The Firm's Role in Displaced Workers' Earnings Losses and Educational Investment Decisions: Evidence from Ohio

Brendan Moore†
Senior Honors Thesis
Department of Economics
April 2018

Abstract

Displaced workers suffer large and persistent earnings losses and also exhibit appreciable returns to schooling. Nevertheless, both the sources of these earnings losses and the likelihood such workers enroll in post-secondary education as a result of displacement are poorly understood. Using employer-employee matched administrative data from Ohio which includes details regarding worker incomes and post-secondary education history, I first confirm that earnings losses for workers displaced in the mid-2000's are large and persistent (26% losses after 4 years). I show that 22% of displaced workers' long-term earnings deficits can be attributed to loss of favorable firm-specific pay premiums. Third, I determine that for every 100 workers involved in a mass layoff, no more than 2 enroll in a public college within a year of displacement. Displacement has a more pronounced effect on enrollment for those from firms with higher pay premiums. Lastly, I provide evidence that some workers anticipate a mass layoff at their firm and, as a result, enroll in college before being laid off.

†This thesis was written during my senior year at Columbia University. I am grateful for the guidance of my advisers, Judy Scott-Clayton and Suresh Naidu. I would also like to thank Michael Best for advising the honors thesis seminar, as well as the seminar participants for their productive and thought-provoking conversation. I gratefully acknowledge Lisa Neilson and the staff of the Ohio Education Research Center, who helped facilitate my use of the restricted data in this study. I thank Marta Lachowska and Christina Patterson for their very helpful feedback on earlier drafts of this paper, and I appreciate the insight of Bentley MacLeod and Miguel Urquiola in my conversations with them about this project. I thank the Community College Research Center at Columbia's Teachers College for accommodating space for me to work in their office. For citation of the most recent version of this paper, please email Brendan Moore (brendan.moore@columbia.edu) and Judith Scott-Clayton (scott-clayton@tc.columbia.edu).

1 Introduction

Economists, policymakers, and lay members of the public routinely demonstrate interest in the difficulties faced by displaced workers, defined as employees with strong sectoral attachment who lose their job due to structural economic reasons. One of the most striking patterns demonstrated by displaced workers – a trend which distinguishes them from those who voluntarily separate or frequently move between jobs – is their large and persistent earnings losses many years after their initial separations.[1]

As the reality of substantial earnings losses became evident through the work of Jacobson, LaLonde, and Sullivan (henceforth JLS), applied economic literature has expended considerable time seeking to explain such phenomena [Krolikowski, 2017] [Carrington and Fallick, 2017]. Recently, those who study displacement have exploited employee-employer linked administrative data to examine the role that employer identity assumes in the earnings losses story [Lachowska et al., 2018]. The model which addresses how firm heterogeneity partially determines wage structure was first developed by Abowd, Kramarz, and Margolis (henceforth AKM) and has been advanced by David Card, Patrick Kline, and co-authors.[2]

One of the most encouraged responses to worker displacement is investment in human capital, particularly as automation of codifiable tasks shifts labor demand in favor of college-educated workers [Autor et al., 2003]. Indeed, displaced workers who attend community college demonstrate appreciable earnings benefits from re-training. Nevertheless, very few workers opt to pursue post-secondary education to curtail the persistent negative earnings shocks associated with displacement.

This paper seeks to address the questions of firm heterogeneity as a source of displaced worker earnings losses and post-secondary enrollment responsiveness to displacement. Regarding firm heterogeneity, because economists have documented that some firms pay higher wages than other employers for equally-skilled workers[3], I investigate whether displaced workers are re-hired by firms which pay lower wage premiums to all of their employees. If firms with higher pay-premiums may tend to undergo mass layoffs and produce displaced workers with greater frequency than other firms, displaced worker earnings over the long-run may be systematically lower than pre-layoff earnings.

Regarding education, [Betts and McFarland, 1995] and [Foote and Grosz, 2017]

[1]See [Jacobson et al., 1993] [Couch and Placzek, 2010] [Von Wachter et al., 2009] [Davis and von Wachter, 2011] [Farber, 2011] as examples of works demonstrating displaced workers' long and sustained earnings losses. Moreover, displacement has also been shown to increase mortality rates [Sullivan and Von Wachter, 2009] and reduce household spending [Stephens Jr, 2001].

[2]In [Card et al., 2013], the authors demonstrate the contribution of firms to rising West German wage inequality in the 1990s and early 2000s. [Card et al., 2018] develops a model in which firms set wages with some degree of market power and work environments are viewed as imperfect substitutes by employees. The authors then show estimations of the AKM model are consistent with a model that includes firm-specific pay premiums as important in wage structure determination.

[3] [Krueger and Summers, 1988] [Van Reenen, 1996] [Macis and Schivardi, 2016]

show that community college enrollment is responsive to adverse shocks to local labor demand. However, due to data limitations, the authors are unable to show if the increased enrollment is driven by the very workers who were displaced. Displaced workers who receive post-secondary training have been shown to exhibit positive and appreciable returns to schooling.[4] Using a unique worker-student matched administratve dataset, this paper will examine the causal effect of displacement on post-secondary enrollment patterns.

This paper's empirical analysis begins by confirming external validity by showing that workers displaced in Ohio during the mid-2000's suffer large and persistent earnings losses on the order of 26% four years after initial displacement, conditional on employment. Although earnings exhibit a substantial partial rebound between their first and second full post-displacement quarters, their recovery stagnates for the subsequent four years. Earnings losses are even more pronounced for workers displaced from industries besides finance and insurance, as well as for those displaced from manufacturing firms. I note the magnitude of these earnings losses is particularly striking given the relatively tight labor market during which this sample of workers was displaced.

Second, by exploiting the data's employee-employer matched nature, I show that firm identity matters for the earnings of both upwardly mobile (those who find reemployment at a firm with a higher wage premium) and downwardly mobile displaced workers. In the context of earnings deficits, I find that 22% of displaced worker earnings losses can be attributed solely to the loss of firm-specific pay premiums.

Lastly, I provide evidence that the exogenous shock of displacement compels some workers to enroll in post-secondary education, but the effect is quite small in absolute terms. Specifically, 0.7% of workers enroll in post-secondary education in a given quarter during the first post-layoff year as a result of being displaced. This quarterly enrollment rate amounts to 1 or 2 of every 100 displaced workers enrolling in school due to layoff during their first post-separation year. However, because the enrollment rate for displaced workers during the baseline period (3 years before displacement) is very low (1.7%), the causal impact of displacement on enrollment is a near 50% increase for this population relative to three years before separation. Importantly, I find evidence that workers anticipate impending layoffs, as the estimated causal impact of *future* displacement on contemporaneous enrollment is statistically significant and positive. This pattern is particularly evident for workers who anticipate displacement from firms with the highest pay premiums.

This paper proceeds as follows. Section 2 provides background on displaced workers earnings losses and their returns to education. Section 3 describes the data, and section 4 outlines the empirical strategy. Section 5 discusses the results, and section 6 concludes.

[4] [Jacobson et al., 2005a]

2 Background Literature: Displaced Workers

2.1 Persistent Earnings Losses

The long-term[5] earnings losses of displaced workers are among the most well-documented empirical findings to arise from the application of microeconometric methods to U.S. state-level Unemployment Insurance (UI) administrative data. JLS first showed in their seminal 1993 paper that early 1980's western Pennsylvania workers suffered deep and sustained shocks to their post-displacement earnings. JLS found that earnings losses in the first year amounted to 66% and, perhaps more-surprisingly, 24% after five years. [Couch and Placzek, 2010], questioning whether such earnings patterns were a historical rarity confined to the steel industry-driven recession of 1980's greater Pittsburgh, studied displaced workers in the 1990's and early 2000's in Connecticut. Couch and Placzek estimate a 49% and 32% decrease in earnings one and five years after displacement, respectively. [Lachowska et al., 2018] reaffirms this finding with the sample of workers from Washington state who were displaced during the Great Recession (48% for one year, 16% after five years).[6] On a national-level, [Von Wachter et al., 2009] use a 30-year panel from the Social Security Administration to estimate the long-term earnings losses of U.S. workers displaced during the 1982 recession and find 20% earnings losses for 10 to 15 years after separation.

Several oft-cited theoretical explanations have emerged for these persistent earnings losses, many relating to pre-displacement worker-firm variables. One theory posits that because worker experience is often firm-specific, involuntary displacement and re-employment at a new firm is particularly costly. Specifically, as workers advance in tenure, they acquire knowledge and skills unique to their firm. Contrasted with experience that contributes to a worker's general human capital, such firm-specific skills will increase productivity only with his or her current employer [Topel, 1991]. A second common explanation involves the prevalence of backloaded compensation packages. Employers offer backloaded pay structures to ensure workers remain credit-constrained and to prevent shirking. In such circumstances, wages increase with tenure as a solution to a moral hazard problem (from the perspective of the firm) [Acemoglu and Autor, 2011]. Such intentional backloading of compensation specifically harms workers who hope to remain in their position but are laid off altogether, as they are unable to realize the benefits their employers reserve specifically for high-tenure workers.

Only very recently has empirical labor literature exploited differences in firm-

[5] In the following literature, defined as 5 years after displacement. When discussing my own results, I will be specific about the exact length of time that constitutes "long-term"

[6] Of note, because Lachowska, Mas, and Woodbury (2018) use data from Washington, one of four states that records hours worked alongside total earnings in its UI data, the authors demonstrate that while hours worked recover fairly well (although not fully) five years post-displacement, hourly wages experience a large negative shock and are very slow to recover in the long-run

specific pay premiums to study the elusive sources of displaced worker earnings losses. Lachowska, Mas, and Woodbury use the techniques of other recent works which have leveraged variation between uniformly higher and lower-paying firms to study income inequality[7] and referral networks.[8] [Lachowska et al., 2018] (hereafter LMW) test whether variation in firm-specific pay premiums reaped by a worker across time explain any of the earnings losses faced by displaced workers, conditional on reemployment at a new firm. They find a relatively small but appreciable share of earnings losses are explained by reemployment at firms which pay lower firm-specific pay premiums, up to 11% in the long-run for the average displaced worker. Because moving to a worse firm only explains a relatively small fraction of long-term earnings losses, LMW suggest that earnings losses are likely attributable to either lost firm-specific human capital (as discussed above) or the loss of a favorable job match.

2.2 Returns to Education for Displaced Workers

As has been discussed, it is clear displaced workers suffer sizable and persistent earnings losses. In response to the prospect of significantly diminished income after displacement, some workers may opt for education or retraining, much of which takes place at local community colleges.[9] Before discussing how my paper will link the JLS, AKM, and education literatures, I will first discuss the evidence of positive returns to education for these unique set of workers.

The empirical labor literature has long struggled to measure the effects of retraining on the earnings of displaced workers because of selection bias. For displaced workers, the decision of whether or not to pursue retraining or education is correlated with observables such as age, previous industry, and liquidity constraints, as well as unobservables such as motivation, ability, and beliefs about retraining's effectiveness. Studies which have sought to measure this effect have concluded that displaced workers demonstrate substantial and sustained benefits from such treatment. Howard Bloom's randomized experimental evaluation of reemployment programs for displaced workers in 1980's Texas found appreciable impacts of retraining on earnings [Bloom, 1990]. The effects of retraining were more sustained for women than men. Accordingly, Bloom concluded that the measured earnings impacts exceeded their program costs only for females. However, the work of Bloom and others who sought to evaluate the effects of retraining programs([Decker and Corson, 1995] [Leigh, 1990]), only allowed for a very short follow-up period, often of

[7] [Card et al., 2013] [Card et al., 2018] [Barth et al., 2016]

[8] [Schmutte, 2014]

[9] This is demonstrated particularly well by [Foote and Grosz, 2017], who leverage mass layoffs, rather than the local unemployment rate, to assess postsecondary enrollment responsiveness. While they are unable to show the increase in enrollment is driven by the precise workers who are laid off, their paper serves as plausible evidence that some displaced workers opt for postsecondary training after separation

only one year.

Estimating the effects of education instead requires longer observational windows because the benefits of education often accrue over a greater period of time. Orley Ashenfelter pioneered the practice of using longitudinal administrative data to address such questions ([Ashenfelter, 1975] [Ashenfelter and Card, 1984] [Heckman et al., 1999]). Jacobson, LaLonde, and Sullivan applied these methods directly for the purpose of estimating the returns to community college education among displaced workers and older workers ([Jacobson et al., 2005a] [Jacobson et al., 2005b]). According to JLS's estimates using administrative data from Washington state, one academic year of community college schooling for displaced (older) workers is estimated to have boosted long-term earnings by about 9% (7%) for men and 13% (10%) for women.

With the understanding that displaced workers experience negative earnings shocks and exhibit positive returns to education, [Ost et al., 2018] ask how the shock of displacement affects education decisions of workers already enrolled in a postsecondary program (given that many community college students both work and attend classes). While displacement lowers the opportunity cost of schooling, it also may render financing education more difficult. Using UI and post-secondary administrative data from Ohio, the authors find that layoffs had a negligible impact on enrollment decisions on the extensive margin. Moreover, students increased the number of classes in which they were enrolled, suggesting the decreased opportunity cost was more influential for the majority of these individuals.

Reflecting the increased interest in employer identity in the determination of earnings, [Engbom and Moser, 2017] demonstrate that higher education degrees are associated with greater representation at the best-paying firms. This descriptive evidence, however, is agnostic about whether the underlying mechanism is more closely aligned with a human capital model or the signaling model. In the human capital model, workers with degrees have developed more skills and are therefore hired at better-paying firms. In a signaling model, a worker's underlying education is not viewed as inherently valuable to better paying firms, but instead provides a signal of the worker's high ability.

3 Data

I utilize two administrative data sources from the state of Ohio to study the links between displacement, firm heterogeneity, 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 (ODFJS), into a repository known as the Ohio Longitudinal Data Archive (OLDA).[10]

The first dataset provides information for all students attending Ohio public institutions of higher education between the years 2000 and 2011. 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 peak enrollment in the fall and spring semesters.

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 my purposes, I can identify the quarter of a displaced worker's separation as well as the quarter of entry at an Ohio public college or university.[11] The earnings data also consist of firm-level variables, including employer identifier, six-digit North American Industry Classification Systems (NAICS) codes, and county of the employer. The identifiers 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. Relative to other states, Ohio has large employment shares in manufacturing and transportation, sectors more likely to produce displaced workers. The panel nature of the data allows for tracking of worker tenure and the enrollment patterns which enables the study of questions that could not be feasibly addressed in previous displaced worker studies.

Nevertheless, there exist several limitations with the Ohio data. First, I am unable to distinguish between workers who leave Ohio, drop out of the labor force, or begin working for non UI-covered employers in the state. The data's omission of contract workers is particularly regrettable as large companies have increasingly shed their role as the direct employer of workers who provide "peripheral services"

[10] 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.

[11] Although work calendar quarters and semesters do not line up exactly, I match quarter 1 (January-March) from the earnings data to the winter term, quarter 2 to the spring term, etc. Such practice is consistent with [Ost et al., 2018], who use the same Ohio dataset

such as a security and janitorial duties [Weil, 2014]. Second, I 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] has shown 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 my research question.

I use the Ohio administrative records to construct two distinct samples: one for analysis of displaced workers, and a considerably larger sample for AKM analysis. The displaced worker study depends the estimated firm-fixed effects resulting from the AKM model. Thus, I will first describe the sample used for AKM estimation and subsequently summarize the displaced worker sample.

3.1 AKM Sample

The AKM sample to which I apply equation (1) (see section 4.1) was constructed from the Ohio quarterly earnings records for calendar years 1999 to 2012. Because the data do not include hours worked and I seek to approximate firm-specific pay premiums paid to full-time employees, I drop worker-quarter observations where a worker has two or more listed jobs. I then follow the method developed by [Sorkin, 2017] of constructing an employee-employer matched panel to study worker movements. Specifically, I subset on continuous spells of employment that last for at least five consecutive quarters to eliminate short-term and seasonal employees. For each employment spell with a distinct employer, I drop the first and last quarter of the spell so to avoid making inferences about earnings based on partial quarters of employment.

Because the AKM model is traditionally estimated on yearly panels rather than quarterly, I annualize the remaining data within each calendar year and multiply the mean quarterly earnings by four to reflect annual earnings (conditional on a worker having two consecutive quarters of earnings from the same primary employer). If this condition is not met, the year for that individual worker is omitted.[12] Lastly, I drop worker-year observations when mean yearly earnings fell short of $3,500. These restrictions yield the "full sample" from column 1 of Table 1.

