Displaced Workers during the Great Recession:
Understanding the Role of Local Labor Markets and Outside Options[1]

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November 2025

Abstract. This paper examines how features of local labor markets and outside options affect the employment and earnings experiences of workers displaced due to a mass layoff during the Great Recession. Motivated by a concentration of job losses, particularly within manufacturing, we study five Midwestern states using linked employer-employee panel data. We focus on two standard measures of labor markets, unemployment rates and housing costs, and construct a new measure of job opportunities called the Job Opportunities Index (JOI), which allows us to combine the number of opportunities in a labor market with expected earnings. We use job to job flows across MSAs to create weighted measures of outside opportunities for each worker. To examine how labor markets shape earnings trajectories after mass layoff, we estimate an earnings model following workers for five years post-displacement. We find that manufacturing workers were most severely affected by displacement, with earnings losses of almost 20 percent five years post mass layoff. We also find that workers in the top decile of labor markets, in terms of job opportunities, experienced half the level of earnings losses of those in the bottom decile. As a complementary analysis, we also study the role of local labor market characteristics in the transition back to employment by estimating a competing risk hazard model, finding that labor market characteristics in both one's origin and outside option MSA shape non-employment duration and location outcomes.

Keywords: Displaced workers; Great Recession; Manufacturing; Local labor markets

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1. Introduction

The wide-spread and devastating long-term impacts of the Great Recession on American workers have been well documented (e.g. Finkelstein, Notowidigdo, Schilbach and Zhang, 2024; Rinz, 2022; Rothstein, 2023; Yagan, 2019), with strong evidence showing the particularly detrimental impacts of this economic crisis on individuals residing in the Midwest as well as those working in manufacturing (Charles, Hurst and Schwartz, 2019). This study contributes to our existing knowledge of the mechanisms driving these impacts by focusing on features of local labor markets and outside options, specifically looking at unemployment rates, housing costs, and a new measure of job opportunities. Our primary research question is: how do the features of both local labor markets and outside options affect the employment experiences of workers displaced by a mass layoff? We measure these experiences both in terms of the earnings post-mass layoff and the joint choice of location and duration to re-employment.

To address this research question, we have created a location-specific worker-level longitudinal data set that combines near-universal quarterly matched employee-employer microdata from the Longitudinal Employer-Household Dynamics (LEHD) dataset with measures of local labor market conditions. Our integrated data allow us to observe displaced workers' MSA, industry, employment history, and demographic information. The longitudinal dimension of the data allows us to capture the labor market experiences of displaced workers including the mass layoffs that began their initial jobless spell, their subsequent labor market earnings, and their geographic mobility for up to five years after job loss.

We use the LEHD to develop and estimate an earnings model for displaced workers, contributing to existing knowledge in several dimensions. Critically given our research question, we allow earnings paths to differ by initial labor market conditions as well as industry. We build on existing approaches to construct a comparison group, but instead of pooling the full sample of non-displaced workers in the same MSA, as is standard in the literature (see for example Lachowska, Mas and Woodbury, 2020 and Schmieder, von Wachter, and Heining, 2023), we separate the sample into two comparison groups, the first includes workers who were in the same establishment and not released during the mass layoff, and the second includes workers at other non-mass layoff establishments but still in the same labor market. The former are generally included in comparisons since the workers in both sets select into the same mass layoff establishment. However, as we show in our subsequent analyses, this sample is also substantially impacted by the mass-layoff event. We thus focus primarily on the set of workers in the same MSA who were employed in a non-mass layoff establishment as our primary comparison group.

To date, research on the role of conditions in the local market and in outside options on the economic recovery of displaced workers has been relatively limited. Our work draws from a new literature examining how outside options shape labor market prospects for workers. Caldwell and Danieli (2024) use the dispersion of a varied set of workers across jobs as a proxy for outside options. Using German administrative data, they find that higher outside options are associated with higher wages. Olivares (2023) uses growth in hiring in other MSAs and historic job-to-job flow rates as measures of outside options and he finds that higher nonlocal labor demand causes increased wage growth for job stayers. We develop a job opportunity index, similar to the approach of Olivares (2023), and examine the impacts of these local and nearby opportunities on the recovery paths of displaced workers.

In related work, Moretti and Yi (2024) use the LEHD to examine labor market size (in terms of industry employment) and re-employment patterns for displaced workers, finding that workers in larger industries within a commuting zone (CZ) experience shorter non-employment spells and smaller earnings losses post mass-layoff. They only include displaced workers in their sample, and their identification is based on a comparison of displaced workers in large and small markets in the same CZ. They provide evidence that there is no unobserved heterogeneity bias due to the sorting of more productive workers into larger sized markets or because large markets tend to have stronger local labor market conditions such that it is easier for displaced workers to find a new job. Note that there is no control group since the sample only includes displaced workers due to firm closure. The treatment here is market size which is continuous and hence the treatment effect is based on differences in treatment intensity.

Our work is complementary to Moretti and Yi (2024) as we focus on the on the role of conditions in the local market and in outside options on the economic recovery of displaced workers. We follow the standard approach in the literate on the earnings paths of displaced workers by estimating an earnings model with dynamic treatment effects (the treatment being the displacement due to mass layoff) and worker fixed effects so identification is based on within worker changes in earnings. Furthermore, the comparison groups are workers in the same mass layoff establishment who were not displaced and workers in non-mass layoff establishments in the same labor market (MSA in our case). Note, we also use a propensity score matching estimator, presented in Appendix C, and show that it makes no difference in the earnings path of displaced workers.

While most of the literature on mass-layoffs focuses on earnings history after displacement, we add to the literature and follow Fallick et al. (2025) by also examining duration until first employment after displacement. We choose to directly estimate duration to re-employment given the critical role of the length of unemployment spells in shaping the workers' earnings trajectory that Fallick et al. (2025) document and our interest in understanding how local and outside options shape re-employment experiences. Our estimates show that both local and outside labor market characteristics shape the timing and location of re-employment.

Our data include 162,000 displaced workers (for whom we have complete earnings data for 143,000 of these workers), 227,000 non-separated workers at mass layoff establishments, and 238,000 workers at non-mass layoff establishments in the same MSA. We find that just over one-half of these displaced workers found stable jobs by the end of the following quarter, but 18 percent took at least two years to become re-employed in a stable job, and 9 percent had not found stable employment after five years. Strikingly, 24 percent of these workers moved to a different MSA to obtain their next stable job.

Overall, we show that the earnings of displaced workers were 15 percent lower, on average, after five years relative to workers at non-mass layoff establishments, findings largely in line with those of the existing literature (Jacobson, LaLonde, and Sullivan (1993), Couch and Placzek (2010), Davis and von Wachter (2011), Lachowska et al. (2020), and Schmieder et al. (2023)). Additionally, by separating our comparison group into two subgroups, we are able to show that workers outside of these mass layoff establishments did not experience real earnings losses on average, but workers that were not-displaced, however employed in the same mass layoff establishments, did experience long-term earnings losses, approximately half as large as the displaced workers, highlighting the importance of separately examining earnings impacts for these two sets of workers.

Our earnings results further document important heterogeneity in post-mass layoff earnings losses across industries, with manufacturing workers experiencing the largest earnings losses, almost double the losses experienced by the average displaced worker in our sample. Where we do not find significant differences five years post mass layoff, however, is when comparing outcomes for workers that moved versus those who did not move. As one might expect, we see that workers who moved experience the largest initial earnings losses, as workers most negatively impacted have the greatest incentives to move and because moving can increase the time it takes to find new employment, but that after five years these two groups experienced similar earnings losses on average. These results provide some evidence that moving on its own may not enable the average worker to overcome the challenges associated with displacement.

Perhaps most importantly, as described above, we show that when looking at MSAs with the strongest labor markets, the top decile according to JOI, workers displaced in these areas experienced no long-term earnings losses, whereas workers employed in MSAs in the bottom decile of the JOI distribution experienced earnings losses of approximately 10 percent. Results are similar when looking at unemployment rates, but it does appear that these measures are capturing different elements of the labor market, as workers in the top decile according to UNEMP continued to experience earnings losses of approximately 5 percent five years after the mass layoff event. We also provide evidence that workers fared better after displacement in MSAs where outside options had lower unemployment rates. In contrast, we see that house prices in local and outside markets do not seem to shape longer term earnings trajectories.

To more directly estimate the relationship between these local labor market features and the transition back to employment, we develop and estimate a model of non-employment duration with competing risks of exiting to a stable job[2] in the same MSA where the worker lost their job or in an outside MSA.[3] In this model we include three measures of both local and outside market conditions: the unemployment rate (UNEMP), the job opportunity index (JOI), and the housing cost index (HCI). For each displaced worker, we specify potential MSA destinations based on the five most likely MSAs

[2] We define a stable job as one where the worker is employed at least four quarters of positive earnings.
[3] We define labor markets to be MSAs and use these terms interchangeably.

in terms of flows of workers between the MSAs.[4] A worker is seen as choosing between their origin MSA and the weighted average of these top five MSAs (the outside option MSA). This model allows us to directly compare the impacts of both local and outside option MSA characteristics on the likelihood that a worker becomes re-employed.

We use several alternative specifications, including ones that control for unobserved heterogeneity using a two-point distribution recommended by Heckman and Singer (1982) and a Gamma distribution, to improve identification. Examining the results, we find that displaced worker re-employment patterns were shaped by labor market characteristics in both their origin MSA and in the outside option MSA. Specifically, we find that UNEMP, JOI, and HCI affected non-employment duration and location outcomes, though not all as hypothesized. A higher unemployment rate is associated with a longer non-employment spell in both local and outside option MSAs. In contrast, results for JOI and HCI conform with expectations. An increase in the JOI in the worker's origin MSA increased the likelihood of finding re-employment in the same MSA and to a smaller extent, decreased the likelihood of finding a stable job in a competing MSA, and a symmetric (but opposite) impact of an increase in the JOI in the competing MSA on the likelihood of exiting joblessness in the home and competing MSAs. To provide context, given the average duration of unemployment in the US is 24 weeks, with a standard deviation of approximately 13 weeks (BLS, 2024) our estimates show that a one standard deviation increase in the job opportunities of a labor market is associated with a reduction in non-employed of 0.1 standard deviations or about 1.3 weeks.

