Community College Program Choices in the Wake of Local Job Losses

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Abstract

Community colleges play an integral role in the U.S. higher education system and are the primary training grounds for a variety of occupations. However, while there is increasing evidence that the labor market returns to a community college education vary by program of study, there is very little research on why students select different programs. 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 exploit the prevalence of mass layoffs and plant closings across counties, industries, and time, and create occupation-specific local layoff measures that align closely with community college programs. 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. Using data on occupational skill composition, I document that students predominantly shift enrollment between programs that require similar skills. These effects are strongest when layoffs occur in business, health, and law enforcement occupations, as well as when they take place in rural counties.

JEL Codes: I21, I23, J23, J24
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1 Introduction

The educational decisions that young people make can have large effects on their long-run labor market outcomes and overall economic well-being. The typical college graduate will earn more than double the earnings of 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), especially 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 research on why students select different college majors focuses on the four-year college sector, which enrolls only about two-thirds of students in the United States (National Center for Education Statistics, 2018). The nearly ten million students who attend two-year community colleges also must decide which fields to study, and their decisions also have large implications for their labor market outcomes.[1] As an example, students who enroll in health programs can expect to experience large earnings gains in the labor market, while students who select other programs may not earn much more than their peers who do not enroll in postsecondary education (Bahr et al., 2015; Belfield and Bailey, 2017; Stevens et al., 2018; Grosz, 2018). In response to these earnings differences, policymakers have recently designed programs that reduce information frictions and aim to steer students into programs that align with local economies. Examples of these efforts include the release of federal Gainful Employment data, which provides students with information on labor market outcomes for certificate programs (U.S. Department of Education, 2017), as well as state initiatives that tie a community college's appropriation funding to its ability to produce degrees in high-demand areas (Snyder and Boelscher, 2018), and financial aid

[1] In this paper, I use the term "community college" to refer to any public institution that primarily offers sub-baccalaureate degrees and certificates. Such institutions are also referred to as junior colleges, technical colleges, or city colleges. In 2014-2015, 9.5 million students enrolled in these institutions, while in 2015-16, 8.9 million students did (National Center for Education Statistics, 2018).

programs that incentivize students to choose in-demand degrees (Allen, 2019). Yet, there is little evidence on the extent to which labor market opportunities affect students' choices or whether students are likely to respond to new information about their labor market prospects.

In this paper, I use administrative data on the college enrollment and program choices 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 occupation-specific local labor market shocks that alter the relative benefit of pursuing different programs in their county. These labor market shocks are likely to be particularly influential to community college students for several reasons. First, community college students tend to remain close to home when attending college and after graduating, making it likely that local labor demand shapes students' expected labor market prospects more than local or national demand.[2] Second, community college programs are generally designed to take two years or less to complete, so community college students may reasonably consider short-term fluctuations in labor demand when choosing which programs to pursue. Finally, many programs at the community college level are closely tied to specific occupations, such as nursing or welding, rather than the broad subjects that typically define majors at four-year colleges. As a result, the expected labor market opportunities associated with programs align closely with labor market opportunities in specific occupations. These close connections to the labor market also enable me to use data on occupational characteristics to better understand students' program choices and to document whether students substitute between similar programs when exposed to local labor market shocks.

My empirical approach exploits the location and timing of mass layoff events and plant closings that affect particular counties and industries. Moreover, I rely on the distribution of occupations across industries to create measures of occupation-specific labor demand shocks that align closely with specific community college programs. Intuitively, these measures isolate layoffs that affect the types of jobs community college graduates would expect to enter and proxy for the local labor demand in those occupations. For example, hospitals employ a

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

large number of healthcare workers with community college credentials, such as nurses, health assistants, and medical billers. Therefore, hospital closures should change the benefit to local students of enrolling in community college health programs. In contrast, mass layoffs at correctional facilities will mostly affect law enforcement professionals —such as correctional officers and administrators —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 types and different amounts of these layoffs, I show that students' program choices at community colleges are sensitive to local labor market conditions. I first document that layoffs occurring in occupations tied to community college programs do not influence students' decisions to enter vocationally-oriented community college programs overall. These layoffs also do not deter students from pursuing postsecondary education. However, conditional on enrolling in vocational programs at community colleges, I find that the types of occupations that experience local labor demand shocks influence what subjects students choose to study. Students are less likely to enter programs that have recently experienced related local labor demand declines in their county. For the average county-cohort pair in the sample, doubling the amount of layoffs students are exposed to in an occupation would reduce enrollment in related programs by 0.3% to 4.6%, depending on the field of study. The largest statistically significant effects come from students' responses to business, health, and law enforcement layoffs, and responses tend to be larger in rural areas.

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

These results contribute to several related lines of literature on how individuals make human capital investment decisions. First, the results add to a large body of empirical work on factors affecting what students study in college, particularly how expected wages affect students' college majors. Most prior work at the four-year college level finds that expected wages play a small but significant role in students' choices, with factors like course enjoyment and perceived ability playing larger roles (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) further document that the occurrence of "superstar" firms with abnormally high stock returns in an industry increases the number of four-year college students majoring in related fields.

Research at the community college level is much more 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. Boudarbat (2008) also shows that Canadian community college students select programs that have higher anticipated earnings. I build on these earlier findings by showing that expected labor market outcomes, measured using exposure to related job losses, affect students' choices across community college programs. Similar to 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. Moreover, the results are driven by students living in rural areas of the state, indicating that a large number of students residing in urban areas do not meaningfully respond to labor market shocks.

Second, this research provides new evidence that labor demand shocks can affect education choices across a variety of margins. Several recent papers exploit layoffs and other local labor market downturns 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. In this paper, I find similar responses to local shocks among a different population of students and also show that students shift enrollment towards programs that require similar skills, which has not been documented in prior work.

Finally, these results add to a growing body of work on the skill content of occupations and educational programs. A substantial literature documents that differences in occupational skill requirements, coupled with technological changes, can explain rising wage inequality and job polarization (Autor et al., 2003; Acemoglu and Autor, 2011; Goos et al., 2014). Moreover, these skill requirements are changing over time (Deming, 2017; Deming and Noray, 2019). Postsecondary programs provide a natural venue for students to develop occupational skills, but little research considers how students' choices of college majors or coursework relate to the skills they will need in the labor market. In this paper, I show how researchers can make use of occupational skill data to analyze the similarity of educational programs and document that layoffs and plant closings induce students to substitute between occupational programs that require similar skills. These findings provide suggestive evidence that students enter community college programs with specific occupational skills of interest in mind and continue to seek out programs that develop those skills when they are exposed to labor market shocks.

2 Conceptual Framework

This paper estimates how local labor market shocks affect students' postsecondary choices, particularly at the community college level. The basic economic intuition of this analysis is that labor market shocks represent changes in local labor demand, which in turn can affect students' expected benefits of pursuing different postsecondary education programs. Assuming that students make schooling choices by comparing the expected costs and benefits of different options (Becker, 1964), any change in the expected benefit of a program has the potential to induce them to make different decisions.

Consider a simplified setting where student i decides between four different postsecondary options: (1) a community college vocational program that leads to a career in occupation group A (e.g. health), (2) a community college vocational program that leads to a career in occupation group B (e.g. business), (3) a four-year college program (leading to a bachelor's degree), or (4) directly entering the labor market.[3] Each alternative leads to a set of likely occupations and 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 associated occupations and the student's taste for the associated occupations. 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. Each alternative is also associated with an expected cost, C_{ij}. Students choose the alternative that maximizes $U_{ij} = U_i(B_{ij}, C_{ij})$, where $\frac{\partial U_{ij}}{\partial B_{ij}} > 0$ and $\frac{\partial U_{ij}}{\partial C_{ij}} < 0$ for all students. That is, a student will choose alternative j if $U_{ij} > U_{ik}$ for all $j \neq k$ and the probability that student i chooses alternative j can be expressed as $P_{ij} = P(U_{ij} > U_{ik})$.

Suppose that student i observes a local labor market shock (i.e., a mass layoff or plant closing) while she is deciding which postsecondary option to pursue. This shock should represent changes in local labor demand, thereby potentially changing the expected earnings (Y_{ij}) of pursuing different postsecondary options. Students' responses 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 related programs by ε_1, while holding all other components of the model constant. In another, the labor market shock affects all occupations

[3]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.

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 both vocational community college program options —she will likely shift her enrollment into the other vocational program. If not, she may decide to no longer enroll in college or may enroll in a four-year college program instead. In contrast, in the second example, the utility student i receives from each will decrease by approximately the same amount across each alternative and students' choices should not be affected.

These examples highlight that the anticipated effects of layoffs depend on the distribution of layoffs across different segments of the economy. As such, the identifying variation used in the analysis comes from the fact that different cohorts within the same county experience different distributions of layoffs before making their postsecondary decisions. These examples also show that labor market shocks can have large effects without inducing students to change whether or where they enroll in college. Namely, students can choose to enter other programs within the vocational community college sector. Previous studies that only consider the effects of layoffs on college entry do not capture this response and potentially miss important labor market implications since the returns to a community college education vary significantly across programs.

3 Institutional Setting & Enrollment Data

The institutional setting for this analysis is the community college market in the state of Michigan. Michigan is home to 28 public community colleges, which together enroll more than 300,000 students annually (Michigan Community College Association, 2019). Local boards of trustees control and govern the colleges but all share two key features. First, all colleges are open enrollment institutions, meaning students can enroll and select a program of study regardless of academic preparation.[4]. Second, the colleges primarily confer certificates and

[4]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)

associate degrees, which may either be vocational or non-vocational.[5] Vocational programs are designed to prepare students for immediate entry into the labor market and have direct links to specific occupations, making the state of the local labor market a particularly relevant consideration for students. In contrast, non-vocational programs contain general education courses and prepare students to transfer to four-year colleges and universities, so they have less natural linkages to the labor market.

3.1 Programs Offered by Michigan's Community Colleges

Due to the deregulated nature of Michigan's community college system, the state does not officially keep track of the programs offered by each college over time. However, in 2011 and 2013, the Department of Treasury published the "Michigan Postsecondary Handbook," which provides information on all colleges in the state for prospective students.[6] In addition, the handbook 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.

I use data from the 2011 handbook to classify programs into vocational and non-vocational categories, as well as to create program groups that I use to analyze students' responses to related layoffs. To begin, I match each CIP code in the program listing 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).[7] 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

[5] Since 2012, Michigan's community colleges have been able to confer bachelor's degrees in a small number of fields not offered by the state's public four-year institutions. However, as of 2016, community colleges had only awarded 116 bachelor's (House Fiscal Agency, 2017).

[6] The handbook can be found on archived versions of the Michigan Student Aid website (`https://www.michigan.gov/mistudentaid/`) and is available from the author upon request.

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

result, some programs may be matched to occupations that are unlikely to be obtained by recent community college graduates. For example, the CIP code for registered nursing (51.3801) is matched to the SOC codes for both registered nurses (29-1141), which is a career attainable by graduates of community college nursing programs, and postsecondary nursing instructors (25-1072), which requires an advanced degree. To ensure all programs are only mapped to attainable occupations, I further match the SOC occupation codes to data on job preparation requirements from O*NET and limit the occupation matches to those that require at least a high school diploma but not necessarily a bachelor's degree.[8] 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 are either general studies programs that enable students to take core classes that transfer to four-year colleges, pre-transfer programs in specific areas, or academic programs that do not have close occupation links.

Appendix Table A.1 provides summary statistics on the programs offered by Michigan's community colleges in 2011. On average, a college offers 117 unique academic programs; however, this value varies from 41 programs at Glen Oaks Community College in the rural southwest area of the state to 319 programs at Oakland Community College in suburban Detroit. The extent to which colleges emphasize vocational programming also varies substantially across institutions. On average, 81% of the programs offered are vocational. However, at Gogebic Community College in the upper peninsula, only 56% of programs are vocational, whereas, at Monroe Community College outside of Detroit, 94% are. Panels B and C present summary statistics separately for associate degree programs and certificate programs, which further emphasize the heterogeneity in program offerings across colleges. Colleges also differ in what types of vocational programs they offer. The five most commonly offered types of 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).[9] There are a total of 118 unique four-digit CIP codes offered, including 38 programs

[8] This restriction corresponds to "job zones" 2 to 4 in the O*NET database.

[9] I use four-digit CIP codes to provide descriptive statistics on the programs offered by colleges because some six-digit CIP codes are very similar and two colleges can reasonably offer the same curriculum but assign programs to different

that are only offered at a single institution. For example, only Wayne County Community College offers a program in dietetics and clinical nutrition services (CIP 51.31) and only Gogebic Community College offers a program in parks, recreation, and leisure facilities management (CIP 31.03). 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 the same or similar two digit SOC occupation codes and, throughout the remainder of the text, refer to the occupations they contain as *community college occupations*.[10] Appendix Table A.2 provides a list of the two-digit SOC codes contained within each group.

3.2 Students Enrolled in Michigan's Vocational Programs

To analyze how enrollment in community college programs responds to layoffs in related occupations, I rely on a student-level administrative dataset provided by the Michigan Department of Education (MDE) and the 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).[11] The high school academic records provide rich information on students' demographic characteristics and academic performance, including race/ethnicity, gender, family economic status, eleventh grade standardized test scores, and census block of residence. 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. To ensure consis-

codes. For example, the six-digit CIP code for health aide programs is 51.2601, while the code for home health aide programs is 51.2602. Both are included in the four-digit CIP code for health aides, attendants, and orderlies (CIP 51.26).

[10]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.

[11]The NSC tracks college enrollment, program enrollment, and completion at 97% of U.S. colleges, including all 28 community colleges in Michigan (National Student Clearinghouse Research Center, 2017a).

tency across cohorts, I focus my analysis on high school graduates' first college enrollment and program choices within six months (180 days) of graduating from high school.[12]

Table 1 provides summary statistics on Michigan's high school graduates disaggregated by their first postsecondary education choices.[13] Column (1) provides average values for a variety of demographic and academic variables across all graduates, column (2) for those who enroll in vocational programs at Michigan's community colleges, column (3) for those who enroll in non-vocational programs at Michigan's community colleges, column (4) for those who enroll in all other colleges, and column (5) for those who do not enroll in any formal postsecondary institution within six months of high school graduation.[14] A non-trivial share of students enroll in vocational and non-vocational community college programs each year: 9% and 14% of graduates, respectively.[15] Students who enroll in vocational programs are more likely to be economically disadvantaged than students in non-vocational programs and also score lower on state standardized tests.[16] 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 the type of programs vocational students choose.[17] 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%

[12]I observe enrollment outcomes for students from their high school graduation until the spring of 2017. For the last cohort in the sample (2016), I observe outcomes for 16 months following high school graduation.

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

[14]98.3% of students who enroll in colleges other than Michigan community colleges enroll in four-year colleges and universities. The remaining 1.7% enroll in out-of-state community colleges or two-year for-profit institutions.

[15]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 6, I show that the results are robust to dropping students who enroll in multiple program groups.

[16]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.

[17]There is some concern that students' program choices may not accurately represent the content of their educational programs. For example, students may indicate that they are enrolled in a program but not take courses that lead to the program's degree. To verify that program choices capture students' educational experiences, I categorize community college courses into the same six occupation groups and tabulate the share of courses taken in different subject areas among students enrolled in different programs. Appendix Figure A.1 presents these results. The figures show that students who indicate enrollment in a given program group take disproportionately more courses, and earn disproportionately more credits, in the subject area of their program than students in other program groups. This finding indicates that program choice measures accurately capture students' educational programs.

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 (83%) and male (94%). In contrast, students who enroll in health programs tend to be non-white (30%) and female (79%). 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.

4 Measuring Local Labor Market Conditions

In my empirical approach, I build on the work by Hubbard (2018) and Foote and Grosz (2019) that uses the prevalence of mass layoffs and plant closings to proxy for changes in local labor demand. A key advantage of these data is that, because events are reported at the establishment level, I can generate counts of reported job losses in small industries and small counties that are typically suppressed 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 the U.S. Census Bureau's Quarterly Workforce Indicators or County Business Patterns, have similar limitations. However, many of these counties and industries experience mass layoffs and plant closings that represent substantial shocks to local employment prospects. Layoff data are also advantageous because they represent sharp declines in local employment that are plausibly exogenous to students' educational choices. Moreover, layoff events are likely representative of the employment changes students observe because they tend to be well-publicized in local communities through newspapers and other media outlets.

My primary source of layoff data is a listing of mass layoffs and plant closings reported to the Michigan Workforce Development Agency (WDA) under the federal Worker Adjustment and Retraining Notification (WARN) Act of 1998. The WARN Act requires employers with 100 or more employees to provide at least 60 days notice to employees ahead of any plant closing affecting 50 or more employees at a single employment site and any 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. Employers must also provide 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 (U.S. Department of Labor, 2019). In Michigan, all WARN notices filed since 2000 are publicly available on the WDA's website.[18] 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).[19] These events are analogous to plant closures in the private sector but particularly affect public law enforcement occupations such as corrections officers.

4.1 Using WARN Data to Generate Occupation-Specific Layoff Exposure

My key innovation is to use the layoff data to both measure general local economic conditions and estimate the prevalence of layoffs in occupations closely related to each of the six community college program groups and use these estimates to proxy for changes in occupation-specific local labor demand. 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.[20] The correctional facility closure data available from the SFA include a record of the name of the correctional facility that closed, along with the year and number of affected workers. For each correctional facility closure, I find related local news articles to approximate the date the closure was announced and the county in which the correctional facility was located.

Panel A of Figure 1 plots the number of mass layoffs, plant closures, and correctional facility closings reported during each academic year from 2001 to 2016, where I define academic years

[18] A listing of notices from 2000 to present-day is available here: `https://milmi.org/warn`.

[19] The listing of facility closures is available here: `http://www.senate.michigan.gov/sfa/Publications/Notes/2019Notes/NotesWin19af.pdf`.

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

as July 1 of year t to June 30 of year $t+1$.[21] 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 corresponding automotive industry collapse hit Michigan especially hard. Panel B shows that the total number of job losses also spiked during 2008. These layoffs occur throughout the state, in both rural and urban areas, which I highlight in Appendix Figure A.2 by plotting the average amount of per capita layoffs that occur in each county from 2001 to 2017.

Because the layoff data does not contain information on the occupations of laid-off workers, I estimate students' exposure to layoffs in each community college occupation group by exploiting the fact that different occupations are concentrated in different industries. I first match all 1,024 entities that experience a layoff to their respective three-digit NAICS industry code using information from company websites and online business databases. 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). For reference, Appendix Table A.3 further provides the largest observed layoff event in each industry.

I then calculate the distribution of different 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

[21] Because firms must file WARN reports 60 days ahead of mass layoffs and plant closings, this time frame approximately corresponds to job losses occurring between September 1 of year t and August 30 of year $t+1$.

health occupational 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.[22] 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.[23] 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.[24]

I operationalize this intuition by using the occupation-by-industry employment shares (α) to estimate layoff exposure within a given occupation group, county, and academic year. Specifically, I estimate the number of layoffs in occupation group g in county c in academic year t as:

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

where Layoffs_{kct} is the number of layoffs in industry k in county c in academic year t, which is identified in the mass layoff data. These measures take into account both the occupations which likely experience layoffs and the size of the layoff events occurring in a given county and year. For example, consider Kalamazoo County during the 2012 academic year. During this year, three firms reported mass layoffs: Hostess Brands, a food manufacturer (15 layoffs); International Paper, a paper manufacturer (77 layoffs); and OneWest Bank, a credit intermediary (168 layoffs).[25] In this same year, community college business occupations, i.e., business

[22] Each May, the BLS reports OES data that capture private sector employment estimates over the previous 2.5 years (Bureau of Labor Statistics, 2017). For consistency, I assign α values to the academic year in which the data was reported. For example, I assign the data reported in May of 2009 to the 2008 academic year.