On this sample, I estimate equation (1) upon the largest connected set, i.e. the greatest collection of workers and firms linked by worker movements over time. As

[12] Because the first and last observed quarters of employment spells are already dropped, this additional constraint regarding two or more consecutive quarters in a calendar year means that most displaced workers will have the year of their transition dropped from the AKM sample. A hypothetical displaced worker who loses her job in the second quarter and is re-employed in the third quarter of a given year will only exhibit two non-consecutive quarters of full earnings at different firms, so it is difficult to make inferences about earnings patterns with these restricted within-calendar year means. See [Lachowska et al., 2018] Appendix B for further discussion

shown by Table 1, half the workers in the original sample are movers. The largest connected set retains 98.75% of worker-year observations, 91% of workers, and 90% of firms from the full annualized panel. Because the largest connected set doesn't omit a substantial share of the data and the mean log earnings of the full and largest connected set are very similar, I can trust the estimates obtained via AKM.

3.2 Displaced Worker Sample

Construction of Sample

Displaced workers are distinct from routine job changers or other unemployed individuals because they have a structural cause for displacement, limited ability to return to a comparable job within a reasonable span of time, and are strongly attached to the sector in which they were employed. Because I use administrative data for this study, I cannot explicitly identify the reason for a worker's separation (quit, discharge for cause, etc.). Consistent with the displaced worker literature, I use separations during a mass layoff to identify workers who separate because of economic distress at the firm.[13] Mass layoffs, which have been exploited by JLS and other researchers as exogenous shocks to a worker's employment, have served as a reliable proxy for structural causes of displacement because most of those who leave a firm during such a period do so involuntarily.

I define a mass layoff as a 30% or more quarter-to-quarter reduction in firm's payroll, which including firm shutdowns. Because some firms exhibit many mass layoffs, I rank a firm's four largest mass layoffs by percentage change during the observed period (2002-2008) and assess only these four events to avoid over-counting. Furthermore, because smaller firms are mathematically more likely to meet this 30% benchmark without a substantial change in absolute employment, I adhere to JLS's practice of excluding firms with fewer than 50 employees from the sample of mass layoff firms.

Upon identifying the various dates of a firm's mass layoffs, I define a displaced worker as someone satisfying the following conditions: the individual (1) is employed at the firm within a year of a given mass layoff, (2) is not employed at the firm the quarter after the mass layoff, (3) exhibits at least three years tenure at that firm[14], (4) holds only one job at the time of job separation, and (5) earns at least minimum

[13] [Flaaen et al., 2017] examines the implications of assuming mass layoffs are a sound proxy for economic distress at the firms by matching administrative datasets with the Survey of Income and Program Participation (SIPP) and Longitudinal Employer Household Dynamics (LEHD), both of which contain worker-provided reasons for separations. The authors find that earning loss estimates using only survey responses are very close to those using only administrative data.

[14] When data is available on worker age, I require that such "high-tenure workers" must also be at least 25 years of age at the time of layoff. This is because very young workers are less likely to experience displacement in a similar fashion as a prime-age workers

wage corresponding to 30 hours per week.[15] Such a definition is closely aligned with JLS.

Additionally, concerning post-displacement characteristics, I require that all displaced workers in my sample stay attached to the labor force in the follow up period. Because my research questions necessitate that a displaced worker will seek future employment, it does not make sense to include in my sample displaced workers who may drop out of the labor force altogether. Thus, I keep only workers who are attached to the labor market, which I define as exhibiting positive earnings in at least 25% of one's post-displacement quarters. Dropping non-attached workers shrinks my displaced worker sample size by only 8%. Importantly, this restriction renders the conclusions about adverse outcomes for displaced workers in this paper are conditional on labor force attachment.

Descriptive Statistics

Table 3 presents descriptive statistics for the sample of workers displaced in Ohio between 2002Q1 and 2008Q4, broken down by patterns of higher education enrollment relative to their time of separation. It is first noteworthy that among the 42,351 displaced workers in the sample, only 3,696 (8.7%) are observed in school anytime post-displacement.[16] In 2008Q4, Ohio's unemployment was 7.6%, far from its Great Recession peak of 11.0% in 2010Q1 [Bureau of Labor Statistics, 2010]. While lengthening the window of eligible displacement to 2009 or 2010 would substantially increase my sample size by including those displaced during the Great Recession, I choose to restrict my timeframe because those who seek schooling after a layoff often take time to enroll (see Figure 1). Thus, I can be confident that in my sample of displaced workers, I observe college entry for nearly all workers who plan to return to school.

Table 3 shows that 30% of the displaced worker sample were laid off from manufacturing firms, unsurprising given Ohio's industrial base,. Column 4 indicates that former manufacturing workers are even more well-represented among those who enrolled and were not observed in post-secondary school prior to displacement, an unsurprising statistic for a sector whose workers traditionally possess no more than a high school diploma. The composition of displaced workers in the Ohio sample differs from three of the most prominent displaced worker studies to use UI data. The displaced sample JLS analyzed from 1980s Pennsylvania included many more from manufacturing (75%) while those analyzed by Couch and Placzek (2000's Connecticut) and LMW (2000's Washington) were less manufacturing-concentrated

[15]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 quarter

[16]For all workers, this observed post-displacement period is at least 3 years, as education data extends to 2011. At a maximum, the data observe 10 years post displacement for those workers displaced in early 2002

(16% and 26%, respectively). The Ohio sample's relative sectoral balance obviates concerns of industrial homogeneity that plagued JLS, but still provides a large share of the manufacturing employees, a group of workers who have traditionally been displaced.

Displaced workers only have demographic information if they are observed at any point in the education data. Columns 2-4 indicate that slightly less than half of Ohio's 8,073 displaced workers with education records are female. This result clashes with JLS, Lachowska, and others who find that between 60-70% of displaced workers are men (gender is observable in their state UI data). However, given that American women enroll and complete college at higher rates than men.[17], this result is likely a reflection of differential propensities of males and females to enroll in college, rather than Ohio's status as an outlier in its gender share of displaced workers.

The two earnings-related panels of Table 3 (AKM quartile and pre-displacement yearly earnings) reinforce each other's findings: the average displaced worker earned roughly $50,000 in the year before separation, and over half of them separated from a top-quartile fixed effect firm. These statistics are similar to those generated by LMW. Figure 2 indicates nearly no Ashenfelter dip in the sample, which contrasts with the findings of previous works.

Table 4 summarizes key variables for the displacement and comparison samples used in this paper's difference-in-difference model. The comparison sample, who are highly tenured at the same firm throughout the panel, outnumber the displaced workers by a ratio of over 12:1. Such a large sample size for the comparison group is instrumental in producing the precise regression-adjusted estimates that will be presented in Section 5. The same share of displaced and comparison workers come from top AKM quartile firms, although a slightly larger share of displaced workers come from lower-quartile firms. The comparison group has significantly higher prelayoff earnings (defined as 2004-2005 earnings) than the displaced sample, but this should not be a threat to identification using the difference-in-difference strategy. It's also evident that both groups have a very low college enrollment rate three years before displacement or in the year 2003 (for displaced and comparison samples, respectively), although the soon-to-be displaced are slightly more likely to be enrolled.

Table A.1 presents earnings and industry variables for all displaced workers by quartile of layoff firm pay premium. 45% of all displaced workers that separated from a top-quartile fixed effect employer come from manufacturing. Former manufacturing employees also represent nearly one-third of all workers displaced from third-quartile firms. The administrative sample lacks information on firm's unionization status. However, according to the Current Population Survey, Ohio had the nation's fourth highest manufacturing unionization rate (23.7%) in 2002, likely contributing to their large representation among firms with high pay premiums. At the

[17] [Goldin et al., 2006] I also confirm this in my own data

low end, one-third of employees from a bottom quartile-paying firm separated from hospitality and food services and another one-fourth in retail. However, as Table 3 notes, these workers from the lowest-paying firms comprise only a small share of the overall displaced sample.

The second panel of Table A.1 displays the average displaced worker pre-earnings by AKM quartile firms, demonstrating the predictable pattern that workers at higher quartile firms earn more. This panel also underscores the magnitude of the earnings differences across quartiles. One year before displacement, the average sample individual at a top quartile firm earns nearly twice that of someone at a second quartile firm.

Besides unionization in manufacturing, there are other plausible explanations for the substantial variation between mean earnings of workers displaced from different quartile firms. According to Joan Robinson's monopsonistic wage setting model, different firm wage premiums arise because more profitable firms seek to hire more workers and therefore pay higher wages to do so. [Robinson, 1969]. Lastly, as indicated by the positive covariance between worker and firm fixed effects in Table 2, there exists sorting between higher-paying firms and workers of higher ability, education-level, and other qualifications.

4 Econometric Framework

This section begins with a description of the AKM model used to identify firm-specific pay premiums for Ohio employers. Then, I describe the standard multi-period difference-in-difference model employed to infer the causal effect of displacement on earnings. Lastly, I discuss my approach of leveraging both estimated firm fixed effects from AKM and enrollment data from Ohio post-secondary schools to infer additional causal impacts of displacement.

4.1 AKM Model

The increased prevalence of matched employee-employer administrative datasets has enhanced the quality and quantity of not only the displaced worker literature, but also research on firm-specific pay premiums. In their seminal research on the French labor market, [Abowd et al., 1999] documented that workers who move between establishments experience wage gains or losses in a highly predictable manner, providing credibility to the claim that "where you work" matters for "what you earn." Using French employment data, AKM developed the following model for log earnings of person i in year t:

$$log(earn)_{ijt} = \alpha_i + \gamma_t + \theta_{j(i,t)} + \varepsilon_{ijt} \tag{1}$$

where α_i are worker fixed effects, γ_t are year fixed effects, $\theta_{j(i,t)}$ are firm fixed effects, and ε_{ijt} is an unobserved time-varying error which may capture shocks to human capital, individual-job match effects, or other transitory shocks. $\theta_{j(i,t)}$ should be interpreted as the earnings premium or penalty (relative to some omitted firm) associated with working at firm j. Just as [Abowd et al., 1999], [Card et al., 2013], [Card et al., 2018] and [Lachowska et al., 2018] have done, I will estimate equation (1) on the universe of 1999-2012 Ohio workers from the UI data, subject to certain sample restrictions. I will then use the estimated $\hat{\theta}_j$'s that correspond to each firm in subsequent analysis regarding displaced worker earnings losses.

The innovation in AKM's approach is the addition of a firm-specific term which allows a person's earnings to vary systematically according to the identity of his or her employer. Of course, in order for α_i and $\theta_{j(i,t)}$ to be separately identified in equation (1), there must be sufficient movement of workers between firms to form a "connected set." Specifically, firms whose workers have not moved to or from other establishments are not linked to others employers by worker transitions and are thus not part of the connected set. Such firms without any movers are inevitable in such a large dataset, but in practice do not substantially reduce the size of the connected set. As illustrated in Table 1, 91% of all workers and 90% of all firms are included in the largest connected set from the Ohio sample.

The resulting variance decomposition for equation (1) is presented in Table 2. I decompose the variance of log earnings into five main components: variance deriving from worker fixed effects, firm fixed effects, year fixed effects, the covariance of worker and firm fixed effects, and a residual.[18] Worker fixed effects explain the largest share of variation in log earnings (53%), although it is clear the firm effects still assume an important role (25% of the variation).[19] Table 2 also signals the presence of sorting between workers and firms, as the covariance between worker and firm fixed effects is positive.

Identifying Assumptions

The two assumptions underlying AKM estimates are additive separability and exogenous mobility. Additive separability requires that upwardly and downwardly mobile job movers have a proportional markup or markdown. To show that additive separability is satisfied for the AKM estimates arising from the Ohio sample, Figure 3 illustrates changes in mean log earnings of upwardly and downwardly mobile workers in the same manner as Card and his co-authors in their 2013 and 2018 papers. Clearly, employer identity matters for earnings determination of workers that change firms: the same workers who move from lower-quartile to higher-quartile firms, despite having the same fixed skills, receive an earnings boost. The most up-

[18]the remaining covariances (between worker and firm fixed effects and year fixed effects) amount to a negligible amount of the overall variance of log earnings

[19]This compares to 22% estimated by [Sorkin, 2017], 21% in [Card et al., 2013] and 20% in LMW

wardly mobile workers experience larger earnings increases than the less upwardly-mobile, and likewise the most downwardly mobile workers exhibit earnings penalties of greater magnitudes than the less-downwardly mobile.

Exogenous mobility, on the other hand, is a stronger assumption and is often not as easily satisfied.[20] Exogenous mobility rules out job sorting based on individual shocks, firm shocks, and match components. For example, if worker i moves from firm A to firm B, exogenous mobility requires i) symmetry about zero

$$\mathbb{E}[\Delta w_{it}|A \rightarrow B] = -\mathbb{E}[\Delta w_{it}|B \rightarrow A]$$

(where w_{it} is wage) and ii) no pre or post-trends during before or after job change

$$\mathbb{E}[\Delta w_{it}|Stayer] = 0$$

Symmetry about zero is clearly evident in Figure 3, as the universe of movers exhibit very strong symmetry between the losses of downwardly mobile and the gains of similarly upwardly mobile workers. For example, workers who transition from the lowest-quartile θ (Q1) firms to the highest-quartile θ (Q4) firms experience a 90 average log point increase in their earnings. Conversely, workers who move from Q4 to Q1 employers exhibit a 95 log point drop in earnings. Those who who move from top or bottom firm to Q2 or Q3 firms likewise exhibit symmetric changes that are smaller in magnitude compared the *most* upwardly or downwardly mobile job changers.

The lack of pre and post-trends may also be satisfied for the majority of workers given Figure 3. The fact there is little change in the mean log earnings of workers who switch firms in the year before their transition would suggest that no pre-trends exist. Similarly, there is no meaningful change in mean log earnings for movers between their first and second year at the destination firm. However, two important groups I analyze in this paper – displaced workers and workers who enroll in post-secondary school – potentially violate the two conditions for exogenous mobility. Specifically, displaced workers may violate the pre/post trends assumption, and job changers who simultaneously pursue higher education violate symmetry about zero.

Figure 4 plots mean log earnings of *displaced workers* by quartile of origin and destination firm, rather than of all movers. Workers displaced from both Q1 and Q4 firms demonstrate a downward trend in earnings prior to their date of separation. Moreover, workers displaced from Q4 firms who find reemployment with lower-θ firms experience growth in earnings in the second full year of their tenure at the destination firm. For this unique class of job changers, it appears the "no pre and post-trends" assumption is violated.

Further, Figure A.3b plots the same type of graph for all job movers (regardless of displaced worker status) who enroll in an Ohio public college or university within

[20] See [Card et al., 2018] for in-depth discussion of the complications regarding exogenous mobility

a year of their movement (either before or after separation). These workers likely receive an idiosyncratic shock to their human capital and do not exhibit the symmetric patterns predicted by AKM. For example, while workers who move from a Q1 to Q4 firm experience an average 120 log point increase in earnings, those who transition from a Q4 to Q1 firm only experience a 50 log point drop. Such asymmetry in the positive direction is evident for all movers, including those transition from Q4 to Q4, who exhibit a 20 log point increase in mean earnings.[21]

Despite these unique cases where the identifying assumptions of AKM are not fully met, its use can still be considered appropriate for subsequent parts of this paper because displaced workers and movers who enroll in college constitute a negligible fraction of the 4.1 million job changers in the panel (1% and 1.5%, respectively). Thus, the estimated $\hat{\theta}_j$'s obtained from equation (1) should be reliable.