The impacts of HCI are opposite in sign to the JOI impacts since this is an increase in costs (housing) versus benefits (job opportunities). Importantly, we show that even after controlling for labor market strength through the JOI, house prices in nearby MSAs create strong barriers to finding employment in outside MSAs, with coefficients slightly larger than those for the JOI index. These results provide novel evidence that both local and outside option opportunities can have a significant impact on the time it takes for displaced workers to re-enter the labor market.

The paper proceeds as follows. Section 2 provides details of the framework and literature that are relevant to our study. Section 3 describes our data. Section 4 lays out our empirical approach and

[4] See Section 3.1 for a more detailed discussion of defining competing MSAs. These are the five most likely destination MSAs for workers departing each sample MSA as measured by the Job-to-Job aggregate LEHD data.

Section 5 describes our estimation results. Section 6 concludes with a discussion about policy implications.

2. Conceptual Framework/Literature

This work contributes to the long history in urban economics of examining whether Marshallian externalities shape a worker's job search (Marshall, 1890). Marshallian externalities are generally described as the benefits afforded by dense concentrations of firms or the thickness of a local labor market (Neffke et al, 2018). We extend our measures to the role of outside options in addition to local features. We also focus on a particularly difficult economic moment for a hard hit region in the United States, thus bringing together many strands of inquiry.

Broadly, our work connects three distinct and inter-related bodies of knowledge to address the question: how do features of local labor markets and outside options shape the employment and earnings trajectories of displaced workers? The first draws from a broader set of impacts of the Great Recession on workers. The second area examines the employment and earnings impacts of job displacement on individual workers. And the third operationalizes Marshallian externalities in several ways, examining a variety of characteristics of local labor markets and outside options on employment and earnings.

There is a large body of work documenting how damaging the Great Recession was for workers over the long term. Foote et al. (2019) examine how aggregate local labor markets respond to mass layoffs in the long run, highlighting one reason why longer term outcomes during the Great Recession were so large and persistent. Isolating four channels through which the local labor force may adjust: in-migration, out-migration, retirement, and disability insurance enrollment, they show that out-migration accounts for more than half of the labor force reduction in the past two decades, but that during and after the Great Recession, instead of out-migration, non-participation accounts for more of the exits following a mass layoff. There has also been work examining the long-term impacts of the Great Recession on individual employment. Song and von Wachter (2014) and Yagan (2019) examine whether employment shocks lead to lasting declines in employment. Both find evidence of a persistent decline in employment as a result of the Great Recession. Yagan shows that the Great Recession imposed longer-term employment and income losses even after falling unemployment rates signaled recovery, and that it contributed to a long-run decline in labor force participation with larger impacts among lower-income workers. Relatedly, Abowd, McKinney and Zhao (2018) use the LEHD to examine longer term individual employment impacts of the Great Recession, focusing on the role of the employer in explaining earnings differences. They find that while differences between working at a bottom- or middle-paying firm are small, gains from working at a top-paying firm are relatively large. Our work contributes to this literature on the cyclical dimension of the costs of layoffs, by examining the potential mediating role of local labor market conditions on the ability of workers displaced during the Great Recession to re-enter the labor market and on their subsequent wages.

A substantial literature addresses the permanent earnings losses suffered by involuntarily displaced workers (Fallick, 1996; Kletzer, 1998; Farber, 2017). The most relevant work by Jacobson, LaLonde, and Sullivan (1993), Couch and Placzek (2010), Davis and von Wachter (2011), Lachowska et al. (2020), and Schmieder et al. (2023) estimates long- term earnings losses in the 12 to 25 percent range. Three of these papers focus on earnings impacts during recessions. Davis and von Wachter (2011) rely on an early version of the LEHD to examine national impacts of job displacement during recessions and expansions, finding long term losses are nearly twice as high for displacements during recessions as for displacements during expansions. Similarly, Schmieder et al. (2023) use administrative data to study costs of job displacement in Germany during both recessions and periods of growth, also finding that earnings impacts nearly double during recessions. Lachowska et al. (2020) examine sources of earnings losses for displaced workers using LEHD-type data for Washington state during the Great Recession and show that losses are largely driven by declines in hourly rates. Importantly, none of these papers examine the role of local labor market characteristics or outside options on displaced workers earnings pathways. Though focusing on a shorter time frame, Moretti and Yi (2024) provide one key exception, examining the importance of industry size within a labor market on displaced workers recovery paths, which we describe in more detail below.

Our work contributes to the set of papers examining unemployment durations for mass laid off workers.[5] Covering a related topic, Andersson et al. (2018) use the LEHD and find evidence that

[5] Early work by Gray and Grenier (1998) uses self-reported data from the Canadian and American Displaced Worker Surveys, finding that higher unemployment rates in Canada seem to play an important role in increasing

better job accessibility within the metropolitan area decreases the duration of joblessness among lower-paid displaced workers. Hellerstein et al. (2019) use the LEHD and find that stronger residence-based labor market networks facilitate re-employment by matching displaced workers to vacancies. In an attempt to reconcile these two disparate literatures, Fallick, et al. (2025) show that the length of a jobless spell is a key mediator of longer term earnings losses. Our work builds on the approaches of these studies to examine how local and outside option labor market features shape both the duration of non-employment and the subsequent earnings losses.

Additionally, our work contributes to a growing body of research that examines features of local labor markets and how they shape the recovery patterns of displaced workers. Bleakley and Lin (2012) find that there is less churn in the labor market in more densely populated areas, and that these results hold for displaced workers as well. Neffke et al. (2018) examines the local industry mix and its impact on earnings losses for displaced workers using German administrative data, finding that in metropolitan areas with a larger share of employment in the worker's pre-displacement industry, workers find employment relatively more quickly and suffer small earnings losses. Kosteas (2019) uses the Displaced Workers Survey (DWS) supplement of the Current Population Survey (CPS) to examine the occupational distance of a worker from their local labor market in comparison to the impact of agglomeration (which they measure as population density). He finds evidence that smaller occupational distances are associated with the increased probability of being employed post-displacement, but he finds no impact of density. Most recently Macaluso (2024) constructs a measure of 'skill remoteness,' or how representative a worker's skill set is of their broader labor market. Using the National Longitudinal Survey of Youth 1979 (NLSY79), he finds that workers laid off in skill-remote jobs are less likely to be re-employed in jobs with similar skill sets and experience lower wages upon re-employment.

Most closely related to our work, Moretti and Yi (2024) use the LEHD to examine how the size of one's industry within their CZ affects the duration of unemployment and earnings impacts for displaced workers, as measured by the set of workers at firms that close (similar to the work of Neffke et al., 2018). They find that when comparing industries in the 90th percentile of the size distribution to those in the 10th percentile, high school and college graduates, respectively, enjoy a

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the length of unemployment spells. However, these data are based on retrospective responses. In addition, there is no link to employer data and thus no way of establishing whether a mass layoff occurred.

9.2 and 12.9 percent higher probability of finding a job within 1 year of displacement. Similarly, they find that earnings are 7.0 and 19.0 percent higher 1 year after displacement, when comparing these same sets of workers. Our work provides a nice complement to these papers as we examine the overall strength of a labor market rather than its size or industry composition, specifically examining the role of local job opportunities and housing costs in both the MSA where an individual is displaced as well as a set of outside options.

3. Data, Sample Construction, and Summary Statistics

The primary data employed in this paper are drawn from the Census' confidential Longitudinal Employer-Household Dynamics (LEHD) dataset. The matched employee – employer LEHD follows most U.S. employmees over time. It covers over 150 million private-sector employees, and as of 2011 includes state and local government employees. This data source has been built at the Census Bureau and draws on several administrative sources, surveys, and censuses. The primary source is confidential information from state Unemployment Insurance (UI) earnings data. It begins by 1999 for most states and provides quarterly information on where workers live and work, their earnings/joblessness history, industry, race, gender, county of birth, and imputed education. This data source has been widely used, often to answer related research questions (Abowd et al., 2009; Andersson et al. 2018; Pollakowski et al, 2022; Haltiwanger et al. 2020; Moretti and Yi, 2024).

We construct two samples of displaced workers for our analysis. For both samples, we limit our analysis to "prime age" workers who are between 25 and 55 years of age and who have earned at least $15,000 over the previous year in the same establishment. Since we aim to identify the impacts of the changing structure of the economy on workers, we view these more tenured workers as those most likely experiencing layoffs that are not tied to personal circumstances. The five Great Lakes states we study, Indiana, Wisconsin, Ohio, Pennsylvania (excluding Philadelphia) and New York (excluding New York City) are drawn from the 28 states for which we have full detailed LEHD data.[6] We access detailed earnings records for all the workers in our five states including those who move into one of our participating states. For workers who take a new job in one of the 22 nonparticipating

[6] This project is being carried out at the Boston Census Research Data Center (RDC). For such projects, each individual state must choose whether its data can be used. In our case, 28 states agreed.

states (plus the District of Columbia), we fortunately know whether and when a worker takes a new job in one of these locations (Vilhuber, 2018), although without knowledge of their earnings.

Our first sample includes 143,000 workers displaced from mass layoffs during the Great Recession, which we define as 2007 Q4 through 2009 Q4,[7] for whom we can follow their complete earnings history; that is, those who are re-employed in their own state or move to one of the 28 states in our approved dataset. We use this sample to estimate our earnings models. Our second sample adds the set of displaced workers who move to one of the 22 states that is not included in our approved set of states. This sample includes 162,000 displaced workers. We rely on this second sample for our non-employment duration models. Since we cannot observe the earnings of workers who become re-employed in one of these locations, we define a worker to be re-employed with a stable job when they have achieved four consecutive quarters of employment.