[23] Appendix Table A.4 presents the three largest average values of α for each occupation group.

[24] In Appendix Table A.5 I compute the correlation between the α values across the six community college occupation groups. Most correlations are negative, indicating that different community college occupations are concentrated in different industries and, therefore, will be affected by different layoff events. Only two correlations are positive: business and STEM occupations, and health and other occupations.

[25] 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 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.

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 $0.067(15) + 0.109(77) + 0.445(168) \approx 84$.[26]

4.2 Distribution of Layoffs Across Occupations

Table 3 provides summary statistics on the layoffs occurring in Michigan counties between the 2001 and 2017 academic years. In addition to estimating the number of layoffs occurring in community college occupations, I use equations (1) and (2) to generate the number of layoffs occurring in other types of occupations. Specifically, I estimate 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.[27] 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.[28] On average, a county-year observation with 10,000 working-age residents experiences 5.3 layoffs in low-skilled occupations, 4.1 layoffs in middle-skill community college occupations, and 1.3 layoffs in high-skilled occupations. Among the community college occupations, 2.1 layoffs occur in the skilled trades, 1.0 occurs in business, 0.5 occur in law enforcement, 0.3 occur in STEM, 0.2 occur in health, and 0.1 occur in other community college occupations. There is substantial variation in the number of layoffs occurring in different occupations, with the standard deviations for each category far exceeding the means. For example, the number of skilled trade layoffs occurring in a county ranges from 0 to nearly 96 per 10,000 working-age residents. Panel B then

[26] To illustrate more examples of county layoffs, Appendix Table A.6 provides information on the three county-year pairs with the largest amount of per capita layoffs in each occupation group from 2001 to 2017, and Appendix Table ?? shows the counties with the largest estimated layoff exposure in each occupation group in each year.

[27] I use O*NET data on job preparation requirements to identify these occupations. Occupations that are not included in the community college program groups and are included in job zone 4 or higher are considered high-skill. All other layoffs are categorized as being low-skill.

[28] 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.

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. Consistent with Panel A, most layoffs that affect community college occupations occur in the skilled trades and business fields.

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, home of the state capital of Lansing and nearly 200,000 residents, and Ontonagon County, a small rural county in the state's upper peninsula with only 4,000 residents. The share of layoffs occurring in each occupation group also varies considerably across counties, which further emphasizes the importance of separately considering the effects of each type of layoff.

4.3 Do Layoffs Capture Relevant Employment Changes?

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

To verify that these proxy measurements capture changes in employment over time and across counties, I compare the available county-by-industry employment data from the QCEW dataset to the analogous county-by-industry layoffs that I identify in the layoff data. One limitation of this analysis is that I am only able to observe employment changes for the 32% of county-industry pairs that have complete employment data in the QCEW series. Nevertheless, the results provide suggestive evidence of the validity of the layoffs observed in the WARN and prison closure data.

I estimate regressions of the following form:

$$\Delta \text{Employment}_{kct} = \alpha + \beta \text{Layoffs}_{kc,t-1} + \varepsilon_{kct} \tag{3}$$

where $\Delta\text{Employment}_{kct}$ is the change in employment in industry k in county c between academic years $t-1$ and t, and $\text{Layoffs}_{kc,t-1}$ is the number of layoffs in industry k in county c in academic year $t-1$.[29] The parameter of interest, β, captures the relationship between layoffs and year-over-year employment change in a given county and industry. If β is equal to -1, then, on average, an additional layoff is associated with an employment reduction of exactly one worker. If $|\beta|$ is less than 1, then an additional layoff reduces employment by less than one worker on average, presumably because some laid-off workers find work at other firms in the same county and industry or other firms are increasing employment at the same time as the layoff. Alternatively, if $|\beta|$ is greater than 1, then an additional layoff reduces employment by more than one worker on average, indicating that there are additional employment reductions, including changes in labor supply, that are not captured in the WARN data.

Table 4 presents estimates of the β parameter using the set of county-industry pairs that have non-missing Michigan employment data for all years from 2001 to 2017. The first column estimates β exactly as specified in equation (3) and produces a statistically significant value of -1.53. This indicates that, on average, every additional layoff in a county-industry pair is associated with an employment decrease of 1.53 workers. Columns (2) through (4) progressively add county, industry, and year fixed effects to account for potential unobservable characteristics that are correlated with layoffs. The estimate remains close to -1 and

[29] I calculate the employment change variable as the difference in end of second quarter employment in years t and $t-1$. This measure corresponds to the net change in employment between June 30th following a cohort's junior year of high school and June 30th following their senior year of high school.

statistically significant in all specifications, indicating that layoffs are likely a strong proxy of local employment changes. To further ensure that layoffs affect related employment across different industries, I separately estimate equation (3) for the twelve NAICS sectors the most layoffs from 2001 to 2017. I present these results visually in Appendix Figure A.3. In all twelve sectors, an additional layoff is associated with a corresponding employment reduction of approximately one worker, again suggesting that layoffs capture true changes in local employment prospects.

4.4 Potential Measurement Error

While industry layoffs predict corresponding industry employment changes quite well, the estimated layoff measures I construct also rely on the distribution of occupations across industries, which could induce measurement error. The layoff exposure measures implicitly assume that layoffs in an occupation are proportional to its national employment shares in industries that experience layoffs. Any deviation of layoffs from these proportions could lead to measurement error in the layoff terms, whereby I inaccurately classify layoffs as affecting one occupation group when, in reality, they affect another. For example, suppose that a hospital reports a mass layoff of 100 workers. Based on industry-by-occupation shares, I estimate that about 55 layoffs should affect community college health occupations, while only about 8 should affect community college business occupations. However, suppose that a hospital was to layoff only their billing or financial services department. This type of layoff would disproportionately affect business occupations rather than health occupations, causing me to overstate the effect of the event on health occupations and understate the effect on business occupations.

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

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

where δ_{XX} is the true effect of layoffs in occupation group X on enrollment in group X

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

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

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

Given the non-classical nature of this measurement error and the fact that ε is unknown, there is no straightforward way to empirically correct for it. However, there are circumstances where measurement error is less likely to occur. Specifically, plant and prison closures are likely to affect all jobs contained within a given facility and, therefore, should align more closely with the industry-by-occupation employment shares than layoffs that only affect a subset of jobs. In Section 6, 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 likely does not drive my results.

5 Effects of Layoffs on Students' Choices

My empirical approach analyzes the extent to which county-level layoffs affect students' decisions to enroll in related community college programs. I use counties as my primary unit of analysis because they are the narrowest geographic areas for which I can identify both layoffs and students, and, in Michigan, a substantial amount of education governance occurs at the county level. Five ISDs are also the basis for community college taxing districts, while another 14 community colleges are organized around a single county. If either high schools or community colleges provide students with local labor market information, then this information transmission likely operates at a county level.

5.1 Enrollment in Different Types of Colleges

I first assess the extent to which layoffs in different occupations affect students' college enrollment decisions, with a focus on whether layoffs in community college occupations induce fewer students to enter vocational programs at community colleges overall. I construct county-level college enrollment shares and estimate equations of the following form:

$$\text{Enroll}_{jct} = \alpha + \textbf{Layoffs}_{ct}\boldsymbol{\beta} + \mathbf{X}_{ct}\boldsymbol{\Gamma} + \theta_c + \delta_t + \varepsilon_{ct} \tag{4}$$

where Enroll_{jct} is the number of students from county c and cohort t, per 100 graduates, who enroll in some postsecondary option j, such as vocational programs at community colleges or four-year college programs. The vector of layoff variables, $\textbf{Layoffs}_{ct}$, captures the number of layoffs, per 10,000 working-age residents, that occur in different occupations in county c while cohort t is in high school. Specifically, I consider layoffs that occur in different community college occupation groups, those that occur in low-skill jobs that require less than an associate's degree, and those that occur in high-skill jobs that require more than an associate's degree. The vector $\mathbf{X}_{ct}$ contains time-varying county control variables that may affect students' choices, such as the average test scores of the cohort or the share of students that are economically disadvantaged, as well as general county economic measures such as the unemployment rate and size of the labor force. θ_c is a county fixed effect that absorbs county-specific preferences for different types of postsecondary education, δ_t is a cohort fixed effect that accounts for changing preferences over time, and ε_{ct} is the error term. Throughout the analysis, I cluster all standard errors at the county level.

The main parameter of interest is the $\boldsymbol{\beta}$ vector, which identifies how layoffs in different types of occupations affect students' decisions to enroll in related types of college programs. Specifically, I consider how layoffs affect whether students enroll in any formal college, in vocational programs at Michigan's community colleges, and in all other college programs. The latter category predominantly consists of non-vocational community college programs, which are designed to lead to students transferring to four-year colleges, as well as enrollment at four-year colleges. 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. 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 this assumption seems reasonable, layoffs are more likely to occur when a county is on a downward economic trajectory, which may in itself affect students' preferences for college attendance. To account for changing preferences, I also estimate specifications that include county-specific linear time trends.[30]

Table 5 presents estimates of the $\boldsymbol{\beta}$ vector in equation (4). Panel A first pools all layoffs into one term, which is common in the previous literature. In this specification, I find that an additional layoff per 10,000 working-age residents increases college enrollment by 0.01 students per 100 graduates, or 0.01 percentage points (pp). Below each estimate, I present the elasticity of enrollment with respect to layoffs at the mean values of the dependent and independent variables. For overall college attendance, the elasticity implies that, for the average county-cohort pair, a 10% increase in layoff exposure increases college enrollment by 0.03%. Alternatively, a doubling of layoff exposure increases enrollment by 0.3%. This increase in college enrollment is predominantly 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.[31] In Appendix Table A.7, I repeat the estimation with county-specific linear time trends and find quite similar results; however, the effect of layoffs on vocational program enrollment is even smaller and statistically indistinguishable from zero.

While the specification estimated in Panel A is common in the previous literature, it is not able to consider the substitution effects outlined in Section 2. To better understand underlying substitution patterns, Panel B separates the layoffs by the type of occupations they affect. The estimates from these specifications are noisier than the coefficients in Panel

[30] An additional concern with the estimation procedure is that scaling the dependent variable by the number of high school graduates in a county will introduce heteroskedasticity in the error term and therefore decrease the precision of the estimates. To address this concern, I also estimate specifications using weighted least squares and the weighting scheme proposed by Solon et al. (2015). This approach produces quite similar results, which are available from the author upon request.

[31] 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), measures layoffs within a 30 mile radius of a student's high school rather than at the county level, and does not separate enrollment in vocational vs. non-vocational programs, all of which could explain the differences in our results.

A and none are statistically significant at conventional levels. However, they still provide suggestive evidence on how students' choices respond to layoffs in related occupations. For example, only layoffs in low-skill and middle-skill jobs contribute to the increase in enrollment in other college enrollment shown in Panel A. In contrast, layoffs in high-skill jobs decrease enrollment in these programs. This finding is consistent with the model in Section 2, where students should be less likely to enter four-year college programs when related high-skill jobs experience layoffs.

A key takeaway from Panel B is that layoffs in community college occupations do not meaningfully affect overall enrollment in community college vocational programs. The estimated coefficient on the community college layoffs term is positive, but close to zero and not statistically significant. I further consider this relationship in Table 6, where I separate the community college layoffs term into the layoffs affecting each of the six community college occupation groups (business, health, skilled trades, STEM, law enforcement, and other). I present specifications with and without county-specific time trends and continue to present the estimated elasticities underneath each coefficient. In both specifications, the effects of layoffs are small and statistically insignificant. Moreover, in all specifications, I fail to reject the joint hypothesis that all coefficients are equal to zero.

In Appendix Table A.8, 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.9, I estimate how layoffs in community college occupations affect credit completion within vocational students' first year of community college enrollment. I find no evidence that layoffs affect total credit completion, nor completion of vocational vs. non-vocational courses.[32] 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 enroll-

[32] 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.

ment. As a result, I concentrate the remainder of the analysis on the choices that students make once enrolled in vocational programs and examine how they shift between programs in response to related layoffs.

5.2 Substitution Between Community College Program Groups

Because layoffs in community college occupations do not affect entry into vocational community college programs, I now limit the sample to students who enroll in vocational programs and estimate how layoffs in different occupation groups affect which programs students choose once they enter community colleges. Specifically, I estimate the following system of six equations:

$$\text{Enroll}_{jct} = \alpha + \sum_{g=1}^{6} \beta_g \text{Layoffs}_{gct} + \mathbf{X}_{ct}\mathbf{\Gamma} + \theta_c + \delta_t + \varepsilon_{ct} \tag{5}$$

where Enroll_{jct} is enrollment in occupation group j among students from county c and cohort t, per 100 students enrolling in vocational programs, and Layoffs_{gct} is a measure of layoffs in occupation group j in county c that affect cohort t.[33] The vector $\mathbf{X}_{ct}$ contains the same variables as in equation (4) and controls for changing demographics and general economic conditions of a county across cohorts.[34] I also include a control variable for layoffs occurring in other occupations not related to community college programs in order to capture all shocks occurring in a local labor market.[35] Also the same as 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 $j \neq g$. As predicted in Section 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,

[33] 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).

[34] Controlling instead for the average characteristics of only students who enroll in vocational programs produces qualitatively similar results. Appendix Figure A.4 shows how the own-layoff effects vary when using different control variables.

[35] Including this control does not meaningfully affect the results, nor does controlling separately for layoffs occurring in low-skill and high-skill occupations. Appendix Figure A.5 presents the own-layoff effects with these different layoff control variables.

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 layoffs, county control variables, and county and cohort fixed effects, 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. Like in Section 5.1, this assumption seems reasonable but could be threatened if there are county-specific trends in occupation-specific job prospects and related program preferences over time. To address this concern, I also estimate specifications that include county-specific linear time trends. An additional concern is that 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 fixed effects with commuting zone fixed effects to account for any unobservable changes in an occupation group's employment in a broader geographic region.

Table 7 presents the substitution matrix created from estimating equation (5) for each of the six occupation groups.[36] 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 1.03 students per 100 who enroll in vocational programs, or by 1.03pp. 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

[36]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.

present the own-layoff elasticities at the mean values of both the dependent and independent variables.[37] On average, a 10% increase in layoffs reduces enrollment in related programs by 0.03% to 0.46%. Alternatively, a doubling of layoff exposure reduces enrollment in related programs by 0.3% to 4.6%. The largest statistically significant effects come from layoffs in the business, health, and law enforcement fields, where a doubling of layoffs reduces enrollment by 4.6%, 0.9%, and 0.9%, respectively. The elasticity of enrollment with respect to skilled trades layoffs is also large (1.2%), but not statistically significant.

Moving horizontally across the columns shows how layoffs induce students to substitute into other types of vocational programs. For example, an additional business layoff per 10,000 county residents increases enrollment in law enforcement programs by about 1.7pp. This coefficient shows that business layoffs induce students to substitute away from business programs and towards law enforcement programs. Similarly, students primarily substitute from health programs into other programs when there are health layoffs. In Appendix Table A.11, I further disaggregate the "other" category and find that most of the substitution occurs in social service programs, such as childcare, although there is also statistically significant substitution into arts and media programs and personal care and culinary programs.[38] 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.

5.3 Explaining Substitution with Occupation Characteristics

While it is interesting to document that health layoffs induce students to substitute towards programs in the "other" category, this finding raises yet another question: why do students

[37] Because I do not find large nor statistically significant effects of layoffs in community college occupations on overall enrollment in vocational community college programs, the estimated elasticities are quite similar if I instead scale the dependent variable by the total number of graduates in a county-cohort pair or by the total number of vocational and non-vocational community college students. Appendix Figure A.6 presents the estimated elasticities using these alternative dependent variables and Appendix Table A.10 presents the substitution matrix where the dependent variable is all graduates and the outside option is not enrolling in vocational community college programs (i.e., not enrolling in college or enrolling in four-year colleges).

[38] In this analysis, I define social service programs as those with 2-digit occupation codes of 21 (Community and Social Service) and 25 (Education, Training, and Library), plus childcare programs (SOC 39-9011); arts and media programs as those with the 2-digit occupation code 27 (Arts, Design, Entertainment, Sports, and Media); and personal care and culinary programs as those with the 2-digit codes 35 (Food Preparation and Serving) and 39 (Personal Care and Service), other than childcare, plus baking programs (SOC 51-3011).

substitute towards these fields and not, say, STEM programs? 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 many of the programs in the other category —such as childcare professionals and cosmetologists —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 when layoffs occur.

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). O*NET contains a wealth of information on worker and job characteristics, including occupation skill requirements. 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.[39] 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 the O*NET data 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

[39] O*NET refers to these as "basic skills." More information on the skill measures is available here: `https://www.onetonline.org/find/descriptor/browse/Skills/`.

programs.[40] I define the distance between program group p and program group s, which experiences the labor market shock, as:

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

where Importance_{js} is the importance of skill j for program group s, Level_{jp} is the required level of skill j for program p, and Level_{js} is the required level of skill j for program group s. Programs that are most similar to program group s in terms of the skills that are most important for group s will have low distance measures, while the least similar programs will have high measures.[41] I standardize the measures such that the least similar pair of program groups has a distance measure of 1.[42]

Figure 3 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.

[40]O*NET provides lists of similar occupations for both career starters and career switchers. They identify these careers by creating Euclidean distance measures of occupational characteristics. More information is available here: `https://www.onetcenter.org/dl_files/Related.pdf`.

[41]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.

[42]Omitting the importance weights or constructing the similarity measure using only differences in skill importance produces very similar results. Appendix Table A.12 illustrates this point by comparing the rank ordering of similar programs across these different measures.

Figure 4 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.[43] This finding further shows that when students are exposed to layoffs in a given field, they seek out enrollment in other programs that require similar skills and helps to explain the substitution patterns presented in Table 7.

One limitation of this analysis is that it combines multiple, potentially distinct programs into the same program group. To investigate substitution patterns between narrower program groups, I re-estimate the system of equations presented in equation (5) using enrollment in the two-digit occupation codes that comprise each program group as the dependent variables. For example, rather than estimating how business layoffs affect enrollment in business programs overall, I separately estimate how business layoffs affect enrollment in management, business and financial operations, legal, sales, and administrative support programs. I present these own-layoff effects in Appendix Figure A.8. I then analyze substitution patterns relative to the two-digit occupation code that experiences the largest own-layoff effect in each program group. Continuing with the business example, I find the largest decrease in business programs comes from management programs. Therefore, I compare the skills of all other two-digit occupation codes to the skills needed for management occupations to see if students are substituting into similar programs. Appendix Figure A.9 shows how the substitution patterns for each program group relate to the skill distance measures. Then, Appendix Figure A.10 plots the pooled substitution effects against the skill distance measures for all six program groups. As in Figure 4, the largest substitution effects occur at the start of the x-axis, and there is a downward slope, indicating that substitution effects are largest in the most similar programs

[43] In Appendix Figure A.7, I re-create the figure using the alternate measures of skill distance shown in Appendix Table A.12. 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.

and diminish as skill distance increases.

