Community College Program Choices in the Wake of Local Job Losses

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Deciding which field to study is one of the most consequential decisions college students make, but most research on the topic focuses on students attending 4-year colleges. To understand how students attending community colleges make field-of-study decisions, I link administrative educational records of recent high school graduates with local mass layoff and plant-closing announcements. I find that declines in local employment deter students from entering closely related community college programs and instead induce them to enroll in other vocationally oriented programs. Students predominantly shift enrollment between programs that lead to occupations requiring similar skills.

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I. Introduction

Large earnings gaps exist among students with the same level of education who pursue different fields of study (Altonji, Blom, and Meghir 2012). And while a growing body of literature shows that students take these gaps into account when selecting college majors (Montmarquette, Cannings, and Mahseredjian 2002; Beffy, Fougere, and Maurel 2012; Long, Goldhaber, and Huntington-Klein 2015; Wiswall and Zafar 2015), the majority of research focuses on the 4-year college sector. The nearly 10 million students who attend 2-year community colleges (National Center for Education Statistics 2018) also decide which fields to study, and their decisions have similarly large implications for their labor market outcomes. For example, graduates of health-care programs experience large earnings gains (Grosz 2020), while some other programs provide minimal returns above a high school diploma (Bahr et al. 2015; Belfield and Bailey 2017; Stevens, Kurlaender, and Grosz 2019). In response, policy makers have begun tying community colleges' funding to the production of degrees in particular fields (Snyder and Boelscher 2018) and designing financial aid programs that incentivize students to choose in-demand programs (Allen 2019; Natanson 2019). Yet there is little evidence on the extent to which labor market opportunities affect community college students' program choices.

In this paper, I use administrative data on the postsecondary education choices of recent Michigan high school graduates to determine how local, occupation-specific job losses affect community college program enrollment. Such losses are likely to be particularly influential to community college students because they tend to remain close to home during college and after graduating, making it likely that local, rather than state or national, labor demand shapes their labor market expectations.[1] Furthermore, community college programs are generally designed to take 2 years or less to complete, so students may weigh short-term fluctuations in labor demand more heavily than 4-year students when choosing their major. Finally, community college programs are often tied to specific occupations, such that the expected labor market opportunities associated with programs align closely with those in specific occupations.

My empirical approach exploits plausibly exogenous variation in students' exposure to local job losses resulting from mass layoffs and plant closings that differentially affect particular occupations. I find that, on average, an additional layoff per 10,000 working-age residents in a county reduces the

[1] The median distance a community college student travels to campus is only 8 miles (Hillman and Weichman 2016), and more than 60% of community college graduates live within 50 miles of the college they attended (Sentz et al. 2018). In Michigan, I estimate that 66% of all students who attend community colleges within 6 months of high school graduation and 86% of those who live in a county with a community college campus attend one located in their county.

share of the county's high school graduates enrolling in related community college programs the following year by 0.8%. Correspondingly, a 1 standard deviation increase in layoff exposure reduces enrollment by 3.8%. This effect is driven by students substituting enrollment between community college programs rather than forgoing higher education opportunities. Leveraging data on occupational skill requirements from the US Department of Labor's Occupational Information Network (O*NET), I document that students primarily shift their enrollment into programs that require similar cognitive and technical skills to the field affected by layoffs.

These results add to a large body of work on students' college major choices. Most prior research at the 4-year college level finds that expected wages modestly influence students' choices (Altonji, Arcidiacono, and Maurel 2016). In the community college setting, Baker et al. (2018) find that students' program choices respond to new information about labor market outcomes, and Grosz (2019) shows that the distribution of community college program completions has kept pace with statewide employment composition changes in California. I build on these findings by showing that county-level job losses also affect students' choices across community college programs. In line with prior work, the magnitude of these effects is small, suggesting that factors outside the labor market play a substantial role in determining students' choices.

This paper also provides new evidence on the effect of local labor market shocks on education choices. Several recent papers show that negative labor market shocks lead to an increase in college enrollment (Hubbard 2018; Foote and Grosz 2020), while positive shocks have the opposite effect (Charles, Hurst, and Notowidigdo 2018). However, few papers consider the occupation- or industry-specific nature of such shocks. Two recent exceptions are Weinstein (forthcoming), who finds that various industry-level shocks affect the composition of college majors at nearby 4-year universities, and Huttunen and Riukula (2019), who find that Finnish children are less likely to enter the same field of study as their parent when their parent has been laid off. I find similar responses to local shocks among a previously unstudied population of students and also show that students shift enrollment toward programs that require similar skills, which has not been documented in prior work.

II. Conceptual Framework

To see the potential effects of mass layoffs and plant closings on students' educational decisions, consider a simplified setting where student i decides between four different postsecondary options: (1) a community college vocational program that leads to a career in occupation group A (e.g., health); (2) a community college vocational program that leads to a career in occupation group B (e.g., business); (3) a 4-year college program (leading to a bachelor's degree); or (4) direct labor market entry.[2] Each alternative, j, is associated with an expected lifetime benefit, Y_{ij}, and an expected cost, C_{ij}. Students choose the alternative that maximizes their utility: $U_{ij} = U_i(Y_{ij} - C_{ij})$, where U_i is some increasing concave function.

Suppose that a plant closing or mass layoff occurs in student i's county before she makes her first postsecondary decision (i.e., before she graduates from high school). Consider one shock that affects only community college health occupations and reduces the expected earnings of pursuing health programs, compared with another where the shock affects all occupations in the economy and reduces Y_{ij} for all alternatives. In the first example, the utility student i receives from entering a community college health program will decrease, and she may choose a different postsecondary option. If the student has a strong taste for vocational education, she will likely shift her enrollment into the other vocational program. If not, she may no longer enroll in college or may enroll in a 4-year college program instead. In contrast, in the second example, the utility student i receives from each alternative will decrease, and the student's choice should be less affected. These examples highlight that the anticipated effects of layoffs depend on the distribution of job losses across different segments of the economy and show that labor market shocks can have large effects without inducing students to change whether or where they enroll in college. Previous studies that consider only the effects of layoffs on college entry do not capture this response and potentially miss important labor market implications, since the returns to a community college education vary significantly across programs.

III. Institutional Setting and Enrollment Data

Michigan is home to 28 public community colleges that enroll more than 300,000 students annually (Michigan Community College Association 2019). All are open-enrollment institutions, meaning that students can enroll regardless of academic preparation.[3] They primarily confer certificates and associate degrees, which may be either vocational or nonvocational in nature.[4] Vocational programs are designed to prepare students for immediate entry

[2] Students may also choose to enroll in a nonvocational pretransfer program at a community college, which I implicitly consider as part of option 3, a 4-year college program.