4.2 JLS Model

Before understanding how firm-specific wage premiums play a role in displaced worker earnings losses and education decisions, I must first estimate the simple effects of displacement on worker earnings. I do so by estimating the following multi-period difference-in-difference specification:

$$y_{ijt} = \alpha_i + \gamma_t + W_{it}'\beta_1 + X_{ijt}'\beta_2 + \sum_{k=-8}^{16} \delta_k \cdot D_{itk} + \varepsilon_{ijt} \tag{2}$$

In equation (2), y_{ijt} are the log of quarterly earnings for worker i in quarter t at firm j; α_i and γ_t are worker and year-quarter fixed effects, respectively; X_{ijt} includes a vector of one-digit NAICS code dummies for worker i's layoff employer j (or the comparison worker's primary employer) interacted with a vector of yearly indicators; and W_{it} is a vector of yearly indicators interacted with pre-displacement earnings (average of the 5-8 quarters before separation for treatment group, average of 2003 earnings for comparison group). D_{itk} is an indicator that equals one if worker i is observed in quarter k relative to displacement in calendar-quarter t, and equals zero otherwise. k assuming the value zero indicates the final quarter of a displaced worker's observed tenure with the displacement employer. δ_k is the baseline displacement effect on earnings in quarter k relative to separation. Because the within-worker residuals cannot be assumed to be independent across time, I cluster at the worker level. Lastly, because "Ashenfelter dips" – drops in earnings that precede displacement – can affect earnings despite displacement not having yet occurred, I allow the index k to assume negative values as low as -8. Since each dis-

[21] To see a similar graphs for the subset of displaced workers who also receive educational training during the time of their transition, refer to Figure A.4. Such workers (defined as the very small intersection of the displaced worker sample and the movers enrolled in school during transition) demonstrate earnings patterns that seem to violate both conditions of exogenous mobility in a predictable manner, given Figures 4 and A.3b

placed worker has at least 3 years of tenure, the "omitted category" for the treated sample includes earnings in quarters -12 $\leq k \leq$ -9.

In order to interpret δ_k as the causal effect of displacement on earnings, the parallel trends assumption – that displaced and non-displaced worker earnings follow the same trend in the pre-treatment period – must be met. According to equation (2), the specified treatment begins 8 quarters prior to displacement, so earnings between the two groups must be parallel in the third year prior to separation. Displaced workers, by definition, are highly-tenured at the time of their layoff, so I require the comparison group of stably employed workers be similarly high-tenured.[22] Even if the high-tenured workers in the comparison group are not comparable to the displaced sample along certain unobservables (such as ability or productivity), so long as the gap between the treatment and stably employed workers is assumed constant prior to treatment and would have remained constant absent displacement, the δ_k coefficients can be interpreted as causal.

To illustrate the validity of the parallel trends assumption in this context, I plot the earnings of displaced workers and the comparison group before and after their separation date (Figure 2).[23] From three years prior to displacement up to the date of separation, the mean quarterly earnings of the displaced and non-displaced cohorts follow the same common trend. Moreover, although these are unconditional[24], the persistent earnings losses are apparent up to four years after displacement. This figure provides convincing evidence that if no such displacement occurred to the treated sample, the earnings of the two groups would have continued growing at the same pace, meaning equation (2) is well-identified.

4.3 JLS-AKM Model

To identify the degree to which firm-specific pay premiums explain the earnings losses of displaced workers, I treat the previously estimated employer fixed effects $\hat{\theta}_j$ as an additional outcome in the displacement process. Once each firm j's $\hat{\theta}$ is estimated from equation (1) on the largest connected set, I then matched the estimated $\hat{\theta}$'s to the worker-quarter observations that correspond to the proper establishment identifier. Thus, a subset of the displaced workers now have corresponding values for $\hat{\theta_{ijt}}$ for every quarter they work for a firm in the largest connected set.[25]

[22] Specifically, a worker must be employed at the same firm for at least 56 of the observed 57 quarters to qualify for the comparison group

[23] In Figure 2, because the comparison group necessarily lack a separation date, I set the median quarter of displacement for the treated group as their date of separation. For the treated group, the date of separation varies for each displaced worker.

[24] Unconditional in the sense that the graph is simply descriptive, not controlling for covariates, and also "unconditional" on work, meaning quarters with zero earnings are included in the mean for displaced workers

[25] It is a proper subset (although it is nearly identical) because unmatched cases occur when a displaced worker's firm (either layoff or destination) was not in the connected set used to estimate equation (1).

I then use these estimated firm effects as a left-hand side variable in the following regression, modeled after equation (2):

$$\hat{\theta_{ijt}} = \alpha_i + \gamma_t + W_{it}'\beta_1 + X_{ijt}'\beta_2 + \sum_{k=-8}^{16} (\omega_k \cdot D_{itk}) + \upsilon_{ijt} \tag{3}$$

Note that the right-hand sides of equations (2) and (3) are identical, meaning the same difference-in-difference reasoning applies. In fact, for equation (3), the parallel trends assumption necessarily holds: because the pre-treatment period is quarters 9 through 12 before displacement, and the displaced sample is employed at the same firm during this time, the then $\hat{\theta_{ijt}}$ – a value that only changes for worker i when she moves firms – is necessarily constant over time. Of course, this constant trend applies for the comparison group as well.

The estimated ω_k's are thus the effect of displacement on the firm-specific component of earnings for worker i in quarter k relative to displacement. In effect, each ω_k estimates

$$\mathbb{E}[\theta_j|\alpha_i, \gamma_t, D_{itk} = 1] - \mathbb{E}[\theta_j|\alpha_i, \gamma_t, D_{itk} = 0]$$

where D_{itk} equals one if a displaced worker is observed in a post-separation quarter, and zero if a displaced worker pre-separation or a stably-employed worker is observed. A negative ω_k for positive values of k would provide evidence of lost employer-specific premiums. Taking the quotient of the ω_k coefficient and δ_k from equation (2) yields the estimated share of earnings losses attributable to lost firm fixed effects k quarters after displacement.

Lastly, I once again employ the JLS difference-in-difference model to assess the effect of displacement on a worker's propensity to enroll in a public post-secondary institution. I estimate the following model on the sample of displaced workers and non-displaced comparisions:

$$enroll_{it} = \alpha_i + \gamma_t + W_{it}'\beta_1 + X_{ijt}'\beta_2 + \sum_{k=-8}^{16} (\pi_k \cdot D_{itk}) + \epsilon_{it} \tag{4}$$

Once again, the right-hand side of equation (4) is the same as that from equations (2) and (3). $enroll_{it}$ is a dummy variable that assumes the value one if worker i in year-quarter t is enrolled at one of Ohio's public colleges or universities. π_k represents the causal effect of displacement on college enrollment k quarters before or after displacement. Equation (4) is well-identified if parallel trends hold, which should be the case because the omitted category encompasses the third year prior to worker displacement. So long as individuals cannot predict that their firm will undergo a mass layoff more than 8 quarters in the future, there should be no reason for the trends of enrollment among future displaced workers and the comparison group to differ.

5 Results

In this section, I first present the results from the "classic JLS" specification (equation (2)) to confirm that displaced workers in Ohio indeed suffer substantial and persistent earnings losses. I also subset on workers displaced from industries besides finance, insurance, and real estate (NAICS 51-56) as well as workers displaced from the manufacturing firms. Second, I examine the degree to which displaced worker earnings losses can be attributed to losses of firm-specific fixed effects. Lastly, I show displacement has only a small causal impact on the absolute number of workers who enroll in post-secondary education. However, because baseline enrollment three years before displacement is low, the effect is large in relative terms. I assess the impact of near-future displacement on school enrollment to show that some workers anticipate impending layoffs and presumably seek to mitigate future earnings losses by attending school.

5.1 Estimates of Lost Earnings

Before examining how firm-specific pay premiums affect displaced worker earnings losses, I must first verify such losses. The first row of panel A in Table 5 summarizes the estimates of short and long-term earnings losses for the full sample of displaced workers in Ohio based on equation (2). In the first full quarter after displacement, workers experience an earnings decrease of 40 log points. It should be noted that because the left hand side variable is log earnings, observations where workers experience zero earnings for a quarter are dropped from the regression. Thus, the presented coefficients provide estimates of the effect of displacement conditional on work.[26]

Four years after displacement (13-16 quarters), workers earn approximately 26% less than they would have if they were not displaced. Such estimates fall well within the bounds of the recent displaced worker literature. LMW and Couch and Placzek estimate long-run earnings losses of 15 log points (LMW) and 32 log points (Couch).[27]

The point estimates from Table 6, Column 2 (as well as coefficients for quarters preceding displacement) are plotted in Figure 5 with 95% confidence intervals. The short and long-term effects of displacement are negative and highly significant. Noticeably, the causal effects of displacement on earnings relative to quarter of separation follow the familiar "dip, drop, and partial recovery" pattern. The deep trough corresponding to the $\delta_{k=1}$ point estimate is likely driven by newly displaced workers

[26]While I considered using the inverse hyperbolic sign or changing zero earnings to ones to avoid an undefined log(0) value, I opted against doing so because it would prevent constructing a "share attributable to firm fixed effects" comparisons like that in Table 5, which only make sense when the mapping of quarterly earnings to quarterly firm-specific fixed effects is defined for all earnings

[27]Both LMW and Couch define the long-run as five years rather than four

being unemployed for part of the following quarter.[28]

On the whole, the substantial long-run earnings losses for displaced workers are quite remarkable, especially considering virtually all of them separated during tight labor markets. Those displaced before 2007 had several years of strong labor markets that may have allowed their earnings to recover more substantially. [Davis and von Wachter, 2011] show that historically, the long-run fortunes of displaced workers are pro-cyclical: workers laid off during tight labor markets recover a greater share of their earnings than those displaced in slack labor markets. However, Davis and von Wachter note that 2003-2005 –when U.S. unemployment was below 6% – was an anomaly, as high-tenured men displaced during these years exhibited long-run earnings losses greater than those displaced at any other time in the previous 25 years (including long-term losses of those displaced from the 1982 recession, when unemployment eclipsed 9%). The magnitude of my estimates in this section are fairly consistent with those presented in [Davis and von Wachter, 2011], although I do not decompose my analysis by year of layoff.

Displaced Workers – non NAICS 51-56

I conduct the same econometric analysis on two subsets of displaced workers that I suspect may represent different earnings patterns than the overall sample: those displaced from industries besides finance, insurance and real estate (FIRE), and those displaced from manufacturing.

Panel B of Table 5 presents the regression-adjusted estimates of short and long-run earnings losses for those displaced from non-FIRE industries. Point estimates for all quarters after displacement are presented in Table A.2. As summarized in Table 3, these individuals represent 92% of the workers displaced in Ohio between 2002Q1 and 2008Q4. In applying equation (2), I likewise drop non-displaced comparison workers who worked in finance, real estate, or insurance from the relevant sample. The non-FIRE displaced workers exhibit short and long-run earnings losses that are greater in magnitude than those of the overall sample. Such workers experienced a 49% drop in earnings in the quarter after displacement, and losses persist on the order of 28% in the long-run. Such results suggest that workers displaced from FIRE industries have a relatively easier time transitioning after layoff from a high-tenure job.

Displaced Workers – Manufacturing

I then analyze the earnings losses exhibited by workers displaced from manufacturing, who represent 30% of the Ohio displaced worker sample. This group of former manufacturing employees represented in my sample were displaced during the

[28]Because the data occur at a quarterly frequency and lack information on hours worked, I cannot verify this claim

brunt of what David Autor and co-authors refer to as the "China shock." China's accession to the World Trade Organization in 2001 accelerated the trend of shrinking U.S. employment in traded industries[29], as workers moved into non-traded jobs or out of work entirely [Autor et al., 2016]. Although I do not calculate the share displaced from manufacturing firms in import-exposed sectors identified by Autor, numerous Ohio local labor markets were among the most highly-exposed to Chinese manufacturing exports between 2000 and 2007 [Autor et al., 2013] [Autor et al., 2016], which coincides with the time frame of my data.

As shown in Panel C of Table 5, former manufacturing employees experience markedly larger earnings losses due to displacement than the overall or non-FIRE samples. They exhibit 72 log point earnings losses in the first quarter after displacement *conditional* on employment. Strikingly, even four years after displacement, they earn 38% less than they would have if they were not displaced, conditional on employment. The point estimates for the effect of displacement on earnings for all quarters are presented in Column 1 of Table A.3. While I do not claim that the source of these mass layoffs is trade-related, to the extent that some Ohio manufacturing shut down as a result of the China shock during the mid-2000s, these results – derived from individual-level microdata rather than aggregated data – may provide circumstantial evidence for [Autor et al., 2013]'s findings of adverse outcomes in regions highly-exposed to import competition.

Displaced Workers – by AKM Quartile

Table A.4 presents the all post-separation displacement coefficients for displaced workers distinguished by AKM quartile of layoff firm. For each column, I estimate equation (2) on the restricted sample of those laid off from a firm whose estimated $\hat{\theta}_j$ belongs to the relevant quartile and the those working continuously for such a firm throughout the panel. Per Table A.4, the largest differences in earnings losses across AKM quartiles are realized in the first quarter after displacement. However, there do not exist noteworthy differential earnings losses between workers displaced from various AKM quartile firms in the long run. For example, 16 quarters after displacement, workers displaced from the lowest quartile firms sustain a 12.6 log point earnings loss, while their counterparts from the highest quartile firms experience 14.6 log point earnings losses.

Several observations should be made in interpreting the results of Table A.4. First, because the comparison groups now reflect only those workers who remained employed at similar $\hat{\theta}_j$ firms, the magnitudes of the point estimates are not comparable to those in Table 6. Indeed, the depressed magnitudes are likely due to the fact that the plurality of displaced workers find re-employment with an firm belonging to the same AKM quartile as their layoff employer. This is represented

[29] Among the most trade-exposed was manufacturing which produced textiles, leather, plastics, toys, rubber, and glass. Substantial U.S production of latter two goods is concentrated in Ohio

by Figure A.1, which divides the displaced worker sample into sixteen bins which correspond to layoff and destination AKM firm quartiles. By the nature of this subgroup analysis, there are necessarily fewer “mobile” displaced workers who change firm quartiles compared to the sample used to produce Table 6. Second, because log points approximate percentages, then workers displaced from top-quartile firms, even if they experience the similar percentage loss in earnings as other workers, still lose more in absolute terms.

5.2 Estimated Losses due to Firm Fixed Effects

According to Table 3, the majority (56%) of displaced workers separated from top-quartile firms and very few separated from bottom-quartile establishments. If displaced workers are systematically re-employed by firms that offer a lower pay premium to all its employees, this would mean a portion of the earnings losses described in section 5.1 can be explained by this downward transition to lower θ firms. I test this hypothesis using model (3).

Table 7 presents regressions results for equations (2) and (3) comparing the magnitudes of displacement effects on log earnings and employer fixed effects, respectively. Columns 1 and 2 display the displacement effects for non-negative quarters for each equation without controlling for level of worker pre-earnings (interacted with a yearly time vector). Columns 3 and 4 add these controls and the point estimates for a given quarter decrease by roughly one log. The addition of these control variables suggest an individual's share of earnings lost from displacement depends on the level of her pre-displacement income.

Column 4 of Table 7 suggests that 16 quarters after displacement, average worker earnings are six log points lower than they would be absent a layoff simply because they were re-employed by a firm with a lower pay premium. The second row of panel A in Table 5 provides the average point estimates for the short-term and long-term effects of displacement on the firm-specific pay premiums reaped by the displaced sample. Figure 6 plots the estimated δ_k and ω_k coefficients for -8 $\leq$ k $\leq$ 16 derived from equations (2) and (3).

As described in Section 4.3, I can calculate the share of losses explained by dividing ω_k by δ_k for positive values of k. The third rows in each panel of Table 5 presents these statistics for each sample of displaced workers. For the overall sample, roughly 22% of a worker's earnings deficits four years after displacement are attributable to employment at firms with lower wage premiums. These results are larger than the shares estimated by LMW for workers displaced in Washington state during the Great Recession (roughly 9%). The difference in our estimates may lie in the types of employment opportunities open to displaced workers in the two states. It could be that displaced workers in Washington more easily transition to middle or high-θ firms than are their Ohio counterparts. My estimates may also differ from

LMW's if workers displaced during tighter labor markets (Ohio sample) struggle to find re-employment at firms with better pay premiums relative to those displaced during recessions (Washington sample), although such an explanation seems counterintuitive.

I conduct the same analysis of displaced workers from non-FIRE industries and displaced manufacturers. These results are summarized in the bottom two rows of panels B and C of Table 5. In addition to exhibiting larger total earnings losses than displaced workers, the loss of firm-specific pay premiums also explain a larger share of the overall losses of the non-FIRE sample (24% vs. 22%). The estimated total losses and losses of firm fixed effects for this group are plotted in Figure 7a.

Once again, displaced manufacturing workers distinguish themselves from the rest of the sample: after four years, half of their total earnings losses can be attributed to the loss of firm-specific pay premiums. Moreover, the estimated losses of firm fixed effects grows slightly over time (as does the share explained), which can be seen in Figure 7b. One explanation for this trend may be that manufacturing workers have a hard time maintaining a new job in the months or early years after displacement. If they are fired or leave their new job, they may once again move to relatively lower-paying firms over time. Figure 7b provides empirical support to the claim that displaced manufacturing workers are particularly vulnerable to employment shocks because a considerable portion of their earnings derived from favorable pay premiums from rent sharing or unionization.