6 Heterogeneity & Robustness

Thus far, I have imposed constant effects of layoffs across students and counties and have only considered how students respond to layoffs that occur in their county during their senior year of high school. Students' responses may vary across demographic groups or county characteristics, and students may also respond to other layoffs —for example, those occurring earlier in their academic careers or outside of their county —because these layoffs also provide information about local labor demand and can affect students' expected benefits of pursuing different postsecondary programs. In the sections that follow, I consider heterogeneous responses to layoffs and provide alternative specifications that incorporate other sources of variation.

6.1 Heterogeneous Effects

Figure 5 considers heterogeneous responses to layoffs by re-estimating the system of equations in equation (5) using different subgroups of students.[44] 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.[45] This type of heterogeneity is particularly relevant in Michigan because a majority of the state's residents

[44] The dependent variable in these specifications is the share of vocational students from the subgroup who enroll in a given program, multiplied by 100: for example, the share of female vocational students who enroll in health programs times 100.

[45] 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`.

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. Future work exploring how students learn about labor market conditions in different types of communities, as well as the accuracy of students' labor market expectations, could be beneficial in explaining these heterogeneous effects.

6.2 Robustness Checks

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 6 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 6 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.[46] Panel C shows how the results change when including this additional set of fixed effects. Again, the estimates

[46]Commuting zones are groups of counties that reflect a local labor market. More information is available here: https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/.

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 and may be better suited to estimating elasticities. First, I estimate equation (5) using the inverse hyperbolic sine of a county's program enrollment as the dependent variable.[47] I then estimate a Poisson specification and a fractional logit specification.[48] In Panel F of Figure 6, I compare the results from these three specifications to the estimated elasticities obtained from the main linear specification. The results are quite similar across the specifications, with a 100% increase in layoff exposure reducing enrollment in related programs by up to 5% and effects varying across fields of study.

6.3 Alternative Sources of Layoff Variation

I now wish to consider how layoffs occurring in different time periods and different areas of the state affect students' program choices. However, incorporating additional sources of variation is difficult in the current empirical setup as I must include additional terms for each of the six relevant layoff groups and repeat the estimation of the system of six equations. For example, to test students' responses to earlier layoffs, I must add lagged values of each of the six layoff terms and perform a joint test of significance across six equations to determine whether

[47] 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.

[48] 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.

the lagged layoffs affect students' choices. To more feasibly test alternative specifications, I instead use a modified empirical strategy that pools the six systems of equations and considers only the own-layoff responses, i.e., the diagonal terms presented in Table 7.

I collapse the data to the county, cohort, and program group level and estimate equations of the following form:

$$\text{Enroll}_{gct} = \alpha + \beta \text{Layoffs}_{gct} + \theta_{ct} + \lambda_{gc} + \delta_{gt} + \varepsilon_{gct} \tag{7}$$

where Enroll_{gct} measures enrollment in occupation group g among students from county c and cohort t, and Layoffs_{gct} measures analogous layoffs that affect cohort t.[49] Consistent with equation (5) and Table 7, I measure enrollment as the number of students enrolling in programs for occupation group g per 100 vocational students from county c and cohort t and layoffs as the number of analogous layoffs per 10,000 working-age residents. The key parameter of interest is β, which estimates how additional layoffs in an occupation group affect enrollment in related community college programs.

To isolate the same source of variation as in equation (5), I rely on a series of interacted fixed effects. First, I include county-by-cohort fixed effects (θ_{ct}), which hold constant the overall economic conditions of a county, including layoffs in other occupations, when a cohort is making their postsecondary choices. I then include a series of occupation group fixed effects interacted with county (λ_{gc}) and cohort fixed effects (δ_{gt}), which hold constant county-specific preferences for programs as well as secular changes in program preferences over time. These interactions are analogous to the county and cohort fixed effects in equation (5), which also absorb county- and cohort-specific preferences for programs. As a result, the identification assumption is the same: any within-county differences in exposure to layoffs across cohorts must be uncorrelated with changes in unobserved preferences for programs.

Table 8 presents estimates of equation (7), 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 same source of variation used in Table 7. The point estimate

[49]In Appendix B, I show that estimating this specification with a logged dependent variable is analogous to estimating a conditional logit specification. I further show that imposing a logit assumption and using quasi maximum likelihood estimation (QMLE) produces a similar elasticity.

is negative and statistically significant and indicates that an additional layoff per 10,000 county residents reduces enrollment in related programs by 0.18 students per 100 who enroll in vocational programs, or about 0.2pp. The estimated elasticity at the mean values of the dependent and independent variables is -0.0081 (i.e., a 100% increase in layoff exposure reduces enrollment in related programs by 0.81%), which is in line with the estimates in Table 7. Column (2) then adds a measure of layoffs occurring in the year following a cohort's high school graduation. Because I restrict the analysis to students' first program choices within 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 close to zero and 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 -0.2 estimate found in Column (1).

Columns (3) and (4) of Table 8 then consider how layoffs occurring earlier in students' lives affect their choices. Column (3) adds additional lags for all years during a cohorts' time in high school. I find negative coefficients on layoffs occurring during students' freshman and sophomore years of high school, although the point estimates are not statistically different from zero. The results are similar in Column (4), where I add four additional lagged layoff measures to account for layoffs beginning when students are in fifth grade. Across both sets of results, the coefficient on layoffs occurring during a cohort's senior year of high school remains stable around -0.2 and is always statistically significant. Moreover, the coefficient on layoffs occurring following a cohort's graduation from high school is near zero and statistically insignificant. Together, these results indicate that students are most responsive when layoffs occur during their senior year of high school when they are most likely to be making postsecondary choices.

Next, I consider how layoffs in other areas of the state affect students' program enrollment decisions. To do so, I estimate equation (7) 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 9 presents these results. Column (1) includes only layoffs occurring within the county, which produces a very similar estimate to the main specification in Table 8. 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 much smaller than the coefficient on county layoffs and is not statistically significant, indicating that students primarily respond to layoffs that occur in their immediate local area.

Finally, I repeat the estimation procedure using subsets of the layoff data. Table 10 presents these estimates. First, I only use layoffs that are a result of facility closures to test for the presence of measurement error.[50] The estimates are similar when using all layoffs and when using only layoffs that are a result of closings: an additional layoff per 10,000 working-age residents reduces enrollment in related programs by 0.28pp, compared to the main specification estimate of about 0.18pp. 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. Second, I only use layoffs that come from events with more than 50 job losses. 50 is the threshold for reporting in the WARN data, but some firms report smaller layoff events.[51] Dropping these observations ensures that the results are not driven by the voluntary reporting of layoffs. I find quite similar estimates when only using these layoffs: an additional layoff per 10,000 working-age residents reduces enrollment in related programs by 0.19pp, which is statistically no different than the main specification estimate.

6.4 Other Responses to Layoffs

I conclude the analysis by estimating how layoffs affect two other educational outcomes of interest: the enrollment choices of students who delay community college entrance beyond the first six months of high school graduation and the retention rates of students once enrolled. For

[50] Plant closings account for 66% of the observed layoff events and 62% of the job losses in Michigan between 2001 and 2017.

[51] About 26% of the events reported under WARN between 2001 and 2017 affected fewer than 50 workers. However, these layoffs only account for 4% of the total job losses.

the first outcome, I restrict the sample to students who graduate from high school between 2009 and 2013 and enroll in vocational community college programs within at some point before 2017 and re-estimate equation (7) for different enrollment timeframes.[52] Figure 7 shows the estimated elasticity of program choice with respect to prior-year layoffs in related occupations. For enrollment within either six or twelve months of high school graduation, a 100% increase in layoff exposure during a cohort's senior year of high school reduces enrollment in related programs by about 1%. This effect continues to hold when I control for layoffs occurring during students freshman, sophomore, and junior years of high school.

When analyzing longer-run enrollment, I cannot observe where students live in the years following high school graduation and, therefore, implicitly assume that students' remain living in the same county that lived in during high school. Because some students will undoubtedly move in the years that follow, this assumption should induce measurement error and attenuate the results. Indeed, I find smaller elasticities of enrollment with respect to prior-year layoffs when consider enrollment 1-4 years following high school graduation. For students enrolling 1-2 years following graduation, I find that a 100% increase in layoff exposure reduces next-year enrollment in related programs by about 0.7-0.9%, depending on the control variables included. However, for enrollment 2-3 or 3-4 years following high school, I do not find a statistically significant effect of layoffs on program enrollment choices. This lack of response could be due to students moving to different counties and experiencing different labor market shocks, or due to students gaining new information about the labor market as they age. Both explanations are fruitful avenues for future work.

Finally, I consider how layoffs affect program retention rates by including all cohorts and estimating equations of the following form:

$$\text{Retention}_{gct} = \alpha + \beta \text{Layoffs}_{gct} + \theta_{ct} + \lambda_{gc} + \delta_{gt} + \varepsilon_{gct} \tag{8}$$

where Retention_{gct} is a measure of the year-over-year retention of students from county c enrolled in program group g in year t, Layoffs_{gct} is a measure of analogous layoffs, and all other terms are defined as in equation (7). My main measure of retention is the number of

[52]This restriction ensures that students have sufficient time to enroll in programs several years following high school graduation.

students from county c who were enrolled in program group g in year $t-1$ and remain enrolled in the same program and community college in year t, per 100 students initially enrolled.[53] This measure is equal to the share of students who remain enrolled in the same college and program in the following year and multiply the share by 100. I also calculate measures of students switching between programs and between colleges, graduating from programs, and not being observed in the data the following year. I measure layoffs as those that occur between July 1st of year $t-1$ and June 30th of year t to capture layoffs that students observe throughout the year in which they are enrolled in a program.

Table 11 presents these results. Column (1) indicates that an additional layoff per 10,000 working-age residents reduces program retention by 0.39pp. The estimated elasticity of retention with respect to layoffs is -0.0043, which means that a 100% increase in layoff exposure reduces retention in related programs by 0.43%. This estimate is about half the size of the decrease in initial program enrollment documented in my earlier results, which is consistent with the fact that students already enrolled in a program likely face a lower marginal cost to finishing. For example, they have likely already completed some of the coursework needed to earn a degree in the subject. I also estimate the effects of layoffs on retention separately for each program group using a modified version of the systems of equations setup.[54] Appendix Table A.13 presents these results, which indicate that the largest elasticities come from students' responses to layoffs in STEM and other programs.

Columns (2) through (5) of Table 11 document what choices students make when layoffs deter them from continuing in vocational programs. While the estimates are imprecise, the largest coefficient appears in Column (5), which measures the share of students who were enrolled in a program in the prior year but are no longer formally enrolled in postsecondary education. In most cases, this means that a student has dropped out of her community college program without earning a degree.[55] Given the large labor market returns to degree completion, this type of substitution effect may negatively impact students' longer-run outcomes and

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

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

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

suggests that policies that assist students in switching between programs after local labor market shocks could improve student outcomes.

7 Conclusion

More than 8 million students enroll in public community colleges in the United States each year, with many entering vocational programs that prepare them for a continually evolving labor market. The returns to these programs vary substantially by field of study, but there is little evidence on how students choose which programs to pursue. In this paper, I study the extent to which students' program choices respond to changes in local labor market conditions in related occupations. To do so, I match detailed administrative data on students' educational decisions with establishment-level data on plant closings and mass layoffs in the state of Michigan. While previous researchers have used similar data to study how local economic conditions affect college enrollment, I provide the first analysis in the literature that matches layoffs to corresponding academic programs and considers how they affect what students study once they enroll in college.

I find that local labor market shocks deter students from entering related programs at community colleges. Specifically, a 100% increase in occupational layoff exposure reduces enrollment in related community college programs by between 0.3% and 4.6%. The largest responses occur when students are exposed to job losses in business, health, and law enforcement fields, as well as when shocks occur in rural areas. Instead, students shift their enrollment into other types of vocationally-oriented community college programs. Using rich data on occupation characteristics from the O*NET database, 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, 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 preferences.

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 global economic downturn. While this produces substantial variation in local labor market conditions across counties and occupations, the results may not generalize to future cohorts or other areas of the country. Additional work that considers how different populations of students respond to local labor market shocks would be a valuable contribution to the literature. Second, my results are limited in that they apply only to the decisions of recent high school graduates. Adults enrolling in community college programs, especially those who lose their jobs during local labor market downturns, may have different preferences for program characteristics and may respond quite differently to local labor market shocks than younger students who are enrolling in college for the first time. Understanding the choices of this population and evaluating interventions meant to promote their employment and earnings are important areas of both future research and public policy.

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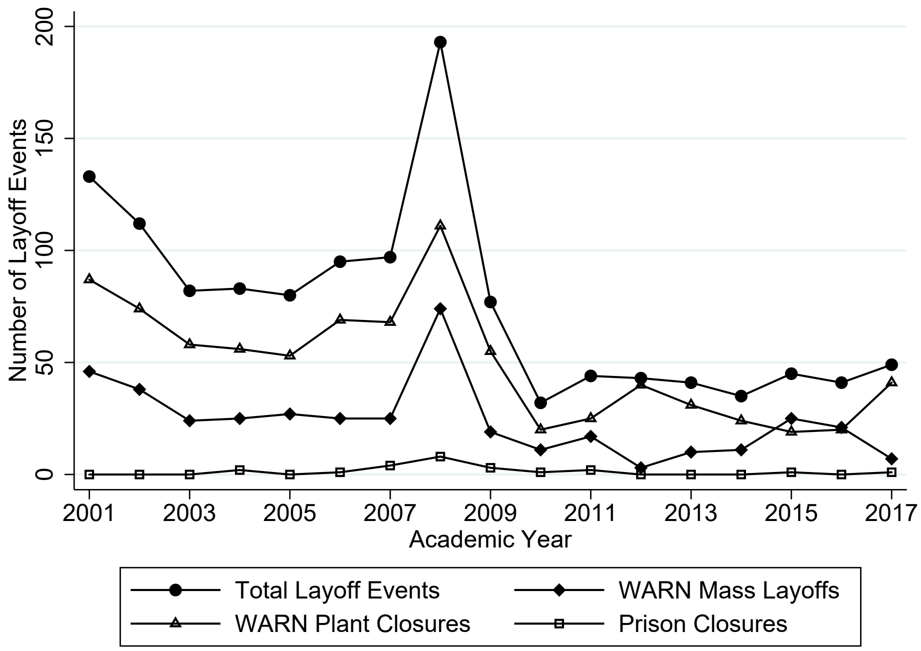
Figure 1: Labor Market Shocks in Michigan, 2001-2017

(a) Layoff Events



(b) Total Job Losses

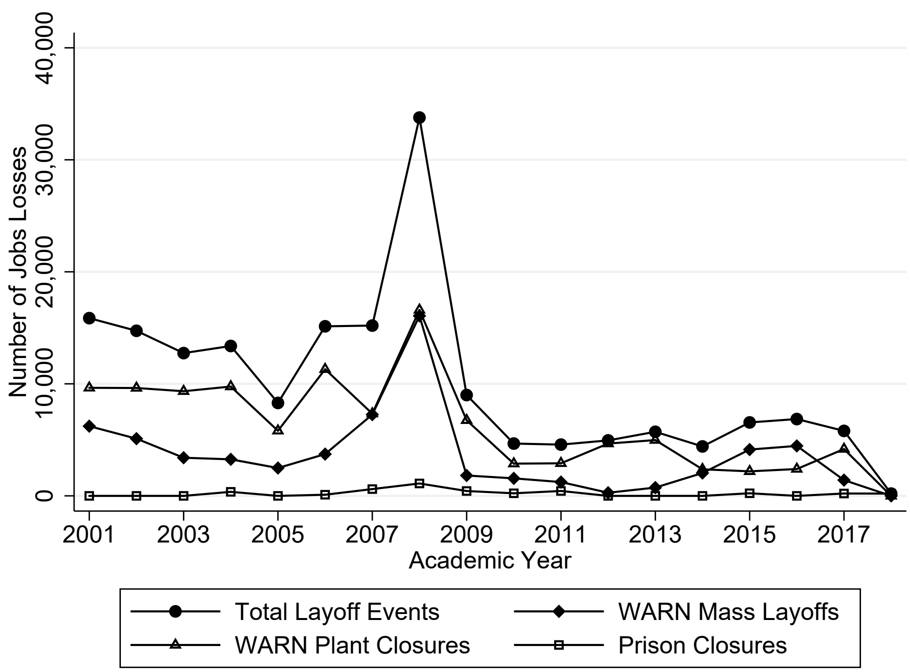
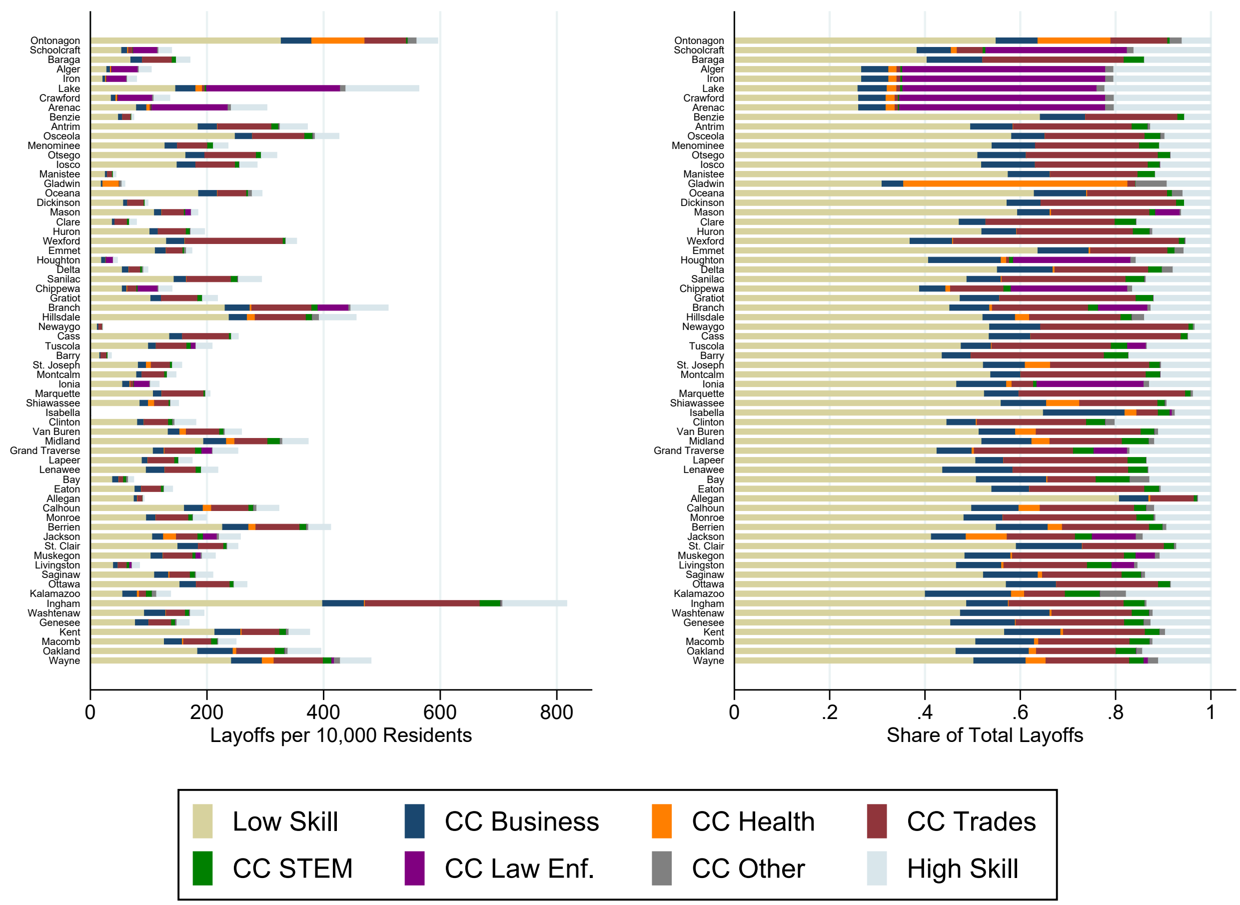