3.1 Local Labor Market Measures

One of our key contributions is a focus on labor market characteristics that theory suggests are important determinants of how displaced workers respond to job loss, specifically unemployment rates, housing costs, and our new measure, a *job opportunity index (JOI)*. This index measures the expected employment benefits to workers residing in the market and is the product of the expected wages once employed and the likelihood of obtaining a job. The JOI is useful in our context as it allows us to create tailored measures of local job opportunities for workers by their skill levels as well as industry. We rely on education supplied by the LEHD, which is imputed by the Census staff and broken out into three groups: at most a high school degree, some college, and at least a BA degree.[8]

To calculate JOI, we use the Job-to-Job (J2J) aggregate LEHD data. For a given MSA, the JOI is equal to the average earnings of J2J job switchers who obtain a new job in that MSA multiplied by the proportion of recent hires and divided by employment in that MSA. When using the worker-level data, we then generate a composite JOI index that assigns the appropriate education-based JOI index given each worker's education level. An increase in JOI represents an increase in labor market

[7] The Great Recession is considered to have 'officially' ended in 2009 Q2, but we include these additional two quarters in our analysis as they encompass a period of elevated mass layoffs, which we display further in the paper.
[8] Neither worker skill levels nor their occupations are provided in the J2J/LEHD data.

opportunities and should increase the local employment success of displaced workers. We generate quarterly JOI indices for 383 MSAs in the U.S (see Appendix A for a more detailed description of this index).

The JOI offers some conceptual improvements on standard measures of labor market opportunities, such as unemployment rates (as used by Schmieder and von Wachter, 2010 and Valleta, 2013 among others). The unemployment rate is comparable to the likelihood of obtaining a job, but it does not take into consideration expected wages in that labor market. The JOI is also related to measures suggested by Heise et al (2024) specifically the quits rate and vacancies per effective searcher, but by combining both vacancies with expected earnings it provides a more direct indicator of both the quantity and quality of opportunities in a given MSA. Zabel and Chance (2024) show that the JOI is obtained naturally from a model of worker mobility. Furthermore, we specify the JOI at workers' education level. The median within MSA correlation for these two statistics is -0.79. Across all MSAs, after controlling for MSA and time fixed effects, the correlation is -0.94. Thus, these two indicators are strongly related. We later report that both are significant in our competing risk model of non-employment duration. This indicates that, though highly correlated, they are picking up different characteristics of the labor market.

For each worker, we also generate the unemployment rate, house price indices, and JOIs for workers' outside options. To construct an appropriate set of options, we choose the top five MSAs based on the worker flows between these and the origin MSA based on the Census J2J data for 2001. These are the five most likely destination MSAs for workers departing from each origin MSA. We then construct the outside option as the weighted average (by the J2J flows) of these top five MSAs. A worker is viewed as choosing between her/his origin MSA and this outside option MSA. All else equal, we anticipate that workers will experience improved employment outcomes both if there are greater opportunities in their origin and outside option MSAs.

While job opportunities serve as measures of the benefits workers receive in each labor market, housing costs represent a key barrier to accessing these benefits. Our measure of housing costs is based on MSA-level house prices. We use data from the 2000 Decennial Census to estimate an MSA-level house price from a hedonic price equation that includes observable structural characteristics. We then update this price (in $2001q1) each quarter using MSA-level house price indices from the

Federal Housing Finance Agency (FHFA). We expect that house prices, particularly in nearby labor markets, will serve as strong barrier to the recovery of displaced workers, both in terms of earnings as well as employment duration.

3.2 Defining Mass Layoffs

We study mass layoffs during the Great Recession, as these separations are highly likely to be the direct consequence of changes in economic conditions. Unlike ordinary separations, mass layoffs represent a more structural source of displacement. We define involuntarily displaced workers as those who have lost jobs due to a mass layoff, including an establishment closure. We consider mass layoffs at the establishment level, rather than at the firm level, as firms with multiple establishments could downsize or close a particular branch rather than spread layoffs evenly across an organization. In the case of an even distribution of layoffs, our measure will still be able to capture these broad layoffs, but in the case of more targeted layoffs at specific establishments our approach will better capture these events. Additionally, a problem with looking at mass layoffs at the firm level is that firms can have establishments in multiple states; thus, focusing on mass layoffs at the firm level with data on a limited number of states motivates defining mass layoffs based on establishments within the state.

We define a mass layoff as one in which 30 percent of an establishment's workers are let go within a four-quarter period, considering establishments with more than 50 workers (Jacobson, et. al., 1993). Following Hellerstein et al. (2019), we require that workers have a relatively strong labor force attachment by focusing on those who have a minimum tenure of four quarters with an establishment and at least $15,000 in annual earnings prior to the beginning of the mass layoff.[9]

We take numerous steps to correctly determine initial establishment level mass layoff events. We require that mass layoffs occur after four consecutive quarters of employer stability; that is, four quarters with either employment gains or with employment losses less than 30 percent. In addition, it is important to ensure that the workers involved did not move along with numerous others to a different establishment. This would be the case, for example, if the establishment was purchased by

[9] We do not consider workers who are rehired to the same establishment within 8 quarters of this separation as displaced. In addition, we also only consider a worker's first mass layoff spell because later mass layoff spells are less likely to be exogenous given that they can be affected by the first mass layoff spell.

another firm and a substantial number of workers were moved by the firm to another establishment, or if a firm's identification number changed due to bankruptcy or buyout. We take care not to consider these cases as mass layoffs. Another problem occurs when employment data are missing in a specific year; in these cases, we have made sure that these are not recorded as establishment closures (and hence mass layoffs).

There are, however, technical issues that we faced in considering employment at the establishment level. They stem from the fact that states provide the Census with worker-level data for the LEHD at the firm level. We then must determine the establishment in the firm where the workers were employed. This is not a problem, of course, for most firms that only have one establishment. For multi-establishment firms, the Census uses a probabilistic method to allocate specific workers to establishments within the firm. Details concerning our use of this procedure are provided in Appendix B.

Figure 1 presents a graph of mass layoffs in the five states in our sample over the period 2002-2014. This figure highlights that our study period captures a time of rising and elevated mass layoffs, particularly within manufacturing. It also supports our decision to extend by two quarters beyond the accepted window for the Great Recession (2007 Q4 to 2009 Q4) given that we continue to see elevated mass layoffs during these last two quarters.

There may be workers who see that the establishment is not doing well and leave just prior to the mass layoff event. If these workers are not typical of the usual workers who exit the establishment in normal times (for example, they might be more productive workers), this can result in the remaining workers being different than if the mass layoff was unanticipated. We generate a sample of "Early Leavers" who exited the mass layoff establishment in the year prior to the mass layoff event and a sample of "Very Early Leavers" who exited in the year before that. We compare the early leavers to both the very early leavers and to the displaced workers and provide evidence in Appendix C: Table 1 that these workers are quite similar, thus providing confidence that this early leaver bias does not arise in our sample.

3.3 Generating Comparison Groups

As our work seeks to examine how features of place shape labor market outcomes for workers displaced during the Great Recession, we construct two sets of comparison groups to provide a counterfactual, each with its own advantages and drawbacks. Instead of pooling the full sample of non-displaced workers in the same MSA, as is standard in the literature, (see for example Lachowska, Mas and Woodbury, 2020 and Schmieder, von Wachter and Heining, 2022) we separate the sample into two groups, the first includes workers who were in the same establishment and not released during the mass layoff, and the second comprises workers at other non-mass layoff establishments but still in the same MSA.[10]

We compare the set of workers who experienced job losses as part of a mass layoff to the outcomes of both (1) non-displaced workers at the mass layoff establishment (referred to as *Comparison Group A)* and (2) non-displaced workers at other establishments in the same labor market (referred to as *Comparison Group B*). To construct Comparison Group B, we include a random sample of the full set of workers in each MSA who do not experience a mass layoff, as the full sample would be prohibitively large. We match the size of this sample to that of the first comparison group. We require all workers in both of our comparison groups to meet the same baseline conditions as our sample of mass layoff workers.

A key advantage of Comparison Group A is that it controls for selection into the establishment. The disadvantage is that these remaining workers may be different, for example more productive, from the laid off workers. Their earnings are also likely to be affected as they are employed at the establishment during the mass layoff event. For this reason, the comparison of the earnings of the displaced and non-separated workers may not capture the full impact of the mass layoff. One advantage of Comparison Group B is that these workers do not suffer from the selection bias of the first comparison group, nor do they experience a mass layoff event. On the other hand, the types of workers who are employed at the non-mass-layoff establishments might be different in observable and unobservable ways from those who work at mass-layoff establishments. Another advantage is that we can compare the earnings of Comparison Group A to those of Comparison Group B to estimate the impact of remaining at a mass layoff establishment. And to a large extent, we control for the unobservable differences by including worker fixed effects in our earnings model.

[10] We also follow the existing literature and do not require that individuals in the comparison group were never displaced, as was stipulated in the seminal work by JLS (1993). Rather, as suggested by Krolikowski (2018), we require that individuals in comparison group were not displaced during the mass layoff window.

3.4 Descriptive Statistics

We begin our empirical analysis by presenting descriptive statistics for our sample of 162,000 workers displaced by mass layoffs, as well as our two comparison groups. In Table 1 we summarize who these workers are in terms of basic demographics, prior earnings, worker history, and industry at baseline. In Table 2, we present an overview of jobless duration spells of the displaced workers preceding re-employment in a stable job from the baseline through five years out.[11]

Table 1 provides an overview of all the 389,000 workers (both displaced workers and non-displaced Comparison Group A in the same establishment) at mass layoff establishments (column 1) and Comparison Group B, the 238,000 workers at non-mass layoff establishments (column 4). We see that the workers at the mass layoff establishments are somewhat younger, have slightly lower prior earnings, have shorter tenure, are more likely to be male, and are significantly more likely than workers in non-mass layoff establishments (Comparison Group B) to be in smaller establishments and in the construction and manufacturing sectors.

Characteristics are also presented for the two sub-groups of all workers at mass layoff establishments: the 162,000 displaced workers (column 2) and the 227,000 non-separated workers, Comparison Group A (column 3). What is quite interesting is that Comparison Group B (column 4) is very similar to Comparison Group A (column 3). The only substantive differences are in gender, industry, as we might expect, and establishment size. Both comparison groups are slightly different from the displaced workers. This is consistent with our prior discussion of the displaced workers not being randomly chosen from the mass layoff establishments. They are younger, have lower prior earnings, and less tenure than the workers in both comparison groups.

As mentioned above, there is a concern that a mass layoff event could be anticipated and hence early leavers would not be typical of exiting workers in normal times, thus making the remaining set of workers experiencing mass layoff less representative of those we may expect to see in more stable times. To address this concern, we compared workers who left in the four quarters leading up to the

[11] Descriptive statistics on the subsample for which we have complete earnings histories are also available from the authors upon request. These results look similar to those of the full sample and are thus suppressed for ease of presentation.

onset of the mass layoff, who we call *early leavers*, with those who left in the four quarters prior to this period, who we label *very early leavers*. The summary statistics for these two groups are provided in Appendix C: Table 1, columns 3 and 4. Columns 1 and 2 present the same statistics that are included in Table 1 for all workers at mass layoff establishments and the displaced workers, respectively. In columns 3 and 4 of Appendix C: Table 1, we see that the means for these variables are nearly identical for the early leavers and the very early leavers. This provides evidence against the assertion that workers anticipate the mass layoff and leave early.

