Community College Program Choices in the Wake of Local Job Losses

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Abstract

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 four-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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1 Introduction

The educational decisions that young people make can substantially affect their long-run labor market outcomes and overall economic well-being. The typical college graduate will earn more than double the typical high school graduate over her lifetime (Hershbein and Kearney, 2014), while also experiencing improved health, less reliance on social safety net programs, and fewer interactions with the criminal justice system (Oreopoulos and Salvanes, 2011). Equally large earnings gaps exist among students with the same level of education who pursue different fields of study (Altonji et al., 2012), and a growing body of literature shows that students take these gaps into account when selecting college majors (Montmarquette et al., 2002; Beffy et al., 2012; Long et al., 2015), particularly when provided with reliable information about the labor market (Wiswall and Zafar, 2015; Hastings et al., 2015; Baker et al., 2018).

However, the vast majority of college major choice research focuses on the four-year college sector. The nearly ten million students who attend two-year community colleges (National Center for Education Statistics, 2018) also must decide which fields to study, and their decisions have similarly large implications for their labor market outcomes. For example, graduates of healthcare programs experience large earnings gains in the labor market, while students who complete some other programs may not earn more than their peers who do not attend college (Bahr et al., 2015; Belfield and Bailey, 2017; Stevens et al., 2019; Grosz, 2019). In response to these earnings differences, policymakers have begun to introduce programs that aim to steer students into programs that align with local economies. Several states tie community colleges' appropriation funding to their ability to produce degrees in high-demand areas (Snyder and Boelscher, 2018), and some recent financial aid programs incentivize students to choose in-demand fields of study (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 education decisions of recent high school graduates in Michigan to analyze how labor market conditions influence community college program enrollments. Specifically, I consider how students' choices respond to local, occupation-specific job losses that alter the relative benefit of pursuing different programs. These types of job losses are likely to be particularly influential to community college students for several reasons. First, community college students tend to remain close to home when attending college and after graduating, making it likely that local labor demand shapes students' expected labor market prospects more than state or national demand.[1] Second, community college programs are generally designed to take two years or less to complete. Thus, while four-year college students may consider longer-run labor market trends when choosing college majors, community college students may be more likely to consider short-term fluctuations in labor demand. Finally, many programs at the community college level are closely tied to specific occupations, such as nursing or welding, rather than the broad subjects that often define majors at four-year colleges. As a result, the expected labor market opportunities associated with programs align closely with labor market opportunities in specific occupations.

My empirical approach exploits plausibly exogenous variation in students' exposure to local job losses resulting from mass layoffs and plant closings. I further rely on the distribution of occupations across industries to create estimated measures of occupation-specific labor demand shocks that align closely with six broad groups of community college programs. By comparing cohorts in the same county that were exposed to different local job losses as they exited high school, I show that students' program choices are sensitive to occupations' local labor market conditions. On average, an additional layoff per 10,000 working-age residents in a county reduces the share of the county's high school graduates enrolling in related community college programs the following year by 0.8%. Correspondingly, a one 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. To explain these substitution patterns, I leverage data on the skills required in different occupations from the U.S. Department of Labor's Occupational Information Network (O*NET) to create measures of skill similarity between community college programs. I then document that students primarily shift their

[1] The median distance a community college student travels to campus is only eight miles (Hillman and Weichman, 2016), and over 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 students who attend community colleges within six months of high school graduation attend one located in their county. This number is 86% for students who live in a county with a community college.

enrollment into programs that require similar cognitive and technical skills to the field affected by layoffs.

These results add to a large body of empirical work on factors affecting which fields students study in college, particularly how expected wages affect students' college majors. Most prior work at the four-year college level finds that, to some extent, expected wages influence students' choices (Altonji et al., 2016). Related research at the community college level is limited, but two recent studies indicate that students attending these institutions are sensitive to expected labor market prospects. Baker et al. (2018) perform an information experiment and find that students' program choices respond to new information about labor market outcomes, particularly the salaries earned by previous graduates. Meanwhile, Grosz (2019) uses a shift-share approach to show that, in California, the distribution of community college program completions has kept pace with statewide employment composition changes. I build on these findings by showing that exposure to job losses also affect students' choices across community college programs. In line with prior work, these effects are rather small in magnitude, suggesting that factors outside of the labor market play a substantial role in determining students' choices.

This paper also provides new evidence that local labor market shocks can affect education choices across a variety of margins. Several recent papers exploit mass layoffs and similar events to study how labor market conditions affect college enrollment (Charles et al., 2018; Hubbard, 2018; Foote and Grosz, 2020). They generally find that poor labor market conditions lead to an increase in college enrollment. A line of literature on the sensitivity of community college enrollment to the business cycle confirms this finding (Betts and McFarland, 1995; Hillman and Orians, 2013). However, few papers consider the occupation- or industry-specific nature of local labor market shocks. Two recent exceptions are Weinstein (2020), who finds that various industry-level shocks affect the composition of college majors at nearby four-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 towards programs that require similar skills, which has not been documented in prior work.

2 Conceptual Framework

The mass layoffs and plant closings I exploit in this paper represent changes in local labor demand, which can affect students' expected benefits of pursuing different postsecondary education programs. To see the potential changes in students' decisions arising from a change in expected benefits, 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 four-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. Students will only be able to respond to the layoff if it occurs prior to their enrollment decision (typically, the spring of the senior year of high school) and will alter their decisions based on how the shock affects the expected benefits of pursuing different educational paths. Assuming the shock occurs with sufficient time for students to respond, consider two extreme examples. In one, the labor market shock only affects community college health occupations and reduces the expected earnings of pursuing health programs, while holding all other components of the model constant. In another, the labor market 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, if the decline is large enough, she will 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, may no longer enroll in college or may enroll in a four-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 timing of the

[2] Students may also choose to enroll in a non-vocational program at a community college. Because these programs are typically designed to assist students in transferring to four-year colleges, I implicitly consider them as part of option (3), a four-year college program.

events and the distribution of job losses across different segments of the economy. Moreover, they show that labor market shocks can have large effects without inducing students to change whether or where they enroll in college. Namely, students can choose to enter other programs within the vocational community college sector. Previous studies that only consider 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.

3 Institutional Setting & Enrollment Data

The institutional setting for this analysis is the community college market in the state of Michigan. Michigan is home to 28 public community colleges, which together enroll more than 300,000 students annually (Michigan Community College Association, 2019). All of the colleges are open enrollment institutions, meaning students can enroll and select a program of study regardless of academic preparation.[3] They primarily confer certificates and associate degrees, which may either be vocational or non-vocational in nature.[4] Vocational programs are designed to prepare students for immediate entry into specific occupations, whereas non-vocational programs typically consist of general education courses that students can transfer to four-year colleges.

3.1 Programs Offered by Michigan's Community Colleges

Michigan does not systematically track the programs offered by each community college over time, which makes it difficult to accurately capture the choice sets faced by students. However, in 2011 and 2013, the Department of Treasury published the "Michigan Postsecondary Handbook," which provides a listing of all programs offered by each of Michigan's community colleges and includes their degree level, number of credits, and six-digit Classification of Instructional Program (CIP) codes. The Workforce Development Agency also maintains an online database of all current

[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 7 out of 209 programs use selective admissions (`https://www.lcc.edu/academics/documents/pdf-policies/selective-admission-programs-criteria.pdf`). 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 (Robles et al., 2019) limits the likelihood that these constraints pose major issues in the analysis that follows.

[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 only awarded 116 bachelor's (House Fiscal Agency, 2017).

programs offered by the state's community colleges. I combine these data sources to classify programs into vocational and non-vocational categories, and to create aggregated program groups that I use to analyze students' responses to job losses in related occupations.

To begin, I match each CIP code listed in one of the program listings to its associated occupation code in the Standard Occupation Classification System (SOC) using a crosswalk developed by the Bureau of Labor Statistics (BLS) and National Center for Education Statistics (NCES). In the crosswalk, a CIP code is only matched 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). For example, physical therapy assistant programs (CIP 51.0806) are matched to physical therapy assistants (SOC 31-2021) and welding technology programs (CIP 48.0508) are matched to welders (SOC 51-4121). One limitation of the crosswalk is that CIP codes are constant across levels of education. As a result, some programs may be matched to occupations that are unlikely to be obtained by recent community college graduates. To ensure all programs are only mapped to attainable occupations, I further match the SOC occupation codes to data on job preparation requirements from O*NET and limit the occupation matches to those in "job zones" 2, 3, and 4: those that require at least a high school diploma, but not necessarily a bachelor's degree. I then define a program as a vocational program if it is matched to an occupation within this subset of attainable occupations. All other programs are considered non-vocational. These programs include general studies programs in which students take core classes that transfer to four-year colleges, pre-transfer programs in specific areas (such as pre-engineering), or academic programs that do not have close occupation links (such as foreign languages).

To provide an overview of the types of programs community college students in Michigan might enter, Appendix Table A.1 presents summary statistics on the programs offered by the state's community colleges in 2011. On average, a college offered 117 unique academic programs, with 81% being vocational. The five most commonly offered vocational programs were those in vehicle maintenance and repair technologies (CIP 47.06), industrial production technologies (CIP 15.06), allied health (CIP 51.09), criminal justice and corrections (CIP 43.01), and business administration (CIP 52.02). To analyze students' choices across this large set of programs, I create six broad groups of programs based on programs' matched occupations: business, health, skilled trades, STEM, 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*.[5] Appendix Table A.2 provides a list of the two-digit SOC codes contained within each group.

3.2 Students Enrolled in Michigan's Vocational Programs

My analysis relies on a student-level administrative dataset provided by the Michigan Department of Education (MDE) and Center for Educational Performance and Information (CEPI). The dataset links the high school records of students who attend Michigan public high schools from 2009 to 2016 to college enrollment and completion records from the National Student Clearinghouse (NSC) and a state-run data repository (STARR).[6] 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, as well as information on the academic programs in which they enroll, the credits they complete, and the awards they receive.

A key advantage of these data over publicly available data sources, such as the Integrated Postsecondary Education Data System (IPEDS), is that a student's program enrollment is recorded each semester she is enrolled in a postsecondary institution. As a result, I am able to analyze how students' initial field of study choice —rather than their field upon graduation —responds to local labor market shocks. This distinction is particularly important in the community college sector as upwards of 80% of students leave community colleges without completing a credential (Ma and Buam, 2016), but still may gain valuable skills and training. A second advantage of the data is the information on students' residences during high school, which allows me to map local labor market shocks to the counties in which students reside while they are making their postsecondary

[5] 95% 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 merge in data on occupational employment from the BLS Occupational Employment Series and assign programs to the occupation group of the matched occupation that had higher statewide employment in 2009.

[6] The restriction of the dataset to students attending public high schools is relatively minor, as only about 5 to 6% of 12th graders in Michigan attend private schools. See: `https://www.mischooldata.org/Other2/DataFiles/StudentCounts/HistoricalNonpublicStudentCounts.aspx` for more information.

education decisions, rather than the counties in which they ultimately attend college.

I focus my analysis on high school graduates' first college enrollment and program choices within six months (180 days) of graduating from high school.[7] This restriction ensures that the county in which a student resides during high school is a valid measure of her local labor market when she makes her first postsecondary choice and limits the possibility that supply-side responses by colleges drive my results when I consider students' responsiveness to layoffs that occur during their final year of high school.[8] Table 1 provides summary statistics on Michigan's high school graduates disaggregated by their first postsecondary education choices. A non-trivial share of students enroll in vocational and non-vocational community college programs each year: 9% and 14% of graduates, respectively.[9] Students who enroll in vocational programs are more likely to be male, non-white, and economically disadvantaged than students in non-vocational programs. They also score lower on state standardized tests, but compared to their peers who do not enroll in college, they are less disadvantaged and more academically prepared. Appendix Table A.6 further disaggregates the summary statistics by students' vocational program choices.[10]

4 Measuring Local Job Losses

My empirical approach builds on work by Hubbard (2018) and Foote and Grosz (2020) that uses the prevalence of mass layoffs and plant closings to proxy for changes in local labor demand. These data are reported at the establishment level, allowing me to generate counts of reported job losses in small industries and small counties that are typically suppressed or imputed in county-level databases. For example, of 8,217 possible county-industry pairs in Michigan (83 counties, 99

[7]While many adults also enroll in community colleges, a large share of high school graduates who will eventually enroll in community colleges do so within this time frame. For the earliest cohort in my data, I estimate that 2/3 of students who enroll within 8 years of high school graduation do so within the first 6 months.

[8]Because Michigan does not provide annual information on the programs offered by each community college, I am unable to directly analyze whether colleges alter course or program offerings in response to local job losses. However, it seems unlikely that, in the short-run, colleges can respond to labor market shocks by altering the programs or courses the offer, as these decisions are typically made months or years in advance. Grosz (2018) also provides evidence that student demand is much more responsive to labor market trends than college supply.

[9]7.9% of community college students simultaneously enroll in a vocational and non-vocational program. I classify these students as enrolling in vocational programs. 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 they have selected. The results are nearly identical if I instead drop students who enroll in multiple program groups.

[10]To verify that program choices accurately capture students' educational experiences, I categorize community college courses into the same six occupation groups and tabulate the share of courses taken in different subject areas among students enrolled in different programs. Appendix Figure A.1 presents these results. The figures show that 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.

NAICS 3-digit subsectors), only 2,633 (32%) have a complete panel of employment data available in the BLS' Quarterly Census of Employment and Wages (QCEW) series. Other data series, such as the County Business Patterns, have similar limitations, which I detail in Appendix B. Layoff data are also advantageous because they represent sharp declines in local employment that are plausibly exogenous to students' educational choices, and are likely representative of the employment changes students observe through newspapers and other media outlets.

My primary source of layoff data is a listing of all mass layoffs and plant closings reported to the Michigan Workforce Development Agency (WDA) under the federal Worker Adjustment and Retraining Notification (WARN) Act of 1989. The WARN Act requires employers with 100 or more employees to provide at least 60 days notice to employees ahead of large, permanent reductions in employment. Two types of events may trigger a WARN notice: (1) a plant closing affecting 50 or more employees at a single employment site, or (2) a mass layoff affecting either 500 or more employees or between 50 and 499 employees that account for at least one-third of the employer's workforce (U.S. 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. To generate analogous job losses in this field, I supplement the WARN data with a listing of correctional facility closures and corresponding staff reductions from Michigan's Senate Fiscal Agency (SFA).

4.1 Using WARN Data to Generate Occupation-Specific Layoff Exposure

Panel A of Figure 1 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 $t+1$.[11] On average, there are about 75 layoff events each year,

[11] The layoff data available from the WDA include a record of the date that each mass layoff or plant closing event was reported to the state, along with the name of the company, the city where the affected operation is located, and the number of affected workers. I drop 19 layoff events (1.35% of the sample) that do not provide sufficient geographic information to assign to a county. The correctional facility closure data available from the SFA include a record of the name of the correctional facility that closed, along with the year and number of affected full-time equivalent

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 Michigan especially hard. Panel B shows that the total number of job losses also spiked during 2008. These layoffs occur throughout the state, in both rural and urban areas, which I highlight in Appendix Figure A.2 by plotting the average amount of per capita layoffs that occur in each county from 2001 to 2017.

