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ABSTRACT

We use employer-employee matched administrative data from Ohio to study the role of firm pay premiums in explaining the large, persistent earnings losses of displaced workers. We estimate that earnings for displaced workers from the mid-2000s are depressed by 22 percent after four years, consistent with prior work. Drawing upon empirical approaches from the displaced worker and firm heterogeneity literature, we then estimate how much of this earnings loss can be explained by the forfeiture of a favorable employer-specific pay premium. Our preferred estimate attributes one quarter (24 percent) of long-run earnings deficits to lost firm pay premiums. Such firm rents explain up to half the earnings deficits for those laid off from manufacturing firms and employers with particularly generous pay policies. We test for sensitivity to different samples from which we derive firm specific-pay premiums and definitions of displacement. Our estimates persist in a narrow range between 16 and 24 percent for the share explained by firm rents, adding to the evidence that firm rents do not explain the majority of earnings or wage losses sustained by displaced workers in the United States.

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1 Introduction

Labor economists have long recognized that workers who experience job displacement suffer large and persistent earnings losses for many years after their initial separations – a pattern not exhibited by voluntary job movers. This scarring effect was first documented twenty-five years ago by the seminal work of Jacobson, LaLonde, and Sullivan (1993) who found that high-tenure workers in Pennsylvania displaced in the early 1980s sustained long-term losses of 25 percent. Many researchers have since used administrative data to study different settings and time periods, all concluding that displacement leads to long-term earnings losses, typically between 15 and 30 percent (Couch, 2001; Jacobson et al., 2005; Von Wachter et al., 2009; Schmieder et al., 2010; Couch and Placzek, 2010). Davis and Von Wachter (2011) find that earnings losses are not only deep and sustained, but also highly countercyclical – deficits are twice as large in present-value terms for layoffs when the unemployment rate is below 6 percent than when it exceeds 8 percent. Schmieder and Von Wachter (2010) show displacement wipes out workers' wage gains even during tight labor markets.

The explanation for these persistent earnings losses is less clear. The inability of traditional models used to study unemployment (Mortensen and Pissarides, 1994) to capture the magnitude and persistence of earnings losses has motivated research aimed at understanding their sources. Jarosch (2015) models a labor market in which jobs vary in both levels of productivity and security. The newly unemployed accept positions lower on the job ladder which are not only lower-paying but also less stable. Krolikowski (2017) also proposes a job ladder model in which the recently re-employed have higher unemployment risk. Huckfeldt (2016) notes that earnings losses are concentrated among workers who find reemployment in lower-paying occupations than they previously held. He then posits that relatively skilled workers search for lower-skilled jobs during a recession with a model that accounts quantitatively for cyclical earnings losses.

A separate possible explanation concerns specific human capital, defined as the knowledge and skills workers acquire which are unique to their current employer or industry but are not valued by other firms or sectors (Topel, 1991; Neal, 1995; Kletzer, 1998). As the stock of specific human capital increases with tenure, earnings likewise rise. However, its value is destroyed upon a worker's separation, resulting in large and perhaps persistent earnings losses. Similarly, certain types of workers and firms can be good matches for each other, enhancing productivity. Lachowska et al. (2018) argue that the loss of a favorable firm-specific match is the main driver of persistent scarring.

A third hypothesis for persistent earnings losses involves the firms themselves. Economists have documented that some firms pay higher wages than others for equally-skilled workers (Krueger and Summers, 1988; Van Reenen, 1996), a conclusion bolstered by the proliferation of studies using employer-employee matched data (Abowd et al., 1999; Bronars and Famulari, 1997; Card et al., 2013; Song et al., 2018). Sustained earnings losses could arise if workers are systematically displaced from high-pay premium firms and subsequently hired and retained by employers offering relatively lower pay premiums. Graham et al. (2019) illustrate a specific mechanism for layoff risk involving firm premiums. Using data from the U.S. Census Bureau, the authors calculate the implied wage premium demanded by workers of a firm with a greater risk of bankruptcy, since highly-leveraged firms are also more likely to shed employees.

Investigating this lattermost channel, Fackler et al. (2017) use administrative data from Germany and find that long-run wage losses are fully explained by the forfeiture of firm wage premiums, implying no role for other channels. Schmieder et al. (2018) likewise use German administrative data to determine that workers switching to smaller and lower-paying firms after job displacement is an important factor in the persistent declines in wages. They estimate upwards of 80 percent of wage losses after three years can be attributed to forgone firm pay premiums.

In stark contrast to Fackler et al. (2017) and Schmieder et al. (2018), the only extant study in the United States finds that firm premiums play a minimal role in explaining earnings losses. Lachowska et al. (2018) builds on Jacobson, LaLonde, and Sullivan (1993) (henceforth JLS) and Abowd, Kramarz, and Margolis (1999) (henceforth AKM) with administrative data from Washington state. The authors conclude that the firm-specific component of pay assumes only a negligible role in the earnings losses of those displaced during the Great Recession (just 9 percent of overall losses). They instead attribute most of losses to forfeited job-specific matches—time-invariant factors which forge a particularly valuable employee-employer pairing—and residual displacement effects, such as loss of seniority (52 percent and 39 percent of losses, respectively).

Given these contrasting findings, a natural question is whether the minimal role of firm pay premiums found by Lachowska et al. (2018) generalizes to the United States more broadly. With that motivation, we use employer-employee matched administrative data from Ohio to investigate the role of firm pay premiums in explaining losses of displaced workers. We first confirm external validity by showing that workers displaced in Ohio between 2002 and 2008 suffer large and persistent earnings losses on the order of 22 percent four years after initial displacement. Although earnings exhibit a partial rebound after the first full post-displacement quarter, recovery stagnates in the following years, consistent with findings from JLS and subsequent literature. We explore heterogeneity by industry, showing earnings losses are even more pronounced for workers displaced from industries besides finance and insurance and for those displaced from manufacturing firms.

Further, we find that forfeiture of a favorable employer-specific pay premium depresses earnings by 5.3 percent after four years, or in other words, nearly one quarter (24 percent) of overall earnings losses. Our regression-adjusted estimates condition on an individual's industry of employment, meaning the loss of favorable firm wage policies is not a simple reflection of displacement from high-wage industries such as manufacturing, which tends to be more unionized and exhibits greater degrees of rent-sharing.

Interpreted alongside Lachowska et al. (2018), our results bolster the evidence that unlike in Germany, firm rents do not explain the majority of earnings losses sustained by displaced workers in the United States. Nevertheless, our estimates are more than twice as large as Lachowska et al. (2018) and suggest firm premiums are an important factor in at least some U.S. labor markets. Because our approach, like the rest of the displaced worker literature, necessarily involves many precise decisions about sample restrictions, we subject our results to a battery of sensitivity checks. We show that different minimum tenure requirements for displaced workers does not change our baseline estimate for the role of firm effects. The "share explained" estimate is also unaffected by more stringent post-layoff labor force attachment conditions.

We also test the sensitivity of our findings to construction of the economy-wide sample on which AKM is estimated. Typically, the AKM specification is estimated on the largest group of workers and firms available in an employee-employer matched dataset because identification relies on individuals moving between jobs. In our case, we choose to omit post-layoff observations of displaced workers from the AKM sample so that firm premium estimates are not a function of the same depressed earnings we seek to decompose. While we prefer this minimal restriction, an alternative approach—one implemented by Lachowska et al. (2018)—involves discarding displaced workers and stably employed comparison workers from the AKM sample entirely. When we instead employ this alternative sample, we find that long-term earnings are depressed by only 3.5 percent by lost firm rents—smaller than our preferred estimate of 5.3 percent. This implies that firm-specific pay premiums losses constitute 16 percent of overall displaced worker earnings losses in the Ohio data, rather than 24 percent.

This difference in AKM sample selection accounts for roughly half of the difference between our preferred estimates and those of Lachowska et al. (2018) using Washington data (who estimate long-run earnings decreased by 1.5 percent due to lost firm premiums, accounting for just 9 percent of overall losses). Beyond AKM, there are numerous institutional settings that might explain the remaining difference in our estimates. For example, the majority of workers in our sample were displaced during a reasonably tight labor market, in contrast with those tracked by Lachowska et al. (2018) who were laid off during the Great Recession. Davis and Von Wachter (2011) show that in the U.S., overall earnings losses are amplified during recessions. Moreover, Schmieder et al. (2018) use German data and show that losses due to firm-specific characteristics are likewise greater during economic downturns, rendering their relative contribution to total losses during a recession ambiguous. Although our panel does not allow us to fully investigate potential cyclicality, we find that the employment-weighted average pay premium of firms with mass layoffs rises sharply in 2008 as the unemployment rate rises. While not definitive, this suggests losses due to firm premiums could be even higher in Ohio during the recession than during the mid-2000s.

Lastly, we discuss the implications that differences in institutional settings may have in explaining differences between the lost firm premium estimates. While the Ohio and Washington displaced samples have the same share of workers who separate from manufacturing, it may be that aerospace producers of the Pacific Northwest offer a smaller firm pay premium than rubber and glass manufacturers in the Industrial Midwest. Additionally, jobs at high-premium firms may be more available to laid off manufacturers in Washington than in Ohio

Despite the difference in magnitude of our estimates, our results are still broadly consistent with the conclusion that firm premiums are less important for displaced worker earnings losses in the U.S. than in Germany. Further work is needed to determine why the magnitude of the effect varies across regions and potentially over the business cycle in the United States. We proceed by describing the data in section 2. Section 3 outlines the empirical strategy based on AKM and JLS. Section 4 reviews our findings, and section 5 concludes.

2 Data

The state of Ohio requires all employers, as part of the state's Unemployment Insurance (UI) payroll tax requirements, to report quarterly earnings for all employees. We utilize two Ohio administrative data sources to study the links between displacement and firm-specific pay premiums. These data are made available through the Ohio Education Research Center (OERC), which assembles data from multiple state agencies, including the Ohio Department of Job and Family Services (ODJFS), into a repository known as the Ohio Longitudinal Data Archive (OLDA).[1]

The first dataset includes information on both firms and private sector, state, and local public employees subject to UI contributions in Ohio between 1999Q3 and 2013Q1. Thus, an observation exists for every quarter an individual has positive earnings at a covered employer in the state of Ohio during this time period. Individual identifiers allow us to identify the quarter of a displaced worker's separation and subsequent employment over time.

[1]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.

The second dataset includes firm-level variables such as an anonymized employer identifier, three-digit North American Industry Classification Systems (NAICS) codes, and county of the employer. The identifiers, all derived from the Quarterly Census of Employment and Wages (QCEW), allow for construction of a firm-size variable by summing across the records associated with a given employer in each quarter. The firm identifiers are consistent across the two datasets, allowing us to link firms and workers.

The Ohio administrative data is particularly advantageous for the purposes of studying displaced workers' earnings patterns. 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, a sector more likely to produce displaced workers. Like the rest of the United States, Ohio experienced recessions in 2001-2002 and 2008-2009, time frames both included in our sample period.

There exist several limitations with the Ohio data. First, we are 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. Second, UI administrative records rarely include demographic characteristics, and only collect characteristics on workers who ultimately claim Unemployment Insurance. We choose *not* to impose that displaced workers claim UI benefits to be eligible for our sample. From 1989-2012, 23% of Americans eligible for UI benefits did not claim them (Auray et al., 2019). By restricting the displaced sample to only unemployed insurance claimants, we would omit a substantial share of the population of interest. Thus, our sample lacks demographic information.

We use the Ohio administrative records to construct two distinct samples: one for implementing the AKM approach to estimate firm-specific pay premia (or "firm fixed effects") (described in section 3.1), and a considerably smaller sample for analyzing the earnings losses of displaced workers (described in sections 3.2 and 3.3). Below, we first describe the sample used for AKM estimation and subsequently summarize the displaced worker sample.

2.1 AKM Sample

The AKM sample is constructed from the Ohio quarterly earnings records for calendar years 1999 to 2012. Because the data do not include hours worked and we seek to approximate firm-specific pay premiums paid to full-time employees, we drop worker-quarter observations where a worker has two or more listed jobs. We then follow the method developed by Sorkin (2018) of constructing an employee-employer matched panel to study worker movements. Specifically, we 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, we 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, we 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. We also drop worker-year observations when average yearly earnings fell short of $3,500.

Lastly, we drop worker-year observations for displaced workers for the years of and after layoff. We do not want to estimate firm-specific pay premiums which are a function of the very earnings changes we seek to partially attribute to lost firm premiums. Including such observations would violate AKM's additive separability assumption, because if the scarring effect of displacement is caused even partially by factors unrelated to firm premiums, expected post-layoff earnings are not the simple sum of individual and firm fixed effects. See Appendix A.1 for further discussion.

Despite this restriction, we keep pre-displacement worker-year observations in the AKM sample because they are negatively-selected on ability[2], so their omission from the sample could bias the estimation of the firm premiums of employers that lay off workers. In section 4, we show this ultimately affects the estimation of our quantity of interest – the share of total earnings losses can be explained by firm premiums. These restrictions yield the preferred "full sample" from column

[2] We document this fact in Appendix A.3.

1 of Table A.1. On this sample, we estimate firm fixed effects using the largest connected set, i.e. the greatest collection of workers and firms linked by worker movements over time.

2.2 Displaced Worker and Comparison Samples

2.2.1 Construction of Samples

Displaced workers are distinct from routine job changers or other unemployed individuals. Per the BLS, 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 we use administrative data, we cannot explicitly identify the reason for a worker's separation (quit, discharge for cause, etc.). Consistent with the displaced worker literature, we use separations during a mass layoff to identify workers who separate because of economic distress at the firm.[3] Mass layoffs, which have been exploited by many since JLS, have served as a reliable proxy for causes of displacement because most of those who leave a firm during such a period do so involuntarily.

Following Davis and Von Wachter (2011), we define a mass layoff as a 30% or more quarter-to-quarter reduction in a firm's employment level. A firm shutdown is counted as a mass layoff. Because some firms exhibit many mass layoffs, we rank a firm's four largest mass layoffs by percentage change during the observed period (2002-2008) and assess only these four events to avoid over-counting. Further, as smaller firms are mathematically more likely to meet this 30% benchmark without a substantial change in absolute employment, we 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, we 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

[3] Flaaen et al. (2019) 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.

at least three years tenure at that firm, (4) holds only one job at the time of job separation, and (5) earns at least minimum wage corresponding to 30 hours per week.[4] While this definition closely aligns with JLS, we impose a tenure requirement of three years rather than six. This less stringent requirement, also followed by Davis and Von Wachter (2011), allows us to study a greater number of displaced cohorts. After presenting our main results, we test the sensitivity of our estimates to a more common tenure requirement of six years at the layoff employer.

Further, because our research question – understanding the share of earnings losses attributable to loss of a firm pay premium – necessitates that a displaced worker will seek future employment, it does not make sense to study those who may drop out of the labor force altogether. As a baseline, we follow much of the displaced worker literature and require that all displaced workers in our sample stay somewhat attached to the labor force in the follow up period, defined as exhibiting positive earnings in at least 25% of one's post-displacement quarters.[5] In Appendix B, we explore sensitivity of our results to this requirement by conditioning on higher attachment (more post-displacement quarters of positive earnings). This sample restriction renders the conclusions about displaced workers in this paper conditional on labor force attachment.

Consistent with JLS and similar papers, we compare the outcomes of our displaced sample to those of a control group to workers who remain continuously employed. Traditionally, the literature has predominantly used a "never displaced" control group in order to isolate the portion of earnings potential that is destroyed when an individual involuntarily loses a specific job (Krolikowski, 2018).

2.2.2 Descriptive Statistics

Table 1 summarizes key variables for the sample of workers displaced in Ohio between 2002Q1 and 2008Q4 and the stably employed comparison sample used our difference-in-difference model. The comparison group, who are highly tenured at the same firm throughout the panel, outnumber the displaced workers by a ratio of 10:1. Such a large sample size for the comparison group is

[4]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.

[5]This baseline sample restriction shrinks our displaced worker sample size by only 8%.

instrumental in producing the precise regression-adjusted estimates that will be presented in section 4. Half of all comparison workers are employed in either manufacturing or education and health services, a combined share similar to the comparison group used by Lachowska et al. (2018).

A similar share of displaced and comparison workers come from the top quartile of firm-specific pay premiums, although a slightly larger share of displaced workers come from lower-quartile firms. The comparison group has significantly higher pre-layoff earnings (defined as 2004-2005 earnings, which is the median layoff time period) than the displaced sample, but we argue this will not threaten identification using the difference-in-difference strategy.

Table 1 also shows that 30 percent of the displaced worker sample were laid off from manufacturing firms, unsurprising given Ohio's industrial base. The composition of displaced workers in the Ohio sample is similar to the primary displaced sample in Washington state from Lachowska et al. (2018) (28 percent). However, the manufacturing share of our sample differs from two other of the most prominent displaced worker studies which use UI data. The displaced sample JLS analyzed from 1980s Pennsylvania included many more from manufacturing (75 percent) while those analyzed by Couch and Placzek (2010) (2000s Connecticut) were less concentrated in manufacturing (16 percent).

The bottom two panels of Table 1 (firm premium quartile and pre-displacement yearly earnings) show that the average displaced worker earned roughly $50,000 in the year before separation, and half of them separated from a firm in the top-quartile of employer pay premiums. These statistics are similar to those generated by Lachowska et al. (2018). The earnings of workers two years before displacement are only slightly lower than earnings the year before, indiciating a relatively minimal "Ashenfelter dip" compared to the early displaced worker literature. Figure 1 likewise indicates no dip before displacement. These findings, however, look similar to displaced worker earnings profiles of more recent work using administrative data by Braxton et al. (2018) and Hyman (2018).