Table 2 presents information on when and where displaced workers find new employment. They found re-employment in a stable job in their origin MSA two-thirds of the time. There is a substantial right tail to this distribution, with 9.2 percent remaining jobless five years after displacement. Finally, though most displaced workers found re-employment in their origin MSA, a significant share, 23.6 percent, found re-employment in a different MSA.

4. Long-Term Earnings Changes for Displaced Workers

Our analysis examines outcomes for workers who lose their jobs in a mass layoff and how they are affected by local and outside options including employment opportunities and housing costs. We focus on labor market outcomes that relate to jobless duration, mobility, and future earnings.

4.1 A Model of Long-Term Earnings Changes

We examine the earnings for workers after the mass layoff. We include the 143,000 workers displaced from mass layoffs for whom we have complete earnings information. And we include the two comparison groups discussed above: the 227,000 non-separated workers in mass layoff establishments (Comparison Group A) and the 238,000 workers at non-mass layoff establishments (Comparison Group B). For Comparison Group B, of course, there is no specific mass layoff event. For each quarter, we choose workers in non-mass layoff establishments in the same MSAs as the mass layoff establishments to be in the comparison group, and we set the relative timing for these workers based on this quarter to be 1 (the same as Comparison Group A).

We specify the following earnings model:

$$\mathrm{Y}_{\mathrm{imst}} = \beta_0 + \sum_{\mathrm{k}=-4}^{23} \mathrm{D}_{\mathrm{kit}} \delta_{\mathrm{k}}^{\mathrm{j}} + \alpha_{\mathrm{i}} + \gamma_{\mathrm{st}} + \varepsilon_{\mathrm{imst}} \qquad (3)$$

where Y_{ismt} is the (real) earnings of worker *i,* in MSA *m*, state *s*, at time *t*, k indexes a set of indicator variables, D_{kit},, which identify the number of quarters before and after displacement, and α_{i} and γ_{st} represent individual and state by quarter fixed effects. We include the four quarters prior to the beginning of the mass layoff event and then follow workers for at least 20 quarters in the post-mass layoff period.

Again, the definition of a mass layoff establishment is one that loses 30 percent of its workforce over four quarters, with the mass layoff event consisting of these 4 quarters and where mass layoff is designated to take place in the fourth of these quarters.

We need to establish the quarter relative to the mass layoff to match up the timing for the three groups. For displaced workers, this is based on when they exit employment. Consider a worker displaced in quarter 3 of the four-quarter period that defines the mass layoff event. While it is the case that this worker's earnings could be affected in quarters 1 and 2, the major impact on earnings will be in period 3 when the layoff occurs. Thus, relative time is set to 0 in quarter 2. Likewise, for a worker who was laid off in quarter 2, relative time is set to 0 in quarter 1. We find that the results of earnings impacts that we display in the figures in Section 5 below better portray this initial major impact on earnings when they are the same for all displaced workers, regardless of the actual quarter they lose their job.[12]

For workers in the two comparison groups, there is no specific quarter when the workers are laid off that defines the mass layoff event, thus we need to specify a time 0 that represents an appropriate comparison point in time. For Comparison Group A, relative time is set to 0 in the quarter before the first of the 4 quarters that determine this mass layoff event. As these workers are also impacted by the mass layoff event, though they do not lose their job in this period, it makes sense to specify the

[12] And note, then, that the displaced workers will have been employed at the mass layoff establishment for 4 to 7 quarters when getting laid off in quarters 1 to 4 of the mass layoff period. This is why we start the index k at -4 in equation (3) since all workers will have been at their establishment for a minimum of 4 quarters before the mass layoff period begins.

period before the mass layoff event begins as the baseline for this group.[13] For Comparison Group B we select a random quarter during our study period as indicating relative time 0 as these workers are not tied to any specific mass layoff event.

We consider several factors that might affect these earnings paths. We interact the relative time indicators in equation (3) with UNEMP, JOI and HCI (for both the origin MSA as well as the outside option MSA) at the time of mass layoff to see how these MSA-level characteristics affect earnings. We also interact these indicator variables with the location of earnings, either the same MSA or the outside option MSA. This measures the potential benefits to workers who move to find a job. Finally, we interact the relative time indicators with industry sector indicators to see how the earnings paths differ by the workers' sector at the time of mass layoff. Since the Great Recession had the largest impact on employment in the manufacturing sector, we expect that the impact on earnings will be larger and the recovery slower for displaced workers in this sector.

4.2 Earnings Results

In this section we provide the earnings model results, examining how the earnings trajectories of the workers in our sample progress over the 20 quarters post-displacement. We display the results for our three key groups: those displaced after a mass layoff (Treated Group), those in mass layoff establishments who were not separated during the mass layoff (Comparison Group A), and those in non-mass layoff establishments (Comparison Group B). Figure 2A shows the change in real quarterly earnings for these three groups. Figure 2B provides the treatment effect (percent difference in earnings) for dislocated workers relative to Comparison Groups A and B and for treatment effect for the non-separated workers at mass layoff establishments (Comparison Group A) relative to Comparison Group B. The relative real earnings of Comparison Group B were very stable over the period covered in this analysis (Figure 2A). This is consistent with how earnings behaved for the bulk of workers during this 20 quarter post-displacement period. And the pre-treatment earnings paths

[13] Note that all workers in our sample were employed at the establishment for the 4 quarters prior to the 4 quarters that determine the mass layoff (time -3 to 0). Since non-separated workers remain employed at the establishment during the four quarters that determine the mass layoff, they are employed at the establishment for at least 8 quarters (time -3 to 4) prior to the end of the post-mass layoff period.

are quite similar for all three groups. This provides support for using workers at non-mass layoff establishments as valid comparisons.

Both Figures 2A and 2B highlight the significant decline in earnings experienced by displaced workers in the first quarter of job loss - a nearly 30 percent decline, on average. This average, however, obscures the heterogeneity of displaced worker experiences. Some found a new full-time job in this first quarter (see Table 2), some had earnings from continuing secondary jobs, while others remained jobless for the full 20 quarter post-displacement period. We observe that there was a gradual increase in average earnings after this initial shock, but average quarterly earnings were still 7.2/11.4 percent lower than those for Comparison Group A/B after nearly five years.

One might presume that the non-separated workers in the mass layoff establishments would serve as a good control for the dislocated workers since they are all from the same establishment (and hence control for sorting across establishments). However, these non-separated workers also suffered earnings losses relative to Comparison Group B. As shown in Figure 2B their earnings were 7.4 percent lower after one year and remained lower by 5 percent after 5 years. This comparison group is nonetheless useful since the outcome path for treated workers could be based in part on the types of establishments likely to have a mass layoff event. Still, comparing the dislocated workers to those workers who remain in the mass layoff establishments can significantly underrepresent the overall losses in earnings for the former group.

One concern regarding these estimates is that they could suffer from selection bias if the characteristics of the treatment group are substantially different from the characteristics of the comparison groups. For example, we showed in Section 3 that the displaced workers were younger, had lower prior earnings, and had shorter job tenure than the workers in Comparison Group B. And while we include worker fixed effects that control for time-invariant (observable and unobservable) worker characteristics, we also employ propensity score matching to better align our Comparison Group B to our treatment group in terms of observables. We first use the samples of dislocated and Comparison Group B workers to estimate a selection model where we regress the indicator of being in the treatment group (dislocated workers) on the characteristics given in Table 1. Second, we estimate the earnings equation based on the samples of dislocated and Comparison Group B workers using the inverse estimated propensity scores as weights. In Appendix C: Figure 1, we provide the percent difference in earnings between the dislocated and Comparison Group B workers based on the results from the unweighted and weighted earning regressions. These results are almost identical. We also get similar results when we carry out the same exercise for Comparison Groups A and B. Thus, we feel comfortable going forward using the full sample of Comparison Group B workers as our primary comparison sample.

Figure 3 displays the earnings paths for displaced workers for separate sectors: Manufacturing, Finance, Accommodations and Food Service, and Other. As expected, earnings losses are greatest for workers in manufacturing where the dislocated workers suffered huge earnings losses in the first quarter after mass layoff (43 percent) and they remained 18 percent below baseline after five years. Accommodation and Food Service workers experienced the smallest impact.

In addition to heterogeneity across industry, we also explored the role of mobility in worker's recovery timeline. Figure 4 displays the percent change in relative real earnings for displaced workers based on re-employment location; the same MSA as when dislocated or the outside option MSA. Here results clearly suffer from non-random selection into location but are still illustrative of the differing experiences of these two sets of workers. We might expect that workers who moved to another MSA did so to take advantage of higher earnings and hence they would experience the lowest decline in earnings. What we see is that there is a slightly larger initial decline in earnings for the movers, although they eventually catch up with displaced workers who found re-employment in the origin MSA. This could reflect the fact that workers who experienced the largest initial loss in earnings were the ones who then saw the largest relative gains by moving.

Figures 5a, 5b, 6a, 6b, 7a and 7b display the earnings paths for displaced workers in MSAs with different levels of the UNEMP, JOI, and HCI in the origin MSA and the outside option MSA at the time of mass layoff. These regressions control for the other two labor market characteristics. These paths are evaluated at the 10th, 25th, 50th, 75th, and 90th percentiles of UNEMP and the JOI and HCI indices. Overall, we find that workers fared better after displacement in MSAs with lower UNEMP and higher JOIs, and to a lesser extent, in outside option MSAs that had lower unemployment rates. However, we find almost no differences in recovery paths between individuals displaced in MSAs with HCIs at different points in the distribution or where the outside option MSA had different HCIs or JOIs.

Focusing first on Figure 5a we see very large differences in the recovery paths of workers displaced in MSAs in the top 10th percentile of the distribution (i.e. the lowest unemployment rates) versus those in the 90th percentile. These differences are quite large. Note that although some of these differences existed before the mass layoff, the magnitude of this gap doubles post-mass layoff. We also see significant differences in recovery paths depending on the unemployment rates of outside option MSAs, though these differences are smaller but still economically significant.