Figure 2: Distribution of Layoffs by County, 2001-2017



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

Figure 3: Substitution into Program Groups Requiring Similar Skills

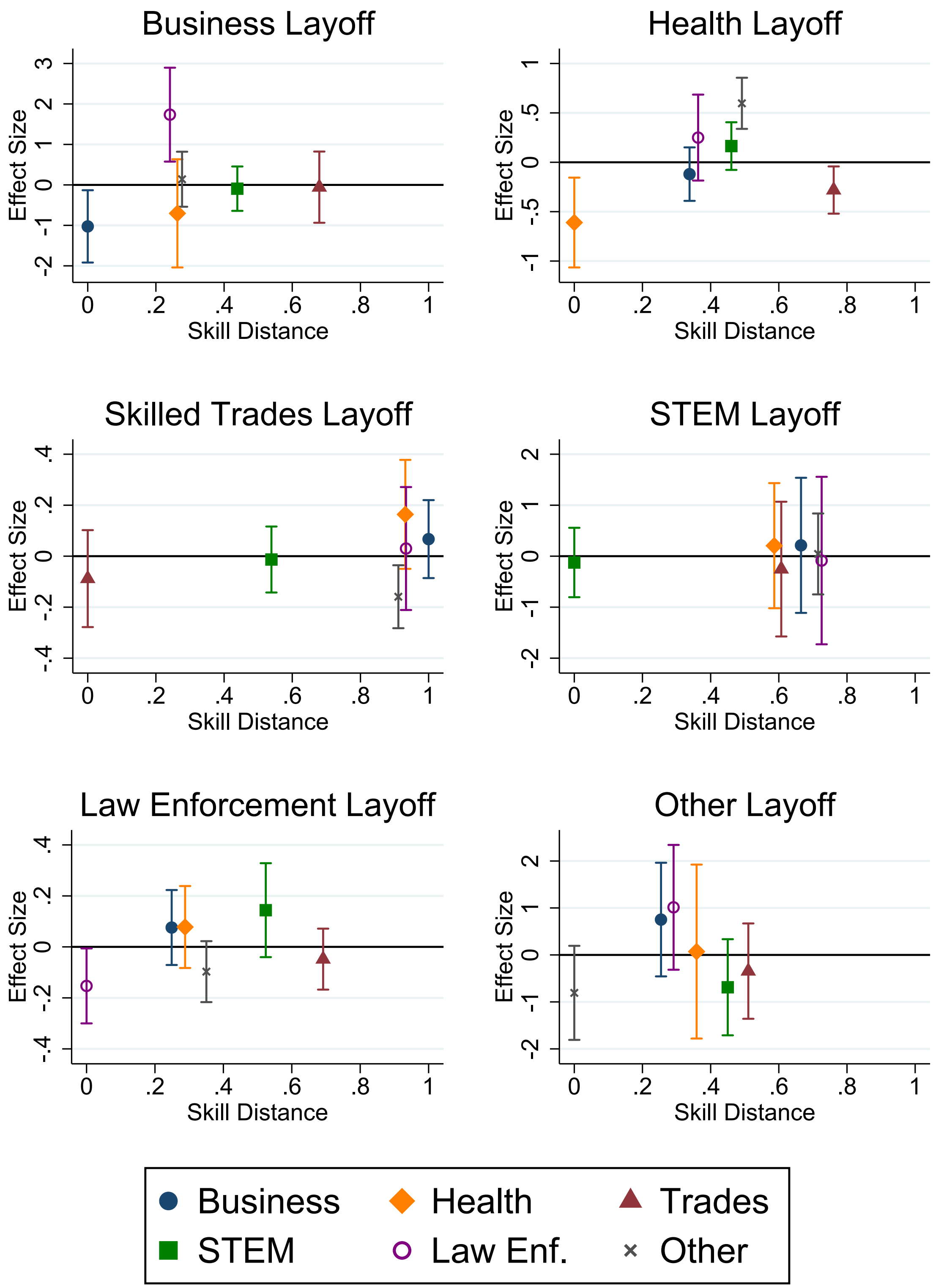


Figure 4: Relationship Between Substitution Effects and Skill Distance

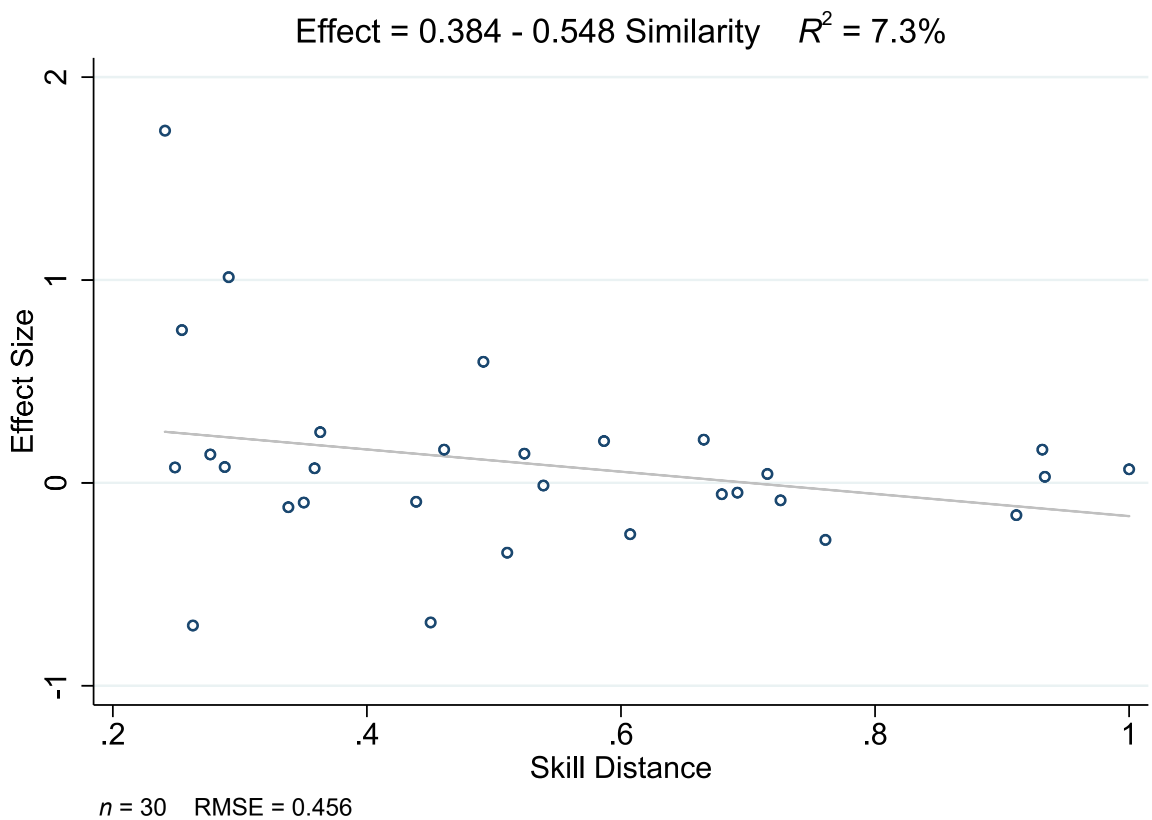
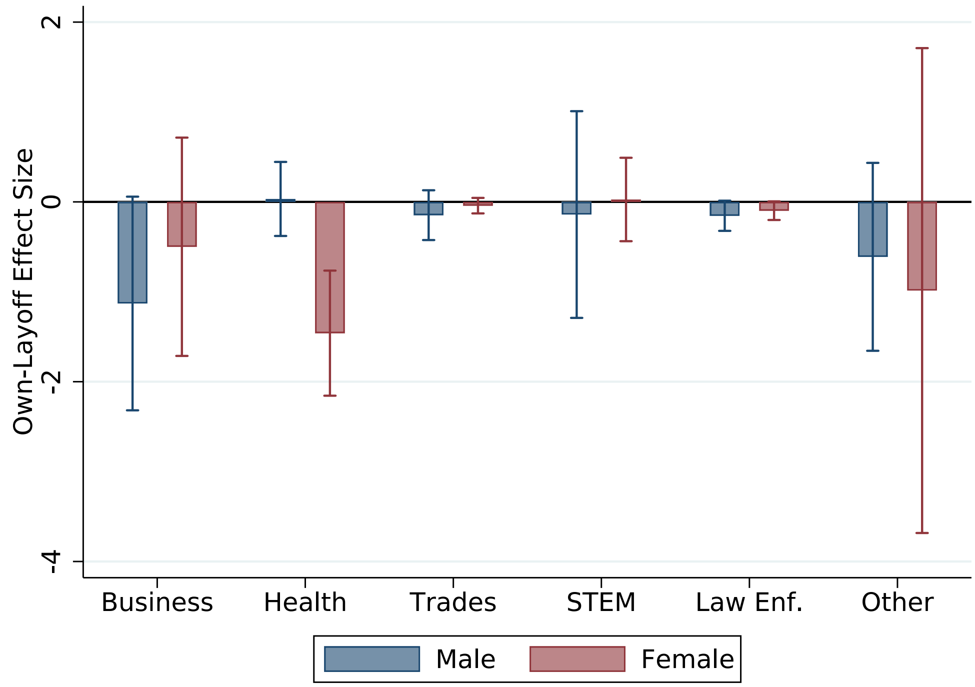


Figure 5: Heterogeneous Own-Layoff Effects

(a) Heterogeneity by Gender



(b) Heterogeneity by County Urbanicity

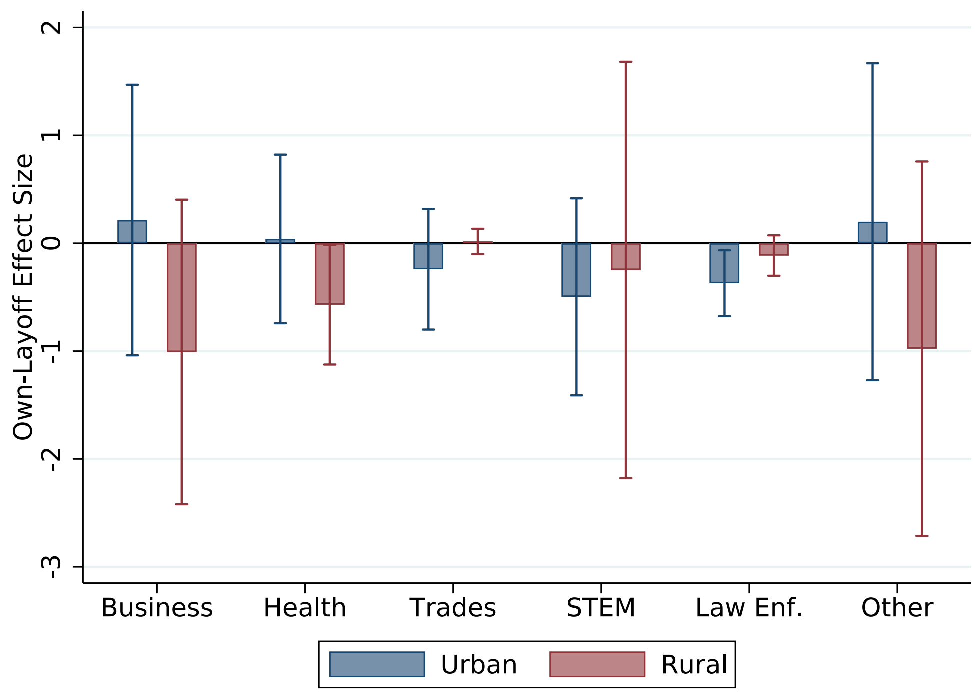
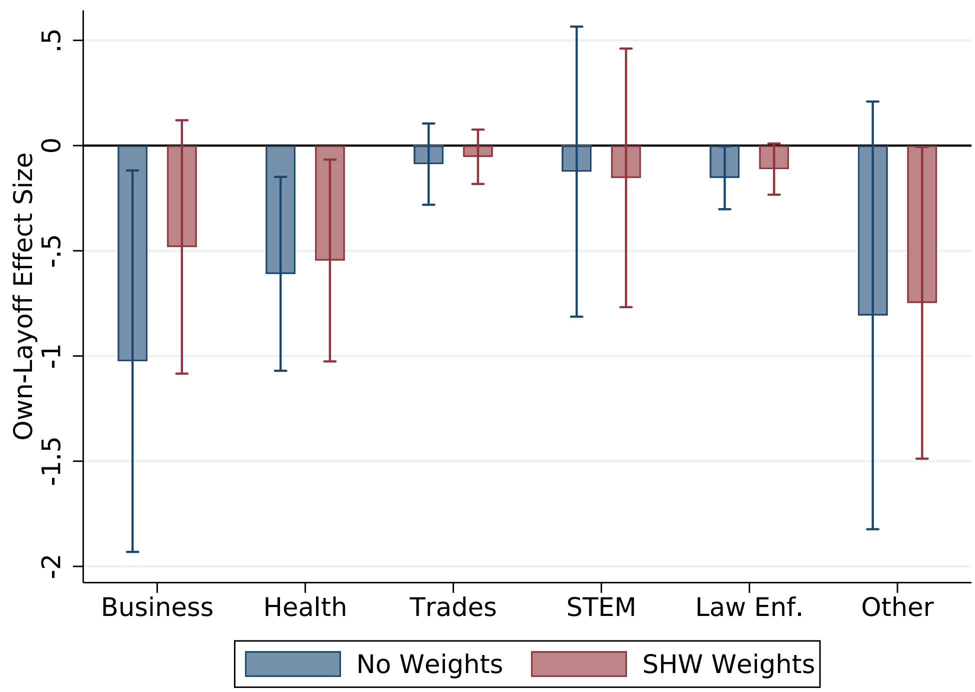
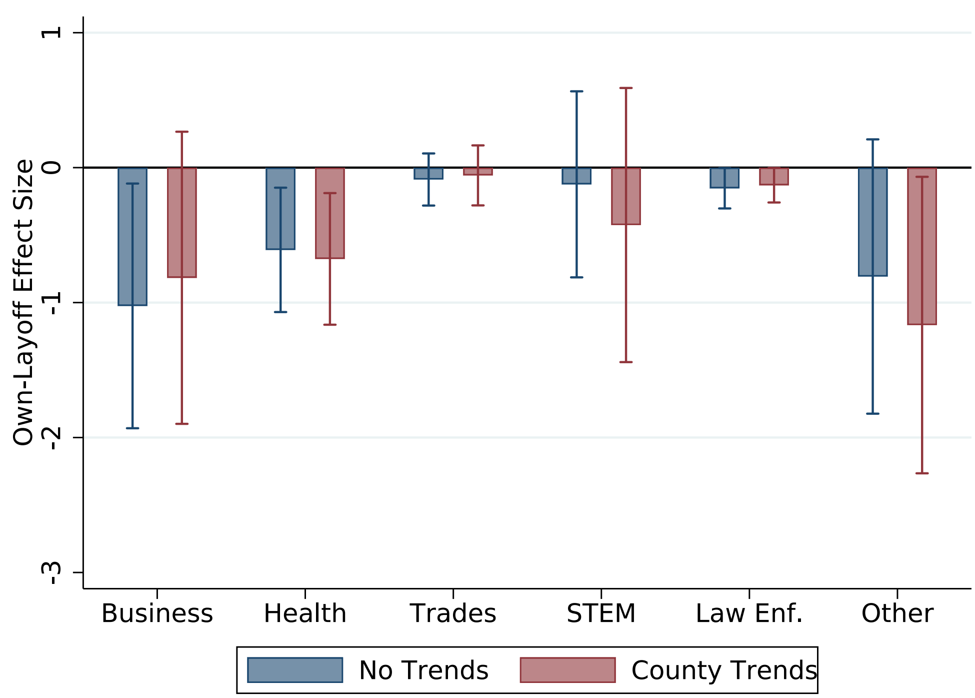


