Community College Program Choices in the Wake of Local Job Losses

Riley K. Acton*

Michigan State University

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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. I further document that students predominantly shift enrollment between programs that lead to occupations requiring similar skills.

JEL Codes: I21, I25, J23, J24
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*Department of Economics, Michigan State University, 486 W Circle Dr., 110 Marshall-Adams Hall, East Lansing, MI 48824, actonril@msu.edu. I gratefully acknowledge that this research used data collected and maintained by the Michigan Department of Education (MDE) and Michigan's Center for Educational Performance and Information (CEPI). The results, information, and opinions presented here solely represent the analysis, information, and opinions of the author and are not endorsed by, or reflect the views or positions of, grantors, MDE and CEPI, or any employee thereof. I would like to thank Scott Imberman, Steven Haider, Stacy Dickert-Conlin, Amanda Chuan, Mike Conlin, and Cody Orr for many productive discussions related to this project. In addition, I am grateful for comments by seminar participants at Michigan State University, University of Michigan, University of Texas at Dallas, University of Notre Dame, Miami University, the Consumer Financial Protection Bureau, the 2019 Association for Education Finance & Policy (AEFP) Annual Conference, the 2019 Society of Labor Economists (SOLE) Annual Meetings, and the 2019 Association for Public Policy Analysis & Management (APPAM) International and Fall Research Conferences.

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 earnings 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, which enrolls only about two-thirds of students in the United States (National Center for Education Statistics, 2018). The nearly ten million students who attend two-year community colleges also must decide which fields to study, and their decisions have similarly large implications for their labor market outcomes. For example, students who enroll in health programs can expect to experience large earnings gains in the labor market. Meanwhile, students who select other programs may not earn much more than their peers who do not enroll in postsecondary education (Bahr et al., 2015; Belfield and Bailey, 2017; Stevens et al., 2018; Grosz, 2018). 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' choices over what programs to pursue.

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 students' choices of community college programs. 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 local or national demand.[1] Second, community college programs are generally designed to take two years or less to complete, so community college students may reasonably consider short-term fluctuations in labor demand when choosing which programs to pursue. 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 typically 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. These close connections to the labor market also allow me to use data on occupation characteristics to document whether students substitute between similar programs when exposed to local labor market shocks.

My empirical approach exploits announcements of mass layoffs and plant closings across time, counties, and industries. Moreover, I rely on the distribution of occupations across industries to create measures of occupation-specific labor demand shocks that align closely with specific community college programs. Intuitively, these measures isolate job losses that affect the types of occupations community college graduates would expect to enter after completing their educational programs. For example, hospitals employ a large number of healthcare workers with community college credentials, such as nurses, health assistants, and medical billers. Therefore, hospital closures should change the benefit to local students of enrolling in community college health programs. In contrast, mass layoffs at prisons will mostly affect law enforcement professionals and, in turn, should alter the benefits of entering community college law enforcement programs.

By comparing cohorts in the same county that were exposed to different amounts of these local job losses, I show that students' program choices at community colleges are sensitive to local

[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 their alma mater (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.

labor market conditions. I first document that layoffs occurring in occupations tied to community college programs do not influence students' decisions to enter vocationally-oriented community college programs overall. However, conditional on enrolling in vocational programs at community colleges, I find that the types of occupations that experience local labor demand shocks influence what subjects students choose to study. Students are less likely to enter programs that have recently experienced related job losses in their county. For the average county-cohort pair in the sample, an additional occupational layoff per 10,000 working-age residents in a county would reduce enrollment in related programs by 0.6% to 4.7%, depending on the field of study.

I then use occupational content data from the U.S. Department of Labor's Occupational Information Network (O*NET) to study how students shift between programs in response to labor market shocks. I create measures of skill similarity between community college programs and document that students primarily shift their enrollment into programs that require similar skills to the field affected by layoffs. Moreover, when occupations that do not have close substitutes experience negative employment shocks, students exhibit a lower degree of responsiveness. This finding suggests that students' abilities to adapt to labor market changes depends on the set of available educational choices and further indicates that supply-side responses by colleges could alter the effects of local labor market downturns.

These results contribute to several related lines of literature on how individuals make human capital investment decisions. First, the results add to a large body of empirical work on factors affecting what 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). Consistent with this finding, a recent line of work shows that the composition of college majors changed following the Great Recession, with more students pursuing "recession-proof" majors (Shu, 2016; Liu et al., 2018; Ersoy, 2019). Choi et al. (2018) also show that the occurrence of "superstar" firms with abnormally high stock returns increases the number of four-year college students majoring in related fields.

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 (2018) 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. He further shows that these trends are primarily due to changes in student demand rather than supply-side responses by colleges. 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.

Second, this research 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, 2019). They generally find that poor labor market conditions lead to an increase in college enrollment, and conversely, that economic booms decrease postsecondary enrollment and completion. 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 (2019), 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.

Finally, these results add to a growing body of work on the link between human capital specificity and occupational mobility. Previous research indicates that workers are more likely to transition between occupations that require similar tasks (Gathmann and Schöenberg, 2010), and that they experience lower earnings losses when switching between occupations that emphasize similar skills (Poletaev and Robinson, 2008). However, there is little work on the extent to which students consider the task or skill content of occupations when choosing educational programs. In this paper, I make use of occupational skill data to analyze the similarity of educational programs and document that layoffs and plant closings induce students to substitute between occupational programs that require similar skills, suggesting that students are aware of differences in occupational characteristics and seek out educational pathways that align with their preferences for work.

2 Conceptual Framework

This paper estimates how community-level job losses affect students' postsecondary choices, particularly at the community college level. The basic economic intuition of this analysis is that job losses occurring through labor market shocks (e.g., mass layoffs and plant closings) represent changes in local labor demand, which in turn 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) directly entering the labor market.[2] Each alternative is associated with an expected lifetime benefit, B_{ij}, where j denotes one of the choices. This expected benefit term is a function of student i's expected earnings in related occupations and the student's taste for the occupations and/or coursework. That is, $B_{ij} = Y_{ij} + \mu_{ij}$, where Y_{ij} is an expected earnings term and μ_{ij} is a taste parameter. For example, the expected benefit to student i of pursuing a community college health program is a combination of the expected earnings in community college health occupations and how much a student expects to enjoy the nature of healthcare work and coursework. Each alternative is also associated with an expected cost, C_{ij}.

Students choose the alternative that maximizes $U_{ij} = U_i(B_{ij}, C_{ij})$, where $\frac{\partial U_{ij}}{\partial B_{ij}} > 0$ and $\frac{\partial U_{ij}}{\partial C_{ij}} < 0$ for all students. That is, a student will choose alternative j if $U_{ij} > U_{ik}$ for all $j \neq k$ and the prob-

[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.

ability that student i chooses alternative j can be expressed as $P_{ij} = P(U_{ij} > U_{ik})$. Suppose that student i observes a plant closing or mass layoff while she is deciding which postsecondary option to pursue. Her response to the shock will depend on how it affects the occupations associated with each alternative. 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 by ε_1, 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} by ε_2 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 —that is, a high μ_{ij} term for the vocational program options —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 will decrease by approximately the same amount across each alternative and students' choices should be minimally affected.

These examples highlight that the anticipated effects of layoffs depend on the distribution of layoffs 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). Local boards of trustees control and govern the colleges, but all institutions share two key features. First, all colleges are open enrollment institutions, meaning students can enroll regardless of academic preparation.[3]. Second, the colleges 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 the labor market and have direct links to specific occupations, whereas non-vocational programs typically consist of general education courses and prepare students to transfer to four-year colleges and universities.

3.1 Programs Offered by Michigan's Community Colleges

Due to the deregulated nature of Michigan's community college system, the state does not systematically track the programs offered by each college over time. 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 programs offered by the state's community colleges. I use data from the handbooks and online database to classify programs into vocational and non-vocational categories, as well as to create the 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).[5] 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

[3]Colleges may set admissions standards for select 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`)

[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).

[5]The crosswalk can be accessed at: `https://nces.ed.gov/ipeds/cipcode/resources.aspx?y=55`.

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. For example, the CIP code for registered nursing (51.3801) is matched to the SOC codes for both registered nurses (29-1141), which is a career attainable by graduates of community college nursing programs, and postsecondary nursing instructors (25-1072), which requires an advanced degree. 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 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).[6]

Appendix Table A.1 provides summary statistics on the programs offered by Michigan's community colleges in 2011. On average, a college offers 117 unique academic programs, with 81% being vocational. The five most commonly offered vocational programs, according to broader four-digit CIP codes, are 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*.[7] Table A.2 provides a list of the two-digit SOC codes contained within each group.

[6]Any programs that explicitly state in their name that they are "pre-transfer" programs are considered non-vocational, regardless of whether an occupational match exists.

[7]Programs can be matched to more than one detailed SOC occupation code, but 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.

3.2 Students Enrolled in Michigan's Vocational Programs

To analyze how enrollment in community college programs responds to job losses in related occupations, I rely on a student-level administrative dataset provided by the Michigan Department of Education (MDE) and Center for Educational Performance and Information (CEPI). The dataset contains high school academic records for all students who attended public high schools from 2009 to 2016 and further links students to college enrollment and completion records from the National Student Clearinghouse (NSC) and a state-run data repository (STARR). The high school academic records provide rich information on students' demographic characteristics and academic performance, including race/ethnicity, gender, standardized test scores, and census block of residence. All variables are measured during students' eleventh grade year, when they complete state standardized tests. The college link provided through the NSC and STARR contains all records of students' enrollments in colleges covered by either database, as well as information on the academic programs in which they enroll, the credits they complete, and the awards they receive. Like the information on colleges' program offerings, program enrollment is recorded using six-digit CIP codes each semester a student is enrolled in a postsecondary institution.

I focus my analysis on high school graduates' first college enrollment and program choices within six months (180 days) of graduating from high school.[8] 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 is deciding her postsecondary choice. Once students graduate from high school, I no longer observe where they reside, and therefore, cannot reasonably assume that the labor market shocks occurring in their high school county are the labor market shocks they actually observe. Moreover, by limiting enrollment choices to those occurring soon after high school graduation, I limit the possibility that supply-side responses by colleges drive my results. For example, it is unlikely that colleges can respond to labor market shocks by altering the programs or courses they offer, as these decisions are typically made months or years in advance.[9]

[8] In order to focus on students who are likely to consider postsecondary education, I drop students enrolled in juvenile detention centers, adult education, or alternative education programs from the analysis. Results are robust to including these students.

[9] 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, Grosz (2018) provides evidence that student demand is much more responsive to labor market trends than college supply.

Table 1 provides summary statistics on Michigan's high school graduates disaggregated by their first postsecondary education choices.[10] Most students graduating from Michigan high schools either do not enroll in college or enroll in colleges outside of the community college sector.[11] However, a non-trivial share of students enroll in vocational and non-vocational community college programs each year: 9% and 14% of graduates, respectively.[12] Students who enroll in vocational programs are more likely to be economically disadvantaged than students in non-vocational programs and also score lower on state standardized tests.[13] They are also more likely to be male and a racial minority. Compared to their peers who do not enroll in college, they are less disadvantaged and more academically prepared.

Table 2 disaggregates the summary statistics by students' vocational program choices.[14] Across the eight cohorts in the sample, about 24% of vocational students enroll in business programs, while 23% enroll in health programs, 8% enroll in the skilled trades, 13% enroll in STEM, 13% enroll in law enforcement, and 20% enroll in other programs, such as culinary arts or graphic design. There are some demographic differences across the program groups. For example, students who enroll in skilled trades programs are overwhelmingly white (84%) and male (94%). In contrast, students who enroll in health programs tend to be non-white (29%) and female (78%). There is less sorting across academic abilities: average math and reading test scores are similarly low across the programs, but nearly all students in each group graduate from high school on time.