A key limitation of the layoff data is that it does not contain information on the occupations of laid-off workers. I therefore 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 NAICS industry code using information from company websites and online business databases. I then calculate the distribution of community college occupations across industries. Let g denote one of the six program/occupation groups outlined in Appendix Table A.2 (for example, health or business) and k denote a three-digit NAICS industry (for example, hospitals or general merchandise stores). The share of industry k's employment that belongs to occupations in group g in year t can be calculated 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 health-related occupations that community college graduates can reasonably enter.

I calculate α_{gkt} for each year, occupation group, and industry using nationally-representative data from the BLS' Occupational Employment Series (OES) for non-government sectors and the American Community Survey (ACS) for government sectors.[12] Continuing with the example from

(FTE) 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. I drop 19 layoff events (1.35% of the sample) that do not provide sufficient geographic information to assign to a county.

[12]The BLS only began publishing state-specific estimates in 2012 and cautions that they are subject to more error than the national-level estimates. Nevertheless, I also construct the α values using Michigan-specific data and find a strong correlation with my preferred nationally-representative estimates. Appendix Figure A.3 plots the α values for each community college occupation group using each 2016 national and Michigan data. The figure shows a strong correlation between the two measures, with a Pearson coefficient of 0.95.

above, I find that, on average, community college health occupations account for 54.4% of employment in the hospital subsector. In contrast, community college health occupations only account for only 1% of employment at general merchandise stores. As a result, layoffs that occur at hospitals should affect these occupations, and therefore alter the benefit of enrolling in community college health programs, much more than layoffs that occur at general merchandise stores.[13]

I operationalize this intuition by using the occupation-by-industry employment shares to estimate layoff exposure within a given occupation group, county, and academic year. Specifically, I estimate 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 take into account both the occupations which likely experience layoffs and the size of the layoff events occurring in a given county and year, while avoiding ad-hoc aggregations of industries that may not align with the occupational training community college students receive.[14]

4.2 Distribution of Layoffs Across Occupations

Table 2 provides summary statistics on the 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 classify all other layoffs into two distinct categories: (1) those occurring in low-skilled occupations that O*NET identifies as requiring less than a high school diploma (job zone 1) and (2) those occurring in high-skilled occupations that O*NET identifies as requiring at least a bachelor's degree (job zone 5). These layoff measures correspond to the types of occupations students would expect to enter if they did not pursue any postsecondary education or if they obtained four-year college degrees.

[13] Appendix Table A.3 presents the three largest average values of α for each occupation group. In Appendix Table A.4 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. Only two correlations are positive: business and STEM occupations, and health and other occupations.

[14] Appendix Table A.5 lists the three county-year pairs with the largest amount of per capita layoffs in each occupation group.

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.[15] On average, a county-year observation with 10,000 working-age residents experiences 5.3 layoffs in low-skilled occupations, 4.1 layoffs in middle-skill community college occupations, and 1.3 layoffs in high-skilled occupations. 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 then calculates the share of layoffs occurring in each category for county-year observations that experience non-zero layoffs. Across the time frame, 369 county-year observations (26%) experience layoffs. On average, 51% layoffs are in low-skilled occupations, while about 37% occur in community college occupations, and 11% occur in high-skilled occupations.

4.3 Potential Measurement Error

As outlined in the previous section, the layoff measures I construct rely on the distribution of occupations across industries. Implicitly, these measures assume that layoffs in an occupation are proportional to its national employment shares in industries 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 8 should affect community college business occupations. However, suppose that a hospital was to layoff only their billing or financial services 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.

Given the non-classical nature of this measurement error, there is no straightforward way to empirically correct for it. However, there are circumstances where measurement error is less likely to occur. Specifically, plant and prison closures are likely to affect all jobs contained within a given

[15] I define working-age residents as those aged 20 to 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`).

facility and, therefore, should align more closely with the industry-by-occupation employment shares than layoffs that only affect a subset of jobs. In Section 5.3, 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.

5 Effect of Job Losses on Enrollment in Related Programs

The conceptual framework in Section 2 outlines two key outcomes of interest for the empirical analysis: (1) the effect of local job losses on enrollment in related community college programs, and (2) the corresponding substitution into other postsecondary options if students are indeed deterred from entering related programs.[16] I begin by estimating the average effect of job losses on enrollment in related community college programs. Then, in Section 6, I document how students substitute between postsecondary programs in response to job losses.

5.1 Empirical Approach

I create measures of program enrollment at the county-year-program level and estimate specifications of the following form:

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

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 $\mathbf{Layoffs}_{gct}$ 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] I primarily consider layoffs that occur during a cohort's senior year of high school, as this is the time period during which students must decide what educational program, if any, they will enter following graduation. The vector $\mathbf{X}_{ct}$ contains time-varying county control variables that may affect students' enrollment choices: the share of graduates that are white, male, and

[16] In Appendix C, I further consider how related educational outcomes, such as delayed enrollment or program retention, respond to layoffs.

[17] My preferred specification scales program enrollments by the number of graduates in a county, as this dependent variable will capture both changes in the share of students enrolling in vocational community college programs overall and substitution between programs. However, in Appendix Figure A.5, I show that the results are quite similar if I scale the dependent variable by total community college enrollment or enrollment in vocational community college programs.

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. 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. Finally, 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. The vector of controls further accounts for changes in economic conditions across counties and over time. As such, the identifying assumption is that there are no unobserved changes in preferences at the county-program level that are correlated with job losses. This assumption rules out the possibility that, for example, firms lay off workers because they know the next cohort of local high school graduates has different education preferences than the last cohort. While such a phenomenon seems unlikely, the assumption could be threatened if there are any contemporaneous shocks that both affect students' education preferences and are correlated with layoffs. 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. Nevertheless, these controls may not adequately capture changes in a county's economic conditions or preferences. As such, I also estimate specifications that 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 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 unobservable changes in students' preferences across the 2009-2016 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:

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

where LargeLayoff_{gc} indicates that occupation group g in county c experiences annual layoffs in the top quartile of the non-zero layoff distribution in some year between 2009 and 2016.[19] $1[t-t^* = k]$ 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 3 or more years before a large layoff and $k = 4$ captures all observations 4 or more years after.

Appendix Figure A.4 plots the β_k estimates, which trace out the trends in program enrollment rates surrounding the large layoff event. Panel A includes the standard set of control variables, while Panel B includes county-by-program linear time trends, and Panel 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 prior to a large layoff. Program enrollments then decline immediately after the large layoff event, but appear to recover in the following years. 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.

5.2 Main Results

Table 3 presents estimates of equation (3), measuring layoffs at different times during a cohort's academic career. Column (1) includes only layoffs occurring during a cohort's senior year of high school. The point estimate is negative and statistically significant, indicating that an additional

[18]Commuting zones 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 only consider a county-program pair's first large layoff event. The sample is restricted to 117 county-program pairs that experience a large layoff between 2009 and 2016.

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 0.012pp. At the mean enrollment rate of 1.5%, this estimate represents a 0.8% decrease in enrollment in related programs. Correspondingly, a one standard deviation increase in layoff exposure reduces enrollment in related programs by 3.83% of the mean. Columns (2) and (3) then add measures of layoffs occurring in earlier years. 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 prior to this year. The largest point estimate comes from layoffs occurring in students' sophomore year of high school, but this effect is about half the size of the effect of layoffs occurring in the senior year of high school and is not consistently statistically significant. 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 et al., 2019) Finally, Column (4) 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 six months of high school graduation, including this measure serves as a natural placebo test: these layoffs have not occurred when students make their postsecondary choices, and thus, should not affect enrollment in related vocational programs. The point estimate on this term is close to zero statistically insignificant, while the estimate on layoffs occurring during a cohort's senior year of high school remains negative and statistically significant.

Next, I consider how layoffs in other areas of the state affect students' program enrollment decisions. To do so, I estimate equation (3) without including 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. Table 4 presents these results. Column (1) includes only layoffs occurring during a cohort's senior year of high school within their own county. This specification produces a very similar estimate to the main specification in Table 3, despite the lack of a program-by-year fixed effect. Column (2) then 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 (3) then separates this measure into layoffs occurring elsewhere in the county's commuting zone and layoffs occurring outside of the commuting zone. The coefficient on layoffs occurring elsewhere in the commuting zone is statistically insignificant, but negative, suggesting that students may respond to layoffs occurring outside of their county, in their general area of the state. The fact 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 with the data available in Michigan, 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.

5.3 Robustness & Heterogeneity

Figure 2 presents several robustness checks of the main 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. First, Panel A addresses the concern of correlated shocks by estimating how the results change when including different control variables in the $\mathbf{X}_{ct}$ vector. 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, Panel B estimates specifications that include either county-by-program linear time trends or program-by-year-by-CZ fixed effects.[20] 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.

Panel C then shows how the estimates change when restricting the layoff events included in the specification. The estimates are similar when using all layoffs and when using only layoffs that are a result of closings, indicating that the potential measurement error outlined in Section 4.3 is not driving the results. I also find similar estimates when only including layoffs that reach

[20] In specifications that include year-by-CZ fixed effects, Monroe County is dropped from the analysis because all other counties in its commuting zone are in Ohio.

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 four-year college applications are due —also produces a similar estimate, indicating that students are not primarily responding to events that occur after they begin to make college decisions. Panel D estimates non-linear specifications that can better handle fractional dependent variables. First, I estimate equation (3) using either the inverse hyperbolic sine or the natural log of a county's program enrollment as the dependent variable.[21] I then estimate Poisson and fractional logit (Papke and Wooldridge, 1996) specifications.[22,23] The main linear specification produces an estimated semi-elasiticity in the middle of the four non-linear estimates, and I fail to reject the hypothesis that the five estimates are different from one another.[24]

Finally, Panels E and F consider heterogeneous effects. Panel E uses the methods proposed by Firpo et al. (2009) to estimate unconditional quantile regressions across the enrollment share distribution. 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. Panel F then estimates separate effects for different subgroups of students. On average, male and female students respond similarly to layoffs, while economically non-disadvantaged students —who may be more informed about local labor market conditions or receive more college guidance from their high schools —are somewhat more responsive than their disadvantaged peers. The main source of heterogeneity comes from the fact that students residing in rural counties are much more responsive to layoffs than students residing in urban counties.[25] This strong 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

[21] I use the transformations proposed by Bellemare and Wichman (2019) to estimate the semi-elasticity.

[22] In the Poisson specification, the dependent variable remains the share of students from a given county and cohort who enroll in a given program. This specification may be interpreted the same as estimating a linear model with the dependent variable as log program enrollment and controlling for log total vocational enrollment and restricting the coefficient to be equal to 1. See Lindo et al. (2018) for more details.

[23] The fractional logit specification is analogous to estimating a standard logit demand specification where the dependent variable is the log of the enrollment share, but allows for the inclusion of county-program-years where no students enroll in a given program.

[24] Appendix Figure A.6 further shows how the results vary when weighting equation (4) by measures of county size. The estimated elasticities are somewhat smaller, but not statistically different from the main results.

[25] I define urban counties as those that the U.S. Census Bureau classifies as "mostly urban" and define all other counties as rural. A list of Michigan's urban and rural counties is available here: `https://www.mlive.com/news/2016/12/michigans_urban_rural_divide_o.html`.

better indicators of future labor market prospects than layoffs in urban areas if an occupation's employment is heavily concentrated in a single firm.

6 Substitution Effects

The results in Section 5.2 indicate that fewer students enroll in community college programs when exposed to related job losses. I now estimate how these job losses affect students' decisions to enroll in other postsecondary options.

6.1 Substitution out of Vocational Sector

I begin by estimating how layoffs in community college occupations affect students' decisions to enroll in vocational community college programs overall. I estimate the following equation:

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

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 5 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. 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 across cohorts, while the vector of controls accounts for changes in economic conditions within a county.

Therefore, 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. I address these concerns by estimating specifications that include county-specific linear time trends or CZ-by-cohort fixed effects, and by including different variables in the vector of controls.

Table 5 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. Across the three columns, the effects of layoffs are small and none are statistically significant at the 5% level.[26] Moreover, in all specifications, I fail to reject the joint hypothesis that all six coefficients are equal to zero, indicating that layoffs in community college occupations do not meaningfully affect overall enrollment in vocational programs. Appendix Figure A.7 provides estimates of β_g when including different control variables in $\mathbf{X}_{ct}$, which are quite similar to the main specification.

In Appendix Table A.8, I consider whether layoffs affect the composition of students enrolling in vocational programs by regressing mean demographic values of vocational students against the vector of layoff measures. I find little evidence that layoffs affect who enrolls in vocational programs, and, in all specifications, I fail to reject the joint hypothesis that the coefficients on all community college layoff terms are equal to zero. Similarly, in Appendix Table A.9, I estimate how layoffs in community college occupations affect credit completion within vocational students' first year of community college enrollment. I find no evidence that layoffs affect total credit completion, nor completion of vocational vs. non-vocational courses.[27] Taken together, these findings show that layoffs in community college occupations do not dissuade students from enrolling in community colleges and pursuing vocational education programs, nor do they change students'

[26]In Appendix Table A.7, I show that layoffs do increase college enrollment. This finding is consistent with prior work that shows college enrollment increases when local economic conditions worsen. I further show that this increase in college enrollment is concentrated in programs that should lead to four-year college degrees, including non-vocational programs at community colleges, while layoffs slightly decrease enrollment in community college vocational programs. This finding is slightly different from Hubbard (2018), who also uses Michigan data and finds that layoffs predominantly increase enrollment in community colleges. However, he uses an earlier sample (2002-2011 academic years) and measures layoffs within a 30-mile radius of a student's high school rather than at the county level, which could explain the differences in our results.

[27]I divide courses into vocational and non-vocational 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 non-vocational.

intensity of enrollment. Thus, the response documented in Section 5.2 must come from students changing which types of vocational programs they pursue.

6.2 Substitution Between Vocational Programs

Because job losses do not deter students from entering vocational community college programs overall, I now consider how students substitute between vocational programs in response to layoffs. I restrict the sample to students who enroll in vocational programs and estimate the following system of six equations:

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

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 $j \neq g$. The own-layoff terms should be negative because layoffs should deter students from enrolling in related programs. The cross-layoff terms should be positive since students would then substitute between programs, but could be negative if there is some measurement error. Moreover, because the dependent variable shares must sum to 100, the sum of a β_g term across the six enrollment outcomes must equal 0. The identifying assumption for the β_j terms to represent causal effects of layoffs on students' choices is that, conditional on all other variables, layoffs in occupation group j must be uncorrelated with unobservable determinants of enrollment in program group g. When $j = g$, this assumption imposes that occupation-specific layoffs are not correlated with changing preferences for corresponding programs within a county. When $j \neq g$, the assumption is that occupation-specific layoffs are not correlated with changing preferences for other programs within a county. As in the previous sections, unobserved changes in preferences or correlated shocks could violate this assumption, so I again estimate specifications with county-specific linear time trends or cohort dummies interacted with commuting zone fixed effects, and with different control variables.

Table 6 presents the substitution matrix created from estimating equation (5) for each of the six occupation groups.[28] The bold diagonal terms represent the effect of an additional layoff per 10,000 county residents in occupation group g on enrollment in related programs. For example, 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 1.02pp. An analogous increase in layoffs reduce enrollment in health programs by 0.61pp and in law enforcement programs by 0.15pp, in other programs by 0.81pp, and by smaller but negative amounts in the skilled trades and STEM. In the bottom panel, I present the own-layoff semi-elasticities at the mean values of both the dependent and 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 coming from the business and health fields. When estimating the systems of equation jointly, I strongly reject the hypothesis that all six diagonal coefficients are equal to zero (p-value$<$0.01), which is consistent with the statistically significant results in Section 5.[29] However, I fail to reject the hypothesis that the coefficients are all different from one another (p-value=0.175).