Figure 6: Robustness Checks for Own-Layoff Effects

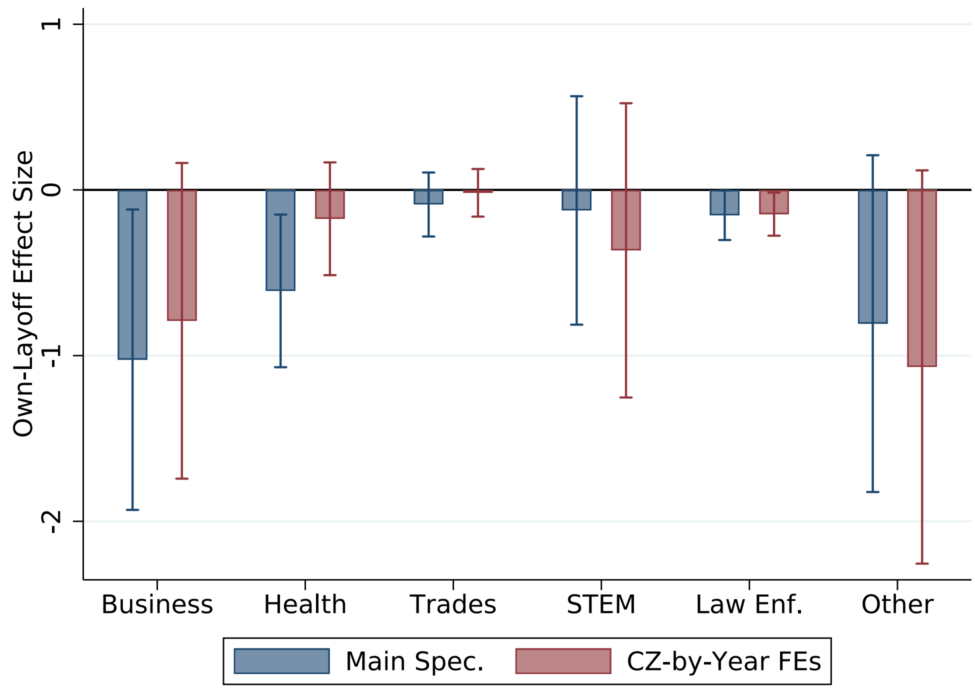
(a) Weighting for Heteroskedasticity



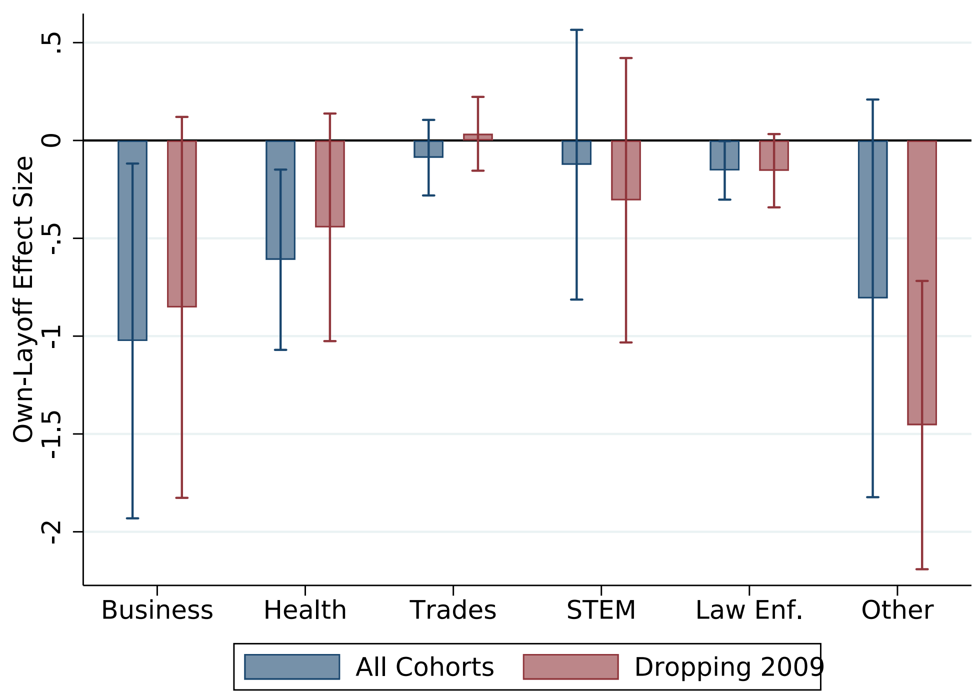
(b) County-Specific Time Trends



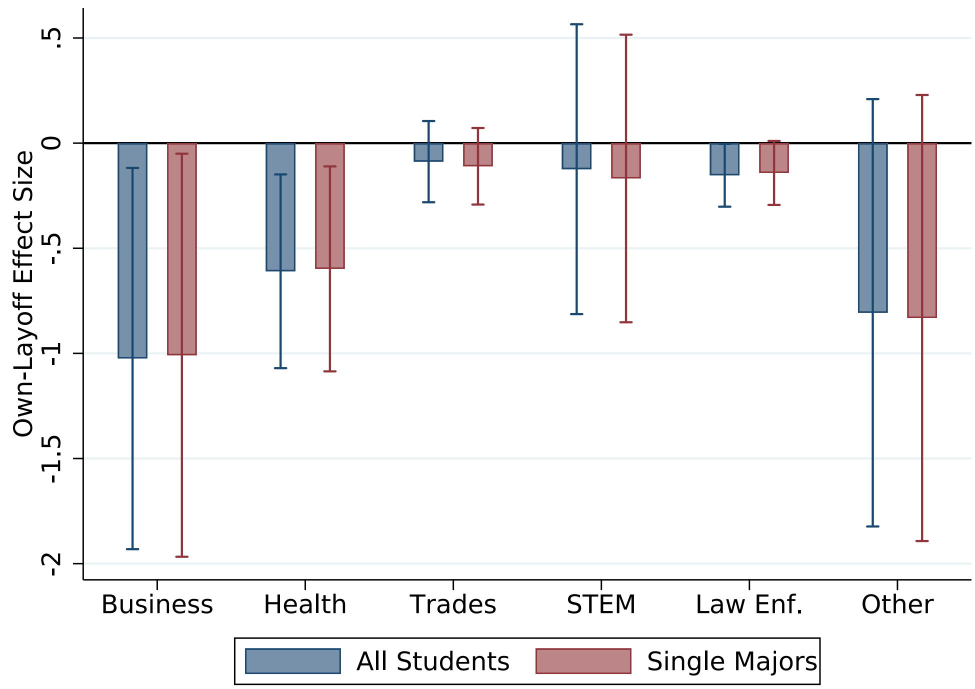
(c) Cohort-by-Commuting Zone Fixed Effects



(d) Dropping 2009 Cohort



(e) Dropping Students Enrolled in Multiple Programs



(f) Non-Linear Specifications

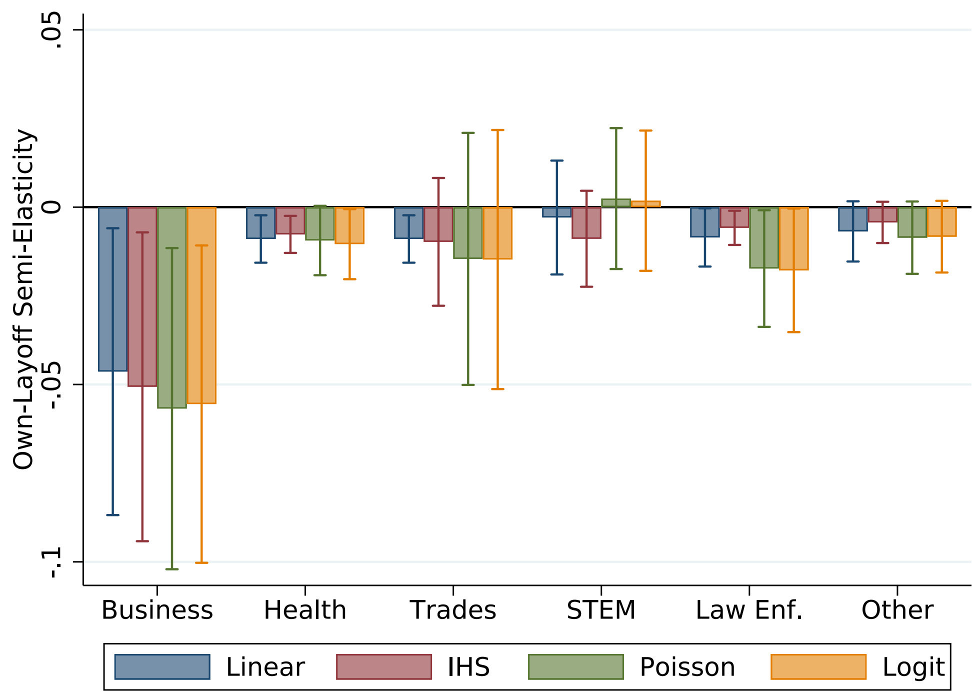


Figure 7: Effect of Layoffs on Program Choice for Later Enrollees

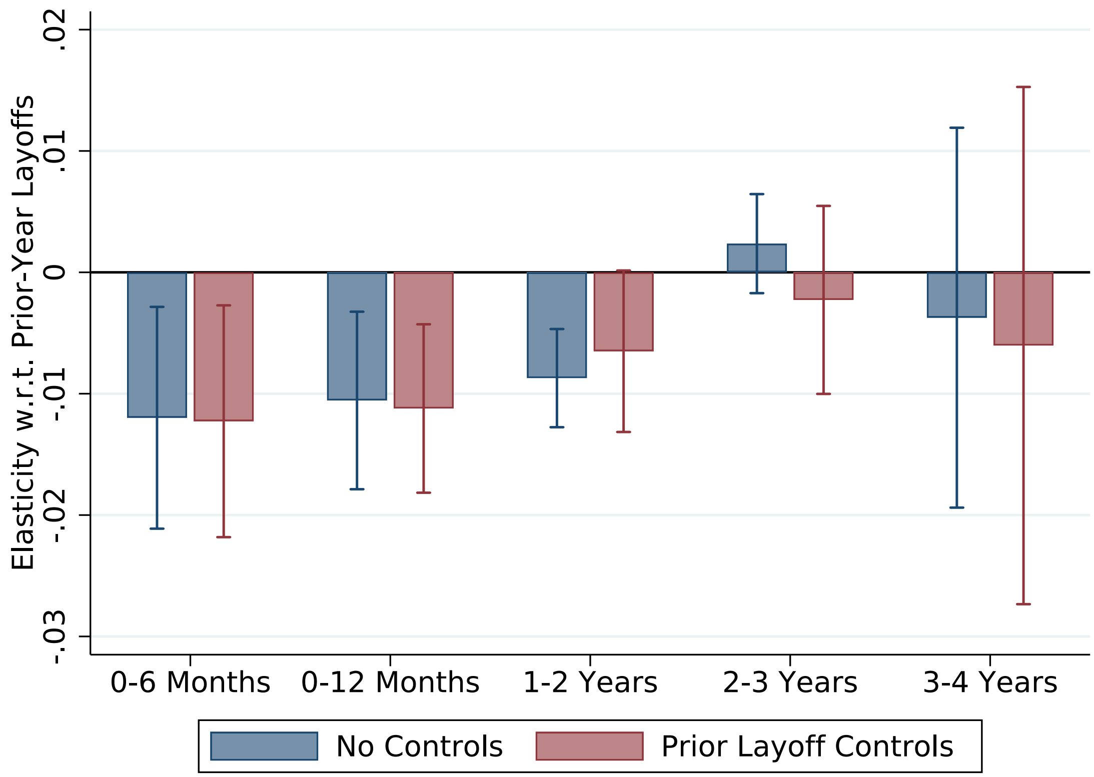


Table 1: Summary Statistics of Michigan's High School Graduates

Variable:	**All Grads (1)**	**CC Voc. (2)**	**CC Non-Voc. (3)**	**Other College (4)**	**No College (5)**
White	0.753	0.730	0.783	0.781	0.715
Black	0.156	0.184	0.134	0.131	0.186
Hispanic	0.042	0.046	0.040	0.028	0.058
Male	0.490	0.535	0.464	0.443	0.541
Economically Disadvantaged	0.343	0.374	0.330	0.224	0.471
English Language Learner	0.025	0.039	0.036	0.010	0.035
Standardized Math Score	0.070	-0.180	-0.041	0.529	-0.337
Standardized Reading Score	0.067	-0.214	-0.057	0.523	-0.326
On-Time Graduation	0.963	0.980	0.983	0.996	0.916
Students	771,140	68,641	105,931	314,355	282,213
Share of Graduates	1.000	0.089	0.137	0.408	0.366

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	0.741	0.695	0.829	0.752	0.741	0.696
Black	0.175	0.213	0.095	0.152	0.179	0.221
Hispanic	0.041	0.052	0.046	0.042	0.049	0.045
Male	0.586	0.214	0.942	0.855	0.646	0.398
Economically Disadvantaged	0.335	0.423	0.356	0.343	0.396	0.375
English Language Learner	0.044	0.052	0.034	0.048	0.031	0.019
Standardized Math Score	-0.068	-0.275	-0.210	0.054	-0.320	-0.256
Standardized Reading Score	-0.172	-0.240	-0.410	-0.080	-0.324	-0.172
On-Time Graduation	0.983	0.981	0.975	0.979	0.980	0.978
Students	16,531	15,675	5,600	8,766	8,634	13,435
Share of Vocational Students	0.241	0.228	0.082	0.128	0.126	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: Relationship Between Estimated Layoffs & Employment Change

	Change in Employment, t-1 to t			
Layoff measure:	**(1)**	**(2)**	**(3)**	**(4)**
Layoffs in county and industry, t-1	-1.534***	-1.522***	-1.493***	-1.467***
	(0.267)	(0.263)	(0.270)	(0.268)
County FEs		X	X	X
Industry FEs			X	X
School Year FEs			X	X
Outcome Mean	-5.443	-5.443	-5.443	-5.443
County-Industry-Year Obs.	39,495	39,495	39,495	39,495
R-squared	0.035	0.035	0.038	0.039

Notes: The sample consists of county-year-industry triads available in the Quarterly Census of Employment and Wages (QCEW) from 2001 to 2017. Only county-industry pairs that have non-missing employment information for the entire panel are included. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Effect of Layoffs on College Enrollment Outcomes

	Number of Students per 100 Graduates Enrolling in:		
Layoffs per 10,000 in:	**No Formal College (1)**	**Vocational Programs (2)**	**All Other Colleges (3)**
Panel A. Total layoffs			
All occupations, t-1	-0.010*	-0.004**	0.015**
	(0.006)	(0.002)	(0.007)
	[-0.003]	[-0.005]	[0.003]
Outcome Mean	42.12	9.000	48.88
County-Year Obs.	664	664	664
R-Squared	0.760	0.666	0.789
Panel B. Layoffs by skill group			
Low-skill	0.008	-0.014	0.006
occupations, t-1	(0.024)	(0.012)	(0.025)
	[0.001]	[-0.007]	[0.001]
Community college	-0.042	0.004	0.039
occupations, t-1	(0.044)	(0.017)	(0.043)
	[-0.004]	[0.002]	[0.003]
High-skill	0.038	0.001	-0.040
occupations, t-1	(0.090)	(0.035)	(0.092)
	[0.001]	[0.000]	[-0.001]
Outcome Mean	42.12	9.000	48.88
County-Year Obs.	664	664	664
R-Squared	0.760	0.667	0.790

Notes: The unit of observation is a county-cohort pair. Outcomes are measured as the number of students who enroll in vocational community college programs within 6 months of high school graduation, per 100 high school graduates in the county and cohort. The coefficients in each column are estimated from a separate regression and represent the β parameters in equation (4), the effect of an additional layoff per 10,000 working age residents in a given occupation group on the outcome of interest. The numbers in brackets below the estimates are the estimated elasticities at the mean dependent and independent variable values. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th grade math and reading test scores; and the county unemployment rate and logged size of the labor force during a cohort's senior year of high school. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: Effect of Community College Layoffs on Overall Vocational Program Enrollment

	Vocational Enrollment per 100 Graduates	
Layoffs per 10,000 in:	**(1)**	**(2)**
Business, t-1	0.064	0.110
	(0.105)	(0.142)
	[0.007]	[0.012]
Health, t-1	0.022	-0.046
	(0.034)	(0.043)
	[0.001]	[-0.002]
Skilled Trades, t-1	0.016	0.004
	(0.021)	(0.032)
	[0.003]	[0.001]
STEM, t-1	-0.101	-0.114
	(0.167)	(0.197)
	[-0.003]	[-0.003]
Law Enforcement, t-1	-0.047	-0.032
	(0.030)	(0.036)
	[-0.004]	[-0.003]
Other, t-1	-0.067	0.092
	(0.162)	(0.187)
	[-0.001]	[0.002]
P-Value for Joint Test	0.104	0.636
County-Specific Trends		X
Outcome Mean	9.000	9.000
County-Year Obs.	664	664
R-squared	0.669	0.754

Notes: The unit of observation is a county-cohort pair. Outcomes are measured as the number of students who enroll in vocational community college programs within 6 months of high school graduation, per 100 high school graduates in the county and cohort. The coefficients in each column are estimated from a separate regression and represent the β parameters in equation (4), the effect of an additional layoff per 10,000 working age residents in a given occupation group on the outcome of interest. The numbers in brackets below the estimates are the estimated elasticities at the mean dependent and independent variable values. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th grade math and reading test scores; and the county unemployment rate and logged size of the labor force during a cohort's senior year of high school. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 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****	-0.703	-0.056	-0.093	1.736***	0.140
	(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**	-0.013	0.030	-0.159**
	(0.078)	(0.109)	**(0.097)**	(0.066)	(0.123)	(0.063)
STEM, t-1	0.213	0.206	-0.253	**-0.124**	-0.086	0.044
	(0.676)	(0.626)	(0.674)	**(0.347)**	(0.838)	(0.405)
Law Enf., t-1	0.076	0.078	-0.048	0.144	**-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 elasticities (at mean):						
	-0.046**	-0.009***	-0.012	-0.003	-0.009**	-0.007
	(0.021)	(0.003)	(0.013)	(0.008)	(0.004)	(0.004)
Outcome Mean	21.66	20.67	14.33	11.84	13.74	17.75
County-Year Obs.	657	657	657	657	657	657
R-squared	0.190	0.506	0.344	0.266	0.258	0.353

Notes: The unit of observation is a county-cohort pair. Outcomes are measured as the number of students who enroll in a given program within 6 months of high school graduation per 100 students who in the county and cohort enroll in vocational programs. The coefficients in each column are estimated from a separate regression and represent the β_j terms in equation (5), effect of an additional layoff per 10,000 working age residents in a given occupation group on the outcome of interest. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th grade math and reading test scores; and the county unemployment rate and logged size of the labor force during a cohort's senior year of high school. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8: Effect of Earlier and Later Layoffs on Related Program Enrollments

	Enrollment in Occupation Group Programs per 100 Vocational Students			
Layoffs per 10,000 in:	**(1)**	**(2)**	**(3)**	**(4)**
Year following graduation		0.076	0.056	0.083
		(0.053)	(0.064)	(0.073)
Senior year of H.S.	-0.181**	-0.171**	-0.184**	-0.160*
	(0.075)	(0.076)	(0.085)	(0.082)
Junior year of H.S.			0.059	0.085
			(0.100)	(0.100)
Sophomore year of H.S.			-0.069*	-0.034
			(0.040)	(0.058)
Freshman year of H.S.			-0.062	-0.027
			(0.053)	(0.048)
8th grade				0.021
				(0.056)
7th grade				0.041
				(0.054)
6th grade				0.062
				(0.064)
5th grade				0.052
				(0.069)
Outcome Mean	16.67	16.67	16.67	16.67
County-Program-Year Obs.	3,942	3,942	3,942	3,942
R-squared	0.357	0.357	0.358	0.359

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 9: Effect of Layoffs in Alternative Geographic Areas on Related Program Enrollments

	Enrollment in Occupation Group Programs per 100 Vocational Students		
Layoffs per 10,000 in:	**(1)**	**(2)**	**(3)**
Own county, t-1	-0.175**	-0.178**	-0.181**
	(0.070)	(0.075)	(0.077)
Rest of state, t-1		0.025	
		(0.139)	
Rest of commuting zone, t-1			-0.022
			(0.033)
State less commuting zone, t-1			0.041
			(0.140)
Outcome Mean	16.67	16.67	16.67
County-Program-Year Obs.	3,942	3,942	3,942
R-squared	0.345	0.345	0.345

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 10: Comparison of Different Types of Layoffs

Layoff measure:	**All Layoffs (1)**	**Closings Only (2)**	**50+ Layoffs Only (3)**
Layoffs per 10,000, t-1	-0.181**	-0.281***	-0.185**
	(0.075)	(0.104)	(0.075)
Outcome Mean	16.67	16.67	16.67
County-Program-Year Obs.	3,942	3,942	3,942
R-Squared	0.357	0.358	0.357

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 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 11: Effect of Layoffs on Retention in Related Programs

	Number per 100 Prior-Year Vocational Students:				
Layoff measure:	**Same Program (1)**	**Different Program (2)**	**Different College (3)**	**Earned Degree (4)**	**Not Observed (5)**
Layoffs per 10,000 in occupation group	-0.389**	-0.005	0.049	0.111	0.234
	(0.155)	(0.077)	(0.053)	(0.070)	(0.156)
Outcome Mean	43.91	12.23	10.38	8.54	25.83
County-Program-Year Obs.	3,354	3,354	3,354	3,354	3,354
R-Squared	0.428	0.489	0.424	0.523	0.432