5.3 Estimated Effects of Displacement on Enrollment

Lastly, I assess the effect displacement assumes in a displaced worker's decision to enroll in post-secondary education. The point estimates from equation (4) are plotted in Figure 8. Since the estimated π_k's can be interpreted as the causal effect of displacement on enrollment, the coefficients can be interpreted in two ways. First, the magnitude is simply the fraction of all displaced workers who enroll in college $k$quarters relative to displacement. Second, the magnitude can be compared to a baseline measure of enrollment before displacement to see the relative changes in enrollment. Given the omitted category includes three years before displacement, I will interpret the results from Figure 8 relative to the enrollment patterns of workers who will be displaced three years in the future.[30]

In the period of time 9-12 quarters prior to displacement, 1.68% of future displaced workers in my sample were enrolled in college in any given semester. According to Figure 8, roughly 0.7% of displaced workers enroll in college in a given semester during the first year post-displacement *as a result* of being displaced. This amounts to a 42% increase in enrollment of this population of workers that can be attributed to the event of displacement. It should be noted that some workers decide

[30]Results from Figure 8 correspond to Tables 8 and A.6

to enroll for multiple semesters and some only enroll once. Therefore, for every 100 displaced workers in my sample, only 1 or 2 decide to enroll in college within a year of displacement as a consequence.[31]

Moreover, Figure 1 shows that roughly half of workers who enroll in college after displacement take more than one year to do so. While the share who enroll *more* than one year later may not all take classes as a consequence of displacement, it nevertheless implies my point estimates obtained for the impact of enrollment are surely a lower bound. This is not to mention, of course, displaced workers who seek training at private schools (DeVry, Kaplan University, etc.) as well as at out-of-state schools. As Figure 8 shows, the effect of displacement on likelihood of enrollment falls slowly to zero after four years post-separation. The post-displacement effects of layoff on enrollment (π_k where $k \geq 0$) are presented in Table 8.

Although the effects of displacement on enrollment are statistically significant and large relative to the baseline, the small magnitude of the point estimates in Table 8 nevertheless suggest that mass layoffs are not a large driver of college or university enrollment for newly displaced workers. [Foote and Grosz, 2017], for example, find that for every 100 workers involved in a mass layoff, first-time fall enrollment in nearby community colleges increases by about 3 students in the following year. My estimate for enrollment (first-time or otherwise) in *any* type of college is no higher than 2 students per 100 displaced workers. Given Foote and Grosz cannot identify which types of student drive this increase in enrollment, my estimates suggest the authors' mechanism extends beyond the channel of displaced workers enrolling in community college as a consequence of being laid off.

Besides enrollment effects after displacement, a second important conclusion can be drawn from examining Figure 8. Specifically, *future* displacement has a small but statistically significant effect on a worker's likelihood of college enrollment. In the quarter before and quarter of official displacement, roughly 0.25% of displaced workers enroll in a post-secondary institution as a result of their impending (certain or uncertain) layoff. Although this point estimate is not large in absolute terms, it is nonetheless larger than the positive effect of earnings on displacement three years after one's quarter of separation. Such evidence is consistent with the practice of firms announcing their closure several many months in advance of their shutdown. It may also be the case workers anticipate an uncertain but probable future layoff due to hard times for the firm. Regardless, it is clear that some workers in the Ohio sample correctly anticipate their displacement and act on this knowledge by enrolling in college before separating from their employer.

[31] In the extreme lower bound, the responsiveness for workers in the first year is 0.7%, the case where every displaced worker is enrolled in all four semesters. The upper bound for this figure is 4(0.7%) = 2.8%, the event in which displaced workers never enroll in more than one semester.

Displaced Workers – by AKM Quartile

Next, I perform subgroup analysis by regressing equation (4) for the subsamples corresponding to the four AKM firm fixed effect quartiles, the results of which are presented in Table 9.[32]

The first column of Table 9 illustrates that the enrollment patterns of individuals displaced from the lowest-quartile firms are not influenced by anticipation of displacement or displacement itself. This subgroup contains the fewest workers and thus the least precise estimates, it is worth noting their values are also very low relative to the other three subgroups. According to the AKM model, the workers represented in column 1 have the largest share of pre-displacement earnings which are explained by their own portable skills. Even if these Q1 workers transition to another low-θ employer, it should be relatively easier for their earnings to recover to pre-displacement levels compared to those displaced from Q2-Q4 firms. If this is the case, Q1 workers would have less of a reason to improve their human capital through schooling if they simply seek to regain pre-displacement wages. Indeed, this is precisely the story that the results of column 1 suggest.

Accordingly, workers displaced from Q2 and Q3 firms (columns 2 and 3) are more likely to enroll in school as a result of layoffs than Q1 workers. Point estimates increase in magnitude almost uniformly for each quartile within a quarter. Effects on enrollment are significant at the 1% level for four (six) of the first twelve post-displacement quarters for Q2 (Q3) workers. While it appears that the enrollment patterns of those displaced from mid-θ firms are responsive to this exogenous employment shock, Table 9 makes clear that this effect only occurs in the post-displacement period, as pre-displacement coefficients for Q2 and Q3 workers are effectively zero.

Estimates for workers displaced from high-θ firms (column 4) show their enrollment responds the most strongly to displacement. Nearly every post-displacement point estimate is positive, significant at the 0.1% level, and of a greater magnitude than estimates for the other subgroups. For many quarters, the point estimates for the Q4 workers are lower than those for the overall sample in Table 8 because the comparison groups being used are different.[33]

Moreover, the Q4 workers are the only subgroup for which pre-displacement point estimates of π_k are positive and significant. Indeed, according to Figure 9, which plots the estimated Q4 π_k's for -8 $\leq k \leq$ 16, displacement effects become positive and significant for the six quarters preceding displacement. Further, a Q4 worker is just as likely to enroll in school as a result of displacement in the quarter before displacement as she is two quarters after. Thus, workers displaced from the highest-quartile firms stand out in their anticipation of displacement, so much so

[32]The samples are identical to those used for Table A.4, described in Section 5.1

[33]The Q4 comparison group, on average, has a higher enrollment rate than the overall comparison group used in Table 8, thus leading to the relatively lower point estimates

that some enroll in school many months before the date of their actual separation.

The results of column 4 of Table 9 may simply be a product of Q4 firms providing more advanced notice of layoffs and shutdowns than lower-quartile firms (a hypothesis that cannot be tested with my data). However, the pre-displacement enrollment effects may also be driven by the same human capital explanation that likely compels relatively high *post*-displacement enrollment for Q4 workers. Specifically, if one assumes Q4 workers i) seek to recover their pre-displacement earnings and ii) are aware that, as employees of a Q4 firm, a relatively smaller share of their earnings can be explained by portable, individual-specific characteristics, then they should be more willing to increase their human capital and future earnings prospects. The same reasoning underpinning post-displacement enrollment can be applied to workers who anticipate a layoff but are not yet displaced.

6 Conclusion

I have sought to accomplish the following objectives: (a) confirm that displaced workers suffer large and persistent earnings losses; (b) estimate the extent to which changes in displaced workers' earnings can be attributed to losses in employer-specific pay premiums; and (c) investigate whether displacement had a causal effect on a worker's propensity to enroll in post-secondary education.

Using employer-employee-student matched administrative data, I estimate that displaced workers face earnings losses of 26% up to four years post-separation using Jacobson, Sullivan and LaLonde's canonical approach. When isolating "traditional" displaced workers, thereby excluding workers displaced from the finance, insurance, and real estate industries, the negative effects of displacement on earnings grow slightly larger in magnitude. Former manufacturing employees who suffer layoffs, meanwhile, endure long-run losses on the order of 40%. The magnitude of these long-run earnings deficits are striking, especially considering the sample analyzed in this paper is comprised of individuals laid off in tight labor markets, when earnings historically rebound more robustly.

After confirming large and persistent displaced worker earnings losses, I contribute to the nascent literature of estimating the share of such losses which can be attributed to reemployment by an employer with a different firm-specific fixed effect ($\hat{\theta}_j$). Four years after displacement, roughly 22% of displaced worker earnings losses can be attributed to the loss of employer-specific pay premiums. The loss of a favorable firm-specific pay premium for those displaced from manufacturing explains 49% of total earnings losses after four years. For the overall sample, given that firm effects account for just a minority share, then unobserved, time-varying reasons such as forfeiting of a favorable job-match are likely crucial to the plight of displaced workers. Nevertheless, my findings assert firm identity assumes a non-trivial role in the elusive earnings losses story.

Lastly, empirical analysis suggests that displacement has only a small absolute effect on a high-tenure worker's likelihood of enrolling in a post-secondary educational institution. For every 100 workers involved in a mass layoff, no more than 2 enroll in a public college within a year of displacement. One year after separation, workers become less likely to enroll in college over time, and the effect of displacement on enrollment falls to zero after four years. I also find that the causal effect of future displacement (one quarter ahead) is positive and significant, suggesting some workers anticipate a layoff and seek to upgrade their human capital before starting a new job.

In analyzing the displaced sample by firm-specific pay premium quartiles, I find workers from the top firms (who represent over half of the sample) are more likely than their counterparts from lower firms to enroll in school during the majority of quarters throughout the displacement process. Workers from bottom-quartile firms do not enroll in school at higher rates as a result of displacement. Moreover, those in my sample from the highest-quartile firms enroll in school well-ahead of their quarter of separation, suggesting they are particularly keen in anticipating firm layoffs and shutdowns. Such evidence is consistent with the theory that workers whose pre-displacement earnings are differentially more explained by non-portable factors (such as firm-specific pay premiums) should be more willing to upgrade their human capital upon displacement.

Given the persistent earnings losses associated with displacement and the positive returns to education for displaced workers described in Section 2, such small effects of displacement on enrollment are all the more puzzling. If education either helps a worker increase her human capital or simply signals ability and "opens the door" to firms with higher pay premiums, displaced workers may be well-served to return to school to mitigate the pronounced earnings and pay-premium losses outlined in this paper. Actions such as those proposed in [Barr and Turner, 2017], which specifically target unemployed (or soon to be unemployed) individuals by encouraging post-secondary enrollment, may be preferable policy intervention in the light of this paper's findings.

Bibliography

[Abowd et al., 1999] Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–333.

[Acemoglu and Autor, 2011] Acemoglu, D. and Autor, D. (2011). Lectures in labor economics. *Manuscript. http://economics. mit. edu/files/4689*.

[Ashenfelter, 1975] Ashenfelter, O. (1975). *The effect of manpower training on earnings: Preliminary results*. US Department of Labor, Office of the Assistant Secretary for Policy, Evaluation and Research.

[Ashenfelter and Card, 1984] Ashenfelter, O. and Card, D. (1984). Using the longitudinal structure of earnings to estimate the effect of training programs.

[Autor et al., 2013] Autor, D., Dorn, D., and Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, 103(6):2121–68.

[Autor et al., 2003] Autor, D., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.

[Autor et al., 2016] Autor, D. H., Dorn, D., and Hanson, G. H. (2016). The china shock: Learning from labor-market adjustment to large changes in trade. *Annual Review of Economics*, 8:205–240.

[Barr and Turner, 2017] Barr, A. and Turner, S. (2017). A letter and encouragement: Does information increase post-secondary enrollment of ui recipients? Technical report, National Bureau of Economic Research.

[Barth et al., 2016] Barth, E., Bryson, A., Davis, J. C., and Freeman, R. (2016). It's where you work: Increases in the dispersion of earnings across establishments and individuals in the united states. *Journal of Labor Economics*, 34(S2):S67–S97.

[Betts and McFarland, 1995] Betts, J. R. and McFarland, L. L. (1995). Safe port in a storm: The impact of labor market conditions on community college enrollments. *Journal of Human Resources*, pages 741–765.

[Bloom, 1990] Bloom, H. S. (1990). *Back to Work. Testing Reemployment Services for Displaced Workers.* ERIC.

[Bureau of Labor Statistics, 2010] Bureau of Labor Statistics, U. S. D. o. L. (2010). Economy at a glance: Ohio. `https://www.bls.gov/eag/eag.oh.htm`. Accessed: 2018-03-08.

[Card et al., 2018] Card, D., Cardoso, A. R., Heining, J., and Kline, P. (2018). Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics*, 36(S1):S13–S70.

[Card et al., 2013] Card, D., Heining, J., and Kline, P. (2013). Workplace heterogeneity and the rise of west german wage inequality. *The Quarterly Journal of Economics*, 128(3):967–1015.

[Carrington and Fallick, 2017] Carrington, W. J. and Fallick, B. (2017). Why do earnings fall with job displacement? *Industrial Relations: A Journal of Economy and Society*, 56(4):688–722.

[Couch and Placzek, 2010] Couch, K. A. and Placzek, D. W. (2010). Earnings losses of displaced workers revisited. *American Economic Review*, 100(1):572–89.

[Davis and von Wachter, 2011] Davis, S. J. and von Wachter, T. (2011). Recessions and the costs of job loss. *Brookings Papers on Economic Activity*, 42(2).

[Decker and Corson, 1995] Decker, P. T. and Corson, W. (1995). International trade and worker displacement: Evaluation of the trade adjustment assistance program. *ILR Review*, 48(4):758–774.

[Engbom and Moser, 2017] Engbom, N. and Moser, C. (2017). Returns to education through access to higher-paying firms: Evidence from us matched employer-employee data. *American Economic Review: Papers & Proceedings*, 107(5):374–378.

[Farber, 2011] Farber, H. S. (2011). Job loss in the great recession: Historical perspective from the displaced workers survey, 1984-2010. Technical report, National Bureau of Economic Research.

[Flaaen et al., 2017] Flaaen, A. B., Shapiro, M. D., and Sorkin, I. (2017). Reconsidering the consequences of worker displacements: Firm versus worker perspective. Technical report, National Bureau of Economic Research.

[Foote and Grosz, 2017] Foote, A. and Grosz, M. (2017). The effect of local labor market downturns on postsecondary enrollment and program choice. In *Association for Education Finance and Policy 42nd Annual Conference*.

[Goldin et al., 2006] Goldin, C., Katz, L. F., and Kuziemko, I. (2006). The homecoming of american college women: The reversal of the college gender gap. *Journal of Economic Perspectives*, 20(4):133–156.

[Heckman et al., 1999] Heckman, J. J., LaLonde, R. J., and Smith, J. A. (1999). The economics and econometrics of active labor market programs. In *Handbook of Labor Economics*, volume 3, pages 1865–2097. Elsevier.

[Jacobson et al., 2005a] Jacobson, L., LaLonde, R., and Sullivan, D. G. (2005a). Estimating the returns to community college schooling for displaced workers. *Journal of Econometrics*, 125(1):271–304.

[Jacobson et al., 2005b] Jacobson, L., LaLonde, R. J., and Sullivan, D. (2005b). The impact of community college retraining on older displaced workers: Should we teach old dogs new tricks? *ILR Review*, 58(3):398–415.

[Jacobson et al., 1993] Jacobson, L. S., LaLonde, R. J., and Sullivan, D. G. (1993). Earnings losses of displaced workers. *The American Economic Review*, pages 685–709.

[Krolikowski, 2017] Krolikowski, P. (2017). Job ladders and earnings of displaced workers. *American Economic Journal: Macroeconomics*, 9(2):1–31.

[Krueger and Summers, 1988] Krueger, A. B. and Summers, L. H. (1988). Efficiency wages and the inter-industry wage structure. *Econometrica: Journal of the Econometric Society*, pages 259–293.

[Lachowska et al., 2018] Lachowska, M., Mas, A., and Woodbury, S. A. (2018). Sources of displaced workers' long-term earnings losses. Technical report, National Bureau of Economic Research.

[Leigh, 1990] Leigh, D. E. (1990). *Does Training Work for Displaced Workers? A Survey of Existing Evidence.* ERIC.

[Macis and Schivardi, 2016] Macis, M. and Schivardi, F. (2016). Exports and wages: rent sharing, workforce composition, or returns to skills? *Journal of Labor Economics*, 34(4):945–978.

[Ost et al., 2018] Ost, B., Pan, W., and Webber, D. (2018). The impact of mass layoffs on the educational investments of working college students. *Labour Economics*, 51:1–12.

[Robinson, 1969] Robinson, J. (1969). *The Economics of Imperfect Competition.* Springer.

[Schmutte, 2014] Schmutte, I. M. (2014). Job referral networks and the determination of earnings in local labor markets. *Journal of Labor Economics*, 33(1):1–32.