[10]Throughout the analysis, students who are enrolled in a community college while enrolled in high school (e.g., through a dual enrollment program) are categorized according to their first enrollment in a different institution within six months of high school graduation. If a student does not enroll in a different institution within six months of high school graduation, she is considered to have not enrolled in college.

[11]98.3% of students who enroll in colleges other than Michigan community colleges enroll in four-year colleges and universities. The remaining 1.7% enroll in out-of-state community colleges or for-profit institutions.

[12]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. In Section 2.6, I show that the results are robust to dropping students who enroll in multiple program groups.

[13]Students are classified as economically disadvantaged if they qualify for free or reduced-price meals under the National School Lunch Program, are in a household that receives food (SNAP) or cash (TANF) assistance, are homeless, are a migrant, or are in foster care.

[14]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. 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.

4 Measuring Local Job Losses

In my empirical approach, I build on the work by Hubbard (2018) and Foote and Grosz (2019) that uses the prevalence of mass layoffs and plant closings to proxy for changes in local labor demand. A key advantage of these data is that events are reported at the establishment level. Therefore, I can 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 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 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, and (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 also 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. If employers do not provide such notice, they are liable to provide each aggrieved employee with back pay and benefits for up to 60 days. Krolikowski and Lunsford (2020) offer additional information on the WARN act and document its value as a labor market indicator.

All WARN notices filed in Michigan are publicly available on the WDA's website. However, the WARN Act does not apply to government entities, which limits my ability to observe layoffs in law enforcement professions —one of Michigan's most popular community college program groups. To overcome this limitation, I supplement the WARN data with a listing of correctional facility closures and corresponding staff reductions from Michigan's Senate Fiscal Agency (SFA). These events are analogous to plant closures in the private sector but particularly affect public law enforcement occupations such as corrections officers.

4.1 Using WARN Data to Generate Occupation-Specific Layoff Exposure

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.[15] 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 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.

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 2016, where I define academic years as July 1 of year t to June 30 of year $t+1$. For example, the 2005 academic year runs from July 1, 2005 to June 30, 2006. On average, there are about 75 layoff events each year, with 24 being mass layoffs, 50 being plant closures, and 1.4 being correctional facility closures. The total number of layoff events spiked to 193 during the 2008 academic year when the Great Recession and automotive industry collapse hit 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 Figure A.2 by plotting the average amount of per capita layoffs that occur in each county from 2001 to 2017.

Because the layoff data does not contain information on the occupations of laid-off workers, I estimate students' exposure to job losses in each community college occupation group by exploit-

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

ing 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. There are 99 unique three-digit codes in the NAICS system, each of which represents a subsector of economic activity. I observe 72 of the 99 subsectors in the layoff data, with the three most common subsectors being transportation equipment manufacturers (21% of observations); general merchandise stores (6% of observations); and professional, scientific, and technical services (5% of observations).

I then calculate the distribution of community college occupations across industries. Explicitly, 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.[16] Continuing with the example from 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.[17] As a result, layoffs that occur at hospitals should affect these occupations, and therefore the benefit of enrolling in community college health

[16]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.

[17]Appendix Table A.3 presents the three largest average values of α for each occupation group.

programs, much more than layoffs that occur at general merchandise stores.[18]

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. For example, consider Kalamazoo County during the 2012 academic year. During this year, three firms reported mass layoffs: Hostess Brands, a food manufacturer (15 layoffs); International Paper, a paper manufacturer (77 layoffs); and OneWest Bank, a credit intermediary (168 layoffs).[19] In this same year, community college business occupations, i.e., business occupations which community college graduates can enter, accounted for 6.7% of employment in food manufacturing, 10.9% of employment in paper manufacturing, and 44.5% of employment in credit intermediaries nationally. As such, a reasonable estimate of the number of business occupation layoffs reported under the WARN system in Kalamazoo County during the 2012-2013 academic year is $0.067(15) + 0.109(77) + 0.445(168) \approx 84$.[20]

4.2 Distribution of Layoffs Across Occupations

Table 3 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 equations (1) and (2) to generate the number of layoffs occurring in low-skilled occupations that require less than an associate's degree and the number of

[18] 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.

[19] Note that the Hostess Brands layoff is below the 50 job loss threshold for required WARN reporting. Firms sometimes voluntarily report smaller layoffs, particularly when they are reporting simultaneous layoffs at facilities across the state. In Section 2.6, I repeat the empirical specifications only using layoffs that meet the 50 job loss threshold and obtain very similar results to the main specification.

[20] To illustrate more examples of county layoffs, Appendix Table A.5 provides information on the three county-year pairs with the largest amount of per capita layoffs in each occupation group from 2001 to 2017.

layoffs occurring in high-skilled occupations that require more than an associate's degree. 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.

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.[21] 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 the number of layoffs occurring in different occupations, with the standard deviations for each category far exceeding the means. For example, the number of skilled trade layoffs occurring in a county ranges from 0 to nearly 96 per 10,000 working-age residents. 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 middle-skill occupations, and 11% occur in high-skilled occupations.

Figure 2 further highlights the variation in layoffs across counties by plotting the layoffs that occur in each occupation group in each county between 2001 and 2017. I do not include counties that do not experience layoffs over this time frame and order all other counties by their average working-age population over this time frame. The left-hand panel plots the total number of layoffs per 10,000 working-age residents in each occupation group while the right-hand panel shows the share of layoffs occurring in each occupation group. The total number of layoffs varies substantially across counties, with both small and large counties experiencing a high number of local labor market shocks over the time frame. For example, the two counties that experience the most per capita layoffs are Ingham County, which has about 200,000 residents, and Ontonagon County,

[21] 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`). The average county-year observation in the data has 71,131 working-age residents.

which only has 4,000 residents. The share of layoffs occurring in each occupation group also varies considerably across counties, further emphasizing the importance of separating layoffs by the types of jobs they affect.

4.3 Potential Measurement Error

Because the layoff data does not contain information on the occupations of laid off workers, 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, whereby I inaccurately classify layoffs as affecting one occupation group when, in reality, they affect another. 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.

More formally, suppose that a single layoff in occupation X occurs. Further, suppose that with probability ε, I will incorrectly classify this layoff as affecting occupation Y. Then, the estimated effect of the layoff on the probability that a student chooses program X will be:

$$\widehat{\delta}_{XX} = (1-\varepsilon)\delta_{XX} + \varepsilon\delta_{XY}$$

where δ_{XX} is the true effect of layoffs in occupation group X on enrollment in group X programs and δ_{YX} is the true effect of layoffs in occupation group Y on enrollment in group X programs. Because $\delta_{XX} \leq 0$ (layoffs deter students from entering related programs) and $\delta_{XY} \geq 0$ (students substitute into other programs), the estimated response will be of a smaller magnitude than the true response and could even be positive if either ε or δ_{XY} is sufficiently large. Correspondingly, the estimated effect of the layoff on the probability that a student chooses program Y will then be:

$$\widehat{\delta}_{YX} = (1-\varepsilon)\delta_{YX} + \varepsilon\delta_{YY}$$

where δ_{YY} is the true effect of layoffs in occupation group Y on enrollment in group Y programs and δ_{YX} is the true effect of layoffs in occupation group Y on enrollment in group X programs. Because $\delta_{YX} \geq 0$ and $\delta_{YY} \leq 0$, the estimated term will be biased downward toward zero and could be negative if either ε or δ_{YY} are sufficiently large.

Given the non-classical nature of this measurement error and the fact that ε is unknown, 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 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.

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 (including direct labor market entry) if students are indeed deterred from entering related programs.[22] I begin by estimating the average effect of job losses on enrollment in related community college programs. Then, in Section 6, I consider heterogeneous effects across occupation groups and document how students substitute between postsecondary programs in response to job losses.

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

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 layoffs in occupation group g that may affect cohort t in county c. I consider two sources of variation in layoffs: timing and location. That is, I consider how students respond to layoffs that occur in different points during their pre-college years and that occur in different geographic areas. The vector $\mathbf{X}_{ct}$ contains time-varying county control variables that may affect students' enrollment choices, such as the average test scores of the cohort or the unemployment rate. 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 time. As such, the identifying assumption for β to represent the causal effect of job losses on students' choices 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 high school graduates has different preferences for college education than the last cohort. While such a phenomenon seems unlikely, the assumption could be threatened if there are county-specific trends in occupation-specific job prospects and program preferences. Thus, I also estimate specifications that include county-by-program linear time trends. Similarly, layoffs may not represent true changes in occupation-specific employment conditions if job losses are absorbed by increased employment in nearby counties. For this reason, I estimate specifications that interact the cohort-by-program fixed effects with commuting zone (CZ) fixed effects to account for any unobservable changes in an occupation group's employment in a broader geographic region.[23]

5.2 Main Results

Table 4 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 time period during which students must decide what educational program, if any, they will enter following graduation. The point estimate is negative and statistically significant, indicating that an additional layoff per 10,000 county residents during this year reduces enrollment in related programs by 0.012 students per 100 graduates, or about 0.012pp. There are several ways to interpret this estimate. 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. Alternative, doubling the amount of per capita layoff exposure the average county-cohort pair experiences reduces enrollment by about 0.6%. These estimates imply that, for the average county, 52 workers being laid off in a given occupation induces one less student to enroll in a related program.

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. Such evidence is consistent with a growing literature highlighting the importance of salience in decision-making (Mullainathan, 2002; Genniaoli and Shleifer, 2010), and particularly, the sensitivity of college

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

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. Indeed, I find that they do not. The point estimate on this variable is positive, but close to zero statistically insignificant. Meanwhile, the estimate on layoffs occurring during a cohort's senior year of high school remains negative, statistically significant, and close to the -0.012.

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 5 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 4, 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 negative, indicating that students also respond to layoffs occurring outside of their county but in their general area of the state. However, the coefficient is smaller than the coefficient on county layoffs and is not statistically significant, again indicating that saliency plays a role in students' decision-making process and that students primarily respond to layoffs that occur in their immediate local area.

5.3 Robustness

Figure 3 presents several robustness checks of the main specification from column (1) in Table 4: the effect of layoffs in a student's county during her senior year of high school on enrollment in related programs. First, Panel A shows 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. Next, Panel B estimates specifications with county-by-program linear time trends and program-by-year-by-CZ fixed effects.[24] These specifications also similar estimates to 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 dropping events that are the result of mass layoffs rather than plant closings, or events that report less than the required 50 job losses. The estimates are similar when using all layoffs and when using only layoffs that are a result of closings. Moreover, the point estimate using only closings is slightly larger in magnitude, which is consistent with the expected effects of measurement error outlined in Section 4.4. I also find quite similar estimates when only including layoffs that reach the 50 job loss threshold, indicating that the voluntary reporting of smaller layoff events does not contaminate the main results. Finally, Panel D estimates non-linear specifications that can better handle fractional dependent variables. First, I estimate equation (3) using the inverse hyperbolic sine of a county's program enrollment as the dependent variable.[25] I then estimate Poisson and fractional logit (Papke and Wooldridge, 1996) specifications.[26,27] All specifications produce similar semi-elasticities to the main linear specification, providing evidence that functional form selection is not driving the results.

[24]In all 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.

[25]The inverse hyperbolic sine (IHS) function approximates the log function but allows values of zero (Burbidge et al., 1988). I use the transformations proposed by Bellemare and Wichman (2019) to estimate elasticities at the mean values of the dependent and independent variables.

[26]In the Poisson specification, the dependent variable remains the share of students from a given county and cohort who enroll in a given program (rather than a raw count variable). 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. However, like the IHS specification, the Poisson approach allows for the inclusion of dependent variables equal to zero. See Lindo et al. (2018) for more details.

[27]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.

