}^{f} + \alpha_{y}^{f} + \varepsilon_{sgy}^{f}, \tag{1}$$

where C_{sgy}^{f} is the log of total course-taking or the number of unique courses available in field f =*{advanced manufacturing, information technology, health sciences}* for school *s*, labor market *g*, and school year *y*. The key variable of interest is L_{gt}^{f}, the log of employment in field *f*, labor market *g*, and time $t \leq y$. Control variables in X_{sgy} include time-varying measures of a school's student composition in terms of gender, race, ethnicity, achievement, exceptionalities, and size. The parameters α_{s}^{f} and α_{y}^{f} are school and year fixed effects, respectively. In this two-way fixed effects model, we interpret estimates of β^{f} as the degree of alignment between changes in field employment in the local labor market and within-school changes in field coursework. This is a dynamic measure of alignment, assessing whether changes in area employment are associated with proportionate changes in course-taking and course availability a short time later. For Equation (1) and each of the models to follow, we allow for correlated errors within school *s*.

Table 3 reports results from estimates of Equation (1). Looking to the first row of results, we show evidence of alignment between a typical Tennessee area's growth in manufacturing employment and school-level growth in course-taking within the advanced manufacturing cluster. Following a 1 percent rise in manufacturing employment, aligned course-taking typically rose 0.759 percent the next year ($t = y\text{-}1$). Some portion of that may be due to student interest and another portion to schools expanding opportunities to take manufacturing courses. A 1 percent rise in manufacturing employment the prior year is associated with a 0.286 percent increase in courses in the cluster. Similarly, Table 3 reports evidence of alignment between changes in manufacturing course-taking, manufacturing course availability, and employment two and three years prior ($t = y\text{-}2$ for the middle panel of results, and $t = y\text{-}3$ for the lower panel), although correlations are smaller and less precise at $t = y\text{-}3$.

Table 3. Estimates of the Impact of Employment on Course-Taking/Offerings by Own Field

Dependent variable	Advanced Manufacturing		Health Science		Information Technology	
	Enrollment	Offering	Enrollment	Offering	Enrollment	Offering
Lag 1 Year						
Adv. Manuf. Emp.	0.759	0.286				
	(0.328)**	(0.131)**				
Health Science Emp.			-0.161	-0.037		
			(0.172)	(0.087)		
Info. Tech. Emp.					0.150	0.155
					(0.147)	(0.073)**
R2	0.888	0.897	0.925	0.941	0.898	0.889
Lag 2 Year						
Adv. Manuf. Emp.	1.139	0.747				
	(0.453)**	(0.196)***				
Health Science Emp.			0.399	-0.094		
			(0.319)	(0.164)		
Info. Tech. Emp.					0.367	0.178
					(0.263)	(0.113)
R^2	0.888	0.899	0.925	0.94	0.898	0.889
Lag 3 Year						
Adv. Manuf. Emp.	0.657	0.462				
	(0.506)	(0.211)**				
Health Science Emp.			0.514	-0.05		
			(0.360)	(0.147)		
Info. Tech. Emp.					-0.056	0.003
					(0.119)	(0.061)
R^2	0.888	0.897	0.925	0.941	0.898	0.889

Notes. Control variables include the percentage of female students in each school; the percentage of Black, Hispanic, and other race/ethnicity students in each school; percentage of male students; the average of students' ninth grade standardized math scores and English scores; the average of students' best ACT scores; the average number of school days that a student was marked as absent, suspended in, and suspended out in each school; percentage of gifted students; percentage of students who have individualized education plans; percentage of students who are ever classified as English Language Learners; and the indicator of missing values of each control covariates. Missing values for control variables are imputed at the mean. Standard errors reported in parentheses are clustered at the school level. */**/*** denotes significance at the 10/5/1 percent level.

Looking next to Table 3 results for health science and information technology, we find smaller, inconsistent, and imprecisely estimated associations between course-taking, course offerings, and growth or changes in related employment. The takeaway inference from Table 3 is that, across four recent school years, changes in the intensity of a typical school's advanced manufacturing CTE were positively aligned with changes in the surrounding area's employment in production occupations, whereas recent changes in health science and information technology CTE were less in sync with affiliated labor markets.