[Sorkin, 2017] Sorkin, I. (2017). Ranking firms using revealed preference. *The Quarterly Journal of Economics.*

[Stephens Jr, 2001] Stephens Jr, M. (2001). The long-run consumption effects of earnings shocks. *Review of Economics and Statistics*, 83(1):28–36.

[Sullivan and Von Wachter, 2009] Sullivan, D. and Von Wachter, T. (2009). Job displacement and mortality: An analysis using administrative data. *The Quarterly Journal of Economics*, 124(3):1265–1306.

[Topel, 1991] Topel, R. (1991). Specific capital, mobility, and wages: Wages rise with job seniority. *Journal of Political Economy*, 99(1):145–176.

[Van Reenen, 1996] Van Reenen, J. (1996). The creation and capture of rents: wages and innovation in a panel of uk companies. *The Quarterly Journal of Economics*, 111(1):195–226.

[Von Wachter et al., 2009] Von Wachter, T., Song, J., and Manchester, J. (2009). Long-term earnings losses due to mass layoffs during the 1982 recession: An analysis using us administrative data from 1974 to 2004. *Unpublished paper, Columbia University.*

[Weil, 2014] Weil, D. (2014). *The Fissured Workplace*. Harvard University Press.

[Xia, 2016] Xia, X. (2016). What explains the rise of for-profit universities? evidence from dental assistant programs. *Columbia University Job Market Paper.*

Tables and Figures

Table 1: Summary Statistics for Full Panel and Largest AKM Connected Set

Full Sample	Full annualized panel	Largest connected set
Number of worker-year observations	58,214,004	57,488,877
Number of workers	8,068,586	7,374,993
Number of employers	394,117	356,200
Number of movers	4,206,119	4,150,715
Log earnings (mean)	10.484	10.433

Source: Author's tabulations of Ohio administrative earnings records, 1999-2012

Table 2: Variance Decomposition of Log Earnings for AKM Model, 1999-2012

	Variance of Outcome and Decomposition into Components						AKM Model Fit	
Outcome	Total Variance	Worker FE (α)	Employer FE (θ)	Year FE (γ)	2cov(α,θ)	Residual	Adj. R^2	RMSE
Log Earnings	0.624	0.328	0.156	0.001	0.052	0.089	0.858	0.295
Share of Variance		0.526	0.249	0.002	0.083	0.143		

Source: Author's tabulations of Ohio administrative earnings records, 1999-2012

Note: The variance estimates arise from the estimated coefficients obtained by estimating equation 1 on the universe of workers in the largest AKM connected set. The decompositions also include covariances between worker and employer fixed effects and year fixed effects. Since they explain around 1 percent of the variation, they are omitted from the table.

Table 3: Descriptive Statistics for Displaced Workers by Schooling

		Attended School: Relative to Displacement		
	Total	Only Before	Before and After	Only After
Characteristics of Layoff Firm				
Construction, Utilities, Mining	0.12	0.13	0.19	0.18
Manufacturing	0.30	0.22	0.21	0.36
Retail Trade	0.11	0.11	0.09	0.07
Finance, Insurance, Real Estate	0.08	0.10	0.09	0.08
Educational & Health Services	0.08	0.16	0.17	0.09
Hospitality & Food Services	0.05	0.03	0.04	0.03
Other Industries	0.26	0.25	0.21	0.19
Total	1.00	1.00	1.00	1.00
Displaced from AKM Firm in				
Bottom quartile	0.09	0.08	0.08	0.07
Second quartile	0.21	0.21	0.21	0.15
Third quartile	0.14	0.14	0.11	0.13
Top quartile	0.56	0.57	0.60	0.65
Total	1.00	1.00	1.00	1.00
Worker Characteristics				
Female (proportion)		0.46	0.51	0.46
Non-white (proportion)		0.14	0.19	0.16
Age at time of displacement		36.83	35.66	39.10
Yearly Pre-Displaced Earnings				
1-4 Quarters Before ($)	49,935	51,000	44,048	47,610
	(39,503)	(30,836)	(27,100)	(30,798)
5-8 Quarters Before ($)	49,672	49,905	42,781	47,383
	(37,475)	(28,192)	(23,726)	(27,977)
N	42,351	4,377	1,688	2,008

Note: Demographic information is only available for workers who attended a public college at any point in the panel. The standard errors of earnings are expressed in parentheses. The second through fourth columns divide the sample of displaced workers who appear in the education data into three disjoint groups: those enrolled only before displacement, only after, and both before and after.

Table 4: Displaced Worker and Comparison Group Characteristics

	Displaced	Comparison
Displaced from AKM Firm in		
Bottom quartile	0.09	0.04
Second quartile	0.21	0.17
Third quartile	0.14	0.23
Top quartile	0.56	0.56
Yearly Pre-Displaced Earnings		
1-4 Quarters Before ($)	49,935	59,444
	(39,503)	(38,585)
5-8 Quarters Before ($)	49,672	58,616
	(37,475)	(38,595)
Enrollment Rates		
9-12 Quarters before displacement:	1.68%	1.40%
N	42,351	521,188

Note: "Displacement" for the comparison sample refers to 2005Q4, which is the is the median layoff date for the displaced sample. Standard errors of earnings are expressed in parentheses. Averages are taken over range of quarters indicated

Table 5: Summary of Estimated Earnings Losses for Displaced Workers

	Q1	Q9-Q12	Q13-16
A. All Workers			
Full losses (logs)	-0.407	-0.261	-0.261
Loss attributable to foregone θ FE	-0.065	-0.057	-0.059
Share attributable	16.0%	21.9%	22.5%
B. All Workers except NAICS 51-56			
Full losses (logs)	-0.492	-0.279	-0.281
Loss attributable to foregone θ FE	-0.023	-0.066	-0.068
Share attributable	4.7%	23.7%	24.2%
C. Manufacturing			
Full losses (logs)	-0.724	-0.389	-0.383
Loss attributable to foregone θ FE	-0.216	-0.177	-0.190
Share attributable	29.8%	45.5%	49.6%

Note: Each entry provides the estimated displacement effect on earnings in the quarter or range of quarters indicated. For ranges, the mean of the corresponding point estimates are presented. All such point estimates are significant at the $p < 0.001$ level. Estimates are based on equations 2 and 3. The "share attributable" is simply the quotient of the loss attributable coefficient over the full loss coefficient.

Table 6: Estimated Effects of Displacement on Earnings

	(1) Earnings (in \$1,000s)	(2) Log Earnings
Quarter since displacement		
0	0.296***	-0.187***
	(0.0515)	(0.0043)
1	-4.839***	-0.407***
	(0.0512)	(0.0061)
2	-3.810***	-0.255***
	(0.0459)	(0.0045)
3	-3.300***	-0.294***
	(0.0423)	(0.0049)
4	-2.686***	-0.238***
	(0.0587)	(0.0043)
5	-3.042***	-0.256***
	(0.0428)	(0.0042)
6	-3.132***	-0.261***
	(0.0431)	(0.0042)
7	-2.995***	-0.255***
	(0.0424)	(0.0045)
8	-2.826***	-0.246***
	(0.0457)	(0.0042)
9	-3.144***	-0.271***
	(0.0631)	(0.0043)
10	-3.102***	-0.265***
	(0.0454)	(0.0043)
11	-2.968***	-0.262***
	(0.0457)	(0.0046)
12	-3.065***	-0.245***
	(0.0514)	(0.0043)
13	-3.372***	-0.267***
	(0.0520)	(0.0045)
14	-3.458***	-0.265***
	(0.0526)	(0.0045)
15	-3.259***	-0.279***
	(0.0821)	(0.0051)
16	-3.083***	-0.234***
	(0.1599)	(0.0045)
Observations	30912515	30675650

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Estimated Effects of Displacement on Earnings and AKM Fixed Effects

	(1) Log earnings	(2) θ log earnings	(3) Log earnings	(4) θ log earnings
Quarter since displacement				
0	-0.174***	-0.00215***	-0.181***	-0.00294***
	(0.0043)	(0.0005)	(0.0043)	(0.0005)
1	-0.402***	-0.0639***	-0.409***	-0.0648***
	(0.0061)	(0.0019)	(0.0061)	(0.0019)
2	-0.250***	-0.0481***	-0.258***	-0.0491***
	(0.0045)	(0.0016)	(0.0045)	(0.0016)
3	-0.286***	-0.0524***	-0.295***	-0.0535***
	(0.0049)	(0.0016)	(0.0049)	(0.0016)
4	-0.223***	-0.0527***	-0.233***	-0.0538***
	(0.0043)	(0.0016)	(0.0043)	(0.0016)
5	-0.248***	-0.0528***	-0.258***	-0.0540***
	(0.0042)	(0.0016)	(0.0042)	(0.0016)
6	-0.254***	-0.0535***	-0.265***	-0.0548***
	(0.0042)	(0.0017)	(0.0042)	(0.0017)
7	-0.248***	-0.0554***	-0.259***	-0.0567***
	(0.0045)	(0.0017)	(0.0045)	(0.0017)
8	-0.230***	-0.0555***	-0.241***	-0.0569***
	(0.0042)	(0.0017)	(0.0042)	(0.0017)
9	-0.260***	-0.0558***	-0.272***	-0.0573***
	(0.0044)	(0.0017)	(0.0044)	(0.0017)
10	-0.255***	-0.0563***	-0.267***	-0.0578***
	(0.0043)	(0.0017)	(0.0043)	(0.0017)
11	-0.251***	-0.0556***	-0.264***	-0.0572***
	(0.0046)	(0.0017)	(0.0046)	(0.0017)
12	-0.227***	-0.0548***	-0.239***	-0.0565***
	(0.0043)	(0.0018)	(0.0043)	(0.0018)
13	-0.256***	-0.0561***	-0.269***	-0.0578***
	(0.0046)	(0.0018)	(0.0045)	(0.0018)
14	-0.253***	-0.0574***	-0.266***	-0.0591***
	(0.0045)	(0.0019)	(0.0045)	(0.0019)
15	-0.267***	-0.0574***	-0.279***	-0.0592***
	(0.0051)	(0.0019)	(0.0051)	(0.0019)
16	-0.216***	-0.0571***	-0.229***	-0.0590***
	(0.0045)	(0.0019)	(0.0045)	(0.0019)
Pre-Displacement Earnings	No	No	Yes	Yes
Observations	30675650	30636253	30675650	30636253

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Estimated Effects of Displacement on Enrollment for Post-Displacement Quarters

	(1)
	Enrollment
Quarter since displacement	
0	0.0021**
	(0.0007)
1	0.0051***
	(0.0007)
2	0.0080***
	(0.0007)
3	0.0090***
	(0.0007)
4	0.0076***
	(0.0007)
5	0.0075***
	(0.0007)
6	0.0075***
	(0.0007)
7	0.0066***
	(0.0007)
8	0.0049***
	(0.0007)
9	0.0051***
	(0.0007)
10	0.0047***
	(0.0007)
11	0.0048***
	(0.0006)
12	0.0033***
	(0.0006)
13	0.0018**
	(0.0006)
14	0.0025***
	(0.0006)
15	0.0012*
	(0.0005)
16	0.0006
	(0.0005)
Observations	32079372

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

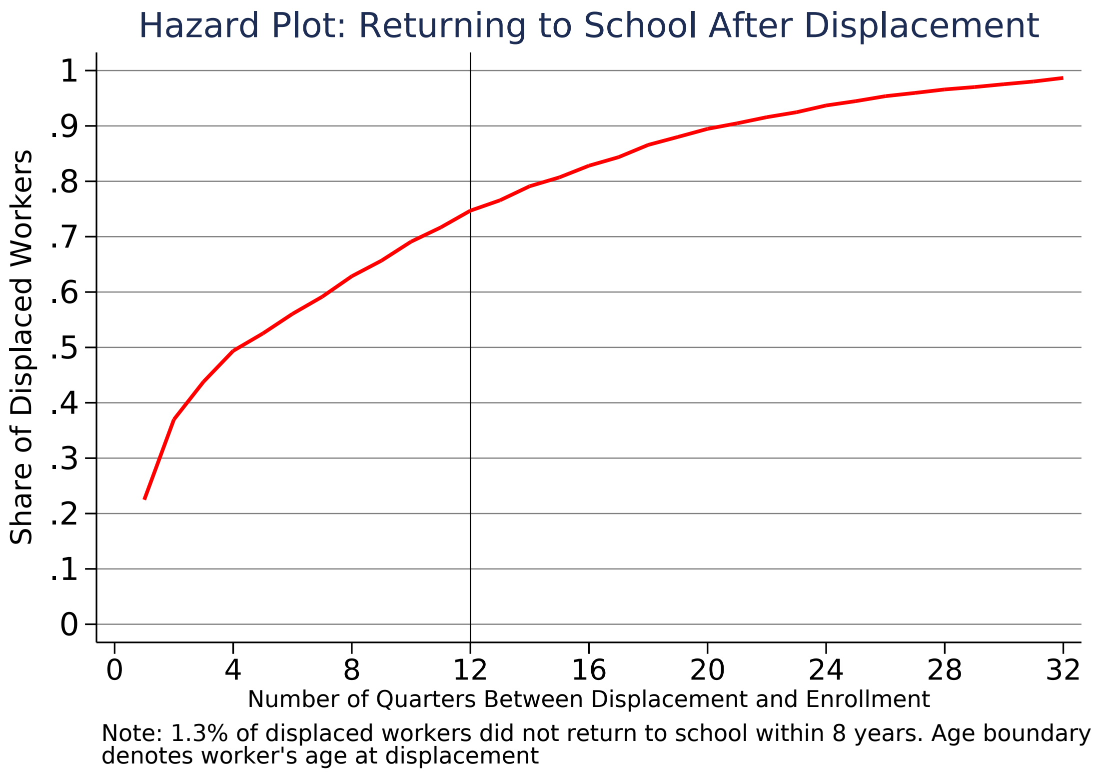
Table 9: Estimated Effects of Displacement on Enrollment, by Layoff $\hat{\theta}_j$ Quartile

	(1) Lowest	(2) 2nd Quartile	(3) 3rd Quartile	(4) Highest
Quarter since displacement				
-4	-0.0017	-0.0020	-0.0000	0.0046***
	(0.0020)	(0.0014)	(0.0015)	(0.0009)
-3	0.0009	0.0016	-0.0014	0.0026**
	(0.0021)	(0.0013)	(0.0012)	(0.0008)
-2	-0.0007	0.0014	0.0012	0.0047***
	(0.0021)	(0.0014)	(0.0014)	(0.0009)
-1	0.0018	0.0026	0.0018	0.0055***
	(0.0022)	(0.0014)	(0.0014)	(0.0009)
0	0.0004	-0.0026*	0.0023	0.0071***
	(0.0021)	(0.0013)	(0.0015)	(0.0009)
1	-0.0021	0.0033*	0.0010	0.0007
	(0.0022)	(0.0015)	(0.0015)	(0.0010)
2	0.0018	0.0015	0.0026	0.0058***
	(0.0023)	(0.0015)	(0.0016)	(0.0012)
3	0.0008	0.0036*	0.0053***	0.0064***
	(0.0020)	(0.0014)	(0.0015)	(0.0011)
4	0.0008	0.0033*	0.0011	0.0057***
	(0.0021)	(0.0014)	(0.0015)	(0.0011)
5	0.0028	0.0049***	0.0053***	0.0025**
	(0.0022)	(0.0014)	(0.0015)	(0.0010)
6	0.0010	0.0023	0.0026	0.0053***
	(0.0021)	(0.0014)	(0.0015)	(0.0010)
7	0.0015	0.0038**	0.0064***	0.0036***
	(0.0020)	(0.0013)	(0.0015)	(0.0010)
8	0.0019	0.0028*	0.0000	0.0046***
	(0.0022)	(0.0014)	(0.0014)	(0.0010)
9	0.0017	0.0038**	0.0043**	0.0029**
	(0.0019)	(0.0013)	(0.0015)	(0.0009)
10	-0.0008	0.0022	0.0039**	0.0036***
	(0.0019)	(0.0013)	(0.0015)	(0.0010)
11	0.0024	0.0041**	0.0060***	0.0019*
	(0.0019)	(0.0013)	(0.0015)	(0.0009)
12	0.0005	0.0028*	-0.0005	0.0036***
	(0.0020)	(0.0013)	(0.0014)	(0.0010)
Observations	1301752	5399281	7269809	17606693