6 Substitution Effects

The results in Section 2.5 indicate that fewer students enroll in community college programs when exposed to related job losses. This response primarily occurs when the job losses take place in a student's own county during her senior year of high school. In order to better understand how this response may affect students' longer-run outcomes, I now estimate how these job losses affect students' decisions to enroll in other postsecondary options.

6.1 Substitution out of Vocational Programs

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

$$\text{VocationalEnroll}_{ct} = \alpha + \sum_{g=1}^{6} \beta_g \text{Layoffs}_{gc,t-1} + \mathbf{X}_{ct}\Gamma + \theta_c + \delta_t + \varepsilon_{ct} \tag{4}$$

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, $\mathbf{Layoffs}_{gc,t-1}$, 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. As in equation (3), the vector $\mathbf{X}_{ct}$ contains time-varying county control variables that may affect students' choices, including the number of layoffs that occur in non community college occupations. θ_c is a county fixed effect that absorbs county-specific preferences for different types of postsecondary education (as θ_{gc} does in the previous estimating equation) and δ_t is a cohort fixed effect that accounts for changing preferences over time (as δ_{gt} does in the previous estimating equation). ε_{ct} is the error term. I continue to cluster all standard errors at the county level.

The β vector identifies how layoffs in different types of occupations affect students' decisions to enroll in related types of college programs. The identifying assumption is that, after controlling for secular trends through the cohort fixed effects, any within-county variation in layoffs is uncorrelated with within-county variation in unobserved college preferences. As in Section 5, this assumption seems reasonable, but could be threatened if there are unobserved changes in preferences or economic opportunities over time. Therefore, I also estimate specifications with county-specific linear time trends or cohort dummies interacted with commuting zone fixed effects.

Table 6 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.[28] 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 affect enrollment in vocational programs.

In Appendix Table A.7, I further consider whether layoffs in community college occupations 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.8, 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.[29] 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' intensity of enrollment. Thus, the response documented in Section 2.5 must come from students changing which types of vocational programs they pursue.

[28] In Table A.6, I show that, overall, layoffs 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.

[29] I use course codes and information from community college catalogs to divide all courses into vocational and non-vocational groups. I define vocational courses as those in the same fields that are included in the six vocational program groups of interest, while all other courses are considered non-vocational.

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:

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

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 occuring in school year $t-1$, per 10,000 working-age residents in the county.[30] The vector $\mathbf{X}_{ct}$ contains the same variables as in equation (4), θ_c is a county fixed effect, δ_t is a cohort fixed effect, and ε_{ct} is the error term. I again cluster all standard errors at the county level.

The coefficient β_g will represent the "own-layoff" effect when $j = g$ and will represent a "cross-layoff" effect when $j \neq g$. As predicted in Section 2.2, 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. This restriction implies that any decrease in enrollment in a given program group due to related layoffs must be offset by students enrolling in other vocational community college programs.

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

[30] Because 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).

layoffs are not correlated with changing preferences for other programs within a county. As in the previous sections, unobserved changes in preferences or economic opportunities could violate this assumption, so I again estimate specifications with county-specific linear time trends or cohort dummies interacted with commuting zone fixed effects.

Table 7 presents the substitution matrix created from estimating equation (5) for each of the six occupation groups.[31] 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 enrollees, 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 of the table, I present the own-layoff 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.

Moving horizontally across the columns 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.9, 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. Although not statistically significant, the estimates further suggest that students substitute from law enforcement programs towards business, STEM, and health programs when there are law enforcement layoffs.

[31]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.

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? Based on the conceptual framework presented in Section 2, 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. For example, health programs and several programs in the other category —such as childcare professionals —focus on serving one's community and require a high level of person-to-person interaction, so it seems reasonable that students would substitute between these programs.

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. The cognitive skill category contains ten measures of skills "that facilitate learning or the more rapid acquisition of knowledge," such as mathematics, reading comprehension, and writing. The social skills category contains six measures of skills that are "used to work with people to achieve goals," such as negotiation and service orientation. The technical skills category contains eleven measures of skills "used to design, set-up, operate, and correct malfunctions involving application of machines or technological systems," such as repairing and programming. For each occupation and skill measure, O*NET reports a standardized importance score and standardized level score. Both measures range from 0 to 100, but each provides different information. The importance score describes how important a particular skill is to an occupation, with higher values indicating more importance. The level score characterizes the degree to which the skill is required to perform the occupation, with higher values indicating a higher requirement.

I use these data elements to create a Euclidean distance measure that identifies program groups that require similar skills. 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:

$$\text{Distance}_{ps} = \sqrt{\sum_{j=1}^{27} \text{Importance}_{js}(\text{Level}_{jp} - \text{Level}_{js})^2} \tag{6}$$

where Importance_{js} is the importance of skill j for program group s, Level_{jp} is the required level of skill j for program p, and Level_{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 in terms of the skills that are most important for careers in group s will have the lowest distance measures.[32] I standardize the measures such that the least similar pair of program groups has a distance measure of 1.

Figure 4 plots the coefficients in Table 7 against this skill distance measure. Each panel shows the effect of a different type of layoff on enrollment in each program group. For example, the upper left panel shows that business layoffs decrease enrollment in business programs but increase enrollment in law enforcement programs, which is the most similar program group to business. A similar pattern emerges in the second panel, where health layoffs decrease enrollment in health programs but increase enrollment in law enforcement and other programs, both of which are fairly similar to health. Layoffs in law enforcement and other community college occupations also induce students to enroll in similar programs. However, when there are layoffs in STEM and skilled trades, students are not substantially deterred from enrolling in related programs. This lack of a response may be due to the lack of nearby substitutes in which students could enroll. For example, all of the non-STEM program groups have a distance measure of 0.5 or greater, indicating that they require quite different skills than STEM occupations do. This difference is not surprising as STEM occupations tend to require much more mathematical skills than non-STEM occupations.

Figure 5 provides further evidence that students substitute into similar programs by pooling all of the substitution effects and plotting them against their respective skill distance measures. The largest substitution effects appear at the left end of the x-axis, indicating that students mostly substitute into programs that are similar to those affected by layoffs. Moving across the x-axis, there is a downward slope showing that students are less likely to enroll in programs that require

[32] To create level and importance 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.

substantially different skills. A simple linear fit of the data indicates that moving from the most similar to the most different program group reduces the substitution effect by 0.55, where I measure effect sizes as the impact of an additional layoff per 10,000 county residents on enrollment per 100 vocational students.[33] In Appendix D, I consider substitution patterns between more narrowly-defined program groups and find that the general pattern of students substituting towards similar programs still holds.

6.4 Heterogeneity & Robustness

Figure 6 considers heterogeneous responses to layoffs by re-estimating the system of equations in equation (5) using different subgroups of students. First, in Panel A, I consider how the effects vary across genders. Because there is substantial sorting across genders in community college programs, it is reasonable to think that male and female students may respond differently to layoffs in various fields. Indeed, I find that the responses to health layoffs are predominantly driven by female students, who account for nearly 80% of enrollment in health programs. The responses to business, skilled trades, STEM, and law enforcement layoffs tend to come from male students, who make up the majority of enrollment in these programs. However, the estimates for these fields are noisier and are not significantly different between male and female students.

In Panel B, I show how the effects vary across urban and rural counties.[34] This type of heterogeneity is particularly relevant in Michigan because a majority of the state's residents reside in urban areas, but those areas comprise little of the state's land area. Moreover, there are documented differences in racial composition, political leanings, and educational attainment across rural and urban areas in the state (Citizens Research Council of Michigan, 2018). I find that the responses to layoffs are predominantly driven by rural counties, except for law enforcement layoffs, which mostly affect urban counties. This strong response could be the result of geographic preferences of students' in rural areas to remain in their local communities or differences in information networks in these areas. For example, rural news outlets may have fewer events to cover and, therefore,

[33]In Figure A.4, I re-create the figure using alternate measures of skill distance. The results are quite similar, with an additional layoff per 10,000 county residents reducing the effect size by 0.73 when using only differences in skill levels and by 0.62 when using only differences in skill importance.

[34]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`.

may devote more attention to a local layoff or business closure. Layoffs in rural areas may also be better indicators of future labor market prospects than layoffs in urban areas, particularly if an occupation's employment is heavily concentrated in one firm that then closes or downsizes.

I next perform a series of robustness checks that test the sensitivity of the results to alternative specifications. First, because scaling the dependent variable by the number of vocational students in a given county and cohort may introduce heteroskedasticity, I estimate the substitution matrix using the refined weighting schemed proposed by Solon et al. (2015). Panel A of Figure 7 presents the own-layoff effects using this approach. The point estimates and corresponding standard errors are quite similar with or without weights. Second, because layoffs may be more likely to occur when a county is on a downward economic trajectory, Panel B of Figure 7 shows how the estimates change when including county-specific linear time trends. The results are also quite similar with and without trends. I also estimate specifications that include cohort-by-commuting zone fixed effects to capture changing economic conditions or program preferences that are unique to geographic regions within the state. Panel C shows how the results change when including this additional set of fixed effects. Again, the estimates are quite similar to the main specification.

Panel D then shows how the results change when dropping the 2009 cohort, who graduated during the height of the Great Recession in Michigan and may have faced additional challenges in both accessing higher education and entering the labor market. The estimates are somewhat noisier when I do not include this cohort, but the effect sizes remain similar. Panel E further shows how the estimates change when I drop any student who enrolls in more than one program group from the analysis. The results are nearly identical when restricting the sample in this way.

Finally, because the dependent variable represents county-level enrollment shares, I estimate several alternative specifications that are designed to handle fractional data. As in Section 5.3, I first estimate inverse hyperbolic sine, Poisson, and fractional logit specifications. I then implement a fractional multinomial logit specification that jointly estimates all coefficients in Table 7, while imposing that each enrollment outcome must fall between 0 and 100, and the shares must sum to 100 (Buis, 2017). In Panel F of Figure 7, I compare the results from these three specifications to the estimated elasticities obtained from the main linear specification. The semi-elasticities are quite similar across the specifications, with an additional layoff per 10,000 working-age residents reducing enrollment in related programs by up to 5% and effects varying across fields of study.

7 Conclusion

More than 8 million students enroll in public community colleges in the United States each year, with many entering vocational programs that prepare them for a continually evolving labor market. The returns to these programs vary substantially by field 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 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. However, when layoffs occur in fields that do not have clear substitutes, such as STEM occupations and the skilled trades, students are less likely to shift their enrollment to alternative programs.