Appendix Figures A.8 and A.9 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 generally the effects are larger for non-disadvantaged students and those residing in rural counties. The results are robust to a variety of alternative specifications, including weighting to correct for heteroskedasticitcy (Solon et al., 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 non-linear estimation procedures. Appendix Table A.10 further shows that the own-layoff effects are similar, although somewhat attenuated, when using raw industry-level layoffs instead

[28]The sample consists of 657 (98.9%) county-cohort pairs where at least one student enrolls in vocational programs. Restricting the sample to counties that have non-zero vocational enrollment in every year of the data produces nearly identical results.

[29]Note that, since the same regressors appear in every equation and there are no cross-equation restrictions, estimating each equation separately is algebraically equivalent to jointly estimating the system using feasible generalized least squares (Wooldridge, 2010).

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 1.7pp. This coefficient shows that business layoffs induce students to substitute away from business programs and towards law enforcement programs. Similarly, students primarily substitute from health programs into other programs when there are health layoffs. In Appendix 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 towards business, STEM, and health programs when there are law enforcement layoffs.

6.3 Explaining Substitution with Occupation Characteristics

While it is interesting to document that health layoffs induce students to substitute towards programs in the "other" category, this finding raises yet another question: *why* do students substitute towards these fields? 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 use data on occupation characteristics from the U.S. Department of Labor's Occupational Information Network (O*NET), which contains a wealth of information on worker and job characteristics, including the skills required in different occupations. I characterize community college program groups using measures of three dimensions of skill requirements for related occupations: cognitive skills, social skills, and technical skills.

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 this data to create a Euclidean distance measure that identifies program groups associated with similar occupations. The measure is similar to that used by O*NET to identify similar careers but, to my knowledge, has not previously been used to identify similar college programs. I define the distance between program group p and program group s, which experiences the labor market shock, as:

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

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 distance measures.[30] 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 3 plots the off-diagonal coefficients from Table 6 against their corresponding skill distance metrics.[31] 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. Table 7 then presents regression estimates of these relationships. As shown in the figures, there is a negative and statistically significant relationship between the substitution effect sizes and skill distance, particularly with respect to cognitive and technical skills. These results indicate that, when exposed to layoffs, students are more likely to substitute towards training programs that lead to similar occupations than they are to substitute towards programs that lead to very different career paths.

These substitution patterns could benefit students in the long-run if they are able to 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

[30] To create measures for program groups, I create a weighted average of all occupations that belong to the group where weights are proportional to the total enrollment of Michigan students over the time frame of the data. For example, nursing receives a high weight in the health program group because it is one of the most popular programs. Appendix Table A.12 provides the program group level skill measure for each cognitive, technical, and social skill provided in the O*NET database and Appendix Table A.13 presents the skill distance metric for each pair of program groups, when using all O*NET skill measures.

[31] Appendix Figure A.10 presents the relationship between the substitution effects and distance measures separately for each type of layoff.

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 towards when exposed to layoffs in health occupations, such as childcare or culinary services, tended to have lower or null 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' labor market outcomes is an important area for future research.

7 Conclusion

More than 8 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. In this paper, I study the extent to which students' program choices respond to changes in local labor market conditions in related occupations. To do so, I match detailed administrative data on students' educational decisions with establishment-level data on plant closings and mass layoffs in the state of Michigan. While previous researchers have used similar data to study how local economic conditions affect college enrollment, I provide the first analysis in the literature that matches layoffs to corresponding academic programs and considers how they affect what fields students study once they enroll in college.

I find 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. Using rich data on occupation characteristics, I document that students primarily substitute into programs that lead to occupations that require similar skills. These results have several policy implications for Michigan's community colleges and national education policy efforts. For example, 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 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 geographic trends, or geographic constraints. Ideally, educators would provide students with context to understand local labor market events and assist them in making informed choices that best align with their varied preferences and constraints.

Nevertheless, these results also have limitations. First, the majority of local labor market shocks I observe come during the aftermath of the Great Recession in a state that was particularly affected by the collapse of the automotive industry. While this setting produces substantial variation in local labor market conditions, the results may not generalize to future cohorts or other areas of the country. Second, my results are limited in that they 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 have different preferences for program characteristics and may respond quite differently to local labor market shocks than younger students who are enrolling in college for the first time. 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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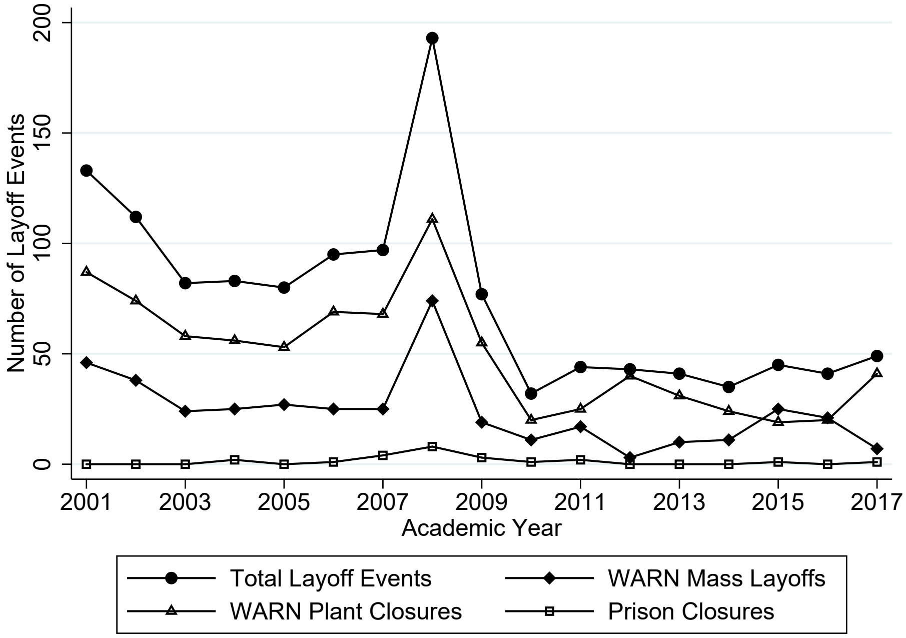
Figure 1: Labor Market Shocks in Michigan, 2001-2017

(a) Layoff Events



(b) Total Job Losses

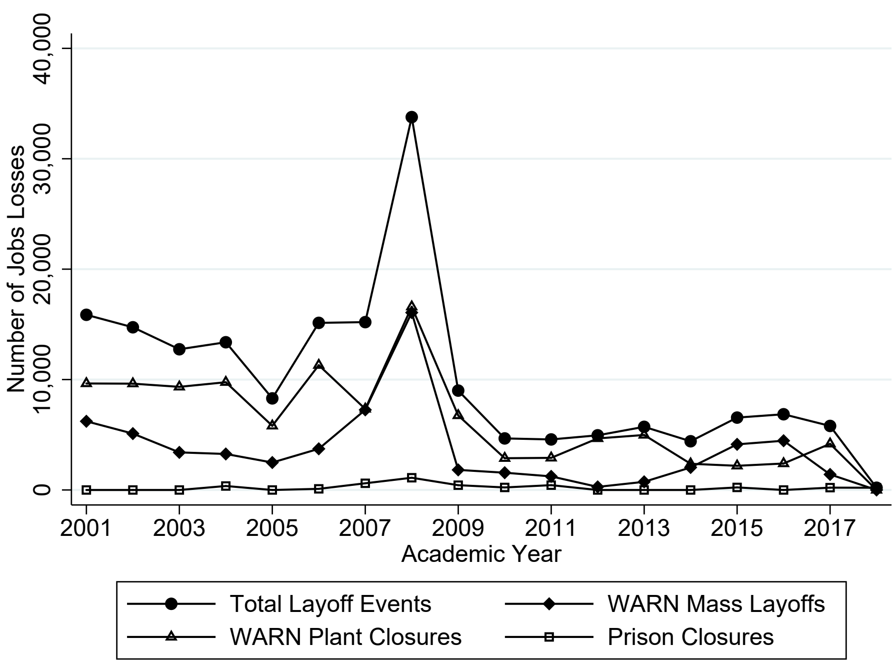
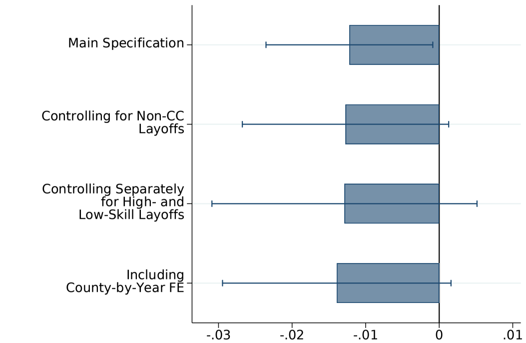
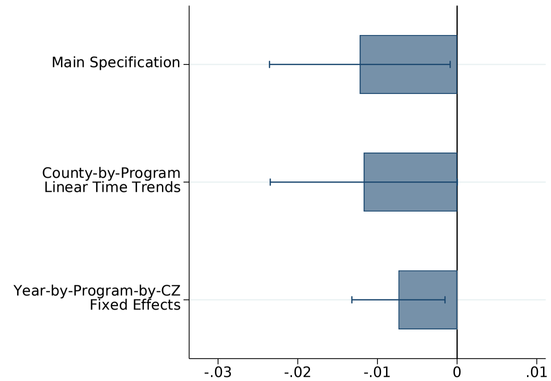


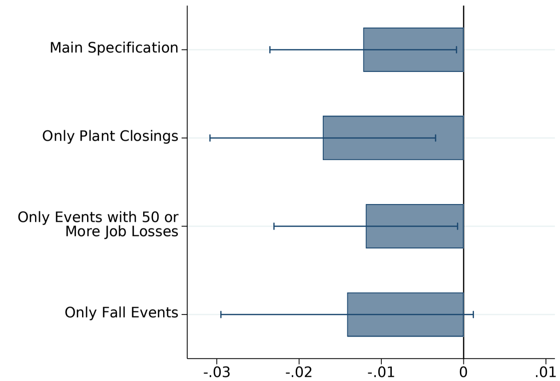
Figure 2: Robustness & Heterogeneity



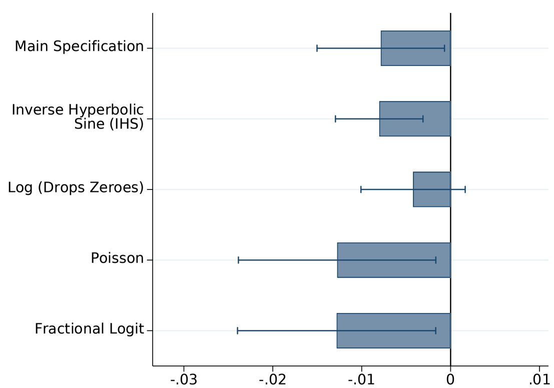
(a) Different Control Variables



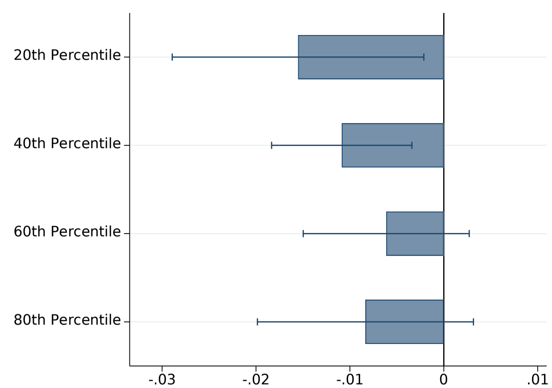
(b) Trends and CZ Fixed Effects



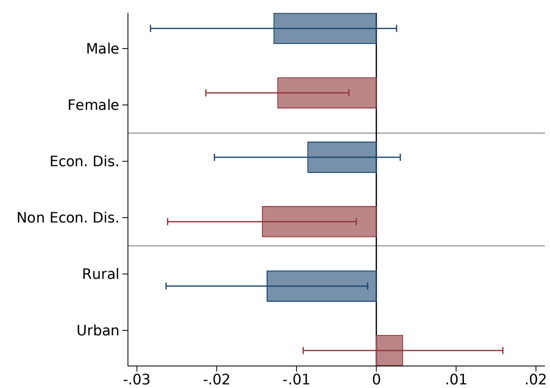
(c) Exclusion of Layoff Events



(d) Non-Linear Specifications (Semi-Elasticities)



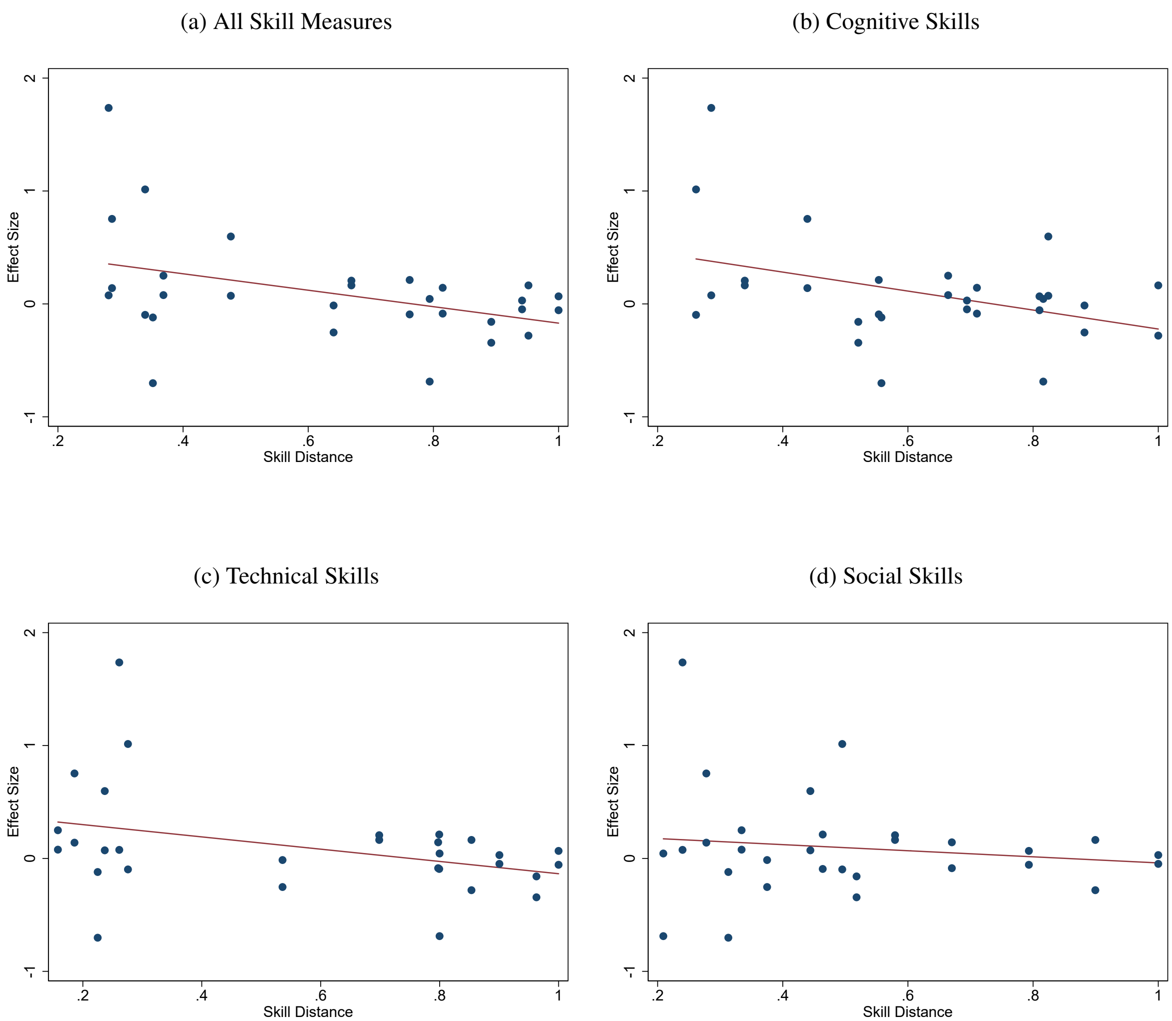
(e) Quantile Regression



(f) Heterogeneous Effects

Notes: Each figure presents estimates of β from equation (3) under different specifications. Unless otherwise indicated, all regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th 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.

