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Community College Program Choices in the Wake of Local Job Losses

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Abstract

Deciding which field to study is one of the most consequential decisions college students make, but most research on the topic focuses on students attending four-year colleges. To understand how students attending community colleges make field of study decisions, I link administrative educational records of recent high school graduates with local mass layoff and plant closing announcements. I find that declines in local employment deter students from entering closely related community college programs and instead induce them to enroll in other vocationally-oriented programs. 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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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. The nearly ten million students who attend two-year community colleges (National Center for Education Statistics, 2018) also must decide which fields to study, and their decisions have similarly large implications for their labor market outcomes. For example, students who enroll in healthcare programs can expect to experience large earnings gains in the labor market, while students who select other programs may not earn 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' program choices.

In this paper, I use administrative data on the education decisions of recent high school graduates in Michigan to analyze how labor market conditions influence 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 state or national demand.[1] Second, community college programs are generally designed to take two years or less to complete. Thus, while four-year college students may consider longer-run labor market trends when choosing college majors, community college students may be more likely to consider short-term fluctuations in labor demand. Finally, many programs at the community college level are closely tied to specific occupations, such as nursing or welding, rather than the broad subjects that 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.

My empirical approach exploits plausibly exogenous variation in students' exposure to local job losses resulting from mass layoffs and plant closings. I further rely on the distribution of occupations across industries to create estimated measures of occupation-specific labor demand shocks that align closely with six broad groups of community college programs. 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 and health assistants. Therefore, hospital closures should change the benefit to local students of enrolling in community college healthcare 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 local job losses as they exited high school, I show that students' program choices are sensitive to occupations' local labor market conditions. On average, an additional layoff per 10,000 working-age residents in a county reduces the share of the county's high school graduates enrolling in related community college programs by 0.8%. Correspondingly, a one standard deviation increase in layoff exposure reduces enrollment by 3.8%. This effect is most pronounced when layoffs occur in a student's county during her senior year of high school, and is driven by students substituting enrollment between community college programs, rather than forgoing higher education opportunities.

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

To explain these substitution patterns, I leverage data on the skills required in different occupations from the U.S. Department of Labor's Occupational Information Network (O*NET) to create measures of skill similarity between community college programs. I then document that students primarily shift their 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 two 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 which fields students study in college, particularly how expected wages affect students' college majors. Most prior work at the four-year college level finds that, to some extent, expected wages influence students' choices (Altonji et al., 2016). 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.

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 U_i is some increasing, concave function. That is, a student will choose alternative j if $U_{ij} > U_{ik}$ for all $j \neq k$ and the probability 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

[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.

vocational program. If not, may no longer enroll in college or may enroll in a four-year college program instead. In contrast, in the second example, the utility student i receives from each alternative will decrease and the student's choice should be less affected.

These examples highlight that the anticipated effects of layoffs depend on the 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.

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 nonvocational programs typically consist of general education courses and prepare students to transfer to four-year colleges and universities.

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.

[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).

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 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 (291141), 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.[7] 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*.[8] Table A.2 provides a list of the two-digit SOC codes contained within each group.

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

[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] The current version of the appendix is available at: https://www.rileyacton.com/research.

[8] 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.

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.[9] 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.[10]

Table 1 provides summary statistics on Michigan's high school graduates disaggregated by their first postsecondary education choices. A non-trivial share of students enroll in vocational and non-vocational community college programs each year: 9% and 14% of graduates, respectively.[11]Students who enroll in vocational programs are more likely to

[9] 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.
[10] 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.
[11] 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.

be economically disadvantaged than students in non-vocational programs and also score lower on state standardized tests.[12] 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.[13] 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.

Measuring Local Job Losses

In my empirical approach, I build on 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 this type of 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

[12] 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.
[13] 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.