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 there are local labor market shocks. 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 local labor market conditions. However, it is not clear whether this responsiveness is a result of the salience of local events or geographic preferences. Ideally, educators would urge students to consider both local and non-local labor market opportunities to make informed choices that best align with their geographic 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. Additional work analyzing how students respond to local labor market shocks in other contexts would be a valuable contribution to the literature. Second, my results are limited in that they apply only to the decisions of recent high school graduates. 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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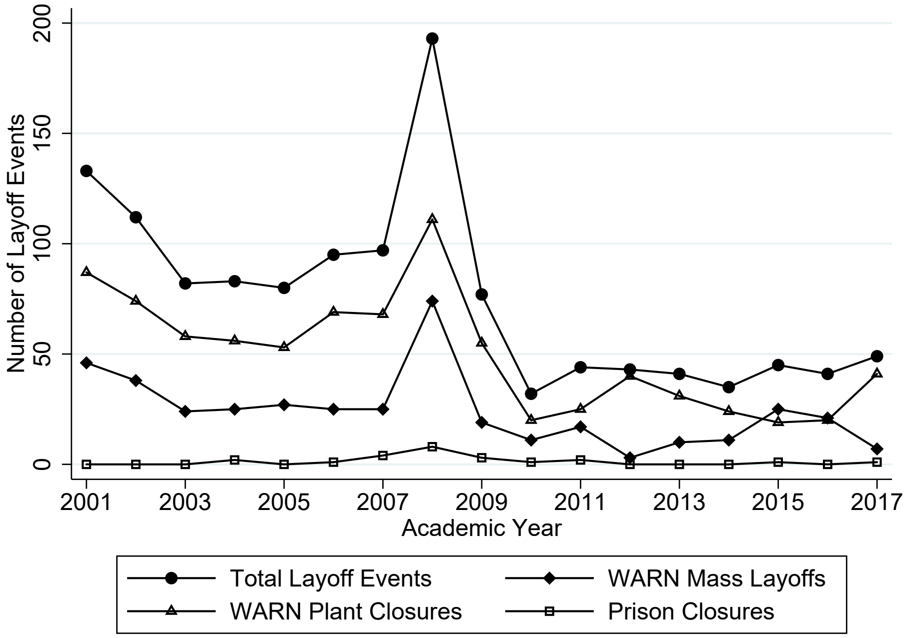
Figure 1: Labor Market Shocks in Michigan, 2001-2017

(a) Layoff Events



(b) Total Job Losses

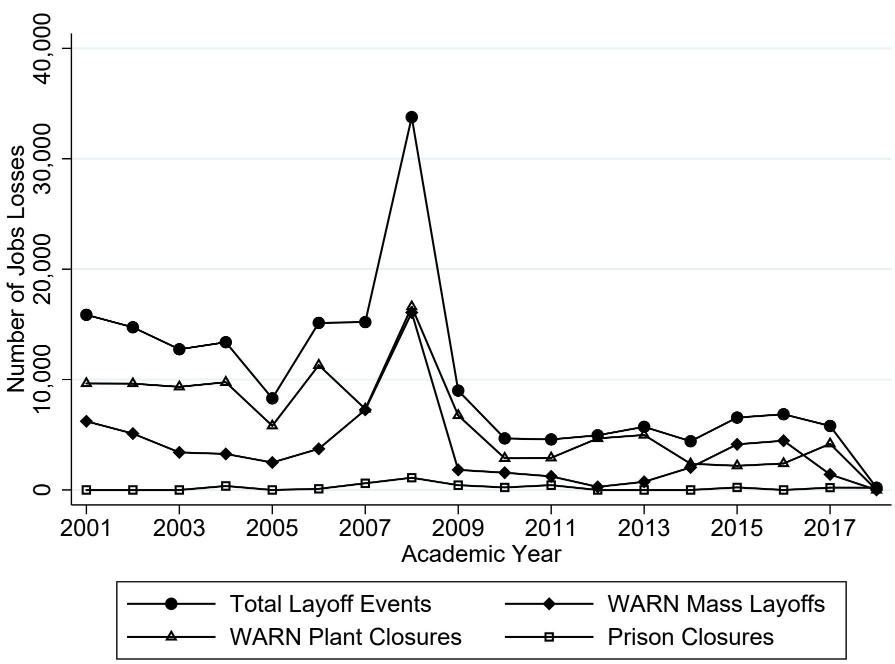
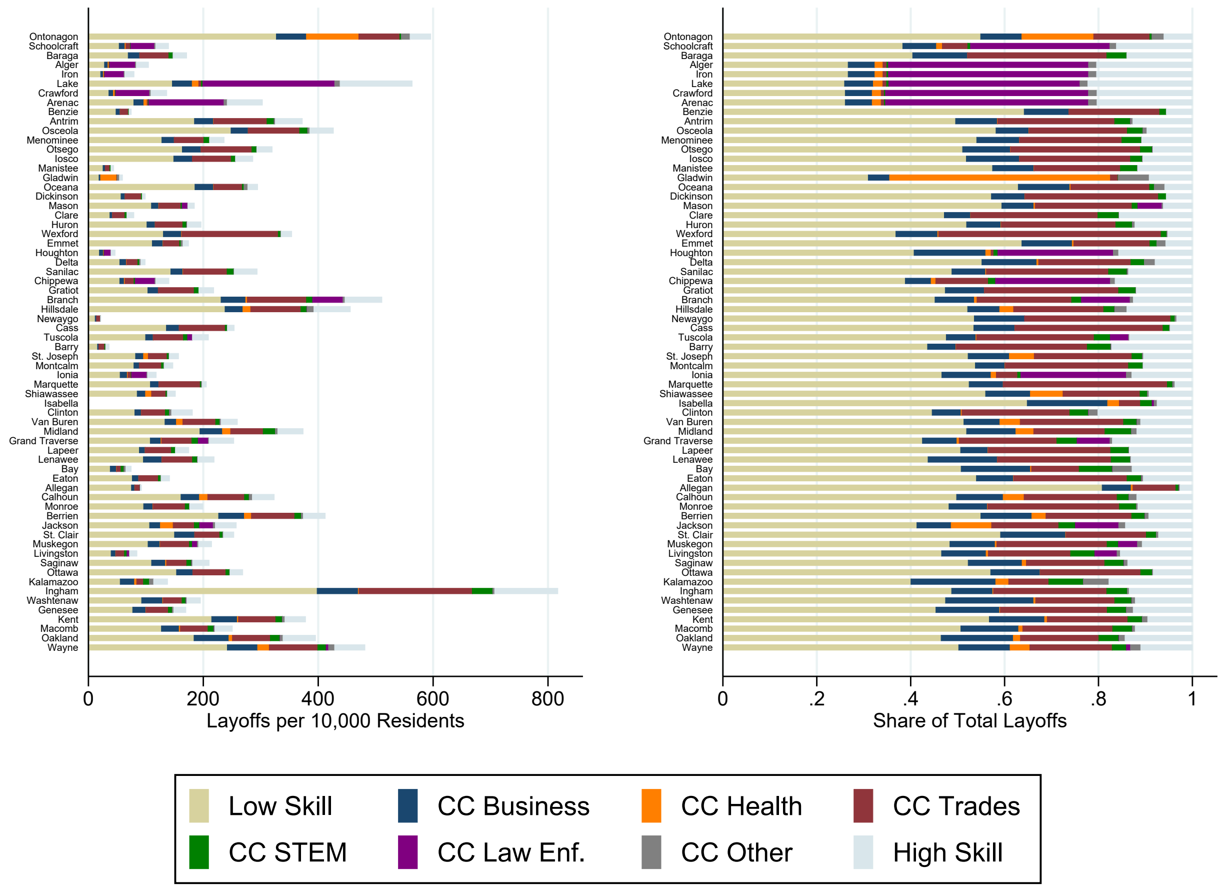


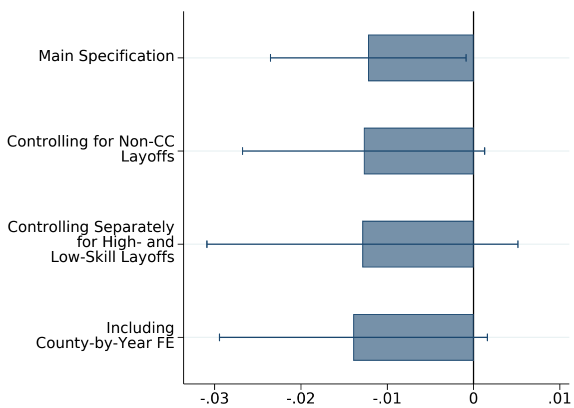
Figure 2: Distribution of Layoffs by County, 2001-2017



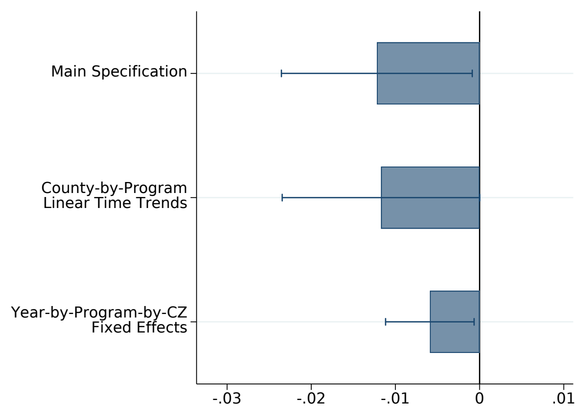
Notes: The sample consists of the 66 (79.5%) Michigan counties that experience layoffs between 2001 and 2017. The left-hand panel shows the total number of layoffs in each type of occupation per 10,000 working-age residents (averaged over the time frame). The right-hand panel shows the share of total layoffs occurring in each type of occupation.