In Figure 6a, we also see a wide dispersion in the recovery paths of workers based on the JOIs where mass layoff occurred. Even after 20 quarters post displacement, workers who were initially laid off in MSAs with JOIs in the 90th percentile experienced earnings losses almost 10 percent lower than individuals in the 10th percentile. In fact, we see that workers in MSAs with JOIs in the 90th percentile experienced no earnings losses 20 quarters past mass layoff. In contrast with UNEMP, we see no difference in recovery paths for workers based on the JOIs of their outside options. In the case of housing costs, Figure 7a and 7b, we find no differences in recovery paths for workers after displacement. Together these findings highlight the importance of labor market characteristics in shaping a worker's recovery path. Most strikingly, workers that were displaced in labor markets in the 90th percentile according to JOI experience no earnings losses five years post displacement.

5. A Competing Risks Analysis of Jobless Duration and Mobility

While the previous section shows results for earnings paths of displaced workers at mass layoff establishments, it misses an important part of the worker experience after displacement, the non-employment duration until re-employment and the joint decision of where to accept new employment, which research has shown is a key determinant of the earnings paths (Fallick et al., 2025). Since consideration of location and its characteristics is a key element of our analysis, we develop a hazard model of jobless duration with two potential re-employment outcomes: employment in the origin MSA, and employment in the outside option MSA.

5.1 Model

To measure jobless duration and mobility, we use the LEHD to observe the future employment of displaced workers on a quarterly basis. To more clearly identify the impact of local labor market characteristics on the re-employment experiences of workers, we focus on the full sample of displaced workers rather than the subsample for whom we have complete earnings records. Given that we do not have complete earnings paths for this set of workers (as some move to states for which we do not have access to the earnings records) we need to define new employment using the identifier developed by Vilhuber (2018), which is an indicator for whether the individual is employed. One measure of new employment used by Andersson, et al. (2018) is to look for the first instance of positive earnings (Andersson, et al. 2018). Our approach is to specify that a worker exits joblessness if we observe four consecutive quarters of positive earnings. We take this approach given that identifying workers who find stable jobs could be the focus of policies to support re-employment. This approach allows us to include workers who find jobs in the 28 states for which we have full labor market information and workers who find stable jobs in the 22 states plus the District of Columbia for whom we do not have complete earnings information.

We set the quarter that the worker is displaced due to the mass layoff to be period 1.[14] Let Y_{imsdt} = 1 if non-employed, = 2 if employed in the same MSA, and = 3 if employed in the outside option MSA for individual *i* in MSA *m* at the time of the mass layoff, industrial sector *s*, duration *d*, and time *t*. The indirect utility function is:

$$\mathrm{U}^{\mathrm{k}}_{\mathrm{imsd}} = \alpha_{\mathrm{k}} + \mathrm{X}_{\mathrm{i0}}\beta_{\mathrm{k}} + \mathrm{MSA}^{\mathrm{o}}_{\mathrm{mt}}\gamma_{\mathrm{k}} + \mathrm{MSAN}^{\mathrm{o}}_{\mathrm{mt}}\delta_{\mathrm{k}} + \nu_{\mathrm{kt}} + \eta_{\mathrm{ks}} + \mathrm{h}(\mathrm{d};\lambda_{\mathrm{k}}) + \varepsilon^{\mathrm{k}}_{\mathrm{imsd}} \qquad (1)$$

Then $$\mathrm{Y}_{\mathrm{imsdt}} = \begin{cases} 1 \text{ if remain non-employed if } \mathrm{U}^{1}_{\mathrm{msdt}} > \mathrm{U}^{\mathrm{k}}_{\mathrm{msdt}} \text{ for k} = 2,3 \\ 2 \text{ if exit non-employment in the same MSA if } \mathrm{U}^{2}_{\mathrm{msdt}} > \mathrm{U}^{\mathrm{k}}_{\mathrm{msdt}} \text{ for k} = 1,3 \\ 3 \text{ if exit non-employment in the outside option MSA if } \mathrm{U}^{3}_{\mathrm{msdt}} > \mathrm{U}^{\mathrm{k}}_{\mathrm{msdt}} \text{ for k} = 1,2 \end{cases}$$

where $X_{i,0}$ is a vector of individual characteristics in period 0 (prior to the mass layoff) that includes age, prior tenure and earnings, race, gender, and industry $\mathrm{MSA}^0_{\mathrm{mt}}$, is a vector of MSA characteristics in MSA *m* in period 0 and observed in period t, $\mathrm{MSAN}^0_{\mathrm{mt}}$ is a weighted average of characteristics in the five MSAs that make up the outside option MSA, ν_{kt} and $\eta_{ks,o}$ are time and industry (prior to mass layoff) fixed effects, and h(d; λ_k) captures duration dependence where d is spell duration.

[14] Note that this could be in any of the 4 quarters that make up the mass layoff event.

$\mathrm{MSA}_{\mathrm{mt}}^{0}$ represents the three factors, the JOI, UNEMP and HCI that we have already developed in the paper. These measures correspond to the MSA where the worker was employed at the time of mass layoff. $\mathrm{MSAN}_{\mathrm{mt}}^{0}$ includes the JOI, UNEMP, and HCI corresponding to the other competing risk: the outside option MSA. As discussed above, for these characteristics, we take weighted averages of five MSAs based on the frequency of job-to-job flows (J2J) that we obtain from the aggregated J2J LEHD data in 2001. Additionally, we include average weekly unemployment insurance benefits by state from the UI Data Summary published by the Department of Labor as a measure of the generosity of the unemployment insurance system in each state. Existing research shows that state level generosity plays a role in shaping individual responses to job losses (see for example Acosta et al., 2025). We anticipate that displaced workers will be less likely to become re-employed as these benefits increase.

Assume that the $\varepsilon_{\mathrm{imsd}}^{\mathrm{k}}$'s are iid with Gumbel (type 1 extreme value) distribution and $\alpha_{\mathrm{k}} = \beta_{\mathrm{k}} = \gamma_{\mathrm{k}} = \delta_{\mathrm{k}} = \lambda_{\mathrm{k}} = v_{\mathrm{kt}} = \eta_{\mathrm{ks}} = 0$ (a necessary normalization) then the competing risk (multinomial logit) model is specified as follows:

$$\mathrm{Prob}\left(\mathrm{Y}_{\mathrm{imsdt}} = 1 | \mathrm{X}_{\mathrm{i0}}, \mathrm{MSA}_{\mathrm{mt}}^{0}, \mathrm{MSAN}_{\mathrm{mt}}^{0}\right) = \frac{1}{1 + \sum_{\mathrm{j=2}}^{3} \exp\left(\alpha_{\mathrm{j}} + \mathrm{X}_{\mathrm{i0}}\beta_{\mathrm{j}} + \mathrm{MSA}_{\mathrm{mt}}^{0}\gamma_{\mathrm{j}} + \mathrm{MSAN}_{\mathrm{mt}}^{0}\delta_{\mathrm{j}} + v_{\mathrm{jt}} + \eta_{\mathrm{js}}^{0} + \mathrm{h}\left(\mathrm{d}, \lambda_{\mathrm{j}}\right)\right)} \quad (2)$$

and

$$\mathrm{Prob}\left(\mathrm{Y}_{\mathrm{imsdt}} = \mathrm{k} | \mathrm{X}_{\mathrm{i,0}}, \mathrm{MSA}_{\mathrm{mt}}^{0}, \mathrm{MSAN}_{\mathrm{mt}}^{0}\right) = \frac{\exp\left(\alpha_{\mathrm{k}} + \mathrm{X}_{\mathrm{i0}}\beta_{\mathrm{k}} + \mathrm{MSA}_{\mathrm{mt}}^{\mathrm{o}}\gamma_{\mathrm{k}} + \mathrm{MSAN}_{\mathrm{mt}}^{\mathrm{o}}\delta_{\mathrm{k}} + v_{\mathrm{kt}} + \eta_{\mathrm{ks}} + \mathrm{h}\left(\mathrm{d}; \lambda_{\mathrm{k}}\right)\right)}{1 + \sum_{\mathrm{j=2}}^{3} \exp\left(\alpha_{\mathrm{j}} + \mathrm{X}_{\mathrm{i0}}\beta_{\mathrm{j}} + \mathrm{MSA}_{\mathrm{mt}}^{0}\gamma_{\mathrm{j}} + \mathrm{MSAN}_{\mathrm{mt}}^{0}\delta_{\mathrm{j}} + v_{\mathrm{jt}} + \eta_{\mathrm{js}}^{0} + \mathrm{h}\left(\mathrm{d}, \lambda_{\mathrm{j}}\right)\right)} \quad \mathrm{k} = 2,3 \quad (3)$$

And now the parameters β_{k}, γ_{k}, δ_{k}, and λ_{k} measure the probability of experiencing outcome 2 or 3 (getting a job in the same or outside option MSA) relative to outcome 1 (non-employment) conditional on worker and MSA characteristics.

We expect that as the UNEMP/JOI in the origin MSA decreases/increases, the likelihood of exiting non-employment in the same MSA/outside option MSA will increase/decrease. In contrast, we expect that an increase in the JOI in the outside option MSA will cause the likelihood of exiting non-employment in the same (outside option) MSA to possibly decrease (increase). We expect the opposite results when considering an increase in HCI as this represents an increase in costs versus benefits.

Given our interest in analyzing the impacts of own and outside labor market factors on re-employment behavior that includes mobility, this is best carried out using a multinomial logit model since this provides different estimates of these impacts for the two competing risks; finding a job in the origin (at time of displacement) labor market and the outside option. This would be untenable using many competing MSAs and doing so would better fit a conditional logit framework where only one set of impacts are estimated (and there is only one competing risk: exit from non-employment).

