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ABSTRACT

Displaced workers suffer large and persistent earnings losses. These losses can be mitigated by returning to school, yet the extent to which such workers enroll in post-secondary education in response to displacement is poorly understood. Using employer-employee-student matched administrative data from Ohio, we provide the first direct evidence of workers' enrollment responses following mass layoffs in the United States. Close to 10% of these displaced workers enroll in public two- or four-year colleges after displacement, with the typical enrollment persisting for five semesters, and 29% completing a degree. However, much of this enrollment may have occurred regardless of the displacement. To estimate a causal effect, we compare displaced workers over time to similar non-displaced workers. We estimate that for every 100 displaced workers, only about 1 is ever induced to enroll in a public college as a result. This effect is concentrated almost entirely among displaced manufacturing workers, who enroll at a rate of 2.5 per every 100. Such workers with lower within-firm earnings and from local labor markets with limited for-profit college options are the most likely to enroll in public institutions.

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1 Introduction

Highly-tenured workers who lose their jobs in mass layoffs suffer large and persistent earnings losses many years after their initial separations. This "scarring effect" curtails earnings by 15 to 20% even two decades after displacement (Davis and Von Wachter, 2011). Community college credentials and retraining programs that specifically target displaced workers can ameliorate these losses, even for older workers and those in particularly distressed industries and regions (Jacobson, LaLonde, and Sullivan, 2005a,b; Hyman, 2018). In the absence of other constraints, such workers might seek to upskill when faced with such grim economic prospects.

Surprisingly, very few studies have attempted to directly estimate the causal effect of job displacement on postsecondary enrollment among those who were actually displaced. While prior literature has established that community college enrollment rises when the labor market is weak (Barrow and Davis, 2012; Hillman and Orians, 2013; Foote and Grosz, 2019), this is not necessarily informative regarding the effects on displaced workers themselves. Enrollment induced by poor labor markets may come primarily from individuals besides those who lost their job: workers who voluntarily leave their jobs to return to school, recent high school graduates who opt to pursue college instead of entering a weak labor market, and those whose college choices are indirectly affected via the financial situations of their parents. One paper which directly examines job displacement and subsequent postsecondary enrollment is Frenette et al. (2011). The authors use the Canadian Longitudinal Worker File to compare enrollment before and after 2003 for workers displaced in 2003 versus similar workers who were not displaced, they find that job displacement for Canadian workers age 25-44 increases postsecondary enrollment by 0.6 to 1.3 percentage points over the subsequent four years, from a baseline enrollment rate of about 10% among a non-displaced comparison group.

It is not clear whether the findings of Frenette et al. (2011) would translate to an American setting, given the differences in UI policies, educational options, and safety net programs (Card and Riddell, 1993; Card and Oreopoulos, 2019; Jones and Riddell, 2019). For example, Barr and Turner (2015, 2018) find that specific UI policy factors influence the enrollment response of unemployed workers in the United States[1] – among them, UI benefit duration, the ease with which UI recipients can claim benefits while enrolled, and whether agencies are proactive about informing unemployed workers of available financial aid. Further, the relative "push" of weaker labor markets and "pull" of more generous disability insurance (DI) in the U.S. compared to Canada may induce some Americans workers who would have otherwise sought retraining to instead take up DI (Milligan and Schirle, 2019). To illustrate this point, in U.S. regions that were highly exposed to Chinese import competition in the 1990s and 2000s, the per capita increase in Social Security DI payments was more than thirty times that of Trade Adjustment Assistance (TAA), the federal program which incentivizes retraining for workers displaced by foreign trade (Autor et al., 2013). For these and other reasons, it is not obvious whether Frenette et al.'s (2011) findings would generalize to an American setting. Our paper provides the first direct evidence using micro-level data of the effect of job displacement on college enrollment in the United States.

Using employer-employee-student matched administrative data from Ohio, we identify workers who lose their job in a mass layoff between 2002 and 2009 and find 9% enroll in public two- or four-year colleges after displacement. The typical enrollment spell persists for five semesters, and 29% of these displaced workers attain a degree after being laid off. However, much of this enrollment may have occurred regardless of an individual's career disruption. Using a dynamic two-way fixed effects approach similar to Jacobson, LaLonde, and Sullivan (1993), we estimate the causal effect of job displacement on postsecondary enrollment. Our preferred model includes linear worker-specific time trends in addition to worker fixed effects, and all specifications include a comparison group of non-displaced workers. We find that the enrollment response to job displacement is very small: for every 100 displaced workers, only 1 is ever induced to enroll in a public college within four years of layoff. Most of the "enrollment effect" occurs within the first year of displacement.

Our identifying assumption is that displacement is orthogonal to unobserved, non-linear trends in employment or human capital. If a worker receives a positive or negative shock that affects both postsecondary enrollment decisions and displacement, our approach will incorrectly attribute any

[1] The authors do not restrict their samples to highly-tenured displaced workers

change in enrollment trajectories to the effect of displacement. While it is not possible to rule out every possible alternative explanation, we find that our results are robust to a range of sensitivity checks, including models that exclude the individual-specific trends, models that utilize alternative measures of enrollment, and models examining effects for shutdowns versus mass layoffs separately.

After presenting our main results, we then explore how these enrollment effects differ by industry of displacement. We show this effect is almost entirely concentrated in the manufacturing sector, which comprises just 29% of our displaced sample. Within a year of displacement, more than 2 workers per every 100 laid off from manufacturing firms enrolled in college. After three years, this effect grew to 2.5 workers. Our sample (laid off between 2002 and 2009) spans the period when U.S. manufacturing employment's decades-long decline fell at its fastest rate (Pierce and Schott, 2016), so the relative value of switching industries may be particularly high for these workers. Nevertheless, our findings suggest that even in this declining industry, few workers respond to job loss by seeking postsecondary retraining.

We then restrict our sample to manufacturing employees to explore whether heterogeneity in these effects follows the patterns we would predict based upon economic theory. First, we present evidence that a worker's likelihood of enrollment depends strongly on her income prior to layoff, specifically relative to coworkers. Because lower earners (within a firm) are typically younger and have less educational attainment, one would predict these workers may be differentially more likely to pursue schooling after displacement. Although we document that even the highest-paid displaced manufacturing employees are drawn to college after layoff, middle- and low-earners are more likely to seek retraining. For instance, three years after layoff, the displaced from the bottom-tercile of firm earnings distribution are more than three times as likely to enroll in college than those laid off from the top tercile.

Next, we examine whether a displaced workers' geographic proximity to Ohio institutions of higher education relates positively with likelihood of enrollment, consistent with economic theory (lower economic cost of enrollment for workers nearby) and past empirical evidence (Card, 1993). While proximity to a higher concentration of public colleges doesn't predict increased public enrollment, we document that enrollment in public institutions are depressed in local labor markets with a higher concentration of for-profit schools. Our study complements previous evidence that public and for-profit schools are substitutes (Laband and Lentz, 2004; Cellini, 2009; Cellini et al., 2020).

We find that other dimensions of heterogeneity do not predict a displaced worker's likelihood of college enrollment. For example, despite the fact that those laid off in the third calendar quarter (July to September) may be better-positioned to swiftly transition to college in the autumn semester compared to those displaced in the fourth quarter, we conclude that the season of one's layoff does not explain variation in subsequent enrollment. Similarly, while firm size or whether the firm closes permanently (as opposed to simply shedding workers) could theoretically influence workers post-layoff educational decisions, we detect no empirical relationship.

Our heterogeneity analysis lends credibility to our causal interpretation of the effects of job loss on enrollment. To the extent that our baseline estimates were driven by selection bias rather than a causal mechanism, we would not necessarily expect our estimation to yield these patterns of heterogeneity. Further work is needed to determine how many displaced workers retrain at private, for-profit, or non-college institutions and whether the postsecondary training programs effectively match displaced workers with new jobs. We proceed by summarizing related literature in section 2 and describing the data in section 3. Section 4 outlines the empirical strategy. Section 5 reviews our findings, and section 6 discusses and concludes.

2 Previous Literature

For workers displaced in mass layoffs and plant closings, the consequences of job loss are large and extend beyond when they are unemployed (Jacobson et al., 1993; Charles and Stephens, 2004; Brand et al., 2008). On average, these workers experience a 20% reduction in their earnings up to two decades after the displacement occurred (Von Wachter et al., 2009). Displaced workers are also more likely to suffer health issues, end up on the disability rolls, or die following job loss (Autor and Duggan, 2003; Sullivan and Von Wachter, 2009). The long-run earnings losses of displaced workers are associated with a declining demand for a certain set of job- or industry-specific skills (Jacobson et al., 2005b). Employees with specific skills in waning industries experience lower earnings even after they are reemployed full-time because their old skills are less valuable to other employers and more difficult to transfer to emerging and growing sectors (LaLonde and Sullivan, 2010).

The job displacement literature is linked to a well-developed scholarship on the impact of retraining on earnings. This literature estimates substantial returns to college and shows that it takes time for the benefits of training to be realized. In their studies, Jacobson, LaLonde, and Sullivan (2005a,b) link administrative earnings records with community college transcripts for workers displaced from their jobs in Washington State. They estimate returns to one year of college to be about 9% for men and about 13% for women. The authors also show that returns to community college for displaced workers may be limited in the short-term but increases over time. In more recent work, Hyman (2018) exploits quasi-random assignment of TAA cases to investigators of differing approval leniencies to estimate that that the program boosts earnings by $50,000 over a decade for displaced workers through its extended unemployment benefits, job search assistance, and retraining subsidies. Finally, using a similar dataset and time period as we examine here, Leung and Pei (2020) apply a matching strategy that compares UI claimants from Ohio who enrolled in further education to similar claimants who did not. They find that enrollees earned about 7% more than non-enrollees three to four years after enrollment.

Although this research demonstrates that retraining through community colleges can reduce the skills gaps of some of these displaced workers and mitigate their earnings losses, the extent to which such workers enroll in postsecondary education in response to displacement is poorly understood. Theoretically, in the absence of other constraints, labor market downturns decrease the opportunity cost of postsecondary enrollment by reducing current labor market opportunities.

The literature studying the impact of losing one's job on educational investment has largely focused on settings with high unemployment or in a recession (Betts and McFarland, 1995; Card and Lemieux, 2001; Berger and Kostal, 2002). In a more recent study, Barr and Turner (2015) estimate the college enrollment response during the Great Recession by examining the interaction of labor market conditions and state-specific UI policies and how this affects postsecondary enrollment. They find that individuals in their mid to-late twenties are proportionally more responsive to cyclical variation in economic conditions and that an additional 10 weeks of UI benefits increases the likelihood of enrollment among unemployed workers by about 1.8 percentage points.

Far less attention has been devoted to the causal effect of job displacement on postsecondary enrollment among those who were actually displaced and often face especially difficult readjustments. Foote and Grosz (2019) estimate the effect of local labor market downturns measured by local mass layoff events on two-year college enrollment using aggregate data at the commuting-zone level and applying a generalized difference-in-difference approach with year and commuting-zone fixed effects. Three years after a mass layoff, they find that for every 100 workers involved, 3 enrolled in a two-year college and 2 completed a credential. While their analysis spans the entire country and includes for-profit institutions, it is conducted at the aggregate level and therefore cannot pinpoint whether individuals enrolling are the same ones who were laid off. Moreover, geographic mobility could be a confounding factor in this context, although the authors argue that the role of migration was muted during periods of labor market exits from mass layoffs (Foote et al., 2019).

Ost et al. (2018) also studied the effects of mass layoffs on educational investments, but among working college students who are already enrolled and experience a layoff while enrolled. They compare students who worked at firms that had a mass layoff in their first year enrolled to students who worked at firms that had a mass layoff in their third year enrolled. They find that layoff leads to a considerable reduction in the probability of employment while in school, but it has little impact on enrollment decisions at the extensive margin. On the intensive margin, they find that layoff leads to an increase in enrolled credits. While the authors use the same administrative data that we use in this study, their analytical sample and research question are focused on individuals who are already enrolled prior to a layoff.

Our study is most similar to Frenette et al. (2011), who exploit micro-level variation in individual job displacement and consider the impact of mass-layoff on the postsecondary enrollment of workers in the Canadian context. They find that workers affected by mass layoff events are slightly more likely to subsequently enroll in college compared to workers not affected by mass layoff events. Using a strategy of individual fixed effects with a control group comparing enrollment before and after 2003 for workers displaced in 2003 versus similar workers who were not displaced, they find that job displacement for Canadian workers age 25-44 increases postsecondary enrollment by 0.6 to 1.3 percentage points over the subsequent four years, from a baseline enrollment rate of about 10% among a non-displaced comparison group.

Our study is the first to use micro-level data to measure the direct effect of job displacement on college enrollment in the United States. Aided by the richness of our worker-student matched administrative data, our work is also the first to examine heterogeneity in these effects, including by industry, geography, and earnings rank within the firm.

3 Data

We utilize three administrative data sources from the state of Ohio to study the links between displacement and education decisions. These data are made available through the Ohio Educational Research Center (OERC), which assembles data from multiple state agencies, including the Ohio Department of Higher Education (ODHE) and the Ohio Department of Job and Family Services (ODJFS), into a repository known as the Ohio Longitudinal Data Archive (OLDA).[2]

The first dataset provides information for all students attending Ohio public institutions of higher education between the years 2000 and 2011.[3] The data, which aggregate student performance to the student-by-semester level, includes credits earned, institution attended, degree information, as well as demographic variables such as race, age, and gender. All schools have four semesters corresponding to winter, spring, summer and fall, with the vast majority of schools experiencing

[2] The Ohio Longitudinal Data Archive is a project of the Ohio Education Research Center (http://www.oerc.osu.edu/oerc.osu.edu) and provides researchers with centralized access to administrative data. The OLDA is managed by The Ohio State University's CHRR (https://chrr.osu.edu/chrr.osu.edu) in collaboration with Ohio's state workforce and education agencies (http://www.ohioanalytics.gov/ohioanalytics.gov), with those agencies providing oversight and funding. For information on OLDA sponsors, see http://chrr.osu.edu/projects/ohio-longitudinal-data-archive.

[3] We have data on Ohio Technical Centers (OTCs) as well, a network of noncredit career development programs operated by local educational institutions, but do not use it in our analysis because only 1% of displaced workers in our sample (769 individuals) matched to the OTC dataset.

peak enrollment in the fall and spring semesters. We follow the approach employed by Jepsen et al. (2014) in which we assign the spring semester a start date of the first quarter and end date of the second quarter; the summer term is assigned a start date of the second quarter and an end date of the third quarter; and the fall semester is assigned a start date of the third quarter and an end date of the fourth quarter. From this dataset, we can construct a binary measure of enrollment as well as a discrete measure of number of classes taken.

The second dataset includes information on both firms and private sector, state, and local public employees subject to Unemployment Insurance (UI) contributions in Ohio between 1999Q3 and 2013Q1. Thus, an observation exists for every quarter an individual has positive earnings in the state of Ohio during this time period. Importantly, the earnings records include individual identifiers that link to the education data. Thus, for our purposes, we can identify the quarter of a displaced worker's separation as well as the quarter of entry at an Ohio public college or university.

The third dataset includes firm-level variables such as employer identifier, three-digit North American Industry Classification Systems (NAICS) codes, and county of the employer.[4] The identifiers, all derived from the Quarterly Census of Employment and Wages (QCEW), allow for construction of a firm-size variable by summing across the records associated with a given employer in each quarter.

The Ohio administrative data is particularly advantageous for the purposes of studying displaced workers' earnings patterns and education decisions. Ohio is the seventh largest U.S. state by population and lies at the heart of America's manufacturing region that has experienced several decades of deindustrialization. Between 2005 and 2016, three of top ten "trade-displaced" ZIP codes as calculated from Department of Labor estimates were located in Ohio (Hyman, 2018). The longitudinal nature of the data enables the tracking of worker tenure and enrollment patterns, facilitating the study of questions which could not be feasibly addressed in previous displaced worker studies which relied on information at a highly aggregated geographic level, such as Census division (Betts and McFarland, 1995) or commuting zone (Foote and Grosz, 2019).

[4]Note that the employer county data reflects the location of the enterprise. For multi-unit employers, the location of work may not be accurate for a given employee.

The Ohio data nevertheless have some limitations, typical of state administrative UI and education databases. First, we are unable to distinguish between individuals who leave Ohio, exit the labor force, or begin working for non UI-covered employers in the state. Second, we lack demographic information for workers who did not attend Ohio public institutions during the selected timeframe. Third, the education data does not include enrollment records at any private institutions or at public institutions outside of the state of Ohio. Although displaced workers may seek to retrain at private institutions, Xia (2016) shows that two-year for-profit schools respond more strongly to incentives from governmental financial aid availability than local demand for certain skills, the latter of which would be more relevant to our research question. Nevertheless, we use information on location of for-profit colleges to shed light on the role such institutions play for displaced workers.

We use the Ohio administrative records to construct a sample of displaced workers and a comparison group for our analysis of postsecondary enrollment patterns. We describe the construction of such samples below.

3.1 Displaced Sample

Displaced workers are typically defined as individuals with stable work histories who involuntarily separate from a firm because of a mass layoff and are unlikely to be recalled to their prior job – features which distinguish them from routine job changers or other unemployed individuals (Kletzer, 1998). Because we use administrative data, we cannot explicitly identify the reason for a worker's separation (quit, discharge for cause, etc.). Consistent with the displaced worker literature, we use separations during a mass layoff to identify workers who separate because of economic distress at their firm. Despite concerns that this approach misclassifies voluntary movers as displaced workers, Flaaen et al. (2019) shows that mass layoffs identified in administrative data serve as a reliable proxy for involuntary displacement.[5]

[5]Specifically, Flaaen et al. (2019) merges the Longitudinal Employer Household Dynamics (LEHD), an administrative dataset, with the Survey of Income and Program Participation (SIPP), which contains worker-provided reasons for separations. The authors find that earning loss estimates using only survey responses are very close to

We define a mass layoff as a 30% or more quarter-to-quarter reduction in firm's level of employment, a convention aligned with Davis and Von Wachter (2011). A firm shutdown is counted as a mass layoff. Because some firms exhibit many mass layoffs, we rank a firm's four largest mass layoffs by percentage change during the observed period (2002-2009) and assess only these four events to avoid over-counting. Furthermore, because small employers are mathematically more likely to meet this 30% benchmark without a substantial change in absolute employment, we adhere to Jacobson et al.'s (1993) practice of excluding firms with fewer than 50 employees from the sample of mass layoff firms.

Upon identifying dates of mass layoffs, we define a displaced worker as someone satisfying the following conditions: the individual (1) worked at a firm experiencing a firm shutdown or mass layoff in 2002q1 through 2009q4 within one year prior to the layoff date; (2) is not employed at the firm the quarter after the mass layoff; (3) worked at the firm continuously for at least three years prior to displacement; (4) holds only one job at the time of job separation; (5) earns the equivalent of at least minimum wage corresponding to 30 hours per week.[6] This definition aligns with Davis and Von Wachter (2011). Choosing a less-stringent tenure requirement (three years rather than six) allows use to study a greater number of displaced cohorts.[7]

We choose not to impose certain sample restrictions common in studies which examine the effect of job loss on future earnings if the conditioning behavior is correlated with or influenced by the decision to re-enroll. For example, we do not condition that workers in our sample remain attached to the labor force in the post-layoff period. While such a condition may be sensible for studying the wage scarring effects of unemployment, we are interested in the educational rather than employment outcomes of displaced workers. Some workers, particularly those who are not burdened by credit constraints, may opt to devote several years to schooling without balancing

those using only administrative data.