Figure 3: Robustness Checks

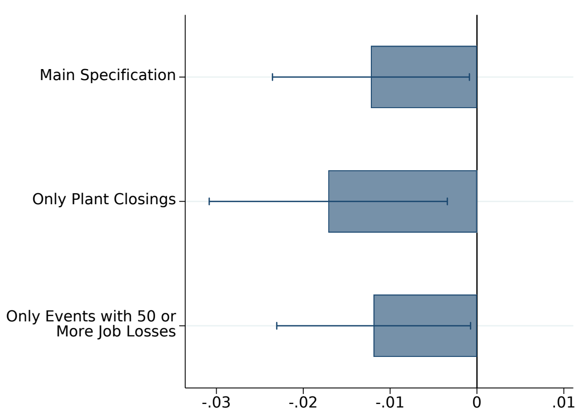
(a) Different Control Variables



(b) Trends and CZ Fixed Effects



(c) Exclusion of Layoff Events



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

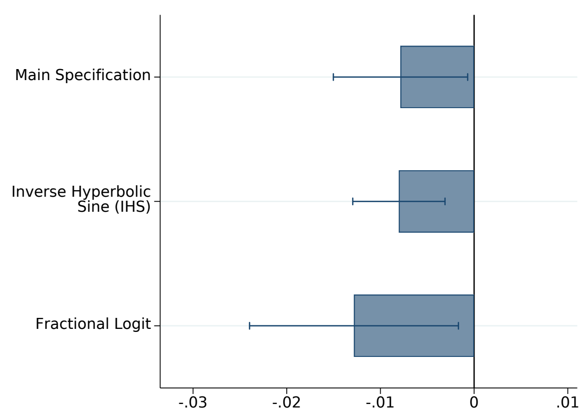


Figure 4: Substitution into Program Groups Requiring Similar Skills

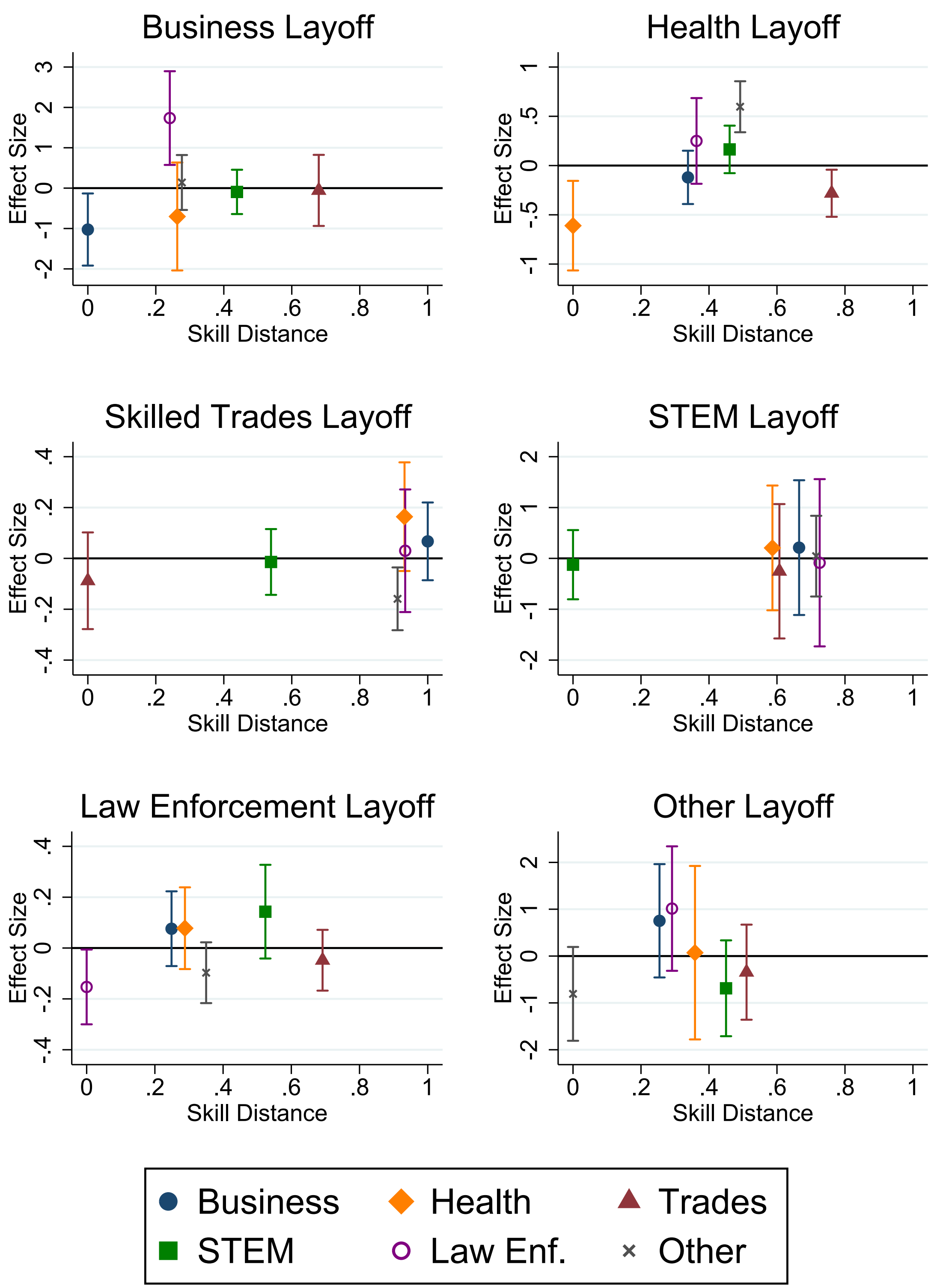


Figure 5: Relationship Between Substitution Effects and Skill Distance

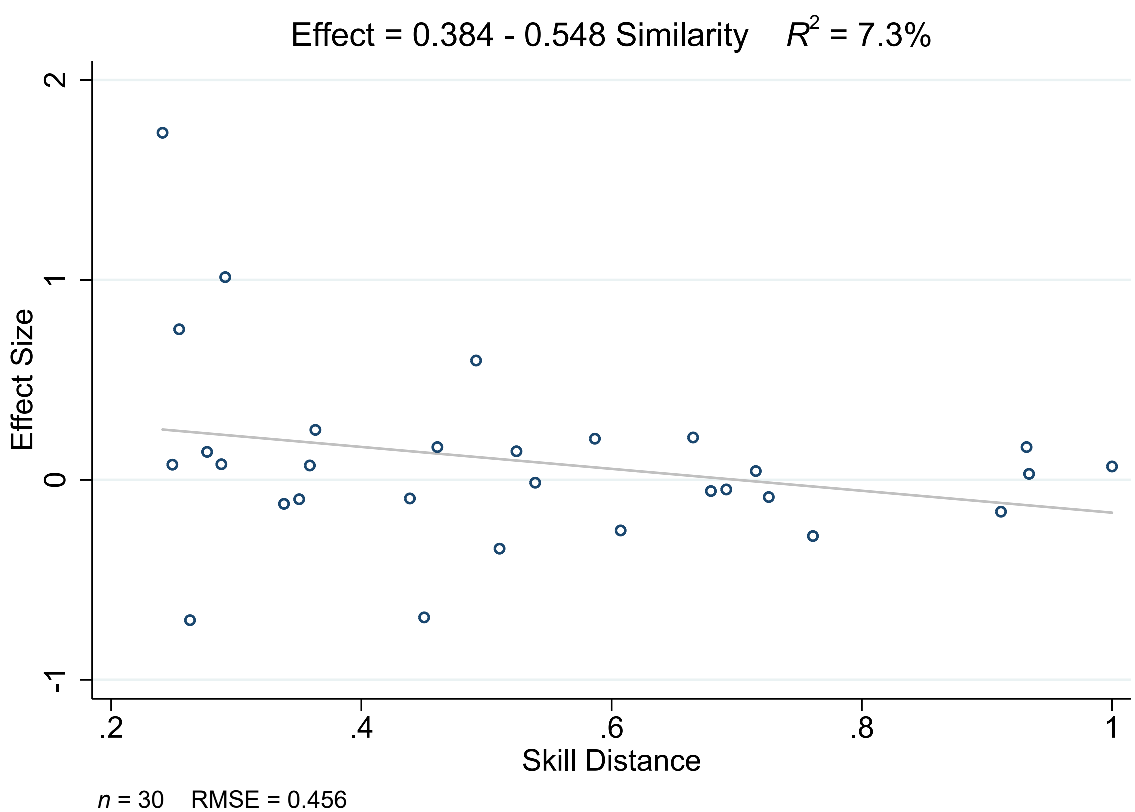
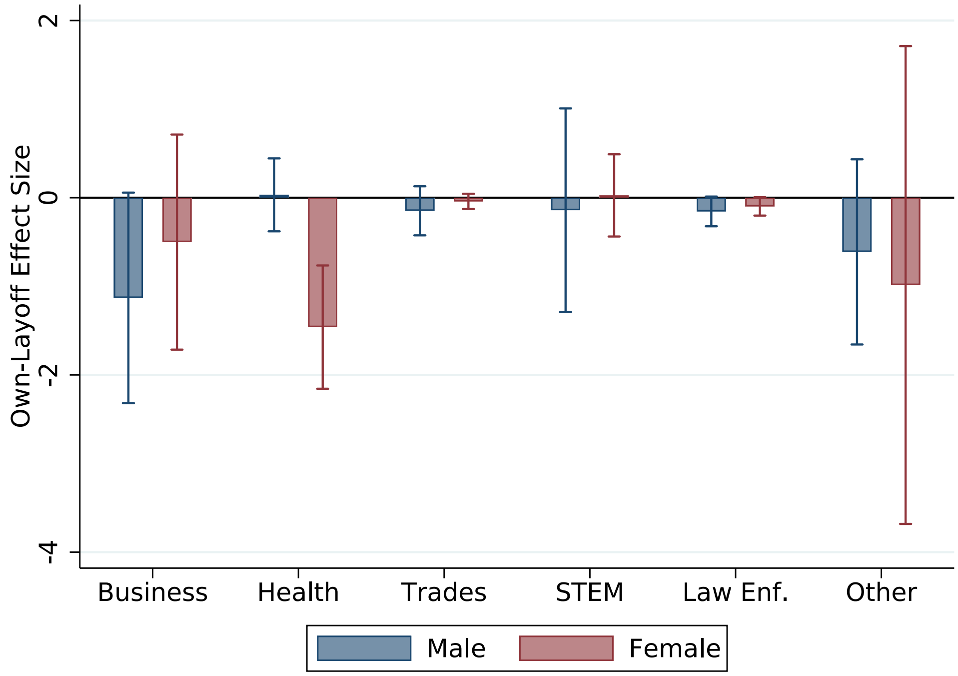


Figure 6: Heterogeneous Own-Layoff Effects

(a) Heterogeneity by Gender



(b) Heterogeneity by County Urbanicity

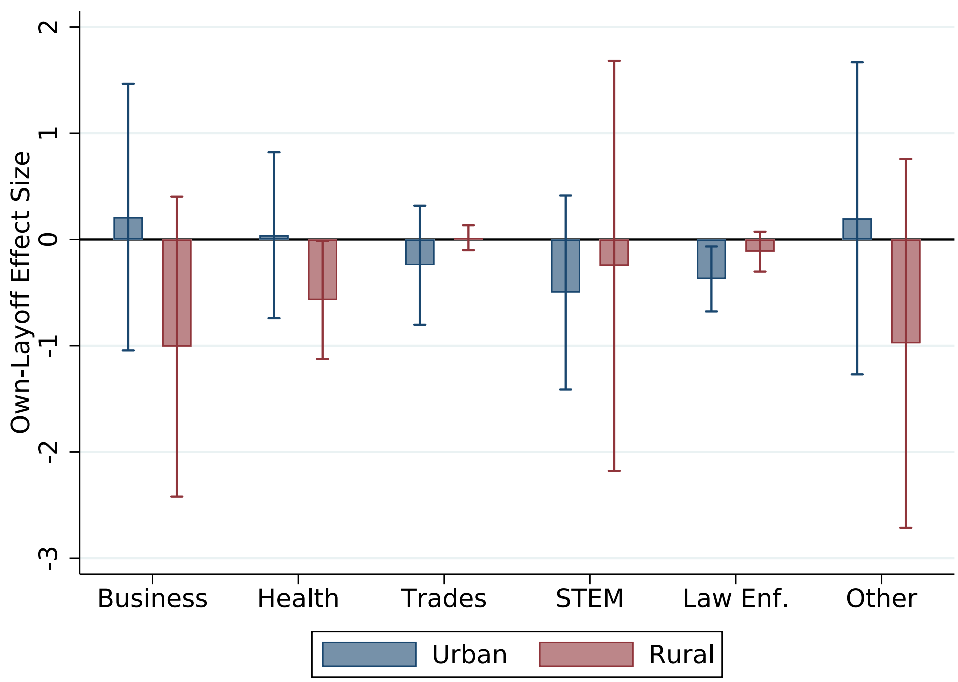
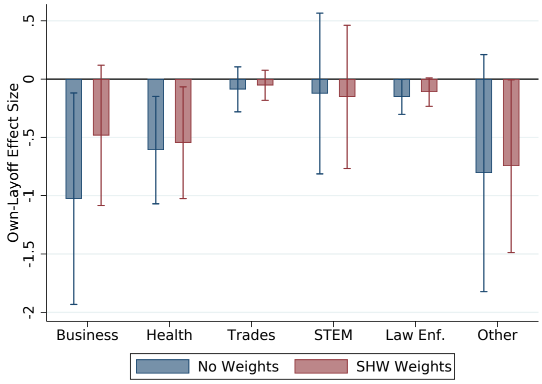
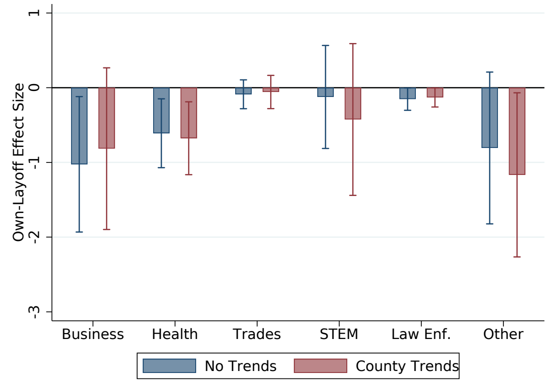