WARN notice: (1) a plant closing affecting 50 or more employees at a single employment site, or (2) a mass layoff affecting either 500 or more employees or between 50 and 499 employees that account for at least one-third of the employer's workforce (U.S. Department of Labor, 2019). Employers must give written notice of the anticipated layoff to the employees' representative (e.g., a labor union), the chief local elected official (e.g., the mayor), and the state dislocated worker unit. 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.

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.[14] The correctional facility closure data available from the SFA include a record of the name of the correctional facility that closed, along with the year and number of affected full-time equivalent (FTE) workers. For each correctional facility closure, I find related local news articles to approximate the date the closure was announced and the county in which the correctional facility was located.

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

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

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

group by exploiting the fact that different occupations are concentrated in different industries. I first match all 1,024 entities that experience a layoff to their respective three-digit NAICS industry code using information from company websites and online business databases. 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.[15] 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.[16] As a result, layoffs that occur at hospitals should affect these occupations, and therefore the benefit of enrolling in community college health programs, much more than layoffs that occur at general merchandise stores.[17]

I operationalize this intuition by using the occupation-by-industry employment shares to estimate layoff exposure within a given occupation group, county, and academic

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[15] 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.
[16] Appendix Table A.3 presents the three largest average values of α for each occupation group.
[17] 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.

year. Specifically, I estimate the number of layoffs in occupation group g in county c in academic year t as:

$$\text{Layoffs}_{gct} = \sum_{k} \alpha_{gkt} Layoffs_{kct} \tag{2}$$

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).[18] 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 $0.067(15)+0.109(77)+0.445(168) \approx 84$.[19]

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 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.[20] 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

[18] 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.

[19] 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.

[20] 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.

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 is home to the state capitol of Lansing and has about 200,000 residents, and Ontonagon County, 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.

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:

$$\hat{\delta}_{XX} = (1 - \varepsilon)\delta_{XX} + \varepsilon\delta_{YX}$$

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 $\delta_{YX} \geq 0$ (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_{YX} is sufficiently large. Correspondingly, the estimated effect of the layoff on the probability that a student chooses program Y will then be:

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

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, indicating that measurement error is unlikely to be driving the results.

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.[21] 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.

Empirical Approach

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

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

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

where Enroll_{gct} is the number of students from county c and cohort t who enroll in community college programs in group g, per 100 high school graduates, and $\mathbf{Layoffs}_{gct}$ is a vector of the number of layoffs per 10,000 working-age residents in occupation group g that may affect cohort t in county c. 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 $\boldsymbol{X}_{ct}$ 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 $\boldsymbol{\beta}$ 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.[22]

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

[22] 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.

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.[23]

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 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

[23] I obtain this estimate by re-estimating equation (2.3) with the dependent variable scaled by the average number of graduates in a county and the independent variable scaled by the average number of working-age residents in a county. The β parameter then represents the effect of an additional layoff on enrollment in the average county. Thus, $1/\beta$ provides the number of layoffs needed to induce one student not to enroll in the average county.

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.

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 $\boldsymbol{X_{ct}}$ 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 that include either county-by-program linear time trends or 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 either the inverse hyperbolic sine or the natural log 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] The main linear specification produces a point estimate in the middle of the four non-linear estimates, and I fail to reject the hypothesis that the five estimates are different from one another. Thus, the functional form selection does not appear to be 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.

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.

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:

$$\text{VocationalEnroll}_{ct} = \alpha + \sum_{g=1}^{6} \beta_g \text{Layoffs}_{gc,t-1} + \boldsymbol{X_{ct}\Gamma} + \theta_c + \delta_t + \varepsilon_{ct} \quad (4)$$

where $\text{VocationalEnroll}_{ct}$ is the number of students from county c and cohort t, per 100 graduates, who enroll in vocational community college programs at community colleges. The vector of layoff variables, $\text{Layoffs}_{gc,t-1}$, captures the number of layoffs, per 10,000 working-age residents, that occur in different community college occupation group g in county c during cohort t's senior year of high school. As in equation (3), the vector $\boldsymbol{X_{ct}}$ 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.

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.