[3] Colleges may set admissions standards for individual programs, but most programs do not have such requirements. For example, at Lansing Community College, one of the largest in the state, only 10 of more than 200 programs currently use selective admissions (https://www.lcc.edu/academics/selective-admissions.html). Similarly, programs may face capacity constraints, which would attenuate the estimated effects of labor market shocks on substitution between programs. The level of program aggregation I use and the prevalence of course-level, rather than program-level, constraints limit the likelihood that these constraints pose major issues in the analysis.

[4] Since 2012, Michigan's community colleges have been able to confer bachelor's degrees in a small number of fields. However, as of 2016, community colleges had awarded only 116 bachelor's degrees (House Fiscal Agency 2017).

into specific occupations, whereas nonvocational programs typically consist of general education courses that students can transfer to 4-year colleges.

A. Mapping Community College Programs to Occupations

To analyze how local labor market shocks affect enrollment in related community college programs, I first map all of Michigan's community college programs to related occupations using data from the state's Department of Treasury and Workforce Development Agency.[5] I match each program's six-digit Classification of Instructional Program (CIP) code to its associated Standard Occupation Classification (SOC) code using a crosswalk developed by the Bureau of Labor Statistics (BLS) and the National Center for Education Statistics. The crosswalk matches a CIP code to an occupation if "programs in the CIP category are preparation directly for entry into and performance in jobs in the SOC category" (National Center for Education Statistics 2011, 3), but programs may be matched to occupations that require more than an associate's degree. To ensure that programs are mapped to occupations community college graduates may enter, I further match the occupation codes to job preparation requirements from O*NET and limit the occupation matches to those that require at least a high school diploma but not necessarily a bachelor's degree. I then define a program as vocational if it is matched to an occupation within this subset of attainable occupations. All other programs, including pretransfer programs, are considered nonvocational. I further create six broad groups of programs based on programs' matched occupations: business, health, skilled trades, STEM (science, technology, engineering, and mathematics), law enforcement, and other. I create these groupings by combining programs that are matched to similar two-digit SOC occupation codes and, throughout the remainder of the text, refer to the occupations they contain as "community college occupations."[6] Table A.2 (tables A.1–A.13, B.1, C.1, C.2 are available online) provides a list of the two-digit SOC codes contained within each group.

B. Enrollment in Michigan's Community College Programs

I obtain community college program enrollment data from an administrative data set provided by the Michigan Department of Education and the Center for Educational Performance and Information that links Michigan

[5] The Workforce Development Agency maintains an online database of all current programs offered by the state's community colleges. In 2011 and 2013, the Department of Treasury additionally published the Michigan Postsecondary Handbook, which provides a listing of all programs offered by each college. Table A.1 presents summary statistics of these offerings in 2011.

[6] Ninety-five percent of programs are matched to only one two-digit SOC occupation code. For the 5% (22 programs) that are matched to more than one two-digit SOC code, I assign programs to the occupation group of the matched occupation that had higher statewide employment in 2009.

public high school graduates from 2009 to 2016 to college enrollment records from the National Student Clearinghouse and a state-run data repository (Student Transcript and Academic Record Repository, or STARR).[7] The high school records provide basic information on students' demographic characteristics, including their race, gender, economic disadvantage status, and census block of residence. The college link contains all records of students' enrollments in colleges covered by the databases and information on the academic programs in which they enroll.

I focus my analysis on high school graduates' first college enrollment and program choices within 6 months (180 days) of graduating from high school.[8] Table 1 provides summary statistics on Michigan's high school graduates disaggregated by their postsecondary education choices within this time frame. A nontrivial share of students enroll in vocational and nonvocational community college programs each year: 9% and 14% of graduates, respectively.[9] Students who enroll in vocational programs are more likely to be male, nonwhite, and economically disadvantaged than students in nonvocational programs. They also score lower on state standardized tests, but compared with their peers who do not enroll in college, they are less disadvantaged and more academically prepared. Table A.3 further disaggregates the summary statistics by students' vocational program choices.[10]

IV. Measuring Local Job Losses

I measure students' exposure to local job losses using a listing of all mass layoffs and plant closings reported under the federal Worker Adjustment

[7] The restriction of the data set to students attending public high schools is relatively minor, as only about 5%–6% of twelfth graders in Michigan attend private schools. See https://www.mischooldata.org/historical-nonpublic-student-counts for more information.

[8] While many adults also enroll in community colleges, I estimate that two-thirds of graduates of the class of 2009 who enroll in community colleges within 8 years of high school graduation do so within the first 6 months. Appendix C (apps. A–C are available online) considers enrollment decisions over a longer time horizon, as well as the effects of layoffs on program retention.

[9] A total of 7.9% of community college students simultaneously enroll in a vocational and nonvocational program. I classify these students as enrolling in vocational programs. A total of 6.3% of vocational students enroll in more than one six-digit CIP code. If a student enrolls in two programs and one of the programs is in the "other" category, I assign the student to the alternative program. Otherwise, I randomly assign the student to enroll in one of the programs she has selected. The results are nearly identical if I instead drop students who enroll in multiple program groups.

[10] Figure A.1 tabulates the share of courses taken in different subject areas among students enrolled in different programs. Students who indicate enrollment in a given program group take disproportionately more courses and earn disproportionately more credits in the subject area of their program than students in other program groups.

Table 1
Summary Statistics of Michigan's High School Graduates

Variable	All Graduates (1)	CC Vocational (2)	CC Nonvocational (3)	Other College (4)	No College (5)
White	.760	.738	.789	.785	.723
Black	.150	.176	.128	.128	.178
Hispanic	.041	.046	.040	.027	.057
Male	.490	.537	.465	.443	.543
Economically disadvantaged	.333	.366	.324	.222	.461
English language learner	.025	.039	.036	.010	.035
Standardized math score	.095	−.165	−.028	.532	−.305
Standardized reading score	.087	−.205	−.048	.524	−.303
On-time graduation	.971	.984	.986	.997	.931
Students	734,928	66,292	103,032	306,532	259,072
Share of graduates	1.000	.090	.140	.417	.353

NOTE.—The sample consists of all graduates of Michigan public high schools from 2009 to 2016 who have nonmissing demographic and geographic information and are not enrolled in juvenile detention centers, adult education, or alternative education programs. College and program choices are defined as a student's first enrollment choice within 6 months (180 days) of graduating high school. For example, the sample in col. 2 consists of all students who first enroll in vocational programs in Michigan's community colleges within 6 months of high school graduation. CC = community college.

and Retraining Notification (WARN) Act of 1989.[11] The WARN Act requires employers with 100 or more employees to provide at least 60 days' notice to employees ahead of either a plant closing affecting 50 or more employees at a single employment site or a mass layoff affecting either 500 or more employees or between 50 and 499 employees who account for at least one-third of the employer's workforce (US Department of Labor 2019). Employers must give written notice of the anticipated layoff to the employees' representative (e.g., a labor union), the chief local elected official (e.g., the mayor), and the state dislocated worker unit, or they are liable to provide employees with back pay and benefits for up to 60 days. However, government entities do not face these regulations, which limits my ability to observe layoffs in law enforcement professions—one of Michigan's most popular community college program groups. Therefore, I supplement the WARN data with a listing of correctional facility closures and corresponding staff reductions from Michigan's Senate Fiscal Agency.