Figure 7: Robustness Checks for Own-Layoff Effects

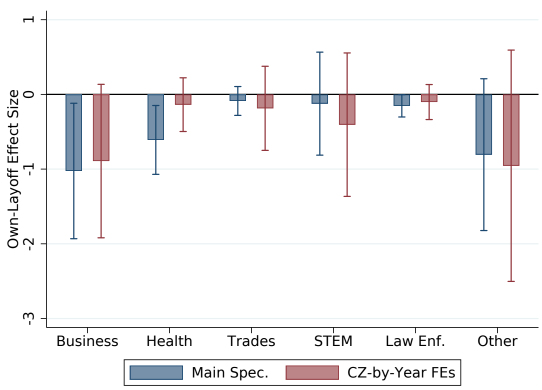
(a) Weighting for Heteroskedasticity



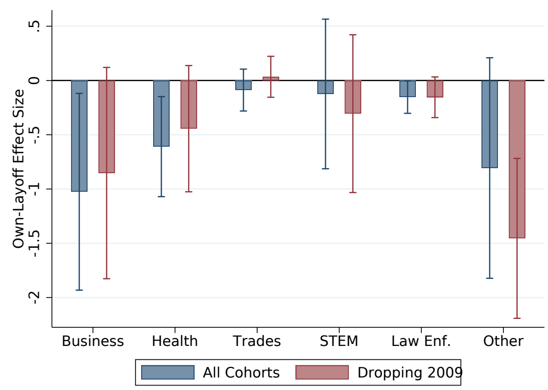
(b) County-Specific Time Trends



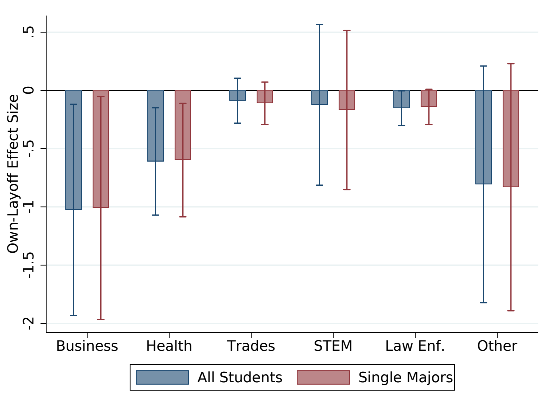
(c) Cohort-by-Commuting Zone Fixed Effects



(d) Dropping 2009 Cohort



(e) Dropping Students in Multiple Programs



(f) Non-Linear Specifications

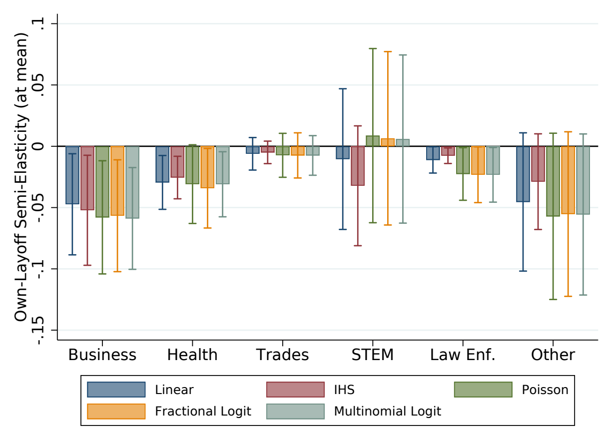


Table 1: Summary Statistics of Michigan's High School Graduates

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. College and program choices are defined as a student's first enrollment choice within 6 months 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 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 3: 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 4: 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 standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Effect of Job Losses in Alternative Geographic Areas

	Enrollment in Occupation Group Programs per 100 Vocational Students		
Layoffs per 10,000 in:	**(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 (7), the effect of an additional layoff per 10,000 working age residents in a given occupation group on enrollment in corresponding programs. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: 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	0.009	0.016	0.003
	(0.013)	(0.017)	(0.012)
Health, t-1	0.002	-0.006	0.011*
	(0.005)	(0.005)	(0.006)
Skilled Trades, t-1	0.002	0.001	0.003
	(0.002)	(0.004)	(0.003)
STEM, t-1	0.018	0.001	0.002
	(0.015)	(0.018)	(0.014)
Law Enforcement, t-1	-0.000	-0.001	-0.000
	(0.002)	(0.002)	(0.002)
Other, t-1	0.012	0.021	0.015
	(0.027)	(0.024)	(0.023)
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 (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, 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: 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

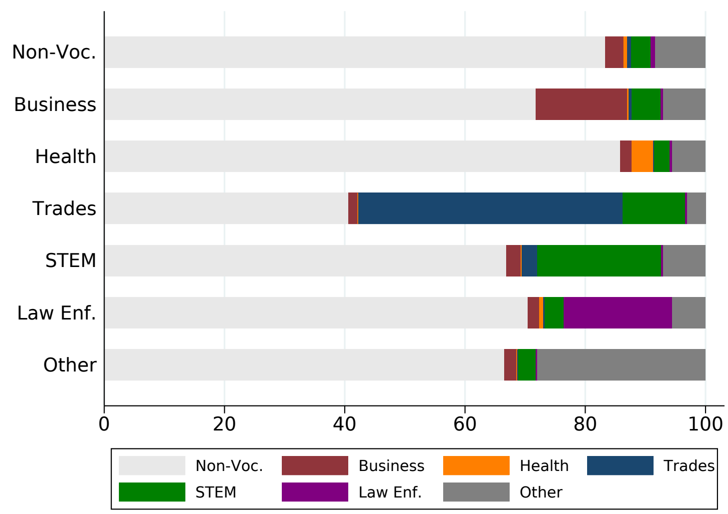
Notes: The unit of observation is a county-cohort pair. Outcomes are measured as the number of students who enroll in a given program within 6 months of high school graduation per 100 students who in the county and cohort enroll in vocational programs. The coefficients in each column are estimated from a separate regression and represent the β_j terms in equation (5), 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Online Appendix: Not for Publication

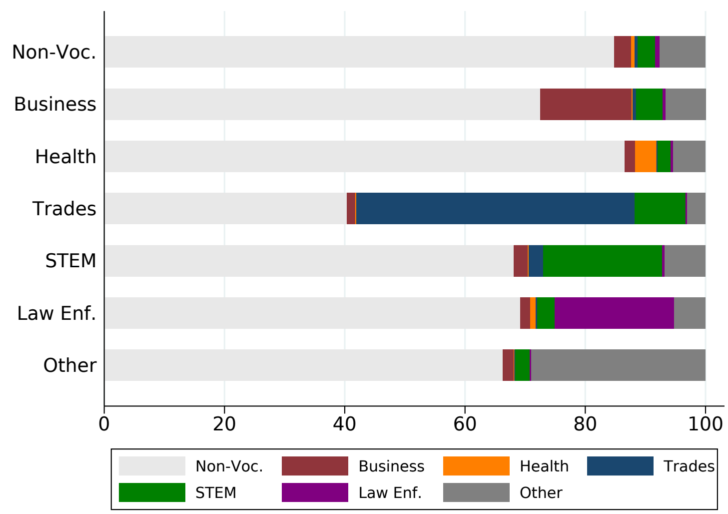
A Additional Figures & Tables

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

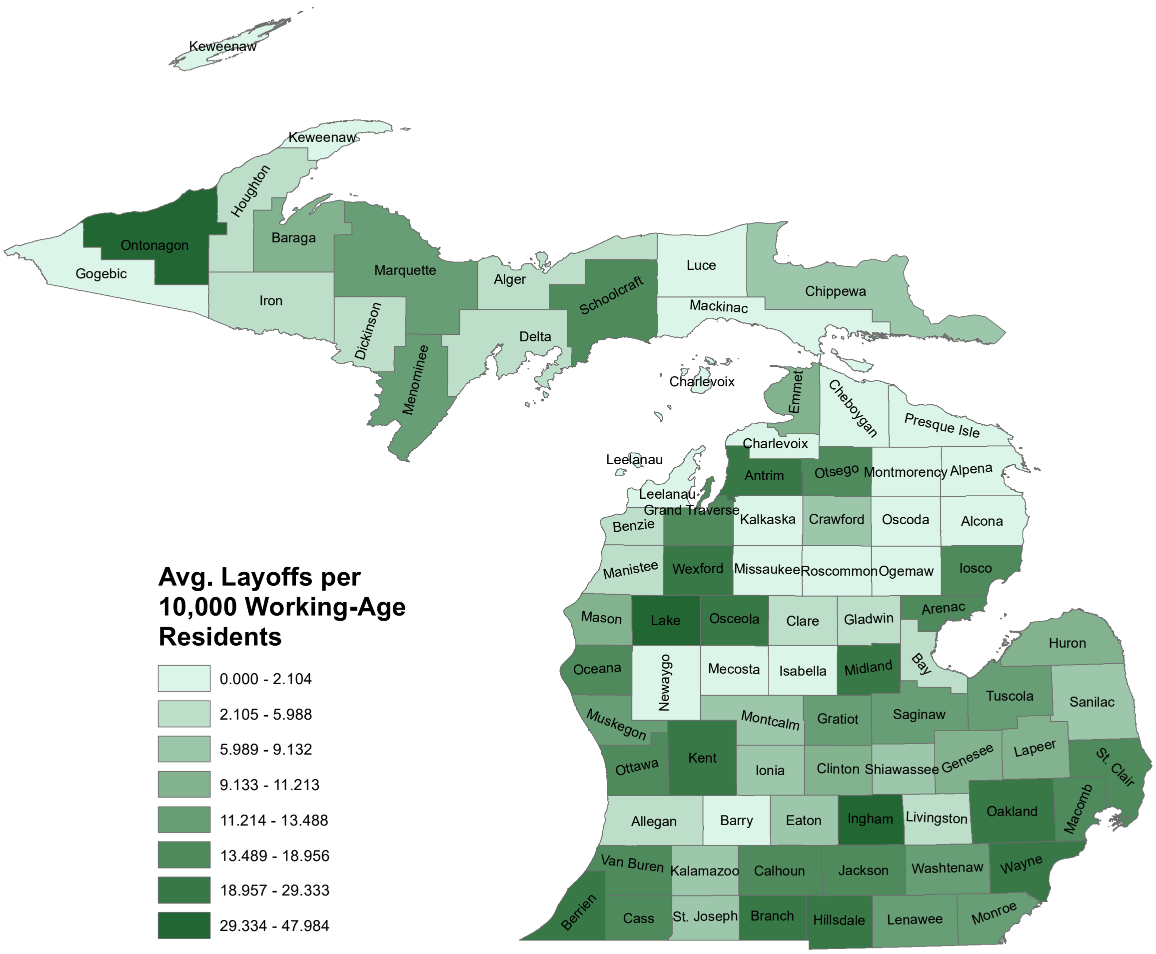


Figure A.3: Correlation Between National and State-Specific Industry Employment Shares, 2016