[6]Quarterly earnings corresponding to the minimum wage (in 2014 inflation adjusted dollars) is $2,163 in the quarter before displacement. This corresponds to earning $5.15/hour, Ohio's minimum wage from 2002-2006, for 30 hours per week for one full quarter.

[7]Lachowska et al. (2019) show that job displacement depresses long-run hours worked for employees with higher tenure (6 years) compared to lower tenure (3-4 years). To the extent that this suggests our sample is less attached to the labor force and more likely to return to school after layoff, our study's baseline estimates could be even lower if we restricted to six years of pre-displacement tenure.

a full-time work schedule. This sample selection criterion renders our paper's conclusions about educational choices relevant for all displaced workers, not just those attached to the labor force.

Likewise, we also do not impose that displaced workers claim unemployment insurance benefits upon job loss because, once again, such a condition influences one's decision to enroll in postsecondary education (Barr and Turner, 2018). Further, such a restriction would omit a substantial share of the population of interest from the sample. Auray et al. (2019) find that from 1989-2012, 23% of Americans eligible for UI benefits did not claim them. Moreover, the insured unemployment rate – defined as the number of unemployed individuals receiving UI benefits as a percentage of the labor force – during the Great Recession never eclipsed 5.0% even as the overall unemployment rate peaked at 10.0%.

3.2 Comparison Sample

We then create a sample of individuals who are not displaced throughout the whole panel. On these comparison and displaced samples, we estimate our multi-period individual fixed effects model, described in section 4, to compare enrollment outcomes before and after displacement. Traditionally, the displaced worker literature has used a "never displaced" control group of workers who remain continuously employed in order to isolate the share of future potential earnings that is destroyed when an individual involuntarily separates from a particular job. However, in our case, the outcome of interest is the likelihood of post-secondary enrollment instead of earnings. Thus, there is no need to compare a displaced worker to one who remained continuously at the same job.

We define a non-displaced worker as someone satisfying the following conditions: the individual (1) is continuously employed (but not necessarily at the same employer) throughout the whole panel (1999-2012); (2) had at least 3 years of tenure at any firm; (3) earns at least minimum wage corresponding to 30 hours per week. These latter two restrictions ensure our comparison group is similar to our treatment group, which has these same requirements. By limiting our comparison group to those who are continuously employed, we would if anything overstate the effects on education college enrollments. This comparison group has a higher opportunity cost of college enrollment, and would presumably be less sensitive to other factors driving education enrollments.

4 Empirical Approach

To infer the causal effect of displacement on various educational outcomes, we apply the standard multi-period individual fixed effect with comparison group model that has frequently been used to measure the effect of job loss on earnings (Jacobson et al., 1993; Davis and Von Wachter, 2011; Lachowska et al., 2019; Moore and Scott-Clayton, 2019). Our preferred measure of enrollment is $cumul\_enroll_{it}$, an indicator which assumes zero for each worker i until the first time she enrolls in a public college or university. $cumul\_enroll_{it}$ equals one during the period of first enrollment, and remains one for the rest of the panel regardless of worker i's enrollment status.

On the sample of displaced workers and non-displaced comparisons, we estimate

$$cumul\_enroll_{it} = \alpha_i + \gamma_t + \lambda_i \cdot t + W_{it}\beta + \sum_{k=-2}^{12} \delta_k \cdot D_{itk} + \varepsilon_{it} \tag{1}$$

where the variable of interest D_{itk} is an indicator that equals one if worker i is observed in quarter k relative to displacement in time period t, and equals zero otherwise. The final quarter of a displaced worker's observed tenure with the layoff firm is reflected when k assumes the value zero. We allow the index k to assume negative values as low as -2, because a worker may enroll in college in anticipation of a layoff that has not yet occurred. k assumes a maximum value of 12, thus restricting measurement of the effect of displacement to three full post-layoff years. The "omitted category" for the treated sample includes earnings in quarters -8 $\leq k \leq$ -3. Because the within-worker residuals cannot be assumed to be independent across time, we cluster at the worker level.

In equation (1), α_i are worker fixed effects which absorb an individual's constant propensity to enroll in public college over the length of the panel. Year-quarter time fixed effects, γ_t, capture any non-linear time effects of enrollment common across all workers (such as during the beginning of the Great Recession). We include worker-specific linear time trends, denoted by λ_i, which absorb any linear differential trend across workers. These worker-specific time trends account for the fact that the change in one's likelihood of enrolling college over time is much greater for some workers than others. For example, workers in different industries or occupations may have systematically different enrollment trends over time, even in the absence of displacement. These worker-specific trends will thus also control for differential trends by industry or occupation. Similarly, older workers are typically less likely to enroll in postsecondary school because they have fewer years left in the labor market to reap the returns of such education. Because we suspect the probability of enrollment is correlated with worker age[8], we consider one of the main values of worker-specific linear time trends in this case is to account for potentially differential time trends by age. Lastly, recognizing that workers with lower earnings are more likely to be displaced and, holding other factors constant, should be differentially more likely to enroll in college to increase future earnings, we further control for pre-layoff earnings interacted with time dummies. Specifically, W_{it} is a vector of year-quarter indicators interacted with the log of pre-displacement earnings (average of the 5-8 quarters before separation for the treatment group, average of 2003 earnings for comparison group), capturing any non-linear differential time-trends by pre-displacement earnings.

In order to identify $\hat{\delta}_k$ coefficients from equation (1) as a causal effect of displacement, we need to assume that displacement was orthogonal to unobserved, non-linear trends in employment or human capital. For example, if a worker receives a positive or negative shock that affects both post-secondary enrollment decisions and displacement, our approach will attribute any change in enrollment patterns to displacement rather than to this other shock. Another concern would be if employers specifically target workers for displacement that they know are planning to return to school. While it is not possible to fully rule out all alternative explanations, we do test the sensitivity of our results to alternative specification choices. We include several robustness checks in Appendix A, including models without individual-specific trends and examining effects for shutdowns versus mass layoffs separately. In addition, we also run our main specification separately for subgroups by industry, geography, and earnings percentile.

[8]Like many state administrative employment datasets, our sample lacks information on employees' ages.

We use several measures of enrollment throughout our analysis. Our preferred dependent variable is the cumulative indicator of any enrollment, $cumul\_enroll_{it}$, as defined above. We also examine an alternative point-in-time measure of enrollment, $enroll_{it}$, which indicates enrollment in an institution of higher education for worker i in year-quarter t.[9] Additionally, we use transcript information to construct a cumulative measure of college credits attained, $cumul\_credit_{it}$, as a dependent variable in robustness checks.

5 Results

5.1 Descriptive statistics on displaced workers and college enrollment

Table 1 describes basic characteristics of the displaced and non-displaced samples. Displaced workers are slightly more likely to have ever enrolled in a 2-year institution but less likely to have ever enrolled in a 4-year institution compared to non-displaced workers. Pre-displacement earnings are slightly lower for displaced workers than comparison workers in 2005Q1. There are also notable differences in their industry composition: displaced workers are substantially more likely than comparison workers to have been employed in construction, manufacturing, transportation and warehousing, and administrative, support, and waste management. Nearly half of all displaced workers were laid off from three 2-digit NAICS industries: manufacturing, construction, and retail trade.

Table 2 provides further details about displaced workers who enrolled in postsecondary education at some point between 2000 and 2011. The first column describes those who ever enrolled, the second describes those who enrolled after displacement, and the third describes displaced workers who enrolled for the first time as undergraduates after displacement. By comparing the sample size in the second column of Table 2 to the total sample of displaced workers from Table 1, we note that just under 10% of displaced workers exhibit a spell of post-layoff enrollment. The three samples are

[9] We consider $enroll_{it}$ a less illuminating measure with respect to the question of how many workers enroll in college as a result of displacement because resulting $\hat{\delta}_k$ coefficients only reveal how many displaced workers are induced to enroll at a given point in time. In theory, the set of workers who enroll in year-quarter k_0 relative to displacement could be the same or an entirely different set of individuals for all values t where $t \neq k_0$.

broadly similar in terms of their demographics and academic characteristics, although those who enroll for the first time (in our sample window) after displacement are older at the time of layoff and first enrollment than their peers. Interestingly, while the majority of enrollment for all three groups occurs at two-year institutions, 37% of displaced workers enrolled in a four-year institution after displacement, and 7% enrolled in a graduate program.

Displaced workers enroll in a wide range of fields, but health, engineering, and business are the most popular. Among those who enroll after layoff, 29% of them earn a degree within two years of displacement. Note that only 37% of workers who enrolled after job loss were unemployed in the quarter after displacement, and 51% were working more than part-time. Thus, the decision to return to school or continue seeking work is not a mutually exclusive one for displaced workers.

Data limitations prevent us from comparing the demographic information of workers who enroll in college to those who do not enroll. Nevertheless, we find roughly half of the displaced workers who enroll in an institution of higher education are female and 15% are non-white (Table 2). Among such workers, the median age at displacement and enrollment were 32 and 35, respectively.

Table 3 further describes patterns of educational enrollment and attainment for displaced workers who pursued school after layoff. On average, most displaced workers enroll as part-time students within two years after displacement and remain enrolled for over a year. Among those who earn a degree within four years after displacement (about 30% of displaced workers), about 40% earn an associate's degree, and 30% earn a bachelor's and 12% attain a master's degree.

We explore enrollment patterns of displaced workers according to the industry of their layoff employers in Table 4. Among our sample who enrolls in college after job loss, workers displaced from industries with lower-earnings—retail trade, transportation and warehousing, arts and entertainment, and food and accommodation services—skew much younger than the rest of the sample (median age 24 at layoff), while displaced manufacturing employees are substantially older (age 38). Nearly two-thirds of workers displaced from education and health services who seek postsecondary training do so at 4-year institutions, while this number is only 25% for manufacturing (the vast majority attend 2-year schools). Those displaced from education and health are the only group which pursue graduate enrollment at any appreciable rate (23%), while upwards of 95% of displaced workers from all other sectors attend undergraduate programs.

We also examine fields of study pursued by displaced workers from different industries. Many former manufacturing employees study engineering upon college enrollment (22% compared to 16% of overall displaced workers who enroll after layoff). Unsurprisingly, 39% of those laid off from education and health services pursue postsecondary training in health-related fields (and another 9% in education). This group is also disproportionately likely to pursue social and behavioral sciences (14% compared to 9% average). Those originating from the aforementioned low-wage industries pursue many different areas of study after job loss, including health (20%), business (17%), social and behavioral science (14%), arts and humanities (12%), and natural science and mathematics (10%).

5.2 Main Results

Before turning to effects on enrollment, it is useful to establish that the workers in our sample experience the same employment and earnings outcomes of displacement as has been documented by prior research. Figure 1 illustrates the well-documented effects of job displacement on employment and earnings for workers in our Ohio sample.[10] Four years after job loss, 15% of workers are not employed. They earn roughly 25% less than they would if they had not been displaced, a number consistent with the literature since Jacobson et al. (1993). Using the same administrative data and a very similar displaced sample, Moore and Scott-Clayton (2019) estimate about a 10-12 percentage point negative effect of displacement in a mass layoff on the likelihood of employment several years later. It is possible some of these unemployed individuals are enrolled in an institution of higher education, many are likely searching for a job, retired, or accepting public benefits such as disability insurance which keep them out of the labor force. Moreover, a number of the displaced workers who do enroll in school may be working full- or part-time contemporaneously.

Figure 2 plots two different measures of the enrollment rate for the comparison sample and cohort

[10]Coefficients plotted in Figure 1 result from specifications similar to equation (1), with employment status or log earnings as a dependent variable. These specifications do not use worker-specific linear time trends.

displaced in 2006Q1 and provides plausible evidence that our displaced and comparison samples follow similar enrollment trends prior to displacement. The point-in-time enrollment rate from Figure 2a exhibits a declining trend over time, likely representing age effects (enrollment declines as individuals get older). Figure 2b plots a cumulative enrollment rate, which increases over time but at a decreasing rate. The figure suggests that job displacement may have a positive effect on college enrollment. Further, enrollment appears to increase modestly at the time of or just before layoff. We quantify this effect by estimating the impact of displacement in the 2 quarters preceding layoff in specification (1).

Figure 3 plots the estimated coefficients from our main specification (listed in Table 5), which can be interpreted as the cumulative effect of job displacement on public college enrollment. We find that the enrollment response to job displacement is statistically significant but very small: for every 100 displaced workers, only 1 is ever induced to enroll in a public college within three years of layoff. Nearly the entire effect of displacement on enrollment occurs in the first year after layoff. The stability of the $\hat{\delta}_k$ coefficients for $k > 4$ suggest that virtually no new workers are induced to enroll after the first year.

We subject our main finding, that displacement has a positive but limited effect on public college enrollment, to several robustness checks in Appendix A. First, we apply our preferred specification *without* worker-specific linear time trends – to the displaced and comparison sample. Figure A.6 estimates a noticeably larger but still limited effect of 2.5 workers per every 100 who enroll as a result of displacement. Additionally, we use two alternative measures of enrollment: a quarter-varying enrollment indicator (as from Figure 2a) and a cumulative measure of college credits attained, constructed from student-level transcript information. Both suggest a small but positive effect of displacement on enrollment (Figures A.7 and A.8).

These results are highly consistent with Frenette et al. (2011) who find that for every 100 displaced workers in Canada, one worker is induced to return to school. Most of the "enrollment effect" occurs within the first year after displacement. Even though effects of displacement on enrollment seem small, it's worth noting that the causal effect of displacement on employment is only about 10 percentage points (Moore and Scott-Clayton, 2019).

5.3 Heterogeneity in Enrollment Effects

5.3.1 Industry of Layoff

We first explore whether propensity to enroll in college as a result of displacement varies considerably by industry. Theory might suggest that workers in industries such as manufacturing facing permanent disruptions (Baily and Bosworth, 2014; Pierce and Schott, 2016) might be more likely to return to school to retrain rather than try to find another similar job. On the other hand, older displaced workers have a shorter time horizon to recoup the payoff from additional educational investment and may be overrepresented in industries facing permanent disruptions like manufacturing.[11]

To maintain statistical power, we divide our displaced and non-displaced comparison samples into four broad industrial groups: manufacturing (NAICS 31-33), educational services, health care and social assistance (NAICS 61-62), wholesale trade, retail trade, transportation and warehousing, arts, entertainment, recreation, accommodation and food services (NAICS 42, 44-45, 48-49, 71, 72), and a remaining miscellaneous group. We apply equation (1) separately to each group. Results are presented in Figure 4 and Appendix Table A.3.

Former manufacturing employees clearly drive the bulk of the college enrollment response to displacement. These workers exhibit a strong enrollment response soon after displacement, as 2 in every 100 manufacturing workers had enrolled in college just four quarters after layoff. After four years, more than 2.5 displaced Ohio manufacturers pursued public college as a result. These workers contrast sharply with those laid off from other sectors, who do not appear to be induced to public college enrollment after job loss. While those laid off from retail, wholesale, transportation and warehousing, arts, entertainment, food and accommodation exhibit a modest significant positive effect in the first post-layoff year, after three years their likelihood of enrollment is not distinguishable from zero. Displaced workers in education, health, and the "other" category never

[11] Because of Ohio sample's limitations on demographic information, we examine demographics by industry of layoff for those in the Displaced Workers Supplement (DWS) of the Current Population Survey in Appendix C. We document that those laid off from manufacturing are, on average, among the oldest displaced workers (Table C.2).

enroll in college at a significant rate.

Because employees displaced from manufacturing account for the vast majority of those who consequently enroll, we focus our subsequent heterogeneity analysis on these workers. Restricting to a more homogenous set of workers in the same industry will allow to better assess how enrollment responses to displacement vary along other dimensions. As Table 4 describes, these laid off individuals are much more likely to enroll in two-year institutions than other displaced workers. Their most common fields of study are health, engineering, and business. At a national level, displaced manufacturing workers are older (average age at layoff is 44 years) and more likely to be male (62%). Over half have only a high school diploma or less (Table C.2).

5.3.2 Within-Firm Earnings

It is well-documented that earnings increase with firm-tenure (and therefore age) (Brown, 1989; Topel, 1991). While we cannot observe age for all workers directly, displaced workers with lower within-firm earnings may be younger and have more years remaining in their careers. These lower-paid, often younger workers may find schooling a more attractive pursuit after losing their job than their higher-paid counterparts. Even holding age and other factors constant, one might expect workers with lower incomes to be differentially likely to pursue postsecondary education to increase their human capital and future earnings. This may be especially true in manufacturing, as the highest-paid workers are often engineers or production managers, whose positions require a bachelor's degree and whose skills may be in higher demand at other firms. Those who worked as former assemblers and machinists, positions that are less well-remunerated and don't require a college degree, may have fewer attractive destinations in the labor market. Therefore, we investigate whether the enrollment effect varies by a worker's position within the earnings distribution at her layoff firm.

We divide displaced and comparison manufacturing workers by tercile of earnings within the firm and apply equation (1).[12] Despite splitting the sample by within-firm earnings, we still control

[12] A displaced worker is assigned an earnings tercile based on her earnings in the last full quarter before layoff. Terciles for a comparison worker are assigned based on earnings in 2005Q1.

for a worker's pre-layoff earnings interacted with time. As Figure 5 illustrates, the percentile of a worker's within-firm earnings strongly predicts college enrollment after layoff. Four quarters after displacement from a manufacturing firm, 4 workers per every 100 from the bottom tercile enrolled in college as a result, compared to just 2 and 1 from the middle and top terciles, respectively. Three years after layoff, the lowest-paid workers are still more than three-times as likely to have enrolled in college than those laid off from the top of the earnings distribution. The finding that lower-earning workers are more likely to enroll in college after displacement is robust to whether workers are divided into two or four groups (Appendix Figure A.1).

5.3.3 Geographic Access to College

We next investigate how job loss may have differential effects on enrollment patterns of manufacturing workers with varying proximity to public and for-profit colleges. We assign each displaced and non-displaced comparison worker a local labor market based on the county of her employer according to the Commuting Zone (CZ) scheme developed by Tolbert and Sizer (1996). CZs are clusters of counties that are characterized by commuting ties which are strong within-region and weak across regions. We then classify each of Ohio's seventeen multi-county CZs[13] as either high- or low-access in terms of higher education based on the number of institutions in the local labor market. We first designate high- and low-access CZs for public colleges, and then within this stratification we classify CZs by relative availability of for-profit institutions using data on location of for-profits from the Urban Institute's Education Data Portal in order to examine whether for-profit access may depress public enrollment.[14]

Because our data is limited to enrollment records at public universities, we cannot directly observe those who retrain at private institutions, including for-profit colleges. In 2009, for-profits accounted for 9% of nationwide enrollment in degree-granting schools. Deming et al. (2012) find that

[13]Two CZs – Huntington, WV and Parkersburg, WV – include only one Ohio county as they are mostly part of West Virginia, so we drop the small number of workers employed in these counties for geographic analysis.