3 Empirical Approach

This section begins with a description of the model used to identify firm-specific pay premiums for Ohio employers. Then, we describe the standard multi-period difference-in-difference model employed to infer the causal effect of displacement on earnings. Lastly, we discuss our approach of leveraging estimated firm fixed effects to understand the role the firm plays in displaced worker earnings losses.

3.1 AKM Model

The increased prevalence of matched employee-employer administrative datasets has enhanced the quality and quantity of research on both displaced workers and firm-specific pay premiums. In their seminal research on the French labor market, AKM document 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 matched employer-employee data, AKM developed the following model for log earnings of person i working at firm j in year t:

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

α_i are worker fixed effects, which captures the component of earnings that moves with a worker regardless of her employer. $\theta_{j(i,t)}$ are firm fixed effects[6], reflecting the earnings premium or penalty (relative to some omitted firm) associated with working at firm j. γ_t are year 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. We estimate equation (1) on the universe of 1999-2012 Ohio workers from the UI data (subject to certain sample restrictions described in subsection 2.1). We then use the $\hat{\theta}_j$ estimates which correspond to each firm in subsequent analysis regarding displaced worker earnings losses.

[6] An estimated $\hat{\theta}_j$ resulting from equation 1 is constant for a given firm, thus θ could be applied a subscript of j alone. However, because equation 1 describes worker i's earnings in time t as a function of her employer's pay premium, and recognizing workers change employers, we subscript θ with j as a function of i and t.

In order to separately identify α_i and $\theta_{j(i,t)}$ 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 during the length of the panel 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, meaning the AKM estimates should be trustworthy for the population. As illustrated in Table A.1, 89% of all workers and 88% of all firms are included in the largest connected set from the Ohio sample.[7]

The variance of log earnings for equation (1) can be decomposed 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.[8] Because a goal of this paper is to show how the sources of estimated displaced worker earnings losses are sensitive to sample selections, we report variance decompositions for candidate samples on which AKM can be run in Appendix Table A.2. In all samples, worker fixed effects explain the largest share of variation in log earnings (49-51%), although it is clear the firm effects still assume an important role (24-25% of the variation). This compares to 22% estimated by Sorkin (2018), 21% in Card et al. (2013) and 20% in Lachowska et al. (2018). Table A.2 also suggests sorting between workers and firms, as the covariance between worker and firm fixed effects is positive.

3.2 JLS Model

Before investigating the role of firm-specific wage premiums in explaining displaced worker earnings losses, we must first estimate the simple effects of displacement on worker earnings. We do so by

[7]In the extreme case of no worker movement between firms during the panel, the connected set would have zero works or firms. A connected set including roughly 90% of workers and firms is typical of other papers using AKM such as Card et al. (2013), Card et al. (2018), and Lachowska et al. (2018).

[8]The remaining covariances, between worker and year fixed effects and firm and year fixed effects, amount to a negligible amount of the overall variance of log earnings.

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. In the final quarter of a displaced worker's observed tenure with the layoff employer, k assumes the value zero. 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, we cluster at the worker level. Lastly, because "Ashenfelter dips" – drops in earnings that precede displacement – can affect earnings despite displacement not having yet occurred, we allow the index k to assume negative values as low as -8. Since each displaced 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 eight 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 we require the comparison group of stably employed workers be similarly high-tenured.[9] 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

[9]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.

treatment and stably employed workers is 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, we plot the earnings of displaced workers and the comparison group before and after their separation date (Figure 1).[10] 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 the lines plotted are not regression-adjusted, the persistent earnings losses are apparent up to four years after displacement. This figure provides supporting 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, suggesting equation (2) is well-identified.

3.3 JLS-AKM Model

To assess the role firm-specific pay premiums assume in the earnings losses of displaced workers, we follow Lachowska et al. (2018) and treat the previously estimated employer fixed effects $\hat{\theta}_j$ as an additional outcome in the displacement process. We match the $\hat{\theta}$'s obtained from estimating equation (1) to the worker-quarter observations that correspond to the proper firm identifier in the displaced and comparison groups summarized in Table 1. Specifically, displaced worker i at firm j in year-quarter t is assigned a corresponding value for $\hat{\theta}_{j(i,t)}$ – her firm-specific pay premium that partially determines earnings – which only varies when she switches employers. All individuals – including displaced workers – have a $\hat{\theta}_{j(i,t)}$ for the entire panel while employed.[11]

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

$$\hat{\theta}_{j(i,t)} = \alpha_i + \gamma_t + W_{it}\beta_1 + X_{ijt}\beta_2 + \sum_{k=-8}^{16} (\omega_k \cdot D_{itk}) + \upsilon_{ijt} \qquad (3)$$

[10]In Figure 1, because the comparison group necessarily lack a separation date, we 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.

[11]There is a very small share of displaced workers who are unmatched to a $\hat{\theta}_j$ because one of their employers (either layoff or destination firm) was not in the connected set used to estimate equation (1).

Note that the right-hand sides of equations (2) and (3) are identical, meaning the same difference-in-difference reasoning applies. The parallel trends assumption for equation (3) is particularly straightforward: because the displaced sample is required to be employed at the same firm during the pre-treatment period (quarters 9 through 12 before layoff), then $\hat{\theta}_{j(i,t)}$ – which only changes for worker i when she moves firms – remains constant in the pre-period. Workers in the comparison group – who never change employers – possess a constant firm-specific pay premium throughout the panel.

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. The quotient of the ω_k coefficient and δ_k from equation (2) approximates the share of earnings losses attributable to lost firm fixed effects k quarters after displacement.[12]

4 Results

4.1 Estimates of Lost Earnings

The first row of panel A in Table 2 summarizes the estimates of short and long-term earnings losses for the full sample of 40,419 Ohio workers displaced between 2002q1 and 2008q4. In the first full quarter after displacement, workers' earnings decrease by 34 log points. Observations where workers experience zero earnings for a quarter are dropped from the regression. This is because we seek

[12] As will be discussed in the results section, we prefer to translate the coefficients (in log points) to percentages and take their ratio. Although the difference is slight, it can be more meaningful for large magnitudes and more accurately reflects the desired quantity of interest – what share of earnings losses are due to forfeited firm premiums.

to understand how forfeited firm premiums explain earnings losses, so we do not want to consider losses that result from working for no firm at all. Thus, the presented coefficients provide estimates of the effect of displacement conditional on employment.[13] Because many who find re-employment in the quarter after displacement may only work a partial quarter, it is likely that this drastic drop is driven substantially by reduced work hours over the quarter. Of greater interest are long-run earnings effects, which we spend the remainder of the paper examining.

Four years after displacement, workers earn approximately 25.2 log points less on average than they would have if they were not displaced.[14] Converting log points to percentage terms, we estimate long-term earnings for displaced workers are about 22 percent less than their pre-displacement earnings [exp(-0.252) - 1]. Such estimates fall well within the bounds of the recent displaced worker literature. Lachowska et al. (2018) estimate long-run earnings losses of 15 log points (14%) while Couch and Placzek (2010) estimate 32 log points (27%).[15] Figure 2 plots the baseline displaced worker earnings losses profile for up to four years after job loss.[16] 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. For robustness, we run equation (2) without controlling for the level of a displaced worker's pre-layoff earnings (see Table B.2). We find a nearly identical earnings profile and estimate earnings losses of 21 percent.

The long-run earnings losses for workers in the Ohio sample – who all separated between 2002q1 and 2008q4 – are quite substantial given their time of displacement in the business cycle. Ohio's unemployment rate[17] only eclipsed 7 percent once between 2002 and 2008, and stayed below 6

[13] While we considered using the inverse hyperbolic sign or changing zero earnings to ones to avoid an undefined log(0) value, we opted against doing so because it would prevent constructing a "share attributable to firm fixed effects" comparisons like that in Table 2, which only make sense when the mapping of quarterly earnings to quarterly firm-specific fixed effects is defined for all earnings.

[14] Throughout the paper, we refer to figures four years post-displacement to mean the average of the coefficients for quarters 13-16 relative to separation

[15] Both papers define the long-run as five years rather than four.

[16] A table of point estimates and standard errors for Figure 2 is found in Appendix Table B.2, Column 3. Column 1 of this Table shows point estimates of the same regression without controlling for pre-earnings interacted with year dummies.

[17] Aggregating monthly rates at a quarterly frequency

percent for 16 of the 28 total quarters. However, the 2000's expansion may be an exception to Davis and Von Wachter (2011)'s finding that long-run earnings losses of displaced workers are mitigated when the labor market is strong. They also note that the 2003-2005 period – when U.S. unemployment was below 6 percent – 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 quarter-century (including losses sustained by those displaced in the 1982 recession, when unemployment eclipsed 9 percent).

We conduct the same analysis on two subsets of displaced workers that may experience different earnings patterns: those displaced from any industry besides finance, insurance and real estate (FIRE), and those displaced specifically from manufacturing. We examine these groups because they may have a harder time adjusting in the labor market and may also have less savings to smooth consumption during unemployment (Gruber, 1997). We study manufacturing in particular because of our particularly attractive setting to study the industry. During our layoff window from 2002 to 2008, the number of workers in manufacturing decreased by 22 percent in Ohio but just 11 percent nationally. Our time frame also coincides with the brunt of the post-WTO accession "China shock." Rubber and glass manufacturing – among the most exposed industries to Chinese imports in the early 2000s, as detailed by Autor et al. (2013) – were heavily concentrated in Ohio.

Panel B of Table 2 presents the regression-adjusted estimates of short and long-run earnings losses for those displaced from non-FIRE industries, who represent 93% of all displaced workers in our sample (Table 1). In applying equation (2), we likewise drop workers from finance, real estate, or insurance firms in the comparison group 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 40 log point drop in earnings in the quarter after displacement, and losses persist on the order of 22 percent (25.3 log points) in the long-run.[18] These slightly-larger earnings deficits after four years suggest that those displaced from FIRE industries have a relatively easier time transitioning after losing a high-tenure job. If they are more likely to find reemployment in

[18]Point estimates for all quarters after displacement are presented in Table B.5, Columns 1 and 3.

the same sector, this could speak to the enhanced role of industry-specific human capital.[19]

Table 2, Panel C summarizes earnings losses associated with displacement from manufacturing firms. These deficits are markedly larger than those of the rest of the sample. They exhibit 55 log point earnings losses in the first quarter after separation. Strikingly, even four years after displacement, they earn 29 percent (34.6 log points) less than they would have if they were not displaced, conditional on employment.[20] These long-run estimates hover around the largest estimates in the literature for all displaced workers, which consistently measures losses between 15-30% in a diverse set of labor market contexts.

4.2 Estimated Losses due to Firm Fixed Effects

According to Table 1, roughly half of displaced workers separate from firms in the top-quartile of pay premiums and very few separate from the bottom-quartile. If displaced workers are systematically re-employed by firms that offer a lower pay premium to all employees, then a portion of the earnings losses described in section 4.1 can be explained by this downward transition to lower θ_j firms. We approach this question using model (3).

Figure 3 plots the estimated δ_k and ω_k from regression equations (2) and (3) for quarter k relative to displacement, -8 $\leq k \leq$ 16. These represent the estimated displacement effects on log earnings and employer-specific pay premiums, respectively. 16 quarters after displacement, average worker earnings are roughly five log points lower than they would be absent a layoff because of re-employment at a firm with a lower pay premium. The second row of panel A in Table 2 provides the average point estimates for the short and long-term effects of displacement on the firm-specific component on earnings.

We can calculate the share of losses explained by dividing the percentage earnings losses attributable to firm pay premiums by overall earnings deficits.[21] These statistics are presented in the third rows

[19] See Neal (1995) and Sullivan (2010)

[20] Point estimates for the effect of displacement on earnings for all quarters are presented in Table B.6.

[21] Although this share is approximated by $\hat{\omega}_k/\hat{\delta}_k$ for positive values of k, we choose instead to convert all log changes to percentage changes and use the percentages to calculate share attributable to forgone firm premiums. This is because $\hat{\delta}_k$ is sometimes estimated at upwards of 30 log points, which does not well approximate a 30% change.

of each panel of Table 2. For the overall sample, roughly 24 percent of a worker's earnings deficits four years after displacement are attributable to employment at firms with lower pay premiums. Laid off manufacturing employees can attribute over half of their sizable long-run earnings losses to forfeited firm-specific pay premiums. Strikingly, the earnings deficits for displaced manufacturing employees deriving from loss of a favorable firm premium nearly match the magnitude for the *overall* earnings losses for the general sample. Charts similar to Figure 3 for these two subsets of displaced workers – as well as tables of point estimates and standard errors – can be found in the appendix.[22]

Our main results follow a practice of nearly all displaced worker papers using administrative data by conditioning that workers have positive earnings in 25% of post-displacement quarters (and positive earnings in at least one quarter of every post-layoff calendar year). As a robustness check on our finding that firm premiums explain one-quarter of overall earnings losses, we subject our sample to more stringent requirements of post-layoff attachment. While both the overall earnings losses and losses due to firm premiums shrink with more stringent requirements of 50% and 75% attachment, the share of losses attributable to firm effects remains remarkably stable around 25 percent.[23] Further, while our lack of information on hours prevents us from directly estimating the share of long-run *wage* scarring explained by firm fixed effects, in Appendix B.3 we provide estimates for this quantity guided by Lachowska et al.'s (2018) results for the hour-wage decomposition of long-run earnings scarring.

4.2.1 Workers Displaced from Top AKM Quartile Firms

Given a large share of our sample is displaced from firms offering a top-quartile pay premium $\hat{\theta}_j$, we estimate equations (2) and (3) on a restricted sample of displaced workers who lost a job from a top quartile firm and a comparison group stably employed at such a firm. Earnings losses for this group are shown in Figure B.6a and summarized in panel D of Table 2. Like other displaced workers, they experience a sharp initial earnings drop (40 log points) one quarter after separation. After four years, they earn 29 percent (34 log points) less than they would have absent a layoff.

[22] Appendix B, Figure B.5 and Tables B.5 and B.6.

[23] Point estimates provided in Appendix B, Table B.3 and Figures B.3 and B.4.

Not only does this subset of workers suffer larger long-run earnings losses compared to the overall sample, but they also earn nearly $10,000 more per year. Thus, the pre-displacement income gap and higher percentage loss yield much larger deficits in absolute terms.

Panel D of Table 2 also suggests such workers have "more to lose" by separating from their employer, as we attribute half of their total earnings deficits to loss of a favorable firm-specific pay premium. For this group, earnings are depressed by 15 to 16 percent by firm pay premiums alone. The overall earnings deficits, losses due to firm premiums, and the share of losses premiums explain are all comparable to figures for the manufacturing subsample, even though two-thirds of this group separated from an industry besides manufacturing. This suggests the importance of firm pay premiums is not limited to manufacturing layoffs.

Roughly 25 percent of our displaced sample separates from high-$\hat{\theta}_j$ firms but finds re-employment at another top-quartile pay premium firm.[24] Panel E of Table 2 confirms that even the "luckiest" laid off workers are still systematically displaced in lower-paying firms on average. These workers suffer 16 percentage point long-run earnings deficits, only 2 percentage points of which are due to receiving a lower pay premium.[25]

4.3 Sensitivity of Estimates to Sample Construction

The JLS-AKM framework necessarily involves many precise decisions about sample restrictions for both stages of estimation. Past displaced worker studies which use UI administrative records from U.S. states vary in how they construct their preferred displaced sample (Jacobson et al., 1993; Couch and Placzek, 2010; Lachowska et al., 2018; Ost et al., 2018). Further, researchers using the JLS-AKM framework can reasonably exclude workers designated as displaced from the sample to which AKM is applied. Thus, the resulting $\hat{\theta}_j$ estimates from equation (1) – and in turn, the share of firm premiums on earnings losses – may vary substantially with small adjustments in the sample restrictions.

[24] See Figure B.2 in Appendix B.

[25] Graphs of the total and firm effect losses for both of the "top-quartile" displaced groups are presented in Figure B.6.

In this section, we explore how our estimates change with constructions of different samples and if it could account for disagreement between past work on the role of firm rents. Fackler et al. (2017) and Schmieder et al. (2018) conclude that firm premiums are either the sole or overwhelming source of displaced worker earnings losses in Germany. On the other hand, Lachowska et al. (2018) find that for workers in Washington state during the Great Recession, firm effects depress long-run earnings by 1.5 percent accounting for just 9 percent of overall losses.

4.3.1 Tenure Requirements

Job displacement studies which use administrative data always condition on some degree of worker tenure. We require workers only have three years of tenure at the same firm prior to displacement, following Jacobson et al. (2005) and Davis and Von Wachter (2011). However, many studies (Jacobson et al., 1993; Couch and Placzek, 2010; Lachowska et al., 2018) require six years for their sample. We opt for shorter tenure requirements due to a limited panel length, as we sought a displaced sample with more displaced cohorts while still allowing for a sufficient follow-up period.

We test the sensitivity of our results to tenure requirements by running modified versions of equations (2) and (3) on the comparison group and a group of displaced workers which all have at least six years tenure at their layoff firm. We follow Lachowska et al. (2018) by estimating displacement effects (δ_k and ω_k) for five years before and four year after separation ($-20 \leq k \leq 16$), assigning the omitted category to the sixth pre-displacement year. Workers in this sample are laid off between 2005q1 and 2008q4. The results of these specifications are summarized in Table 2, Panel F and the estimated displacement effects are plotted in Figure 4.