A. Generating Occupation-Specific Layoff Exposure

Figure 1*A* plots the number of mass layoffs, plant closures, and correctional facility closings reported during each academic year from 2001 to 2017, where I define academic years as July 1 of year *t* to June 30 of year

[11] The annual WARN listings are available from Michigan's Bureau of Labor Market Information and Strategic Initiatives (https://milmi.org/warn). Appendix B compares these data to other commonly used sources of labor market data.

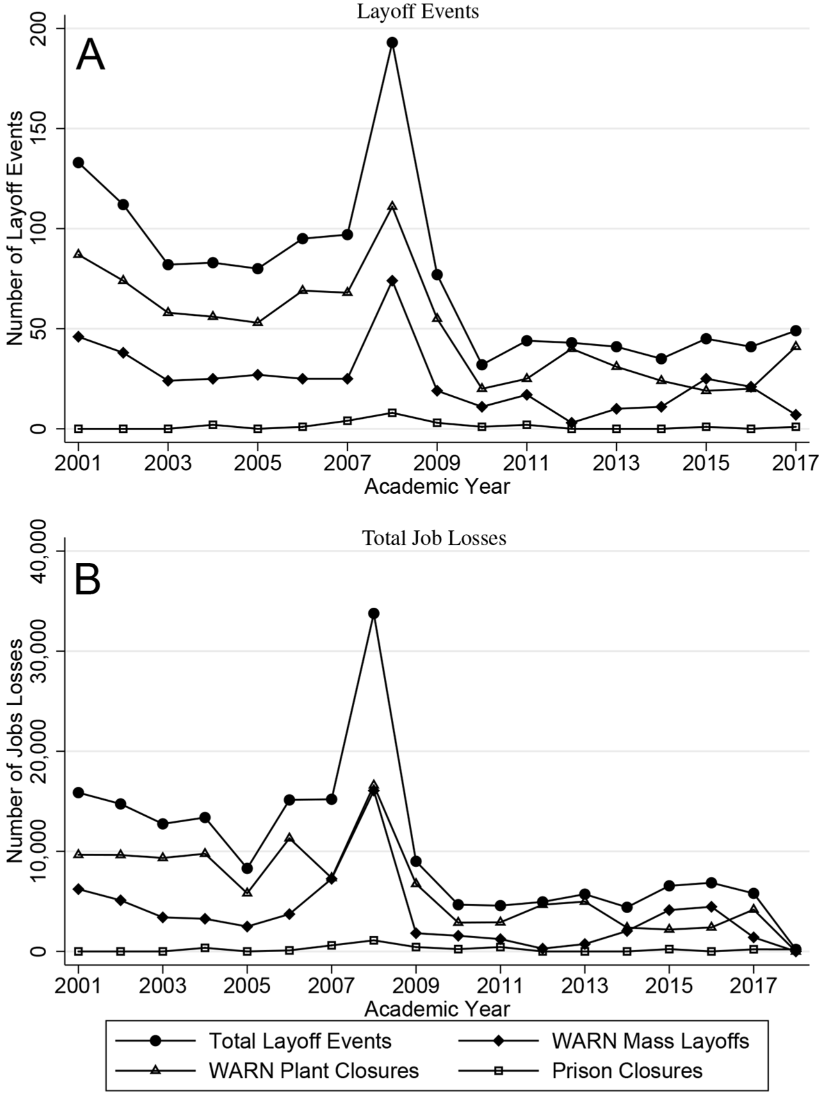

FIG. 1.—Labor market shocks in Michigan, 2001–17. WARN = Worker Adjustment and Retraining Notification Act.

$t + 1$.[12] On average, there are about 75 layoff events each year, with 24 being mass layoffs, 50 being plant closures, and 1.4 being correctional facility closures. The total number of layoff events spiked to 193 during the 2008 academic year, when the Great Recession and automotive industry collapse hit

[12] The WARN data include a record of the date that each event was reported to the state, the name of the company, the city where the affected operation is located, and

Michigan especially hard. Figure 1*B* shows that the total number of job losses also spiked during 2008. Layoffs occur in both rural and urban areas of the state, which I highlight in figure A.2 (figs. A.1–A.11, B.1, B.2, C.1 are available online) by plotting the average amount of per capita layoffs that occur in each county from 2001 to 2017.

I do not observe the occupations of laid-off workers, so I estimate students' exposure to job losses in each community college occupation group by exploiting the fact that different occupations are concentrated in different industries. I first match all 1,024 entities that experience a layoff to their respective three-digit North American Industry Classification System industry code using information from company websites and online business databases. I then calculate the share of employment in industry k that belongs to occupations in group g in year t as

$$\alpha_{gkt} = \frac{\text{Employment}_{gkt}}{\text{Employment}_{kt}}, \tag{1}$$

where Employment_{gkt} is the total employment in occupations in group g in industry k in year t and Employment_{kt} is total employment in industry k in year t. For example, if g is the health occupation group and k is the hospital subsector, then α will capture the share of employment in hospitals that belongs to community college health occupations.

I calculate α_{gkt} for each year, occupation group, and industry using nationally representative data from the BLS's Occupational Employment Series for nongovernment sectors and the American Community Survey for government sectors.[13] Continuing with the example from above, I find that community college health occupations account for 54.4% of employment in the hospital subsector but only 1% of employment at general merchandise stores. Thus, hospital layoffs should affect health occupations much more than layoffs at general merchandise stores.[14] I operationalize this intuition by

the number of affected workers. The correctional facility closure data include a record of the name of the correctional facility that closed, along with the year and number of affected full-time equivalent workers. For each correctional facility closure, I find related local news articles to approximate the date the closure was announced and the county in which the correctional facility was located. Across the two data sources, I drop 19 events (1.35% of the sample) that do not provide sufficient geographic information to assign to a county.

[13] The BLS began publishing state-specific estimates in 2012 but cautions that they are subject to more error than the national-level estimates. Figure A.3 plots the α values for each community college occupation group using each 2016 national and Michigan data and shows a strong correlation between the two measures.

[14] Table A.4 presents the three largest average values of α for each occupation group. In table A.5 I compute the correlation between the α values across the six community college occupation groups. Most correlations are negative, indicating that different community college occupations are concentrated in different industries and, therefore, will be affected by different layoff events.

estimating the number of layoffs in occupation group g in county c in academic year t as

$$\text{Layoffs}_{gct} = \sum_k \alpha_{gkt}\text{Layoffs}_{kct}, \tag{2}$$

where Layoffs_{kct} is the number of layoffs in industry k in county c in academic year t, which is identified in the mass layoff data. These measures capture the size of layoff events and the occupations they are likely to affect while avoiding ad hoc aggregations of industries that may not align with the occupational training community college students receive.[15]

B. Distribution of Layoffs across Occupations

Table 2 provides summary statistics on layoffs occurring in Michigan counties between the 2001 and 2017 academic years. In addition to estimating the number of layoffs occurring in community college occupations, I use the same approach outlined above to estimate the number of layoffs occurring in low-skilled occupations that O*NET identifies as requiring less than a high school diploma and in high-skilled occupations that O*NET identifies as requiring at least a bachelor's degree. These layoff measures correspond to the types of occupations students would expect to enter if they did not pursue postsecondary education or if they obtained bachelor's degrees.