Standard errors in parentheses

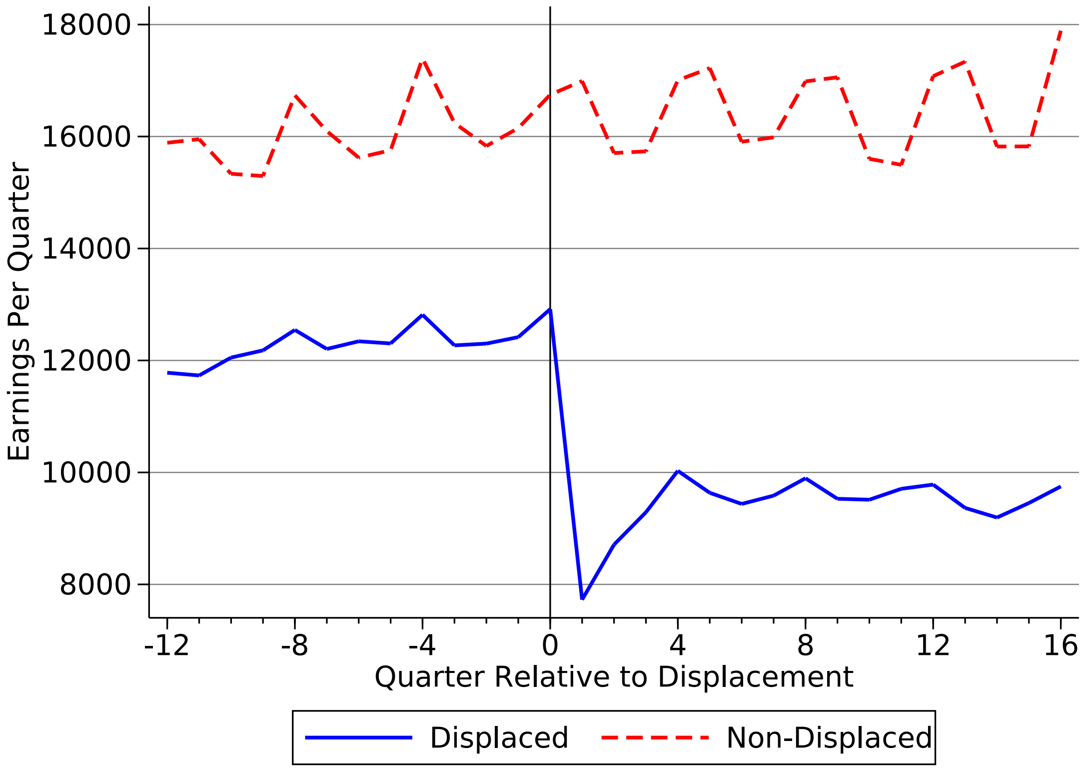
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1: Hazard Plot: Time Between Worker Displacement and College Enrollment



Note: This figure is a cumulative distribution function of the number of quarters between a worker's displacement and enrollment in an Ohio institution of higher education among workers who separated between 2002Q1 and 2008Q4 and were not enrolled in school before displacement (N = 3,636). Within three years of displacement, 75% of displaced workers that sought schooling had already enrolled."

Figure 2: Earnings Profile of Displaced and Non-Displaced Workers



Note: This figure shows quarterly earnings profiles (2012 constant dollars) of workers displaced in Ohio between 2002Q1–2008Q4 (blue) and workers who remained at the same firm from 1999Q1–2012Q4 with no more than one quarter of zero earnings (red). Earnings are unconditional, meaning they include observations of zero. Because the comparison group did not experience displacement, for them the vertical bar denotes the median quarter of displacement for the treated group (2005Q4)."

Figure 3: Mean Log Earnings of Movers Classified by Quartile of Firm Effects (θ) for Origin and Destination Firms

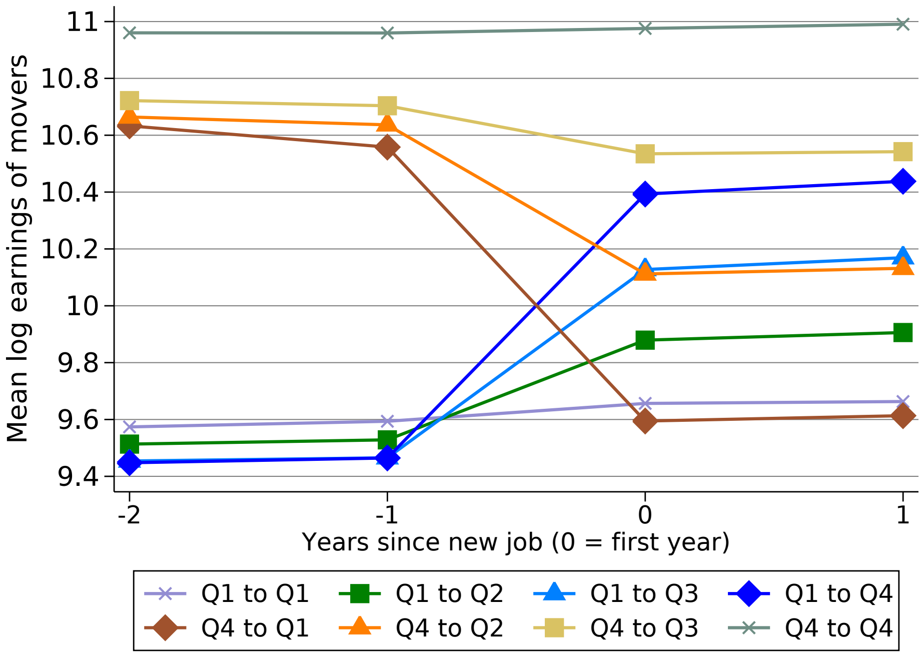
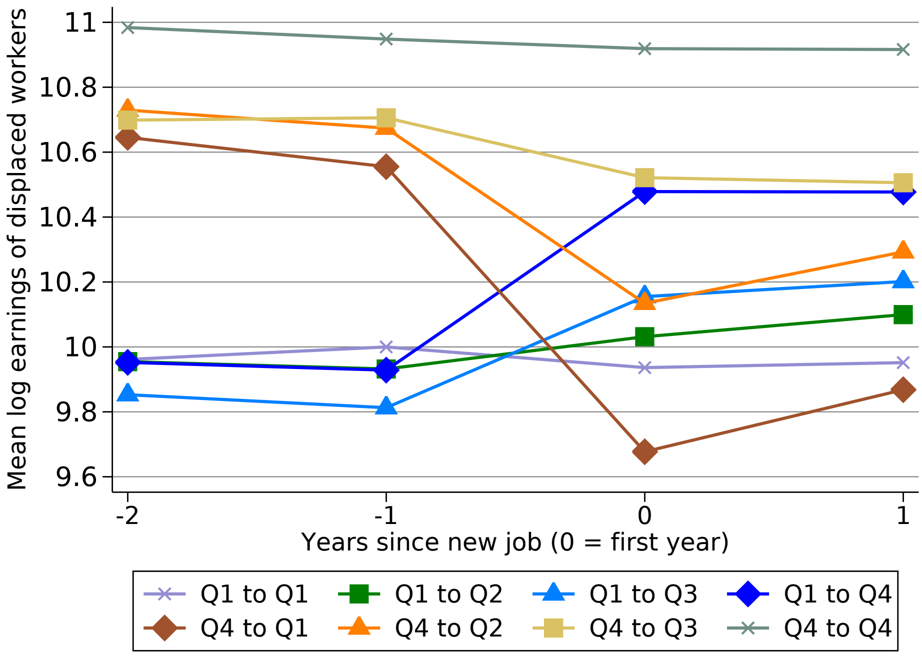
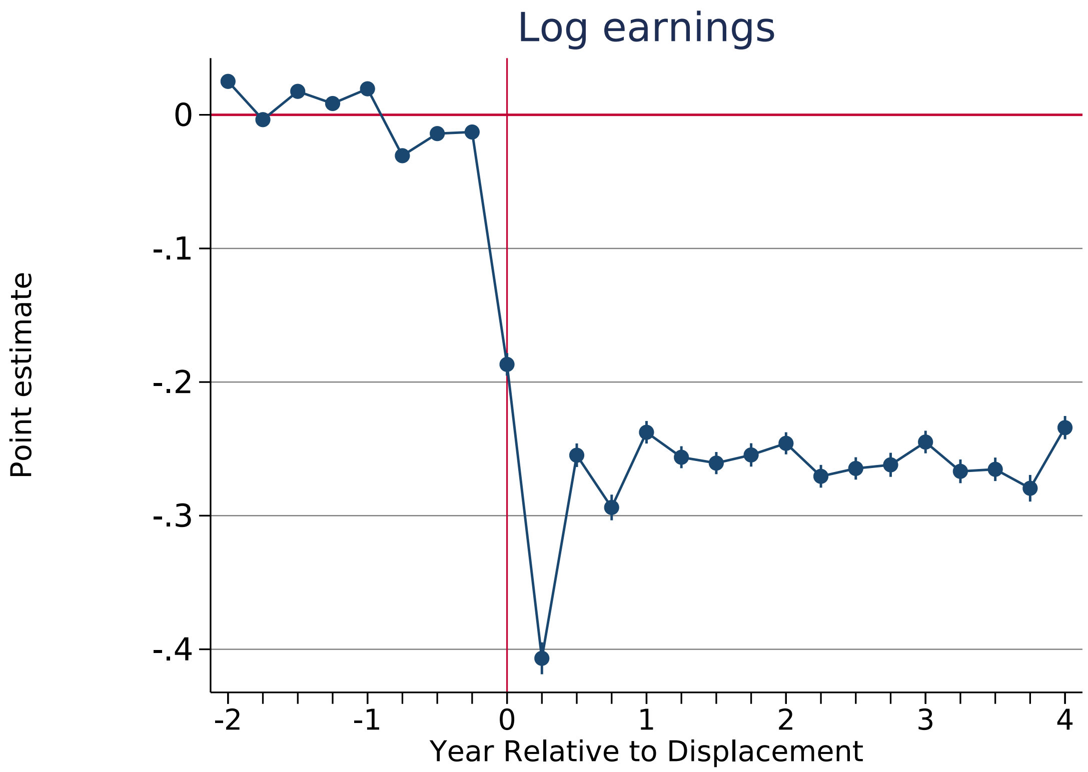


Figure 4: Mean Log Earnings of Displaced Workers Classified by Quartile of Firm Effects (θ) for Origin and Destination Firms



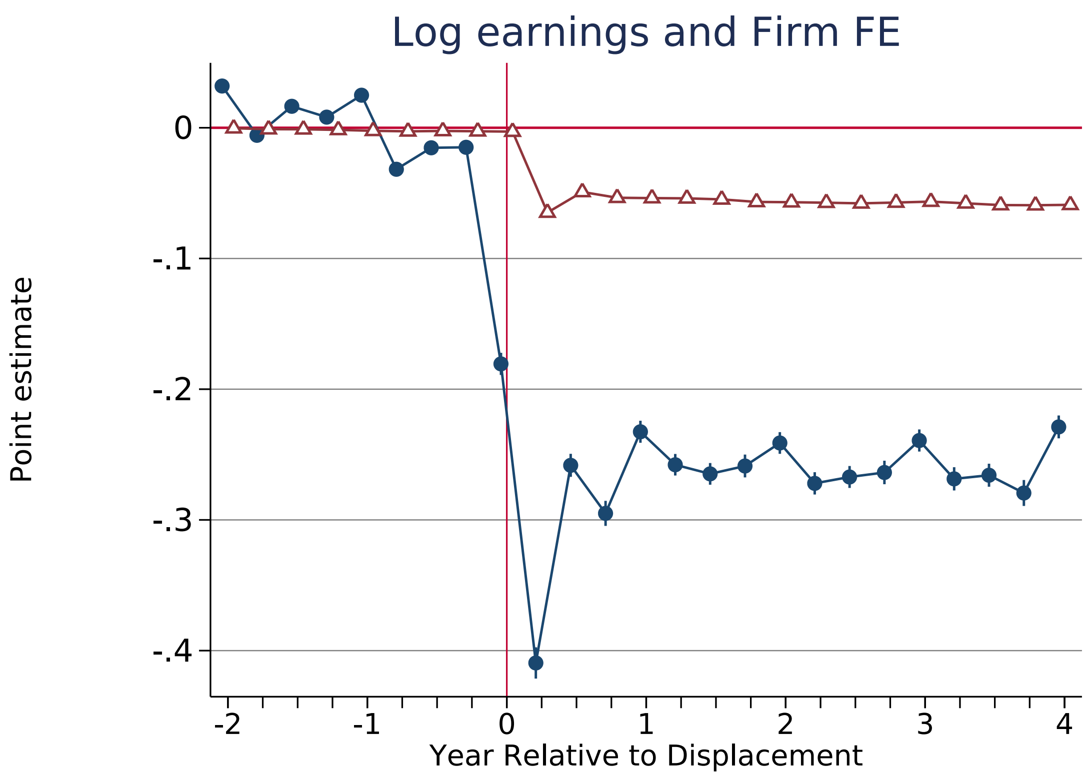
Note: These figure shows mean yearly earnings of (displaced) workers observed in 1999-2012 (2002-2008) in Ohio who changed jobs in the interval and both the preceding job and new job for two or more years. Jobs are classified into quartiles of establishment fixed effects based on the estimation of the AKM model.

Figure 5: Regression-Adjusted Estimates of Earnings Losses due to Displacement



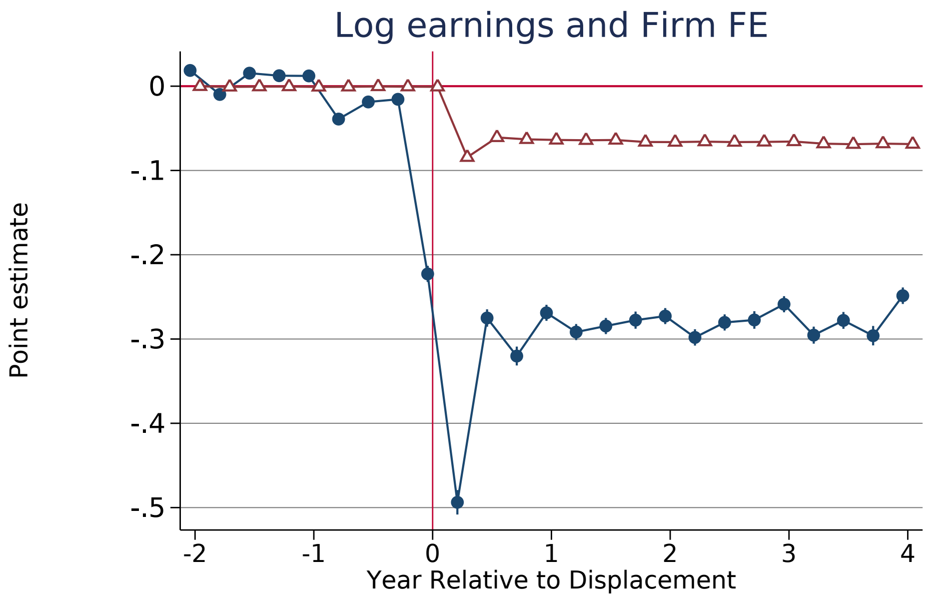
Note: Figure shows estimated δ_ks – logarithm of quarterly earnings lost due to displacement – based on equation 2 with the log of earnings as the dependent variable. Whiskers (which are very small) denote 95-percent confidence intervals based on standard errors clustered by worker. Vertical line denotes quarter of displacement. These estimates correspond to Column 2 of Table 6