Displaced workers with higher tenure suffer larger long-run earnings losses (32 percent) than those in our overall sample (22 percent), consistent with past empirical findings (Couch and Placzek, 2010; Lachowska et al., 2018) and theoretical explanations summarized by Carrington and Fallick (2017). However, losses due to forfeited firm effects are also substantially larger. Ultimately, the share of overall losses explained by firm effects remains at 24 percent for the high tenure group, (Table 2, Panel F), identical to our baseline estimates for the share explained.

4.3.2 AKM construction

Given that our estimates are not sensitive to tenure requirements, we next adjust the construction of the economy-wide AKM sample to which equation (1) is applied. Typically, AKM is estimated on the entire sample of workers and firms to maximize the size of the largest connected set. However, displaced worker's post-layoff earnings exhibit a residual scarring effect which violates the AKM identifying assumption that earnings are additive in firm and worker fixed effects.[26] One solution to this issue (as followed by Lachowska et al. (2018)) is to go further and omit all displaced and comparison group worker-year observations from the sample which they estimate AKM. Our approach drops only the post-displacement observations, under the argument that dropping displaced workers entirely could lead to skewed estimates of firm premiums $\hat{\theta}_j$. Either approach could plausibly satisfy the AKM identifying assumptions. To assess how much this choice matters, we test the sensitivity of our estimates to alternative AKM sample construction.[27]

We find that estimated losses due to firm premiums – and thus the share of overall deficits they explain – are moderately sensitive to AKM sample selection. Figure 5 plots results from Ohio for firm premium losses using two different AKM sample constructions. Omitting comparison and displaced workers altogether reduces our estimated earnings losses due to firm premiums by as much as one-third. Because overall estimated earnings losses do not depend on firm fixed effects resulting from the AKM sample, the corresponding share explained by pay premiums likewise declines with the use of the alternative AKM sample, from 24 percent to 16 percent.

The sensitivity shown in Figure 5 suggests that when displaced and comparison workers are omitted from the AKM sample, either the estimated $\hat{\theta}_j$ for layoff firms are lower or estimated $\hat{\theta}_j$ for firms that hire newly-displaced workers are higher (or both). We find evidence for the former case. Estimated fixed effects for mass layoff employers are larger for our preferred AKM sample than for

[26] In other words, a worker's post-displacement earnings is not the sum of her individual fixed effect and the fixed effect of her firm. The error term in equation (1) is not conditional mean zero due to negative scarring effects of displacement (loss of seniority, loss of a good match, etc.). See Appendix section A.1 for further explanation and discussion.

[27] The variance decomposition of log earnings is very similar across various AKM samples, as shown in Appendix Table A.2.

the alternative sample (see Appendix A). The same relationship holds for the difference between the estimated firm fixed effects of layoff firms and non-layoff firms. The result is robust to various definitions of "layoff firm."[28]

The reason for this sensitivity in estimated firm premiums to the AKM sample construction reflects the well-documented fact that displaced workers are negatively selected on the part of their earnings that is portable (in our case, the estimated worker fixed effect $\hat{\alpha}_i$) (Gibbons and Katz, 1991). Following Gulyas (2016), in Appendix Figure A.2 we present a binscatter of average change in a firm's employment against the firm's average worker quality. We find that firms which contract by 30% or more (layoff firms) experience an increase in their average worker quality, suggesting the workers they shed were negatively selected on $\hat{\alpha}_i$. Such negative selection has implications for estimation of $\hat{\theta}_j$ for layoff firms in particular: when the AKM sample omits displaced workers altogether (rather than including their pre-layoff observations), estimated $\hat{\alpha}_i$'s of incumbent workers are biased upwards, thereby depressing the estimated firm premiums. While both sample constructions are valid for the JLS-AKM framework, we prefer our sample because it accounts for the fact displaced workers are negatively selected. In any case, while this choice has non-trivial consequences for assessing the role of firm fixed effects in explaining earnings losses for displaced workers, it does not radically change the estimate.

4.3.3 Comparison to Previous Estimates

Our finding that firm rents explain only 24 percent of long-run earnings losses bolsters Lachowska et al.'s (2018) conclusion that such premiums are not the primary cause of earnings scarring for workers in the United States (just 9 percent). However, our estimates are more than twice as large as their results and suggest a more pronounced role for firm rents. Two key differences in our empirical approaches involve tenure requirements and AKM construction: Lachowska et al. (2018) impose longer tenure for displaced workers and construct the alternative AKM sample described in subsection 4.3.2. We have shown the former discrepancy is inconsequential for the share explained

[28] Appendix Table A.5 compares estimated firm premiums by layoff status.

estimates. The latter adjustment, however, attenuates our estimate in Lachowska et al.'s (2018) direction, as illustrated by Figure 5. The difference in AKM sample selection appears to account for roughly half of the difference between our estimates and Lachowska et al.'s (2018). The difference in the other direction between our Ohio estimates and Schmieder et al.'s (2018) from Germany are not explained by tenure requirements or AKM sample, however, because both papers follow the same sample construction.

Beyond the difference in AKM construction, important institutional factors likely explain the remaining difference in our estimates. For example, while all of the workers in Lachowska et al. (2018) are displaced during the Great Recession, the bulk of workers in our paper separate during a tight labor market. If losses resulting from forgone firm premiums are acyclical, such premiums may explain a relatively smaller share of overall losses during an economic downturn compared to an expansion because total earnings deficits are larger during a recession (Davis and Von Wachter, 2011). However, there are various reasons to believe displaced workers forfeit a different kind of firm premium over the business cycle. For example, large employers – which offer well-documented wage premiums (Brown and Medoff, 1989; Bloom et al., 2018) and are less sensitive during economic downturns than their smaller counterparts (Gertler and Gilchrist, 1994; Fort et al., 2013) – displace a greater share of all laid off workers in business cycle peaks than troughs.[29] Indeed, Schmieder et al. (2018) provide evidence that the magnitude of earnings losses deriving from firm premiums in Germany are countercyclical.

To investigate whether the business cycle may account for our estimates being moderately larger than those of Lachowska et al. (2018), we plot the average pay premium of layoff firms in Ohio against the state's unemployment rate in Figure 6. Although most workers we analyze are displaced in a tight labor market, our layoff window extends to the eve of the Great Recession in 2008.[30] Both the unweighted and employment-weighted average pay premium of layoff firms in Ohio appear to drop

[29]According to the Job Openings and Labor Turnover Survey (JOLTS) Experimental Firm Size Class Statistics from the Bureau of Labor Statistics (2018b), firms with more than 500 employees accounted for 46% of all employee layoffs in 2017 as opposed to 36% in 2010.

[30]We are unable to analyze multiple year-cohorts of workers displaced in the Great Recession (2008-2010) using JLS-AKM because our follow-up period would be cut short of four years.

as the labor market improves. However, as the unemployment rate spikes in 2008, the employment-weighted mean $\hat{\theta}_j$ of layoff firms likewise rises markedly. If this series moves with the unemployment rate throughout the business cycle, it could suggest firm premiums would explain even *more* than one quarter of long-run earnings losses, rather than less. In other words, the difference in time periods between our analysis and Lachowska et al. (2018) does not appear to explain the larger estimates we find.

Another possible explanation is the difference in industry mix between Ohio and Washington. While the share of workers who are displaced from manufacturing does not vary between the Ohio and Washington samples (27 percent), it may be that rubber, steel, or glass manufacturing plants of Ohio confer a more generous pay premium than airplane manufacturers concentrated in Washington state. If manufacturing employees in Ohio forfeit a larger firm-specific wage premium than those in Washington, on average, this could explain at least part of the remaining gap between our papers' estimates. Unfortunately, there is no way to test this empirically with only the Ohio data.

5 Conclusion

Highly-tenured displaced workers suffer large and persistent earnings losses many years after their initial separations, the sources of which have long been a puzzle for labor economists. We first verify that workers in Ohio displaced in the mid-2000s have similar experiences, earning 22 percent less than they otherwise would have four years after displacement. Losses are substantially larger for those shed from manufacturing firms. We then seek to address one potential driver of earnings scarring by showing that firm-specific pay premiums explain a meaningful share of overall displaced worker earnings losses in Ohio, although they are not the primary source. Specifically, we show long-run earnings of workers who lose their job in a mass layoff are lower by 5.3 percent due exclusively to the loss of a favorable firm pay premium. This accounts for 24 percent of long-run earnings losses. For those separating from manufacturing firms, premium-forfeiture leads to earning losses of 17 percent, explaining over half of long-run deficits.

Because the JLS-AKM framework necessarily involves many precise decisions about sample restrictions for both stages of estimation, we subject our findings to a battery of sensitivity checks. We find that our 24 percent "share explained" estimate is invariant to applying higher tenure conditions to the displaced worker sample. Subjecting the displaced sample to more stringent post-displacement labor force attachment conditions, such as requiring workers have positive earnings in at least half of all post-layoff quarters, does not change our result that one-quarter of the displaced worker earnings scar is attributable to forgone firm rents.

Our preferred AKM sample accounts for negative selection of displaced workers on ability. However, applying an alternative AKM sample modestly attenuates our estimate from 24 to 16 percent. We discuss the theoretical reasons why modifying the AKM sample to exclude displaced workers altogether would lead to a smaller estimate for the role of forgone firm-specific rents. Whether employer pay premiums explain one-sixth or one-quarter of long-run earnings losses, it implies other factors—among them, skill depreciation while unemployed, loss of seniority, and forfeiture of positive "match effects"—are all potential sources of the remaining 75 percent of the earnings scar.

While our estimates for losses due to firm premiums and the share of overall deficits they explain are still more than twice as large as evidence from Washington state, they are still broadly consistent with Lachowska et al.'s (2018) findings that firm premiums play a much smaller role in the U.S. than in Germany. While greater tenure requirements imposed by Lachowska et al. (2018) for displaced workers do not account for a difference in the "share explained" estimates between Ohio and Washington, AKM sample construction accounts for roughly half of the differences. We then discuss the implications of differences in settings, comparing mid-2000s Ohio to Washington during the Great Recession. While both states displace a similar proportion of workers from the manufacturing sector, we speculate that Ohio firms offer a more generous premium to workers who will be laid off in the future than their counterparts in Washington. Additionally, jobs at high-premium firms may have been more available to laid off manufacturers in Washington than in Ohio. Regarding the business cycle, data limitations prevent us from investigating how losses due to firm premiums change with fluctuations in the unemployment rate. However, our data suggest such losses would, if anything, increase for workers laid off during a downturn, confounding differences with Lachowska et al. (2018) but consistent with Schmieder et al.'s (2018) findings for Germany.

Our study is constrained by the usual obstacles facing displaced worker papers which use administrative data. We are unable to assess the outcomes of displaced workers who leave the state, Although 10 percent of all displaced workers move as a result of their layoff (Bureau of Labor Statistics, 2018a), we are unable to assess outcomes of those who leave the state. Thus, we consider such individuals unattached to the labor force and thus exclude them from our analysis. If such individuals recoup more of their pre-layoff earnings or find re-employment at higher-paying firms than fellow displaced workers who stay put, our estimates of the magnitude of losses may be biased upwards. Our UI data's limited demographic information means we are unable to control for key variables such as worker age. Further, while we believe the AKM model accurately describes the wage structure across firms and workers and provides a valuable estimate of firm-premiums, it does not perfectly describe the labor market. The static nature of AKM imposes that worker mobility doesn't depend on prior employment history. AKM doesn't consider tenure in explaining wages, nor does it allow for complementarities between workers and firms if it does not include an interaction term.

Further work is needed to study how firm premiums in the U.S. change over the business cycle and how this could affect outcomes for workers who lose their job during an economic downturn. Workers laid off during a recession are different on numerous dimensions from those displaced during a recession. The same is true for firms which shed workers at different points in the cycle. A framework like JLS-AKM which describes the cost of job loss would ultimately want to account for such changes in worker and firm composition over the business cycle.

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Table 1: Descriptive Statistics for Displaced Workers and Comparison Group

	Displaced	Comparison
Industry of Layoff Firm		
Construction, Utilities, Mining	0.12	0.04
Manufacturing	0.30	0.26
Retail Trade	0.12	0.06
Finance, Insurance, Real Estate	0.08	0.07
Transportation & Warehousing	0.03	0.05
Educational & Health Services	0.08	0.24
Hospitality & Food Services	0.05	0.01
Displaced from AKM Firm in		
Bottom quartile of firm pay premiums	0.09	0.03
Second quartile	0.18	0.15
Third quartile	0.23	0.29
Top quartile	0.50	0.53
Yearly Pre-Displaced Earnings		
1-4 Quarters Before ($)	49,689	59,444
	(39,550)	(38,585)
5-8 Quarters Before ($)	49,343	58,616
	(37,226)	(38,595)
N	40,419	521,188

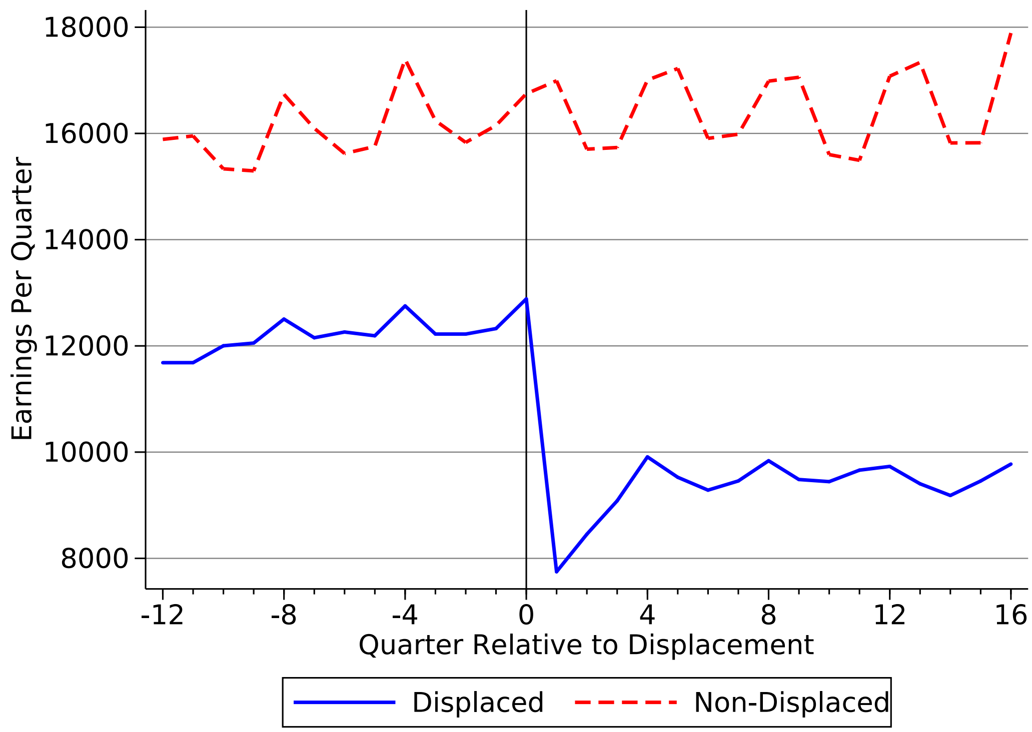
Note: Standard errors for earnings are expressed in parentheses. Reported industry shares do not sum to 1 due to a small amount of the samples in other NAICS industries. Firm pay premiums refer to the premia or penalties for a worker's log annual earnings associated with employment at a specific firm (relative to an omitted firm) and are estimated via the AKM method. Earnings are inflation-adjusted to USD$2012 using the CPI-U.