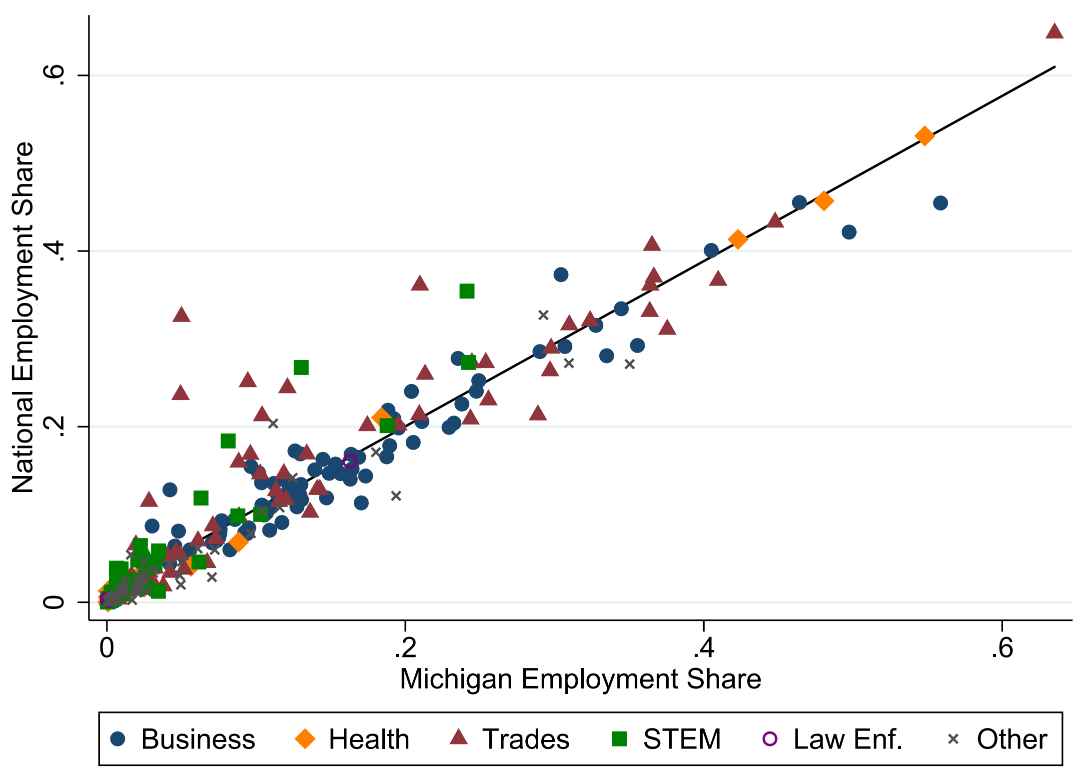
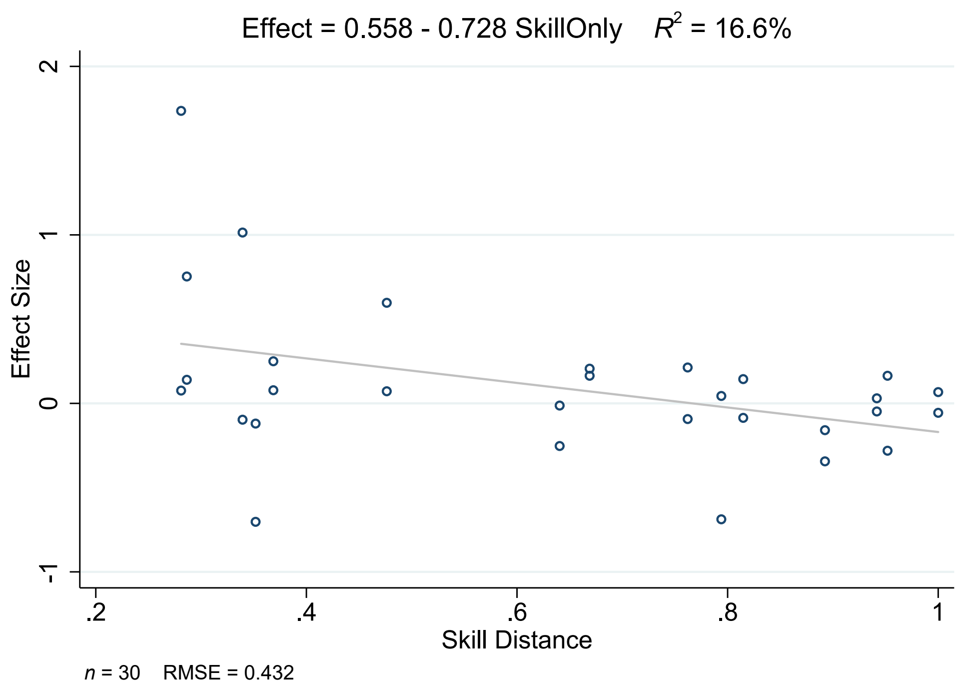


Figure A.4: Relationship Between Substitution Effects
& Skill Distance Using Alternate Measures of Skill Distance

(a) Differences in Skill Levels Only



(b) Differences in Skill Importance Only

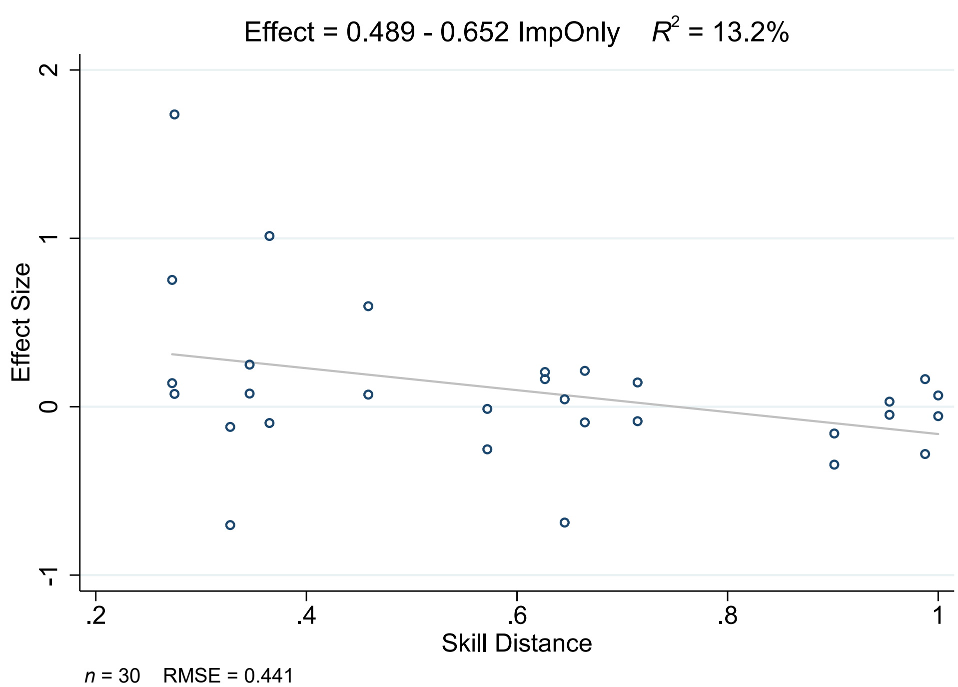


Table A.1: Programs Offered by Michigan's Community Colleges

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

* 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 Concentration of Occupation Groups

NAICS	**Industry Title**	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

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 figure is 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: Effect of Layoffs on College Enrollment Outcomes

	Enrollment per 100 Graduates in:			
Layoffs per 10,000 in:	**No Formal College (1)**	**CC Vocational Programs (2)**	**CC Non-Voc. Programs (3)**	**Four-Year Colleges (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	-0.004	-0.012	0.019	-0.002
occupations, t-1	(0.020)	(0.013)	(0.016)	(0.022)
Community college	-0.041	0.004	0.011	0.026
occupations, t-1	(0.035)	(0.017)	(0.021)	(0.027)
High-skill	0.058	-0.002	-0.069	0.012
occupations, t-1	(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.7: 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.8: 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.9: 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), 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

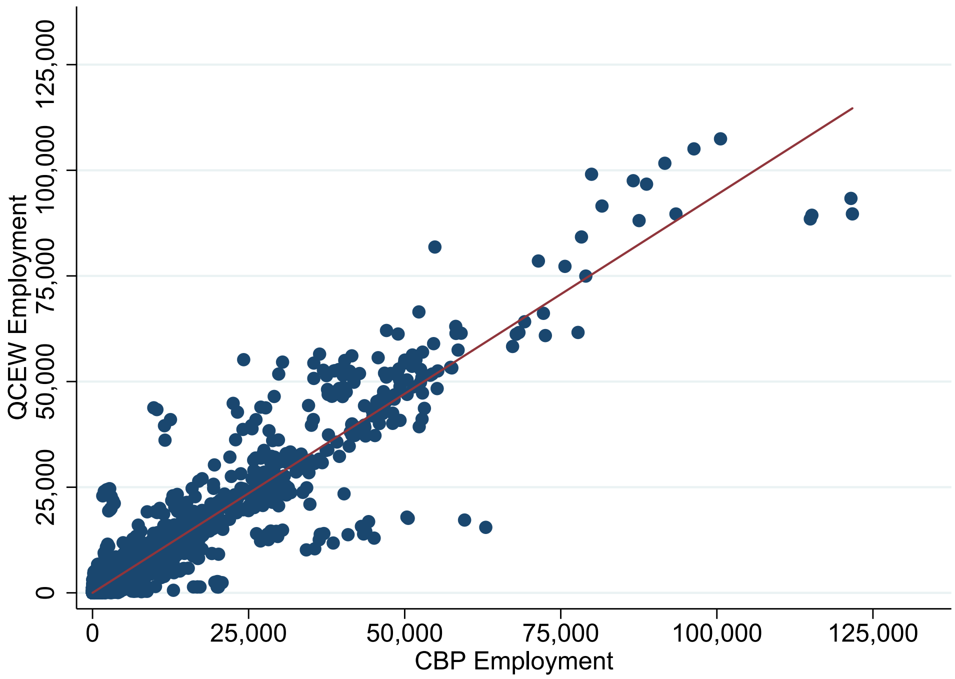
B Comparing Layoffs to Other Employment Data Sources

The estimated layoff measures used throughout the analysis are designed to capture changes in local labor demand in a given occupation group and county. They 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).

Nevertheless, 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 by less than one worker on average, presumably because some laid-off workers find work at other

[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.

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

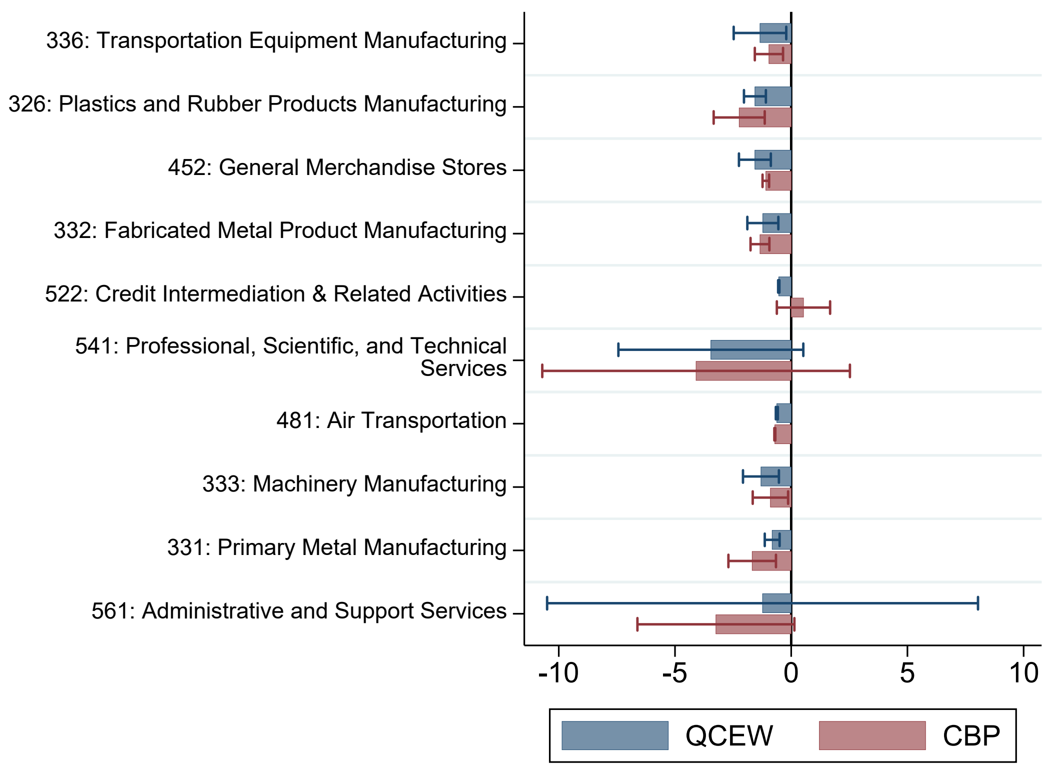
Notes: The sample consists of all county-by-industry pairs that have non-zero employment between 2001 and 2016 in either the QCEW or CBP dataset. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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.