Panel A presents summary statistics on the number of layoffs occurring per 10,000 working-age residents in a given county, year, and occupation group.[16] On average, a county with 10,000 working-age residents experiences 5.2 layoffs in low-skilled occupations, 4.2 layoffs in middle-skilled community college occupations, and 1.3 layoffs in high-skilled occupations in a given year. Among the community college occupations, 2.1 layoffs occur in the skilled trades, 1.0 occurs in business, 0.5 occur in law enforcement, 0.3 occur in STEM, 0.2 occur in health, and 0.1 occur in other community college occupations. There is substantial variation in layoff exposure across counties, with the standard deviations for each category far exceeding the means. Panel B shows that, on average, 51% of layoffs affect low-skilled occupations, while about 38% occur in community college occupations and 11% occur in high-skilled occupations.

C. Potential Measurement Error

The occupation group layoff measures implicitly assume that layoffs in an occupation are proportional to its national employment shares in industries

[15] Table A.6 lists the three county-year pairs with the largest amount of per capita layoffs in each occupation group.

[16] I define working-age residents as those aged 20–64 and obtain annual county-level estimates of this population from the Census Bureau's Population Estimates Program (https://www.census.gov/programs-surveys/popest.html).

Table 2
Summary Statistics of Layoffs in Michigan, 2001–17

Layoff Category	Mean (1)	SD (2)	Min (3)	Max (4)
	A. Layoffs per 10,000 Working-Age Residents			
Non-CC low skill	5.191	16.22	.000	290.3
CC business	.992	2.853	.000	45.75
CC health	.214	2.652	.000	88.23
CC trades	2.073	7.134	.000	95.56
CC STEM	.294	.971	.000	14.98
CC law enforcement	.518	6.302	.000	138.9
CC other	.108	.608	.000	14.10
Non-CC high skill	1.263	4.483	.000	69.81
County-year observations	1,411	1,411	1,411	1,411
	B. Share of Total Layoffs (County-Year Pairs with Nonzero Total Layoffs)			
Non-CC low skill	.510	.158	.142	.909
CC business	.117	.067	.028	.451
CC health	.019	.070	.000	.552
CC skilled trades	.173	.121	.000	.648
CC STEM	.033	.037	.000	.234
CC law enforcement	.020	.084	.000	.432
CC other	.015	.029	.000	.219
Non-CC high skill	.114	.075	.002	.510
County-year observations	369	369	369	369

Note.—The sample consists of all county-year observations from 2001 to 2017. Layoffs in each category are estimated using local industry layoffs and national occupation-by-industry shares. See sec. IV.A for more details. CC = community college; STEM = science, technology, engineering, and mathematics.

that experience layoffs. Any deviation of layoffs from these proportions could lead to measurement error in the layoff terms. For example, suppose that a hospital reports a mass layoff of 100 workers. Based on industry-by-occupation shares, I estimate that about 55 layoffs should affect community college health occupations, while only about eight should affect community college business occupations. However, suppose that the hospital lays off only their billing department. This type of layoff would disproportionately affect business occupations rather than health occupations, causing me to overstate the effect of the event on health occupations and understate the effect on business occupations.

While there is no straightforward way to correct for this nonclassical measurement error, there are situations where it is less likely to affect the results. Plant and prison closures—as opposed to mass layoffs—are likely to affect all jobs contained within a given facility and, therefore, should align more closely with the industry-by-occupation employment shares than layoffs that affect only a subset of a facility's workers. In section V.C, I conduct the empirical analysis using only layoffs that are a result of facility closures and find quite similar results to my main specification, indicating that measurement error is unlikely to be driving the results.

V. Effect of Job Losses on Enrollment in Related Programs

A. Empirical Approach

I estimate the effect of local job losses on enrollment in related community college programs with the following specification:

$$\text{Enroll}_{gct} = \alpha + \textbf{Layoffs}_{gct}\beta + \mathbf{X}_{ct}\boldsymbol{\Gamma} + \theta_{gc} + \delta_{gt} + \varepsilon_{gct}, \tag{3}$$

where Enroll_{gct} is the number of students from county c and cohort t who enroll in community college programs in group g, per 100 high school graduates, and $\textbf{Layoffs}_{gct}$ is a vector of the number of layoffs per 10,000 working-age residents in occupation group g that may affect cohort t in county c.[17] The vector $\mathbf{X}_{ct}$ contains time-varying county control variables that may affect students' enrollment choices: the share of graduates who are white, male, and economically disadvantaged; average math and reading test scores; the county's unemployment rate; and the log of the size of the county's labor force. The term θ_{gc} is a program-by-county fixed effect that accounts for unobserved differences in program preferences across counties, δ_{gt} is a program-by-cohort fixed effect that captures unobserved changes in program preferences over time, and ε_{gct} is an idiosyncratic error term. Throughout the analysis, I cluster all standard errors at the county level.

The fixed effects capture two important sources of unobserved heterogeneity: differences in preferences for community college programs across counties and across time. Thus, the identifying assumption is that there are no changes in unobserved determinants of students' program choices at the county-program level that are correlated with job losses. This assumption could be threatened if there are contemporaneous shocks that affect both the local labor market and students' education preferences. I account for the presence of general county-level economic shocks by controlling for the county's unemployment rate and logged size of the labor force. In additional specifications, I further control for the number of layoffs occurring in non-community-college low-skill and high-skill occupations or replace these time-varying county controls with a county-by-cohort fixed effect that captures all unobserved characteristics of a given county and cohort.