Table 2: Summary of Estimated Earnings Losses for Displaced Workers

	Q1	Q9-Q12	Q13-16
A. All Workers			
Full losses (logs)	-0.335	-0.259	-0.252
Loss attributable to foregone θ FE	-0.057	-0.056	-0.054
Share attributable	19.6%	23.9%	23.8%
B. All Workers except NAICS 51-56			
Full losses (logs)	-0.395	-0.262	-0.253
Loss attributable to foregone θ FE	-0.069	-0.060	-0.059
Share attributable	20.4%	25.3%	25.6%
C. Manufacturing			
Full losses (logs)	-0.546	-0.376	-0.346
Loss attributable to foregone θ FE	-0.186	-0.179	-0.182
Share attributable	40.3%	52.4%	57.0%
D. Displ. from top-quartile firm (any)			
Full losses (logs)	-0.409	-0.342	-0.340
Loss attributable to foregone θ FE	-0.151	-0.164	-0.174
Share attributable	41.8%	52.3%	55.4%
E. Displ. from & re-empl. at top-quartile			
Full losses (logs)	-0.214	-0.191	-0.172
Loss attributable to foregone θ FE	-0.023	-0.024	-0.022
Share attributable	11.7%	13.7%	13.6%
F. High-Tenure (6+ years)			
Full losses (logs)	-0.452	-0.374	-0.392
Loss attributable to foregone θ FE	-0.083	-0.075	-0.079
Share attributable	21.8%	23.3%	23.6%

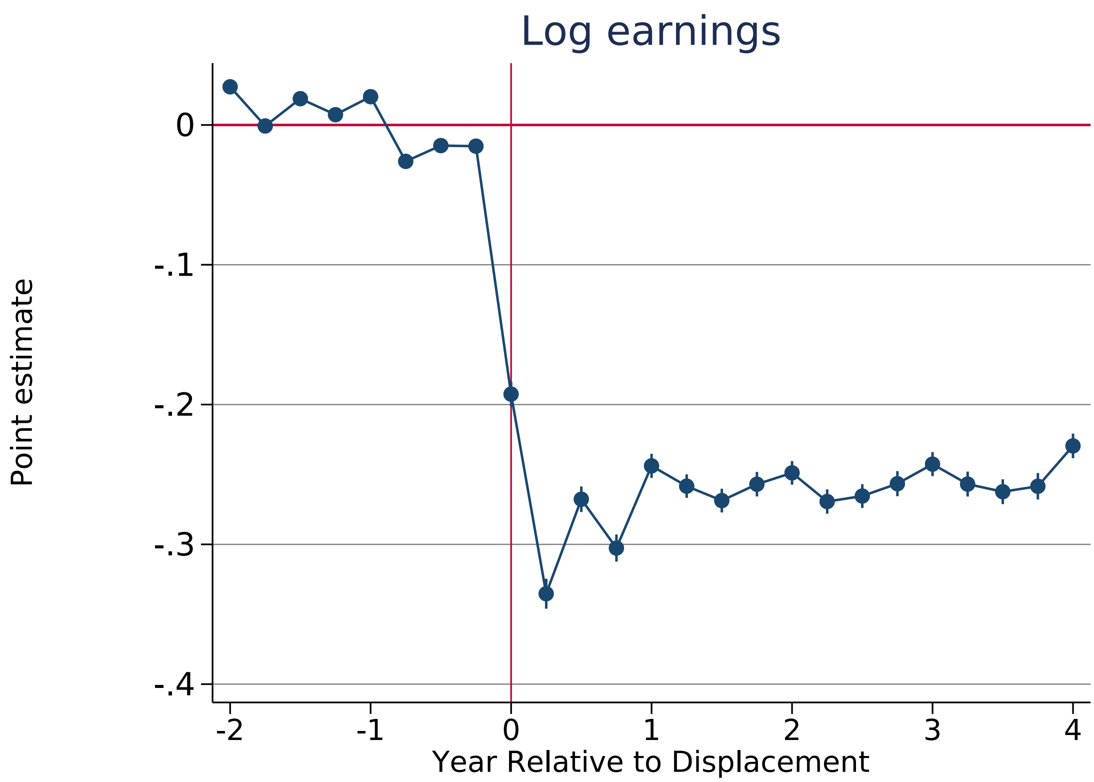
Note: Each entry provides the estimated displacement effect on earnings in the quarter or range of quarters indicated. For ranges, the mean of the corresponding point estimates are presented. All such point estimates are significant at the $p < 0.001$ level. Estimates are based on equations 2 and 3. To calculate "share attributable" we convert logs to percentages using $\Delta\ y\% = exp(\beta)$ - 1 where β equals the mean of the log coefficients reported in the table. We then take the quotient of the percent earnings change due to firm premiums and overall percent change in earnings.

Figure 1: Earnings Profile of Displaced and Non-Displaced Workers



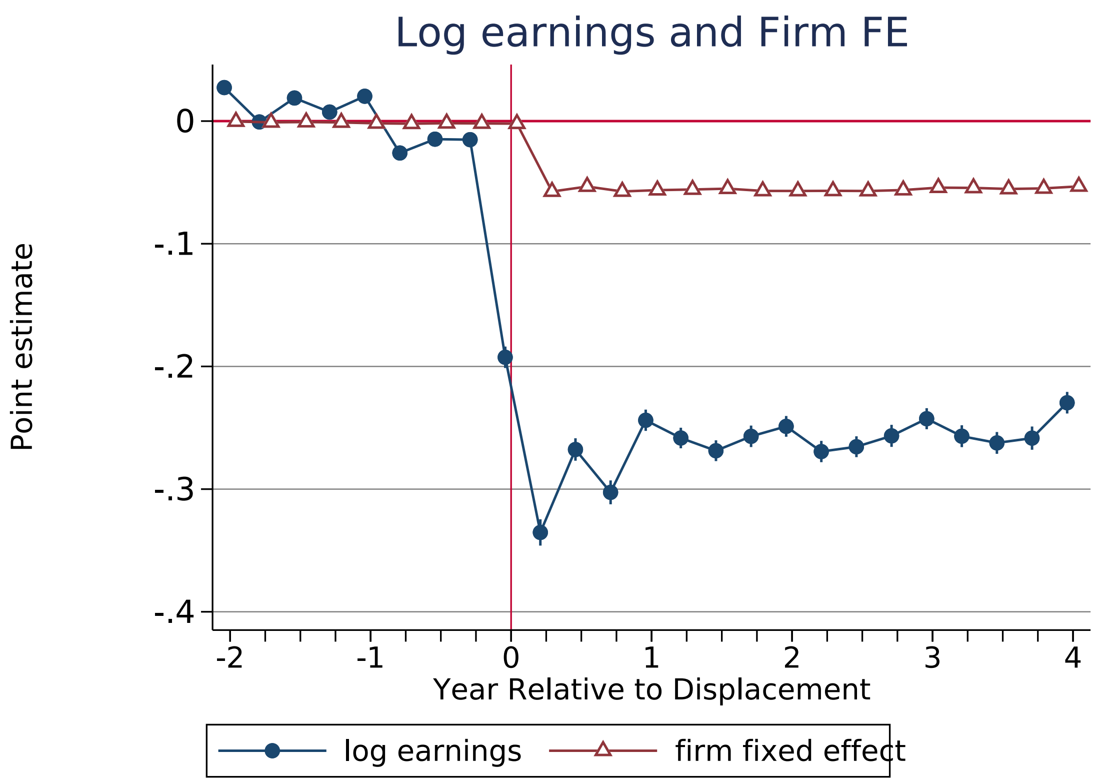
Note: This figure shows quarterly earnings profiles (2012 constant dollars) of workers displaced in Ohio between 2002Q1–2008Q4 (blue) and workers who remained at the same firm from 1999Q1–2012Q4 with no more than one quarter of zero earnings (red). Earnings include observations of zero. Because the comparison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

Figure 2: Regression-Adjusted Estimates of Earnings Losses due to Displacement



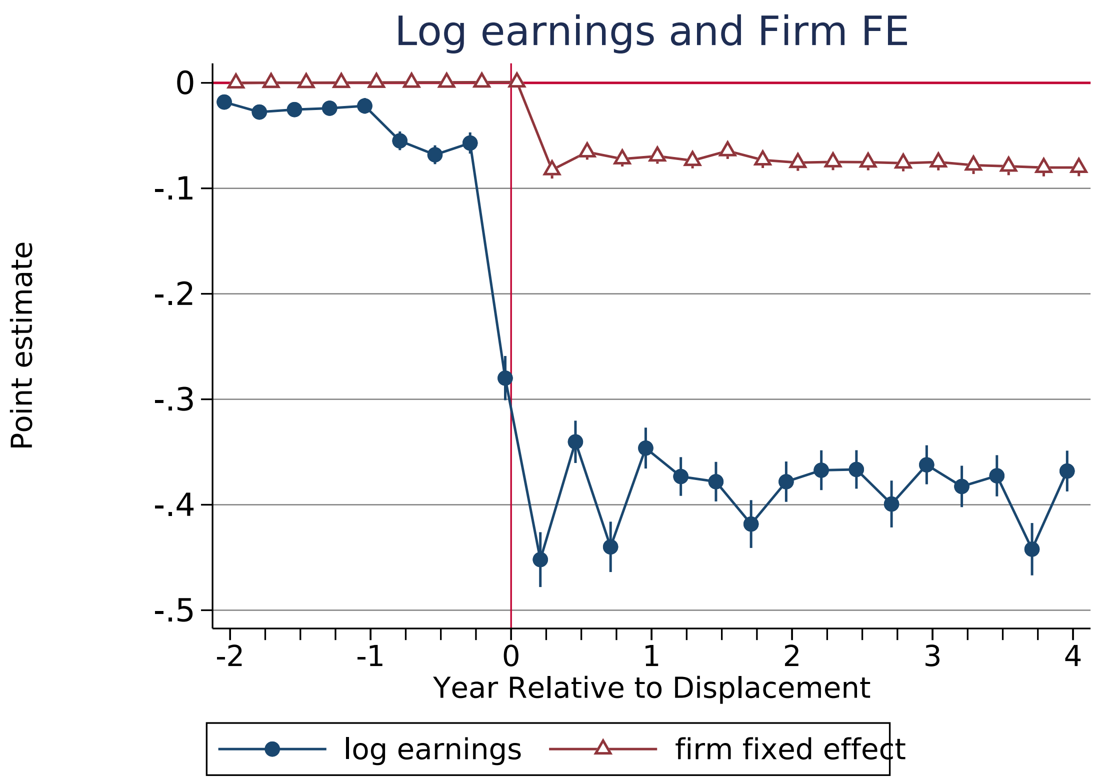
Note: Figure shows estimated δ_ks – logarithm of quarterly earnings lost due to displacement – based on equation 2 with the log of earnings as the dependent variable. Whiskers (which are very small) denote 95-percent confidence intervals based on standard errors clustered by worker. Vertical line denotes quarter of displacement. Estimates for δ_ks for positive values of k are listed in Column 3 of Table B.2

Figure 3: 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 for positive values of k correspond to Columns 3-4 of Table B.2.

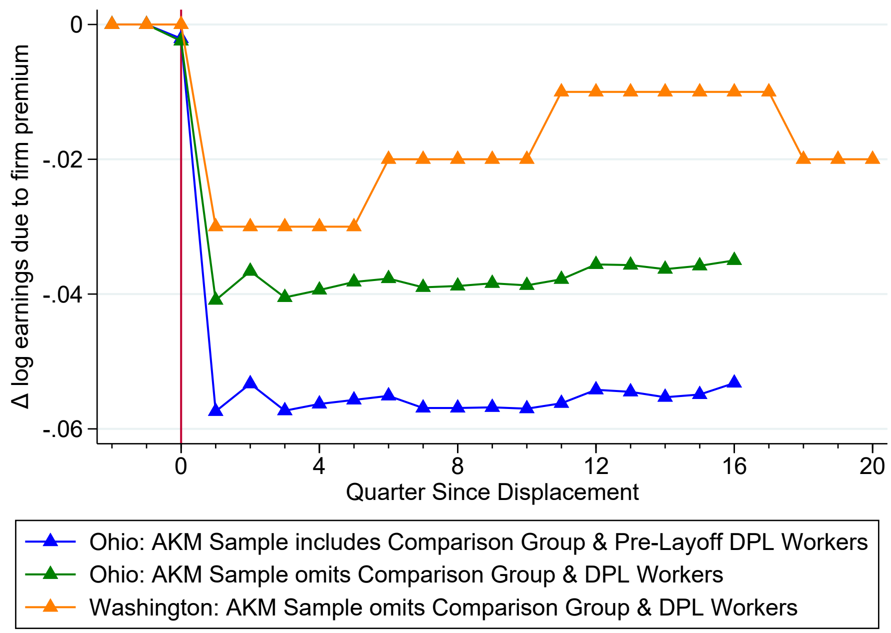
Figure 4: Estimated Displacement Effects on Earnings: Overall and due to Foregone Employer FE; Six Years Tenure



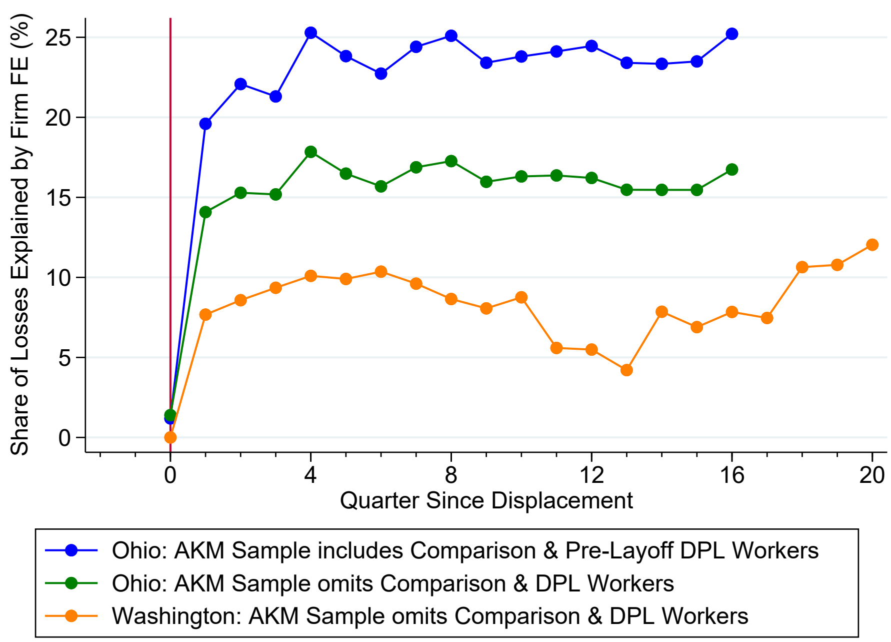
Note: Figure plots the estimated δ_k and ω_k coefficients from modified versions of equations 2 (blue) and 3 (red) (see text). Coefficients for -20 $\leq k \leq$ -9 not shown. Whiskers (which are very small) denote 95-percent confidence intervals based on standard errors clustered by worker. Vertical line denotes quarter of displacement. These estimates for positive values of k correspond to Columns 1 and 2 of Table B.4.

Figure 5: Earnings Losses due to Foregone Firm FE based on AKM Sample Selection: Ohio and Washington Estimates

(a) Firm FE $\hat{\theta}_j$ on Earnings

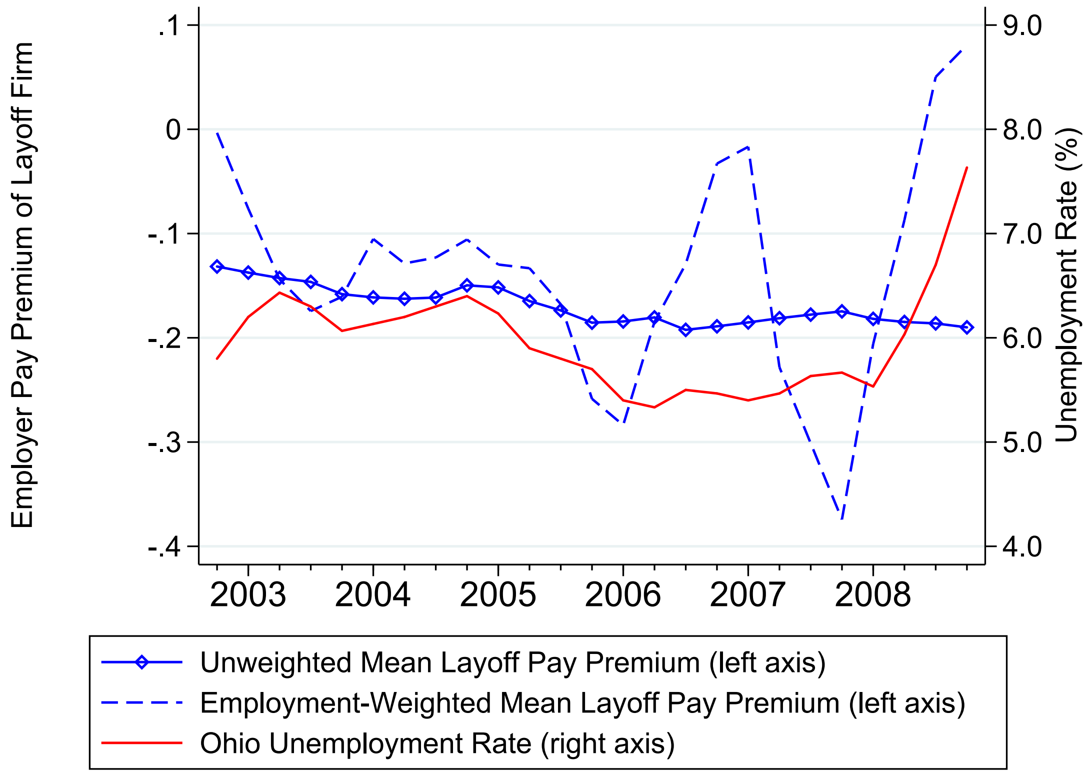


(b) Share of Earnings Losses Explained



Note: The top panel plots $\hat{\omega}_k$ coefficients from equation (3). Corresponding point estimates are listed in Table A.4. The bottom panel converts $\hat{\omega}_k$ and $\hat{\delta}_k$ to percentages and takes the quotient, representing the share of earnings losses attributable to forgone firm pay premium. 95% confidence intervals are not shown, but all point estimates for $k > 0$ are highly significant. Orange lines represent reported figures in Lachowska et al. (2018), who use Washington state data and follow a similar approach.

Figure 6: Average Layoff Firm Premium and Ohio Unemployment Rate



Source: Authors' calculations from Ohio administrative data and Local Area Unemployment Statistics (LAUS) from the Bureau of Labor Statistics.

Note: The blue solid line plots the four-quarter moving average of the estimated $\hat{\theta}_j$ for all firms which experience a mass layoff in a particular quarter between 2002q1 and 2008q4. The dashed blue line plots the four-quarter moving average of the estimated $\hat{\theta}_j$ for all firms which experience a mass layoff weighted by the firm's employment four quarters prior to the quarter of layoff. The red line represents Ohio's seasonally adjusted unemployment rate plotted at a quarterly frequency by averaging the monthly unemployment rate within a quarter.