In order to interpret β^f estimates as the causal effect of local labor market dynamics on course availability and selection (research question #2), we need to assume that variation in L^f_{gt} is conditionally independent of unobserved determinants of C^f_{sgy}. That assumption would be violated if, for example, unobserved factors were driving dynamics in enrollment choices as well as employment fluctuations in a given field. For example, it is possible that the state recruited more employers in these fields while supporting expansion of related high school CTE offerings. This sort of intentional alignment has practical relevance but is not equivalent to the causal relationship implied by Equation (1).

In pursuit of causal inferences around the second research question, we also estimate Equation (2),

$$C^f_{sgy} = \sum_{f=1}^{F} L^f_{gt}\beta^f + X_{sgy}\gamma^f + \alpha^f_s + \alpha^f_y + \varepsilon^f_{sgy} \qquad (2)$$

where we simultaneously control for L^f_{gt} describing the labor market in three priority fields as well as all other fields. If changes in course enrollments for advanced manufacturing, for example, are more aligned with manufacturing employment than with employment in less relevant industries, we would be more confident in a causal effect of the local labor market. We estimate Equation (2) separately for each field of interest.

Table 4 lists results for Equation (2). As in Table 3, we find little evidence of systematic alignment between the health or information technology workforce and CTE course-taking or course offerings in those fields, but for manufacturing, Equation (2) results are similar to Equation (1) results reported in Table 3. In particular, a 1 percent increase in manufacturing employment is associated with a 0.987 percent increase in advanced manufacturing course-taking one year later and a 1.743 percent increase two years later, as well as a 1.179 percent increase in course offerings for the advanced manufacturing cluster. Within that same window of time, employment dynamics in health, information technology, or other occupations have no significant bearing on advanced manufacturing CTE. When we look for an advanced manufacturing CTE response to labor market fluctuations three years prior (results shown in the bottom panel of Table 4), results are less suggestive of dynamic alignment over that longer window of time. Advanced manufacturing CTE has no significant association with related employment growth three years prior. It is, however, negatively associated with health science and information technology employment and strongly and positively associated with employment in all other occupations.

Table 4. Estimates of the Impact of Employment by All Field

	Advanced Manufacturing		Health Science		Information Technology	
	Enrollment	Offering	Enrollment	Offering	Enrollment	Offering
	(1)	(2)	(3)	(4)	(5)	(6)
Lag 1 Year						
Adv. Manuf. Emp.	0.987	0.158	-0.184	-0.037	0.007	-0.078
	(0.415)**	-0.175	-0.382	-0.149	-0.387	-0.187
Health Science Emp.	-0.515	-0.318	-0.194	-0.077	-0.354	0.012
	-0.457	(0.187)*	-0.335	-0.151	-0.423	-0.19
Info. Tech. Emp.	0.041	0.02	0.034	-0.007	0.164	0.105
	-0.201	-0.083	-0.158	-0.075	-0.174	-0.086
Other Occupations Emp.	0.263	0.727	0.243	0.137	0.386	0.332
	-0.763	(0.341)**	-0.483	-0.258	-0.672	-0.326
R2	0.8883	0.8974	0.9251	0.9407	0.8978	0.8893
Lag 2 Year						
Adv. Manuf. Emp.	1.743	1.179	0.072	0.238	-0.358	-0.035
	(0.589)***	(0.245)***	-0.387	-0.172	-0.453	-0.213
Health Science Emp.	-0.545	-0.252	0.25	-0.21	0.532	0.133
	-0.511	-0.215	-0.431	-0.218	-0.444	-0.243
Info. Tech. Emp.	-0.198	-0.108	-0.046	-0.035	0.339	0.103
	-0.346	-0.134	-0.209	-0.094	-0.265	-0.115
Other Occupations Emp.	-1.033	-1.059	0.525	0.073	0.995	1.167
	-1.785	-0.719	-1.164	-0.476	-1.338	(0.676)*
R2	0.8888	0.8993	0.9252	0.9409	0.8983	0.8899
Lag 3 Year						
Adv. Manuf. Emp.	0.628	0.32	-0.007	0.214	-0.913	-0.292
	-0.63	-0.261	-0.325	-0.17	(0.418)**	-0.232
Health Science Emp.	-1.071	-0.502	0.444	-0.18	0.42	-0.118
	(0.512)**	(0.210)**	-0.44	-0.189	-0.466	-0.237
Info. Tech. Emp.	-0.4	-0.098	0.002	0.041	-0.212	-0.149
	(0.187)**	-0.07	-0.106	-0.063	-0.134	(0.071)**
Other Occupations Emp.	3.747	2.076	0.418	0.188	4.558	3.562
	(2.143)*	(0.891)**	-1.495	-0.81	(1.764)**	(0.860)***
R2	0.8885	0.8979	0.9252	0.9409	0.8988	0.891
Observations	1622	1622	1622	1622	1622	1622