A second threat to identification is the possibility of unobserved county-specific trends in students' preferences for different types of community college programs. I address this concern in several ways. First, I estimate specifications

[17] My preferred specification scales program enrollments by the number of graduates in a county. In fig. A.6 I show that the results are similar if I scale the dependent variable by total community college enrollment or enrollment in vocational community college programs.

that control for lagged layoff measures to test for students' responsiveness to earlier layoff events and ensure I appropriately account for any autocorrelation in layoffs. Second, I estimate versions of equation (3) that include county-by-program linear time trends to account for any trends in students' preferences across the 2009–16 cohorts. Third, I estimate specifications that interact the cohort-by-program fixed effects with commuting zone (CZ) fixed effects to account for any unobservable year-over-year changes in a program group's employment prospects or desirability in a broader geographic region.[18]

Finally, I follow Foote and Grosz (2020) and explicitly test for trends in program choices leading up to large layoff events by estimating the following event study specification:

$$\begin{aligned}\text{Enroll}_{gct} = \alpha + &\sum_{k=-3,k\neq 0}^{4} \beta_k \text{LargeLayoff}_{gc} \times 1[t - t^* = k] \\ &+ \mathbf{X}_{ct}\Gamma + \theta_{gc} + \delta_{gt} + \varepsilon_{gct},\end{aligned} \tag{4}$$

where LargeLayoff_{gc} indicates that occupation group g in county c experiences annual layoffs in the top quartile of the nonzero layoff distribution in some year between 2009 and 2016.[19] The term $1[t - t^* = k]$ is a binary variable indicating that cohort t graduates k years following the large layoff that occurs in year t^*. I bin the end points such that $k = -3$ captures all observations three or more years before a large layoff and $k = 4$ captures all observations four or more years after.

Figure A.4 plots the β_k estimates, which trace out the trends in program enrollment rates surrounding the large layoff event. Figure A.4*A* includes the standard set of control variables, figure A.4*B* includes county-by-program linear time trends, and figure A.4*C* interacts the program-by-year fixed effects with CZ fixed effects. Across the three specifications, there is little evidence to suggest declining enrollment leading up to a layoff event; if anything, program enrollments increase in the years before a large layoff and decline immediately after. These estimates provide validity to treating variation in layoff exposure as an exogenous shock to students' postsecondary choices and align closely with the main results that follow.

B. Main Results

Table 3 presents estimates of equation (3), measuring layoffs at different times during a cohort's academic career and across different geographic areas.

[18] CZs are groups of counties that reflect a local labor market. Throughout the analysis, I use the 1990 CZ delineations (see https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/).

[19] I consider only a county-program pair's first large layoff event. There are 117 county-program pairs that experience a large layoff between 2009 and 2016.

Table 3
Effect of Job Losses on Enrollment in Related Community College Programs

	Enrollment in Occupation Group Programs per 100 High School Graduates					
Layoffs per 10,000 in	(1)	(2)	(3)	(4)	(5)	(6)
Own county, t (postgraduation)				.007		
				(.005)		
Own county, $t-1$ (senior year of high school)	−.012**	−.014**	−.014**	−.011*	−.012**	−.012**
	(.006)	(.007)	(.007)	(.006)	(.006)	(.006)
Own county, $t-2$ (junior year of high school)		−.002	−.003	−.001		
		(.004)	(.005)	(.005)		
Own county, $t-3$ (sophomore year of high school)		−.008**	−.008*	−.006		
		(.004)	(.004)	(.004)		
Own county, $t-4$ (freshman year of high school)		−.004	−.005	−.002		
		(.004)	(.004)	(.004)		
Rest of state, $t-1$ (senior year of high school)					.003	
					(.012)	
Rest of commuting zone, $t-1$ (senior year of high school)						−.008
						(.009)
State less commuting zone, $t-1$ (senior year of high school)						.007
						(.013)
Program-by-county fixed effects	X	X	X	X	X	X
Program-by-cohort fixed effects	X	X	X	X		
Own county, $t-5$ to $t-8$ controls			X	X		
Outcome mean	1.57	1.57	1.57	1.57	1.57	1.57
County-program-year observations	3,984	3,984	3,984	3,984	3,984	3,936
R^2	.488	.489	.490	.490	.476	.479

NOTE.—The unit of observation is a county-cohort-program triad. Outcomes are measured as the number students who initially enroll in a given vocational program within 6 months of high school graduation per 100 graduates in the county. The coefficients in each column are estimated from a separate regression and represent variants of β in eq. (3), the effect of an additional layoff per 10,000 working-age residents in a given occupation group on enrollment in corresponding programs. All regressions include controls for the share of graduates who are white, male, and categorized as economically disadvantaged; average eleventh-grade math and reading test scores; and the county unemployment rate and logged size of the labor force. All standard errors are clustered at the county level.
* $p < .10$.
** $p < .05$.

Column 1 includes only layoffs occurring in a student's own county during her senior year of high school—the year during which students must decide what educational program, if any, they will enter following graduation. The estimated coefficient indicates that an additional layoff per 10,000 county residents during this year reduces enrollment in related programs the following year by 0.012 students per 100 graduates, or about 0.012 percentage points.

At the mean enrollment rate of 1.5%, this estimate represents a 0.8% decrease in enrollment in related programs. A 1 standard deviation increase in layoff exposure reduces enrollment in related programs by 3.83% of the mean.

Column 2 adds measures of layoffs occurring earlier in a cohort's high school tenure, and column 3 further controls for layoffs in the 4 years before high school entry. In both specifications, the estimate on layoffs occurring in a cohort's senior year of high school remains negative and statistically significant, but there are little effects of layoffs occurring in prior years. These results indicate that students primarily respond to layoffs occurring in the year leading up to their postsecondary decision point, which is consistent with recent papers that highlight the sensitivity of college major choice to recent events (Xia 2016; Patterson, Pope, and Feudo 2019).

Column 4 then adds a measure of layoffs occurring in the year following a cohort's high school graduation. Because I restrict the analysis to students' first program choices within 6 months of high school graduation, including this measure serves as a natural placebo test: these layoffs have not yet occurred when students make their postsecondary choices and, thus, should not affect their enrollments. The point estimate on this term is close to zero and statistically insignificant, while the estimate on layoffs occurring during a cohort's senior year of high school remains negative and statistically significant.

Finally, columns 5 and 6 consider how layoffs in other areas of the state during a cohort's senior year of high school affect students' enrollments. These specifications omit the occupation group–by–cohort fixed effects (δ_{gt}), as this term absorbs any statewide changes in student preferences for a program, including the effects of statewide layoffs. Column 5 first adds a measure of layoffs occurring in the rest of the state. The coefficient on this measure is close to zero and statistically insignificant, indicating that, on average, layoffs occurring elsewhere in the state do not affect students' program choices. Column 6 then separates this measure into layoffs occurring elsewhere in the county's CZ and layoffs occurring outside the CZ. The coefficient on layoffs occurring elsewhere in the CZ is statistically insignificant but negative, suggesting that students may respond to layoffs occurring outside their county, in their general area of the state. That students respond to layoffs in their local area—but not to those elsewhere in the state—could be driven by a lack of information on statewide labor market events or could be a rational response to the geographic constraints faced by students. While I am not able to disentangle these explanations, developing a better understanding of the roles that labor market information and geographic constraints play in community college students' decision-making processes is a fruitful area for future work.