[14]The Urban Institute's data combines information from Integrated Postsecondary Education Data System (IPEDS), the Department of Education's College Scorecard, and the National Historical Geographic Information System (NHGIS)

relative to other institutions, for-profits educate a larger fraction of minority, disadvantaged, and older students and more often grant degrees for short programs at the certificate and AA levels, suggesting they may be more prominent school avenues for displaced workers. Thus, displaced workers may seek retraining at easily accessible for-profits rather than public colleges. When Foote and Grosz (2019) estimate the enrollment response to mass layoff events, they do not find any statistically significant enrollment response at for-profit institutions (in contrast to their findings on public enrollment). However, their point estimate is still more than 50% as big as their estimate for public enrollment (1.5 for-profit enrollees per 100 displaced workers, versus 2.8 at public colleges), suggesting that for-profits may attract displaced workers at higher rates than they attract other types of students.

First, focusing on proximity to public institutions, we classify six CZs – Cincinnati, Cleveland, Columbus, Dayton, Portsmouth, and Toledo – as 'high-access' given they host at least 7 public colleges or universities. These CZs are home to employers which displace roughly 70% of the overall sample. Figure 6 presents estimates from specification (1) when splitting the manufacturing sample by high- and low-public college access CZ. In the first post-layoff year, roughly two workers out of every 100 enroll in college regardless of their geographic proximity to public colleges. After three years, these numbers diverge slightly, as roughly 2.5 (3.5) workers of every 100 displaced in a CZ with high (low) proximity to public schools are induced to enroll. The medium-run cumulative effect of displacement on enrollment follows a similar trajectory for both sets of workers: a strong push into enrollment in the first few quarters followed by two years of a gradually increasing effect. Further robustness checks at the county-level (rather than CZ-level) bolster the finding that geographic proximity to public institutions does not strongly predict enrollment propensity (Appendix Figure A.5).

Next, we further classify each high- or low-public college access CZ by its relative geographic concentration of for-profits using county-level data from the Urban Institute.[15] Figure 7 presents

[15]This classification designates Dayton, Portsmouth, and Toledo as high-public and low-for-profit local education markets and Canton, Lorain, and Youngstown as low-public and high-for-profit markets. The remaining CZs are either high- or low-access for both types of schools. For a full list of CZs, their classifications, and number of institutions, see Table B.1.

the results of equation (1) for these four distinct samples of workers, describing the effect of displacement on *public* college enrollment by geographic proximity to both for-profits and public institutions. Interestingly, workers are less likely to enroll in public colleges if displaced in local markets with higher concentration of for-profits. This pattern is consistent with other evidence for the substitutability of for-profits and community colleges for displaced workers seeking to retrain. The effect of displacement on public enrollment does not strongly correlate with the number of public options available.[16]

Specifically, workers displaced in local education markets with few for-profit institutions were the most likely to enroll in public college as a result. One year after displacement in these areas, roughly four in 100 displaced workers responded by enrolling. On the other hand, workers in markets with many for-profit institutions enrolled in public colleges at much lower rates in response to job loss. In the first post-displacement year, less than two such displaced manufacturing workers per every 100 enrolled in college. This result depends little on whether workers had many nearby public college options, although enrollment for "high-public, high-for-profit" workers was slightly higher than for "low-public, high-for-profit" counterparts in the first post-layoff year.

In Appendix A.2, we test other dimensions of heterogeneity which could have predictive power for displaced workers' enrollment patterns, such as calendar-quarter of layoff, firm size, and firm shutdown status. In each instance, roughly two of every 100 displaced manufacturing workers from various subgroups were induced to enroll in college.

6 Discussion and Conclusion

Despite the documented benefits of postsecondary education after a mass layoff (Jacobson et al., 2005a,b), job displacement is found to be associated with only a modest increase in college enrollment. For every 100 displaced workers, only about 1 is ever induced to enroll in a public college within four years of layoff. Workers are most likely to pursue higher education in the first post-layoff

[16] This may be because CZs with many public options also may have more alternative job options for displaced workers, or it may indicate that one public option is as useful as multiple public options when it comes to enrollment decisions.

year, with the median enrollment spell lasting five semesters. Very few workers are induced into enrollment beyond the first few quarters post-layoff. The sizable difference between these small causal estimates and the post-layoff probability of displaced workers' college enrollment observed in the data (9%) suggests that the majority of displaced individuals who enroll in college post-displacement would have likely done so even the absence of a job loss.

Our causal estimates are comparable to those from the limited empirical work on postsecondary enrollment patterns of displaced workers in other settings. Our baseline estimate that 1 out of every 100 displaced workers enrolls in college as a result of displacement is similar to Frenette et al. (2011), who estimate an effect of between 0.6 to 1.3 workers for every 100 displaced workers in Canada.[17] Our estimates are also in line with those from Foote and Grosz (2019), who estimate that for every 100 workers involved in mass layoff, 3 enrolled in a two-year college after three years.[18]

Our quantitatively-small estimate of displacement's effect on college enrollment, if anything, may overstate the true response we seek to measure. To obtain a causal estimate, we followed the displacement-earnings literature's long-standing approach by comparing the outcomes of our displaced sample's to those of a stably-employed control (Jacobson et al., 1993; Davis and Von Wachter, 2011; Lachowska et al., 2019). Our dynamic difference-in-difference model, which controls for individual-specific trends over time, assumes that displaced and comparison workers do not differentially deviate from these trends over time except for the effects of displacement. However, to the extent this assumption is violated (for example if some third factor contributes to both higher displacement and higher enrollment, or if employers displace workers they expect to enroll), this violation is likely to overestimate the enrollment response because workers in the continuously-attached comparison group exhibit such a high degree of employment stability that there could be less of motive for this group to seek postsecondary schooling at any point during their tenure.

Our findings of the heterogeneous effects of job loss on enrollment support our causal interpre-

[17] Frenette et al.'s (2011) estimates vary based on definition of displacement. Their definition most similar to ours (using mass layoffs to proxy for job displacement) yields estimates of 0.6% for males and 1.3% for females.

[18] Although Jacobson et al. (2005a) do not estimate a reduced-form effect of job loss on enrollment, the authors document that roughly 15% of displaced workers in 1990s Washington state later enroll in a 2-year community college. Although this is larger than our sample's post-layoff enrollment rate of 9%, the magnitudes of these descriptive patterns are reasonably aligned.

tation. For example, we find that manufacturing workers laid off in local labor markets with many public higher education institutions are much more likely to enroll in college before, at the time of, and long after displacement. Proximity to colleges has been shown to relate positively with enrollment (Card, 1993), suggesting our causal analysis of enrollment propensity by public college access is consistent with expectations. Further, our conclusion that displaced workers in local labor markets with more for-profit institutions are less likely to enroll in public colleges than counterparts in low-for-profit markets (independent of public-college concentration) accords with prior research indicating that public and for-profit schools are substitutes (Laband and Lentz, 2004; Cellini, 2009; Cellini et al., 2020).

A possible explanation for the small magnitude of effects could be that those who do experience persistent employment and earnings declines following a layoff may also face greater financial constraints (Ganong and Noel, 2019), depressing college enrollment. Student aid policies and labor market policies – including UI – can play a role in determining how and whether displaced workers engage in postsecondary education (Barr and Turner, 2015). Information failures could also play a role if displaced workers are not aware of the aid available to them. During the Great Recession, the State of Ohio sent out letters to UI recipients proactively informing them of their eligibility for federal Pell Grants. Barr and Turner (2018) studied this policy, exploiting the idiosyncratic timing of when the letters were sent in different areas, and concluded that the letters significantly increased the likelihood of college enrollment.[19]

Finally, while our estimated effect of displacement on college enrollment appears objectively small, it is worth placing the magnitude of this finding in context of post-displacement employment patterns, which indicate that most displaced workers quickly return to other jobs. For example, (Moore and Scott-Clayton, 2019) estimate a 10-12 percentage point negative effect of layoff on likelihood of employment several years later using the same administrative data and a very similar displaced sample. Lachowska et al. (2019) estimate an even smaller long-term impact on employ-

[19]Note, however, that according to Unemployment Insurance summary data from the US Department of Labor from 2019Q4, only 3 in 10 unemployed workers received UI benefits, so even these letters would not reach all the displaced workers considered in our sample. Further, Ohio did not send letters to UI recipients until December 2009, after the period of displacements that we examine in this analysis.

ment (a 3-4 percentage point decline) on displaced workers in Washington State during the Great Recession. It would be surprising for the share seeking retraining to be larger than the share remaining jobless in the years following separation. Still, interpreted along with other evidence, our results suggest that more work may be needed to ensure that college enrollment is an accessible option for displaced workers seeking to retrain.

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Figures

Table 1: Descriptive Statistics for Displaced and Comparison Group

	Displaced	Comparison
Industry of Layoff Firm		
Agriculture, Fishing, Hunting	0.008	0.001
Mining, Quarrying, Oil and Gas Extract	0.006	0.003
Utilities	0.001	0.010
Construction	0.100	0.021
Manufacturing	0.285	0.240
Wholesale Trade	0.029	0.057
Retail Trade	0.107	0.090
Transportation and Warehousing	0.078	0.031
Information	0.019	0.027
Finance and Insurance	0.083	0.074
Real Estate and Rental Leasing	0.008	0.011
Professional, Scientific, and Technical	0.038	0.042
Management of Companies and Enterprises	0.006	0.008
Administrative, Support, Waste Management	0.058	0.028
Educational Services	0.021	0.111
Health Care and Social Assistance	0.052	0.142
Arts, Entertainment, Recreation	0.025	0.006
Accommodation and Food Services	0.042	0.027
Other Services	0.019	0.015
Public Administration	0.012	0.053
Yearly Pre-Layoff Earnings		
1-4 Quarters Before ($)	49,888	54,153
	(38,976)	(37,491)
Higher Education		
Ever Enrolled in 2-Year Institution	0.113	0.094
Ever Enrolled in 4-Year Institution	0.062	0.086
N	68,547	898,040

Note: Standard errors for earnings are expressed in parentheses. Table lists the share of workers displaced from various industries between 2002q1 and 2009q4. Earnings are in inflation-adjusted to USD$2012 using the CPI-U. Industries are listed at 2-digit NAICS level. Because the comparison group is never displaced, industries represent their industry of employment in 2005q1. “Pre-layoff earnings” for the comparison group is four times their 2005q1 earnings.

Table 2: Summary Statistics: Displaced Workers with Enrollment Records

	Displaced Workers, 2002q1-2009q4		
	Ever enrolled, 2000-2011	Enrolled Post-Displacement	First Time UG Enroll Post Displacement
Basic Demographics			
Female	0.48	0.48	0.49
Non-white	0.14	0.14	0.15
Age at Displacement (median)	32	32	35
Age at First Enrollment (median)	35	35	38
Enrollment			
Any Enrollment in 2-yr Institution	0.72	0.76	0.77
Any Enrollment in 4-yr Institution	0.39	0.37	0.32
Any Undergraduate Enrollment	0.95	0.96	0.94
Any Graduate Enrollment	0.06	0.07	0.08
CIP Area at First Enrollment			
Arts & Humanities	0.14	0.11	0.12
Business	0.16	0.15	0.16
Education	0.05	0.05	0.05
Engineering	0.16	0.16	0.15
Health	0.16	0.20	0.21
Law	0.01	0.01	0.01
Natural Science & Mathematics	0.08	0.09	0.08
Services	0.04	0.04	0.04
Social & Behavioral Sciences	0.09	0.09	0.07
Trades & Repair Technicians	0.03	0.03	0.04
Degree Attainment			
Earned Degree w/i 2yrs of Displacement	N/A	0.29	0.25
Employment			
Unemployed quarter after layoff	0.36	0.37	0.40
More than Part-Time Employment	0.54	0.51	0.50
N	10,780	6,306	4,197

Note: The first column includes workers displaced between 2002q1 and 2009q4 with any record of enrollment at an Ohio public college or university (community college, 4-year undergraduate, or graduate program) between 2000 and 2011. This group includes workers who pursued higher education before and/or after displacement. The second column isolates displaced workers who enroll in a public college or university after displacement, regardless of enrollment status before job loss. The third column includes only workers who enroll in an undergraduate institution for the first time after they are displaced.

Table 3: Displaced Workers: Educational Attainment

	Years From Displacement to Enrollment	
	0-2 years	2-4 years
Enrollment		
Any Enrollment in a 2-yr Institution	0.732	0.725
Any Enrollment in a 4-yr Institution	0.331	0.344
Any Undergraduate Enrollment	0.943	0.943
Any Graduate Enrollment	0.066	0.070
Any Full-Time (FT) Enrollment	0.429	0.392
Any Part-Time (PT) Enrollment	0.869	0.874
Attainment		
# Courses Enrolled within 2 or 4 years	11.99	11.96
# Quarters Enrolled within 2 or 4 years	4.656	4.934
# Quarters Enrolled FT w/i 2 or 4 years	1.327	1.251
# Quarters Enrolled PT w/i 2 or 4 years	3.062	3.295
Earned Degree w/i 2 or 4yrs of Displacement	0.302	0.325
Among Those Completing Degree After Layoff		
Less than one-year award	0.060	0.053
Associate's degree	0.432	0.415
Bachelor's degree	0.289	0.305
Master's degree	0.120	0.135
First-professional degree	0.009	0.011
Doctoral degree	0.022	0.011
N	6,031	4,297

Note: First column provides enrollment and attainment variable means for displaced workers who enroll in an institution of higher education any time within the first two years after their displacement (including workers who were enrolled prior to displacement). The second column provides means for the same variables for displaced workers who enroll in an institution of higher education anytime between 2 and 4 years after their displacement. Because some workers enroll in the year after displacement and continue schooling for many years, the two groups are not disjoint. However, the 2-4 group is also not a proper subset of the 0-2 group. Attainment variables for courses and quarters enrolled correspond to either "within 2 years" for the first column or "within 4 years" for the second column.

Table 4: Summary Statistics: Displaced Workers with Enrollment Records by Industry of Layoff

	Displaced Workers, Enrolled Post-Layoff			
	Manufacturing	Educ/Health	RWTAEFA	Other
Basic Demographics				
Age at Displacement (median)	38	33	24	34
Enrollment				
Any Enrollment in 2-yr Institution	0.82	0.63	0.67	0.81
Any Enrollment in 4-yr Institution	0.25	0.62	0.53	0.29
Any Undergraduate Enrollment	0.98	0.86	0.98	0.96
Any Graduate Enrollment	0.02	0.23	0.08	0.06
CIP Area at First Enrollment				
Arts & Humanities	0.07	0.07	0.12	0.12
Business	0.17	0.06	0.17	0.15
Education	0.02	0.09	0.08	0.04
Engineering	0.22	*	0.08	0.21
Health	0.23	0.39	0.20	0.16
Law	0.02	*	*	*
Natural Science & Mathematics	0.10	0.11	0.10	0.07
Services	0.03	0.03	0.05	0.05
Social & Behavioral Sciences	0.06	0.14	0.14	0.07
Trades & Repair Technicians	0.03	*	*	0.05
Employment				
Unemployed quarter after layoff	0.52	0.45	0.33	0.40
More than Part-Time Employment	0.41	0.39	0.46	0.52
N	1,240	575	1,446	3,045

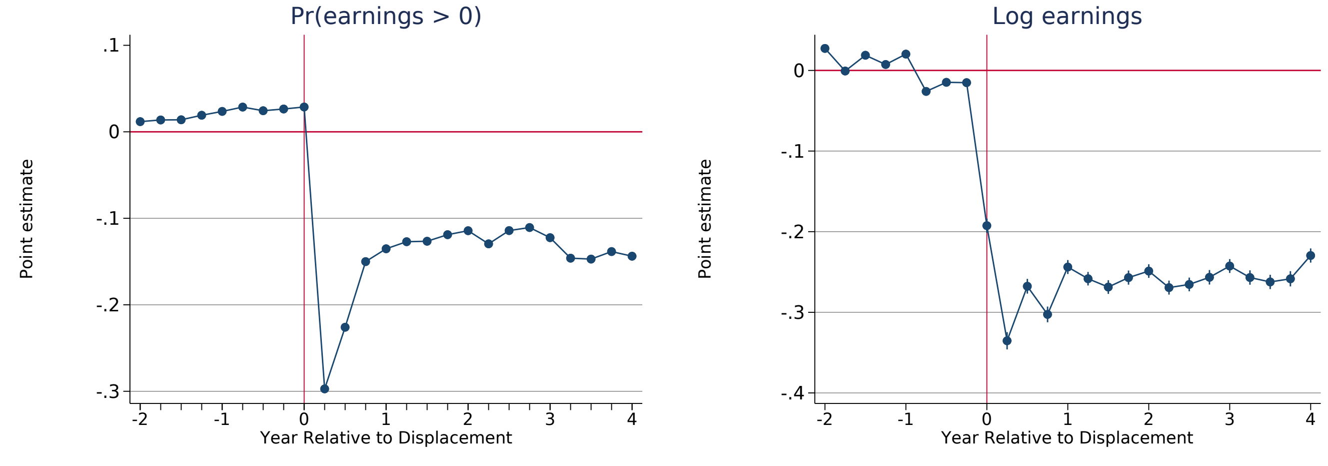
Note: This table splits the sample of workers who enroll in a public college after displacement (column 2 of Table 2) by broad industrial category of their layoff employer. The sample includes workers displaced between 2002q1 and 2009q4 with any record of enrollment at an Ohio public college or university after layoff and until 2011. Enrollment rates within a column may sum to more than 1 because workers enroll at multiple types of institutions. RWTAEFA includes workers displaced from Retail Trade, Wholesale, Transportation & Warehousing, Arts & Entertainment, and Food & Accommodation Services. Other includes remaining displaced workers laid off from firms outside manufacturing, education and health services, and RWTAEFA. * indicates that the cell value suppressed, as it represents less than 10 individuals.