One issue is that, given the complexity of the competing risk model, we do not control for worker fixed effects. As an alternative, we consider two bivariate logit models where workers exit to jobs in their own MSA and to jobs in the outside option MSA

$$\mathrm{Prob}\left(\mathrm{Y}_{\mathrm{imsdt}} = 1 | \mathrm{X}_{\mathrm{i0}}, \mathrm{MSA}^{0}_{\mathrm{mt}}, \mathrm{MSAN}^{0}_{\mathrm{mt}}\right) = \frac{1}{1+\exp\left(\alpha_{\mathrm{k}} + \mathrm{X}_{\mathrm{i0}}\beta_{\mathrm{k}} + \mathrm{MSA}^{0}_{\mathrm{mt}}\gamma_{\mathrm{k}} + \mathrm{MSAN}^{0}_{\mathrm{mt}}\delta_{\mathrm{k}} + \nu_{\mathrm{kt}} + \eta^{0}_{\mathrm{ks}} + \mathrm{h}\left(\mathrm{d}, \lambda_{\mathrm{k}}\right) + \mathrm{u}_{\mathrm{i}}\right)} \tag{4}$$

and

$$\mathrm{Prob}\left(\mathrm{Y}_{\mathrm{imsdt}} = \mathrm{k} | \mathrm{X}_{\mathrm{i,0}}, \mathrm{MSA}^{0}_{\mathrm{mt}}, \mathrm{MSAN}^{0}_{\mathrm{mt}}\right) = \frac{\exp\left(\alpha_{\mathrm{k}} + \mathrm{X}_{\mathrm{i0}}\beta_{\mathrm{k}} + \mathrm{MSA}^{\mathrm{o}}_{\mathrm{mt}}\gamma_{\mathrm{k}} + \mathrm{MSAN}^{\mathrm{o}}_{\mathrm{mt}}\delta_{\mathrm{k}} + \nu_{\mathrm{kt}} + \eta_{\mathrm{ks}} + \mathrm{h}\left(\mathrm{d}; \lambda_{\mathrm{k}}\right) + \mathrm{u}_{\mathrm{i}}\right)}{1+\exp\left(\alpha_{\mathrm{k}} + \mathrm{X}_{\mathrm{i0}}\beta_{\mathrm{k}} + \mathrm{MSA}^{0}_{\mathrm{mt}}\gamma_{\mathrm{k}} + \mathrm{MSAN}^{0}_{\mathrm{mt}}\delta_{\mathrm{k}} + \nu_{\mathrm{kt}} + \eta^{0}_{\mathrm{ks}} + \mathrm{h}\left(\mathrm{d}, \lambda_{\mathrm{k}}\right) + \mathrm{u}_{\mathrm{i}}\right)} \quad \mathrm{k} = 2,3 \tag{5}$$

We then control for Individual fixed effects in two ways. First, we specify a two point distribution for u_i (Heckman-Singer, 1982) and second, we specify that u_i has a Gamma distribution.[15]

[15] hshaz and pgmhaz8, respectively, in Stata.

5.2 Estimation/Results

We present the results for the competing risk model of jobless duration and mobility in Table 3 and Figure 8. Our results include separate sets of parameter estimates for the two re-employment outcomes: employed in same MSA and employed in the outside option MSA. This allows us to examine the differential impacts of factors that affect re-employment on the location of re-employment. The key variables of interest are our measure of the unemployment rate (UNEMP), job opportunities (JOI) and housing costs (HCI). We include measures of these three variables for the origin MSA and for the outside option MSA. This allows us to see how changes in these variables in different locations affect the likelihood of exiting joblessness in each competing risk outcome.

Our results are generally in line with our expectations. Figure 8 (drawn from the results in Table 3) summarizes the estimated effects of UNEMP, JOI, and HCI on locational re-employment outcomes. Starting at the left side of Figure 8, we see that a one standard deviation increase in UNEMP, JOI, and HCI in the worker's origin MSA leads to a change in the likelihood of finding re-employment in the same MSA of -0.08, 0.10, and -0.03 standard deviations, respectively. We refer to this as the direct effect. We see that UNEMP and JOI have an equal but opposite impact on the probability of re-employment whereas the impact of HCI is smaller in magnitude. Furthermore, the magnitude of the coefficient estimates for UNEMP and JOI show little change when we exclude the other measure from the model. This indicates that they are picking up different characteristics of the labor market. In terms of JOI, this impact can reduce time non-employed by 0.1 standard deviations, or about 1.3 weeks (given the average duration of unemployment in the US is 24 weeks, with a standard deviation of approximately 13 weeks). (BLS, 2024)

The right hand side of Figure 8 also shows a similar impact of a one standard deviation increase in UNEMP, JOI, and HCI in the outside option MSA on the likelihood of exiting joblessness in the outside option MSA (-0.107, 0.079, and -0.040 standard deviations, respectively, Table 3 column 4). Intuitively what we learn from this exercise is that job opportunities, as measured by the UNEMP and JOI, have a strong 'pull' effect in terms of increasing the likelihood of employment in one's home MSA as well as increasing the likelihood of a move into a neighboring MSA. These magnitudes are also quite large. Comparing these results to other coefficients in this regression[16] we see that a one standard deviation increase in the JOI increases the probability of finding new employment as much as being in the 45-49 age bracket relative to the 25-29 age bracket (the youngest). On the other hand, the "push" factor of an increase in HCI is relatively smaller.

Next, we consider the cross effects. Generally, we believe that these should have the opposite effects compared to the direct effects. First, the impact on the probability of re-employment in the outside option MSA due to a one standard deviation increase in UNEMP, JOI, and HCI in the worker's origin MSA (2nd set of results in Figure 8) is -0.027, -0.063, and 0.003 standard deviations (Table 3 column 4), respectively. Whereas the impact on the probability of re-employment in the origin MSA due to a one standard deviation increase in UNEMP, JOI, and HCI in the worker's outside option MSA (3rd set of results in Figure 8) is -0.037, -0.073, and 0.072 standard deviations (Table 3 column 3), respectively. Thus, our expectation is met by JOI and HCI, but the result is opposite for UNEMP. For JOI, the negative impact of an increase in JOI in the outside option MSA on re-employment in the origin MSA may arise as workers take extra time in expanding their job search to the outside option MSA and they might then be less willing to take a job locally as they search for better jobs in the outside option MSA. The fact that the impact is opposite of what is expected for UNEMP indicates that it is picking up other factors affecting re-employment than just the change in UNEMP.

6. Conclusion/Implications

To date, research on displaced workers has been limited by lack of attention to how features of both the local and the outside option labor market characteristics shape earnings and employment outcomes. We use a location-specific longitudinal data set, combining near-universal quarterly matched employee-employer microdata from the Longitudinal Employer Household Dynamics (LEHD) with local labor market measures to study medium- and long-run employment outcomes for workers displaced in five Great Lakes states during the Great Recession. Our unique approach underscores the importance of considering labor market characteristics in both the origin MSA and outside option locations. We provide a detailed examination of how local labor markets shape displaced workers' re-employment experiences. Our empirical approach, which includes both a

[16] Results for the control variables are suppressed for ease of presentation, but available from the authors upon request.

competing risks model of jobless duration and mobility and a long-term earnings model, allows us to examine how our key measures of local and outside option labor market characteristics shape the probability that a displaced worker will find re-employment in either their own MSA or an outside option, as well as how this shapes their longer-term earnings trajectory.

We find that 62 percent of displaced workers attain stable employment within one quarter after mass layoff and nine percent do not find such employment within five years. We find that , 67 percent of displaced workers find stable employment in their origin MSA labor market and a full 24 percent find re-employment in another MSA.

We find large and persistent long-term declines in earnings for displaced workers after mass-layoff, even among movers, of about 12 percent, in line with the existing literature. The largest earnings losses are for individuals working in manufacturing. We also find persistent long-term declines in earnings for non-separated workers at mass layoff establishments of about 5 percent, which has not been previously identified in the literature. Significantly, we find that job opportunities and housing costs at time of mass layoff appear to play a substantial role in earnings impacts. When looking at MSAs with the strongest labor markets (in terms of job opportunities) workers displaced in these areas experience no long-term earnings losses.

To simultaneously explore duration of non-employment and the associated mobility with re-employment, we develop and estimate a competing risks model of jobless duration where non-employed workers exit to a stable job in the origin MSA or the outside option MSA. We include measures of the local and outside option labor market characteristics in our duration model. We find that these play a substantive role in determining whether displaced workers are re-employed in their origin MSA or in the outside option MSA.

The results indicate that job opportunities, as measured by the UNEMP and JOI, have a strong 'pull' effect in terms of increasing the likelihood of employment in one's home MSA as well as increasing the likelihood of a move into a neighboring MSA. On the other hand, the "push" factor of an increase in HCI is relatively smaller.

Our results provide some policy-relevant context when considering the role of the federal government in supporting displaced workers. While our results were obtained for the Great Recession period, we believe that some of our results are sufficiently strong to be applied to other points in the business cycle. First, given how significant local labor market characteristics are in terms of affecting the time to re-employment for displaced workers and of affecting earnings losses post-mass layoff, this indicates the potential importance of adjusting the timing and amount of federal aid provided to mass laid off workers based on local labor market conditions. Currently the Workforce Innovation and Opportunities Act (WIOA) authorizes National Dislocated Worker Grants, which is competitive funding to support workers in states and local areas experiencing disasters, emergencies or "major economic dislocations" (Bradley, 2015). Our results suggest that these allocations could be administered in a parallel fashion to how HUD provides rental assistance of different levels depending on the cost of housing in a neighborhood (Collinson, 2019).

Second, our findings provide additional support for the growing body of work on local industrial policies and place-based investments (Austin, Glaeser and Summers, 2018; Aiginger and Rodrik, 2020). As our paper focuses on variation in labor markets within the Midwest during the Great Recession, our work demonstrates that even the variation in job opportunities across these metropolitan areas has a significant impact on both the time it takes a worker to find re-employment as well as the earnings of the job they secure. An example of such a policy is the Regional Technology and Innovation Hubs (Tech Hubs) program created by the Biden administration.[17] As these programs are implemented, we hope to examine the extent to which they support the ability of displaced workers to re-enter the labor market.

Third, the enduring nature of the earnings losses we observe for displaced workers is also highly relevant to informing optimal design of the U.S. wage insurance program. Between 2002 and 2022, the U.S. Trade Adjustment Assistance (TAA) program provided wage insurance to workers aged 50 and over who were laid off in a trade-related displacement.[18] These workers received both funding to cover job training costs for up to three years and extended UI payments during training. Recent research on this program finds that it increased short-run employment probabilities and though it leads to slightly higher earnings in the short term due to increased employment, long-term earnings

[17] https://www.eda.gov/funding/programs/regional-technology-and-innovation-hubs
[18] https://www.nytimes.com/2024/12/20/opinion/trade-adjustment-assistance.html?smid=em-share

were not different among treated vs. non-treated workers (Hyman et al, 2021). These results combined with ours suggest that if and when Congress begins designing a new program to assist displaced workers, wage insurance programs should be adjusted based on local labor market characteristics in addition to industry and worker characteristics.