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:

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

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 occurring in school year $t-1$, per 10,000

[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.

working-age residents in the county.[30] The vector $\boldsymbol{X_{ct}}$ 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.

The coefficient β_g will represent the "own-layoff" effect when $j=g$ and will represent a "cross-layoff" effect when $j=g$. 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 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 semi-elasticities at the mean values of both the dependent and independent variables. An additional layoff per 10,000 working-age county residents reduces enrollment in related programs by between 0.6% and 4.7%, with the largest statistically significant effects coming from the business and health fields.

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

[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).

[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.

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.

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:

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

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 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

[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.

[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.

program groups and find that the general pattern of students substituting towards similar programs still holds.

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, 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

[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.

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.

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. 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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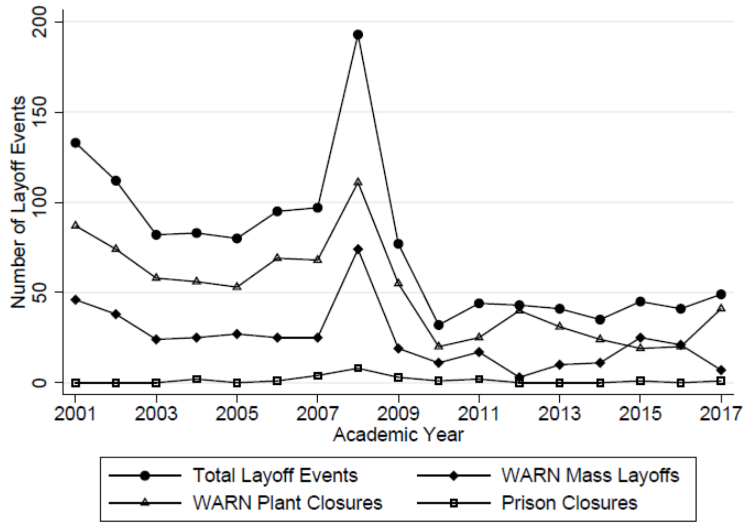
Appendix