Table 5: Cumulative Effect of Displacement on Enrollment, 2002-2009

Quarter rel. to displacement	
-2	0.0002
	(0.0003)
-1	0.0011*
	(0.0005)
0	0.0013*
	(0.0006)
1	0.0046***
	(0.0008)
2	0.0071***
	(0.0009)
3	0.0086***
	(0.0010)
4	0.0088***
	(0.0011)
5	0.0089***
	(0.0012)
6	0.0087***
	(0.0014)
7	0.0087***
	(0.0015)
8	0.0090***
	(0.0016)
9	0.0087***
	(0.0017)
10	0.0091***
	(0.0018)
11	0.0088***
	(0.0019)
12	0.0087***
	(0.0021)
Observations	44,291,188

Results from specification (1). Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1: Effect of Displacement on Employment and Earnings

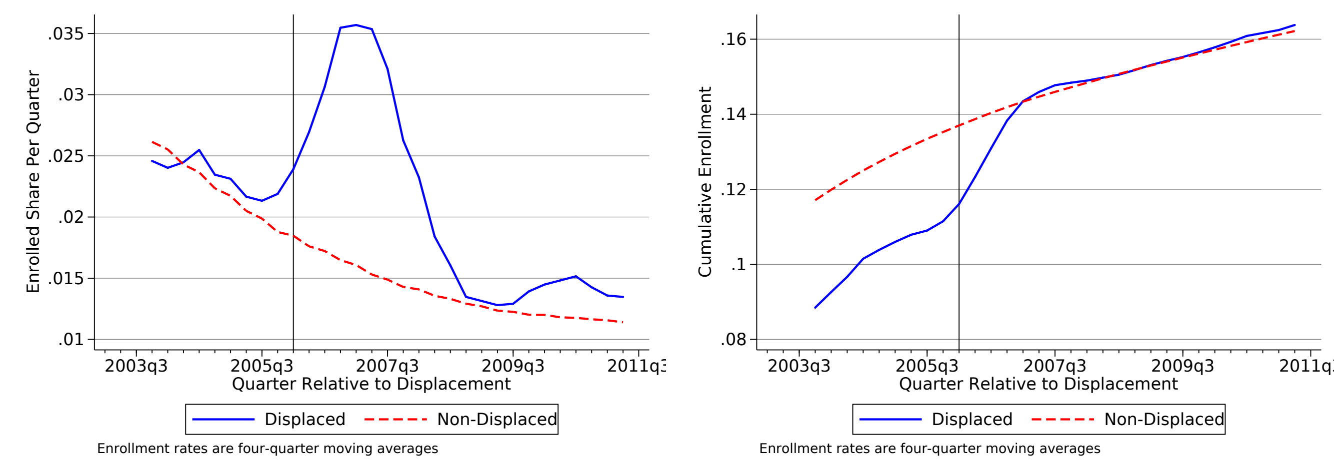


(a) Probability of Employment

(b) Log(earnings)

Note: Figure plots the estimated effect of displacement on a worker's probability of being employed (panel a) and log of earnings (panel b) in a given quarter compared to a stably employed comparison group (always employed at same employer). Whiskers (very small) denote 95-percent confidence intervals based on standard errors clustered by worker. Displaced sample is laid off between 2002q1 and 2008q4 (total sample for the paper is 2002-2009).

Figure 2: Enrollment Rates of Displaced and Non-Displaced Workers

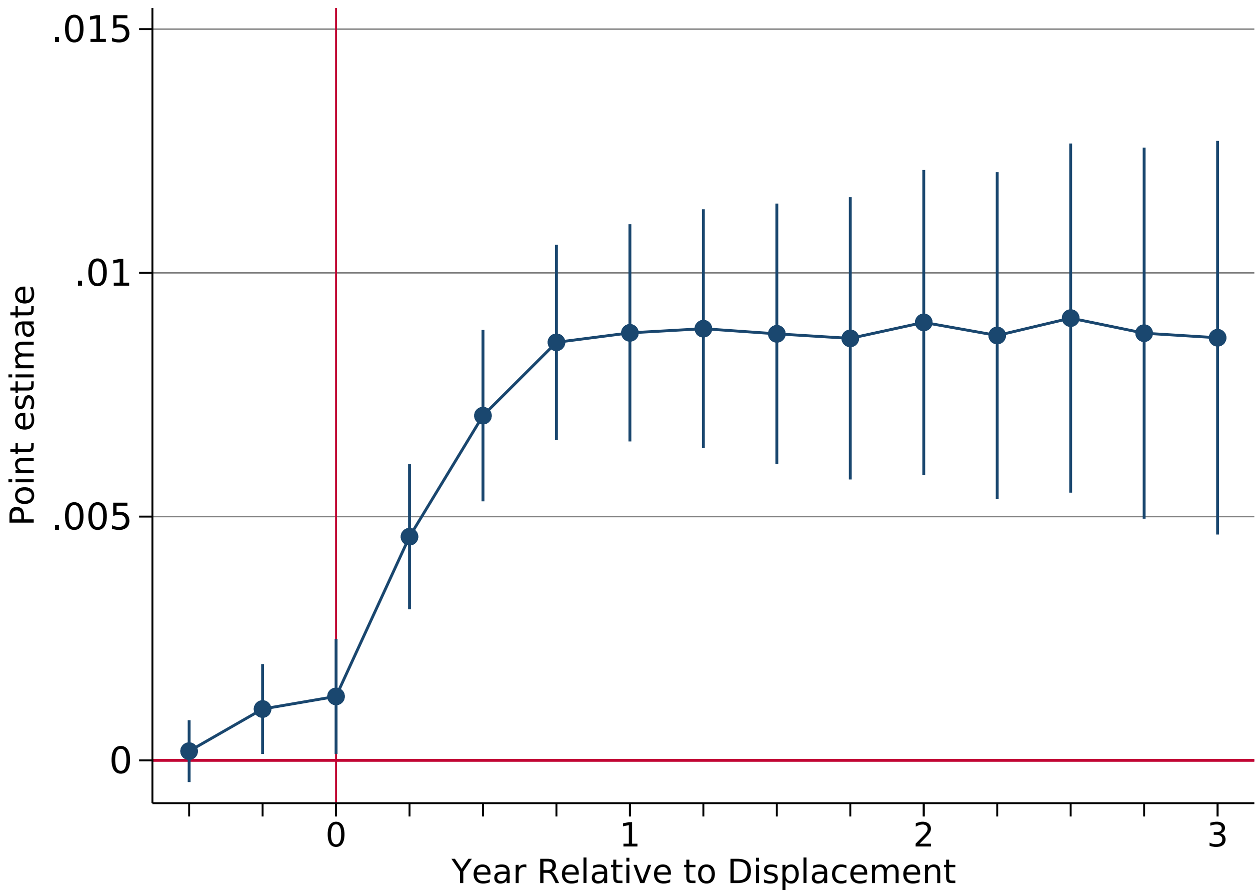


(a) Enrollment (point-in-time)

(b) Cumulative Enrollment

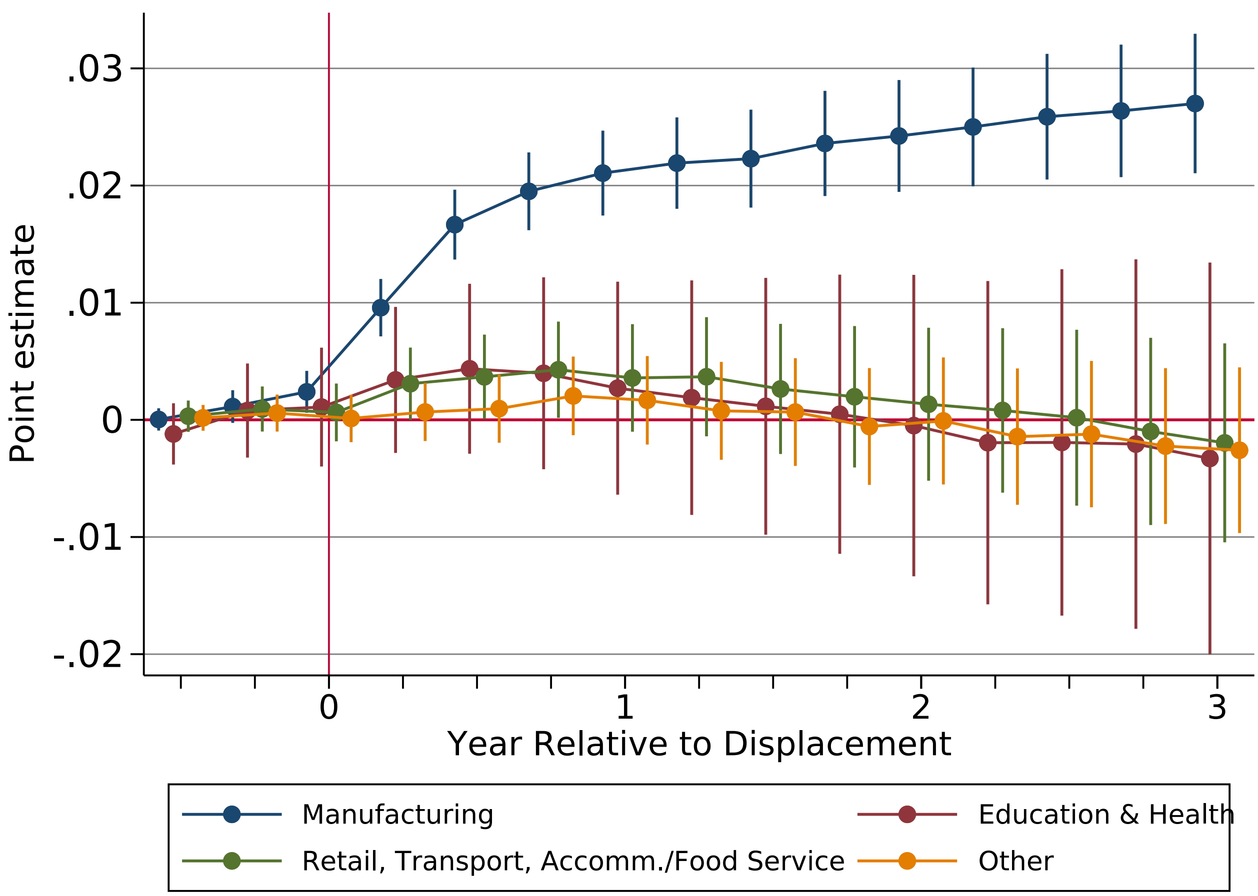
Note: Panels (a) and (b) plot the four-quarter moving averages of point-in-time and cumulative enrollment rates, respectively, for the cohort of workers displaced in 2006q1 and a comparison group attached to the labor force.

Figure 3: Cumulative Effect of Displacement on Enrollment, Displaced 2002-2009



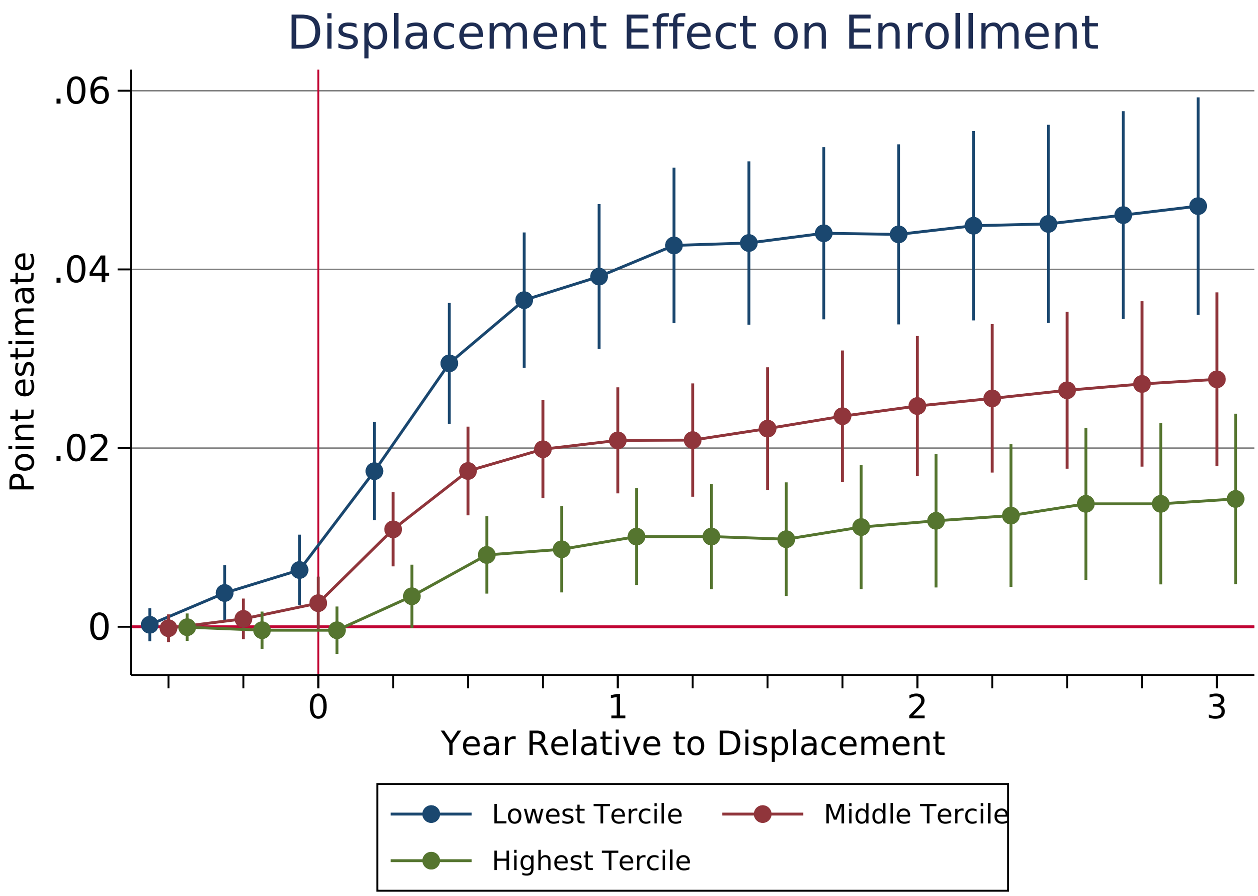
Note: Figure plots the estimated $\hat{\delta}_k$'s from equation (1). Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Displaced sample is laid off between 2002q1 and 2009q4. Coefficients with standard errors are listed in Table 5.

Figure 4: Cumulative Effect of Displacement on Enrollment by Industry of Layoff



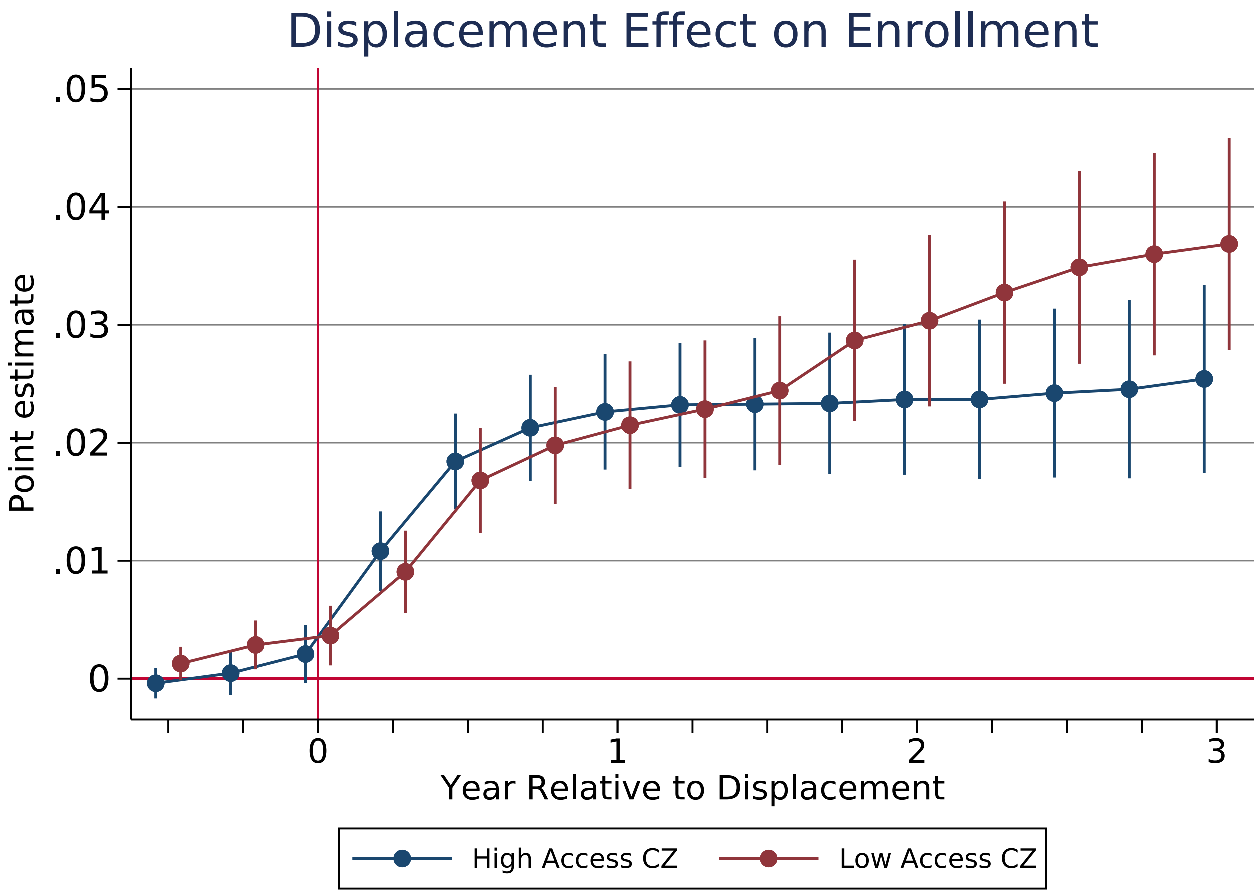
Note: Figure plots the $\hat{\delta}_k$'s from equation (1) estimated separately for workers displaced from employers (or stably employed at) in manufacturing (23% of displaced and comparison workers), education and health services (24%), retail, wholesale, transport and warehousing, arts and entertainment, accommodations and food services (20%), or other industries (33%). Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Displaced sample is laid off between 2002q1 and 2009q4. Point estimates and standard errors are listed in Appendix Table A.3.