Appendix A

In Appendix A, we discuss our application of AKM with the goal of obtaining firm-specific pay premiums that can be used to infer displaced worker earnings losses attributable to forgone firm rents. Section A.1 provides a more in-depth discussion of AKM and identifying assumptions. Section A.2 discusses the implications of sample selection for the groups of workers and firms on which AKM is run. This section also provides variance decompositions and regression table output for various AKM sample selection.

A.1 AKM Overview

AKM's methodology can be applied to employer-employee matched datasets with the intention of provide further explanatory power in the model of worker earnings. The approach, which exploits movement of workers between firms, is typically estimated on a seven-year panel (Bloom et al., 2018; Song et al., 2018). In our setting, however, a lengthier (13-year) panel is appropriate. We use the JLS-AKM framework described in section 3.3 which requires constant firm premiums throughout the panel so to infer the earnings losses due to firm premiums that accrue to workers after displacement.

Beyond sufficient movement of workers between firms, the of the firm fixed effects estimated from equation (1) rely critically on sufficient movement of workers between firms. Beyond employer-switching, one can only interpret estimated firm effects with true firm-specific differences pay policies if underlying assumptions of additive separability and conditional random mobility are met.

Additive separability requires that upwardly and downwardly mobile job movers have a proportional markup or markdown. We find plausible evidence for additive separability by examining changes in mean log earnings of upwardly and downwardly mobile workers in Figure A.1. We follow Card et al. (2013) by categorizing firms into four quartiles based on $\hat{\theta}_j$. 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 upwardly mobile workers experience larger earnings increases than less upwardly-mobile ones, and likewise the most downwardly mobile workers exhibit earnings penalties of greater magnitudes than the less-downwardly mobile.

The second assumption of conditional random mobility (CRM), sometimes called exogenous mobility, rules out job sorting based on individual shocks, firm shocks, and match components. For example, if worker i moves from firm j_1 to firm j_2, CRM requires i) symmetry about zero

$$\mathbb{E}[\Delta y_{it}|j_1 \rightarrow j_2] = -\mathbb{E}[\Delta y_{it}|j_2 \rightarrow j_1]$$

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

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

Symmetry about zero is evident in Figure A.1. 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 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. Further, movers in Figure A.1 exhibit a lack of pre and post-trends in mean log earnings, with little change for workers who switch firms in the year before their transition and between their first and second year at the destination firm. See Card et al. (2018) for an in-depth discussion of the complications involved in satisfying CRM.

Lastly, while the AKM approach excels in settings with two-sided unobserved heterogeneity, we are also well-aware of the model's shortcomings. AKM is a necessarily static model, meaning worker mobility does not depend on earnings conditional on worker or firm heterogeneity. AKM also cannot consider worker tenure in explaining wages. Further, the degree of sorting between workers and firms may be understated because the sampling error in the firm and worker fixed effects are negatively correlated. Bonhomme et al. (2019) and Lentz et al. (2018) propose frameworks to obviate these concerns while still leveraging the benefits of employer-employee matched data.

A.2 AKM Sample Selection

In the vast majority of papers which use AKM, equation (1) is estimated on the entire sample of workers and firms in the connected set. However, the aim of this paper is to study displaced workers who exhibit substantial wage scarring after job loss. When AKM is run on a sample that includes displaced workers for all years they are present in the panel, the earnings of displaced workers, unlike typical workers, are *not* additive in their worker and firm fixed effect after they separate from their layoff employer. For example, a worker laid off from a bottom-quartile firm who finds re-employment at a top-quartile firm receives an average pay increase of only 55 log points upon movement. However, the earnings of a displaced worker moving in the opposite direction with respect to firm pay premiums drop by 90 log points. This suggests displaced worker earnings after displacement are characterized by equation (1) where the error term ε_{ijt} is not conditional mean zero. Thus, displaced worker earnings in post-layoff periods should be omitted from any potential AKM sample.

Both our paper and Lachowska et al. (2018) omit post-layoff year-worker observations for displaced workers from the AKM sample. Thus, both approaches plausibly satisfy AKM's identifying assumptions. However, Lachowska et al. (2018) also choose to omit both displaced workers altogether and comparison workers (used in the difference-in-difference model) from the sample on which they run AKM. We opt against this restriction for reasons provided in subsection 4.3.2.

Below we provide numerous tables of variance decompositions and regression-adjusted estimates that use alternative AKM sample selections instead of our own preferred sample. These results and figures serve as a robustness check for our results by examining sensitivity to AKM sample selection.

A.3 Negative Selection of Displaced Workers shown with AKM

In this section, we illustrate that displaced workers are negatively selected and that their omission in the AKM sample systematically changes the premium estimate $\hat{\theta}_j$ for firms that lay off workers.

First, Figure A.2 presents a binscatter of the average change in a firm's employment against that firm's average worker quality. Firm j's average worker quality is defined as

$$\bar{\hat{\alpha}}_{j(i,t)} = \frac{1}{N_{jt}} \sum_{i=1}^{N_{jt}} \hat{\alpha}_{i(j,t)}$$

where N_{jt} is the number of employees at firm j in time t and $\hat{\alpha}_{i(j,t)}$ is the estimated individual fixed effect of worker i at firm j in time t. The individual fixed effects are estimated from equation (1) on the sample described in section 2. As firms in Ohio contract by 30% or more in a year, their average worker quality increases, meaning the workers who were shed had lower estimated fixed effects. This implies displaced workers are negatively selected on ability.

We believe this negative selection explains why pay premium estimates for the same firm vary substantially depending on the AKM sample restrictions described in Appendix A.2. In Table A.5, we compare how the estimated mean firm pay premium $\hat{\theta}_j$ of "mass layoff firms" changes depending on the AKM sample. For completeness, we provide results for four different definitions of mass layoff firms, described in the table notes.

Table A.5 illustrates several features about different firm premium estimates that arise from AKM. First, regardless of AKM sample and definition of mass layoff firm, "layoff firms" have larger estimated firm premiums than employers that do not lay off workers. Second, pay premium estimates for layoff firms are always higher in our preferred sample (AKM I) than in a sample which omits displaced workers but keeps comparison workers (AKM II). This suggests that by not including negatively-selected displaced workers, AKM underestimates the value of pay premiums for layoff firms but they are only identified by a positively-selected subsample of the firm's employees.

Because the average estimated pay premium for non-layoff firms also changes slightly depending on the AKM sample, the last column of the table reports the difference $\hat{\theta}_j^{ML}$ - $\hat{\theta}_j^{non-ML}$ to underscore that lay off firms always have a higher estimated firm-specific pay premium under AKM sample I compared to AKM sample II. The difference in firm premiums depending on AKM sample illustrated in Table A.5 ultimately explains why the regression-adjusted estimates equation (3) vary by AKM sample (see Figure 5a).

It should be noted that while Table A.5 compares our preferred AKM sample to one that omits displaced workers entirely but keeps comparison workers, the figures in the main body compare results from our sample to an AKM sample that omits *both* displaced and comparison workers. This is because in Table A.5, we seek to isolate the "marginal effect" of omitting displaced workers from AKM on the resulting estimated firm premiums for employers that lay off workers. However, when we compare our preferred sample to one that omits both displaced and comparison workers, the same relationship holds.

Table A.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	51,139,118
Number of workers	7,374,993	6,577,019
Number of employers	343,475	301,733
Number of movers	4,206,119	3,967,005
Log earnings (mean)	10.484	10.485

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

Table A.2: Variance Decomposition of Log Earnings AKM Model into Components By Sample

Sample	Includes Disp	Includes Comp	Total Variance	Worker FE (α)	Employer FE (θ)	Year FE (γ)	2cov(α,θ)	Resid
Ohio								
AKM I	✓	✓	0.610	0.310	0.149	0.001	0.033	0.117
				0.509	*0.244*	*0.002*	*0.055*	*0.191*
AKM II		✓	0.611	0.311	0.149	0.001	0.034	0.116
				0.509	*0.244*	*0.002*	*0.056*	*0.190*
AKM III			0.623	0.305	0.154	0.001	0.036	0.127
				0.490	*0.248*	*0.002*	*0.058*	*0.204*
Washington								
LMW (2018)			0.596	0.309	0.123	0.004	0.101	0.064
				0.519	*0.207*	*0.006*	*0.169*	*0.107*

Source: Authors' tabulations of Ohio administrative earnings records, 1999-2012, as well as reported decomposition estimates reported in the Appendix by Lachowska et al. (2018).

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 subject to different sample restrictions. Specifically, whether observations for the comparison group or displaced workers (*before* displacement) described in section 3.2 are included when estimating AKM via equation 1. The share of the variance explained by each component is denoted in italics below its listed variance. 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. Lachowska et al. (2018)'s sample covers 2002-2014, while ours cover 1999-2012.

Table A.3: Displacement Effects on Earnings and Firm Effects: $\hat{\theta}_j$ Estimated via AKM without Pre-Layoff Displaced Workers but Including Comparison Group (Sample II)

	(1)	(2)	(3)	(4)
	Log earnings	θ log earnings	Log earnings	θ log earnings
Quarter since displacement				
0	-0.159***	0.00133**	-0.165***	0.000533
	(0.0038)	(0.0004)	(0.0038)	(0.0004)
1	-0.309***	-0.0392***	-0.317***	-0.0401***
	(0.0054)	(0.0018)	(0.0054)	(0.0018)
2	-0.213***	-0.0251***	-0.220***	-0.0260***
	(0.0040)	(0.0014)	(0.0040)	(0.0014)
3	-0.301***	-0.0457***	-0.309***	-0.0468***
	(0.0050)	(0.0017)	(0.0050)	(0.0017)
4	-0.213***	-0.0366***	-0.221***	-0.0377***
	(0.0039)	(0.0015)	(0.0039)	(0.0015)
5	-0.186***	-0.0343***	-0.195***	-0.0356***
	(0.0038)	(0.0015)	(0.0038)	(0.0015)
6	-0.250***	-0.0385***	-0.260***	-0.0398***
	(0.0042)	(0.0017)	(0.0042)	(0.0017)
7	-0.200***	-0.0349***	-0.210***	-0.0362***
	(0.0040)	(0.0016)	(0.0040)	(0.0016)
8	-0.210***	-0.0347***	-0.221***	-0.0361***
	(0.0038)	(0.0016)	(0.0038)	(0.0016)
9	-0.192***	-0.0343***	-0.203***	-0.0358***
	(0.0039)	(0.0016)	(0.0039)	(0.0016)
10	-0.221***	-0.0347***	-0.232***	-0.0362***
	(0.0038)	(0.0016)	(0.0038)	(0.0016)
11	-0.198***	-0.0338***	-0.209***	-0.0353***
	(0.0041)	(0.0016)	(0.0041)	(0.0016)
12	-0.198***	-0.0324***	-0.210***	-0.0340***
	(0.0039)	(0.0016)	(0.0039)	(0.0016)
13	-0.231***	-0.0368***	-0.243***	-0.0385***
	(0.0043)	(0.0018)	(0.0043)	(0.0018)
14	-0.237***	-0.0381***	-0.249***	-0.0399***
	(0.0044)	(0.0019)	(0.0043)	(0.0019)
15	-0.219***	-0.0328***	-0.231***	-0.0346***
	(0.0044)	(0.0017)	(0.0044)	(0.0017)
16	-0.216***	-0.0314***	-0.228***	-0.0332***
	(0.0040)	(0.0017)	(0.0039)	(0.0017)
Pre-Displacement Earnings	No	No	Yes	Yes
Observations	30855435	30807334	30855435	30807334

Standard errors in parentheses

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

Table A.4: Displacement Effects on Earnings and Firm Effects: $\hat{\theta}_j$ Estimated via AKM without Pre-Layoff Displaced Workers or Comparison Group (Sample III)

	(1) Log earnings	(2) θ log earnings	(3) Log earnings	(4) θ log earnings
Quarter since displacement				
0	-0.186***	-0.00162***	-0.192***	-0.00245***
	(0.0045)	(0.0005)	(0.0045)	(0.0005)
1	-0.327***	-0.0400***	-0.335***	-0.0409***
	(0.0055)	(0.0019)	(0.0055)	(0.0019)
2	-0.259***	-0.0356***	-0.267***	-0.0366***
	(0.0047)	(0.0018)	(0.0047)	(0.0018)
3	-0.293***	-0.0394***	-0.302***	-0.0405***
	(0.0050)	(0.0018)	(0.0050)	(0.0018)
4	-0.234***	-0.0382***	-0.244***	-0.0394***
	(0.0044)	(0.0018)	(0.0044)	(0.0018)
5	-0.248***	-0.0370***	-0.258***	-0.0382***
	(0.0043)	(0.0018)	(0.0043)	(0.0018)
6	-0.258***	-0.0364***	-0.268***	-0.0377***
	(0.0043)	(0.0018)	(0.0043)	(0.0018)
7	-0.245***	-0.0376***	-0.257***	-0.0390***
	(0.0045)	(0.0018)	(0.0045)	(0.0018)
8	-0.237***	-0.0374***	-0.249***	-0.0388***
	(0.0043)	(0.0018)	(0.0043)	(0.0018)
9	-0.257***	-0.0369***	-0.269***	-0.0384***
	(0.0044)	(0.0019)	(0.0044)	(0.0019)
10	-0.253***	-0.0371***	-0.265***	-0.0387***
	(0.0044)	(0.0019)	(0.0043)	(0.0019)
11	-0.243***	-0.0362***	-0.256***	-0.0378***
	(0.0046)	(0.0019)	(0.0046)	(0.0019)
12	-0.229***	-0.0340***	-0.242***	-0.0356***
	(0.0044)	(0.0019)	(0.0044)	(0.0019)
13	-0.244***	-0.0340***	-0.256***	-0.0357***
	(0.0046)	(0.0020)	(0.0045)	(0.0020)
14	-0.249***	-0.0345***	-0.262***	-0.0363***
	(0.0046)	(0.0020)	(0.0045)	(0.0020)
15	-0.245***	-0.0340***	-0.258***	-0.0358***
	(0.0049)	(0.0020)	(0.0048)	(0.0020)
16	-0.216***	-0.0332***	-0.229***	-0.0350***
	(0.0045)	(0.0020)	(0.0045)	(0.0020)
Pre-Displacement Earnings	No	No	Yes	Yes
Observations	30,627,047	30,545,348	30,627,047	30,545,348

Standard errors in parentheses

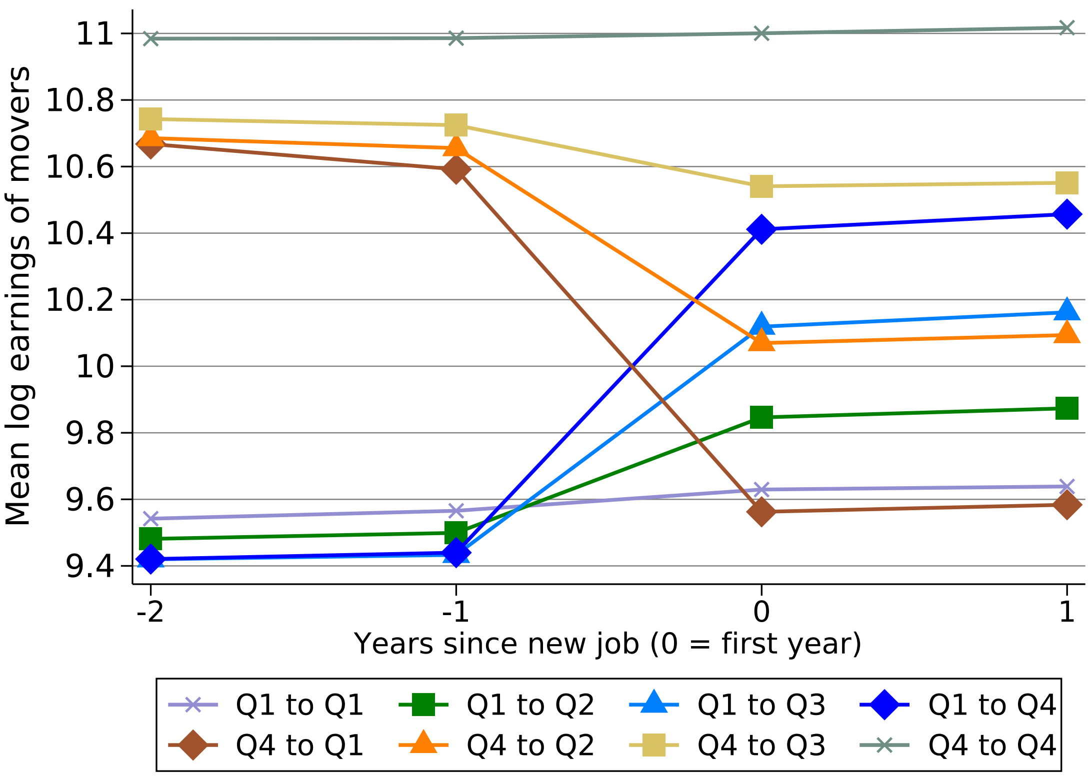
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.5: Firm-Specific Pay Premium Comparison by AKM Regression Sample

	Includes		M. Layoff Firms		Mean $\hat{\theta}$		ML - Non-ML
	Disp	Comp	N	Share Q4	Non-ML	ML Firm	Diff in $\bar{\hat{\theta}}$
A. Ever Had Layoff							
AKM I	✓	✓	6,578	0.268	-0.2251	-0.1729	0.0522
AKM II		✓	6,328	0.253	-0.2243	-0.1960	0.0283
B. Multiple Layoffs							
AKM I	✓	✓	6,522	0.268	-0.2251	-0.1741	0.0510
AKM II		✓	6,273	0.252	-0.2243	-0.1975	0.0268
C. Only 2008 layoffs							
AKM I	✓	✓	75	0.307	-0.2251	-0.0863	0.1388
AKM II		✓	74	0.306	-0.2243	-0.0931	0.1312
D. Manufacturing							
AKM I	✓	✓	644	0.407	-0.2251	0.0313	0.2564
AKM II		✓	625	0.376	-0.2243	0.0048	0.2291