Figure 1: Labor Market Shocks in Michigan, 2001-2017

(a) Layoff Events



(b) Total Job Losses

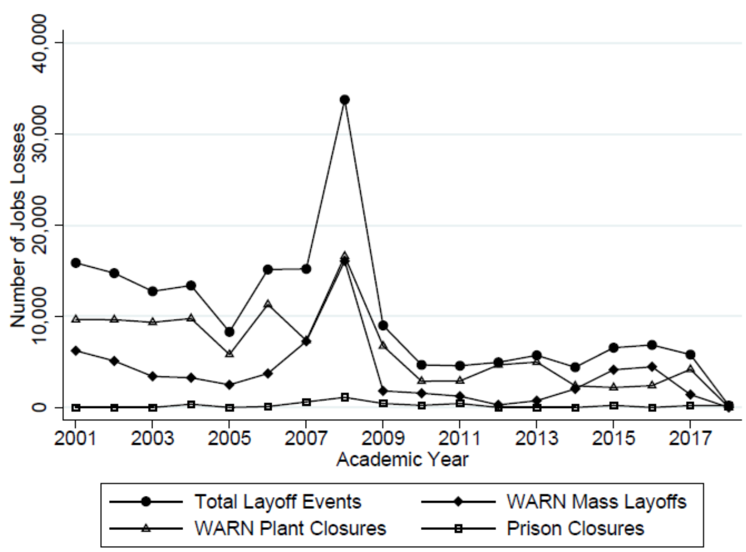
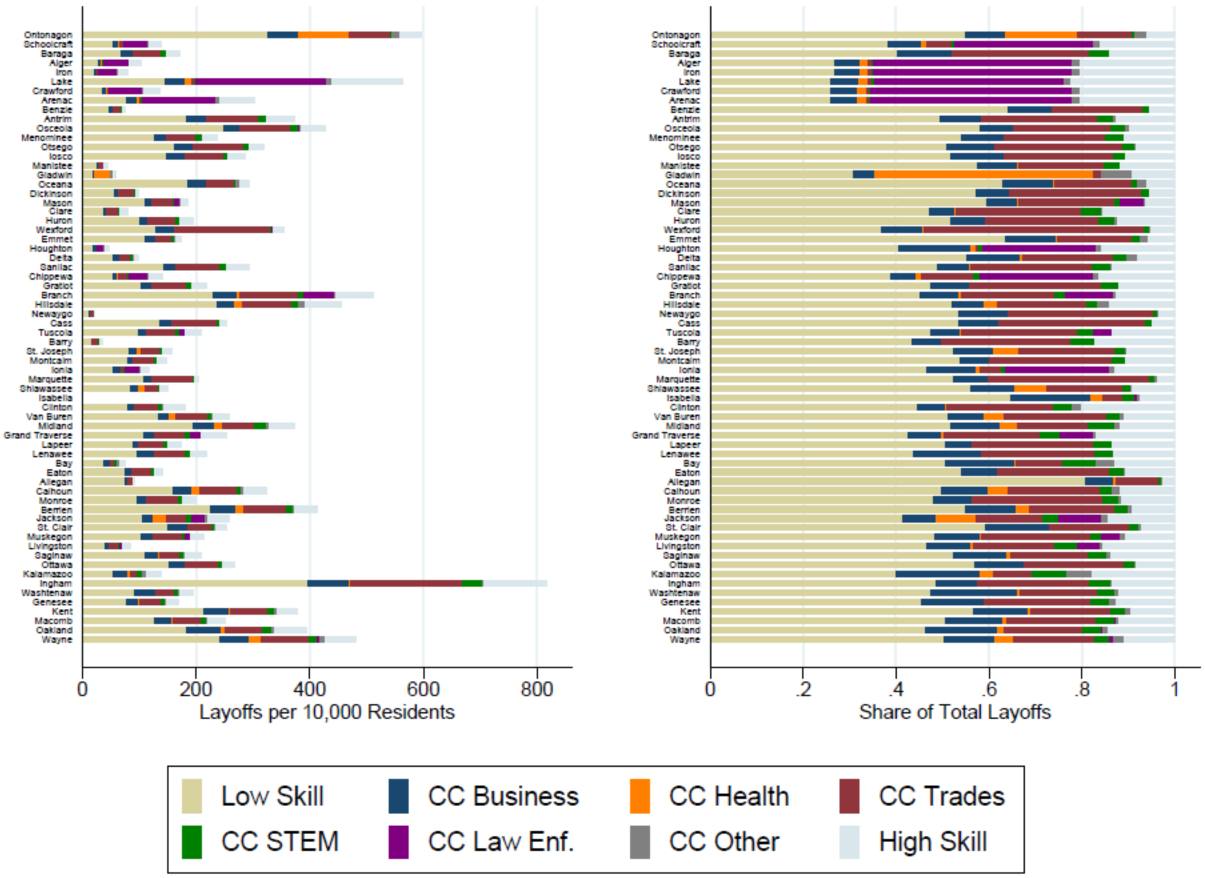