Notes. Control variables include the percentage of female students in each school; the percentage of Black, Hispanic, and other race/ethnicity students in each school; percentage of male students; the average of students' ninth grade standardized math scores and English scores; the average of students' best ACT scores; the average number of school days that a student was marked as absent, suspended in, and suspended out in each school; percentage of gifted students; percentage of students who have individualized education plans; percentage of students who are ever classified as English Language Learners; and the indicator of missing values of each control covariates. Missing values for control variables are imputed at the mean. Standard errors reported in parentheses are clustered at the school level. */**/*** denotes significance at the 10/5/1 percent level.

Finally, we take a longer view of course enrollment dynamics by differencing Equation (1) and estimating the following

$$\Delta C_{sg}^{f} = \alpha + \Delta L_{g}^{f}\beta^{f} + \Delta X_{sg}\gamma^{f} + \eta_{sg}^{f}, \tag{3}$$

where ΔC_{sgy}^{f} is the change in log course enrollments for field f between the first and last year of currently available transcript data (2013-14 and 2016-17), and ΔL_{g}^{f} is the change in log employment in that field. In addition to estimating Equation (3) as a reduced form, we instrument for ΔL_{g}^{f} using a Bartik-style interaction between the pre-existing importance of field f to the local labor market (defined as the share of area employment in that field in 2012) and national growth in employment in that field, excluding area g (Bartik, 1991). In order to interpret β^{f} causally, the instrument for each field needs to be a strong predictor of local employment growth in that field, and furthermore, we need to assume that the instrument does not affect CTE course-taking or course offerings except through its strong relationship with the labor market.

Equation (3) results are listed in Table 5. Panel C reports estimates of the first-stage effect of Bartik instruments on changes in field-specific employment. The instrument is strong for each field, although of the opposite sign as theorized for information technology. On average, information technology employment fell in areas with a larger pre-existing share of the workforce in information technology, contrary to the pattern observed for manufacturing and health occupations. This puzzle is in part due to one outlier metro area with a very large decline in information technology employment, although Table 5 results are similar when we exclude schools in this area.

Table 5. Estimates of the Impact of Employment on Course-Taking/Offerings by Own Field

Dependent variable	Advanced Manufacturing		Health Science		Information Technology	
	Enrollment	Offering	Enrollment	Offering	Enrollment	Offering
Panel A: OLS						
Adv. Manuf. Emp.	0.749	0.172				
	(0.410)*	(0.167)				
Health Science Emp.			-0.314	-0.179		
			(0.255)	(0.117)		
Info. Tech. Emp.					0.037	0.164
					(0.218)	(0.101)
R^2	0.08	0.036	0.143	0.093	0.087	0.125
Panel B: IV						
Adv. Manuf. Emp.	-0.127	0.001				
	(0.597)	(0.339)				
Health Science Emp.			0.094	-0.755		
			(0.587)	(0.264)***		
Info. Tech. Emp.					-0.202	0.205
					(0.809)	(0.392)
R^2						
Panel C: First Stage						
Bartik IV for Employment	59.723		44.468		-35.873	
	(4.309)***		(7.466)***		(6.243)***	
F Statistic	192.1		35.48		33.02	
Observations	371		371		371	

Notes. The control variables include the growth rate from 2013 to 2016 of the following variables: percentage of female students in each school; the percentage of Black, Hispanic, and other race/ethnicity students in each school; percentage of male students; the average of students' ninth grade standardized math scores and English scores; the average of students' best ACT scores; the average number of school days that a student was marked as absent, suspended in, and suspended out in each school; percentage of gifted students; percentage of students who have individualized education plans; percentage of students who are ever classified as English Language Learners. Standard errors that reported in parentheses are clustered at school level. */**/*** denotes significance at the 10/5/1 percent level.