C. Robustness and Heterogeneity

Figure A.5 presents several robustness checks of the specification from column 1 in table 3: the effect of layoffs in a student's county during her senior year of high school on enrollment in related programs.[20] First, figure A.5*A* addresses the concern of correlated economic shocks. Including the number of layoffs occurring in low-skill and high-skill occupations, either together or separately, does not meaningfully change the estimated coefficient. Similarly, replacing the vector of covariates with a county-by-cohort fixed effect produces a nearly identical estimate that is statistically significant at the 10% level. Next, figure A.5*B* estimates specifications that include either county-by-program linear time trends or program-by-year-by-CZ fixed effects.[21] These specifications are also similar to the estimates from the main specification, indicating that unobserved changes in local economic conditions are not driving the results.

Figure A.5*C* then shows how the estimates change when excluding different layoff events. The estimates are similar when using all layoffs and when using only layoffs that are a result of closings, indicating that measurement error is not driving the results. I also find similar estimates when including only layoffs that reach the 50-job-loss threshold, suggesting that the voluntary reporting of smaller layoff events does not contaminate the main results. Restricting layoffs to those that occur before January of a student's senior year—the month in which many 4-year college applications are due—also produces a similar estimate, indicating that students are primarily responding to events that occur before they begin making college decisions. Figure A.5*D* estimates nonlinear specifications that can better handle fractional dependent variables. The main linear specification produces an estimated semielasiticity in the middle of the nonlinear estimates, and I fail to reject the hypothesis that the five estimates are different from one another.

Figure A.5*E* estimates unconditional quantile regressions across the enrollment share distribution (Firpo, Fortin, and Lemieux 2009). The effects are largest at the bottom of the enrollment distribution, indicating that layoffs mostly deter students from entering programs that are not popular among high school graduates in their county. Finally, figure A.5*F* estimates separate effects for different subgroups of students. On average, male and female students respond similarly to layoffs, while economically nondisadvantaged students—who may be more informed about local labor market conditions or receive more college guidance—are somewhat more responsive than their disadvantaged peers. Students residing in rural counties are much more responsive to layoffs than students residing in urban counties.[22] This strong

[20] Figure A.7 further shows how the results vary when weighting eq. (4) by measures of county size. The estimated elasticities are somewhat smaller but not statistically different from the main results.

[21] Monroe County is dropped from specifications that include year-by-CZ fixed effects because all other counties in its CZ are in Ohio.

[22] I define urban counties as those that the US Census Bureau classifies as "mostly urban" and define all other counties as rural. A list of Michigan's urban and rural

response in rural areas could be the result of different geographic preferences or information networks in these areas. For example, rural news outlets may have fewer events to cover and, therefore, may devote more attention to a local layoff or business closure. Layoffs in rural areas may also be better indicators of future labor market prospects than layoffs in urban areas if an occupation's employment is heavily concentrated in a single firm.

VI. Substitution Effects

A. Substitution out of Vocational Sector

I now consider how students substitute toward other postsecondary education options when layoffs deter them from entering related vocational community college programs. I begin by estimating the effects of layoffs on overall enrollment in vocational programs as

$$\text{VocationalEnroll}_{ct} = \alpha + \sum_{g=1}^{6} \beta_g \text{Layoffs}_{gc,t-1} + \mathbf{X}_{ct}\Gamma + \theta_c + \delta_t + \varepsilon_{ct}, \quad (5)$$

where $\text{VocatonalEnroll}_{ct}$ is the number of students from county c and cohort t, per 100 graduates, who enroll in vocational community college programs at community colleges. The vector of layoff variables, $\text{Layoffs}_{gc,t-1}$, captures the number of layoffs, per 10,000 working-age residents, that occur in different community college occupation group g in county c during cohort t's senior year of high school—the year in which the results in section V indicate students are most sensitive to job losses. The vector $\mathbf{X}_{ct}$ contains the same time-varying county control variables as equation (3), plus the number of layoffs that occur in non-community-college occupations. The term θ_c is a county fixed effect that absorbs county-specific preferences (as θ_{gc} does in the previous estimating equation), and δ_t is a cohort fixed effect that accounts for changing preferences across cohorts (as δ_{gt} does in the previous estimating equation); ε_{ct} is the error term.

The β_g parameters identify how layoffs in different types of occupations affect students' decisions to enroll in vocational community college programs overall. As in equation (3), the fixed effects capture unobserved heterogeneity in student preferences across counties and cohorts, so the identifying assumption is that there are no unobserved changes in preferences at the county level that are correlated with changes in a county's exposure to layoffs. Once again, this assumption could be threatened if there are unobserved trends in preferences or economic opportunities over time or if there are other county-specific shocks that are correlated with layoffs, which I address by estimating specifications that include county-specific linear time trends

counties is available at https://www.mlive.com/news/2016/12/michigans_urban_rural_divide_o.html.

Table 4
Effect of Community College Layoffs on Overall Vocational Program Enrollment

	Vocational Enrollment per 100 Graduates		
Layoffs per 10,000 in	(1)	(2)	(3)
Business, $t-1$	.085	.146	−.029
	(.118)	(.149)	(.112)
Health, $t-1$	.015	−.057	.100*
	(.041)	(.046)	(.056)
Skilled trades, $t-1$	.021	.005	.023
	(.022)	(.032)	(.026)
STEM, $t-1$	.161	.005	.019
	(.138)	(.163)	(.122)
Law enforcement, $t-1$	−.001	−.009	−.001
	(.016)	(.021)	(.014)
Other, $t-1$	.107	.189	.133
	(.241)	(.215)	(.208)
p-value for joint test	.351	.607	.314
County-specific trends		X	
Year-by-CZ fixed effects			X
Outcome mean	9.40	9.40	9.40
County-year observations	664	664	656
R^2	.671	.761	.809

NOTE.—The unit of observation is a county-cohort pair. Outcomes are measured as the number of students who enroll in vocational community college programs within 6 months of high school graduation per 100 high school graduates in the county and cohort. The coefficients in each column are estimated from a separate regression and represent the β parameters in eq. (5), the effect of an additional layoff per 10,000 working-age residents in a given occupation group on the outcome of interest. The numbers in parentheses below the estimates are the estimated elasticities at the mean dependent and independent variable values. All regressions include controls for the share of graduates who are white, male, and categorized as economically disadvantaged; average eleventh-grade math and reading test scores; and the county unemployment rate, logged size of the labor force, and the number of layoffs per 10,000 working-age residents in non-community-college occupations during a cohort's senior year of high school. All standard errors are clustered at the county level. CZ = commuting zone; STEM = science, technology, engineering, and mathematics.
* $p < .10$.

or CZ-by-cohort fixed effects and by including different variables in the vector of controls.

Table 4 presents the estimates of equation (4). Column 1 is the baseline specification, column 2 includes county-specific linear time trends, and column 3 includes cohort-by-CZ fixed effects.[23] In each specification, the effects of layoffs are small, none are statistically significant at the 5% level, and I fail to reject the joint hypothesis that all six coefficients are equal to zero.[24] In table A.8, I regress demographic characteristics of vocational students against the vector of layoff measures and find little evidence that layoffs affect the

[23] Figure A.8 shows that the estimates are quite similar when including different control variables.