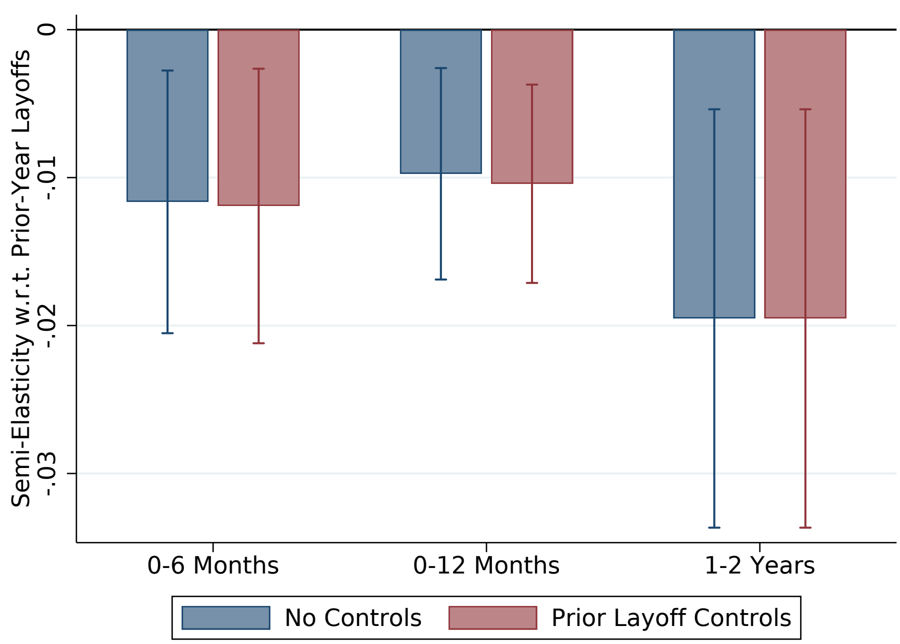
Figure B.2: Relationship between Layoffs and Employment Changes, by Sector



C Other Responses to Layoffs

To supplement the main analysis, I also analyze how layoffs affect two other educational outcomes of interest: the enrollment choices of students who delay community college entrance beyond the first six months of high school graduation and the retention rates of students once enrolled. For the first outcome, I restrict the sample to students who graduate from high school between 2009 and 2013 and enroll in vocational community college programs within at some point before 2017 and re-estimate equation (3) in the main text for different enrollment timeframes.[1] Figure C.1 shows the estimated elasticity of program choice with respect to prior-year layoffs in related occupations. For enrollment within either six or twelve months of high school graduation, an additional layoff per 10,000 county working-age residents during a cohort's senior year of high school reduces enrollment in related programs by about 1%. This effect continues to hold when I control for layoffs occurring during students freshman, sophomore, and junior years of high school.

Figure C.1: Effect of Layoffs on Program Choice for Later Enrollees



[1]To control for time-varying county characteristics that I may not observe in my data, I include county-by-cohort fixed effects in these specifications.

When analyzing longer-run enrollment choices, I cannot observe where students live in the years following high school graduation and, therefore, implicitly assume that students' remain living in the same county that lived in during high school. Nevertheless, for students enrolling in vocational community college programs in the 1-2 years following graduation, I find similar effects of layoffs on program choices. Figure B.3.1 shows that an additional layoff per 10,000 students reduces enrollment in the following year by about 2%. The magnitude of this estimate suggests that older students may be even more responsive to local labor market shocks, which is an important topic for future work.

I also consider how layoffs affect program retention rates by including all cohorts and estimating 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.[2] This measure is equal to the share of students who remain enrolled in the same college and program in the following year and multiply the share by 100. 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

[2] 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.

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.[3] 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 coefficient 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.[4] 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[3]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.

[4]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).

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

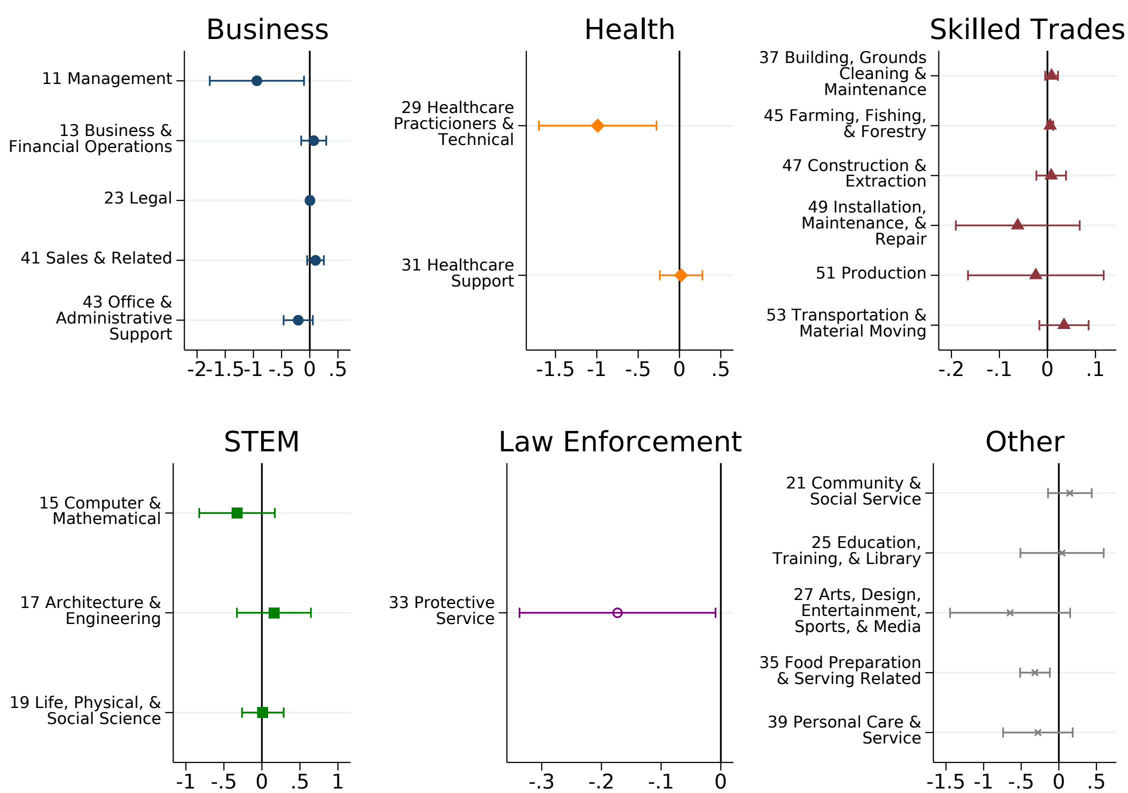
	Retention per 100 Students in:					
	Business	**Health**	**Trades**	**STEM**	**Law Enf.**	**Other**
Layoff measure:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Layoffs per 10,000 in	-0.250	-0.082	-0.364	-1.307	-0.226	-3.600***
own occupation group	(0.546)	(0.275)	(0.246)	(0.951)	(0.204)	(1.358)
Outcome 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

D Substitution Between Narrower Program Groups

One limitation of the main analysis is that it combines multiple, potentially distinct programs into a single program group. To investigate substitution patterns between narrower program groups, I re-estimate the system of equations presented in equation (5) of the main text using enrollment in the two-digit occupation codes that comprise each program group as the dependent variables. For example, rather than estimating how business layoffs affect enrollment in business programs overall, I separately estimate how business layoffs affect enrollment in management, business and financial operations, legal, sales, and administrative support programs. I present these own-layoff effects in Appendix Figure D.1.

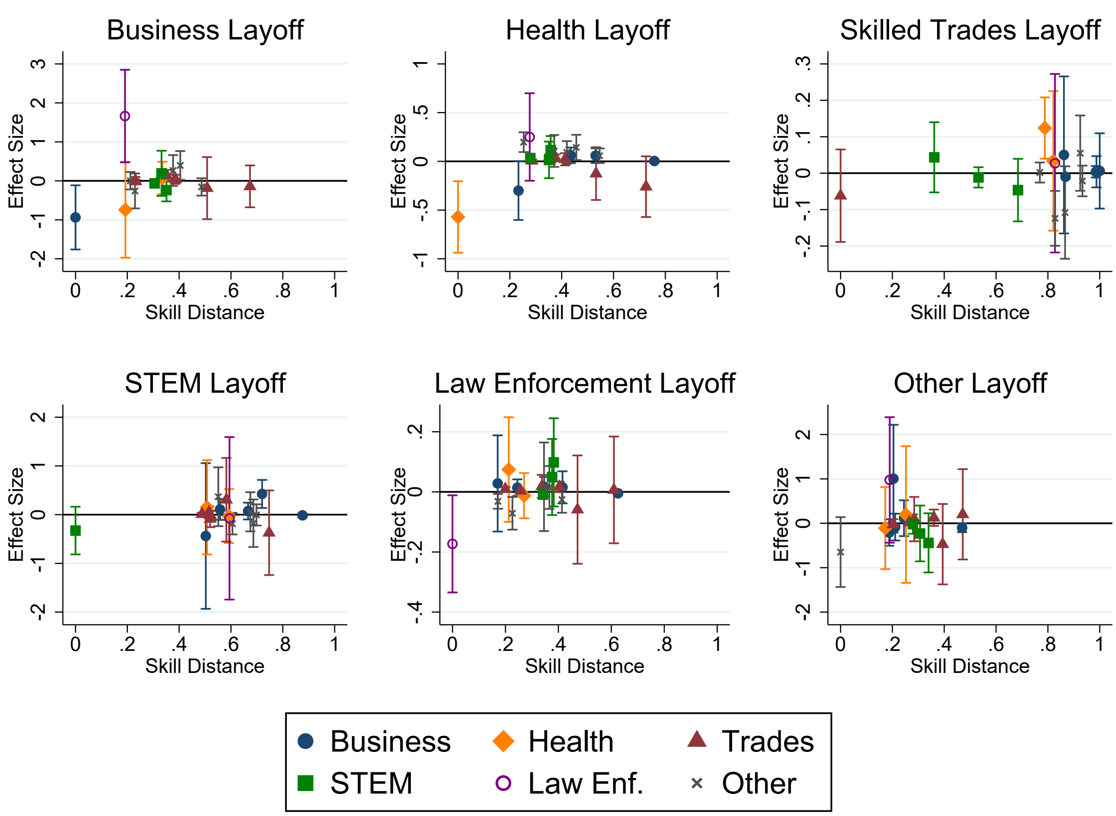
Figure D.1: Effect of Layoffs on Enrollment in Narrower Program Groups



The results indicate that the reduction in business program enrollment is driven by students forgoing enrollment in management-related programs, such as business administration, and the reduction in healthcare programs is driven by students forgoing enrollment in healthcare practitioner programs, such as nursing. The reductions in enrollment in skilled trades programs are driven by programs in the installation, maintenance, and repair and production categories, which includes auto mechanic and welding degrees. The responses to STEM and other layoffs are not substantially different across each program group's occupational categories.

Next, I analyze substitution patterns relative to the two-digit occupation code that experiences the largest own-layoff effect in each program group. For example, because the largest decrease in business program enrollment comes from the management group, I compare the skills of all other two-digit occupation codes to the skills needed for management occupations to see if students are substituting into similar programs. Appendix Figure D.2 shows how the substitution patterns for each program group relate to the skill distance measures.

Figure D.2: Substitution into Narrower Program Groups Requiring Similar Skills



Appendix Figure D.3 then plots the pooled substitution effects against the skill distance measures for all six program groups. As in Figure 5 in the main text, the largest substitution effects occur at the start of the x-axis, and there is a downward slope, indicating that substitution effects are largest in the most similar programs and diminish as skill distance increases. However, the results are less precise when considering enrollment in smaller program categories.

Figure D.3: Relationship Between Substitution Effects & Skill Distance, Narrower Programs