Fourth, our results highlight the importance of outside options in affecting the duration of non-employment and mobility. Austin et al (2018) show that intra-county migration has been falling since before 1960 and inter-county migration has been falling since 1990. They claim that this provides support for place-based policies in areas with persistently high unemployment (Austin et al., 2018). Ganong and Shoag (2017), Kaplan and Schulhofer-Wohl (2017), and Chance and Zabel (2024) show that this is related to the decline in net benefits of moving related to job opportunities (benefits) and house prices (costs). Our results thus lend support to an effective placed-based policy that improves the ability of workers to benefit from outside options by, say, providing housing cost subsidies for movers in these areas in the Midwest that have experienced high levels of mass layoffs.

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Table 1. Characteristics of Workers, Mass Layoff and Non-Mass Layoff

	Mass Layoff Establishments			Non-Mass Layoff Establishments
	All Workers (1)	Displaced Workers (2)	Non-Displaced Workers (3)	Non-Displaced Workers (4)
Age				
25-29	0.112	0.130	0.099	0.103
30-34	0.139	0.150	0.132	0.135
35-39	0.162	0.163	0.161	0.159
40-44	0.178	0.173	0.181	0.174
45-49	0.196	0.185	0.203	0.200
50-55	0.214	0.199	0.225	0.228
Earnings				
$15,000-$29,999	0.252	0.312	0.209	0.230
$30,000-$44,999	0.305	0.297	0.311	0.288
$45,000-$59,999	0.192	0.163	0.213	0.213
$60,000-$74,999	0.111	0.092	0.124	0.123
$75,000-$89,999	0.059	0.054	0.062	0.061
$90,000+	0.082	0.081	0.082	0.085
Tenure				
4 Quarters	0.242	0.292	0.206	0.176
5-8 Quarters	0.305	0.336	0.283	0.262
9-16 Quarters	0.162	0.143	0.175	0.192
16+ Quarters	0.292	0.230	0.337	0.371
Race/Ethnicity				
Non-Hispanic White	0.844	0.811	0.867	0.876
Black	0.088	0.111	0.071	0.075
Non-Black Hispanic	0.041	0.046	0.037	0.025
Other	0.028	0.032	0.025	0.023
Gender				
Male	0.641	0.597	0.673	0.483
Female	0.359	0.403	0.327	0.518
Industry				
Extraction/Utilities/Construction	0.092	0.062	0.114	0.030
Manufacturing	0.422	0.349	0.474	0.180
Wholesale Trade/Retail Trade/Transportation	0.139	0.186	0.105	0.137
Information/Finance/Real Estate/Professional	0.209	0.233	0.193	0.196
Education/Health	0.092	0.127	0.067	0.335
Arts/Entertainment/Accommodation/Food	0.022	0.030	0.016	0.024
Other Industry	0.024	0.013	0.031	0.098
Establishment Size				
50-500 Employees	0.704	0.698	0.709	0.579
501-2000 Employees	0.204	0.192	0.213	0.255
2000+ Employees	0.092	0.110	0.079	0.167
Number of Observations	389,000	162,000	227,000	238,000

Notes: Calculations from LEHD data. Baseline worker characteristics. Earnings are in 2000 dollars. Sample includes displaced workers, non-displaced workers at mass layoff establishments and non-displaced workers at non mass layoff establishments for whom we can identify whether or not they experience stable employment.

Table 2. Transitions to a Permanent Job after Displacement, Mass Layoff Workers

Employment Status (after 20 quarters)	
Still Without Stable Job	9.2%
Re-employed Same MSA	67.2%
Re-employed Different MSA	23.6%
Joblessness Spell	
<1 Quarter	36.1%
1 Quarter	25.8%
2-3 Quarters	8.9%
4-7 Quarters	11.1%
8+ Quarters	18.0%
Number of Observations	162,000

Notes: Calculations from LEHD data. Sample includes displaced workers for whom we can identify whether or not they experience stable employment post mass layoff.

Table 3. Duration/Mobility Model Results:
Probability of Finding New Employment by Geographic Location

	Estimates		Standardized Coefficients	
	Same MSA	Different MSA	Same MSA	Different MSA
VARIABLES	(1)	(2)	(3)	(4)
Unemployment Rate: Origin MSA	-0.065	-0.039	-0.075	-0.027
	(0.003)**	(0.004)**		
Unemployment Rate: Outside Option MSA	-0.039	-0.183	-0.037	-0.107
	(0.006)**	(0.009)**		
Job Opportunity Index: Origin MSA	0.005	-0.005	0.104	-0.063
	(0.0002)**	(0.0003)**		
Job Opportunity Index: Outside Option MSA	-0.003	0.005	-0.073	0.079
	(0.0002)**	(0.0002)**		
Housing Cost: Origin MSA	-0.003	0.001	-0.025	0.003
	(0.0002)**	(0.0003)		
Housing Cost: Outside Option MSA	0.006	-0.006	0.072	-0.040
	(0.0003)**	(0.0004)**		
Observations	813,000	813,000		
Individuals	162,000	162,000		

Standard errors in parentheses, *** p<0.01 ** p<0.05 * p<0.1

Notes: Calculations from LEHD data. Includes all individuals experiencing mass layoffs for whom we can identify stable employment. Estimates presented in columns (1) and (2) and standardized coefficients presented in columns (3) and (4).

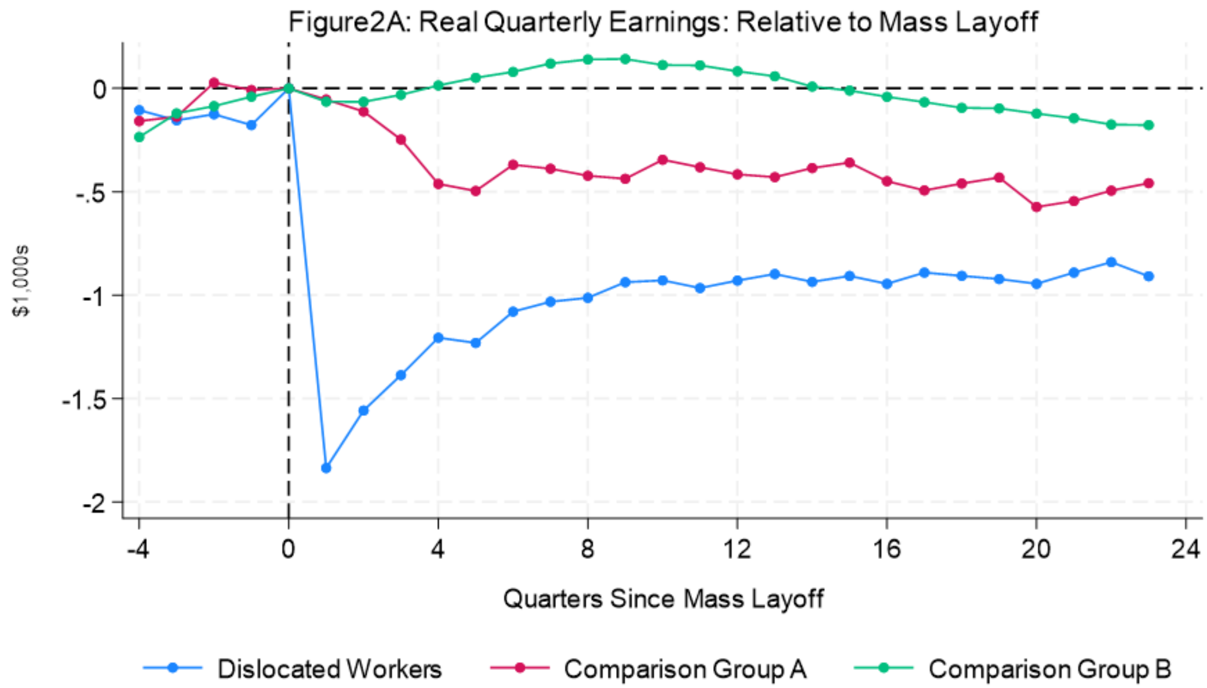
Table 4. Duration/Mobility Model Results: Alternative Specifications

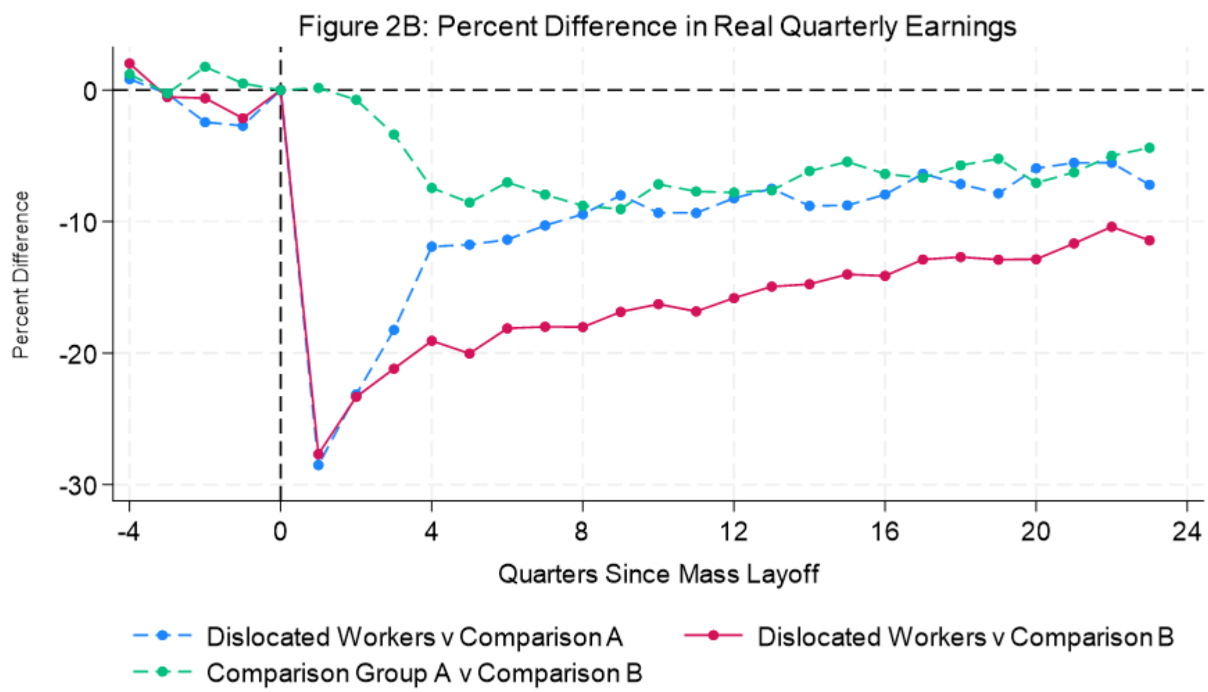
	Logit		Heckman Singer		Gamma	
	Same MSA	Different MSA	Same MSA	Different MSA	Same MSA	Different MSA
VARIABLES	(1)	(2)	(1)	(2)	(3)	(3)
Unemployment Rate: Origin MSA	-0.074	-0.029	-0.083	-0.020	-0.091	-0.021
Unemployment Rate: Outside Option MSA	-0.040	-0.110	-0.018	-0.158	-0.023	-0.153
Job Opportunity Index: Origin MSA	0.104	-0.060	0.070	-0.033	0.077	-0.032
Job Opportunity Index Outside Option MSA	-0.073	0.078	-0.027	0.034	-0.029	0.035
Housing Cost: Origin MSA	-0.024	0.003	-0.011	0.003	-0.013	0.001
Housing Cost: Outside Option MSA	0.069	-0.039	0.069	-0.047	0.081	-0.046
Observations	813,000	813,000				
Individuals	162,000	162,000				