Figure 5: Cumulative Effect of Displacement from Manufacturing on Enrollment by Earnings Tercile within Layoff Firm



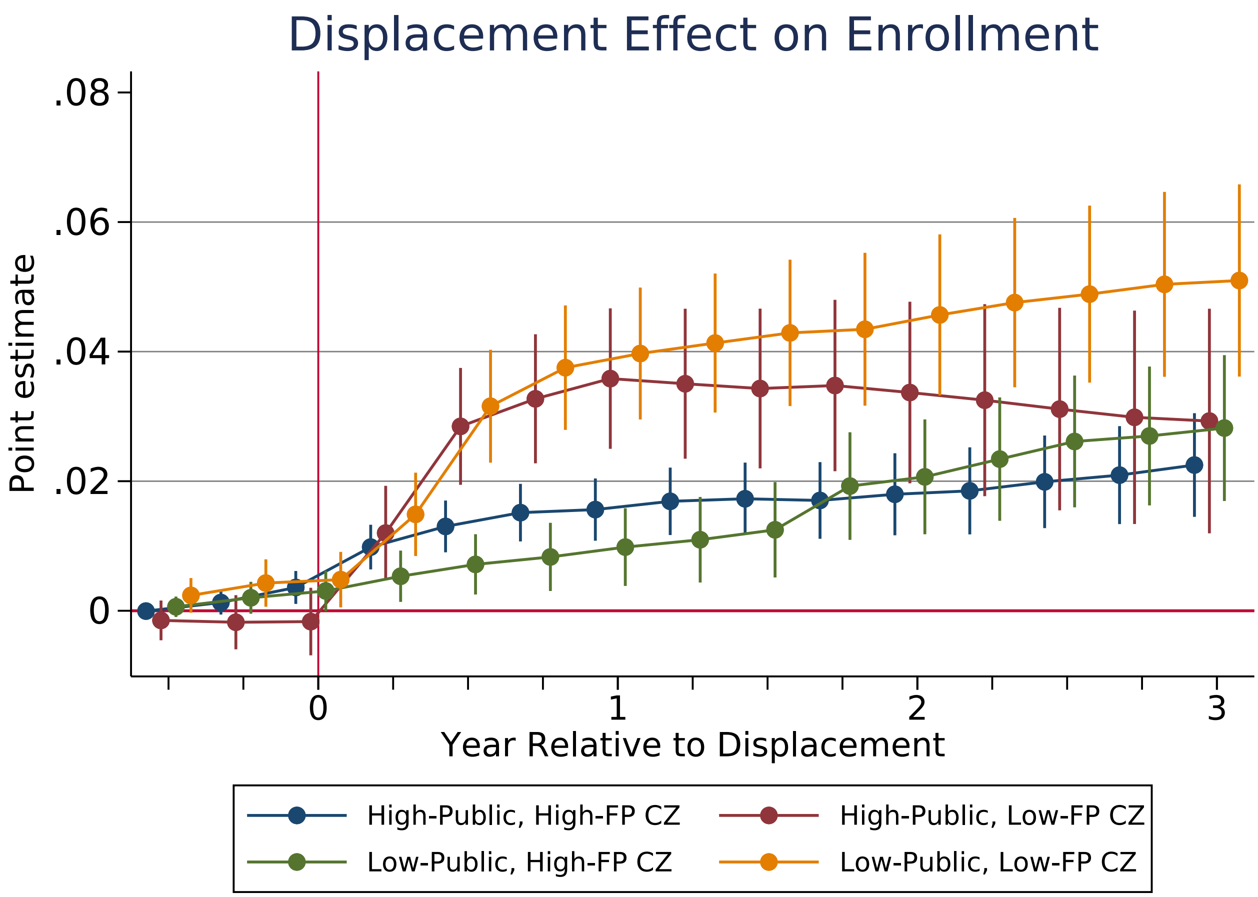
Note: Figure plots the $\hat{\delta}_k$'s from equation (1) estimated separately for displaced manufacturing workers with earning in the lowest, middle, and highest tercile of their firm at the time of layoff. The comparison workers are similarly split by wage tercile and include those who were employed at a manufacturing firm for at least three consecutive years. Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Displaced sample is laid off between 2002q1 and 2009q4. Displaced and comparison workers in the lowest, middle, and highest tercile comprise 20%, 35%, and 45% of the manufacturing sample, respectively. Point estimates and standard errors are listed in Appendix Table A.4.

Figure 6: Cumulative Effect of Displacement from Manufacturing on Enrollment by Local Labor Market Proximity to Public Higher Education



Note: Figure plots the $\hat{\delta}_k$'s from equation (1) estimated separately for workers displaced from employers located in high vs. low college access commuting zones (CZs). Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Displaced sample is laid off between 2002q1 and 2009q4. Point estimates and standard errors are listed in Appendix Table A.7. "High-access CZs" are those which host seven or more public institutions of higher education (four-year universities, branch campuses, community colleges, or technical colleges). Appendix Table B.1 lists each CZ's classification as high- or low-access with respect to public institutions. Workers displaced in the Parkersburg and Huntington, WV commuting zones are excluded because their CZs only include one Ohio county. 64% of displaced workers were laid off in high-access CZs and 36% from low-access CZs.

Figure 7: Cumulative Effect of Displacement from Manufacturing on Enrollment by Proximity to Public and For-Profit Institutions



Note: Figure plots the $\hat{\delta}_k$'s from equation (1) estimated separately for manufacturing workers displaced from employers located in commuting zones (CZs) classified by access to both public and for-profit college. CZs are divided according to public college access as in Figure 6, and then divided by high- and low- for-profit access within these groups according to locations of for-profits in 1999. "High-access public, high-access for-profit" CZs include Cincinnati, Cleveland, and Columbus (blue), representing 43% of the displaced manufacturing sample. "High-access public, low-access for-profit," including Dayton, Portsmouth, and Toledo (red), represents 21% of the sample. "Low-access public, high-access for-profit," including Canton, Lorain, and Youngstown (green), represents 22% of the sample. "Low-access public, low-access for-profit," including Athens, Defiance, Findlay, Lima, Mansfield, Steubenville, Washington, Wheeling (WV), and Zanesville (yellow), represents 14% of the sample. Workers displaced in the Parkersburg and Huntington, WV commuting zones are excluded because their CZs only include one Ohio county. Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Displaced sample is laid off between 2002q1 and 2009q4. Point estimates and standard errors listed in Table A.8.

Appendix

A Further Results

In Appendix A, we present further results and robustness checks for our paper's analysis.

A.1 Tables Corresponding to Main Body

Tables presenting point estimates and standard errors for regression results presented in Figures 4, 5, 6, and 7 are listed in this section. The tables are Table A.3, A.4, A.7 and A.8, respectively.

A.2 Heterogeneity

As a sensitivity check for our results in Figure 6, we conduct similar analysis at the county rather than commuting zone level. Specifically, we apply equation (1) when splitting samples according to whether manufacturing workers were employed (or laid off) in a county with a public community college (Figure A.5a). A list of community colleges and corresponding counties is provided in Table B.2. We find that workers displaced in "community college counties" are initially more likely to enroll than those without a community college in their county. After three years, however, the estimated effects on cumulative enrollment converge, such roughly 3 per every 100 displaced manufacturing workers pursue postsecondary training regardless of whether their county is home to a community college.

In Figure A.5b, we restrict this sample of displaced and comparison workers to those employed in counties *without* 4-year non-branch universities ("main universities" specified in Table B.3). Among these manufacturing employees for whom enrollment in a nearby 4-year university is less accessible due to geography, we estimate a larger enrollment response among those laid off in counties *without* a community college (4 per every 100 compared to 3 after three post-displacement years). We believe the results of Figures A.5a and A.5b, taken together, bolster our finding that increased proximity to public postsecondary institutions does not correlate with higher post-displacement enrollment.

Beyond heterogeneity explored in the main body of the text, in this section we investigate whether the effect of displacement on enrollment varied by other characteristics, including calendar quarter of layoff, firm size, and whether or not a firm shut down operations. Similar to the main text, we restrict our analysis to the subset of displaced workers laid off from manufacturing firms and comparison group workers who were employed for at least three years at a manufacturing plant.

If laid off between October and December, a worker may need to wait almost a full year to enroll if they want to start at the beginning of a school year, while those displaced between July and September may be able to start a new program immediately. This difference in season of layoff may change the individual's cost-benefit assessment and thus lead to differences in enrollment patterns. We examine this hypothesis in Figure A.2, which applies equation (1) separately to the workers displaced from manufacturing firms by calendar quarter of layoff and a common group of comparison manufacturing workers. Note that for this analysis, the quarter of layoff is defined as the last quarter of non-zero earnings at the displacement firm, such that a worker with non-zero earnings at the firm in Q3 and zero earnings at the firm in Q4 would be considered a Q3 layoff. The enrollment effects for displaced manufacturing workers are low across the board with limited seasonal variation. One year after job loss, between 1 and 2 out of every 100 manufacturing workers has been induced to enroll in public college regardless of calendar-quarter of layoff.

We also analyze enrollment patterns of workers by layoff firm characteristics, such as employer size and whether it fully shut down as opposed to implementing a mass layoff. One may speculate that firm size may have predictive power regarding how many displaced workers ultimately pursue postsecondary retraining. Historically, certain large firms have partnerships with local community colleges that may heighten workers' awareness of retraining options (Johnson, 1996; Roueche et al., 1995). Moreover, because large firms are subject to the Worker Adjustment and Retraining Notification (WARN) Act—which requires employers to provide at least 60 days of notice before plant closure or a mass layoff—affected employees could search for opportunities to enroll before separating from their job.[20]

To investigate this, we classify our displaced and non-displaced comparison samples by size of employer, designating a "large firm" and "small firm" group and applying equation (1) separately to each. We allow both 500 workers and 1,000 workers to serve as the cutoff for classification as a small or large firm. Figure A.3 underscores, however, that the size of the firm is not predictive of the share of displaced workers who are induced to enroll. In each case, roughly 2.5 per every 100 manufacturing workers enroll as a result of layoff.

Lastly, we study enrollment effects by firm shutdown status – proxied by a firm's unique identifier disappearing in the employer records or if employment level drops to zero – because many individuals' jobless spells end with "recall hires," reemployment at the firm from which they separated (Fujita and Moscarini, 2017; Albertini and Fairise, 2018). If newly-displaced workers expect to be recalled by their employers, they may be less likely to seek retraining to change occupations while jobless.[21] In addition, examining firm shutdowns separately from mass layoffs may also address the identification concern that employers might non-randomly target specific workers for layoffs that may correlate with these workers' expected enrollment trends.

We apply equation (1) to the comparison group and the subset of displaced workers who lose their jobs in firm shutdowns, rather than simply any mass layoff. We classify displaced workers to have lost their job in a firm shutdown if they were employed within six quarters of a shutdown. We choose this window (as opposed to classifying only those workers who remain with the firm until the last period) because, in addition to the fact mass layoffs often occur in the months or years before a shutdown, many workers quit due to economic distress at the firm in anticipation of an impending shutdown (Flaaen et al., 2019).[22] Figure A.4 compares the baseline estimates from specification (1)

[20] Specifically, WARN applies to employers with 100 or more employees (excluding new and seasonal workers) to provide at least 60 calendar days advance written notice of a plant closing and mass layoff affecting 50 or more employees at a single site of employment.

[21] According to Handwerker and Mason (2012), the Mass Layoff Statistics program documents that roughly half of firms which contracted substantially according to administrative data records reported that expected to recall some workers in the future.

[22] In the recent case of General Motors' Lordstown Assembly Complex in Lordstown, Ohio, GM first announced layoffs in November 2016 effective in 2017Q1. In 2018Q2, it announced a second wave of layoffs. Finally, in November 2018 GM announced its intention to close the Lordstown plant, which was idled in March 2019 (Maher, 2018; Lendel et al., 2019). For those Lordstown employees who left GM several months before March, while the proximate reason for separation may have been finding a new job, their ultimate reason for leaving was the firm distress and impending

for the entire displaced sample with those for the subset of workers laid off in a firm shutdown (26% of all displaced manufacturing workers). Similar to firm size, whether a firm shut down operations does not predict whether a worker subsequently enrolls in a public college.

A.3 Other Measures and Specifications for Enrollment Effect

As mentioned in Section 4, we estimate the effect of job displacement on postsecondary enrollment with variations of specification (1) as a robustness check.

The following equation is similar to (1) but omits worker-specific linear time trends.

$$cumul\_enroll_{it} = \alpha_i + \gamma_t + W_{it}\beta + \sum_{k=-2}^{12} \delta_k \cdot D_{itk} + \varepsilon_{it} \tag{2}$$

Figure A.6 presents the point estimates and 95% confidence intervals resulting from equation (2) applied to the overall sample of displaced and comparison workers. Three years post-layoff, this measure estimates that 2.5 per every 100 displaced workers subsequently enrolls in college compared to just 1 in our baseline estimates from equation (1).

We use transcript information to construct a cumulative measure of college credits attained, $cumul\_credit_{it}$, as a further robustness check for our finding that displacement has a limited but positive effect on public college enrollment. While $cumul\_enroll_{it}$ only assumes the values of 0 or 1, $cumul\_credit_{it}$ is a cumulative and unbounded above.

$$cumul\_credit_{it} = \alpha_i + \gamma_t + \lambda_i \cdot t + W_{it}\beta + \sum_{k=-2}^{12} \delta_k \cdot D_{itk} + \varepsilon_{it} \tag{3}$$

Figure A.7 presents the results of equation (3) applied to the overall displaced and comparison sample. While we estimate virtually no effect in the quarters leading up to job loss, just one year after separation, roughly 12 college credits have been attained by displaced workers for every 100 laid off. After three years, this effect rises to over 30 credits. Figure A.7 suggests a reasonable degree of enrollment persistence. However, given a typical college course amounts to 3 credits, we consider this further evidence that the effect of displacement on enrollment is fairly limited.

Lastly, we use a shorter time horizon and a point-in-time measure of enrollment, $enroll_{it}$, as a dependent variable in equation 4. Figure A.8 presents the results.

$$enroll_{it} = \alpha_i + \gamma_t + \lambda_i \cdot t + W_{it}\beta + \sum_{k=-2}^{12} \delta_k \cdot D_{itk} + \varepsilon_{it} \tag{4}$$

While displacement does not have a statistically significant effect on postsecondary enrollment during the calendar-quarter of layoff, we estimate a positive effect in the following quarters. The effect peaks in the third full post-layoff quarter and fades to near-zero after two years. Using the point-in-time enrollment measure, we estimate that three quarters after layoff, 1 worker for every 100 displaced enrolled was enrolled in college as a result.

shutdown.

Table A.1: Industry of Displacement by Calendar Quarter of Layoff

	Quarter of Displacement			
	1st	2nd	3rd	4th
Industry				
Construction, Utilities, Mining	0.087	0.120	0.115	0.118
Manufacturing	0.403	0.297	0.329	0.201
Retail Trade	0.098	0.126	0.081	0.147
Transportation & Warehousing	0.016	0.039	0.033	0.019
Finance, Insurance, Real Estate	0.046	0.038	0.052	0.215
Educational & Health Services	0.111	0.081	0.078	0.061
Hospitality & Food Services	0.029	0.046	0.064	0.047
Other	0.210	0.253	0.248	0.192
N	15,151	15,442	15,095	22,859

Note: Table lists the share of workers displaced from different industries during a given calendar quarter. The 1st quarter corresponds to a mass layoff during January–March. The 2nd quarter is April–June, the 3rd quarter is July–September, and the 4th quarter is October–December.

Table A.2: Displaced Worker Descriptive Statistics by Firm Shutdown Status

	Displaced in Firm Shutdown	
	Yes	No
Industry of Layoff		
Construction, Utilities, Mining	0.112	0.111
Manufacturing	0.278	0.297
Retail Trade	0.268	0.063
Transportation & Warehousing	0.018	0.028
Finance, Insurance, Real Estate	0.044	0.129
Educational & Health Services	0.072	0.083
Hospitality & Food Services	0.041	0.048
Other	0.167	0.241
Yearly Pre-Layoff Earnings		
1-4 Quarters Before ($)	44,837	51,746
	(34,619)	(40,398)
Firm Characteristics		
Average Number of Employees	846	1,463
Std. Dev. of Yearly Earnings ($)	30,582	39,923
Median Annual Earnings ($)	32,950	43,957
N	17,281	51,266

Note: Table lists the share of workers displaced between 2002q1 and 2009q4 from different industries by whether or not they were laid off in a firm shutdown. Standard deviation of pre-displacement earnings is in parentheses. Earnings are in inflation-adjusted to USD$2012 using the CPI-U.

Table A.3: Cumulative Effect of Displacement on Enrollment by Layoff Industry

	Manufacturing	Educ/Health	RWTAEFA	Other
Quarter rel. to displacement				
-2	0.0000	-0.0012	0.0003	0.0002
	(0.0005)	(0.0013)	(0.0007)	(0.0006)
-1	0.0011	0.0008	0.0009	0.0006
	(0.0007)	(0.0020)	(0.0010)	(0.0008)
0	0.0024**	0.0011	0.0006	0.0001
	(0.0009)	(0.0026)	(0.0013)	(0.0010)
1	0.0096***	0.0034	0.0031*	0.0007
	(0.0013)	(0.0032)	(0.0016)	(0.0013)
2	0.0167***	0.0044	0.0037*	0.0010
	(0.0015)	(0.0037)	(0.0018)	(0.0015)
3	0.0195***	0.0040	0.0043*	0.0020
	(0.0017)	(0.0042)	(0.0021)	(0.0017)
4	0.0211***	0.0027	0.0036	0.0017
	(0.0018)	(0.0046)	(0.0023)	(0.0019)
5	0.0219***	0.0019	0.0037	0.0008
	(0.0020)	(0.0051)	(0.0026)	(0.0021)
6	0.0223***	0.0012	0.0026	0.0007
	(0.0021)	(0.0056)	(0.0028)	(0.0023)
7	0.0236***	0.0005	0.0020	-0.0006
	(0.0023)	(0.0061)	(0.0031)	(0.0025)
8	0.0242***	-0.0005	0.0013	-0.0001
	(0.0024)	(0.0066)	(0.0033)	(0.0028)
9	0.0250***	-0.0019	0.0008	-0.0014
	(0.0026)	(0.0070)	(0.0036)	(0.0030)
10	0.0259***	-0.0019	0.0002	-0.0012
	(0.0027)	(0.0075)	(0.0038)	(0.0032)
11	0.0264***	-0.0021	-0.0010	-0.0022
	(0.0029)	(0.0080)	(0.0041)	(0.0034)
12	0.0270***	-0.0033	-0.0020	-0.0026
	(0.0030)	(0.0085)	(0.0043)	(0.0036)
Observations	10,362,772	10,450,584	8,992,820	14,485,012

Note: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; RWTAEFA: Retail, Wholesale, Transportation & Warehousing, Arts & Entertainment and Food & Accommodation

Table A.4: Cumulative Effect of Displacement from Manufacturing on Enrollment by Within-Firm Tercile of Earnings

Quarter rel. to displacement	Lowest	Middle	Highest
-2	0.0002	-0.0002	-0.0000
	(0.0009)	(0.0008)	(0.0008)
-1	0.0038*	0.0009	-0.0004
	(0.0016)	(0.0012)	(0.0011)
0	0.0064**	0.0026	-0.0004
	(0.0020)	(0.0015)	(0.0014)
1	0.0174***	0.0109***	0.0034
	(0.0028)	(0.0021)	(0.0018)
2	0.0295***	0.0174***	0.0080***
	(0.0034)	(0.0025)	(0.0022)
3	0.0366***	0.0199***	0.0087***
	(0.0039)	(0.0028)	(0.0025)
4	0.0392***	0.0209***	0.0101***
	(0.0041)	(0.0030)	(0.0028)
5	0.0427***	0.0209***	0.0101***
	(0.0044)	(0.0032)	(0.0030)
6	0.0430***	0.0222***	0.0098**
	(0.0047)	(0.0035)	(0.0032)
7	0.0440***	0.0236***	0.0112**
	(0.0049)	(0.0038)	(0.0035)
8	0.0439***	0.0247***	0.0119**
	(0.0051)	(0.0040)	(0.0038)
9	0.0449***	0.0256***	0.0124**
	(0.0054)	(0.0042)	(0.0041)
10	0.0451***	0.0265***	0.0138**
	(0.0057)	(0.0045)	(0.0043)
11	0.0461***	0.0272***	0.0138**
	(0.0059)	(0.0047)	(0.0046)
12	0.0471***	0.0277***	0.0143**
	(0.0062)	(0.0050)	(0.0049)
Observations	2,212,479	4,000,350	5,192,558

Note: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Samples are divided by within-firm tercile of earnings in 2005Q1 (for comparison group) or in the quarter prior to displacement (for displaced group).