As a reduced form (Panel A), Equation (3) results for advanced manufacturing course-taking and course offerings are similar to what we found from Equations (1) and (2), but differencing the model reduces precision. Growth in manufacturing employment is associated with growth in manufacturing course-taking, and although confidence intervals for the first point estimate are wide, we cannot rule out a proportionate relationship. Nevertheless, in Panel B of Table 5, we do not see evidence of a causal link between growth in area manufacturing employment (specifically, growth induced by national shocks to the manufacturing industry) and growth in a school's advanced manufacturing CTE. The point estimate is negative and statistically insignificant.

Equation (3) instrumental variable estimates for health science and information technology CTE are also not indicative of a causal alignment between those clusters and related employment growth. On the contrary, a 1 percent rate of growth in health employment between 2012 and 2015 is tied to a 0.755 percent decline in the rate of growth in health course offerings.

PRELIMINARY INFERENCES AND FUTURE WORK

This interim report describes results of a research design that was pre-registered in March 2020.[4] We take an aggregate view of CTE course-taking, course availability, and area employment and test for dynamic alignment as well as a causal relationship connecting labor market fluctuations to changes in affiliated CTE course-taking. Looking across four recent school years, we find that changes in a school's advanced manufacturing CTE have been roughly in proportion to changes in nearby production employment 1-2 years prior. This dynamic alignment may have been coincidental or driven by external factors, however, rather than a direct response of students and schools to area employment. Where an area's manufacturing employment grew in response to national trends, we did not detect a chain reaction effect on engagement in advanced manufacturing CTE. For health science and information technology CTE, we did not detect evidence of coincidental or causal alignment.

Ongoing work will expand on this research design in four ways. First, we will work to extend the timeline of observed CTE cluster engagement to school years prior to 2013-14 and after 2016-17. This will afford us more statistical power to detect aggregate changes and allow us to test for CTE responsiveness during the early years of recovery from the Great Recession. Second, we will descriptively explore whether students have better labor market outcomes coming out of programs that are better aligned to labor market conditions. Third, we will compute Rotemberg (1983) weights to better understand how each metro area is contributing to identification of Equation (3) as well as the plausibility of that model's identifying assumptions (Goldsmith-Pinkham et al., 2020). Fourth, we will use student-level data to look below the surface of aggregate results by, for example, assessing whether student responsiveness differs by grade level, prior achievement, race, or gender.

[4] This report describes findings from a research design that was registered on the Open Science Framework: osf.io/kq2cw.

ACKNOWLEDGMENTS

We are grateful to Jonathon Attridge, Eden Morrison, Steve Playl, and Sarah Williams for their thoughtful comments and answers to our technical and institutional questions and to the 2019 and 2020 CTEx meeting participants for their feedback. We additionally thank Hebeh Hindieh for excellent research assistance. Finally, we are grateful to the Georgia Policy Labs' CTEx consortium, including Japera Hemming and Tyler Rogers for project management and planning. This project is ongoing, and comments are most welcome. Any errors are our own.

REFERENCES

Altonji, J. G. (1992). *The effects of high school curriculum on education and labor market outcomes* (No. w4142). National Bureau of Economic Research.

Attewell, P., & Domina, T. (2008). Raising the bar: Curricular intensity and academic performance. *Educational Evaluation and Policy Analysis*, *30*(1), 51-71.

Bartik, T. J. (1991). Who benefits from state and local economic development policies? W.E. Upjohn Institute. Kalamazoo.

Blom, E., Cadena, B. C., & Keys, B. J. (2015). Investment over the business cycle: Insights from college major choice. Working paper.

Carruthers, C. K., and C. Jepsen. (2020). Vocational Education: An International Perspective. Working Paper. Working paper.

Cullen, J. B., Levitt, S. D., Robertson, E., & Sadoff, S. (2013). What can be done to improve struggling high schools? *Journal of Economic Perspectives*, *27*(2), 133-52.

Dougherty, S. M., Gottfried, M. A., & Sublett, C. (2019). Does Increasing Career and Technical Education Coursework in High School Boost Educational Attainment and Labor Market Outcomes? *Journal of Education Finance*, *44*(4), 423-447.

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, *110*(8), 2586-2624.

Gonzales, J. and D. Gong. (2019). Tennessee Gov. Bill Lee proposes more than $25 million to fund vocational training program. *The Tennessean*.

Goulas, S., & Megalokonomou, R. (2019). Which degrees do students prefer during recessions? *Empirical Economics*, *56*(6), 2093-2125.