[24] In table A.7 I show that, overall, layoffs increase enrollment in programs that should lead to 4-year college degrees, including nonvocational programs at community colleges, while layoffs slightly decrease enrollment in community college vocational programs.

composition of students enrolling in vocational programs. Similarly, in table A.9, I find no evidence that layoffs affect total credit completion or completion of vocational versus nonvocational courses.[25] Taken together, these findings show that layoffs in community college occupations do not dissuade students from enrolling in community colleges and pursuing vocational education.

B. Substitution between Vocational Programs

Because job losses do not deter students from entering vocational community college programs overall, the response documented in section V.B must come from students changing which types of vocational programs they pursue. To estimate these effects, I restrict the sample to students who enroll in vocational programs and estimate the following system of six equations:

$$\text{ProgramEnroll}_{jct} = \alpha + \sum_{g=1}^{6}\beta_g \text{Layoffs}_{gc,t-1} + \mathbf{X}_{ct}\Gamma + \theta_c + \delta_t + \varepsilon_{ct}, \quad (6)$$

where $\text{ProgramEnroll}_{jct}$ is enrollment in occupation group j among students from county c and cohort t, per 100 students enrolling in vocational programs, and $\text{Layoffs}_{gc,t-1}$ is the number of layoffs in occupation group j in county c occurring in school year $t - 1$, per 10,000 working-age residents in the county. The vector $\mathbf{X}_{ct}$ contains the same variables as in equation (5), θ_c is a county fixed effect, δ_t is a cohort fixed effect, and ε_{ct} is the error term. The coefficient β_g will represent the "own-layoff" effect when $j = g$ and will represent a "cross-layoff" effect when $j \neq g$. Once again, the identifying assumption is that there are no unobserved changes in preferences at the county level that are correlated with changes in a county's exposure to layoffs, and I continue to estimate specifications with county-specific linear time trends or cohort dummies interacted with CZ fixed effects and with different control variables.

Table 5 presents the substitution matrix created from estimating equation (5) for each of the six occupation groups. The boldface diagonal terms represent the effect of an additional layoff per 10,000 county residents in occupation group g on enrollment in related programs. An additional layoff per 10,000 county residents in business programs reduces enrollment in business programs by 1.02 students per 100 enrolls, or by 1.02 percentage points. An analogous increase in layoffs reduce enrollment in health programs by 0.61 percentage points and in law enforcement programs by 0.15 percentage points, in other programs by 0.81 percentage points, and by smaller but negative amounts in the skilled trades and STEM. In the bottom panel, I present the own-layoff semielasticities at the mean values of both the dependent

[25] I divide courses into vocational and nonvocational groups using course codes and information from course catalogs. I define vocational courses as those in the same fields that are included in the six vocational program groups, while all other courses are considered nonvocational.

Table 5
Substitution between Community College Program Groups

	Enrollment per 100 Vocational Students in					
Layoffs per 10,000 in	Business (1)	Health (2)	Trades (3)	STEM (4)	Law Enforcement (5)	Other (6)
Business, $t-1$	**−1.025****	−.702	−.056	−.093	1.736***	.141
	(.456)	(.682)	(.449)	(.280)	(.592)	(.347)
Health, $t-1$	−.120	**−.610****	−.281**	.164	.250	.597***
	(.138)	**(.232)**	(.122)	(.123)	(.222)	(.132)
Skilled trades, $t-1$	.067	.164	**−.088**	−.014	.030	−.159**
	(.078)	(.109)	**(.097)**	(.066)	(.123)	(.063)
STEM, $t-1$	.212	.206	−.253	**−.124**	−.086	.044
	(.676)	(.626)	(.674)	**(.347)**	(.839)	(.405)
Law enforcement, $t-1$	.076	.078	−.048	.143	**−.153****	−.097
	(.075)	(.082)	(.061)	(.094)	**(.075)**	(.061)
Other, $t-1$	.753	.072	−.344	−.688	1.014	**−.807**
	(.617)	(.945)	(.518)	(.522)	(.678)	**(.511)**
Own-layoff semielasticities (at mean)	−.047**	−.029***	−.006	−.010	−.011**	−.046
	(.021)	(.011)	(.007)	(.029)	(.005)	(.029)
Outcome mean	21.66	20.67	14.33	11.84	13.74	17.75
County-year observations	657	657	657	657	657	657
R^2	.190	.506	.344	.266	.258	.353

NOTE.—The unit of observation is a county-cohort pair. Outcomes are measured as the number of students who enroll in a given program within 6 months of high school graduation per 100 students in the county and cohort who enroll in vocational programs. Only county-cohort pairs with nonzero vocational enrollment are included in the sample. The coefficients in each column are estimated from a separate regression and represent the β_j terms in eq. (6), the effect of an additional layoff per 10,000 working-age residents in a given occupation group on the outcome of interest. All regressions include controls for the share of graduates who are white, male, and categorized as economically disadvantaged; average eleventh-grade math and reading test scores; and the county unemployment rate, logged size of the labor force, and the number of layoffs per 10,000 working-age residents in non-community-college occupations during a cohort's senior year of high school. All standard errors are clustered at the county level. STEM = science, technology, engineering, and mathematics.
** $p < .05$.
*** $p < .01$.

variable and the independent variables. An additional layoff per 10,000 working-age county residents reduces enrollment in related programs by between 0.6% and 4.7%, with the largest statistically significant effects occurring in business and health. When estimating the system of equations jointly, I reject the hypothesis that all six diagonal coefficients are equal to zero ($p < .01$) but fail to reject the hypothesis that the coefficients are all different from one another ($p = .175$).

Figures A.9 and A.10 present heterogeneous effect estimates and robustness checks for these own-layoff effects. There is some heterogeneity by gender, with the response to health layoffs almost entirely driven by female students, and effects tend to be larger for nondisadvantaged students and those residing in rural counties. The results are robust to a variety of alternative specifications, including weighting to correct for heteroskedasticity

(Solon, Haider, and Wooldridge 2015), including county-specific linear time trends or CZ-by-year fixed effects, dropping students graduating at the height of the Great Recession (2009), including different control variables, or using nonlinear estimation procedures. Table A.10 further shows that the own-layoff effects are similar, although somewhat attenuated, when using raw industry-level layoffs instead of the transformed occupation-level layoff measures.

Moving horizontally across the columns then shows how layoffs induce students to substitute into other types of vocational programs. For example, an additional business layoff per 10,000 county residents increases enrollment in law enforcement programs by about 1.7 percentage points, while students primarily substitute from health programs into other programs when there are health layoffs. In table A.11, I further disaggregate the "other" category and find that most of the substitution occurs in social service programs, such as childcare, although there is also statistically significant substitution into arts and media programs and personal care and culinary programs. The estimates further suggest that students substitute from law enforcement programs toward business, STEM, and health programs when there are law enforcement layoffs.