Figure 6: Estimated Displacement Losses due to Foregone Employer Fixed Effects

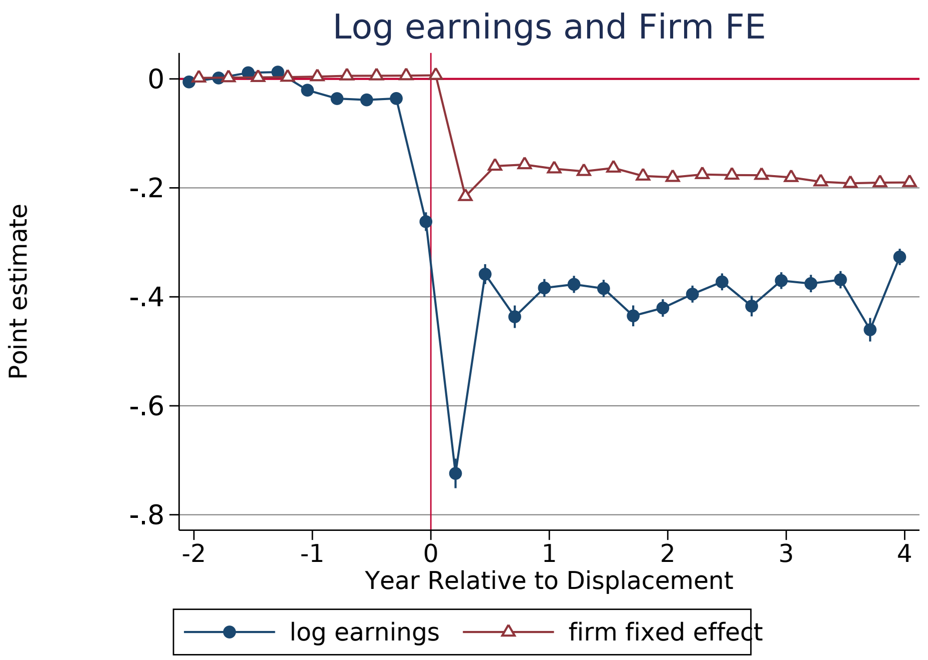


Note: Figure plots the estimated δ_k and ω_k coefficients from equations 2 (blue) and 3 (red). Whiskers (which are very small) denote 95-percent confidence intervals based on standard errors clustered by worker. Vertical line denotes quarter of displacement. These estimates correspond to Columns 3-4 of Table 7

Figure 7: Estimated Displacement Losses due to Foregone Employer Fixed Effects; Subsets of Displaced Workers



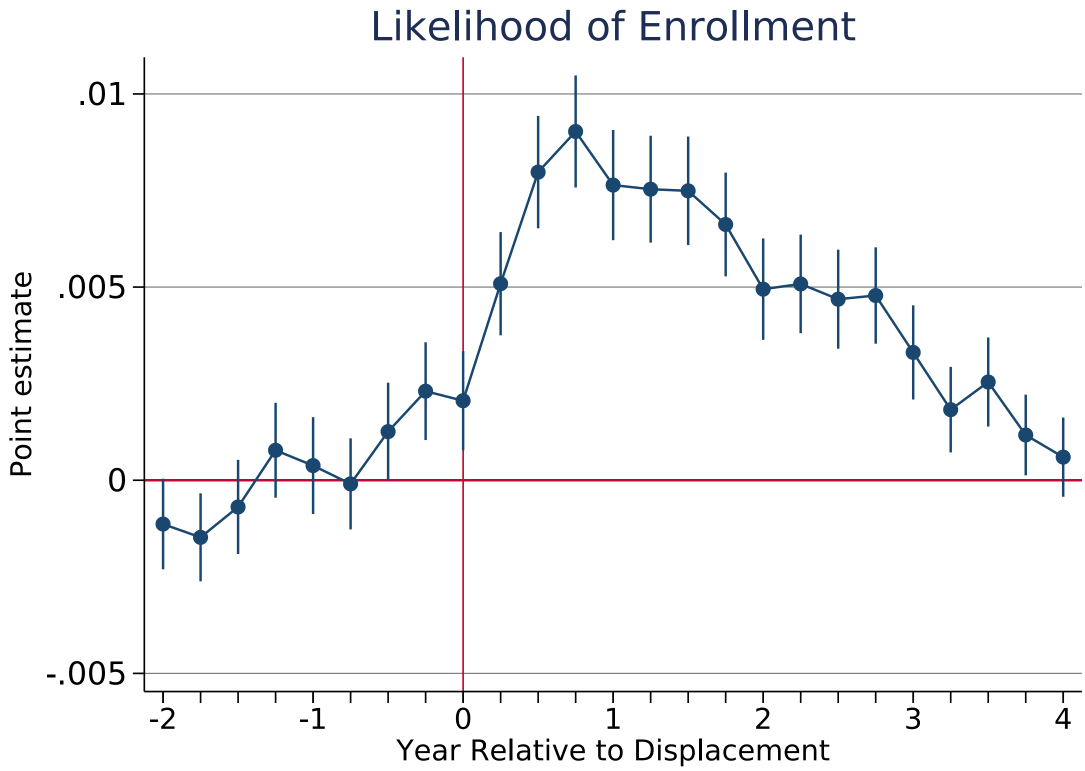
(a) All Displaced Workers Excluding NAICS 51-56



(b) Manufacturing

Note: These figures plot the δ_k and ω_k coefficients from equations 2 (blue) and 3 (red) for two different subpopulations of displaced workers. The top panel shows estimates for losses of workers displaced from industries besides NAICS 51-56 (finance, real estate, insurance) relatively to a comparison group that also omits NAICS 51-56. The bottom panel presents the same estimates for workers displaced from manufacturing relative to workers who remained highly-tenured in manufacturing. Whiskers (very small) denote 95-percent confidence intervals based on standard errors clustered by worker. Vertical line denotes quarter of displacement.

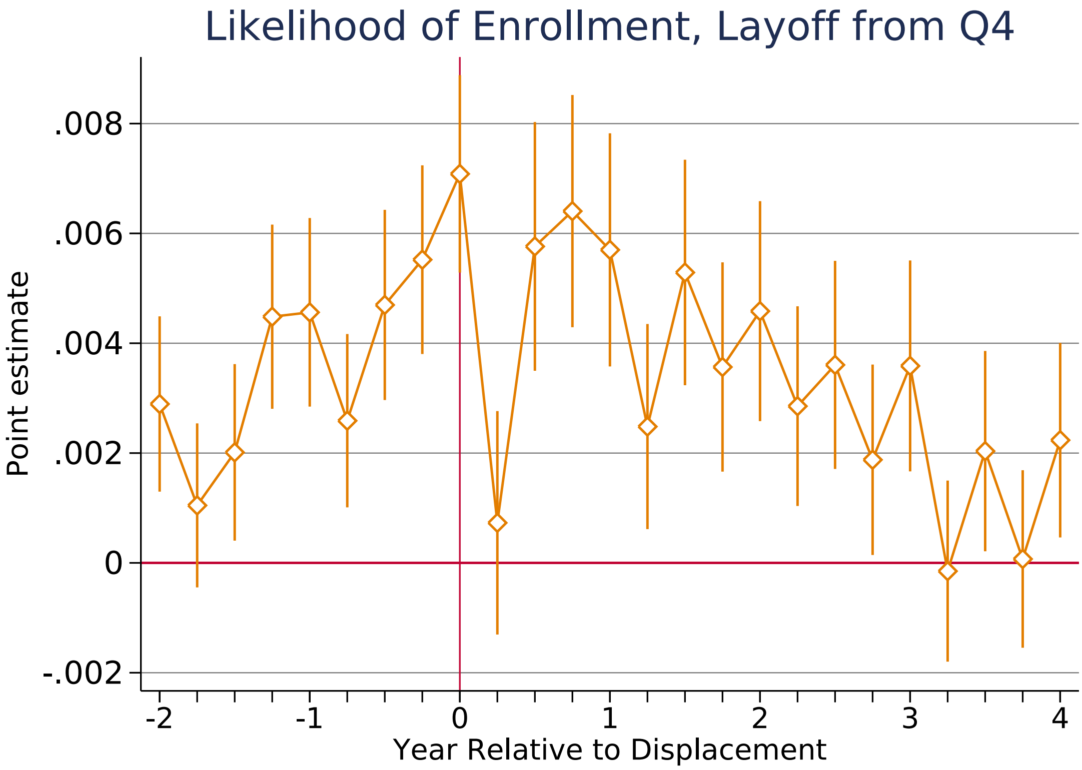
Figure 8: Estimated Effects of Displacement on Post-Secondary Enrollment



Note: Figure plots the estimated π_k from equation (4). Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Vertical line denotes quarter of displacement. These estimates correspond to the point estimates from Tables 8 and A.6. Semester-based enrollment (of which there are four periods per year) is matched roughly to calendar-quarters used to measure displacement. Enrollment includes at an Ohio public technical college, community college, university branch campus or flagship university, but does not include enrollment at private or non-Ohio schools

.

Figure 9: Estimated Effects of Displacement on Enrollment for Workers Displaced from Q4 firms



Note: Figure plots the estimated π_k from equation (4) for displaced workers and controls from Q4 firms. Whiskers denote 95-percent confidence intervals based on standard errors clustered by worker. Vertical line denotes quarter of displacement. These estimates correspond to the point estimates from Table 9. Semester-based enrollment (of which there are four periods per year) is matched roughly to calendar-quarters used to measure displacement. Enrollment includes at an Ohio public technical college, community college, university branch campus or flagship university, but does not include enrollment at private or non-Ohio schools

.

Appendices

Table A.1: Descriptive Statistics: Displaced Workers by Layoff Firm Pay Premium

	Quartile of Layoff Firm by Pay Premium			
	Lowest	2nd	3rd	Highest
Industry of Layoff Firm				
Construction, Utilities, Mining	0.01	0.05	0.16	0.16
Manufacturing	0.02	0.05	0.30	0.45
Retail Trade	0.27	0.28	0.06	0.03
Finance, Insurance, Real Estate	0.02	0.02	0.04	0.12
Educational & Health Services	0.01	0.16	0.13	0.05
Hospitality & Food Services	0.33	0.07	0.00	0.00
Other Industries	0.34	0.37	0.31	0.19
All Industries	1.00	1.00	1.00	1.00
Yearly Pre-Displaced Earnings				
1-4 Quarters Before ($)	24,704	35,491	43,598	61,186
	(22,053)	(28,848)	(34,049)	(42,341)
5-8 Quarters Before ($)	24,970	36,420	43,608	60,313
	(22,149)	(29,787)	(31,347)	(39,584)
N	3,916	8,875	6,089	23,544

Note: This table presents summary statistics of pre-displacement characteristics for workers displaced between 2002Q1 and 2008Q4, separated by the AKM-estimated quartile of their layoff firm.

Table A.2: Estimated Effects of Displacement on Earnings for Workers Displaced from Industries besides NAICS 51-56

	(1) Earnings ($1,000s)	(2) Earnings ($1,000s)	(3) Log Earnings	(4) Log Earnings
Quarter since displace				
0	-0.395***	-0.395***	-0.227***	-0.227***
	(0.046)	(0.046)	(0.005)	(0.005)
1	-5.323***	-5.323***	-0.492***	-0.492***
	(0.054)	(0.054)	(0.007)	(0.007)
2	-3.837***	-3.837***	-0.272***	-0.272***
	(0.049)	(0.049)	(0.005)	(0.005)
3	-3.421***	-3.421***	-0.319***	-0.319***
	(0.045)	(0.045)	(0.006)	(0.006)
4	-3.239***	-3.239***	-0.273***	-0.273***
	(0.044)	(0.044)	(0.005)	(0.005)
5	-3.314***	-3.314***	-0.289***	-0.289***
	(0.044)	(0.044)	(0.005)	(0.005)
6	-3.223***	-3.223***	-0.281***	-0.281***
	(0.044)	(0.044)	(0.005)	(0.005)
7	-3.092***	-3.092***	-0.276***	-0.276***
	(0.044)	(0.044)	(0.005)	(0.005)
8	-3.148***	-3.148***	-0.276***	-0.276***
	(0.046)	(0.046)	(0.005)	(0.005)
9	-3.335***	-3.335***	-0.295***	-0.295***
	(0.071)	(0.071)	(0.005)	(0.005)
10	-3.080***	-3.080***	-0.279***	-0.279***
	(0.047)	(0.047)	(0.005)	(0.005)
11	-2.939***	-2.939***	-0.278***	-0.278***
	(0.048)	(0.048)	(0.005)	(0.005)
12	-3.195***	-3.195***	-0.264***	-0.264***
	(0.054)	(0.054)	(0.005)	(0.005)
13	-3.563***	-3.563***	-0.292***	-0.292***
	(0.053)	(0.053)	(0.005)	(0.005)
14	-3.407***	-3.407***	-0.280***	-0.280***
	(0.056)	(0.056)	(0.005)	(0.005)
15	-3.175***	-3.175***	-0.298***	-0.298***
	(0.097)	(0.097)	(0.006)	(0.006)
16	-3.135***	-3.135***	-0.253***	-0.253***
	(0.200)	(0.200)	(0.005)	(0.005)
NAICS Dummies	No	Yes	No	Yes
Observations	24126624	24126624	23938499	23938499

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Estimated Displacement Effects on Earnings and AKM Fixed Effects, Manufacturing Only

	(1) Log earnings	(2) θ log earnings
Quarter since displacement		
0	-0.262***	0.00666***
	(0.0087)	(0.0006)
1	-0.724***	-0.216***
	(0.0138)	(0.0038)
2	-0.358***	-0.160***
	(0.0093)	(0.0029)
3	-0.437***	-0.157***
	(0.0105)	(0.0029)
4	-0.384***	-0.165***
	(0.0083)	(0.0029)
5	-0.377***	-0.170***
	(0.0080)	(0.0030)
6	-0.385***	-0.163***
	(0.0081)	(0.0032)
7	-0.435***	-0.178***
	(0.0098)	(0.0031)
8	-0.420***	-0.181***
	(0.0082)	(0.0031)
9	-0.395***	-0.175***
	(0.0079)	(0.0031)
10	-0.373***	-0.176***
	(0.0079)	(0.0032)
11	-0.417***	-0.177***
	(0.0096)	(0.0032)
12	-0.370***	-0.181***
	(0.0078)	(0.0032)
13	-0.376***	-0.189***
	(0.0082)	(0.0033)
14	-0.369***	-0.192***
	(0.0081)	(0.0034)
15	-0.460***	-0.190***
	(0.0110)	(0.0034)
16	-0.327***	-0.190***
	(0.0077)	(0.0033)
Observations	7515763	7508463

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: Estimated Effects of Displacement on Earnings, by Layoff $\hat{\theta}_j$ Quartile

	(1) Lowest	(2) 2nd Quartile	(3) 3rd Quartile	(4) Highest
Quarter since displacement				
0	-0.139***	-0.220***	-0.221***	-0.178***
	(0.014)	(0.009)	(0.010)	(0.006)
1	-0.110***	-0.344***	-0.277***	-0.280***
	(0.020)	(0.012)	(0.011)	(0.008)
2	-0.142***	-0.257***	-0.160***	-0.188***
	(0.017)	(0.011)	(0.009)	(0.005)
3	-0.172***	-0.244***	-0.152***	-0.251***
	(0.017)	(0.010)	(0.009)	(0.007)
4	-0.148***	-0.212***	-0.173***	-0.150***
	(0.016)	(0.010)	(0.009)	(0.005)
5	-0.155***	-0.246***	-0.212***	-0.173***
	(0.016)	(0.010)	(0.009)	(0.005)
6	-0.149***	-0.215***	-0.209***	-0.198***
	(0.017)	(0.010)	(0.009)	(0.005)
7	-0.156***	-0.210***	-0.165***	-0.217***
	(0.016)	(0.010)	(0.009)	(0.006)
8	-0.119***	-0.187***	-0.226***	-0.165***
	(0.017)	(0.010)	(0.010)	(0.005)
9	-0.169***	-0.245***	-0.239***	-0.187***
	(0.017)	(0.010)	(0.010)	(0.005)
10	-0.175***	-0.206***	-0.209***	-0.203***
	(0.018)	(0.010)	(0.010)	(0.005)
11	-0.175***	-0.200***	-0.170***	-0.220***
	(0.017)	(0.010)	(0.010)	(0.006)
12	-0.133***	-0.163***	-0.192***	-0.176***
	(0.017)	(0.010)	(0.010)	(0.005)
13	-0.164***	-0.224***	-0.192***	-0.189***
	(0.018)	(0.010)	(0.010)	(0.006)
14	-0.182***	-0.190***	-0.190***	-0.184***
	(0.018)	(0.010)	(0.010)	(0.005)
15	-0.151***	-0.168***	-0.159***	-0.166***
	(0.018)	(0.010)	(0.010)	(0.005)
16	-0.126***	-0.151***	-0.146***	-0.146***
	(0.018)	(0.010)	(0.010)	(0.005)
Observations	1211474	5196010	7111827	17116942

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.5: Estimated Effects of Displacement on Earnings and AKM Fixed Effects for Workers Displaced from Top-Quartile Firms