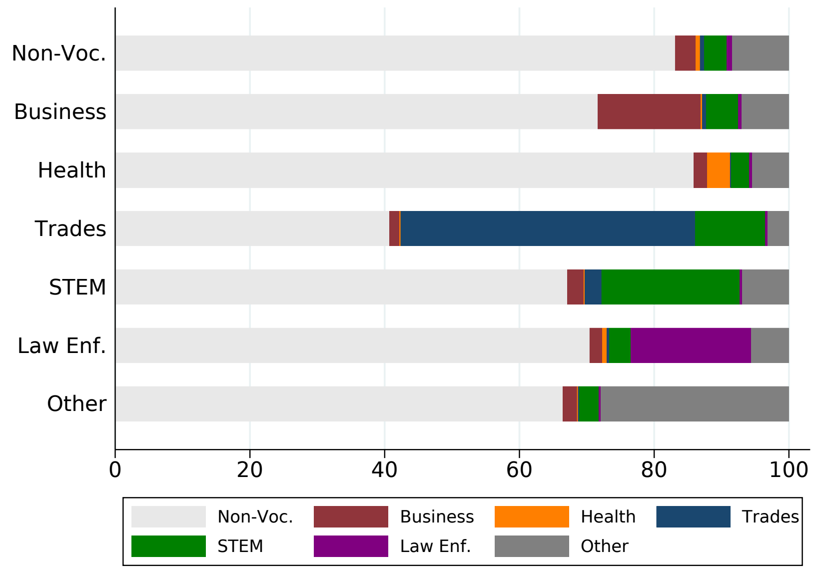
Notes: The unit of observation is a county-year-program triad. Each coefficient is estimated from a separate regression and represents β in equation (8), the effect of an additional layoff per 10,000 working age residents in a given occupation group on retention in related programs. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A Appendix: Additional Figures & Tables

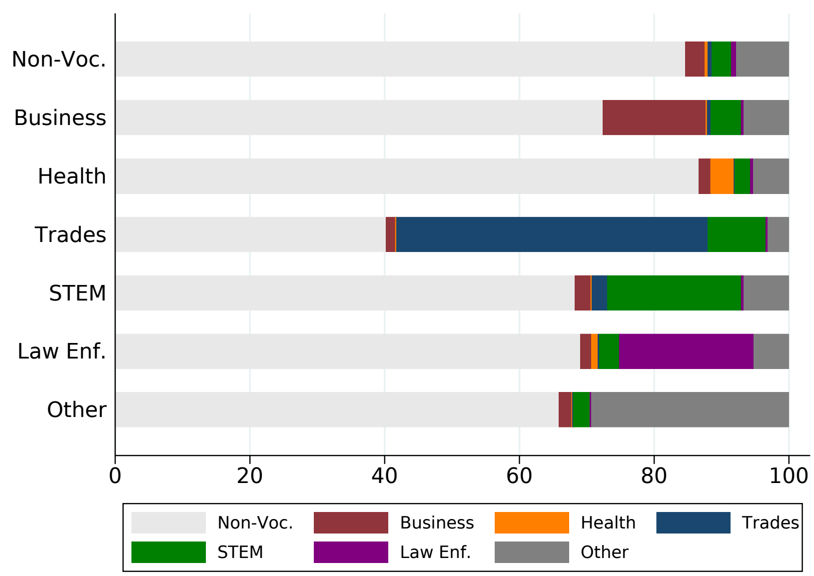
A.1 Additional Figures

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

(a) Share of Courses Taken



(b) Share of Credits Completed



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

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

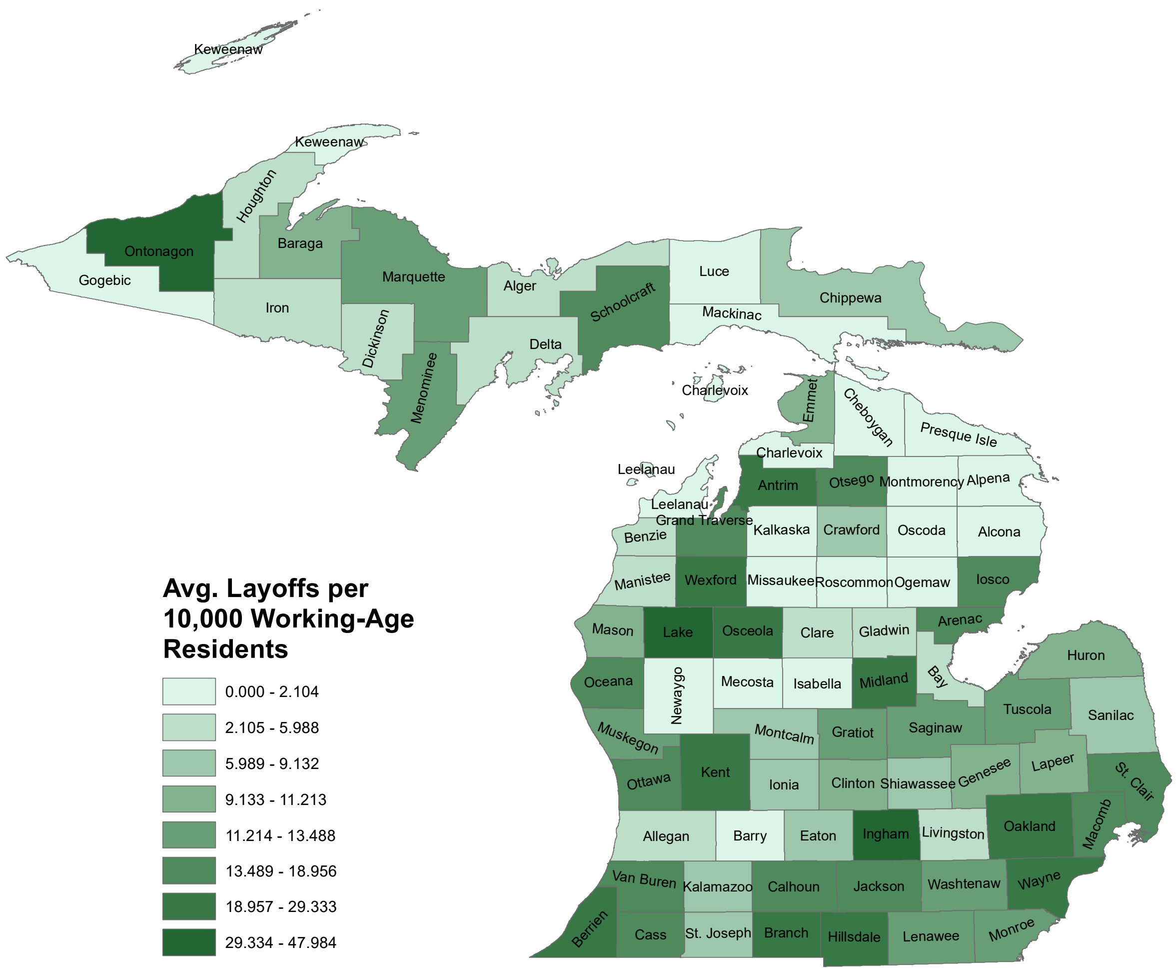
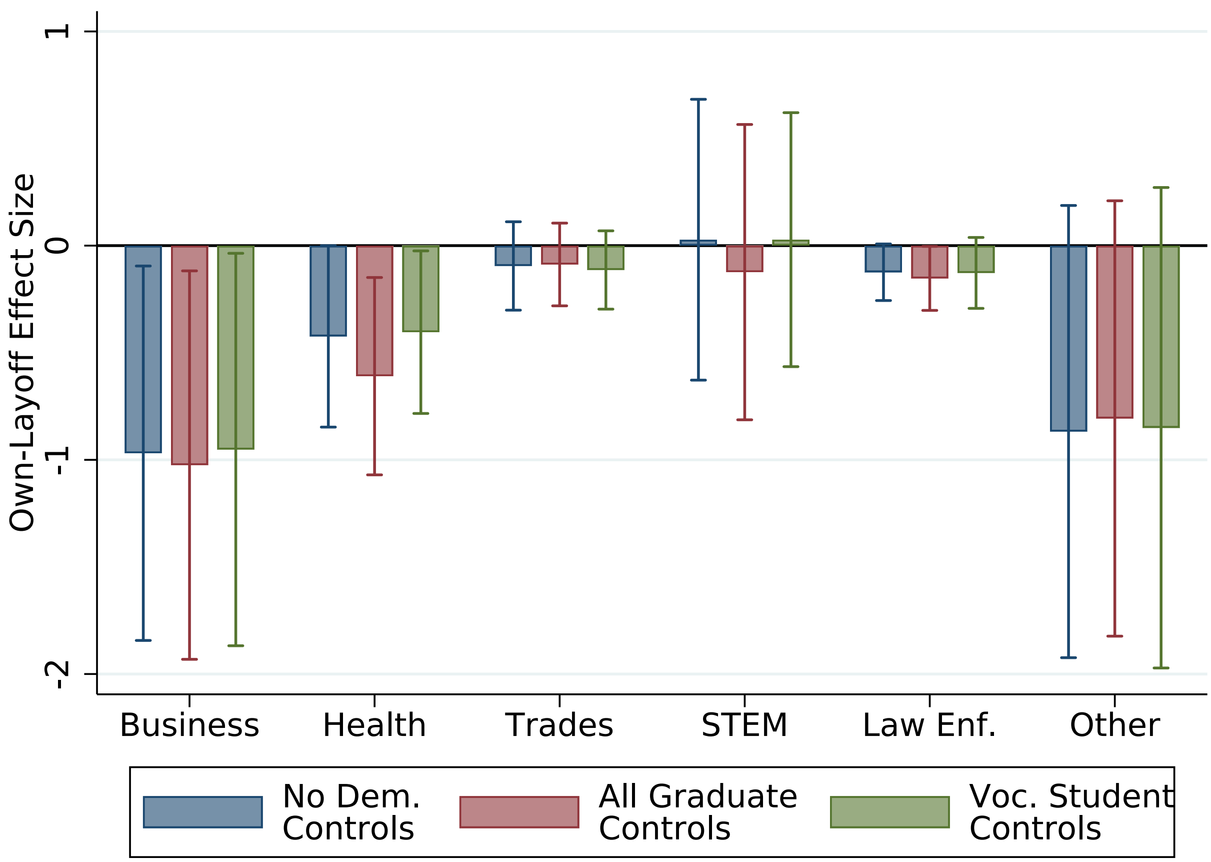


Figure A.3: Correlation Between Layoffs and Employment Changes by NAICS Sectors

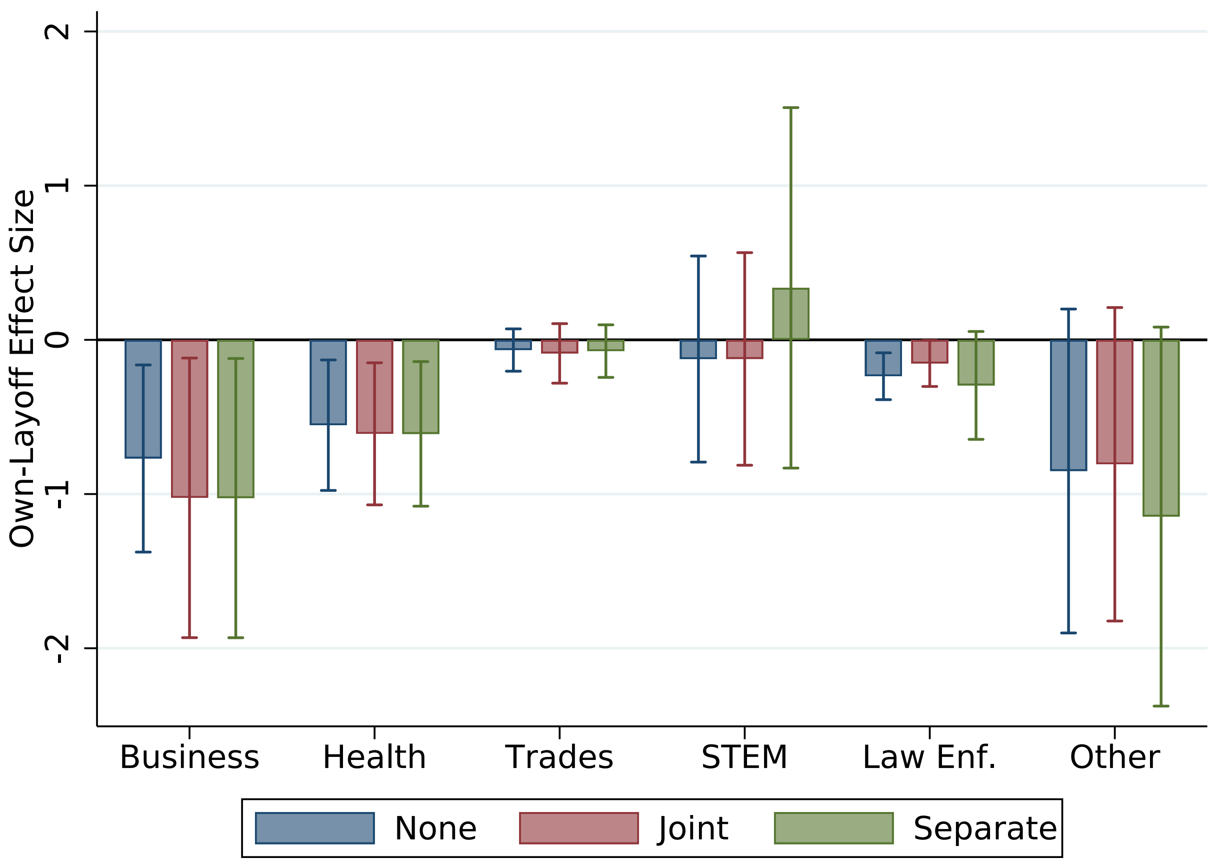
Notes: Each bar represents an estimate of β from equation (3), the effect of an additional layoff in a county-industry-year cell on analogous employment change, where the sample is restricted to the 3-digit NAICS code of interest. The red line is positioned at -1 to indicate when an additional layoff is associated with an employment reduction of exactly 1 worker. All standard errors are clustered at the county level.

Figure A.4: Own Layoff Effects, Different County Control Variables



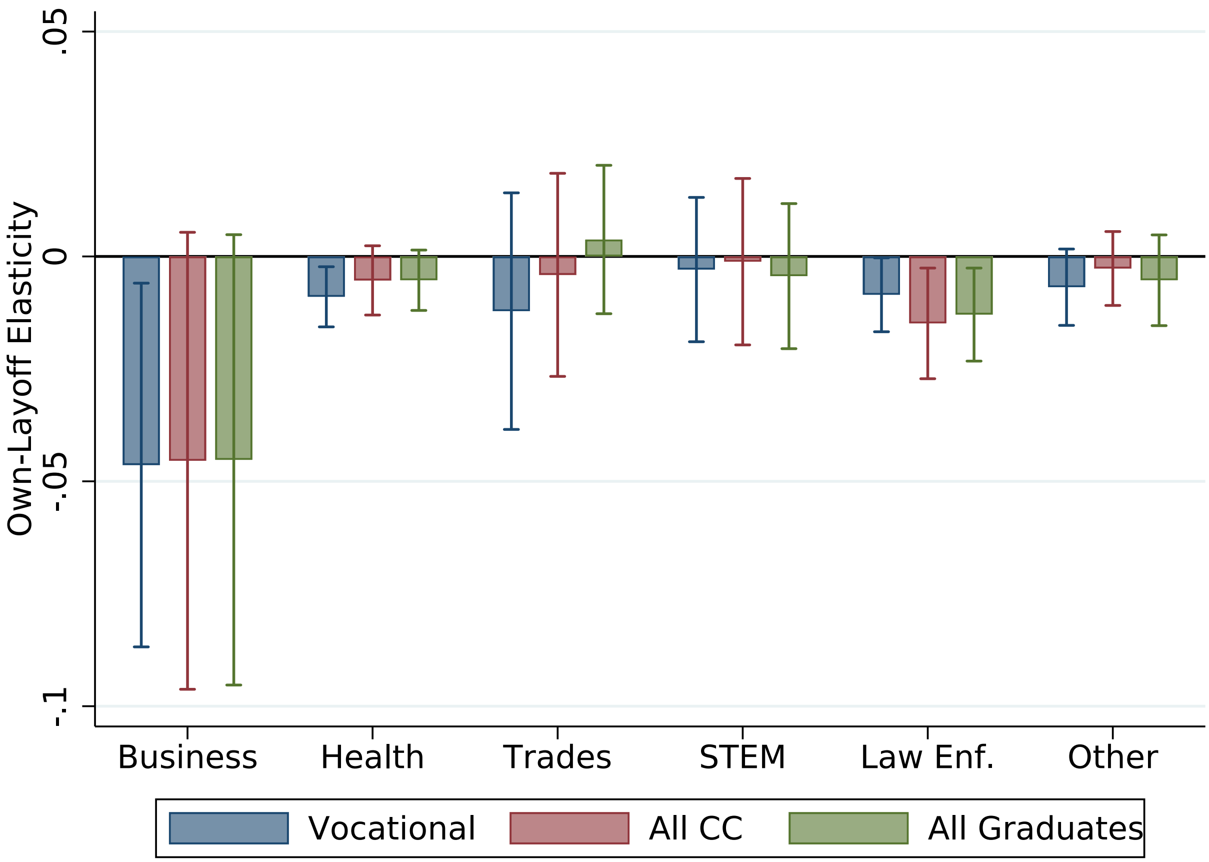
Notes: Each bar represents the own-layoff effect estimated from equation (5) under a different set of control variables. The first bar does not control for any demographic variables, the second bar controls for demographic variables (% white, % male, % economically disadvantaged, average math score, and average reading score) averaged across a county's high school graduates, and the third bar controls for demographic variables averaged only across students who enroll in vocational programs. All standard errors are clustered at the county level.

Figure A.5: Own Layoff Effects, Different Non-CC Layoff Control Variables



Notes: Each bar represents the own-layoff effect estimated from equation (5) when including different non-community college layoff terms. The first bar does not control for any layoffs occurring outside of community college occupations. The second includes a control for the number of layoffs occurring in all non-community college occupations, and the third includes separate controls for layoffs occurring in low-skill and high-skill occupations. All standard errors are clustered at the county level.

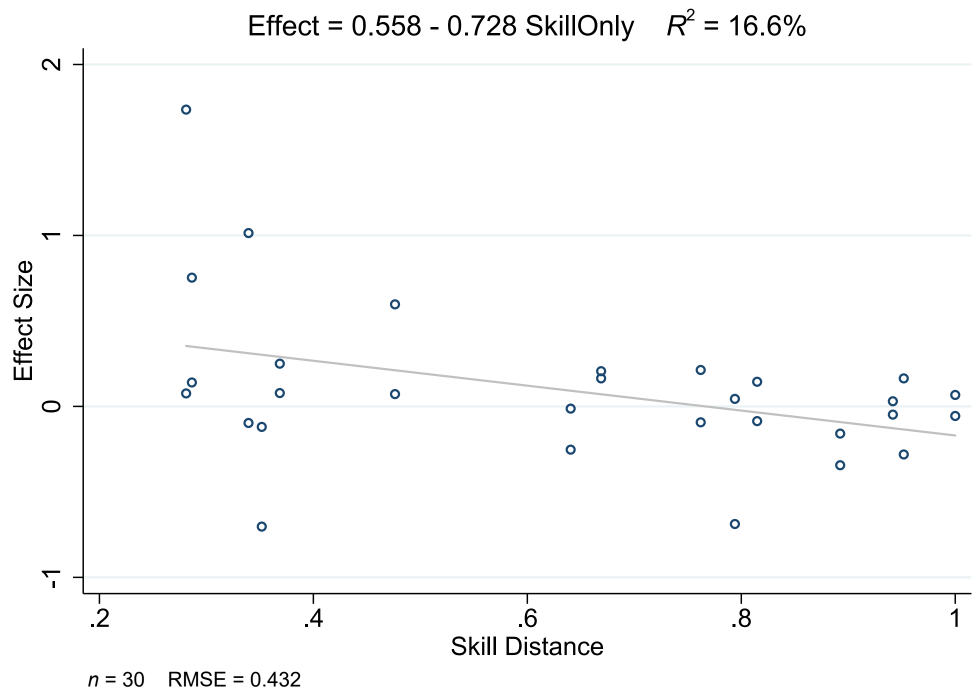
Figure A.6: Own Layoff Elasticities with Different Dependent Variable Denominators



Notes: Each bar represents the own-layoff effect estimated from equation (5) when using different dependent variables. The first bar presents the main specification where the dependent variable is enrollment per 100 vocational students. The second bar scales enrollment by 100 community college students and the third bar scales enrollment by 100 high school graduates. All standard errors are clustered at the county level.