Figure 2: Distribution of Layoffs by County, 2001-2017



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

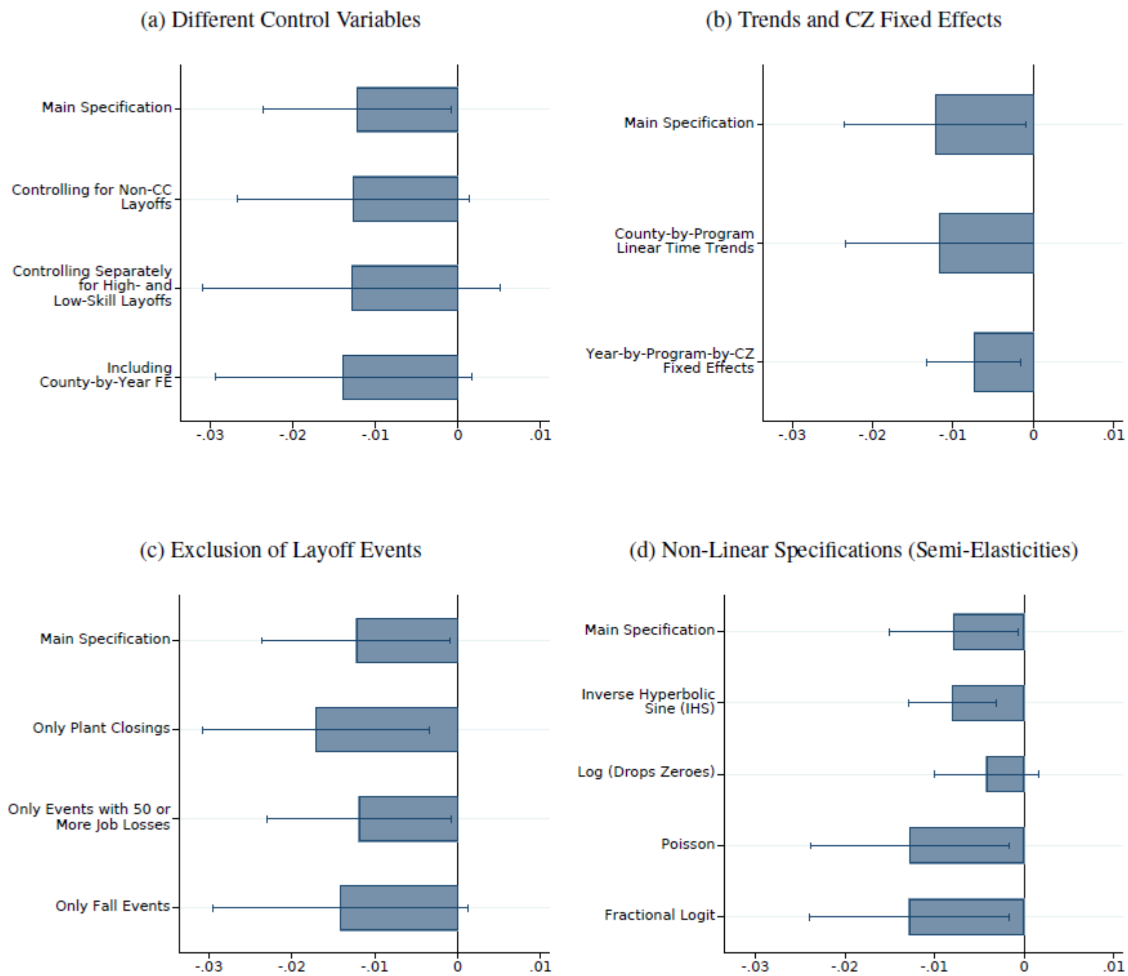