Figure 3: Relationship Between Substitution Effects and Skill Distance



Notes: Each panel plots the off-diagonal coefficients from Table 6 against the skill distance metrics outlined in Section 6.3. Panel A uses all 27 skill measures from the O*NET database, while Panel B uses only the cognitive skill measures, Panel C uses only the technical skill measures, and Panel D uses only the social skill measures.

Table 1: Summary Statistics of Michigan's High School Graduates

Variable:	**All Grads (1)**	**CC Voc. (2)**	**CC Non-Voc. (3)**	**Other College (4)**	**No College (5)**
White	0.760	0.738	0.789	0.785	0.723
Black	0.150	0.176	0.128	0.128	0.178
Hispanic	0.041	0.046	0.040	0.027	0.057
Male	0.490	0.537	0.465	0.443	0.543
Economically Disadvantaged	0.333	0.366	0.324	0.222	0.461
English Language Learner	0.025	0.039	0.036	0.010	0.035
Standardized Math Score	0.095	-0.165	-0.028	0.532	-0.305
Standardized Reading Score	0.087	-0.205	-0.048	0.524	-0.303
On-Time Graduation	0.971	0.984	0.986	0.997	0.931
Students	734,928	66,292	103,032	306,532	259,072
Share of Graduates	1.000	0.090	0.140	0.417	0.353

Notes: The sample consists of all graduates of Michigan public high schools from 2009 to 2016 who have non-missing 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 column (2) consists of all students who first enroll in vocational programs in Michigan's community colleges within 6 months of high school graduation.

Table 2: Summary Statistics of Layoffs in Michigan, 2001-2017

Layoff category:	**Mean (1)**	**S.D. (2)**	**Min. (3)**	**Max. (4)**
Panel A. Layoffs per 10,000 Working-Age Residents				
Non-CC Low Skill	5.250	16.395	0.000	290.3
CC Business	1.024	2.991	0.000	45.75
CC Health	0.210	2.647	0.000	88.23
CC Trades	2.080	7.134	0.000	95.56
CC STEM	0.307	0.991	0.000	14.98
CC Law Enf.	0.518	6.302	0.000	138.9
CC Other	0.106	0.596	0.000	14.10
Non-CC High Skill	1.263	4.483	0.000	69.81
County-Year Obs.	1,411	1,411	1,411	1,411
Panel B. Share of Total Layoffs (County-Year Pairs with Non-Zero Total Layoffs)				
Non-CC Low Skill	0.512	0.155	0.142	0.909
CC Business	0.118	0.066	0.028	0.451
CC Health	0.019	0.070	0.000	0.552
CC Skilled Trades	0.173	0.120	0.000	0.648
CC STEM	0.033	0.037	0.000	0.234
CC Law Enf.	0.020	0.0844	0.000	0.432
CC Other	0.015	0.029	0.000	0.219
Non-CC High Skill	0.114	0.075	0.002	0.510
County-Year Obs.	369	369	369	369

Notes: 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 Section 4.1 for more details.

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

	Enrollment in Occupation Group Programs per 100 H.S. Graduates			
Layoffs per 10,000 in:	**(1)**	**(2)**	**(3)**	**(4)**
Year following graduation				0.007
				(0.005)
Senior year of H.S.	-0.012**	-0.014**	-0.014**	-0.011*
	(0.006)	(0.007)	(0.007)	(0.006)
Junior year of H.S.		-0.002	-0.003	-0.001
		(0.004)	(0.005)	(0.005)
Sophomore year of H.S.		-0.008**	-0.008*	-0.006
		(0.004)	(0.004)	(0.004)
Freshman year of H.S.		-0.004	-0.005	-0.002
		(0.004)	(0.004)	(0.004)
8th grade			-0.007	-0.004
			(0.005)	(0.004)
7th grade			0.005	0.007
			(0.005)	(0.006)
6th grade			-0.002	-0.000
			(0.004)	(0.004)
5th grade			0.002	0.004
			(0.005)	(0.005)
Outcome Mean	1.57	1.57	1.57	1.57
County-Program-Year Obs.	3,984	3,984	3,984	3,984
R-squared	0.488	0.489	0.490	0.490

Notes: 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 equation (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 that are white, male, and categorized as economically disadvantaged; average 11th 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Effect of Job Losses in Alternative Geographic Areas

Layoffs per 10,000 in:	**Enrollment in Occupation Group Programs per 100 Vocational Students** (1)	(2)	(3)
Own county, t-1	-0.012**	-0.012**	-0.012**
	(0.006)	(0.006)	(0.006)
Rest of state, t-1		0.003	
		(0.012)	
Rest of commuting zone, t-1			-0.008
			(0.009)
State less commuting zone, t-1			0.007
			(0.013)
Outcome Mean	1.57	1.57	1.57
County-Program-Year Obs.	3,984	3,984	3,936
R-squared	0.476	0.476	0.479

Notes: 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 vocational students in the county. The coefficients in each column are estimated from a separate regression and represent variants of β in equation (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 that are white, male, and categorized as economically disadvantaged; average 11th grade math and reading test scores; and the county unemployment rate and the county unemployment rate and logged size of the labor force. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: 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	0.085	0.146	-0.029
	(0.118)	(0.149)	(0.112)
Health, t-1	0.015	-0.057	0.100*
	(0.041)	(0.046)	(0.056)
Skilled Trades, t-1	0.021	0.005	0.023
	(0.022)	(0.032)	(0.026)
STEM, t-1	0.161	0.005	0.019
	(0.138)	(0.163)	(0.122)
Law Enforcement, t-1	-0.001	-0.009	-0.001
	(0.016)	(0.021)	(0.014)
Other, t-1	0.107	0.189	0.133
	(0.241)	(0.215)	(0.208)
P-Value for Joint Test	0.351	0.607	0.314
County-Specific Trends		X	
Year-by-CZ Fixed Effects			X
Outcome Mean	9.40	9.40	9.40
County-Year Obs.	664	664	656
R-squared	0.671	0.761	0.809

Notes: 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 equation (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 brackets below the estimates are the estimated elasticities at the mean dependent and independent variable values. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: Substitution Between Community College Program Groups

	Enrollment per 100 Vocational Students in:					
	Business	**Health**	**Trades**	**STEM**	**Law Enf.**	**Other**
Layoffs per 10,000 in:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Business, t-1	**-1.025****	-0.702	-0.056	-0.093	1.736***	0.141
	(0.456)	(0.682)	(0.449)	(0.280)	(0.592)	(0.347)
Health, t-1	-0.120	**-0.610****	-0.281**	0.164	0.250	0.597***
	(0.138)	**(0.232)**	(0.122)	(0.123)	(0.222)	(0.132)
Skilled Trades, t-1	0.067	0.164	**-0.088**	-0.014	0.030	-0.159**
	(0.078)	(0.109)	**(0.097)**	(0.066)	(0.123)	(0.063)
STEM, t-1	0.212	0.206	-0.253	**-0.124**	-0.086	0.044
	(0.676)	(0.626)	(0.674)	**(0.347)**	(0.839)	(0.405)
Law Enf., t-1	0.076	0.078	-0.048	0.143	**-0.153****	-0.097
	(0.075)	(0.082)	(0.061)	(0.094)	**(0.075)**	(0.061)
Other, t-1	0.753	0.072	-0.344	-0.688	1.014	**-0.807**
	(0.617)	(0.945)	(0.518)	(0.522)	(0.678)	**(0.511)**
Own-layoff semi-elasticities (at mean):						
	-0.047**	-0.029***	-0.006	-0.010	-0.011**	-0.046
	(0.021)	(0.011)	(0.007)	(0.029)	(0.005)	(0.029)
Outcome Mean	21.66	20.67	14.33	11.84	13.74	17.75
County-Year Obs.	657	657	657	657	657	657
R-squared	0.190	0.506	0.344	0.266	0.258	0.353

Notes: 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 who in the county and cohort enroll in vocational programs. The coefficients in each column are estimated from a separate regression and represent the β_j terms in equation (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 that are white, male, and categorized as economically disadvantaged; average 11th 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: Relationship Between Substitution Effects and Skill Distance

	All **(1)**	**Cognitive** **(2)**	**Technical** **(3)**	**Social** **(4)**
Similarity	-0.728*	-0.840*	-0.543*	-0.270
	(0.367)	(0.448)	(0.267)	(0.358)
Observations	30	30	30	30
R-Squared	0.166	0.161	0.135	0.019

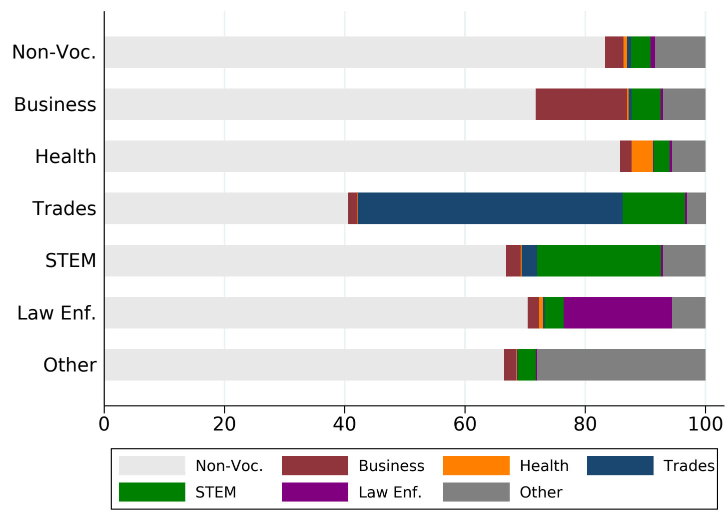
Notes: Each coefficient is estimated from a separate regression and corresponds to the analogous figure in Figure 3. Robust standard errors are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Online Appendix: Not for Publication

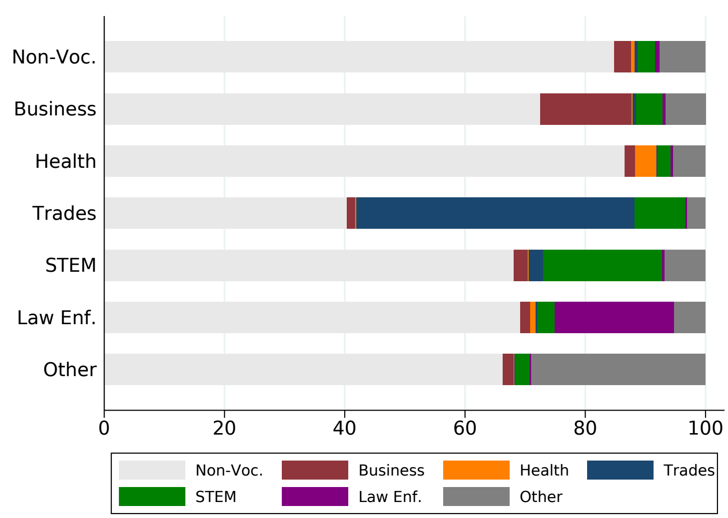
A Additional Figures & Tables

Figure A.1: Differences in Course-Taking and Credit Completion by CC Program Group

(a) Share of Courses Taken



(b) Share of Credits Completed



Notes: Each bar represents the share of courses taken or credits completed in different areas of study among students pursuing a program in the designated program group (e.g., business, health, etc.). The sample consists of all students who enroll in Michigan community colleges within six months of high school graduation. Only courses taken and credits completed within the first academic year following high school graduation are included.