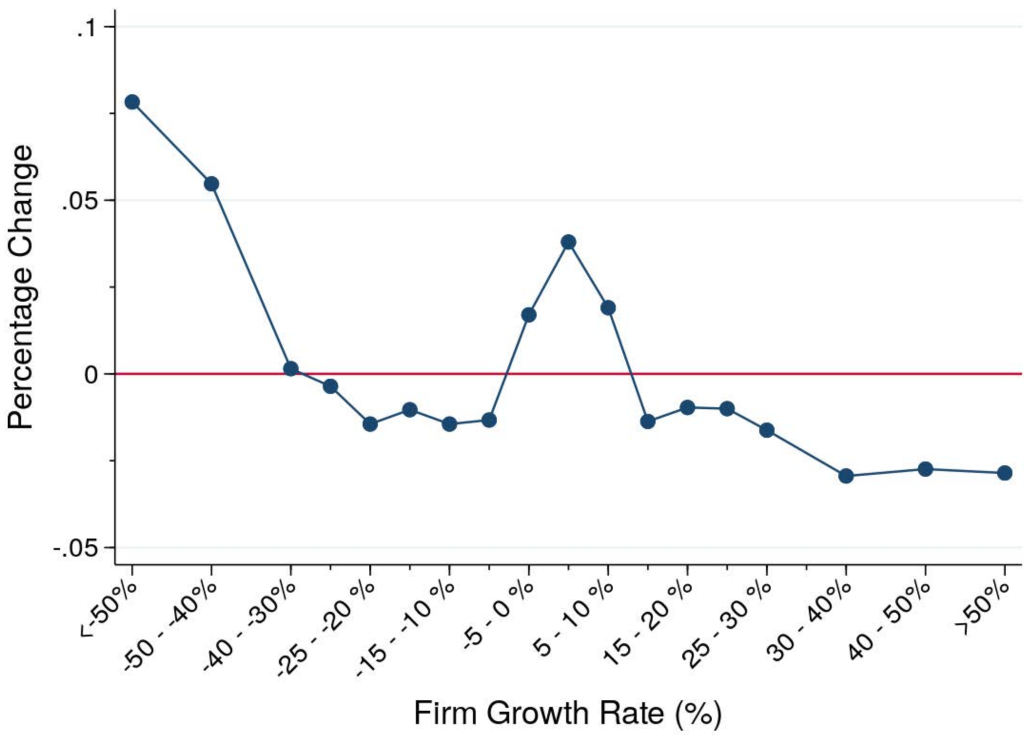
Note: Results are obtained running AKM (equation 1) on two samples. AKM Sample I – our preferred sample – is the largest connected set of all non-displaced workers and displaced workers during the years before their displacement. AKM Sample II is the largest connected set that omits displaced workers entirely, however the sample includes workers used in the comparison group used in equation 2 for difference-in-difference methodology. The first two columns list the number of layoff firms and the share of these layoff firms that are top-quartile (Q4) pay premium firms. Column 3 and 4 show the mean $\hat{\theta}_j$ of non-layoff firms and layoff firms, respectively. The fifth and final column expresses the difference between column 4 and column 3. A "layoff firm" assumes a different definition in each panel. Panel A compares the mean value of $\hat{\theta}_j$ non-layoff firms to firms that ever laid off workers between 2002 and 2008. Panel B compares non-layoff firms to firms that had multiple layoffs during 2002-2008. Panel C compares non-layoff firms to firms whose first layoff came in 2008. Panel D compares non-layoff firms to manufacturing firms that had layoffs in 2002-2008.

Figure A.1: Mean Log Earnings of Movers Classified by Quartile of Firm Effects (θ) for Origin and Destination Firms



Note: This figure shows mean yearly earnings of workers observed in 1999-2012 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 firm fixed effects based on the estimation of the AKM model.

Figure A.2: Change in Average Worker Quality



Note: This figure shows the percentage change of average employee fixed effect by firm growth rates for firms in the Ohio administrative data. Growth rate bins are five percentage points in width between -25% and 25%, and ten otherwise. The sample consists of all firms with size > 30. Firm growth rates and percentage changes in average worker quality are yearly.

Appendix B

In Appendix B, we describe our displaced sample in further detail (B.1) and subject our estimates to a battery of sensitivity tests (B.2). Lastly, we combine our displaced worker earnings loss estimates from Section 4 and previous research with information on hours worked to estimate the role of firm premiums in hourly wage scarring (B.3).

B.1 Supplemental Displaced Worker Information

Table B.1 summarizes earnings and industry variables for all displaced workers by quartile of layoff firm pay premium. 34% of all displaced workers who separate from an upper-quartile fixed effect employer come from manufacturing. 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, potentially contributing to their large representation among firms with high pay premiums. At the 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 1 in the body of the paper notes, these workers from the lowest-paying firms comprise only a small share of the overall displaced sample.

The second panel of Table B.1 displays the average displaced worker pre-earnings by AKM quartile firms, demonstrating the predictable pattern that workers at higher AKM quartile firms earn more. The numbers underscore the magnitude of the earnings differences across quartiles. One year before displacement, the average sample individual at a top quartile firm earns $25,000 more per year than 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. In a monopsonistic wage setting model like that from Robinson (1969), different employer wage premiums arise because more profitable firms that seek to hire more workers must pay higher wages to do so. Lastly, the positive covariance between worker and firm fixed effects shown in Appendix Table A.2 reflects sorting patterns between higher-paying firms and workers of higher ability, educational attainment, or occupational skill.

Separately, in Table B.2, we provide the point estimates and standard errors that accompany Figure 3 for the time of displacement and sixteen quarters thereafter. Although the regression estimates the effect of displacement on earnings for the eight quarters preceding displacement, these coefficients are not included in the table.

Figure B.1 displays the estimated coefficients and standard errors for the following specification:

$$emp_{it} = \alpha_i + \gamma_t + W_{it}\beta_1 + X_{ijt}\beta_2 + \sum_{k=-8}^{16} \delta_k \cdot D_{itk} + \varepsilon_{it} \tag{4}$$

The right-hand side of equation (4) is identical to that of equation (2). On the left-hand side is an indicator for whether worker i is employed in time t. The resulting $\hat{\delta}_k$'s are interpreted as the effect of displacement on a worker's probability of employment k quarters relative to their separation.

Table B.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	0.02	0.05	0.11	0.16
Manufacturing	0.02	0.04	0.35	0.42
Retail Trade	0.26	0.35	0.04	0.04
Transportation & Warehousing	0.01	0.04	0.04	0.02
Finance, Insurance, Real Estate	0.02	0.02	0.05	0.14
Educational & Health Services	0.01	0.08	0.20	0.04
Hospitality & Food Services	0.33	0.08	0.00	0.00
Other Industries	0.30	0.34	0.21	0.18
Total	1.00	1.00	1.00	1.00
Yearly Pre-Displaced Earnings				
1-4 Quarters Before ($)	25,047	33,651	44,388	62,492
	(22,024)	(28,733)	(32,083)	(43,528)
5-8 Quarters Before ($)	25,386	34,240	44,712	61,366
	(21,875)	(29,071)	(30,748)	(40,097)
N	3,606	7,455	9,323	20,104

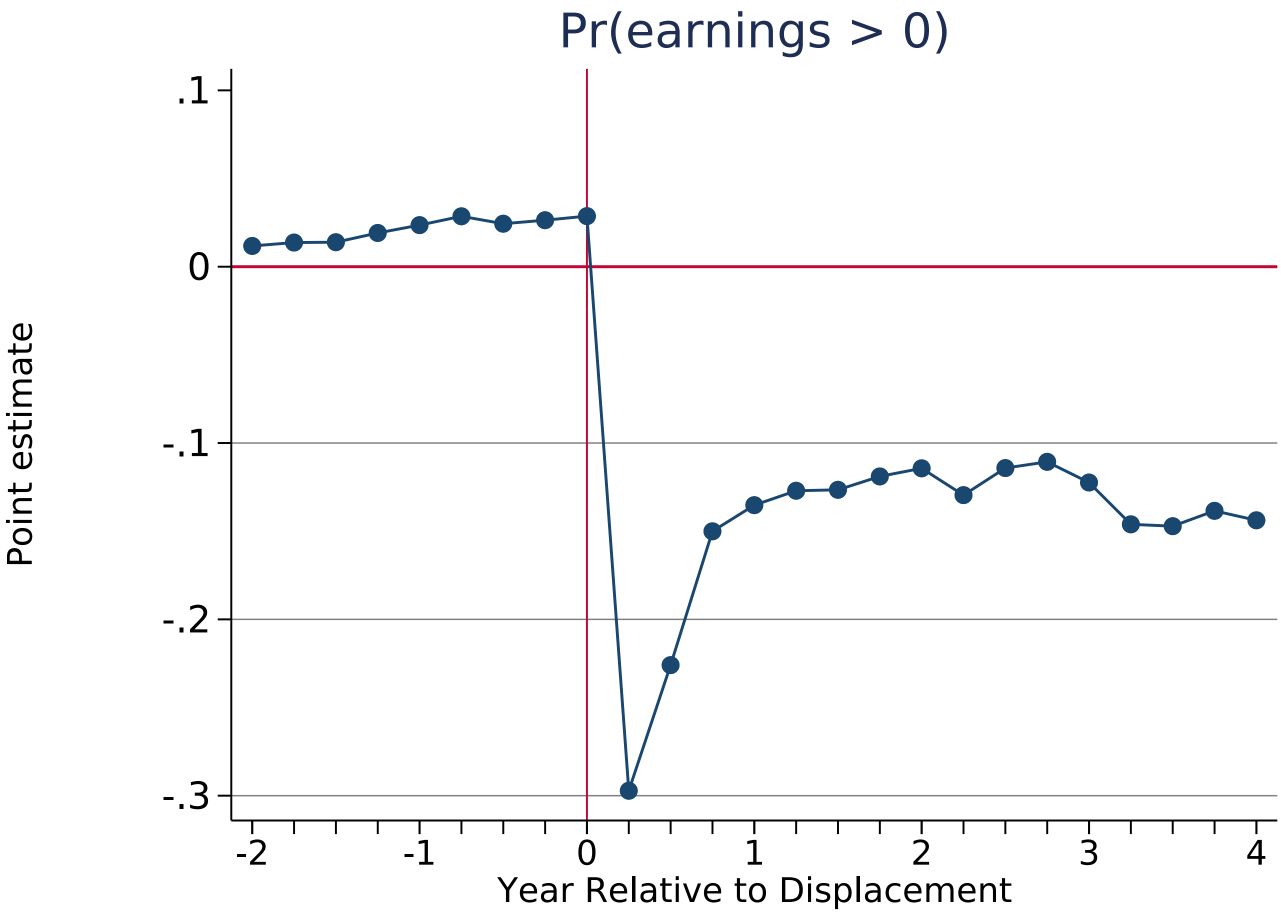
Table B.2: Effects of Displacement on Earnings and AKM Firm Fixed Effects

	(1) Log earnings	(2) θ log earnings	(3) Log earnings	(4) θ log earnings
Quarter since displacement				
0	-0.186***	-0.00120**	-0.193***	-0.00209***
	(0.0045)	(0.0005)	(0.0045)	(0.0005)
1	-0.327***	-0.0564***	-0.335***	-0.0574***
	(0.0055)	(0.0018)	(0.0055)	(0.0018)
2	-0.259***	-0.0523***	-0.268***	-0.0533***
	(0.0047)	(0.0018)	(0.0047)	(0.0018)
3	-0.294***	-0.0562***	-0.303***	-0.0573***
	(0.0050)	(0.0017)	(0.0050)	(0.0017)
4	-0.234***	-0.0550***	-0.244***	-0.0563***
	(0.0044)	(0.0017)	(0.0044)	(0.0017)
5	-0.248***	-0.0544***	-0.258***	-0.0557***
	(0.0043)	(0.0018)	(0.0043)	(0.0018)
6	-0.258***	-0.0537***	-0.269***	-0.0551***
	(0.0043)	(0.0018)	(0.0043)	(0.0018)
7	-0.246***	-0.0555***	-0.257***	-0.0569***
	(0.0045)	(0.0018)	(0.0045)	(0.0018)
8	-0.237***	-0.0554***	-0.249***	-0.0569***
	(0.0043)	(0.0018)	(0.0043)	(0.0018)
9	-0.257***	-0.0552***	-0.269***	-0.0568***
	(0.0044)	(0.0018)	(0.0044)	(0.0018)
10	-0.253***	-0.0553***	-0.265***	-0.0570***
	(0.0044)	(0.0019)	(0.0043)	(0.0018)
11	-0.244***	-0.0545***	-0.257***	-0.0562***
	(0.0046)	(0.0019)	(0.0046)	(0.0019)
12	-0.230***	-0.0525***	-0.243***	-0.0542***
	(0.0044)	(0.0019)	(0.0044)	(0.0019)
13	-0.244***	-0.0526***	-0.257***	-0.0545***
	(0.0046)	(0.0019)	(0.0045)	(0.0019)
14	-0.249***	-0.0534***	-0.262***	-0.0553***
	(0.0046)	(0.0020)	(0.0045)	(0.0020)
15	-0.245***	-0.0529***	-0.258***	-0.0549***
	(0.0049)	(0.0020)	(0.0048)	(0.0019)
16	-0.216***	-0.0513***	-0.230***	-0.0532***
	(0.0045)	(0.0020)	(0.0045)	(0.0020)
Pre-Displacement Earnings	No	No	Yes	Yes
Observations	30,628,063	30,585,770	30,628,063	30,585,770

Standard errors in parentheses

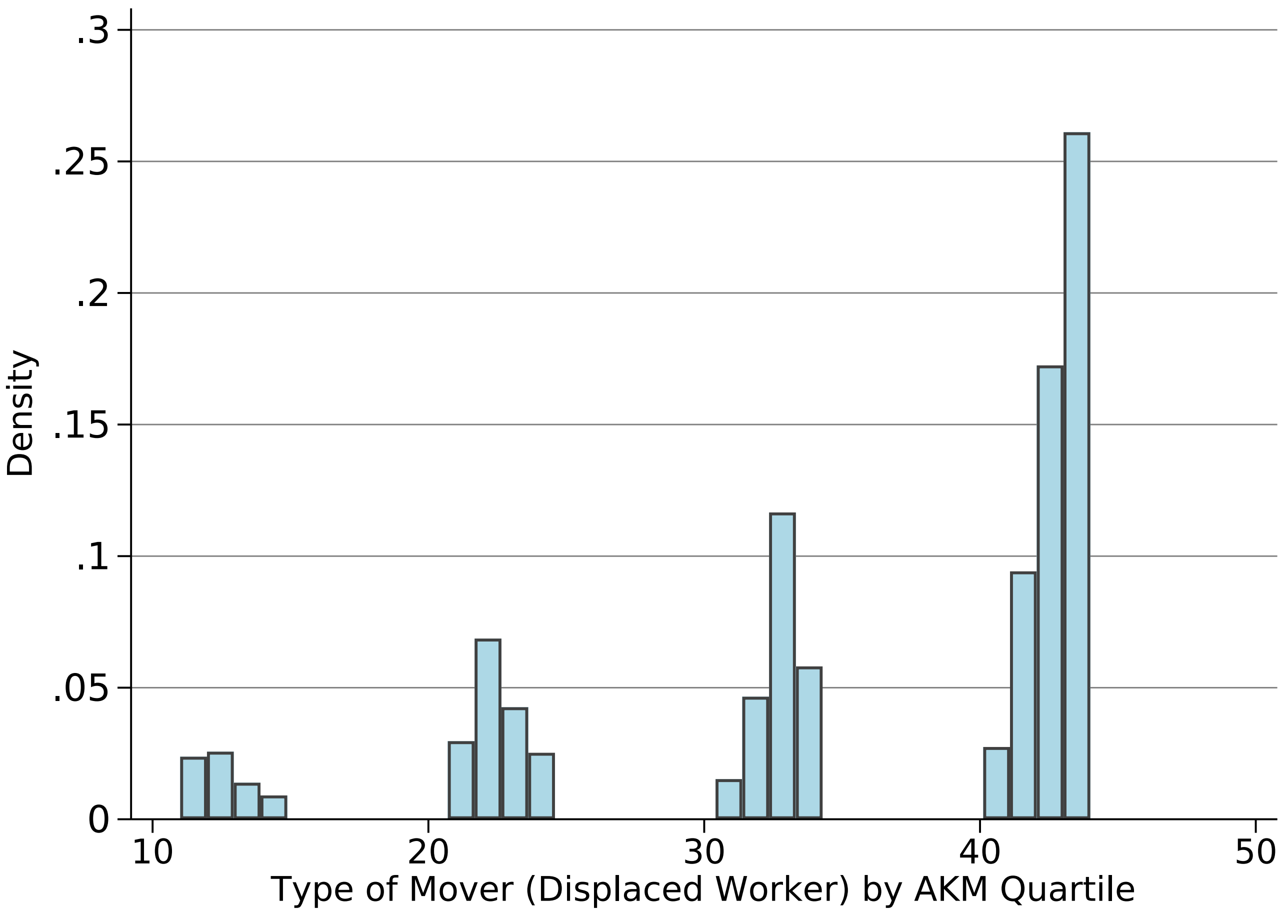
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure B.1: Effects of Displacement on Probability of Employment



Note: This plots the point estimates for equation 4. The results are interpreted as the causal effect of displacement on probability of being employed in the kth quarter after separation.