Figure A.7: Relationship Between Substitution Effects & Skill Distance Using Alternate Measures of Skill Distance

(a) Differences in Skill Levels Only



(b) Differences in Skill Importance Only

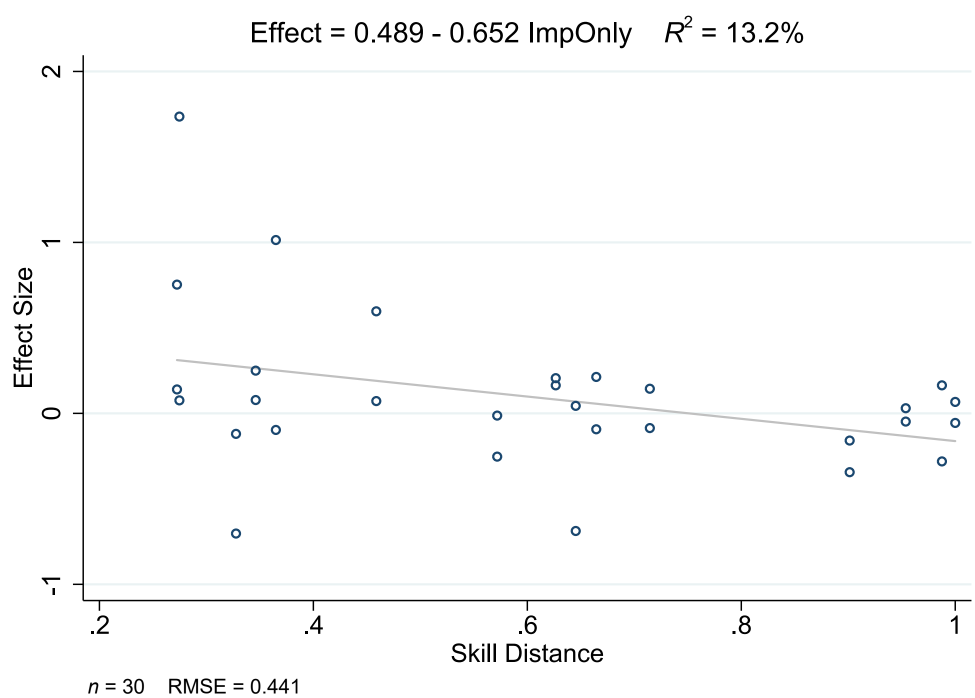


Figure A.8: Effect of Layoffs on Enrollment in Narrower Program Groups

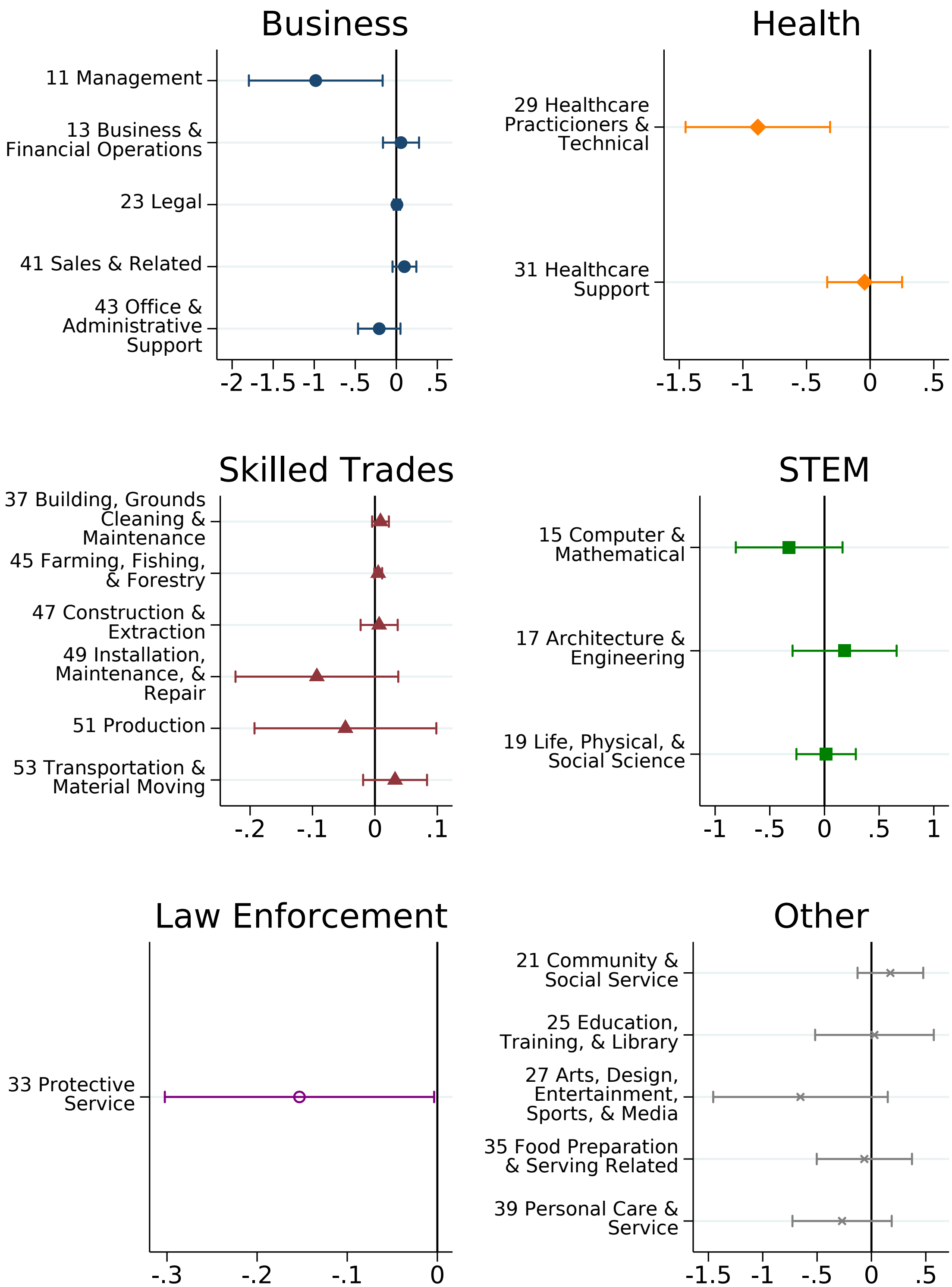


Figure A.9: Substitution into Narrower Program Groups Requiring Similar Skills

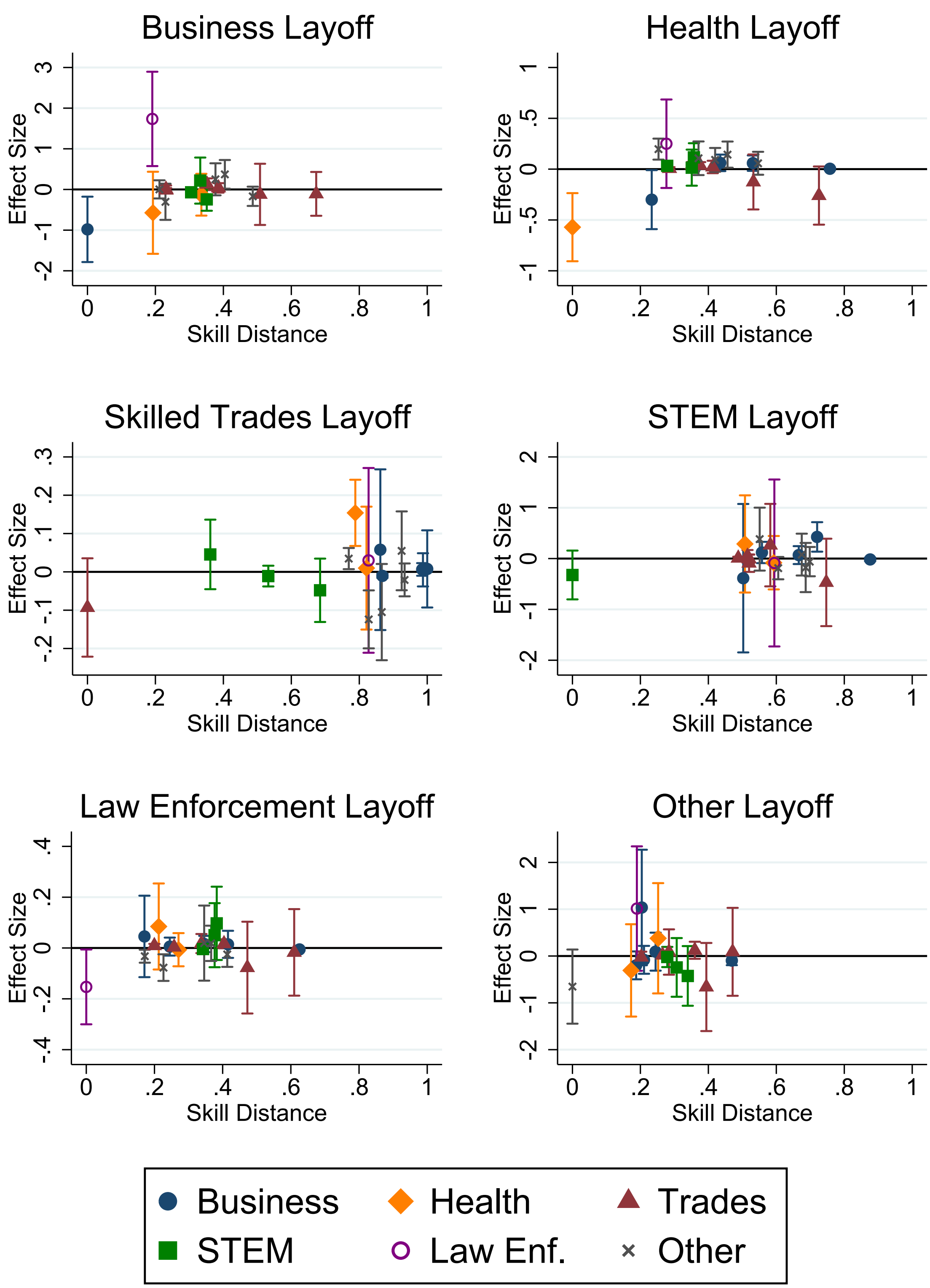
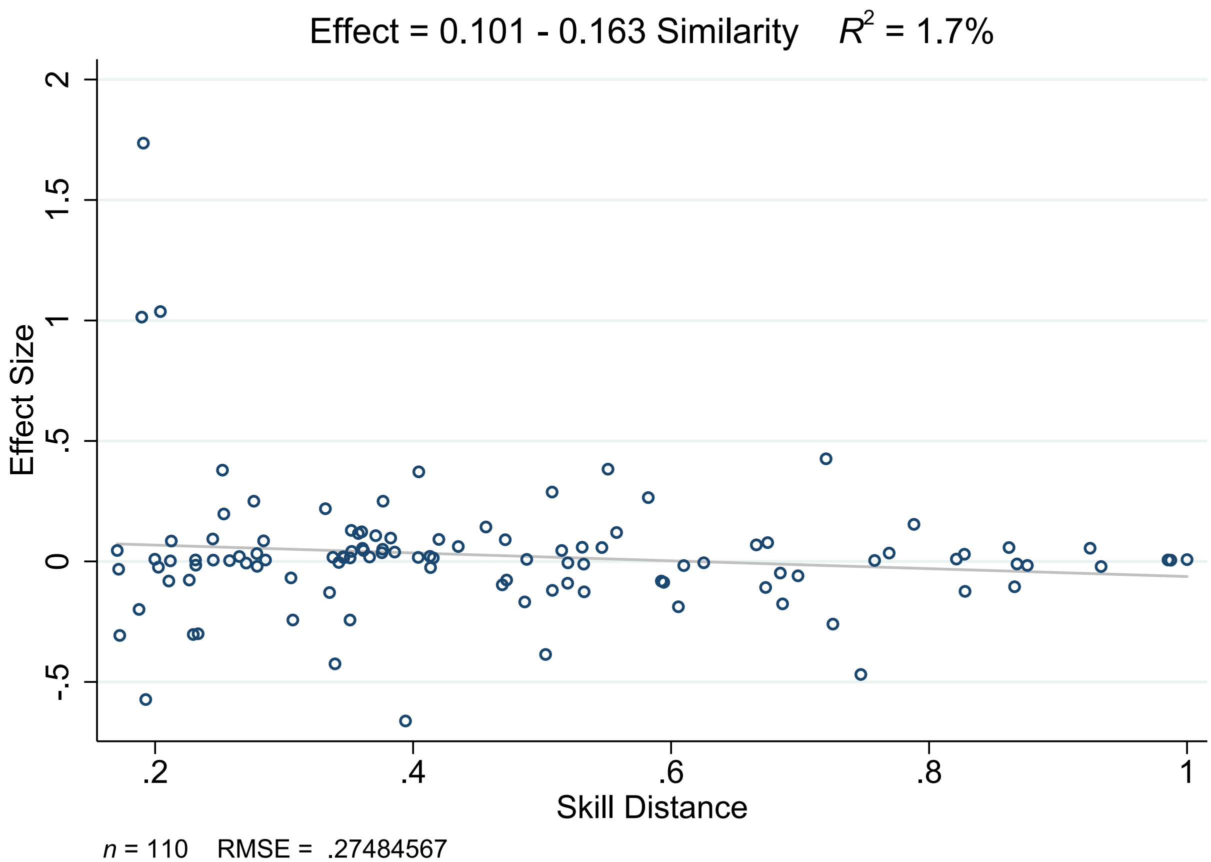


Figure A.10: Relationship Between Substitution Effects & Skill Distance, Narrower Programs



A.2 Additional Tables

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

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

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

Table A.2: Program Groups and Associated Occupation Codes

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

* Programs matched to the 3-digit code 51-3 (Food Processing Workers) are included in the "Other" group because they are generally part of Culinary Arts programs that are mostly matched to the 2-digit code 35 (Food Preparation and Serving Related). Results are robust to including these programs in either group.

** Programs matched to the 6-digit code 53-3011 (Ambulance Drivers and Attendants) are included in the "Health" group because they are generally part of Emergency Medical Services programs that are mostly matched to the 2-digit code 29 (Healthcare Practitioners and Technical). Results are robust to including these programs in either group.

Table A.3: Largest Layoffs by 3-Digit NAICS Code

NAICS	Industry Title	County	Year	Company	Layoffs
111	Crop Production	Ottawa	2016	Zelenka Farms	300
212	Mining (except Oil and Gas)	Wayne	2008	U. S. Steel (Great Lakes Works)	2038
221	Utilities	Wayne	2008	Michigan Waste Energy	150
236	Construction of Buildings	Oakland	2007	Centex Homes (Midwest Region)	75
237	Heavy and Civil Engineering Construction	Oakland	2008	B&V Construction	121
238	Specialty Trade Contractors	Midland	2008	Design Craftsmen, LLC	93
311	Food Manufacturing	Wayne	2001	IBP Foods Company	554
312	Beverage and Tobacco Product Manufacturing	Oakland	2008	Coca Cola Enterprises, Incorporated	127
314	Textile Product Mills	St. Clair	2011	GMA Cover Corp.	260
316	Leather and Allied Product Manufacturing	Wayne	2001	Connolly North America, Llc	246
321	Wood Product Manufacturing	Kent	2007	Trussway LTD	260
322	Paper Manufacturing	Wayne	2006	Digitron Packaging Incorporated	436
323	Printing and Related Support Activities	Washtenaw	2017	Edwards Brothers Malloy Printing	142
325	Chemical Manufacturing	Midland	2015	Dow Chemical Company	700
326	Plastics and Rubber Products Manufacturing	Macomb	2008	Cadence Innovation	780
327	Nonmetallic Mineral Product Manufacturing	Eaton	2009	Owens Illinois (Brockway Glass Containers)	137
331	Primary Metal Manufacturing	Calhoun	2001	Hayes Albion Corporation	496
332	Fabricated Metal Product Manufacturing	Ottawa	2008	Shape Corp.	400
333	Machinery Manufacturing	Wayne	2002	Detroit Diesel Corp.	700
334	Computer and Electronic Product Manufacturing	Wayne	2008	Technicolor Video Services of Michigan	563
335	Electrical Equipment, Appliance, and Component Manufacturing	Berrien	2009	Whirlpool Corp.	216
336	Transportation Equipment Manufacturing	Oakland	2008	GM Lake Orion Assembly Plant	2801
337	Furniture and Related Product Manufacturing	Ottawa	2001	Herman Miller	317
339	Miscellaneous Manufacturing	Kent	2006	Yamaha Music Manufacturing, Inc.	184
423	Merchant Wholesalers, Durable Goods	St. Clair	2006	Collins & Aikman	515
424	Merchant Wholesalers, Nondurable Goods	Wayne	2007	SuperValu	366
441	Motor Vehicle and Parts Dealers	Oakland	2001	Penske Auto Center - Troy	73
442	Furniture and Home Furnishings Stores	Kent	2004	Steelcase	600
443	Electronics and Appliance Stores	Washtenaw	2013	ReCellular, Inc.	94
444	Building Material and Garden Equipment and Supplies Dealers	Ottawa	2017	Gardens Alive! Farms	295