Figure A.2: Average Layoffs in Michigan Counties, 2001-2017

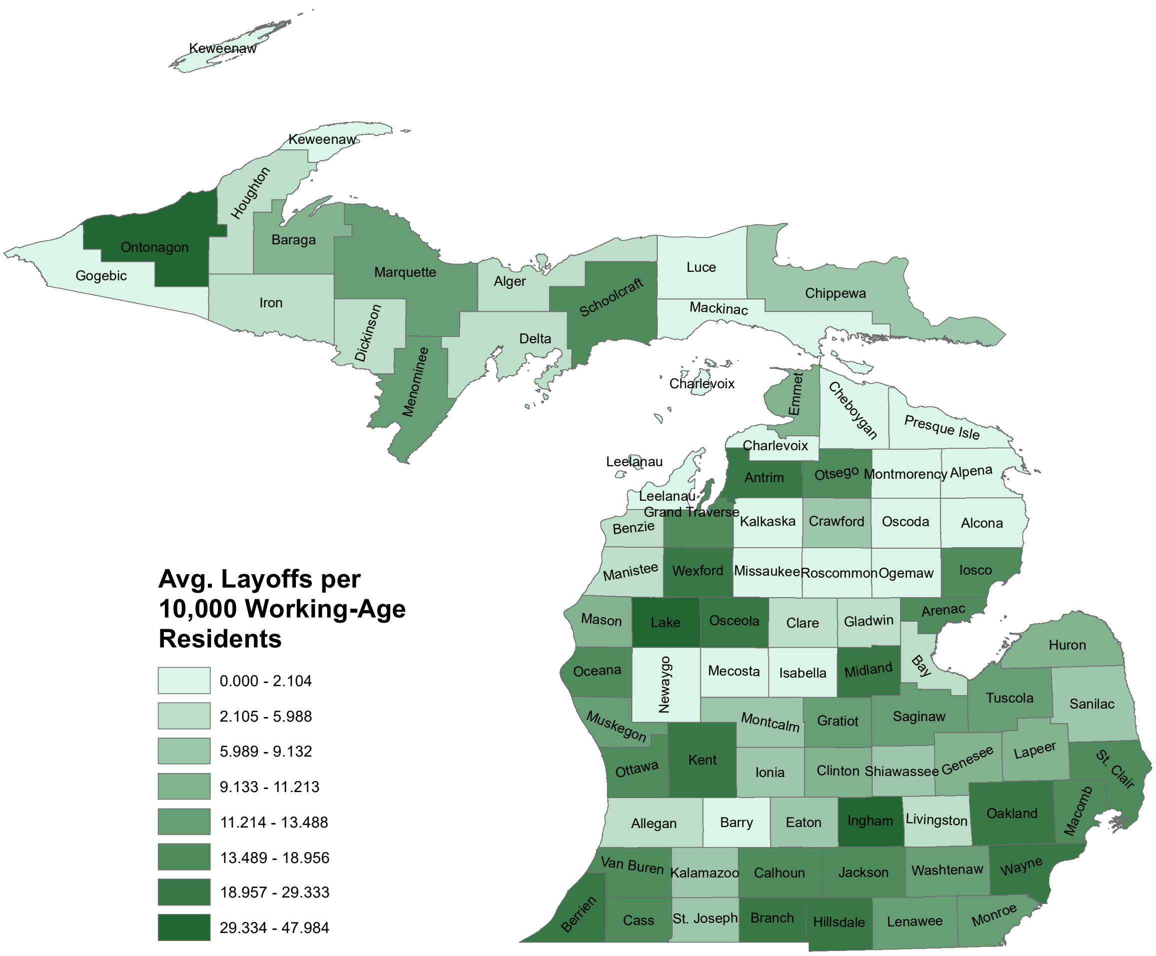
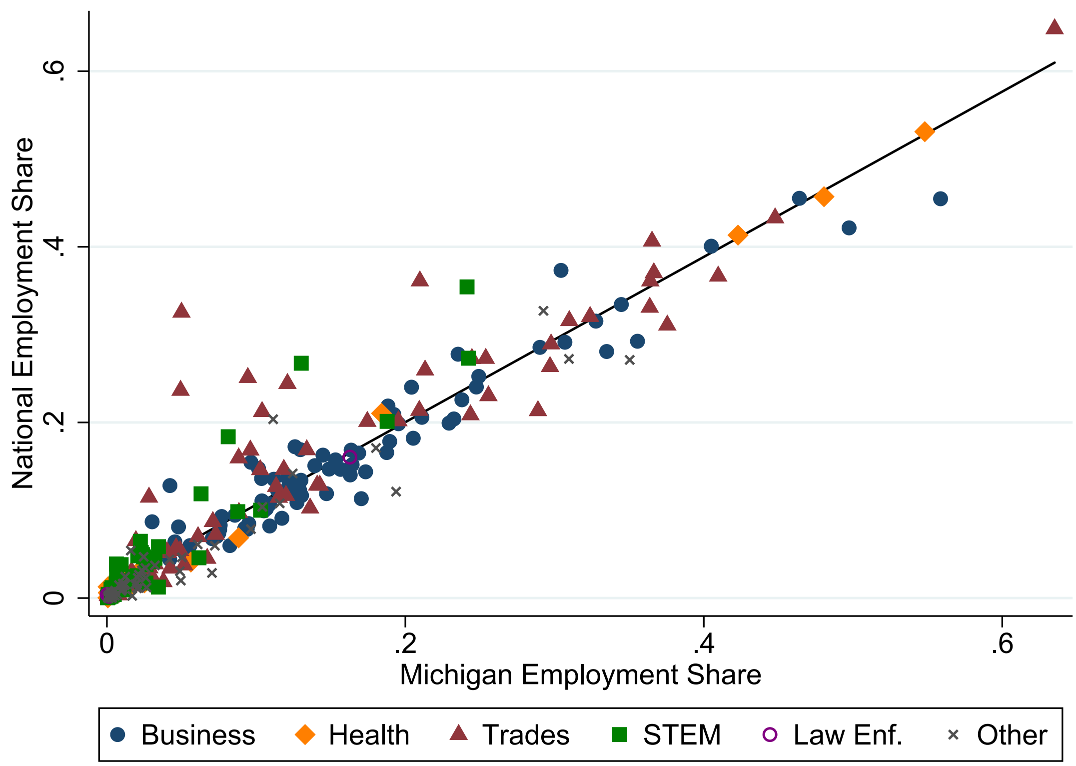


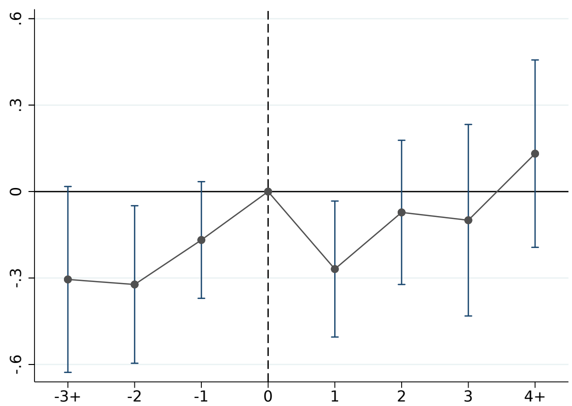
Figure A.3: Correlation Between National and State-Specific Industry Employment Shares, 2016



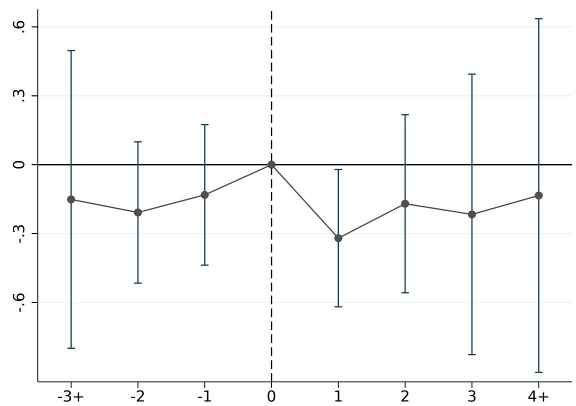
Notes: Each marker represents a NAICS three-digit industry with non-zero employment in a given community college program/occupation group. The national employment share is calculated from the 2016 BLS Occupational Employment Series national estimates. The Michigan employment share is calculated from the 2016 BLS Occupational Employment Series state-specific estimate.

Figure A.4: Enrollment Trends Surrounding Large Layoff Events

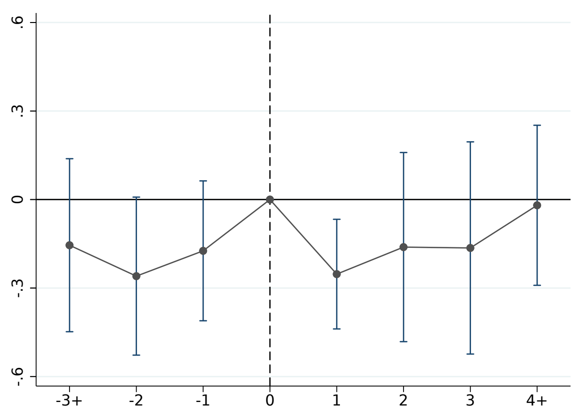
(a) Main Specification



(b) Including County-by-Program Linear Time Trends

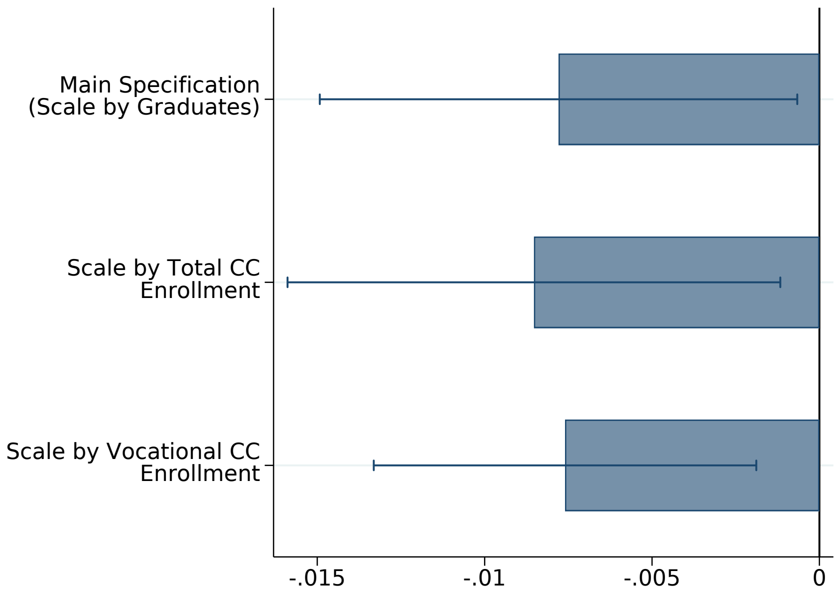


(c) Including Program-by-Year-by-CZ Fixed Effects



Notes: Each figure plots the β_k estimates from equation (4), indicating the change in program enrollment surrounding a large layoff event in corresponding occupations. All specifications include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th grade math and reading test scores; and the county unemployment rate and logged size of the labor force. Panel B additionally includes county-by-program linear time trends, while Panel C includes program-by-year-by-CZ (commuting zone) fixed effects. All standard errors are clustered at the county level.

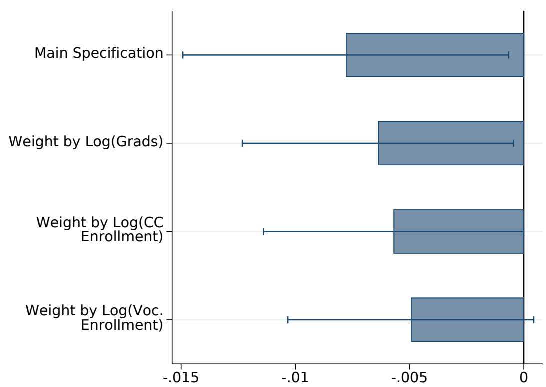
Figure A.5: Semi-Elasticities with Different Denominators



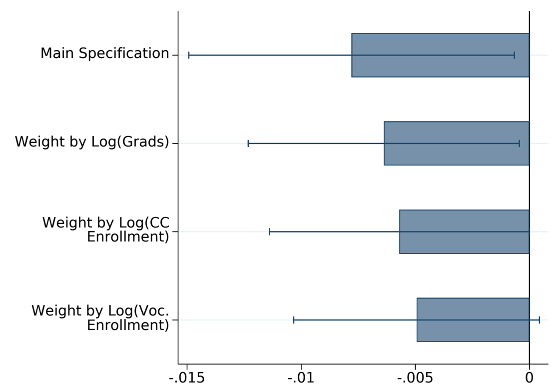
Notes: Each bar provides the estimated semi-elasticity from equation (3), i.e. the percent change in enrollment in a given vocational community college program due to an additional layoff in related occupations per 10,000 working-age residents in the county. The top bar scales the dependent variable by the number of graduates in the county, the middle bar scales by the total enrollment in community college programs, and the bottom bar scales by enrollment in vocational community college programs. Standard errors are clustered at the county level and 95% confidence intervals are shown.

Figure A.6: Semi-Elasticities with County-Level Weights

(a) Share Specification (All Counties)

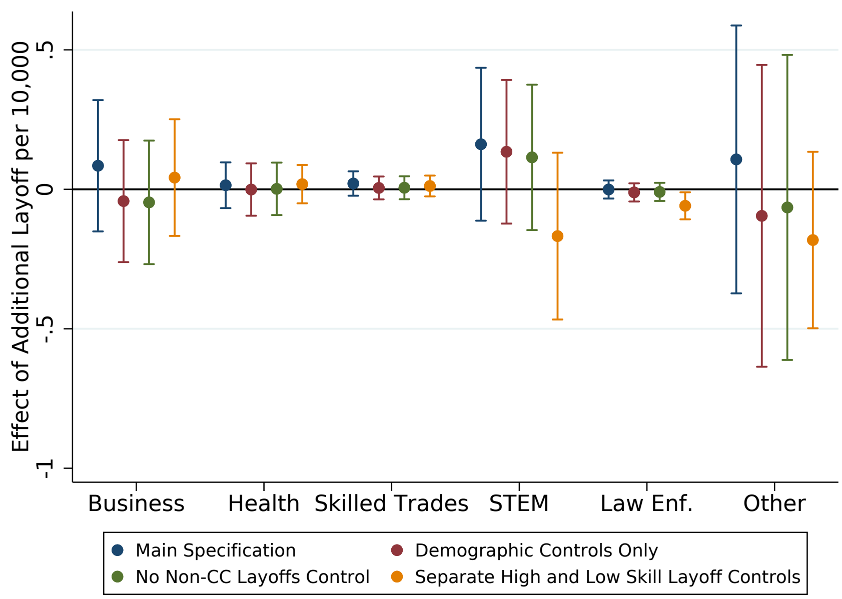


(b) IHS Specification (All Counties)



Notes: Each bar in each panel provides the estimated semi-elasticity from equation (3), i.e. the percent change in enrollment in a given vocational community college program due to an additional layoff in related occupations per 10,000 working-age residents in the county. The top bar does not include weights, the second bar weights by the log of the average number of graduates in a county between 2009 and 2016, the third bar weights by the log of the average community college enrollment, and the bottom bar weights by the log of the average enrollment in vocational community college programs (the weight is equal to 0 if a county's average vocational enrollment is less than 1). Panel A uses the full sample of counties and main specification, while Panel B uses an inverse hyperbolic sine transformation of the dependent variable. Standard errors are clustered at the county level and 95% confidence intervals are shown.

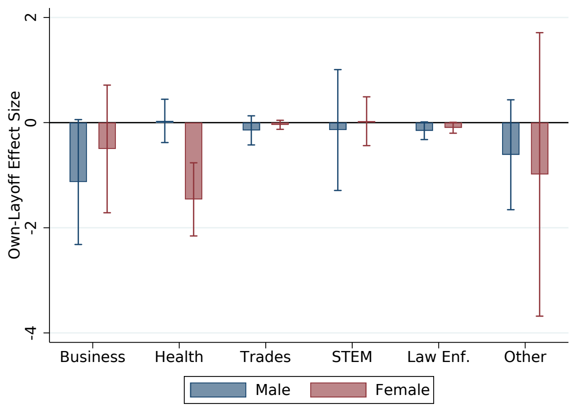
Figure A.7: Overall Enrollment in Vocational Programs, Different Control Variables



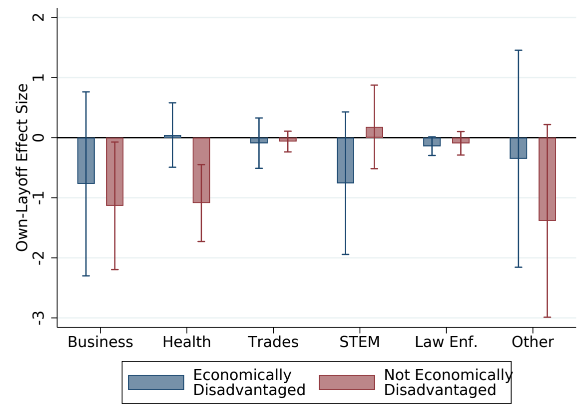
Notes: Each plotted coefficient represents one of the β parameters in equation (4), the effect of an additional layoff per 10,000 working age residents in a given occupation group on overall enrollment in vocational programs, when including different control variables. The "Main Specification" controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th 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. The "Demographic Controls Only" specification controls for the share of graduates that are white, male, and categorized as economically disadvantaged, as well as average 11th grade math and reading test scores. The "No Non-CC Layoffs Control" specification includes all the variables in the "Demographic Controls Only" specification, plus the county unemployment rate and logged size of the labor force. The "Separate High and Low Skill Layoff Controls" duplicates the main specification, but separates the number of layoffs per 10,000 working-age residents in non community college occupations into those occurring in low-skill and high-skill occupations. In all specifications, standard errors are clustered at the county level.