Table A.5: Cumulative Effect of Displacement from Manufacturing on Enrollment by Earnings Relative to Firm Median

Quarter rel. to displacement	Below Median	Above Median
-2	0.0003	-0.0001
	(0.0007)	(0.0006)
-1	0.0027*	0.0000
	(0.0012)	(0.0009)
0	0.0048**	0.0006
	(0.0015)	(0.0011)
1	0.0155***	0.0052***
	(0.0021)	(0.0015)
2	0.0249***	0.0106***
	(0.0025)	(0.0019)
3	0.0298***	0.0118***
	(0.0028)	(0.0021)
4	0.0311***	0.0136***
	(0.0030)	(0.0023)
5	0.0335***	0.0133***
	(0.0032)	(0.0025)
6	0.0345***	0.0133***
	(0.0034)	(0.0027)
7	0.0354***	0.0149***
	(0.0036)	(0.0029)
8	0.0352***	0.0162***
	(0.0038)	(0.0031)
9	0.0362***	0.0168***
	(0.0040)	(0.0034)
10	0.0366***	0.0180***
	(0.0042)	(0.0036)
11	0.0374***	0.0183***
	(0.0045)	(0.0038)
12	0.0380***	0.0189***
	(0.0047)	(0.0040)
Observations	4,158,847	7,246,640

Note: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Samples are divided by within-firm tercile of earnings in 2005Q1 (for comparison group) or in the quarter prior to displacement (for displaced group).

Table A.6: Cumulative Effect of Displacement from Manufacturing on Enrollment by Within-Firm Quartile of Earnings

Quarter rel. to displacement	Lowest Quartile	2nd Quartile	3rd Quartile	4th Quartile
-2	0.0003	0.0000	-0.0001	-0.0002
	(0.0013)	(0.0009)	(0.0009)	(0.0009)
-1	0.0031	0.0022	0.0006	-0.0006
	(0.0020)	(0.0014)	(0.0013)	(0.0012)
0	0.0066*	0.0035*	0.0022	-0.0011
	(0.0026)	(0.0018)	(0.0017)	(0.0016)
1	0.0175***	0.0141***	0.0081***	0.0021
	(0.0035)	(0.0026)	(0.0022)	(0.0021)
2	0.0308***	0.0210***	0.0142***	0.0068**
	(0.0044)	(0.0031)	(0.0027)	(0.0026)
3	0.0372***	0.0251***	0.0165***	0.0070*
	(0.0049)	(0.0034)	(0.0030)	(0.0029)
4	0.0399***	0.0255***	0.0190***	0.0081*
	(0.0053)	(0.0036)	(0.0033)	(0.0033)
5	0.0427***	0.0276***	0.0182***	0.0084*
	(0.0056)	(0.0039)	(0.0035)	(0.0036)
6	0.0430***	0.0291***	0.0186***	0.0078*
	(0.0060)	(0.0042)	(0.0037)	(0.0039)
7	0.0438***	0.0300***	0.0207***	0.0090*
	(0.0063)	(0.0044)	(0.0040)	(0.0043)
8	0.0438***	0.0297***	0.0229***	0.0093*
	(0.0066)	(0.0047)	(0.0043)	(0.0046)
9	0.0447***	0.0308***	0.0243***	0.0091
	(0.0070)	(0.0049)	(0.0046)	(0.0049)
10	0.0451***	0.0313***	0.0267***	0.0092
	(0.0073)	(0.0052)	(0.0048)	(0.0052)
11	0.0453***	0.0324***	0.0273***	0.0092
	(0.0077)	(0.0055)	(0.0051)	(0.0056)
12	0.0451***	0.0336***	0.0283***	0.0095
	(0.0080)	(0.0058)	(0.0054)	(0.0059)
Observations	1,460,934	2,697,813	3,374,825	3,871,815

Note: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Samples are divided by within-firm tercile of earnings in 2005Q1 (for comparison group) or in the quarter prior to displacement (for displaced group).

Table A.7: Cumulative Effect of Displacement from Manufacturing on Enrollment by Local Labor Market Proximity to Public Higher Education

Quarter rel. to displacement	High-Access	Low-Access
-2	-0.0004	0.0013
	(0.0007)	(0.0007)
-1	0.0005	0.0029**
	(0.0010)	(0.0011)
0	0.0021	0.0037**
	(0.0012)	(0.0013)
1	0.0108***	0.0091***
	(0.0017)	(0.0018)
2	0.0184***	0.0168***
	(0.0021)	(0.0023)
3	0.0213***	0.0198***
	(0.0023)	(0.0025)
4	0.0226***	0.0215***
	(0.0025)	(0.0028)
5	0.0232***	0.0229***
	(0.0027)	(0.0030)
6	0.0233***	0.0244***
	(0.0029)	(0.0032)
7	0.0233***	0.0287***
	(0.0031)	(0.0035)
8	0.0237***	0.0303***
	(0.0033)	(0.0037)
9	0.0237***	0.0327***
	(0.0035)	(0.0039)
10	0.0242***	0.0349***
	(0.0037)	(0.0042)
11	0.0245***	0.0360***
	(0.0039)	(0.0044)
12	0.0254***	0.0369***
	(0.0041)	(0.0046)
Observations	8,233,008	3,844,001

Note: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Samples are divided by within-firm tercile of earnings in 2005Q1 (for comparison group) or in the quarter prior to displacement (for displaced group).

Table A.8: Cumulative Effect of Displacement from Manufacturing on Enrollment by Local Labor Market Proximity to Public and For-Profit Higher Education

Quarter rel. to displacement	High-Public High-FP	High-Public Low-FP	Low-Public High-FP	Low-Public Low-FP
-2	-0.0001	-0.0015	0.0006	0.0024
	(0.0006)	(0.0016)	(0.0008)	(0.0014)
-1	0.0013	-0.0018	0.0020	0.0043*
	(0.0009)	(0.0021)	(0.0013)	(0.0019)
0	0.0036**	-0.0017	0.0031	0.0048*
	(0.0013)	(0.0027)	(0.0016)	(0.0022)
1	0.0098***	0.0120**	0.0053**	0.0149***
	(0.0018)	(0.0037)	(0.0020)	(0.0033)
2	0.0130***	0.0285***	0.0072**	0.0316***
	(0.0020)	(0.0046)	(0.0024)	(0.0044)
3	0.0151***	0.0327***	0.0083**	0.0375***
	(0.0023)	(0.0051)	(0.0027)	(0.0049)
4	0.0156***	0.0358***	0.0098**	0.0397***
	(0.0025)	(0.0055)	(0.0031)	(0.0052)
5	0.0169***	0.0350***	0.0110**	0.0413***
	(0.0027)	(0.0059)	(0.0034)	(0.0055)
6	0.0173***	0.0343***	0.0125***	0.0429***
	(0.0028)	(0.0063)	(0.0038)	(0.0058)
7	0.0170***	0.0348***	0.0192***	0.0435***
	(0.0030)	(0.0067)	(0.0042)	(0.0060)
8	0.0180***	0.0337***	0.0207***	0.0457***
	(0.0032)	(0.0072)	(0.0045)	(0.0063)
9	0.0185***	0.0325***	0.0234***	0.0476***
	(0.0034)	(0.0076)	(0.0049)	(0.0067)
10	0.0199***	0.0311***	0.0261***	0.0489***
	(0.0036)	(0.0080)	(0.0052)	(0.0070)
11	0.0209***	0.0299***	0.0270***	0.0504***
	(0.0039)	(0.0084)	(0.0055)	(0.0073)
12	0.0225***	0.0293***	0.0282***	0.0510***
	(0.0041)	(0.0088)	(0.0057)	(0.0076)
Observations	5,874,402	2,358,606	2,257,531	1,586,470

Note: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Samples are divided by within-firm tercile of earnings in 2005Q1 (for comparison group) or in the quarter prior to displacement (for displaced group).

Table A.9: Cumulative Effect of Displacement from Manufacturing on Enrollment by Calendar Quarter of Layoff

Quarter rel. to displacement	Jan-Mar	Apr-Jun	Jul-Sep	Oct-Dec
-2	-0.0016	-0.0017	-0.0011	-0.0017
	(0.0009)	(0.0015)	(0.0012)	(0.0011)
-1	-0.0016	-0.0022	0.0013	-0.0013
	(0.0014)	(0.0019)	(0.0019)	(0.0015)
0	-0.0019	-0.0025	0.0007	0.0015
	(0.0017)	(0.0023)	(0.0022)	(0.0021)
1	0.0069**	0.0016	0.0080**	0.0055*
	(0.0024)	(0.0029)	(0.0030)	(0.0026)
2	0.0112***	0.0111**	0.0097**	0.0139***
	(0.0028)	(0.0035)	(0.0034)	(0.0032)
3	0.0141***	0.0112**	0.0125***	0.0155***
	(0.0032)	(0.0038)	(0.0038)	(0.0036)
4	0.0137***	0.0134**	0.0127**	0.0171***
	(0.0035)	(0.0042)	(0.0041)	(0.0040)
5	0.0131***	0.0138**	0.0131**	0.0170***
	(0.0038)	(0.0045)	(0.0045)	(0.0043)
6	0.0124**	0.0137**	0.0123*	0.0177***
	(0.0041)	(0.0050)	(0.0049)	(0.0046)
7	0.0152***	0.0139**	0.0108*	0.0179***
	(0.0045)	(0.0054)	(0.0053)	(0.0050)
8	0.0147**	0.0133*	0.0101	0.0188***
	(0.0048)	(0.0057)	(0.0056)	(0.0054)
9	0.0150**	0.0131*	0.0100	0.0185**
	(0.0051)	(0.0061)	(0.0060)	(0.0057)
10	0.0147**	0.0117	0.0094	0.0210***
	(0.0054)	(0.0065)	(0.0064)	(0.0061)
11	0.0135*	0.0106	0.0098	0.0217***
	(0.0057)	(0.0068)	(0.0068)	(0.0064)
12	0.0137*	0.0089	0.0084	0.0234***
	(0.0060)	(0.0072)	(0.0071)	(0.0068)
Observations	10,327,405	10,301,977	10,302,310	10,308,711

Note: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Samples are divided by within-firm tercile of earnings in 2005Q1 (for comparison group) or in the quarter prior to displacement (for displaced group).

Table A.10: Cumulative Effect of Displacement from Manufacturing on Enrollment by Firm Size

Quarter rel. to displacement	< 500 employees	≥ 500 employees
-2	0.0006	-0.0005
	(0.0007)	(0.0007)
-1	0.0022*	0.0002
	(0.0010)	(0.0010)
0	0.0028*	0.0019
	(0.0012)	(0.0013)
1	0.0079***	0.0107***
	(0.0016)	(0.0018)
2	0.0130***	0.0194***
	(0.0020)	(0.0022)
3	0.0169***	0.0212***
	(0.0023)	(0.0024)
4	0.0180***	0.0232***
	(0.0025)	(0.0026)
5	0.0196***	0.0233***
	(0.0027)	(0.0028)
6	0.0206***	0.0231***
	(0.0029)	(0.0030)
7	0.0209***	0.0251***
	(0.0031)	(0.0033)
8	0.0217***	0.0255***
	(0.0033)	(0.0035)
9	0.0220***	0.0266***
	(0.0035)	(0.0037)
10	0.0230***	0.0272***
	(0.0037)	(0.0039)
11	0.0236***	0.0274***
	(0.0039)	(0.0041)
12	0.0234***	0.0286***
	(0.0041)	(0.0043)
Observations	4,595,077	6,810,410

Note: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Samples are divided by within-firm tercile of earnings in 2005Q1 (for comparison group) or in the quarter prior to displacement (for displaced group).

Table A.11: Cumulative Effect of Displacement from Manufacturing on Enrollment by Firm Size

Quarter rel. to displacement	< 1,000 employees	≥ 1,000 employees
-2	0.0005	-0.0005
	(0.0006)	(0.0008)
-1	0.0019*	0.0001
	(0.0009)	(0.0011)
0	0.0027*	0.0020
	(0.0011)	(0.0015)
1	0.0092***	0.0099***
	(0.0015)	(0.0020)
2	0.0163***	0.0169***
	(0.0019)	(0.0024)
3	0.0198***	0.0190***
	(0.0021)	(0.0027)
4	0.0215***	0.0203***
	(0.0023)	(0.0029)
5	0.0234***	0.0199***
	(0.0025)	(0.0031)
6	0.0243***	0.0197***
	(0.0027)	(0.0034)
7	0.0246***	0.0220***
	(0.0028)	(0.0036)
8	0.0251***	0.0227***
	(0.0030)	(0.0039)
9	0.0253***	0.0240***
	(0.0032)	(0.0041)
10	0.0261***	0.0247***
	(0.0034)	(0.0044)
11	0.0266***	0.0250***
	(0.0035)	(0.0046)
12	0.0264***	0.0265***
	(0.0037)	(0.0049)
Observations	6,649,260	4,756,227

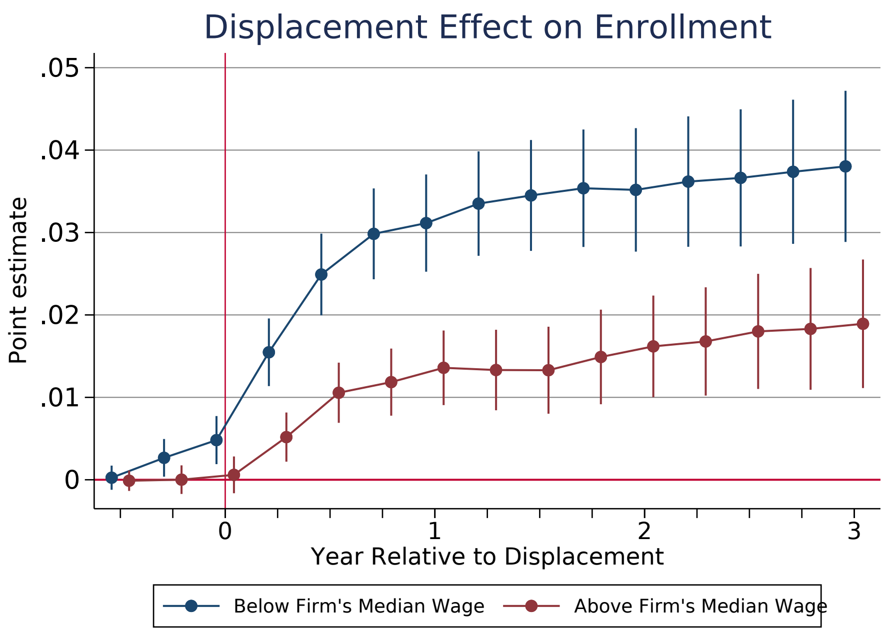
Note: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Samples are divided by within-firm tercile of earnings in 2005Q1 (for comparison group) or in the quarter prior to displacement (for displaced group).

Table A.12: Cumulative Effect of Displacement from Manufacturing Firm Shutdown on Enrollment

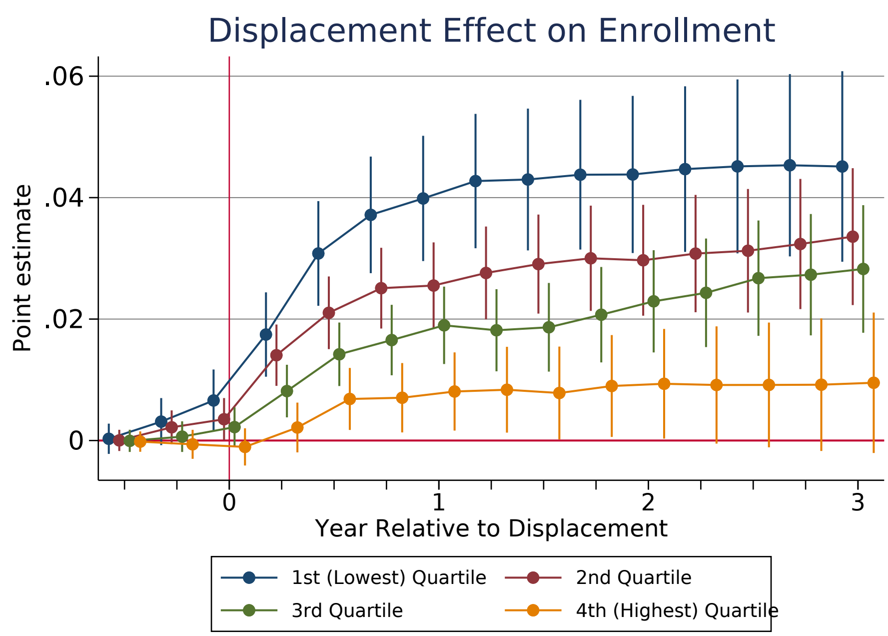
Quarter rel. to displacement	All Displaced from Manufacturing	Displaced in Manufacturing Shutdown
-2	0.0000	-0.0004
	(0.0005)	(0.0011)
-1	0.0011	-0.0000
	(0.0007)	(0.0015)
0	0.0024**	0.0013
	(0.0009)	(0.0019)
1	0.0096***	0.0072**
	(0.0012)	(0.0025)
2	0.0167***	0.0184***
	(0.0015)	(0.0032)
3	0.0195***	0.0197***
	(0.0017)	(0.0034)
4	0.0211***	0.0199***
	(0.0018)	(0.0037)
5	0.0219***	0.0199***
	(0.0020)	(0.0040)
6	0.0223***	0.0202***
	(0.0021)	(0.0043)
7	0.0236***	0.0209***
	(0.0023)	(0.0046)
8	0.0243***	0.0218***
	(0.0024)	(0.0049)
9	0.0250***	0.0216***
	(0.0026)	(0.0052)
10	0.0259***	0.0227***
	(0.0027)	(0.0055)
11	0.0264***	0.0230***
	(0.0029)	(0.0058)
12	0.0270***	0.0249***
	(0.0030)	(0.0061)
Observations	11,405,487	10,312,303

Note: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Samples are divided by within-firm tercile of earnings in 2005Q1 (for comparison group) or in the quarter prior to displacement (for displaced group).