Figure 4: Substitution into Program Groups Requiring Similar Skills

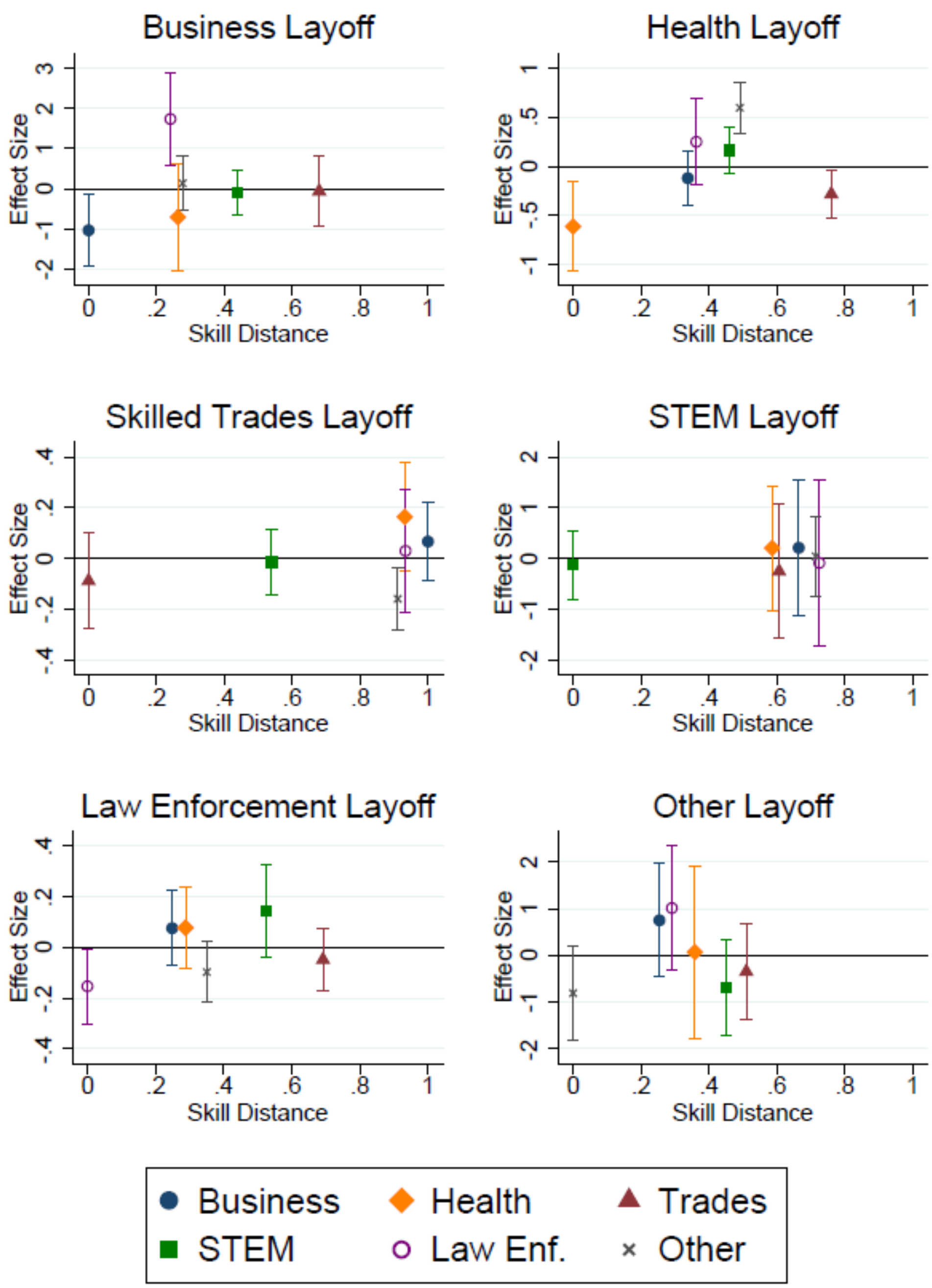