C. Explaining Substitution with Occupation Characteristics

Why might layoffs in business occupations induce students to enroll in law enforcement programs? In a standard utility-maximizing framework, students should substitute into their "next best" alternative program. Given that programs are closely tied to occupations, the next best programs are likely to share similar occupation characteristics. To empirically assess the extent to which students substitute into similar programs, I leverage data on occupation characteristics from the US Department of Labor's O*NET and characterize community college program groups using measures of cognitive, social, and technical skill requirements.

For each occupation and skill measure, O*NET reports a standardized measure that characterizes the degree to which the skill is required to perform the occupation, with higher values indicating a higher requirement. I use these data to create a Euclidean distance measure that identifies program groups associated with similar occupations, which is similar to that used by O*NET to identify closely related careers. I define the distance between program group p and program group s, which experiences the labor market shock, as

$$\text{Distance}_{ps} = \sqrt{\textstyle\sum_{j=1}^{27}(\text{SkillLevel}_{jp} - \text{SkillLevel}_{js})^2}, \qquad (7)$$

where SkillLevel_{jp} is the required level of skill j for program p and SkillLevel_{js} is the required level of skill j for program group s. As a result, the programs that are most similar to program group s will have the lowest

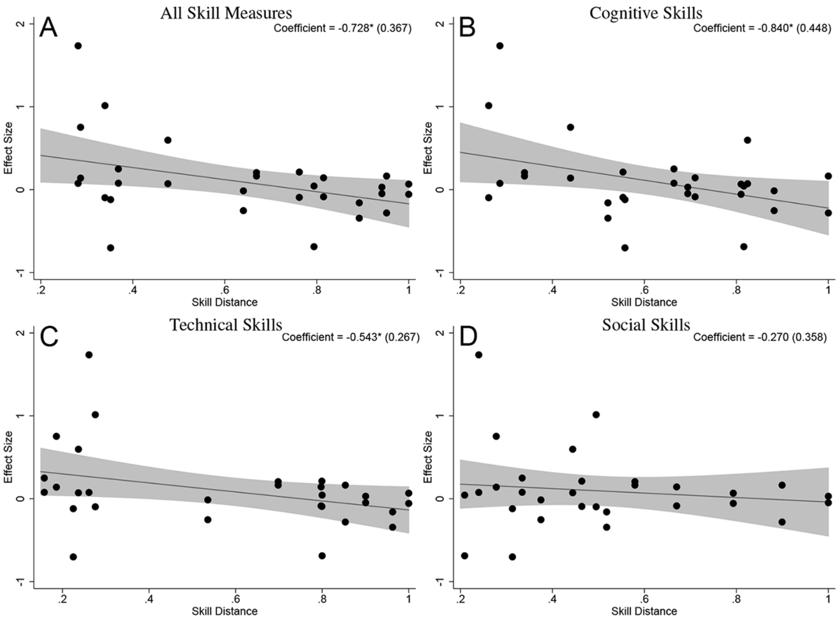

FIG. 2.—Relationship between substitution effects and skill distance. Each panel plots the off-diagonal coefficients from table 5 against the skill distance metrics outlined in section VI.C. *A* uses all 27 skill measures from the Occupational Information Network (O*NET) database, while *B* uses only the cognitive skill measures, *C* uses only the technical skill measures, and *D* uses only the social skill measures. Coefficients are presented from a regression of the substitution effect point estimates against each skill distance metric. Robust standard errors are shown in parentheses. *$p < .10$.

distance measures.[26] I create this distance metric using the cognitive, social, and technical skill measures—both separately and together—and standardize each such that the least similar pair of program groups has a distance measure of 1.

Figure 2 plots the off-diagonal point estimates from table 5 against their corresponding skill distance metrics.[27] I include the estimated coefficient from an analogous regression of substitution effects against skill distance,

[26] The program group skill measures weight the underlying occupation skill measures according to programs' total enrollments over the time frame of the data. For example, nurses receive a high weight in the health program group because nursing is one of the most popular programs. Table A.12 provides the program group level skill measure for each cognitive, technical, and social skill provided in the O*NET database. Table A.13 presents the skill distance metric for each pair of program groups when using all O*NET skill measures.

[27] Figure A.11 presents the relationship between the substitution effects and distance measures separately for each type of layoff.

along with the corresponding robust standard error.[28] When using all the skill measures or the cognitive and technical skill measures independently, there is a clear negative relationship between the estimated substitution effect and the distance from the program affected by layoffs. The effect is also negative, although noisier, when using the social skill measures. These results indicate that when exposed to layoffs, students are more likely to substitute toward training programs that lead to similar occupations than they are to substitute toward programs that lead to very different career paths.

These substitution patterns could benefit students in the long run if they can enter occupations that are both in demand in their local area and a good match to their skills and preferences. However, there is also a risk that temporary labor market shocks deter students from fields with otherwise strong labor market prospects. For example, I find that enrollment in health programs declines as a result of health-related layoffs, but Bahr et al. (2015) find that completing health programs—particularly nursing—led to large labor market gains for Michigan community college students in the early 2000s. Despite sharing similar characteristics, the programs that students substitute toward when exposed to layoffs in health occupations, such as childcare or culinary services, tended to have lower returns. Nevertheless, the returns to community college programs may vary across geography and over the business cycle, so tracking the long-run effects of economic shocks on community college students' outcomes is an important area for future research.

VII. Conclusion

Up to 10 million students enroll in public community colleges in the United States each year, with many entering vocational programs that aim to prepare them for a continually evolving labor market. The returns to these programs vary across fields of study, but there is little evidence on how students choose which programs to pursue. By matching data on students' educational decisions with plant closings and mass layoffs in their communities, I show that local labor market shocks deter students from entering related programs at community colleges. Instead, students shift their enrollment into other types of vocationally oriented community college programs, particularly ones that lead to occupations that require similar skills.

These results suggest that colleges should prepare for students to enter different programs when local labor market shocks occur. Providing community colleges with the resources to expand the supply of alternative programs, particularly those with high labor market returns, could be beneficial to students. High schools and colleges should also carefully consider the type of labor market information they provide students. I find that students are

[28] Robust standard errors are generally larger than conventional ones and never make an otherwise insignificant estimate significant.

particularly sensitive to recent local events. However, it is not clear whether this responsiveness is a result of the salience of these events, a lack of information on broader economic trends, or geographic constraints. Providing students with personalized information and context would likely help them make choices that align with both their preferences and their constraints.

However, these results are somewhat limited by my institutional setting: the aftermath of the Great Recession in a state that was particularly affected by the collapse of the automotive industry. While there was substantial variation in local labor market conditions during this time, the results may not generalize to future cohorts or other areas of the country. Moreover, my results apply only to the decisions of recent high school graduates. Older adults enrolling in community college programs, especially those who lose their jobs during local labor market downturns, may respond quite differently than younger students. Understanding the choices of this population and evaluating interventions meant to promote their employment and earnings are important areas of both future research and public policy.

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