Figure A.1: Cumulative Effect of Displacement from Manufacturing on Enrollment by Earnings Percentile



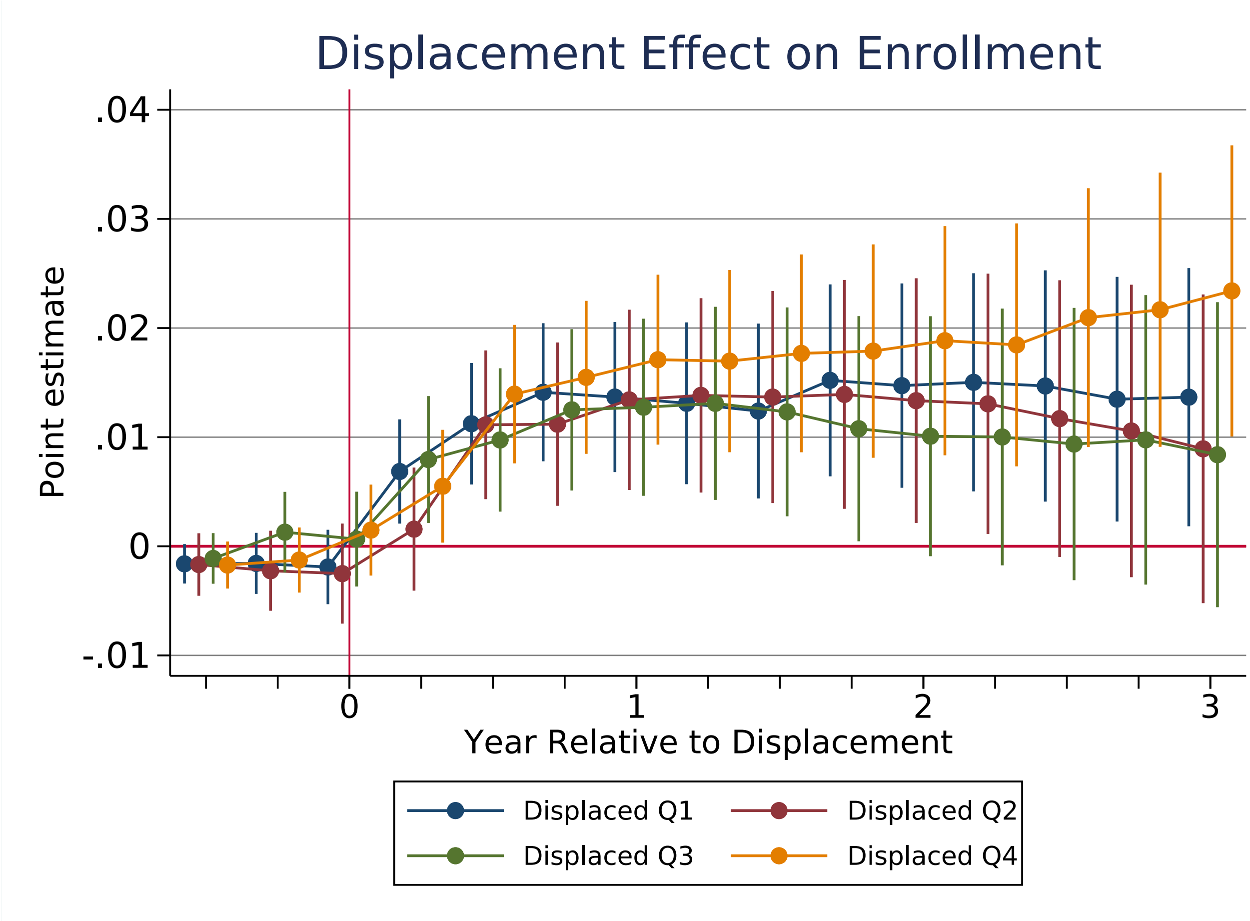
(a) Above/Below Median



(b) Quartile

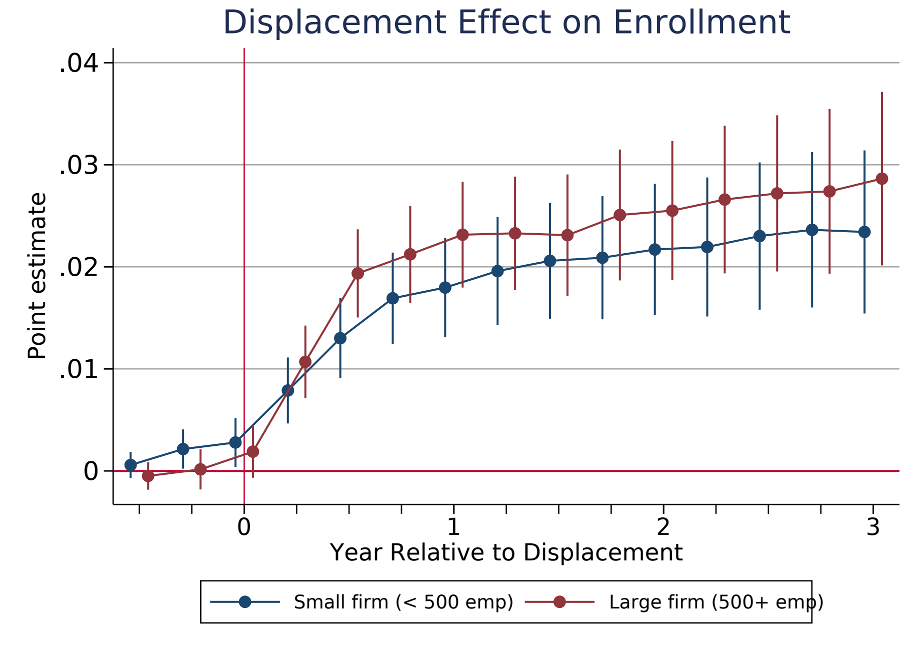
Note: Figures plot the estimated $\hat{\delta}_k$'s from equation (1) split by manufacturing workers' percentile of earnings within the firm. Panel (a) splits workers by earnings relative to the median, and panel (b) split workers by quartiles. Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Displaced sample is laid off between 2002q1 and 2009q4. Point estimates and standard errors are listed in Appendix Tables A.5 and A.6.

Figure A.2: Cumulative Effect of Displacement from Manufacturing on Enrollment by Quarter of Layoff

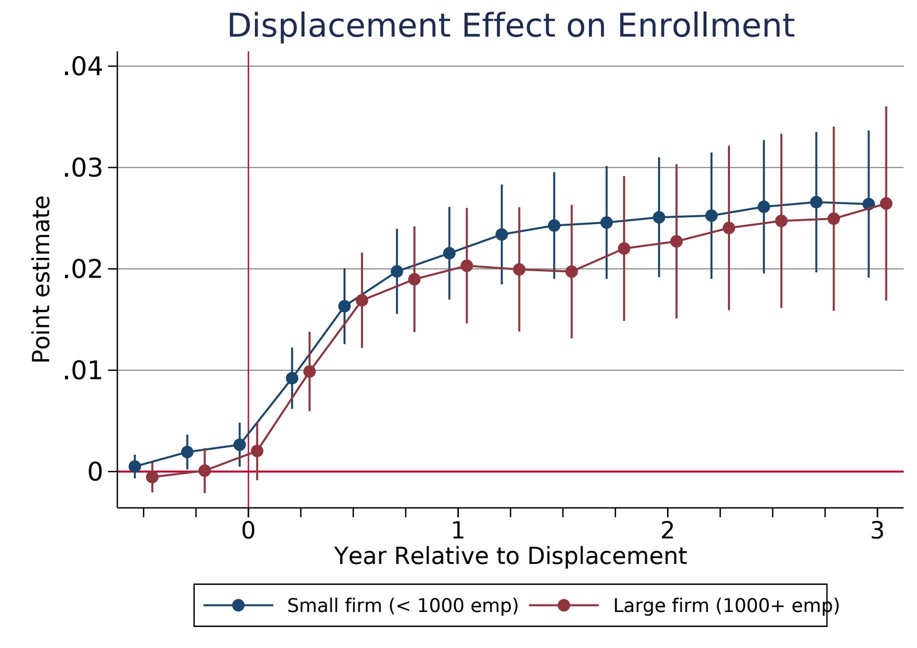


Note: Figure plots the estimated $\hat{\delta}_k$'s from equation (1) for the sample employed by or displaced from manufacturing firms split by calendar quarter of layoff. 30% of the displaced sample was laid off in the first quarter (Jan-Mar), 22% in the second quarter (Apr-Jun), 23% in the third quarter (Jul-Sep), and 25% in the fourth quarter (Oct-Dec). Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Displaced sample is laid off between 2002q1 and 2009q4. Point estimates and standard errors are listed in Appendix Table A.9.

Figure A.3: Cumulative Effect of Displacement from Manufacturing on Enrollment by Firm Size



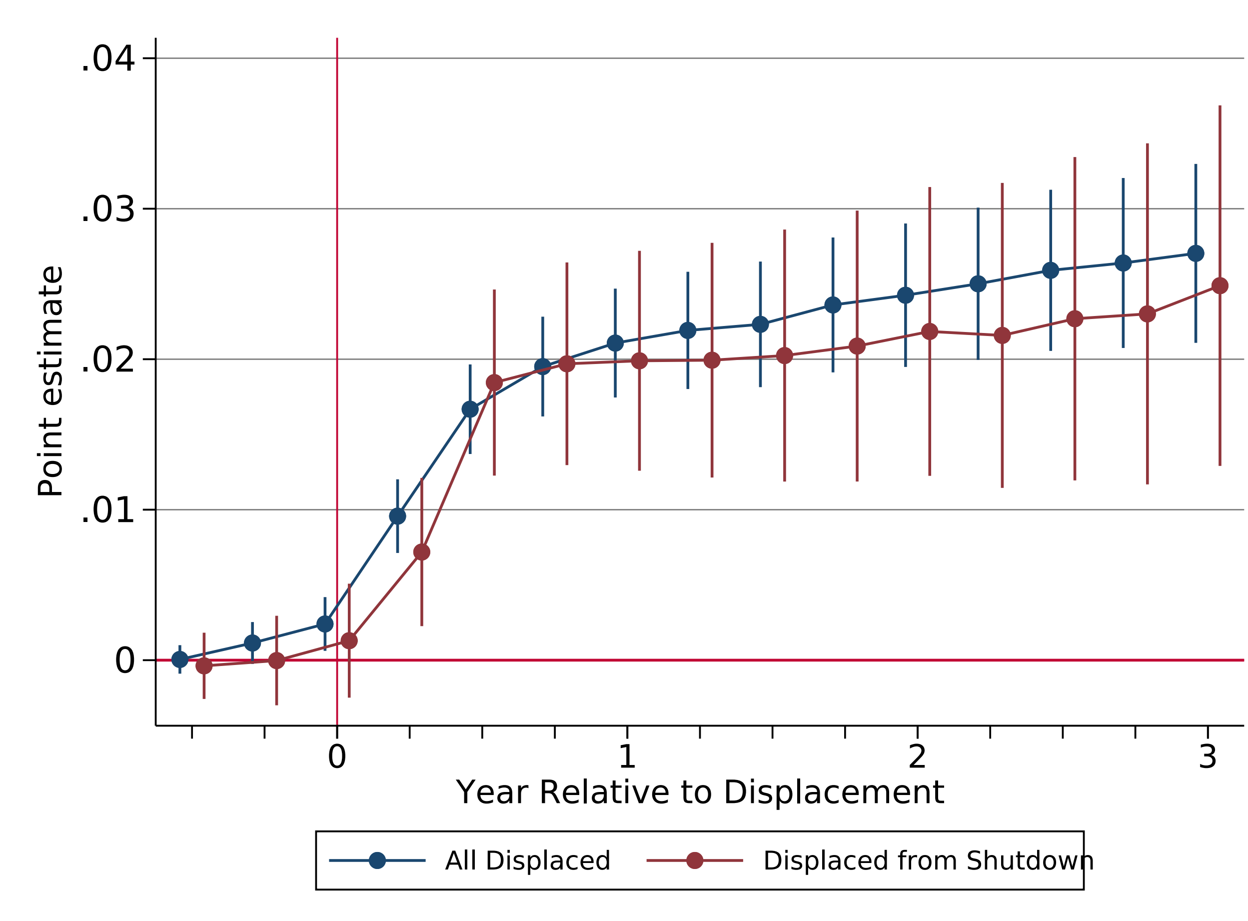
(a) Firm Split: ≥ 500 employees



(b) Firm Split: ≥ 1,000 employees

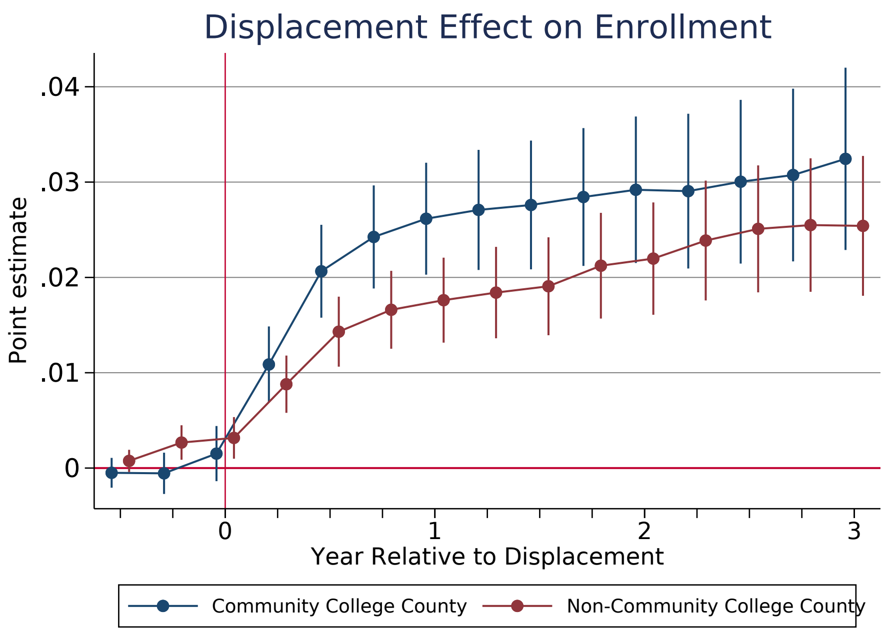
Note: Figures plot the estimated $\hat{\delta}_k$'s from equation (1) split by the size of firm from which manufacturing workers were laid off. In panel (a), a large firm is an employer with more than 500 employees at its maximum size between 2002 and 2009. In panel (b), the cutoff is 1,000 employees. 60% (42%) of displaced manufacturing workers in our sample were laid off from a firm with more than 500 (1,000) workers. Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Displaced sample is laid off between 2002q1 and 2009q4. Point estimates and standard errors are listed in Appendix Tables A.10 and A.11.

Figure A.4: Cumulative Effect of Displacement in Manufacturing Firm Shutdown on Enrollment

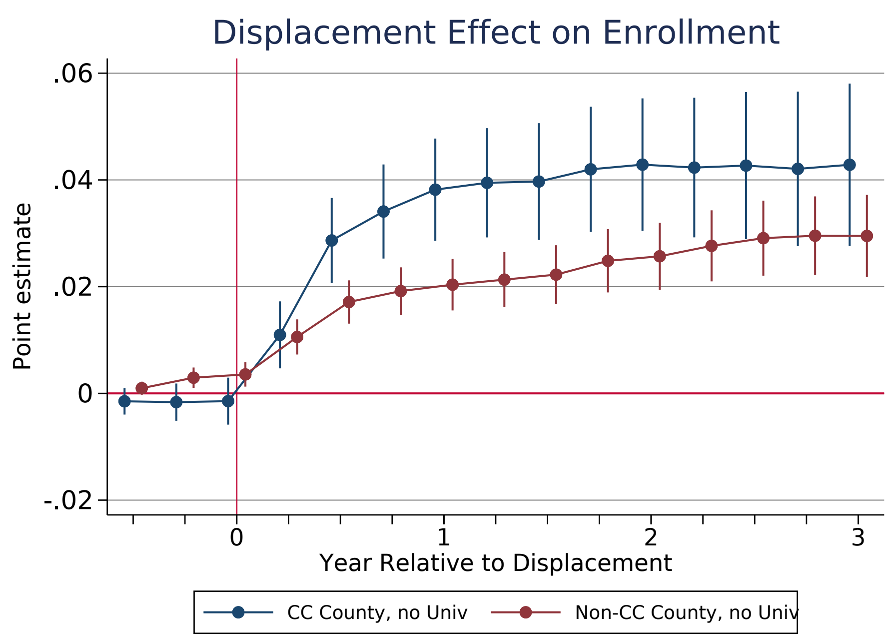


Note: Figure plots the estimated $\hat{\delta}_k$'s from equation (1) for the overall displaced sample (blue) and workers who were displaced in a firm shutdown (red), both compared to a non-displaced comparison sample. 26% of displaced manufacturing employees were laid off in a shutdown, defined as separating within 6 quarters of a firm's closing. Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Displaced sample is laid off between 2002q1 and 2009q4. Point estimates and standard errors are listed in Appendix Table A.12.

Figure A.5: Cumulative Effect of Displacement from Manufacturing on Enrollment by County-Level Community College Proximity



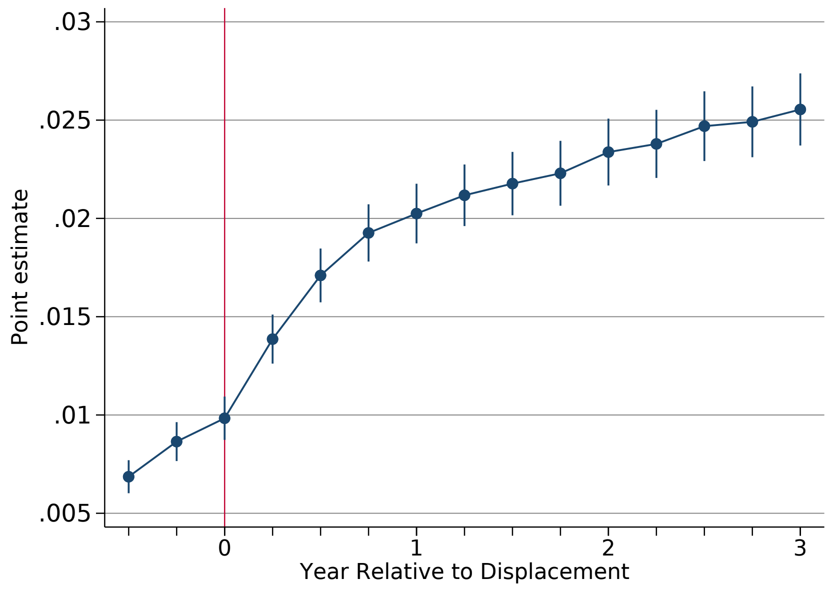
(a) County with and without Community College



(b) County with or without Community College (no 4-year University)

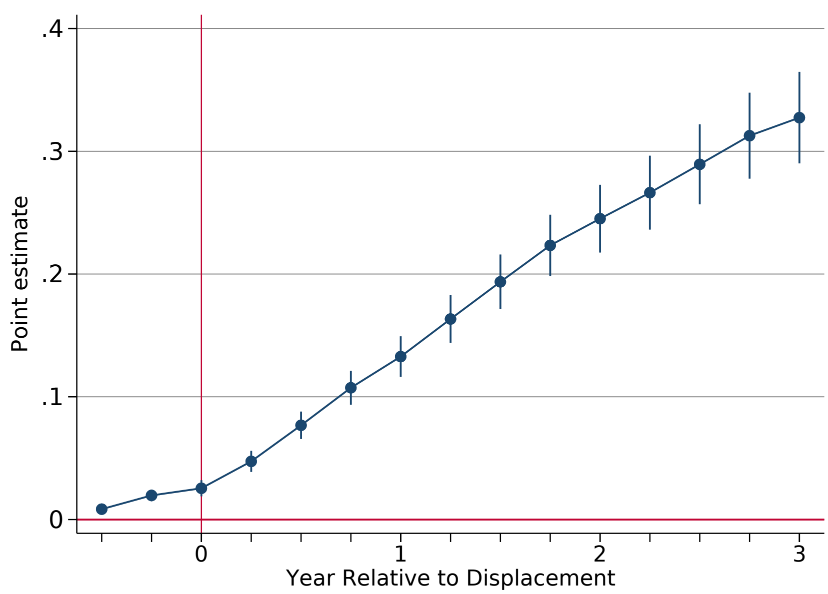
Note: Figures plot the estimated $\hat{\delta}_k$'s from equation (1) split by whether a comparison or displaced manufacturing worker is employed in a county with a public community college. In panel (a), we include displaced and comparison from all 88 Ohio counties. In panel (b), we restrict to those workers in counties without a 4-year university ("main universities" specified in Table B.3). Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Displaced sample is laid off between 2002q1 and 2009q4.