Han, L., & Winters, J. V. (2020). Industry Fluctuations and College Major Choices: Evidence from an Energy Boom and Bust. *Economics of Education Review*, *77*, 101996.

Hanushek, E. A., Schwerdt, G., Woessmann, L., & Zhang, L. (2017). General education, vocational education, and labor-market outcomes over the lifecycle. *Journal of Human Resources*, *52*(1), 48-87.

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

Kemple, J. J., & Willner, C. J. (2008). *Career academies: Long-term impacts on labor market outcomes, educational attainment, and transitions to adulthood* (pp. 4-5). New York, NY: MDRC.

Kreisman, D., & Stange, K. (2020). Vocational and career tech education in American high schools: The value of depth over breadth. *Education Finance and Policy*, *15*(1), 11-44.

Liu, S., Sun, W., & Winters, J. V. (2019). Up in STEM, down in business: Changing college major decisions with the Great Recession. *Contemporary Economic Policy*, *37*(3), 476-491.

Long, M. C., Conger, D., & Iatarola, P. (2012). Effects of high school course-taking on secondary and postsecondary success. *American Educational Research Journal*, *49*(2), 285-322.

Long, M. C., Iatarola, P., & Conger, D. (2009). Explaining gaps in readiness for college-level math: The role of high school courses. *Education Finance and Policy*, *4*(1), 1-33.

Mane, F. (1999). Trends in the payoff to academic and occupation-specific skills: the short and medium run returns to academic and vocational high school courses for non-college-bound students. *Economics of Education Review*, *18*(4), 417-437.

Rose, H., & Betts, J. R. (2004). The effect of high school courses on earnings. *Review of Economics and Statistics*, *86*(2), 497-513.

Rotemberg, J. (1983). Instrument variable estimation of misspecified models. Working paper.

Scott, K., and A. Thompson. (2019). *LEAP 2019: In-Demand Occupations*. Tennessee Department of Economic & Community Development. Nashville.

Sublett, C., & Griffith, D. (2019). How Aligned Is Career and Technical Education to Local Labor Markets?. *Thomas B. Fordham Institute*.

Weinstein, R. (forthcoming). Local labor markets and human capital investments. *Journal of Human Resources*.

Wiswall, M., & Zafar, B. (2015). Determinants of college major choice: Identification using an information experiment. *The Review of Economic Studies*, *82*(2), 791-824.

ABOUT THE AUTHORS

Ge Wu is a Ph.D. student in economics at the University of Tennessee. Her research interests center on the economics of education and environmental policy. She graduated *summa cum laude* with a Bachelor of Arts in economics and a Bachelor of Business Administration in finance from the University of Missouri-Kansas City and earned an M.A. in finance from Purdue University.

Celeste K. Carruthers is an associate professor in the Haslam College of Business at the University of Tennessee (UT) with a joint appointment in the department of economics and the Boyd Center for Business and Economic Research. Her research centers on education policy with crossovers into public economics, labor economics, and economic history. She is editor-in-chief of *Economics of Education Review*, a former member of the Association for Education Finance and Policy Board of Directors, and she has served as a faculty advisor to several fellows in the Harvard Graduate School of Education Strategic Data Project. Before arriving at UT in 2009, Carruthers earned a Ph.D. in economics from the University of Florida, an M.A. in economics from the University of New Hampshire, and a bachelor's degree in economics and accounting from Appalachian State University.

ABOUT THE GEORGIA POLICY LABS

The Georgia Policy Labs (GPL) is a collaboration between Georgia State University and a variety of government agencies to promote evidence-based policy development and implementation. Housed in the Andrew Young School of Policy Studies, GPL works to create an environment where policymakers have the information and tools available to improve the effectiveness of existing government policies and programs, try out new ideas for addressing pressing issues, and decide what new initiatives to scale. The goal is to help government entities more effectively use scarce resources and make a positive difference in people's lives. GPL has three components: The Metro Atlanta Policy Lab for Education works to improve K-12 educational outcomes; the Career and Technical Education Policy Exchange focuses on high-school-based career and technical education in multiple U.S. states; and the Child & Family Policy Lab examines how Georgia's state agencies support the whole child and the whole family. In addition to conducting evidence-based policy research, GPL serves as a teaching and learning resource for state officials and policymakers, students, and other constituents. See more at gpl.gsu.edu.