Figure 5: Relationship Between Substitution Effects and Skill Distance

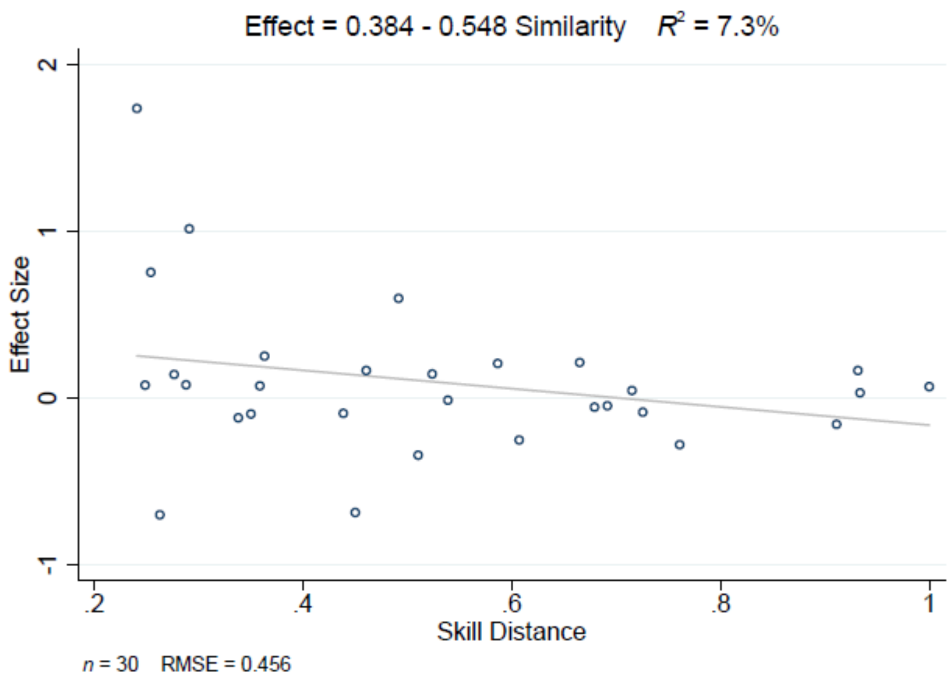
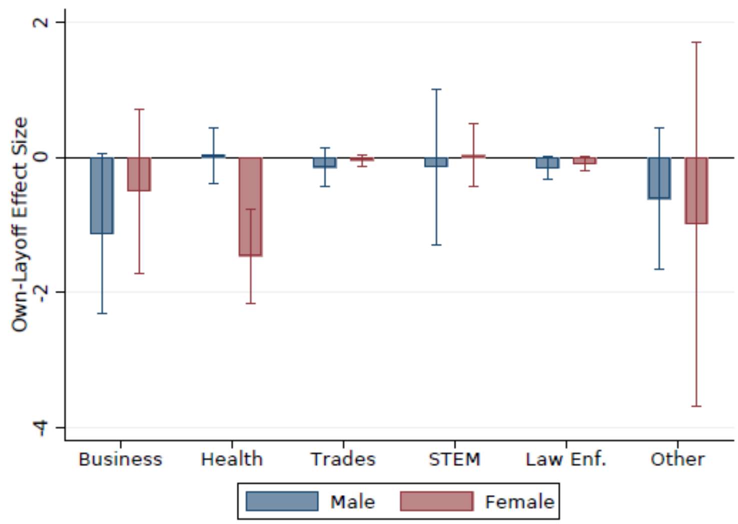