Figure B.2: Histogram of Displaced Workers by AKM Quartile (Origin/Destination Firm)



Note: Histogram plots the share of displaced workers who belong to one of sixteen potential bins that represent their movement between AKM quartile firms. The possible values – 11-14, 21-24, 31-34, 41-44 – refer to the firm quartile of a worker's origin and destination firm during displacement. For example, the bar over the number 42 represents the share of all displaced workers who separated from a Q4 firm and were next re-employed at a Q2 firm (about 9% of the sample). Histogram only considers movement between a displaced workers layoff firm and next firm at which she works, even if she changes employers many times.

B.2 Alternative Displaced Worker Sample Construction

We test the sensitivity of our long-run earnings loss estimates and whether they are explained by lost firm-specific pay premiums to alternative constructions of the displaced sample.

B.2.1 Post-displacement attachment

Our main results follow past literature by restricting the displaced sample to workers with positive earnings in each post-layoff calendar year. Because our administrative data report earnings at a quarterly frequency, this approach effectively conditions on 25% or greater post-displacement attachment. For robustness, we impose more stringent post-layoff attachment requirements on the displaced sample and compare baselines estimates of overall earnings loss estimates (25% attachment) from equation (2) to samples with positive earnings in 50%, 75%, and 90% of post-displacement quarters (Figure B.3). Earnings losses become smaller with higher post-displacement attachment requirements, consistent with the idea that more highly-attached workers are less likely to suffer subsequent unemployment spells which may dampen earnings (Carrington and Fallick, 2017).

We then test whether more stringent attachment requirements also decrease earnings losses attributable to forgone firm pay premiums. Table B.3 presents the estimated coefficients on displacement dummies for equations (2) and (3) for displaced samples with 50% and 75% post-layoff attachment. Figure B.4 plots the coefficients for equation (3) in the top panel and the share of total losses explained by firm premiums in the bottom panel. Despite considerably different attachment requirements, we consistently find that forfeited firm premiums explain roughly one-quarter of total long-run earnings losses.

B.2.2 Pre-displacement tenure

As discussed in section 4, while our main results use a displaced sample with at least three years tenure at the layoff firm, many studies impose a tenure requirement of six years. Figure 4 in the body of the paper shows longer tenure requirements increase the magnitude of both overall losses and losses due to firm premiums. The share of total earnings losses explained by firm premiums, however, is very similar to our baseline estimates (24% after four years). Point estimates and standard errors for Figure 4 are reported in Table B.4.

B.2.3 Displacement industry

Eight percent of displaced workers in the Ohio sample separate from firms in finance, insurance, and real estate (FIRE), industries which have a relatively high probability of displacement despite their relatively small size (Podgursky, 1992; Farber et al., 1993). We apply the JLS-AKM framework to the non-FIRE group of displaced and comparison workers, illustrated in Table B.5 and Figure B.5a.

Similarly, we isolate displaced manufacturing employees (30 percent of the displaced sample) and estimate their earnings losses. These results are presented in Table B.6 and Figure B.5b.

B.2.4 Displacement from top AKM quartile firms

Lastly, we study displaced workers who separate from a "top-quartile firm," meaning an employer in the top 25% of all firms according to their estimated firm pay premium $\hat{\theta}_j$. This group of individuals, roughly half of the total displaced sample, potentially had "the most to lose" from a layoff. Predictably, these workers exhibit large, sustained long-run losses in the long-run (34 log points), more than half of which can be explained by forfeited firm pay premiums. Point estimates and standard errors are provided for this group in the first two columns of Table B.7 and are graphed in Figure B.6a.

Roughly one-quarter of the displaced sample separates from a top-quartile firm but finds re-employment at a separate top-quartile firm (Figure B.2). Thus, we apply the JLS-AKM framework to this smaller subset. Results are listed in the third and fourth columns of Table B.7 and are graphed in Figure B.6b. Unsurprisingly, this group's long-run earnings losses are smaller than the overall sample (just 17 log points). 14% of these losses are explained by lower firm premiums at post-layoff employers, suggesting even the luckiest displaced workers still systematically move to lower-$\hat{\theta}_j$ firms.

Table B.3: Estimated Effects of Displacement on Earnings and AKM Fixed Effects by Post-Layoff Attachment

	50% post-layoff attachment		75% post-layoff attachment	
	Log earnings	θ log earnings	Log earnings	θ log earnings
Quarter since displacement				
0	-0.128***	-0.00108*	-0.108***	-0.00016
	(0.0047)	(0.0005)	(0.0050)	(0.0005)
1	-0.297***	-0.0503***	-0.283***	-0.0489***
	(0.0059)	(0.0020)	(0.0063)	(0.0022)
2	-0.224***	-0.0444***	-0.207***	-0.0417***
	(0.0049)	(0.0019)	(0.0052)	(0.0021)
3	-0.242***	-0.0489***	-0.218***	-0.0458***
	(0.0050)	(0.0019)	(0.0052)	(0.0020)
4	-0.188***	-0.0466***	-0.165***	-0.0431***
	(0.0046)	(0.0019)	(0.0047)	(0.0021)
5	-0.177***	-0.0426***	-0.152***	-0.0389***
	(0.0042)	(0.0019)	(0.0044)	(0.0021)
6	-0.185***	-0.0389***	-0.161***	-0.0345***
	(0.0043)	(0.0019)	(0.0045)	(0.0021)
7	-0.161***	-0.0402***	-0.135***	-0.0357***
	(0.0042)	(0.0019)	(0.0044)	(0.0021)
8	-0.155***	-0.0391***	-0.129***	-0.0342***
	(0.0042)	(0.0020)	(0.0044)	(0.0021)
9	-0.173***	-0.0380***	-0.142***	-0.0324***
	(0.0044)	(0.0020)	(0.0045)	(0.0021)
10	-0.172***	-0.0380***	-0.140***	-0.0322***
	(0.0042)	(0.0020)	(0.0044)	(0.0021)
11	-0.147***	-0.0372***	-0.113***	-0.0317***
	(0.0042)	(0.0020)	(0.0043)	(0.0021)
12	-0.145***	-0.0355***	-0.116***	-0.0307***
	(0.0042)	(0.0020)	(0.0043)	(0.0022)
13	-0.164***	-0.0349***	-0.126***	-0.0297***
	(0.0045)	(0.0020)	(0.0046)	(0.0022)
14	-0.169***	-0.0356***	-0.124***	-0.0298***
	(0.0045)	(0.0021)	(0.0044)	(0.0022)
15	-0.157***	-0.0352***	-0.107***	-0.0287***
	(0.0045)	(0.0021)	(0.0045)	(0.0022)
16	-0.142***	-0.0330***	-0.0944***	-0.0267***
	(0.0044)	(0.0021)	(0.0044)	(0.0022)
Observations	30,411,853	30,371,030	30,293,947	30,253,909

Standard errors in parentheses

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

Table B.4: Effects of Displacement on Earnings and AKM Firm FE: Displaced Workers with 6+ Years Tenure

	(1) Log earnings	(2) θ log earnings
Quarter since displacement		
0	-0.280***	0.000776***
	(0.0107)	(0.0002)
1	-0.452***	-0.0825***
	(0.0133)	(0.0042)
2	-0.340***	-0.0655***
	(0.0102)	(0.0037)
3	-0.440***	-0.0721***
	(0.0122)	(0.0036)
4	-0.346***	-0.0694***
	(0.0099)	(0.0037)
5	-0.373***	-0.0737***
	(0.0094)	(0.0038)
6	-0.378***	-0.0645***
	(0.0096)	(0.0039)
7	-0.418***	-0.0731***
	(0.0116)	(0.0039)
8	-0.378***	-0.0756***
	(0.0098)	(0.0040)
9	-0.367***	-0.0749***
	(0.0096)	(0.0040)
10	-0.367***	-0.0752***
	(0.0093)	(0.0039)
11	-0.399***	-0.0761***
	(0.0113)	(0.0040)
12	-0.362***	-0.0750***
	(0.0094)	(0.0041)
13	-0.383***	-0.0780***
	(0.0100)	(0.0043)
14	-0.373***	-0.0791***
	(0.0100)	(0.0043)
15	-0.442***	-0.0803***
	(0.0127)	(0.0043)
16	-0.368***	-0.0803***
	(0.0099)	(0.0042)
Pre-Displacement Earnings	Yes	Yes
Observations	29,818,250	29,780,376

Standard errors in parentheses

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

Table B.5: Estimated Displacement Effects on Earnings and AKM Fixed Effects, Excluding Workers from NAICS 51-56

	(1) Log earnings	(2) θ log earnings	(3) Log earnings	(4) θ log earnings
Quarter since displacement				
0	-0.228***	0.000991*	-0.236***	-0.0000339
	(0.0051)	(0.0005)	(0.0051)	(0.0005)
1	-0.395***	-0.0689***	-0.405***	-0.0701***
	(0.0066)	(0.0022)	(0.0066)	(0.0022)
2	-0.279***	-0.0610***	-0.289***	-0.0623***
	(0.0055)	(0.0021)	(0.0055)	(0.0021)
3	-0.319***	-0.0629***	-0.330***	-0.0643***
	(0.0058)	(0.0020)	(0.0058)	(0.0020)
4	-0.271***	-0.0618***	-0.283***	-0.0632***
	(0.0050)	(0.0020)	(0.0050)	(0.0020)
5	-0.281***	-0.0612***	-0.294***	-0.0628***
	(0.0050)	(0.0020)	(0.0050)	(0.0020)
6	-0.278***	-0.0590***	-0.292***	-0.0607***
	(0.0051)	(0.0021)	(0.0050)	(0.0021)
7	-0.265***	-0.0614***	-0.279***	-0.0632***
	(0.0052)	(0.0021)	(0.0052)	(0.0021)
8	-0.267***	-0.0614***	-0.281***	-0.0632***
	(0.0050)	(0.0021)	(0.0050)	(0.0021)
9	-0.280***	-0.0603***	-0.296***	-0.0623***
	(0.0051)	(0.0021)	(0.0050)	(0.0021)
10	-0.265***	-0.0607***	-0.280***	-0.0627***
	(0.0050)	(0.0021)	(0.0050)	(0.0021)
11	-0.255***	-0.0603***	-0.271***	-0.0623***
	(0.0053)	(0.0022)	(0.0053)	(0.0021)
12	-0.246***	-0.0584***	-0.262***	-0.0606***
	(0.0050)	(0.0022)	(0.0050)	(0.0022)
13	-0.265***	-0.0597***	-0.281***	-0.0620***
	(0.0052)	(0.0022)	(0.0052)	(0.0022)
14	-0.260***	-0.0598***	-0.276***	-0.0621***
	(0.0052)	(0.0023)	(0.0052)	(0.0023)
15	-0.256***	-0.0585***	-0.273***	-0.0609***
	(0.0056)	(0.0023)	(0.0056)	(0.0022)
16	-0.231***	-0.0578***	-0.248***	-0.0602***
	(0.0051)	(0.0023)	(0.0050)	(0.0023)
Pre-Displacement Earnings	No	No	Yes	Yes
Observations	23,895,853	23,864,070	23,895,853	23,864,070

Standard errors in parentheses

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

Table B.6: Estimated Displacement Effects on Earnings and AKM FE, Manufacturing Only

	(1) Log earnings	(2) θ log earnings
Quarter since displacement		
0	-0.270***	0.00821***
	(0.0092)	(0.0006)
1	-0.546***	-0.186***
	(0.0113)	(0.0034)
2	-0.390***	-0.178***
	(0.0100)	(0.0032)
3	-0.444***	-0.171***
	(0.0107)	(0.0031)
4	-0.395***	-0.175***
	(0.0087)	(0.0032)
5	-0.387***	-0.179***
	(0.0082)	(0.0032)
6	-0.396***	-0.167***
	(0.0084)	(0.0034)
7	-0.432***	-0.184***
	(0.0097)	(0.0033)
8	-0.423***	-0.186***
	(0.0084)	(0.0033)
9	-0.393***	-0.179***
	(0.0082)	(0.0033)
10	-0.367***	-0.179***
	(0.0080)	(0.0034)
11	-0.388***	-0.180***
	(0.0093)	(0.0034)
12	-0.356***	-0.180***
	(0.0079)	(0.0034)
13	-0.347***	-0.185***
	(0.0080)	(0.0034)
14	-0.349***	-0.184***
	(0.0081)	(0.0034)
15	-0.385***	-0.181***
	(0.0097)	(0.0034)
16	-0.302***	-0.179***
	(0.0076)	(0.0034)
Pre-Displacement Earnings	Yes	Yes
Observations	8,052,225	8,040,055

Standard errors in parentheses

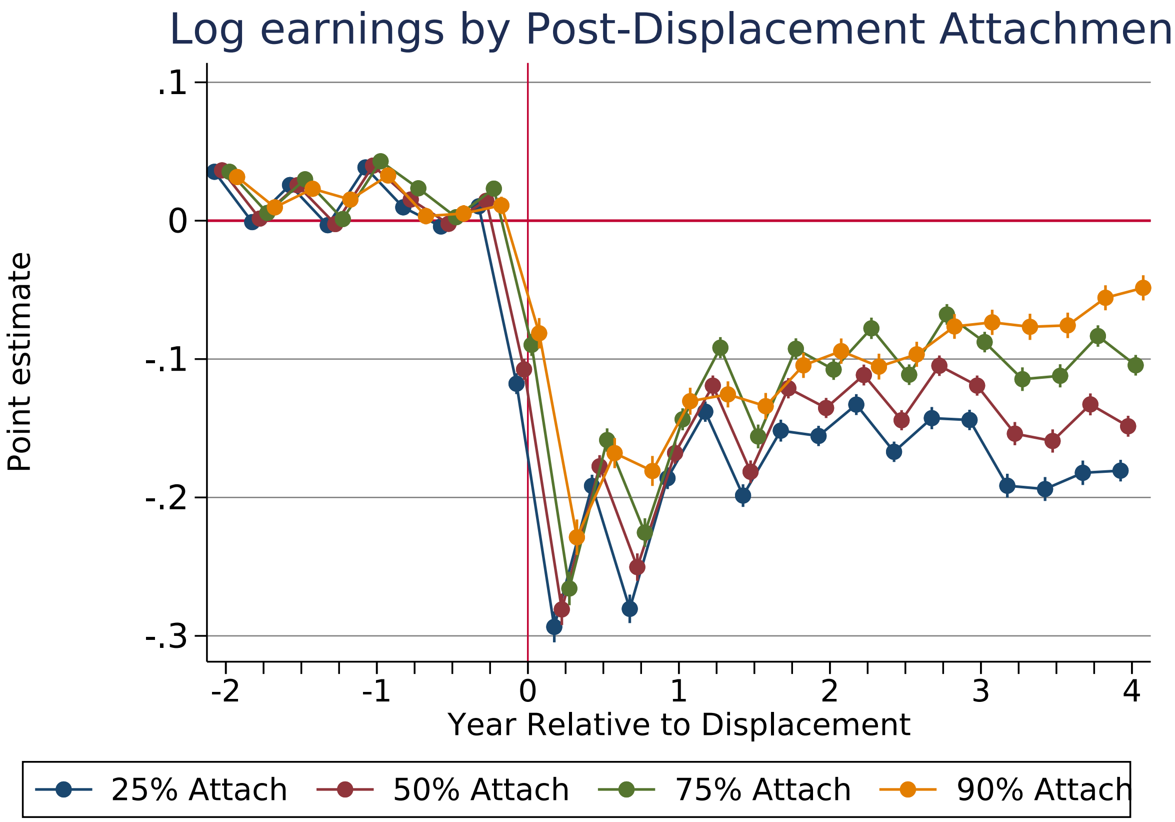
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.7: Effects of Displacement on Earnings and AKM Firm FE for Workers at Top-Quartile Firms

	Any Q4 Displace		Q4 Displace & re-employed	
	Log earn	$\hat{\theta}$ log earn	Log earn	$\hat{\theta}$ log earn
Quarter since displacement				
0	-0.169***	0.00758***	-0.181***	-0.00103***
	(0.007)	(0.001)	(0.007)	(0.000)
1	-0.409***	-0.151***	-0.214***	-0.0227***
	(0.008)	(0.002)	(0.007)	(0.001)
2	-0.342***	-0.145***	-0.210***	-0.0240***
	(0.007)	(0.002)	(0.006)	(0.001)
3	-0.413***	-0.153***	-0.263***	-0.0247***
	(0.008)	(0.002)	(0.008)	(0.001)
4	-0.288***	-0.150***	-0.147***	-0.0237***
	(0.006)	(0.002)	(0.006)	(0.001)
5	-0.307***	-0.152***	-0.171***	-0.0238***
	(0.006)	(0.002)	(0.005)	(0.001)
6	-0.364***	-0.160***	-0.212***	-0.0258***
	(0.006)	(0.002)	(0.005)	(0.001)
7	-0.341***	-0.158***	-0.207***	-0.0261***
	(0.006)	(0.002)	(0.006)	(0.001)
8	-0.322***	-0.161***	-0.151***	-0.0262***
	(0.006)	(0.002)	(0.005)	(0.001)
9	-0.340***	-0.162***	-0.181***	-0.0251***
	(0.006)	(0.002)	(0.006)	(0.001)
10	-0.350***	-0.164***	-0.202***	-0.0249***
	(0.006)	(0.002)	(0.005)	(0.001)
11	-0.350***	-0.165***	-0.206***	-0.0236***
	(0.007)	(0.002)	(0.007)	(0.001)
12	-0.327***	-0.166***	-0.173***	-0.0229***
	(0.006)	(0.002)	(0.006)	(0.001)
13	-0.338***	-0.171***	-0.185***	-0.0218***
	(0.006)	(0.002)	(0.006)	(0.001)
14	-0.346***	-0.176***	-0.189***	-0.0222***
	(0.006)	(0.003)	(0.006)	(0.001)
15	-0.366***	-0.175***	-0.166***	-0.0218***
	(0.007)	(0.002)	(0.005)	(0.001)
16	-0.312***	-0.174***	-0.146***	-0.0206***
	(0.006)	(0.003)	(0.006)	(0.001)
Observations	15,924,435	15,921,496	15,873,865	15,873,865

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; First two columns show results from equations 2 and 3 for any displaced worker who was laid off from top-quartile θ_j firm. The third and fourth columns use as a displaced sample workers laid off from a top-quartile θ_j firm who found re-employment at a new top-quartile firm.