Figure A.8: Heterogeneous Own-Layoff Effects

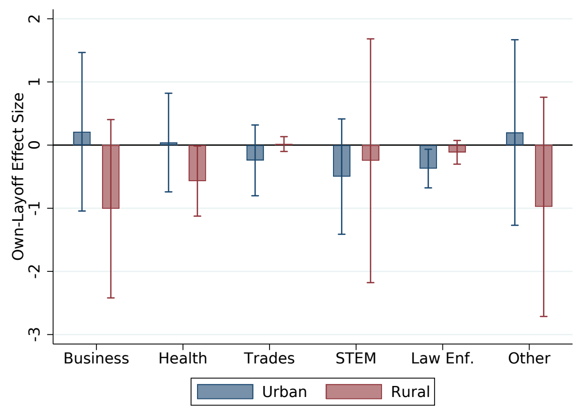
(a) Heterogeneity by Gender



(b) Heterogeneity by Economic Disadvantage Status



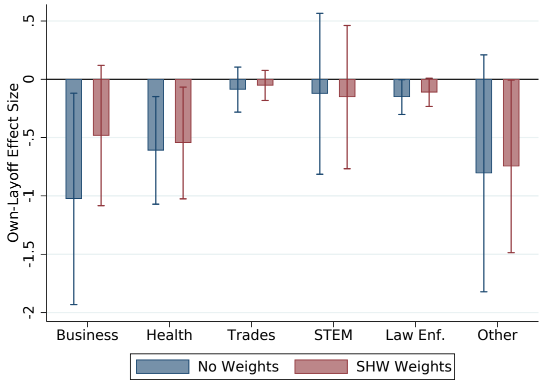
(c) Heterogeneity by County Urbanicity



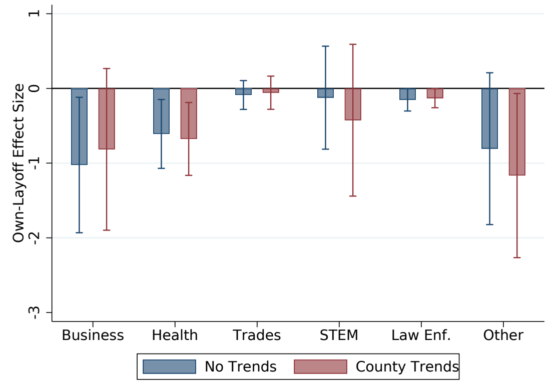
Notes: Each figure presents estimates of the "own-layoff" effects in Table 6 for different subgroups of students. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th grade math and reading test scores; and the county 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.

Figure A.9: Robustness Checks for Own-Layoff Effects

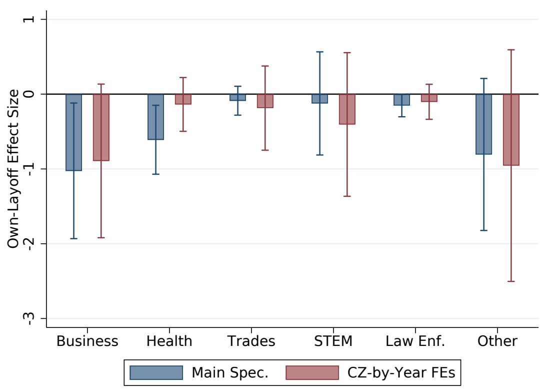
(a) Weighting for Heteroskedasticity



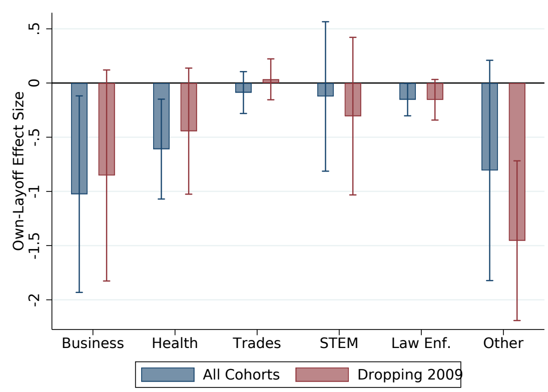
(b) County-Specific Time Trends



(c) Cohort-by-Commuting Zone Fixed Effects

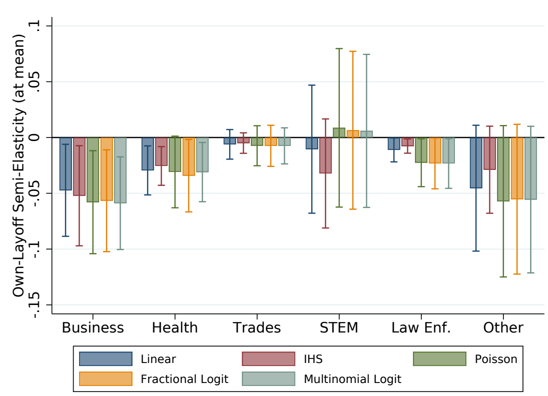


(d) Dropping 2009 Cohort



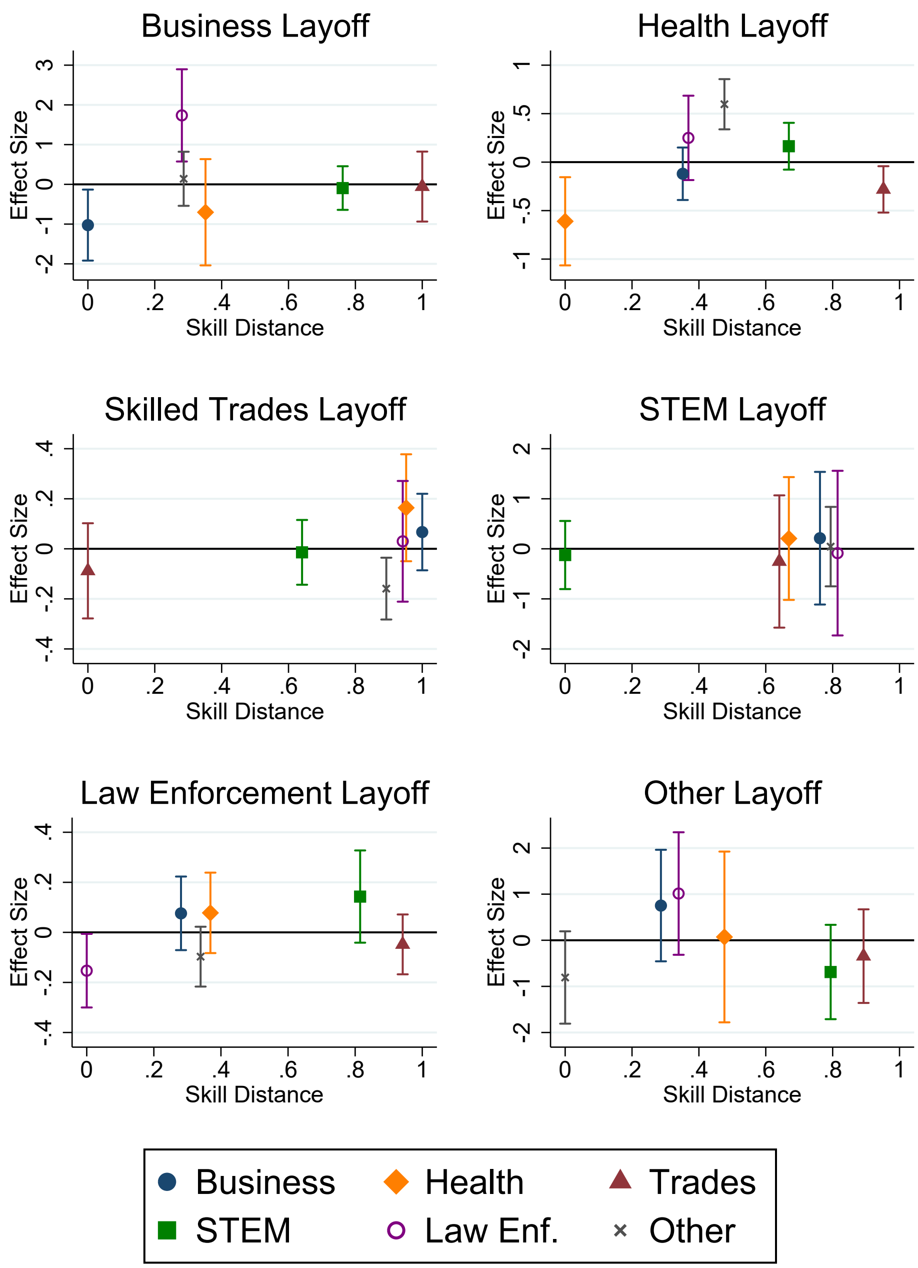
(e) Different Control Variables

(f) Non-Linear Specifications (Semi-Elasticites)



Notes: Each figure presents estimates of the "own-layoff" effects in Table 6 under alternative specifications. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th 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.

Figure A.10: Substitution into Program Groups Requiring Similar Skills



Notes: Each panel plots the coefficients from a single row of Table 6 against the skill distance metric that uses all 27 skill measures from the O*NET database. The coefficient at the skill distance of 0 is the "own-layoff" effect, while all other coefficients are the substitution effects. All standard errors are clustered at the county level.

Table A.1: Programs Offered by Michigan's Community Colleges

Variable:	**Mean (1)**	**S.D. (2)**	**Min. (3)**	**Max. (4)**
Panel A. All Programs				
Total Programs	116.54	67.18	41.00	319.00
Vocational Programs	95.29	59.00	33.00	280.00
Non-Vocational Programs	21.25	13.03	5.00	51.00
Share Vocational	0.81	0.10	0.56	0.94
Panel B. Associate Programs				
Total Programs	59.75	30.11	10.00	142.00
Vocational Programs	45.07	24.42	5.00	124.00
Non-Vocational Programs	14.68	9.94	2.00	37.00
Share Vocational	0.75	0.12	0.49	0.92
Panel C. Certificate Programs				
Total Programs	56.79	40.52	17.00	177.00
Vocational Programs	50.21	36.47	13.00	158.00
Non-Vocational Programs	6.57	5.45	0.00	21.00
Share Vocational	0.88	0.08	0.67	1.00

Notes: The sample consists of Michigan's 28 community colleges during the academic year 2011-2012. Vocational programs are defined as those which can be matched to an occupation that is attainable by community college graduates. Non-vocational programs are all other programs offered by Michigan's community colleges. See the text in Section 2.1 for more details.

Table A.2: Program Groups and Associated Occupation Codes

Program Group	**SOC**	**SOC Title**
Business	11	Management
	13	Business and Financial
	23	Legal
	41	Sales and Related
	43	Office and Administrative Support
Health	29	Healthcare Practitioners and Technical
	31	Healthcare Support
Trades	37	Building and Grounds Cleaning and Maintenance
	45	Farming, Fishing, and Forestry
	47	Construction and Extraction
	49	Installation, Maintenance, and Repair
	51	Production*
	53	Transportation and Material Moving**
STEM	15	Computer and Mathematical
	17	Architecture and Engineering
	19	Life, Physical, and Social Science
Law Enf.	33	Protective Service
Other	21	Community and Social Service
	25	Education, Training, and Library
	27	Arts, Design, Entertainment, Sports, and Media
	35	Food Preparation and Serving Related
	39	Personal Care and Service

Notes: * Programs matched to the 3-digit code 51-3 (Food Processing Workers) are included in the "Other" group because they are generally part of Culinary Arts programs that are mostly matched to the 2-digit code 35 (Food Preparation and Serving Related). Results are robust to including these programs in either group. ** Programs matched to the 6-digit code 53-3011 (Ambulance Drivers and Attendants) are included in the "Health" group because they are generally part of Emergency Medical Services programs that are mostly matched to the 2-digit code 29 (Healthcare Practitioners and Technical). Results are robust to including these programs in either group.

Table A.3: Industries with Highest Employment Shares of Community College Occupations

NAICS	**Industry Title**	**Share (α)**
Business		
524	Insurance Carriers and Related Activities	0.429
522	Credit Intermediation and Related Activities	0.443
425	Wholesale Electronic Markets and Agents and Brokers	0.470
Health		
621	Ambulatory Health Care Services	0.414
623	Nursing and Residential Care Facilities	0.508
622	Hospitals	0.544
Trades		
212	Mining (except Oil and Gas)	0.386
811	Repair and Maintenance	0.449
484	Truck Transportation	0.623
STEM		
511	Publishing Industries (except Internet)	0.187
516	Internet Publishing and Broadcasting	0.216
518	Data Processing, Hosting, and Related Services	0.300
Law Enforcement		
482	Rail Transportation	0.005
921	Executive, Legislative, and Other General Government Support	0.010
922	Justice, Public Order, and Safety Activities	0.411
Other		
515	Broadcasting (except Internet)	0.228
812	Personal and Laundry Services	0.313
624	Social Assistance	0.369

Notes: Employment shares (α) are calculated as outlined in Section 4.1 and averaged over all years 2001-2016.

Table A.4: Correlation Between Occupation Composition Across Industries

	Business	**Health**	**Trades**	**STEM**	**Law Enf.**	**Other**
Business	1.000					
Health	-0.133	1.000				
Trades	-0.258	-0.212	1.000			
STEM	0.328	-0.106	-0.190	1.000		
Law Enf.	-0.106	-0.002	-0.098	-0.051	1.000	
Other	-0.138	0.071	-0.360	-0.011	-0.026	1.000

Notes: Each cell displays a pairwise correlation between the industry employment shares for the occupation groups of interest. See Section 4.1 for more information.

Table A.5: Largest Layoffs by Occupation Group, 2001-2017

County	**Year**	**Size**	**Largest Related Layoff (Jobs Lost)**
Business			
Lake	2005	27.88	Michigan Youth Correctional Facility (204)
Iosco	2008	29.02	Kalitta Air (219)
Ontonagon	2009	45.75	SmurfitStone Container Corp. (150)
Health			
Midland	2015	13.95	MidMichigan Health - Stratford Village (143)
Gladwin	2015	29.72	MidMichigan Health - Gladwin Pines (85)
Ontonagon	2009	88.23	Maple Manor Nursing Home (62)
Trades			
Antrim	2007	61.18	Dura Automotive Systems (300)
Ontonagon	2009	69.30	SmurfitStone Container Corp. (150)
Wexford	2010	95.56	AAR Mobility Systems (282)
STEM			
Antrim	2007	61.18	Dura Automotive Systems (300)
Ingham	2004	9.987	General Motors (3,975)
Midland	2015	14.98	Dow Chemical Company (700)
Law Enforcement			
Lake	2011	87.01	Northlake Correctional Facility (146)
Arenac	2009	131.2	Standish Maximum Facility (281)
Lake	2005	138.9	Michigan Youth Correctional Facility (204)
Other			
Oceana	2008	6.03	Double JJ Resort (150)
Hillsdale	2012	7.45	The Manor Residential Treatment Facility (140)
Ontonagon	2009	14.10	SmurfitStone Container Corp. (150)

Notes: Size is measured as the estimated number of layoffs per 10,000 working-age residents in the county.