445	Food and Beverage Stores	Genesee	2014	Meijer Store 28	248
446	Health and Personal Care Stores	Saginaw	2014	Apothecary Products	68
448	Clothing and Clothing Accessories Stores	Bay	2010	Men's Wearhouse	80
451	Sporting Goods, Hobby, Musical Instrument, and Book Stores	Kent	2016	MC Sporting Goods	250
452	General Merchandise Stores	Wayne	2002	Kmart Corporation 4915	358
453	Miscellaneous Store Retailers	Wayne	2008	Office Depot	115
454	Nonstore Retailers	Oakland	2012	Entertainment Publications, LLC	225
481	Air Transportation	Wayne	2002	Northwest Airlines	984
482	Rail Transportation	Saginaw	2005	CSX Transportation	124
484	Truck Transportation	Wexford	2010	AAR Mobility Systems	282
485	Transit and Ground Passenger Transportation	Wayne	2017	SMART	318
488	Support Activities for Transportation	Kent	2003	Parker Motor Freight	250
491	Postal Service	Wayne	2016	PAE	58
492	Couriers and Messengers	Berrien	2008	DHL Express	336
493	Warehousing and Storage	Kent	2012	Commerce Corporation	267
511	Publishing Industries (except Internet)	Kalamazoo	2009	Design Ware	400
512	Motion Picture and Sound Recording Industries	Kalamazoo	2016	Alamo Drafthouse Cinema	109
515	Broadcasting (except Internet)	Oakland	2008	Comcast	108
517	Telecommunications	Oakland	2011	Verizon Wireless	499
519	Other Information Services	Wayne	2010	Detroit Public Library	70
521	Monetary Authorities-Central Bank	Wayne	2004	Federal Reserve Bank	61
522	Credit Intermediation and Related Activities	Oakland	2001	CitiMortgage	473
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	Wayne	2009	Ameriprise Financial	154
524	Insurance Carriers and Related Activities	Oakland	2004	Metropolitan Life Insurance Comp.	370
525	Funds, Trusts, and Other Financial Vehicles	Oakland	2008	Semperian	53
531	Real Estate	Ingham	2004	ACS State & Local Solutions	63
532	Rental and Leasing Services	Oakland	2011	Acord Leasing, LLC	187
541	Professional, Scientific, and Technical Services	Oakland	2004	EDS	426
561	Administrative and Support Services	Washtenaw	2013	Teleperformance	430
611	Educational Services	Calhoun	2014	Starr Commonwealth	188
621	Ambulatory Health Care Services	Wayne	2002	Riverside Osteopathic Hospital	520
622	Hospitals	Wayne	2006	St. John Detroit Riverview Hospital	1500
623	Nursing and Residential Care Facilities	Oakland	2006	Medilodge of Bloomfield Hills, Inc.	188
624	Social Assistance	Wayne	2013	Head Start	287
711	Performing Arts, Spectator Sports, and Related Industries	Wayne	2017	Live Nation - Filmore Detroit	180

721	Accommodation	Wayne	2012	Hyatt Regency	322
722	Food Services and Drinking Places	Wayne	2013	Sodexo	359
812	Personal and Laundry Services	Wayne	2003	Ampco System	137
813	Religious, Grantmaking, Civic, Professional, and Similar Organizations	Wayne	2012	YWCA of Western Wayne County	134
921	Executive, Legislative, and Other General Government Support	Wayne	2009	City of Romulus	67
922	Justice, Public Order, and Safety Activities	Jackson	2007	Southern Michigan Correctional Facility	435
923	Administration of Human Resource Programs	Wayne	2014	Institute for Public Health	135

Table A.4: Industries with Highest Concentration of Occupation Groups

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

Table A.5: Correlation Between Occupation Composition Across Industries

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

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

Table A.6: Largest Layoffs by Occupation Group, 2001-2017

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

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

Table A.7: Effect of Layoffs on College Enrollment, Including County Time Trends

	Number of Students per 100 Graduates Enrolling in:		
	No Formal College	**Vocational Programs**	**Four-Year Programs**
Layoffs per 10,000 in:	**(1)**	**(2)**	**(3)**
Panel A. Total layoffs			
All occupations, t-1	-0.015*	-0.002	0.016*
	(0.007)	(0.003)	(0.009)
Outcome Mean	42.12	9.000	48.88
County-Year Obs.	664	664	664
R-Squared	0.812	0.753	0.842
Panel B. Layoffs by skill group			
Low-skill occupations, t-1	0.010	-0.004	-0.006
	(0.031)	(0.015)	(0.034)
Middle-skill CC occupations, t-1	-0.052	-0.002	0.055
	(0.061)	(0.017)	(0.056)
High-skill occupations, t-1	0.028	0.012	-0.041
	(0.114)	(0.034)	(0.113)
Outcome Mean	42.12	9.000	48.88
County-Year Obs.	664	664	664
R-Squared	0.813	0.753	0.842

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. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th grade math and reading test scores; and the county unemployment rate and logged size of the labor force during a cohort's senior year of high school. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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

Layoffs per 10,000 in:	**% White** (1)	**% Male** (2)	**% Econ. Dis.** (3)	**Avg. Math Score** (4)	**Avg. Read Score** (5)
Business, t-1	0.006	-0.005	-0.005	0.011	-0.003
	(0.004)	(0.009)	(0.007)	(0.008)	(0.008)
Health, t-1	0.005*	0.005	-0.002	0.002	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Skilled Trades, t-1	-0.001	0.001	-0.001	-0.002	0.000
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
STEM, t-1	-0.009*	-0.001	-0.009	-0.010	0.017
	(0.005)	(0.012)	(0.011)	(0.012)	(0.012)
Law Enforcement, t-1	-0.003**	0.002	0.001	-0.001	0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Other, t-1	-0.028**	0.000	-0.011	-0.011	0.025
	(0.013)	(0.016)	(0.011)	(0.015)	(0.016)
P-Value for Joint Test	0.239	0.659	0.247	0.595	0.693
Outcome Mean	0.870	0.531	0.393	-0.067	-0.144
County-Year Obs.	657	657	657	657	657
R-Squared	0.732	0.220	0.528	0.474	0.391

Notes: The unit of observation is a county-cohort pair. Outcomes are measured as the mean characteristic across all students who enroll in vocational programs. The coefficients in each column are estimated from a separate regression and represent the β parameters in equation (4), the effect of an additional layoff per 10,000 working age residents in a given occupation group on the outcome of interest. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th grade math and reading test scores; and the county unemployment rate and logged size of the labor force during a cohort's senior year of high school. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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

Layoffs per 10,000 in:	**Total Credits (1)**	**Vocational Credits (2)**	**Non-Voc. Credits (3)**
Business, t-1	0.124	-0.024	0.148
	(0.156)	(0.090)	(0.125)
Health, t-1	0.021	0.034	-0.013
	(0.072)	(0.042)	(0.045)
Skilled Trades, t-1	0.001	-0.010	0.011
	(0.026)	(0.017)	(0.020)
STEM, t-1	0.112	-0.030	0.141
	(0.554)	(0.222)	(0.358)
Law Enforcement, t-1	0.035	0.001	0.035
	(0.091)	(0.041)	(0.055)
Other, t-1	0.264	-0.152	0.416
	(0.590)	(0.257)	(0.383)
P-Value for Joint Test	0.939	0.921	0.593
Outcome Mean	17.22	6.40	10.81
County-Year Obs.	657	657	657
R-Squared	0.487	0.494	0.515

Notes: The unit of observation is a county-cohort pair. Outcomes are measured as the mean number of credits completed in the first year of community college enrollment across all students who enroll in vocational programs. The coefficients in each column are estimated from a separate regression and represent the β parameters in equation (4), the effect of an additional layoff per 10,000 working age residents in a given occupation group on the outcome of interest. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th grade math and reading test scores; and the county unemployment rate and logged size of the labor force during a cohort's senior year of high school. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.10: Substitution Matrix for All Graduates

	Enrollment per 100 Graduates in:						
Layoffs per 10,000 in:	**CC Business Programs (1)**	**CC Health Programs (2)**	**CC Trades Programs (3)**	**CC STEM Programs (4)**	**CC Law Enf. Programs (5)**	**Other Voc. Programs (6)**	**No College or Other Colleges (7)**
Business, t-1	**-0.089***	-0.002	0.030	-0.007	0.119**	0.012	-0.064
	(0.050)	(0.058)	(0.032)	(0.029)	(0.049)	(0.028)	(0.105)
Health, t-1	0.002	**-0.032**	-0.022**	0.005	0.014	0.054***	-0.022
	(0.011)	**(0.021)**	(0.008)	(0.009)	(0.024)	(0.011)	(0.034)
Skilled Trades, t-1	0.009	0.010	**0.001**	0.002	0.002	-0.009*	-0.016
	(0.007)	(0.009)	**(0.005)**	(0.004)	(0.010)	(0.005)	(0.021)
STEM, t-1	0.011	-0.022	0.028	**0.024**	-0.112	-0.030	0.101
	(0.089)	(0.078)	(0.058)	**(0.045)**	(0.073)	(0.046)	(0.167)
Law Enforcement, t-1	-0.005	-0.014	0.002	0.014	**-0.028****	-0.017*	0.047
	(0.012)	(0.012)	(0.008)	(0.009)	**(0.013)**	(0.010)	(0.030)
Other, t-1	0.034	-0.049	-0.061	-0.035	0.089	**-0.045**	0.067
	(0.060)	(0.063)	(0.052)	(0.056)	(0.065)	**(0.056)**	(0.162)
Own-layoff elasticities (at mean):							
	-0.045*	-0.005	0.002	0.006	-0.017**	-0.004	
	(0.026)	(0.003)	(0.008)	(0.011)	(0.009)	(0.005)	
Observations	664	664	664	664	664	664	664
R-squared	0.343	0.589	0.473	0.477	0.384	0.481	0.669

Notes: The unit of observation is a county-cohort pair. Outcomes are measured as the number of students who enroll in a given program within 6 months of high school graduation per 100 students who in the county and cohort enroll in vocational programs. The coefficients in each column are estimated from a separate regression and represent the β_j terms in equation (5), effect of an additional layoff per 10,000 working age residents in a given occupation group on the outcome of interest. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th grade math and reading test scores; and the county unemployment rate and logged size of the labor force during a cohort's senior year of high school. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.11: Substitution Between Narrower Community College Programs

	Enrollment per 100 Vocational Students in:							
	Business	**Health**	**Trades**	**STEM**	**Law Enf.**	**Arts & Media**	**Personal & Culinary**	**Social Services**
Layoffs per 10,000 in:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Business, t-1	-1.025**	-0.703	-0.056	-0.093	1.736***	-0.303	0.003	0.440**
	(0.456)	(0.682)	(0.449)	(0.280)	(0.592)	(0.227)	(0.201)	(0.184)
Health, t-1	-0.120	-0.610**	-0.281**	0.164	0.250	0.107	0.144*	0.346***
	(0.138)	(0.232)	(0.122)	(0.123)	(0.222)	(0.084)	(0.083)	(0.073)
Skilled Trades, t-1	0.067	0.164	-0.088	-0.013	0.030	-0.124***	-0.027	-0.008
	(0.078)	(0.109)	(0.097)	(0.066)	(0.123)	(0.039)	(0.057)	(0.031)
STEM, t-1	0.213	0.206	-0.253	-0.124	-0.086	0.383	-0.535**	0.196
	(0.676)	(0.626)	(0.674)	(0.347)	(0.838)	(0.316)	(0.268)	(0.195)
Law Enforcement, t-1	0.076	0.078	-0.048	0.144	-0.153**	-0.077***	-0.088**	0.068
	(0.075)	(0.082)	(0.061)	(0.094)	(0.075)	(0.027)	(0.043)	(0.053)
Other, t-1	0.753	0.072	-0.344	-0.688	1.014	-0.653	-0.123	-0.031
	(0.617)	(0.945)	(0.518)	(0.522)	(0.678)	(0.404)	(0.302)	(0.371)
Outcome Mean	21.66	20.67	14.33	11.84	13.80	9.11	3.39	5.26
Observations	657	657	657	657	657	657	657	657
R-squared	0.190	0.506	0.344	0.266	0.258	0.542	0.313	0.322

Notes: The unit of observation is a county-cohort pair. Outcomes are measured as the number of students who enroll in a given program within 6 months of high school graduation per 100 students who in the county and cohort enroll in vocational programs. The coefficients in each column are estimated from a separate regression and represent the β_j terms in equation (5), effect of an additional layoff per 10,000 working age residents in a given occupation group on the outcome of interest. All regressions include controls for the share of graduates that are white, male, and categorized as economically disadvantaged; average 11th grade math and reading test scores; and the county unemployment rate and logged size of the labor force during a cohort's senior year of high school. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.12: Rank Order of Similar Programs Using Different Measures of Skill Similarity

Comparison:	**Main Distance Measure (1)**	**Difference in Levels Only (2)**	**Difference in Importance Only (3)**
Business	Law Enf.	Law Enf.	Other
	Health	Other	Law Enf.
	Other	Health	Health
	STEM	STEM	STEM
	Trades	Trades	Trades
Health	Business	Business	Business
	Law Enf.	Law Enf.	Law Enf.
	STEM	Other	Other
	Other	STEM	STEM
	Trades	Trades	Trades
Skilled Trades	STEM	STEM	STEM
	Other	Other	Other
	Health	Law Enf.	Law Enf.
	Law Enf.	Health	Health
	Business	Business	Business
STEM	Health	Trades	Trades
	Trades	Health	Health
	Business	Business	Other
	Other	Other	Business
	Law Enf.	Law Enf.	Law Enf.
Law Enforcement	Business	Business	Business
	Health	Other	Health
	Other	Health	Other
	STEM	STEM	STEM
	Trades	Trades	Trades
Other	Business	Business	Business
	Law Enf.	Law Enf.	Law Enf.
	Health	Health	Health
	STEM	STEM	STEM
	Trades	Trades	Trades

Notes: Each column presents the rank ordering of similar programs under different measures of skill similarity. Column (1) uses the main distance measure shown in equation (6), column (2) does not include any measure of skill importance, and column (3) only considers differences in skill importance. In all columns, the programs are ordered from most similar to least similar. For example, under all three measures, business programs are the most similar programs to law enforcement programs while skilled trade programs are the least similar.

Table A.13: Own-Layoff Effects on Program Retention Rates

	Retention per 100 Students in:					
	Business	**Health**	**Trades**	**STEM**	**Law Enf.**	**Other**
Layoff measure:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Layoffs per 10,000 in	-0.179	-0.971	-0.433	-1.067	-0.261	-3.023**
own occupation group	(0.908)	(0.651)	(0.302)	(0.794)	(0.160)	(1.195)
	[-0.002]	[-0.007]	[-0.010]	[-0.004]	[-0.004]	[-0.010]
Outcome Mean	41.05	44.05	43.13	45.11	42.01	43.71
County-Year Obs.	568	568	556	558	561	558
R-Squared	0.274	0.243	0.207	0.222	0.262	0.218

Notes: The unit of observation is a county-cohort pair. Each coefficient is estimated from a separate regression and represents the effect of an additional layoff per 10,000 working age residents in a given occupation group on retention in related programs. The numbers in brackets below the estimates are the estimated elasticities at the mean dependent and independent variable values.All regressions control for layoffs in all community college occupation groups, as well as layoffs in non-community college occupations. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B Appendix: Logit Model of Program Choices

It is straightforward to estimate the effect of layoffs on students' program choices using a discrete choice framework and imposing standard logit assumptions. Let i deonte an individual student, g denote a program choice, c denote a county, and t denote a cohort. Specify the random utility model as:

$$U_{igct} = \beta \text{Layoffs}_{gct} + \nu_{gct} + \varepsilon_{igct} \tag{1}$$

where U_{igct} is the utility that student i in cohort t and county c receives from choosing program g, Layoffs_{gct} is the amount of layoff exposure cohort t in county c experiences in occupation group g, ν_{gct} is an unobserved characteristic that is constant across individuals within a market, and ε_{igct} is an individual taste parameter. Consistent with the linear specification in equation (7), I decompose the unobserved term into three parts: a county-by-cohort component (θ_{ct}), a program-by-county component (λ_{gc}), and a program-by-cohort component (δ_{gt}).

Under the logit assumption that ε_{igct} is independent and identically distributed following the Type I extreme value distribution, the share of students from county c and cohort t that choose choice g is:

$$\text{Share}_{gct} = \frac{\exp(\beta \text{Layoffs}_{gct} + \theta_{ct} + \lambda_{gc} + \delta_{gt})}{\sum_k \exp(\text{Layoffs}_{kct} + \theta_{ct} + \lambda_{kc} + \delta_{kt})} \tag{2}$$

where k indexes the six different program groups. A straightforward approach to estimating the β parameter would be to take the logs of both sides and estimate the transformed equation. Such an approach is analogous to estimating equation (7) with a logged dependent variable rather than a linear dependent variable.[1]

However, a logged specification is undesirable in this setting because over 12% of the share variables in my data are equal to zero and these observations drop out of the estimation when imposing a log transformation. Moreover, these zero shares disproportionately occur in small and rural counties, which are precisely the areas where students are the most sensitive to layoffs in the linear specifications. Instead, I use the quasi maximum-likelihood estimation

[1] Logging both sides yields: $\log(\text{Share}_{gct}) = e_{ct} + \beta \text{Layoffs}_{gct} + \theta_{ct} + \lambda_{gc} + \delta_{gt} + u_{gct}$, where $e_{ct} = -\log(\sum_k \exp(\text{Layoffs}_{kct} + \theta_{ct} + \lambda_{kc} + \delta_{kt}))$ and u_{gct} is the idiosyncratic error term. If I normalize the mean utility (e.g. the utility less the error term) of some outside option to be zero, then $\log(\text{Share}_{0ct}) = e_{ct}$ and the regression equation is the standard logit transformation: $\log(\text{Share}_{gct}) - \log(\text{Share}_{0ct}) = \beta \text{Layoffs}_{gct} + \theta_{ct} + \lambda_{gc} + \delta_{gt} + u_{gct}$. However, because Share_{0ct} is constant across alternatives within a county-cohort pair, it drops out of the estimation with the inclusion of θ_{ct} and we are left with the equation: $\log(\text{Share}_{gct}) = \beta \text{Layoffs}_{gct} + \theta_{ct} + \lambda_{gc} + \delta_{gt} + u_{gct}$. This equation is precisely equation (7) from the main text with a logged dependent variable.

(QMLE) method developed by Papke and Wooldridge (1996). This approach allows for all observations to contribute to the estimation procedure, but ensures that the predicted shares fall within the unit interval.[2]

Appendix Table B.1 below presents the estimated elasticity from the QMLE logit specification and compares it to the linear specification. Elasticities in both specifications are calculated at the mean values of the dependent and independent variables. As noted in Section 6, the linear specification produces an elasticity of -0.0081 (SE = 0.0034), meaning that a 100% increase in layoff exposure reduces enrollment in related programs by 0.81%. The confidence interval for this decrease ranges from -1.46% to -0.15%. The logit specification produces a slightly large, but quite similar, estimate. The estimated elasticity is -0.0124 (SE = 0.0054) and the confidence interval on the enrollment response due to a 100% increase in layoff exposure ranges from -2.31% to -0.18%. These estimates are not statistically different from one another, and thus, the linear specification used in the main text provides a good approximation of a non-linear approach.

Table B.1: Elasticities from Linear and Logit Estimations

	Linear **(1)**	**Logit** **(2)**
Estimated elasticity	-0.0081** (0.0034)	-0.0124** (0.0054)
95% CI of enrollment change due to 100% increase in layoffs	[-1.46%, -0.15%]	[-2.31%, -0.18%]
Outcome Mean	16.67	16.67
Observations	3,942	3,942

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. All standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[2] The QMLE procedure solves the objective function: $\max_{\mathbf{b}} \sum_{i=1}^{n} (1 - \text{Share}_i) \log[1 - G(\mathbf{x}_i \mathbf{b})] + \text{Share}_i \log[G(\mathbf{x}_i \mathbf{b})]$, where i denotes county, cohort, program group triads and $G(\mathbf{x}_i \mathbf{b})$ is the right-hand side of equation (2). Papke and Wooldridge (1996) show that this log-likelihood function produces a consistent estimate of β whenever the conditional mean is correctly specified, regardless of the conditional distribution of the dependent variable of interest (for example, regardless of whether it is discrete, continuous, or some combination of the two).