Figure 6: Heterogeneous Own-Layoff Effects

(a) Heterogeneity by Gender



(b) Heterogeneity by County Urbanicity

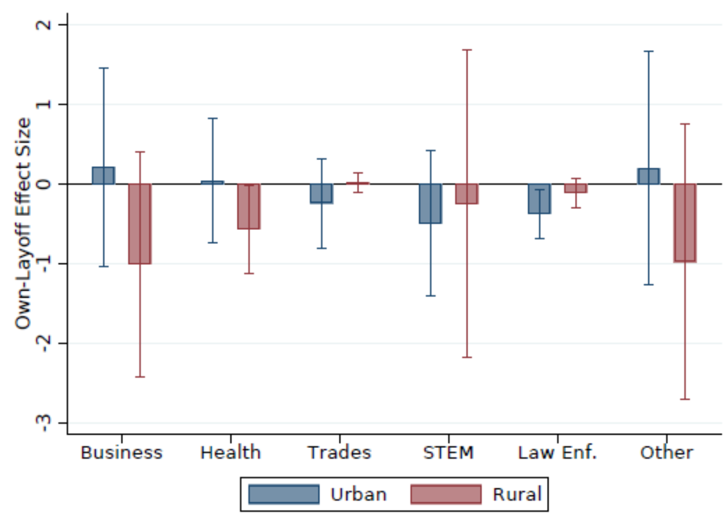


Figure 7: Robustness Checks for Own-Layoff Effects

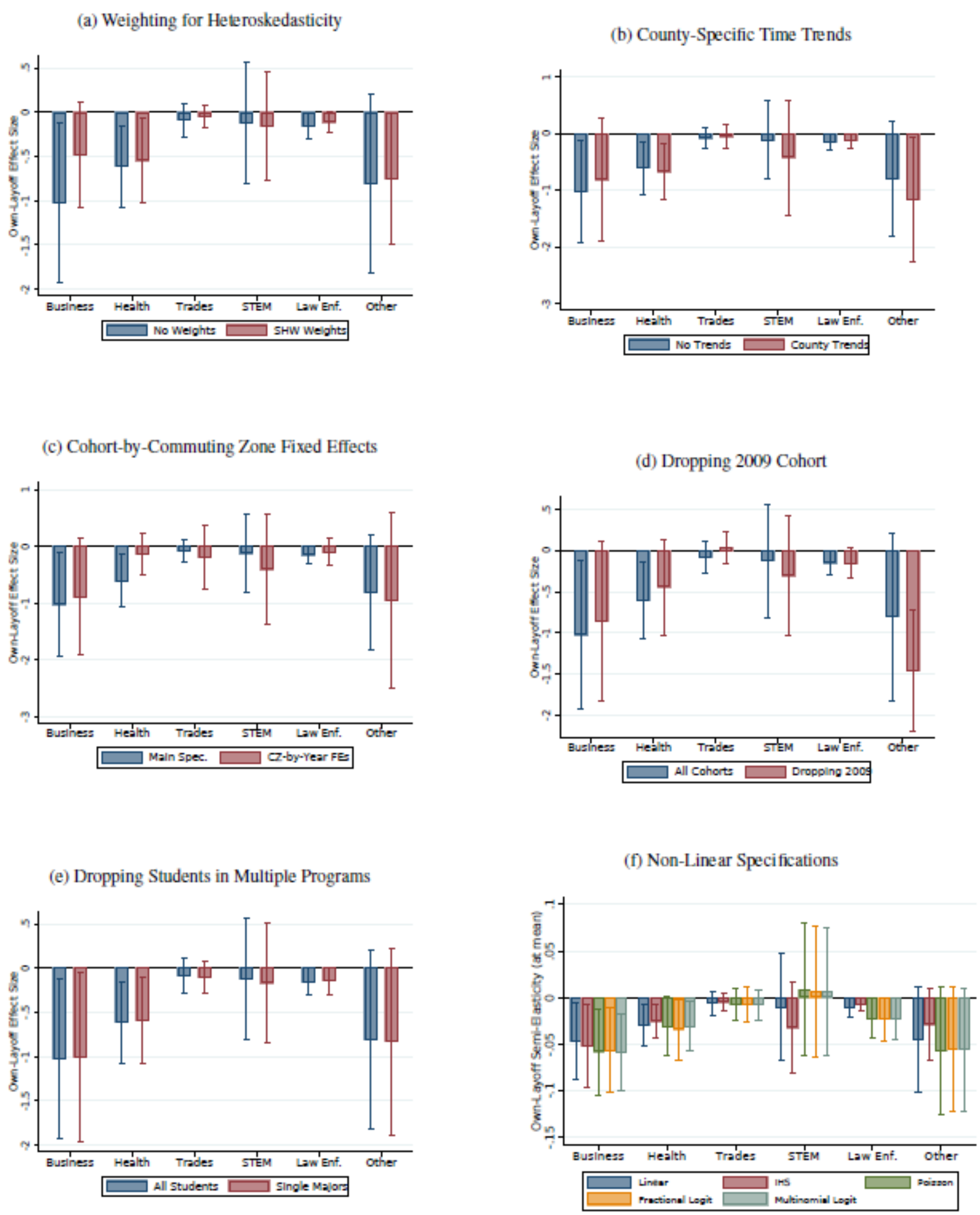


Table 1: Summary Statistics of Michigan's High School Graduates

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), 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.