Table A.6: Summary Statistics of Vocational Students by Program

Variable:	**Business (1)**	**Health (2)**	**Trades (3)**	**STEM (4)**	**Law Enf. (5)**	**Other (6)**
White	0.747	0.705	0.837	0.759	0.750	0.704
Black	0.169	0.203	0.088	0.146	0.171	0.213
Hispanic	0.041	0.051	0.045	0.042	0.049	0.046
Male	0.588	0.216	0.943	0.855	0.653	0.396
Economically Disadvantaged	0.329	0.415	0.348	0.338	0.389	0.366
English Language Learner	0.044	0.053	0.034	0.048	0.031	0.019
Standardized Math Score	-0.056	-0.260	-0.193	0.069	-0.306	-0.242
Standardized Reading Score	-0.162	-0.231	-0.398	-0.072	-0.316	-0.162
On-Time Graduation	0.987	0.984	0.978	0.984	0.984	0.984
Students	16,082	15,080	5,387	8,476	8,288	12,979
Share of Vocational Students	0.243	0.227	0.081	0.128	0.125	0.196

Notes: The sample consists of all graduates of Michigan public high schools from 2009 to 2016 who have non-missing demographic and geographic information and enroll in a vocational program at one of the state's community colleges within 6 months of high school graduation.

Table A.7: Effect of Layoffs on College Enrollment Outcomes

	Enrollment per 100 Graduates in:			
	No Formal College	**CC Vocational Programs**	**CC Non-Voc. Programs**	**Four-Year Colleges**
Layoffs per 10,000 in:	**(1)**	**(2)**	**(3)**	**(4)**
Panel A. Total layoffs				
All occupations, t-1	-0.013**	-0.004*	0.005	0.012**
	(0.006)	(0.002)	(0.005)	(0.005)
Outcome Mean	39.60	9.40	12.56	38.44
County-Year Obs.	664	664	664	664
R-Squared	0.787	0.670	0.731	0.865
Panel B. Layoffs by skill group				
Low-skill occupations, t-1	-0.004	-0.012	0.019	-0.002
	(0.020)	(0.013)	(0.016)	(0.022)
Community college occupations, t-1	-0.041	0.004	0.011	0.026
	(0.035)	(0.017)	(0.021)	(0.027)
High-skill occupations, t-1	0.058	-0.002	-0.069	0.012
	(0.077)	(0.037)	(0.052)	(0.053)
Outcome Mean	39.60	9.40	12.56	38.44
County-Year Obs.	664	664	664	664
R-Squared	0.788	0.670	0.732	0.865

Notes: 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 equation (4), 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 brackets below the estimates are the estimated elasticities at the mean dependent and independent variable values. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th grade math and reading test scores; and the county unemployment rate and logged size of the labor force during a cohort's senior year of high school. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.8: Effect of Layoffs on Composition of Vocational Students

Layoffs per 10,000 in:	**% White** (1)	**% Male** (2)	**% Econ. Dis.** (3)	**Avg. Math Score** (4)	**Avg. Read Score** (5)
Business, t-1	0.007	-0.005	-0.005	0.011	-0.003
	(0.004)	(0.009)	(0.008)	(0.008)	(0.008)
Health, t-1	0.004	0.005	-0.002	0.002	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Skilled Trades, t-1	-0.000	0.001	-0.000	-0.002	-0.000
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
STEM, t-1	0.008	-0.003	-0.007	-0.009	-0.005
	(0.006)	(0.009)	(0.008)	(0.008)	(0.010)
Law Enforcement, t-1	0.000	0.002	0.001	-0.001	-0.003
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Other, t-1	-0.016	-0.001	-0.009	-0.010	0.010
	(0.012)	(0.011)	(0.006)	(0.014)	(0.011)
P-Value for Joint Test	0.456	0.638	0.217	0.217	0.827
Outcome Mean	0.870	0.531	0.393	-0.067	-0.144
County-Year Obs.	657	657	657	657	657
R-Squared	0.728	0.220	0.528	0.474	0.389

Notes: The unit of observation is a county-cohort pair. Outcomes are measured as the mean characteristic across all students who enroll in vocational programs. The coefficients in each column are estimated from a separate regression and represent the β parameters in equation (4), 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 that are white, male, and categorized as economically disadvantaged; average 11th 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.9: Effect of Layoffs on First-Year Course-Taking

Layoffs per 10,000 in:	**Total Credits (1)**	**Vocational Credits (2)**	**Non-Voc. Credits (3)**
Business, t-1	0.007	-0.082	0.089
	(0.216)	(0.108)	(0.152)
Health, t-1	0.019	0.029	-0.010
	(0.086)	(0.050)	(0.049)
Skilled Trades, t-1	0.019	0.000	0.019
	(0.036)	(0.018)	(0.025)
STEM, t-1	0.044	0.006	0.039
	(0.346)	(0.143)	(0.233)
Law Enforcement, t-1	0.034	0.009	0.025
	(0.034)	(0.018)	(0.021)
Other, t-1	0.140	-0.150	0.290
	(0.705)	(0.329)	(0.397)
P-Value for Joint Test	0.952	0.920	0.669
Outcome Mean	17.34	6.46	10.88
County-Year Obs.	657	657	657
R-Squared	0.471	0.482	0.505

Notes: The unit of observation is a county-cohort pair. Outcomes are measured as the mean number of credits completed in the first year of community college enrollment across all students who enroll in vocational programs. The coefficients in each column are estimated from a separate regression and represent the β parameters in equation (4), 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 that are white, male, and categorized as economically disadvantaged; average 11th 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.10: Effect of Industry-Level Layoffs on Substitution Between Community College Programs

	Enrollment in:					
	Business	**Health**	**Trades**	**STEM**	**Law Enf.**	**Other**
Layoffs per 10,000 in:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A. Share Specification						
Retail Trade, t-1	-0.241*	0.318***	0.052	0.005	-0.257	0.123
	(0.131)	(0.115)	(0.075)	(0.086)	(0.180)	(0.283)
Health Care & Social Assistance, t-1	-0.017	-0.322**	-0.089	0.042	0.129	0.257***
	(0.059)	(0.152)	(0.083)	(0.045)	(0.112)	(0.077)
Manufacturing, t-1	-0.049**	0.089*	-0.026	-0.019	0.028	-0.023
	(0.023)	(0.046)	(0.030)	(0.020)	(0.043)	(0.020)
Public Administration, t-1	0.015	0.057**	-0.016	0.041	-0.058***	-0.039*
	(0.023)	(0.025)	(0.019)	(0.040)	(0.019)	(0.020)
All Other Industries, t-1	0.026	0.046	0.024	-0.025	0.002	-0.073**
	(0.044)	(0.039)	(0.018)	(0.029)	(0.047)	(0.028)
Panel B. Inverse Hyperbolic Sine Specification						
Retail Trade, t-1	-0.005	0.014***	0.001	0.010	-0.003	0.006
	(0.004)	(0.005)	(0.005)	(0.007)	(0.004)	(0.012)
Health Care & Social Assistance, t-1	0.002	-0.011**	0.001	-0.000	0.003	0.010***
	(0.002)	(0.005)	(0.004)	(0.003)	(0.006)	(0.003)
Manufacturing, t-1	-0.002**	0.003**	-0.002	0.000	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Public Administration, t-1	0.001	0.002***	-0.000	0.002	-0.002**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
All Other Industries, t-1	0.001	0.004***	0.002	0.000	0.002	-0.002
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Outcome Mean (Share)	21.66	20.67	14.33	11.84	13.74	17.75
Observations	657	657	657	657	657	657

Notes: The unit of observation is a county-cohort pair. Outcomes in Panel A are measured as the number of students who enroll in a given program within 6 months of high school graduation per 100 students who in the county and cohort enroll in vocational programs. Outcomes in Panel B are measured as the inverse hyperbolic sine of the number of students who enroll in a given program within 6 months of high school graduation. The coefficients in each column are estimated from a separate regression and represent the β_j terms in equation (5), 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 that are white, male, and categorized as economically disadvantaged; average 11th 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. Regressions in Panel B further control for logged total enrollment in vocational programs. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.11: Substitution Between Narrower Community College Programs

	Enrollment per 100 Vocational Students in:							
	Business	**Health**	**Trades**	**STEM**	**Law Enf.**	**Arts & Media**	**Personal & Culinary**	**Social Services**
Layoffs per 10,000 in:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Business, t-1	**-1.025****	-0.702	-0.056	-0.093	1.736***	-0.303	0.004	0.440**
	(0.456)	(0.682)	(0.449)	(0.280)	(0.592)	(0.227)	(0.201)	(0.184)
Health, t-1	-0.120	**-0.610****	-0.281**	0.164	0.250	0.107	0.144*	0.346***
	(0.138)	**(0.232)**	(0.122)	(0.123)	(0.222)	(0.084)	(0.083)	(0.073)
Skilled Trades, t-1	0.067	0.164	**-0.088**	-0.014	0.030	-0.124***	-0.027	-0.008
	(0.078)	(0.109)	**(0.097)**	(0.066)	(0.123)	(0.039)	(0.057)	(0.031)
STEM, t-1	0.212	0.206	-0.253	**-0.124**	-0.086	0.383	-0.535**	0.196
	(0.676)	(0.626)	(0.674)	**(0.347)**	(0.839)	(0.316)	(0.268)	(0.195)
Law Enforcement, t-1	0.076	0.078	-0.048	0.143	**-0.153****	-0.077***	-0.088**	0.068
	(0.075)	(0.082)	(0.061)	(0.094)	**(0.075)**	(0.027)	(0.043)	(0.053)
Other, t-1	0.753	0.072	-0.344	-0.688	1.014	-0.652	-0.123	-0.031
	(0.617)	(0.945)	(0.518)	(0.522)	(0.678)	(0.404)	(0.302)	(0.371)
Outcome Mean	21.66	20.67	14.33	11.84	13.74	9.11	3.39	5.26
Observations	657	657	657	657	657	657	657	657
R-squared	0.190	0.506	0.344	0.266	0.258	0.542	0.313	0.322

Notes: 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 who in the county and cohort enroll in vocational programs. I define social service programs as those with 2-digit occupation codes of 21 (Community and Social Service) and 25 (Education, Training, and Library), plus childcare programs (SOC 39-9011); arts and media programs as those with the 2-digit occupation code 27 (Arts, Design, Entertainment, Sports, and Media); and personal care and culinary programs as those with the 2-digit codes 35 (Food Preparation and Serving) and 39 (Personal Care and Service), other than childcare, plus baking programs (SOC 51-3011). The coefficients in each column are estimated from a separate regression and represent the β_j terms in equation (5), 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 that are white, male, and categorized as economically disadvantaged; average 11th 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.12: O*NET Skill Measures by Community College Program Group

	Business (1)	**Health (2)**	**Trades (3)**	**STEM (4)**	**Law Enf. (5)**	**Other (6)**
Panel A. Cognitive Skills						
Active Learning	50.61	53.41	40.38	50.28	46.30	45.95
Active Listening	56.56	57.35	42.20	52.62	56.24	50.80
Critical Thinking	55.74	55.93	45.29	54.42	56.08	49.52
Learning Strategies	44.15	49.52	34.37	43.75	44.33	42.49
Mathematics	38.88	38.10	29.99	49.88	27.84	26.22
Monitoring	54.40	55.40	43.85	51.09	51.35	49.64
Reading Comprehension	56.53	58.77	40.82	56.96	55.13	50.11
Science	14.83	40.91	17.69	37.79	12.74	8.08
Speaking	55.62	55.60	39.90	50.65	55.34	49.99
Writing	53.57	52.42	35.61	50.03	47.75	46.35
Panel B. Technical Skills						
Equipment Maintenance	0.68	2.81	42.18	25.62	2.71	3.55
Equipment Selection	0.65	9.89	35.51	31.48	3.17	9.37
Installation	0.02	0.84	24.59	18.04	0.06	0.99
Operation Monitoring	31.92	37.73	45.75	43.63	35.22	25.75
Operation and Control	19.67	28.87	44.56	32.11	35.80	15.78
Operations Analysis	38.59	28.07	21.45	39.92	23.85	27.87
Programming	9.27	8.26	8.82	35.41	6.41	7.51
Quality Control Analysis	25.96	33.23	46.35	46.77	26.46	25.56
Repairing	0.58	1.92	44.14	24.73	2.77	2.40
Technology Design	13.70	13.28	16.40	34.38	9.07	14.09
Troubleshooting	15.54	20.18	45.15	41.87	16.98	12.17
Panel C. Social Skills						
Coordination	52.39	53.69	40.98	46.16	53.92	48.79
Instructing	44.73	50.93	37.71	46.18	45.92	42.62
Negotiation	49.13	43.26	28.95	36.90	54.33	41.17
Persuasion	47.81	46.54	33.12	40.66	53.32	43.38
Service Orientation	44.96	53.92	38.23	40.39	51.46	42.38
Social Perceptiveness	53.89	59.11	35.68	42.02	55.99	47.75

Notes: Each column shows the average skill levels of occupations associated with a given program group, weighted by total program enrollments from 2009-2016. A higher skill level indicates that the skill is more likely to be required for the occupations associated with the program group.

Table A.13: Skill Distance Metrics Using All O*NET Skill Measures

	Business	**Health**	**Trades**	**STEM**	**Law Enf.**	**Other**
Business	0.000					
Health	0.352	0.000				
Trades	1.000	0.952	0.000			
STEM	0.762	0.669	0.640	0.000		
Law Enf.	0.339	0.369	0.942	0.815	0.000	
Other	0.286	0.476	0.892	0.794	0.339	0.000

Notes: Each cell displays the skill distance metric between two program/occupation groups, when using all skill measures available in O*NET. See Section 6.3 for more information.

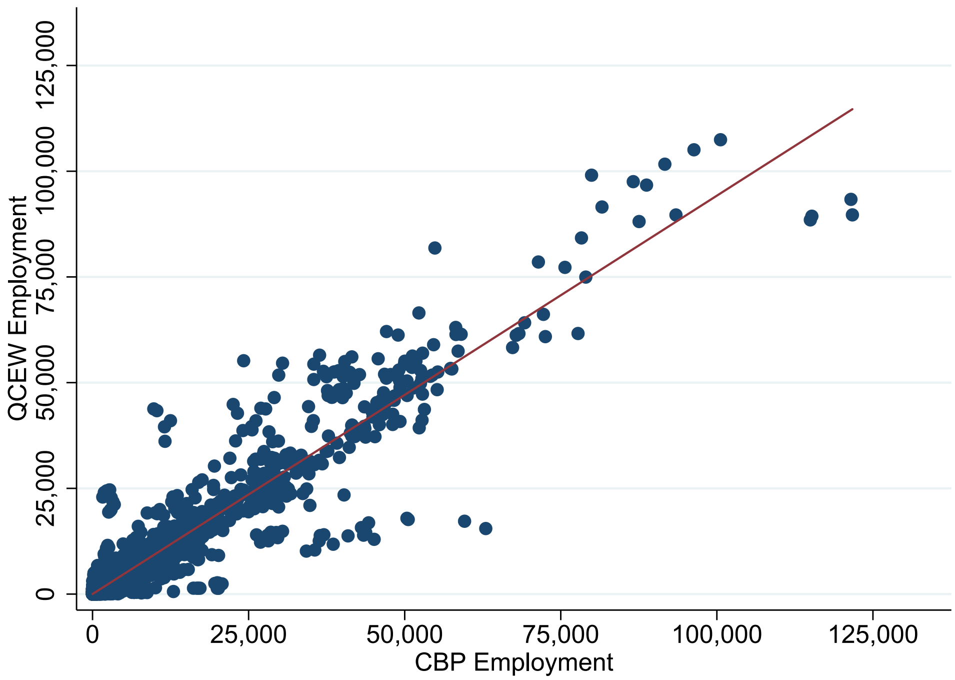
B Comparing Layoffs to Other Employment Data Sources

The estimated layoff measures used throughout the analysis are designed to capture changes in local labor demand in a given county and group of occupations. These measures should not, however, be treated as the exact number of job losses in an occupation group and county because not all layoff events are required to be reported under the WARN Act and, among events that are required to be reported, there is non-compliance in reporting. For example, in 2001, the federal government estimated that only about one quarter of events were required to be reported under the WARN Act and that, of those that were required to be reported, only one-third of were reported to the correct government agencies (United States General Accounting Office, 2003).