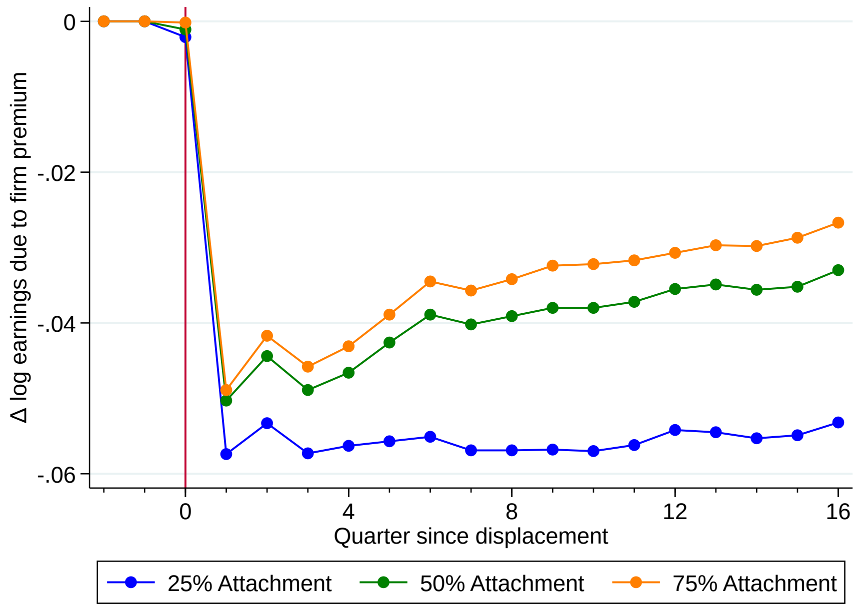
Figure B.3: Sensitivity of Earnings Losses to Different Labor Market Attachment Restrictions



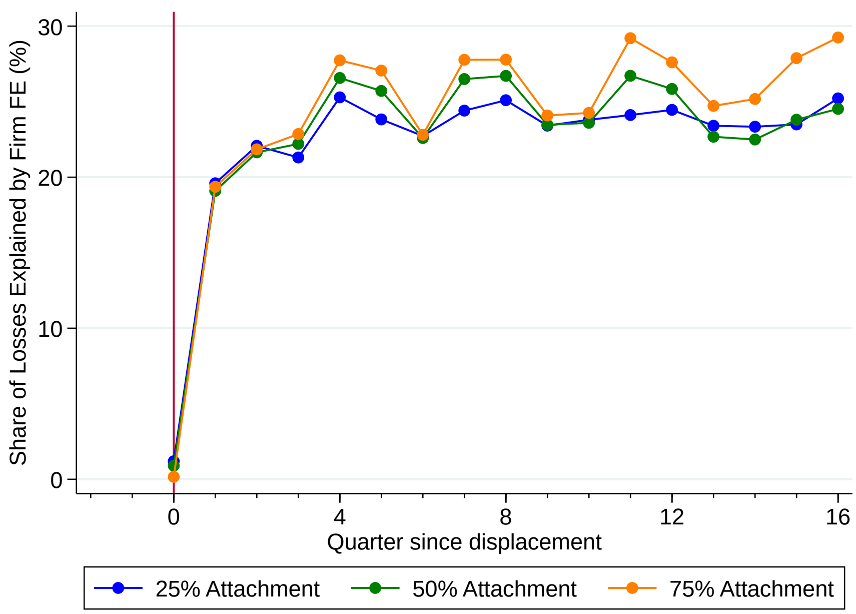
Note: The graph plots estimated $\hat{\delta}_k$ coefficients from equation 2. Whiskers (very small) represent 95% confidence intervals based on standard errors clustered by worker. Vertical line denotes quarter of displacement.

Figure B.4: Estimated Losses due to Foregone Firm Fixed Effect by Attachment

(a) Change in Firm FE $\hat{\theta}_j$ due to Displacement



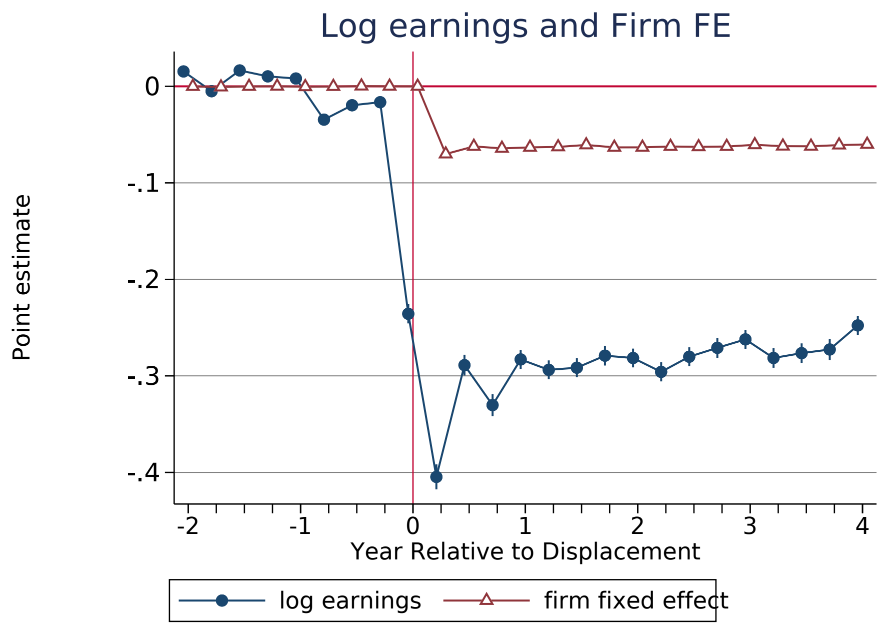
(b) Share of Earnings Losses Explained



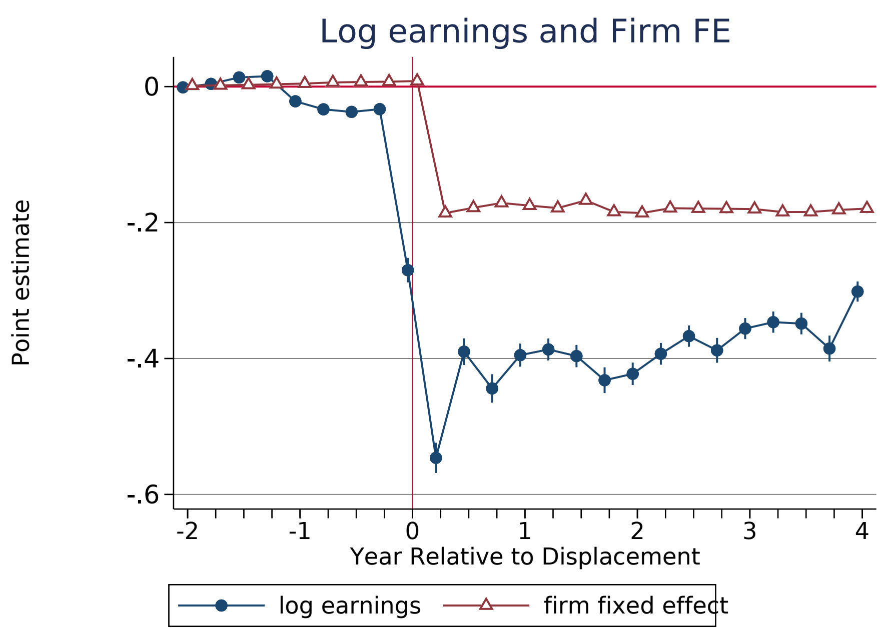
Note: The top panel plots $\hat{\omega}_k$ coefficients from equation 3. The bottom panel converts $\hat{\omega}_k$ and $\hat{\delta}_k$ to percentages and takes the quotient, representing the share of earnings losses attributable to loss of a firm-specific pay premium. 95% confidence intervals for the top panel are not included in the figures but are small. All point estimates for $k > 0$ are highly significant.

Figure B.5: Estimated Losses due to Foregone Firm Fixed Effect; Subsets of Displaced Workers

(a) All Displaced Workers Excluding NAICS 51-56



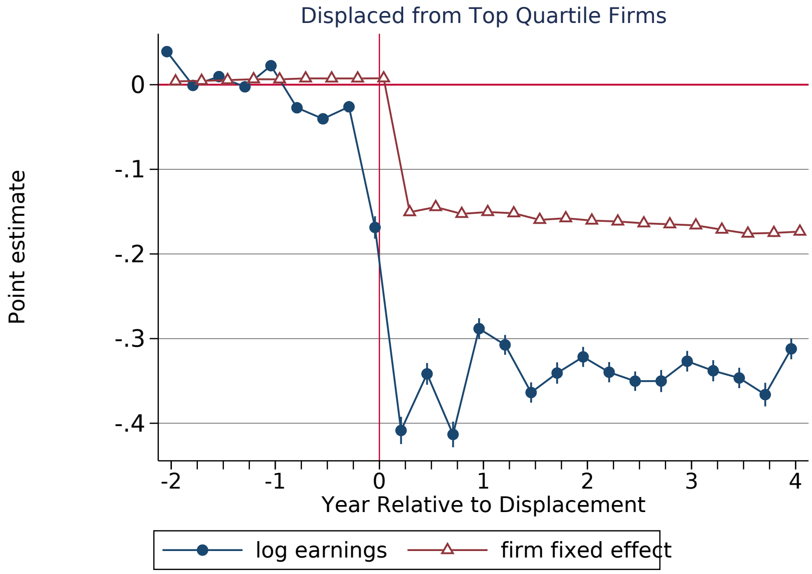
(b) Manufacturing



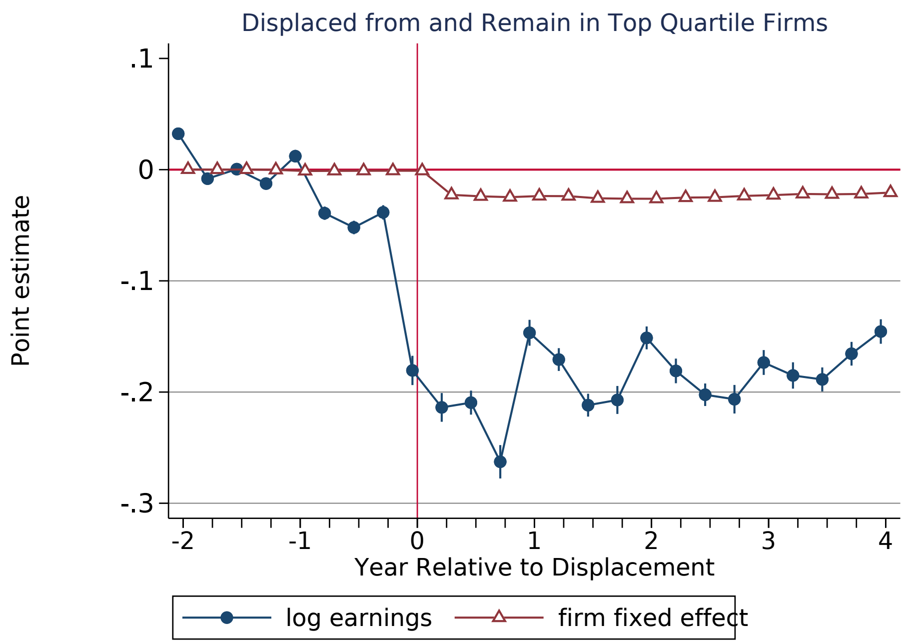
Note: These figures plot the δ_k and ω_k coefficients from equations 2 (blue) and 3 (red) for two different displaced subsamples. The top panel shows estimates for losses of workers displaced from industries besides NAICS 51-56 (finance, real estate, insurance) relative to a comparison group that omits NAICS 51-56. The bottom panel presents the same estimates for workers displaced from manufacturing relative to workers who remain employed in manufacturing. Whiskers (very small) denote 95-percent confidence intervals based on standard errors clustered by worker. Vertical line denotes quarter of displacement. Figures correspond to estimates in Appendix Table B.5.

Figure B.6: Losses due to Foregone Employer Fixed Effects: Displaced from Top Quartile

(a) Any Displaced from Top-Quartile θ_j



(b) Displaced from Top-Quartile θ_j, Re-employed in Top Quartile



Note: These figures plot the δ_k and ω_k coefficients from equations 2 (blue) and 3 (red) for workers who are displaced from firms in the top-quartile of estimated firm fixed effects (θ_j). The top panel shows estimates for any displaced worker separating from a top-quartile firm, regardless where she is re-employed. The bottom panel presents the same estimates for workers displaced from top-quartile firms who find re-employment another top-quartile firm and remain employed in a top firm for the remainder of the panel. Whiskers (very small) denote 95-percent confidence intervals based on standard errors clustered by worker. Vertical line denotes quarter of displacement.

B.3 Wage Loss Estimates

Our paper investigates the role of firm-specific wage premiums in explaining displaced worker earnings losses. However, lack of information on hours worked in Ohio's UI data prevents us from (i) decomposing overall earnings losses into wage and hours components and (ii) estimating the contribution of firm pay premiums to reduced wages for displaced workers – both of which are addressed by Lachowska et al. (2018) and the latter by Schmieder et al. (2018) and Fackler et al. (2017). Instead, we use the hours-wage decomposition from Lachowska et al. (2018) – five years after displacement, 70% of lost earnings for Washington workers displaced during the Great Recession were due to lower wages (the remaining 30% due to reduced work hours) – as a benchmark to estimate corresponding hourly wage results for displaced workers in Ohio.

In Table B.8, we consider several plausible hour-wage decompositions of overall earnings losses to inform estimates of (i) long-run total hourly wage losses for Ohio displaced workers and (ii) the proportion attributable to firm pay premiums for plausible hour-wage decompositions of overall earnings losses. We posit that long-run wage losses are between 13-18% for the Ohio sample, considerably larger than the 4.9% [1.3%] long-run hourly wage losses documented by Lachowska et al. (2018) for long [short] tenured workers.

Lachowska et al. (2018) accurately captures this quantity by running AKM on the log of hourly wages (rather than total earnings) and using those resulting pay premiums in the JLS-AKM framework. Due to our data limitations, we instead assume the variance in firm fixed effects $\hat{\theta}_j$ reflects only employer-specific differences in hourly pay (and not hours worked). This (strong) assumption allows us to obtain the share of long run *wage* losses explained by forfeited firm-specific pay premiums from the quotient of the share of *earnings* losses explained by firm premiums and the share of losses due to lower wages (last column of Table B.8). We estimate firm-pay premiums explain between 29% and 38% of displaced workers' wage losses after four years.

Lachowska et al. (2018) conclude firm premiums only account for 17% of long-run wage scarring in their sample. Interestingly, the authors estimate that while displaced workers clock roughly 5% fewer hours compared to their pre-displacement schedules, they find re-employment at firms with policies compelling employees to work *more* hours relative to their layoff employer (see Table A.1 of Lachowska et al. (2018)). However, the assumption in Table B.8 is that there are no work-hour policy differences between employers. In other words, firm fixed effects from an AKM regression on the log of hours (which cannot be run with our limited Ohio data) would explain none of the difference in hours worked between employees. Thus, if the results of Lachowska et al. (2018) for hours worked holds in Ohio, the reported estimates in column 5 of Table B.8 are understated.

Table B.8: Estimated Wage Losses due to Forgone Pay Premiums for Ohio with Various Hours-Wage Loss Decompositions

Long-Run Estimates from Ohio data		Assumed % earnings loss due to lower wage	Overall Wage Loss	Share of Total Wage Loss due to Firm Premiums
Overall Earnings Loss	Earnings Losses due to Firm Premium $\hat{\theta}_j$			
		60%	13%	38%
22%	23%	70%	15%	33%
		80%	18%	29%

Note: The first two columns report our main estimates of long run earnings loss and share of losses due to firm premiums for the Ohio displaced worker sample from Table 2. We list plausible shares of long-run earnings losses due to diminished wages (with the remainder attributable to reduced hours) in the third column. In Washington, for example, Lachowska et al. (2018) find 70% of overall losses are due to lower hourly wages. Column 4 estimates long-run *wage* losses for displaced workers in Ohio for a given hour-wage decomposition as a product of overall earnings losses and the share of total losses due to lower wages. Column 5 lists the share of total estimated long-run wage losses that are attributable to forfeited firm premiums.