	(1) Log earnings	(2) θ log earnings
Quarter since displacement		
0	-0.178***	-0.00180***
	(0.006)	(0.000)
1	-0.280***	-0.0185***
	(0.008)	(0.001)
2	-0.188***	-0.0171***
	(0.005)	(0.001)
3	-0.251***	-0.0186***
	(0.007)	(0.001)
4	-0.150***	-0.0179***
	(0.005)	(0.001)
5	-0.173***	-0.0184***
	(0.005)	(0.001)
6	-0.198***	-0.0143***
	(0.005)	(0.001)
7	-0.217***	-0.0208***
	(0.006)	(0.001)
8	-0.165***	-0.0209***
	(0.005)	(0.001)
9	-0.187***	-0.0201***
	(0.005)	(0.001)
10	-0.203***	-0.0201***
	(0.005)	(0.001)
11	-0.220***	-0.0193***
	(0.006)	(0.001)
12	-0.176***	-0.0183***
	(0.005)	(0.001)
13	-0.189***	-0.0175***
	(0.006)	(0.001)
14	-0.184***	-0.0181***
	(0.005)	(0.001)
15	-0.166***	-0.0187***
	(0.005)	(0.001)
16	-0.146***	-0.0193***
	(0.005)	(0.001)
Observations	17116942	17116942

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

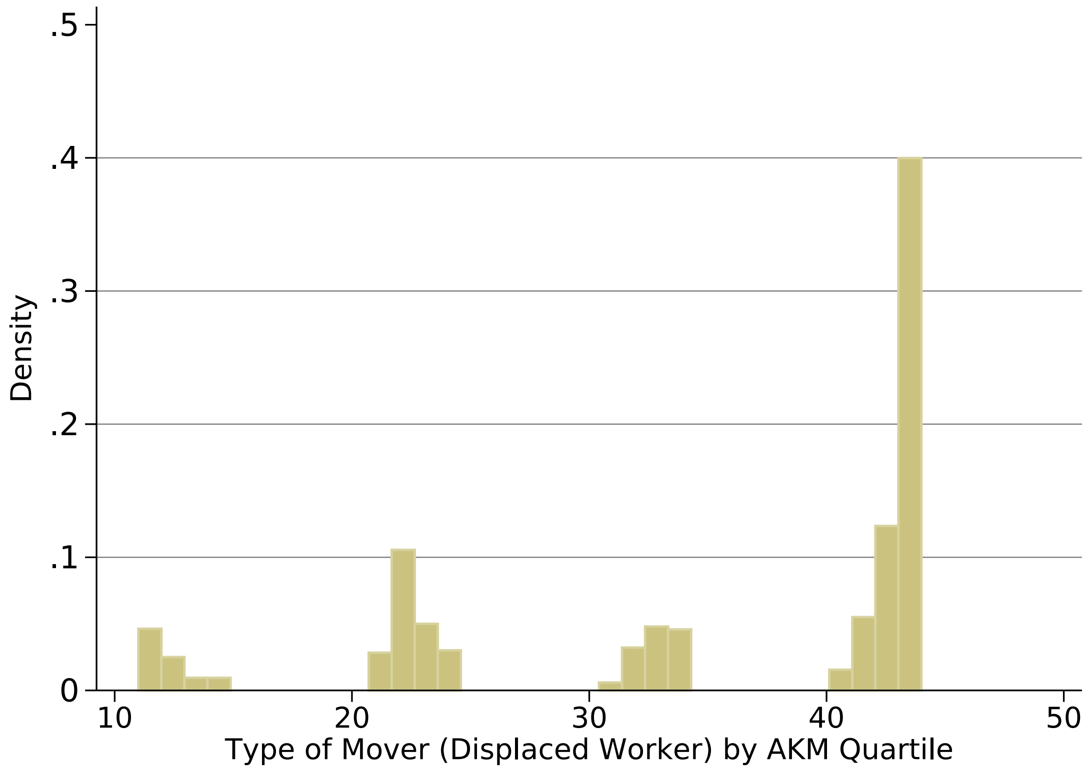
Table A.6: Estimated Effects of Displacement on Enrollment for Pre-Displacement Quarters

	(1)
	Enrollment
Quarter since displacement	
-8	-0.0011
	(0.0006)
-7	-0.0015*
	(0.0006)
-6	-0.0007
	(0.0006)
-5	0.0008
	(0.0006)
-4	0.0004
	(0.0006)
-3	-0.0001
	(0.0006)
-2	0.0013
	(0.0006)
-1	0.0023***
	(0.0006)
0	0.0021**
	(0.0007)
Observations	32079372

Standard errors in parentheses

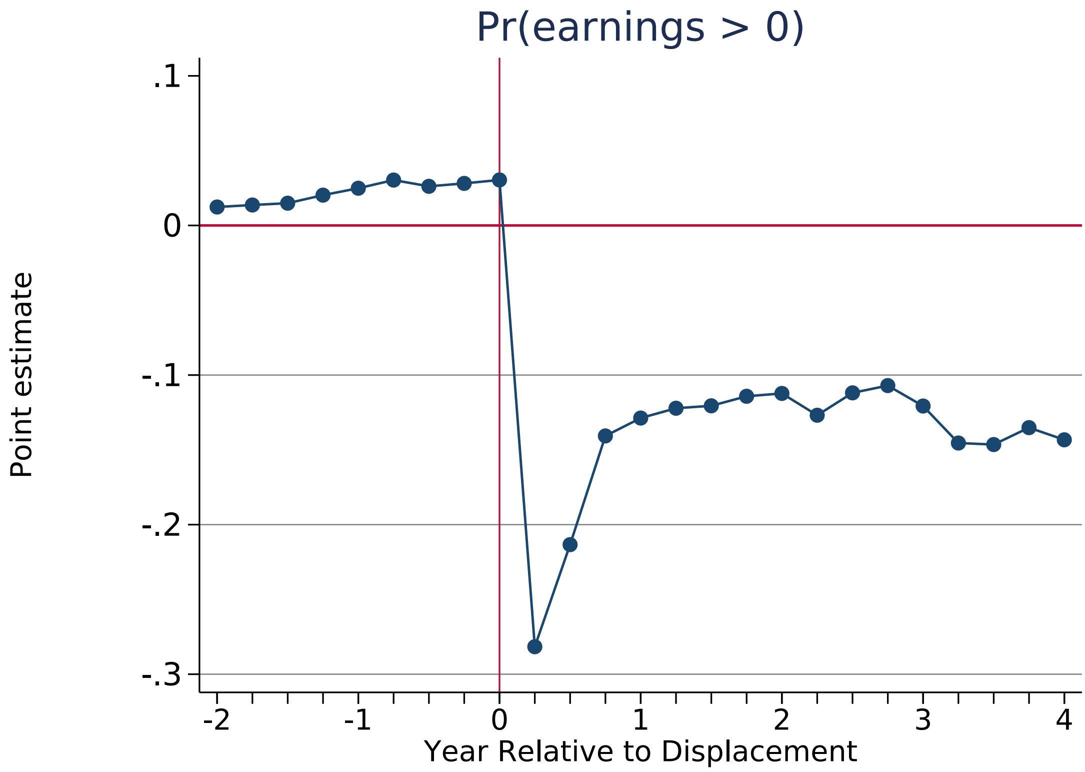
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A.1: Histogram of Displaced Workers by AKM Quartile of Pre and Post-Displacement Firm



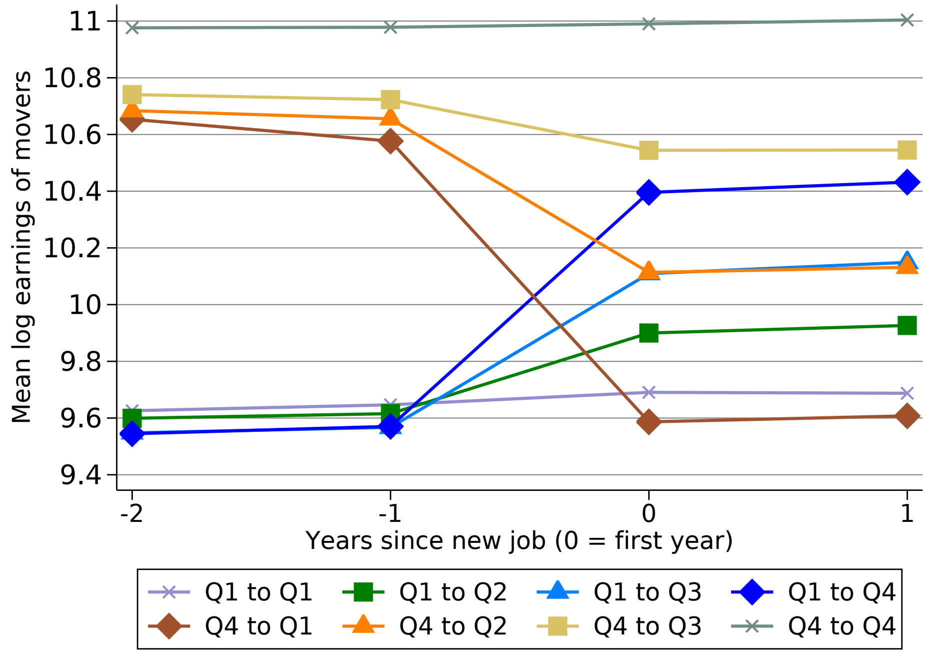
Note: This plots the share of displaced workers who belong to one of sixteen possible bins that represent their movement between AKM quartile firms. The plotted values, 11-14, 21-24, 31-34, and 41-44, refer to the quartile of firm at which an individual was employed before and after displacement. For example, the bar under the number 23 represents the share of displaced workers who were laid off by a Q2 firm and found re-employment at a Q3 firm (about 5% of the sample). The graph only considers the first firm at which an individual works post-displacement, even if he or she moves firms many times.

Figure A.2: Effects of Displacement on Probability of Employment

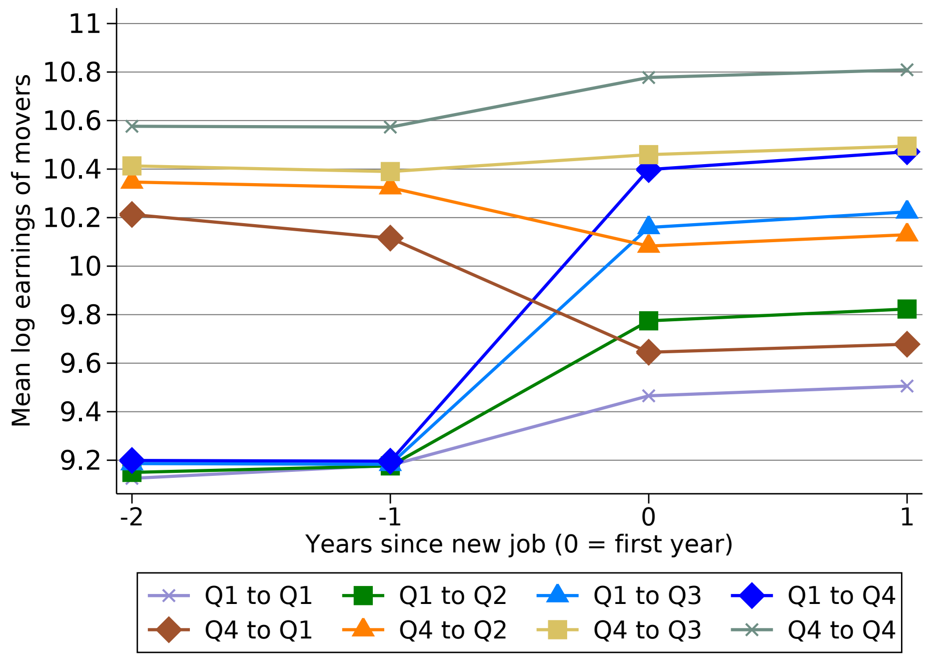


Note: This plots the point estimates for equation (2) with dummy for employment as the right hand side variable. The results are interpreted as the causal effects of displacement on probability of being employed in the kth after separation.

Figure A.3: Mean Earnings of All Movers: By College Enrollment During Move



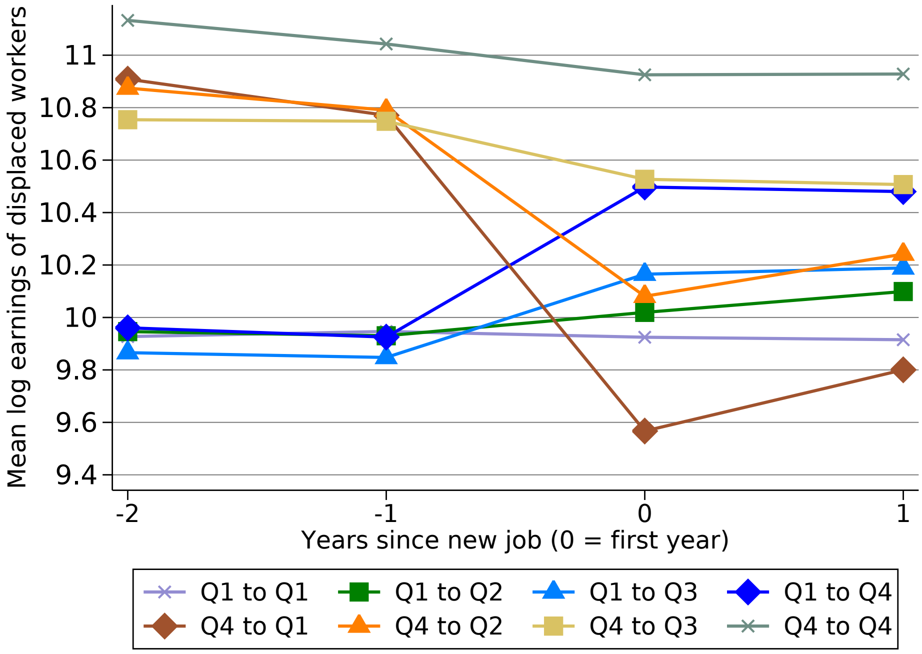
(a) No College



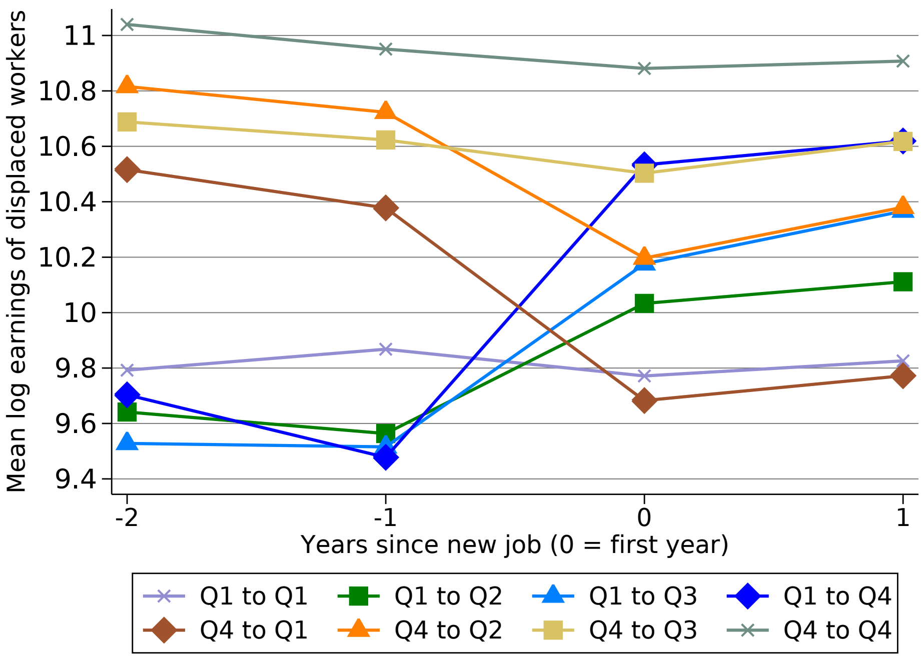
(b) College

Note: These figures shows mean yearly log earnings of all Ohio movers observed in 1999-2012, split by enrollment in college during of the move. “During” is defined as attending school in the calendar year of displacement or the calendar year of starting a new job (often but always consecutive calendar years). Jobs are classified into quartiles of establishment fixed effects based on estimation of the AKM model.

Figure A.4: Mean Earnings of Displaced Workers: By College Enrollment During Move



(a) No College



(b) College

Note: These figures shows mean yearly log earnings of all Ohio displaced workers observed in 2002-2008, split by enrollment in college during of the move. “During” is defined as attending school in the calendar year of displacement or the calendar year of starting a new job (often but always consecutive calendar years). Jobs are classified into quartiles of establishment fixed effects based on estimation of the AKM model.