To verify that these proxy measurements capture true changes in employment over time and across counties, I compare county-by-industry layoffs to analogous employment data from two commonly used employment datasets: the Quarterly Census of Employment and Wages (QCEW) and the County Business Patterns (CBP). The QCEW is published quarterly by the Bureau of Labor Statistics and captures employment in more than 95% of U.S. jobs. However, a large share of its data at the county-by-industry level is suppressed due to privacy concerns. The CBP is released annually by the U.S. Census Bureau and captures the number of establishments and total employment during the week of March 12. Like the QCEW, many county-by-industry cells in the CBP are suppressed to prevent users from inferring information about individual firms. But in contrast to the QCEW, employment counts for some cells in the CBP can be imputed from establishment counts and higher-level geographic and industrial classifications. In the analyses that follow, I use the imputed data provided by Eckert et al. (2020) to maximize the coverage of Michigan's counties.

I begin by comparing the county-by-industry employment counts provided by both the QCEW and CBP. Because the CBP data does not contain information on government employment, I restrict the sample to all non-government NAICS 3-digit sectors. I further restrict the sample to county-by-industry pairs that have non-zero employment counts in all years 2001-2016 in at least one of the datasets. Figure B.1, below, provides a simple scatterplot of employment counts in the two datasets for the 73% of observations (3,630 county-industry pairs) that contain employment information in both datasets. The two measures of employment are highly correlated, with a Pearson's coefficient of 0.95.

Figure B.1: Comparison of Employment Counts in QCEW & CBP



Then, with each dataset, I estimate regressions of the following form:

$$\Delta\text{Employment}_{kct} = \alpha + \beta\text{Layoffs}_{kc,t-1} + \varepsilon_{kct} \quad (1)$$

where $\Delta\text{Employment}_{kct}$ is the change in employment in industry k in county c between March of year $t-1$ and March of year t, and $\text{Layoffs}_{kc,t-1}$ is the number of layoffs in industry k in county c between March of year $t-1$ and March of year t.[1] The parameter of interest, β, captures the relationship between layoffs and year-over-year employment change in a given county and industry. If β is equal to -1, then, on average, an additional layoff is associated with an employment reduction of exactly one worker. If $|\beta|$ is less than 1, then an additional layoff reduces employment

[1]The CBP provides employment counts as of March 12. To track corresponding employment changes in the QCEW, I use the first quarter, third month employment counts.

by less than one worker on average, presumably because some laid-off workers find work at other firms in the same county and industry or other firms are increasing employment at the same time as the layoff. Alternatively, if $|\beta|$ is greater than 1, then an additional layoff reduces employment by more than one worker on average, indicating that there are additional employment reductions, including changes in labor supply, that are not captured in the WARN data. Table B.1 presents the results of this specification using each dataset.

Table B.1: Relationship Between Estimated Layoffs & Employment Change

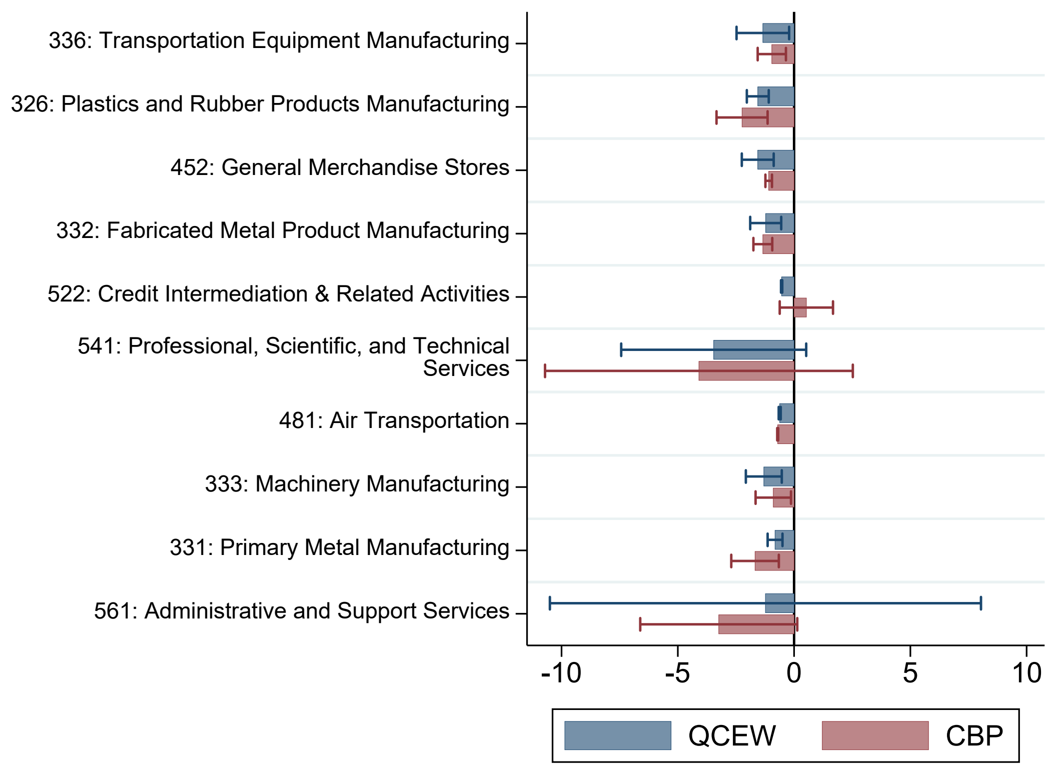
Layoff measure:	**(1)**	**(2)**	**(3)**
Panel A. Quarterly Census of Employment & Wages (QCEW)			
Layoffs in county and industry, t-1	-1.236***	-1.139***	-0.749***
	(0.322)	(0.312)	(0.266)
County, industry, and year FEs		X	X
Interacted FEs			X
County-Year-Industry Obs.	47,399	47,398	47,254
Panel B. County Business Patterns (CBP)			
Layoffs in county and industry, t-1	-0.942***	-0.914***	-0.803***
	(0.196)	(0.196)	(0.202)
County, industry, and year FEs		X	X
Interacted FEs			X
County-Year-Industry Obs.	58,202	58,202	58,186

Notes: The sample consists of all county-by-industry pairs that have non-zero employment between 2001 and 2016 in either the QCEW or CBP dataset. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Column (1) shows that an additional layoff is associated with an employment reduction of 1.2 workers in the QCEW and of 0.94 workers in the CBP data. Column (2) then adds county, industry, and year fixed effects to assess whether the negative relationship continues to hold after controlling for factors that may induce layoffs (e.g., overall economic downturns or industry-specific turnover patterns). When using either dataset, the estimated change in employment due to an additional layoff remains negative, statistically significant and close to -1 when including these fixed effects. Finally, column (3) interacts these fixed effects to mimick the interacted fixed effects in equation (6) in the main text. When controlling for county-by-year, county-by-sector, and sector-by-year effects, an additional layoff reduces employment by 0.75 workers (QCEW) to 0.8 workers (CBP). The estimates remain statistically significant, indicating that the layoff measures are indeed capturing changes in local employment counts.

Finally, to ensure that the relationship between is not driven by select industries, I estimate equation (1) separately for the ten NAICS 3-digit subsectors with the most layoffs in the WARN data. Figure B.2 presents these results. The estimated coefficients are overwhelmingly negative and do not vary substantially by dataset, again indicating that the layoff measures used throughout the paper capture true changes in local employment conditions.

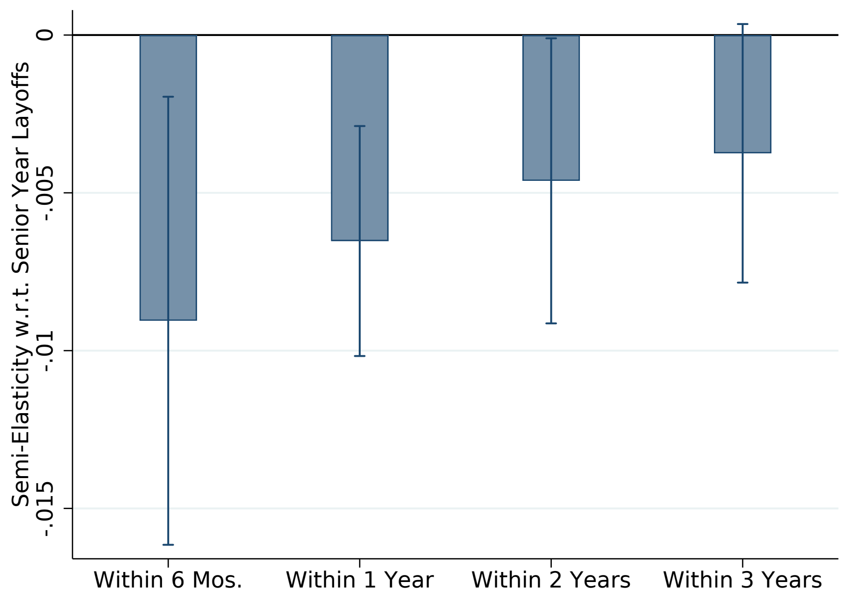
Figure B.2: Relationship between Layoffs and Employment Changes, by Sector



C Other Responses to Layoffs

To supplement the main analysis, I also analyze how layoffs affect two other educational outcomes of interest: (1) the enrollment choices of students beyond the first six months of high school graduation and (2) the retention rates of students already enrolled in vocational community college programs. For the first outcome, I restrict the sample to students who graduate from high school between 2009 and 2013 and re-estimate equation (3) in the main text for different enrollment time frames. Figure C.1 below presents these results.

Figure C.1: Effect of Layoffs on Later Program Choices



Notes: The presents estimates of β from equation (3) in the main text where the outcome variable is measured over different time frames. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th 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.

As in the main results that include all cohorts, an additional layoff per 10,000 county residents in the senior year of high school reduces enrollment in related programs within six months of high school graduation by about 1%. This estimate becomes smaller, but remains negative and statistically significant at the 10% level, as I expand the time frame of enrollment to one year, two year, or three years following high school graduation. The attenuation of the results is consistent with students moving across counties or gaining new information about the labor market as they age, and therefore, being less influenced by shocks that occurred during high school.

Next, I consider how layoffs affect vocational program retention rates. I include all cohorts and estimate equations of the following form:

$$\text{Retention}_{gct} = \alpha + \textbf{Layoffs}_{gct}\beta + \mathbf{X}_{ct}\Gamma + \lambda_{gc} + \delta_{gt} + \varepsilon_{gct} \tag{1}$$

where Retention_{gct} is a measure of the year-over-year retention of students from county c enrolled in program group g in year t, Layoffs_{gct} is a measure of analogous layoffs, and all other terms are defined as in previous equations in the main text. My main measure of retention is the number of students from county c who were enrolled in program group g in year $t-1$ and remain enrolled in the same program and community college in year t, per 100 students initially enrolled.[1] I also calculate measures of students switching between programs and between colleges, graduating from programs, and not being observed in the data the following year. I measure layoffs as those that occur between July 1st of year $t-1$ and June 30th of year t to capture layoffs that students observe throughout the year in which they are enrolled in a program.

Table C.1 presents these results. Column (1) indicates that an additional layoff per 10,000 working-age residents reduces program retention by 0.26pp, or about 0.6%. This estimate is smaller than the decrease in initial program enrollment documented in my earlier results, which is consistent with the fact that students already enrolled in a program likely face a lower marginal cost to finishing. For example, they have likely already completed some of the coursework needed to earn a degree in the subject. I also estimate the effects of layoffs on retention separately for each program group using a modified version of the systems of equations setup.[2] Table C.2 presents these results, which indicate that the largest elasticities come from students' responses to layoffs in STEM and other programs.

Columns (2) through (5) of Table C.1 document what choices students make when layoffs deter them from continuing in vocational programs. While the estimates are imprecise, the largest coeffi-

[1] In these calculations, I only consider enrollment in the college at which students earn the most credits during a given year. That is, if a student enrolls in two colleges within one year, she is assigned to enrollment only at the college in which she earns more credits.

[2] Specifically, I regress a program's retention rate on the vector of layoffs occurring in each occupation group, county control variables, county fixed effects, and cohort fixed effects.

cient appears in Column (5), which measures the share of students who were enrolled in a program in the prior year but are no longer formally enrolled in postsecondary education. In most cases, this means that a student has dropped out of her community college program without earning a degree.[3] Given the large labor market returns to degree completion, this type of substitution effect may negatively impact students' longer-run outcomes and suggests that policies that assist students in switching between programs after local labor market shocks could improve student outcomes.

Table C.1: Effect of Layoffs on Retention in Related Programs

	Number per 100 Prior-Year Vocational Students:				
Layoff measure:	**Same Program (1)**	**Different Program (2)**	**Different College (3)**	**Earned Degree (4)**	**Not Observed (5)**
Layoffs per 10,000 in occupation group	-0.264**	-0.034	-0.008	0.027	0.279**
	(0.128)	(0.027)	(0.043)	(0.052)	(0.129)
Outcome Mean	43.48	11.92	10.62	8.54	25.44
County-Program-Year Obs.	3,364	3,364	3,364	3,364	3,364
R-Squared	0.246	0.300	0.270	0.374	0.276

Notes: The unit of observation is a county-year-program triad. Each coefficient is estimated from a separate regression and represents β in equation (1), the effect of an additional layoff per 10,000 working age residents in a given occupation group on retention in related programs. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th 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 first year of college. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.2: Own-Layoff Effects on Program Retention Rates

	Retention per 100 Students in:					
Layoff measure:	**Business (1)**	**Health (2)**	**Trades (3)**	**STEM (4)**	**Law Enf. (5)**	**Other (6)**
Layoffs per 10,000 in own occupation group	-0.250	-0.082	-0.364	-1.307	-0.226	-3.600***
	(0.546)	(0.275)	(0.246)	(0.951)	(0.204)	(1.358)
Outcome Mean	41.41	43.93	43.98	45.25	41.97	44.37
County-Year Obs.	566	566	560	554	560	558
R-Squared	0.353	0.291	0.253	0.245	0.285	0.233

Notes: The unit of observation is a county-cohort pair. Each coefficient is estimated from a separate regression and represents the effect of an additional layoff per 10,000 working age residents in a given occupation group on retention in related programs. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th 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 first year of college. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[3]Students could also be enrolled in colleges not covered by the NSC data. However, these types of colleges make up less than 1% of U.S. postsecondary institutions overall (National Student Clearinghouse Research Center, 2017).