Figure A.6: Cumulative Effect of Displacement on Enrollment, no Worker-Specific Time-Trends



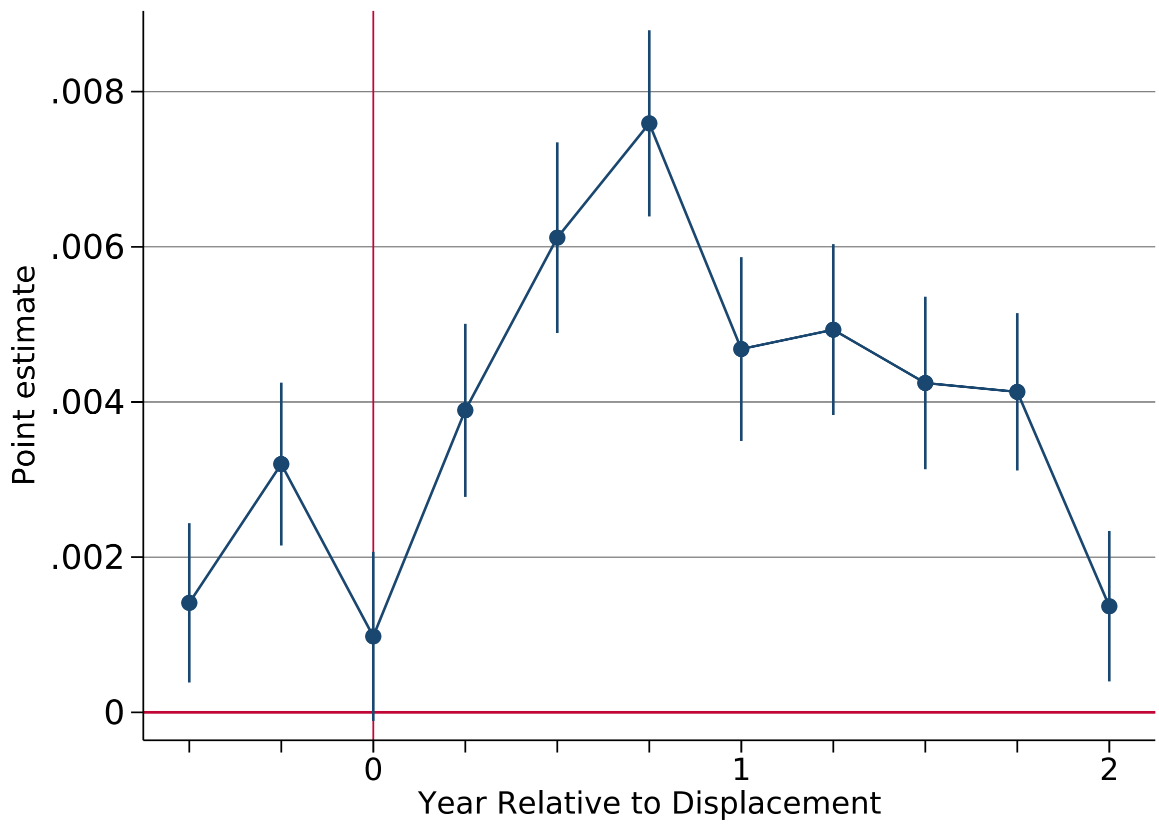
Note: Figure plots the estimated $\hat{\delta}_k$'s from equation (2), which is a modified version of equation (1) which omits worker-specific time trends, for the overall displaced sample and comparison sample. Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Displaced sample is laid off between 2002q1 and 2009q4.

Figure A.7: Effect of Displacement on Enrollment as Measured by Cumulative Credits



Note: Figure plots the estimated $\hat{\delta}_k$'s from equation (3), which uses a measure of cumulative college credits earned as a dependent variable. Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Displaced sample is laid off between 2002q1 and 2009q4.

Figure A.8: Effect of Displacement on Point-in-Time Enrollment



Note: Figure plots the estimated $\hat{\delta}_k$'s from equation (4), a specification with a point-in-time enrollment measure as the dependent variable. Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Displaced sample is laid off between 2002q1 and 2009q4.

B Higher Education in Ohio

Enrollment records for this study come from the Ohio Higher Education Information (HEI) system and cover each of Ohio's public higher education institutions. Table B.1 lists each commuting zone, the number of counties it contains, and the number of 2-year public, 4-year public, and for-profit higher education institutions. The community colleges and universities are listed, along with their locations, in Tables B.2 and B.3.

Table B.1: Ohio Higher Education Availability by Commuting Zone

Commuting Zone Name	# Counties in CZ	Public Institutions	2-Year Public Inst.	4-Year Public Inst.	For-Profit Colleges
High-Public, High-For-Profit					
Cincinnati	6	9	5	4	23
Cleveland	7	11	7	4	51
Columbus	9	10	3	7	22
High-Public, Low-For-Profit					
Dayton	9	7	3	4	14
Portsmouth	5	8	2	6	4
Toledo	5	7	5	2	7
Low-Public, High-For-Profit					
Canton	7	5	1	4	5
Lorain	3	2	1	1	3
Youngstown	3	4	0	4	14
Low-Public, Low-For-Profit					
Athens	3	3	1	2	1
Defiance	3	1	1	0	0
Findlay	5	5	4	1	2
Lima	5	3	0	3	1
Mansfield	5	4	2	2	1
Washington	3	1	1	0	0
Wheeling, WV	2	2	1	1	0
Zanesville	5	3	2	1	1

Note: Comparison and displaced workers employed in the Parkersburg, WV and Huntingon, WV commuting zones are excluded from the geographic analysis because these CZs only include one Ohio county.

Table B.2: Ohio Community Colleges

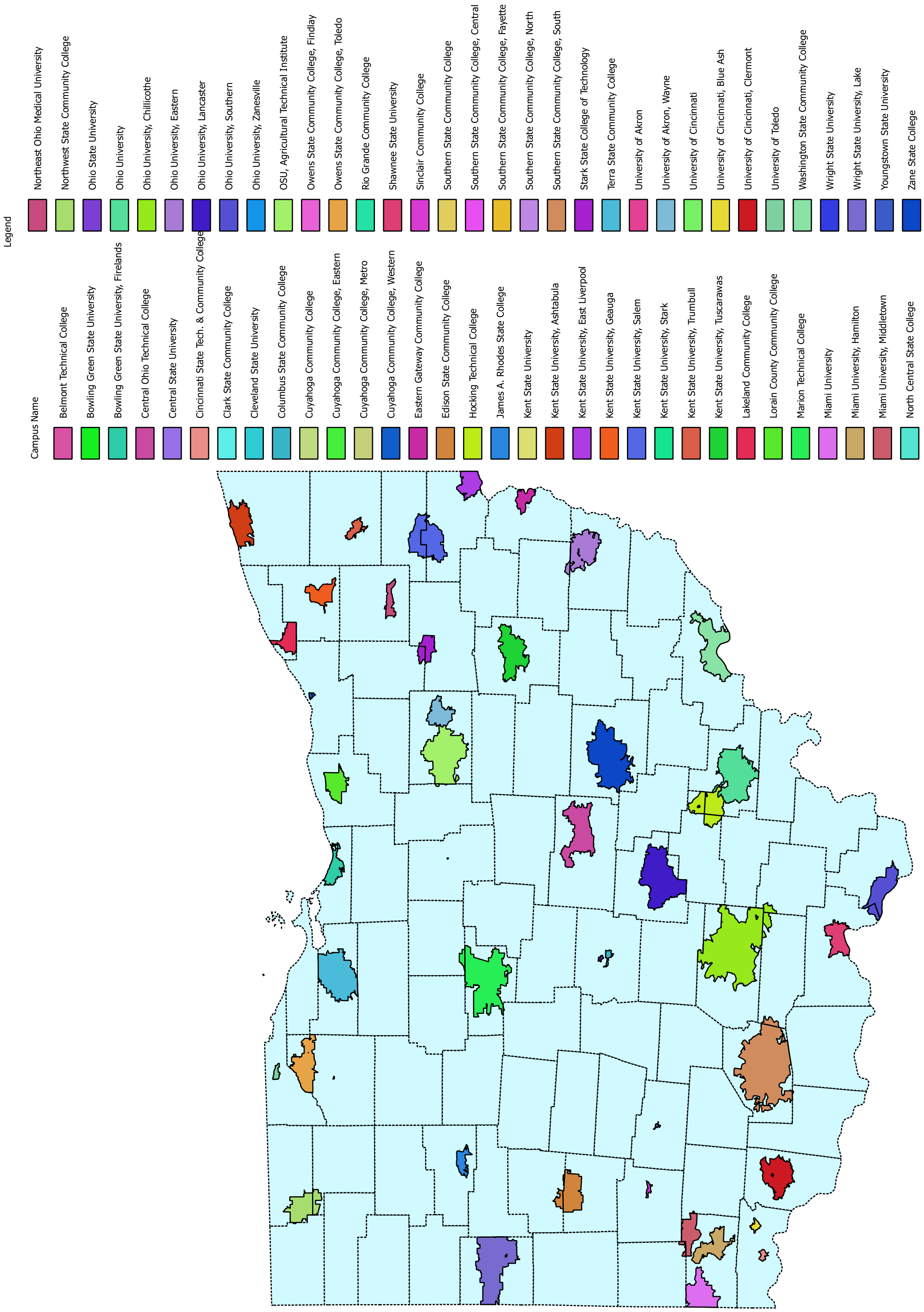
School	City	County	University in County Main	University in County Branch
COTC–Coshocton Campus	Coshocton	Coshocton		
COTC–Knox Campus	Mount Vernon	Knox		
COTC–Pataskala Campus	Pataskala	Franklin	✓	
CSCC–Delaware Campus	Delaware	Delaware		
Cincinnati State Technical & CC	Cincinnati	Hamilton	✓	✓
Clark State–Greene Center	Beakercreek	Greene	✓	
Clark State CC	Springfield	Clark		
Columbus State CC	Columbus	Franklin	✓	
Cuyahoga CC	Cleveland	Cuyahoga	✓	
Edison–Darke County CC	Greenville	Darke		
Edison CC	Piqua	Miami		
Hocking–Logan Campus	Logan	Hocking		
Hocking–Perry Campus	New Lexington	Perry		
Hocking College	Nelsonville	Athens	✓	
Lakeland CC	Kirtland	Lake		
Lorain County CC	Elyria	Lorain		
Northwest State CC	Archbold	Fulton		
Owens –Findlay campus	Findlay	Hancock		
Owens CC	Perrysburg	Wood	✓	
SSCC–Fayette Campus	Washington Court House	Fayette		
SSCC–North Campus	Wilmington	Clinton		
SSCC–South Campus	Sardinia	Brown		
Sinclair CC	Dayton	Montgomery		
Southern State CC	Hillsboro	Highland		
Terra State CC	Fremont	Sandusky		
Washington State CC	Marietta	Washington		

Note: COTC = Central Ohio Technical College; SSCC = Southern State Community College

Table B.3: Ohio Four-Year Colleges and University

School	City	County	Comm. Coll. in County
Main Universities			
Bowling Green State University	Bowling Green	Wood	✓
Central State University	Wilberforce	Greene	✓
Cleveland State University	Cleveland	Cuyahoga	✓
Kent State University	Kent	Portage	
Miami University	Oxford	Butler	
Ohio University	Athens	Athens	✓
Shawnee State University	Portsmouth	Scioto	
The Ohio State University	Columbus	Franklin	✓
University of Akron	Akron	Summit	
University of Cincinnati	Cincinnati	Hamilton	✓
University of Toledo	Toledo	Lucas	
Wright State University	Dayton	Greene	✓
Youngstown State University	Youngstown	Mahoning	
Branch Universities			
Bowling Green State University	Huron	Erie	
Kent State University	Ashtabula	Ashtabula	
Kent State University	East Liverpool	Columbiana	
Kent State University	New Philadelphia	Tuscarawas	
Kent State University	Canton	Stark	
Kent State University	Burton	Geauga	
Kent State University	Salem	Columbiana	
Kent State University	Warren	Trumbull	
Miami University	Hamilton	Butler	
Miami University	Middletown	Butler	
Ohio University	Chillicothe	Ross	
Ohio University	Zanesville	Muskingum	
Ohio University	Lancaster	Fairfield	
Ohio University	Ironton	Pike	
Ohio University	Saint Clairsville	Belmont	
The Ohio State University	Mansfield	Richland	
The Ohio State University	Newark	Licking	
The Ohio State University	Wooster	Wayne	
The Ohio State University	Marion	Marion	
The Ohio State University	Lima	Allen	
University of Akron	Orrville	Wayne	
University of Cincinnati	Batavia	Clermont	
University of Cincinnati	Blue Ash	Hamilton	✓
Wright State University	Celina	Mercer	

Figure B.1: Map of Ohio Public Institutions of Higher Education



C Comparison to Displaced Worker Survey

Our Ohio administrative data includes limitations that are typical of state administrative UI databases, such as inability to distinguish between individuals who leave Ohio, exit the labor force, or begin working for non UI-covered employers in the state. Moreover, although our education data includes a rich set of demographic variables, we lack them for workers in the UI sample. Thus, we only observe characteristics like race, age, and gender for the subset of displaced workers who were enrolled in the Ohio public higher education system at some point during the selected timeframe.

To supplement our Ohio sample's descriptive statistics, we analyze data from the Displaced Workers Surveys (DWS), administered every two years from as a supplement to the Current Population Survey (CPS). The DWS has been utilized in displaced worker studies for several decades (Neal, 1995; Hipple, 1999; Schmieder and Von Wachter, 2010; Farber, 2015). The DWS conveys information unavailable to researchers only using administrative data, such as demographic information, whether notice was given before layoff, whether a jobless displaced worker is searching for employment (i.e. unemployed or not in the labor force) (see Table C.1).[23]

Table C.2 describes the gender and racial composition, average age of layoff, and educational attainment of displaced workers according to the DWS to contextualize our industry heterogeneity analysis in Section 5. Workers displaced from manufacturing, education and health, and public administration are among the oldest, on average, laid off from their jobs. More than half of the workers displaced from construction and mining, food services and hospitality, and manufacturing have only a high school degree or less and have not previously attended college.

Table C.3 compares our Ohio sample to the DWS with respect to workers' industry of displacement. At the broad industrial level (reflecting roughly 1-digit NAICS classification), the sectoral balance of our Ohio displaced worker sample matches the DWS very well. The only difference is our sample has a slightly larger share displaced from manufacturing, perhaps unsurprisingly.

[23] All statistics are survey-weighted using "dwsuppwt."

Table C.1: Characteristics from Displaced Worker Supplement

Variable	Displaced 2002-2005	Displaced 2006-2009
Mean Age at Displacement	42	44
Share Female	0.45	0.41
Share Non-White	0.17	0.17
Share Married	0.62	0.61
Educational Attainment (time of survey)		
< HS Diploma	0.09	0.09
HS Diploma	0.33	0.34
Some College	0.21	0.20
Assoc./Bach. Deg or More	0.37	0.36
Layoff-Related Characteristics		
Mean Years Worked at Lost Job	9	9
Plant Closed Down/Moved	0.44	0.32
Worked Full-Time at Lost Job	0.90	0.88
Received UI Benefits	0.55	0.56
Notice Given Before Displacement		
None Given	0.56	0.61
< 1 Month	0.10	0.12
1-2 Months	0.15	0.13
> 2 Months	0.17	0.12
Employment Status at Time of Survey		
Employed	0.63	0.51
Unemployed	0.22	0.35
Not in Labor Force: Retired/Disabled	0.05	0.05
Not in Labor Force: Other	0.11	0.10
Share by Industry of Layoff		
Manufacturing	0.28	0.23
Construction, Mining	0.08	0.13
Utilities	0.01	0.00
Retail	0.10	0.11
Finance, Insurance, Real Estate	0.09	0.09
Transportation	0.04	0.04
Education & Health	0.10	0.10
Food & Hospitality	0.04	0.04
Wholesale	0.04	0.04
Public Administration	0.01	0.01
Professional, Scientific, Technical	0.07	0.07
Administrative, Support, Waste Manage	0.04	0.03
N	2,596	3,261

Source: IPUMS-CPS Displaced Worker Supplement, www.ipums.org. *Note:* Sample includes civilians age 20+ who lost their job, had at least three years tenure, and were not self-employed at the time of the survey. The first (second) column corresponds to the 2004 and 2006 (2008 and 2010) DWS waves.

Table C.2: Displaced Worker Demographics by Industry of Layoff from DWS

Layoff Industry	Age	Female	Nonwhite	HS or Less	Some College	Degree
Manufacturing	44	0.38	0.17	0.56	0.18	0.26
Construction, Mining	39	0.11	0.12	0.61	0.17	0.23
Utilities	40	0.15	0.00	0.20	0.10	0.70
Retail	42	0.54	0.12	0.43	0.23	0.35
Finance, Insurance, Real Estate	43	0.59	0.25	0.28	0.20	0.52
Transportation	42	0.19	0.12	0.41	0.27	0.32
Education & Health	45	0.78	0.20	0.24	0.27	0.48
Food & Hospitality	37	0.52	0.16	0.56	0.24	0.21
Wholesale	41	0.30	0.12	0.34	0.24	0.42
Public Administration	45	0.33	0.17	0.16	0.27	0.57
Professional, Scientific, Technical	42	0.52	0.15	0.13	0.19	0.68
Administrative, Support, Waste Mgmt	42	0.57	0.28	0.48	0.20	0.33

Source: IPUMS-CPS Displaced Worker Supplement, www.ipums.org. *Note:* Sample includes civilians age 20+ who lost their job, had at least three years tenure, and were not self-employed at the time of the survey. Workers were displaced between 2002 and 2005 (corresponding to the DWS 2004 and 2006 waves, restricting to workers displaced in the last two years). Sample is weighted using "dwsuppwt." Age column represents mean age at layoff.

Table C.3: Displaced Worker Industry Comparison: Ohio sample and DWS

Industry of Layoff	Minaya, Moore, Scott-Clayton	DWS (displaced 2002-2009)
Manufacturing	0.29	0.25
Construction, Utilities, Mining	0.11	0.11
Retail Trade	0.11	0.10
Transportation & Warehousing	0.08	0.04
Education & Health	0.07	0.10
Food Services & Hospitality	0.05	0.04
Other	0.22	0.27
N	68,547	5,857

Note: Left column reflects the Ohio administrative sample displaced between 2002 and 2009 (Table 1). Right reflects national respondents of the DWS displaced during the same time period (2004-2010 waves of the DWS). "Other" industries include Wholesale, Public Administration, Professional, Scientific, and Technical Services, and Administrative, Support, and Waste Management.