Notes: Calculations from LEHD data. Includes all individuals experiencing mass layoffs for whom we can identify stable employment. Standardized coefficients presented.

Figure 1: New Mass layoffs: Quarterly, Selected Insustries
Percent difference from 2007q4

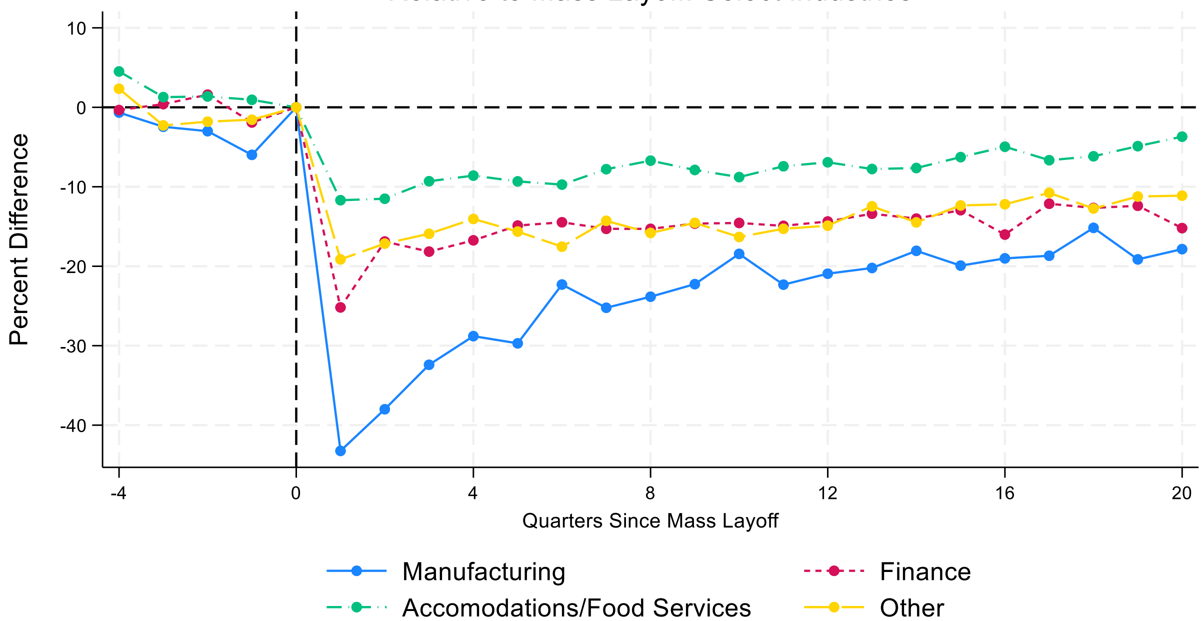
Notes: Calculations from LEHD data, for all establishments in our five sample states, in all industries as well as within three key sectors. Estimates of establishment level mass layoff events between 2002 and 2015. Estimates are seasonally adjusted. Vertical lines represent the beginning/end of the Great Recession +2, which is our key study period.





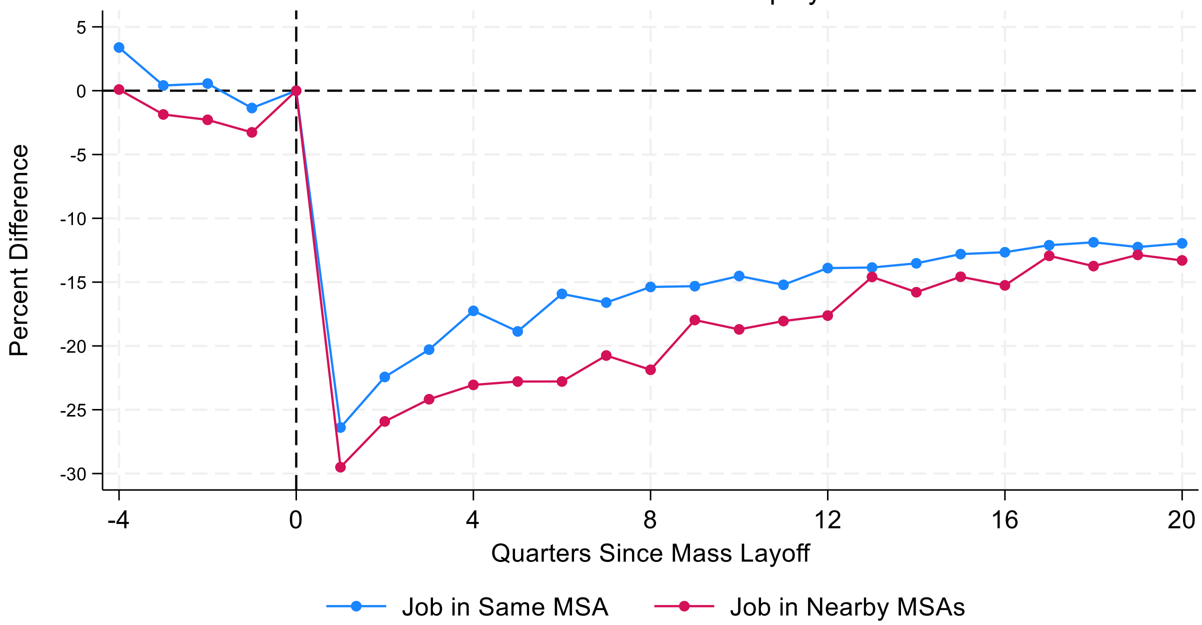
Notes: Calculations from LEHD data. Includes all individuals experiencing mass layoffs for whom we can identify earnings. Differences are relative to earnings in the quarter prior to Mass Layoff. Comparison Group A represents workers who were not separated from mass layoff establishments. Comparison Group B represents workers who were not employed in mass layoff establishments.

Figure 3: Percent Difference in Earnings: for Dislocated Workers Relative to Mass Layoff: Select Industries

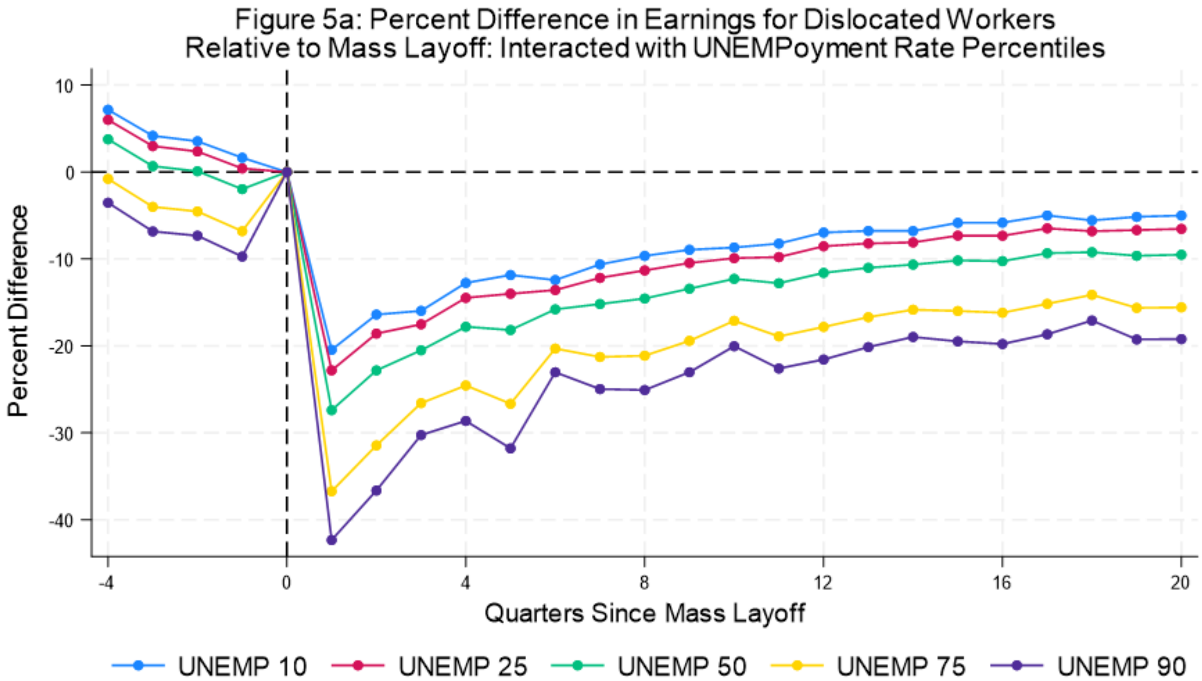


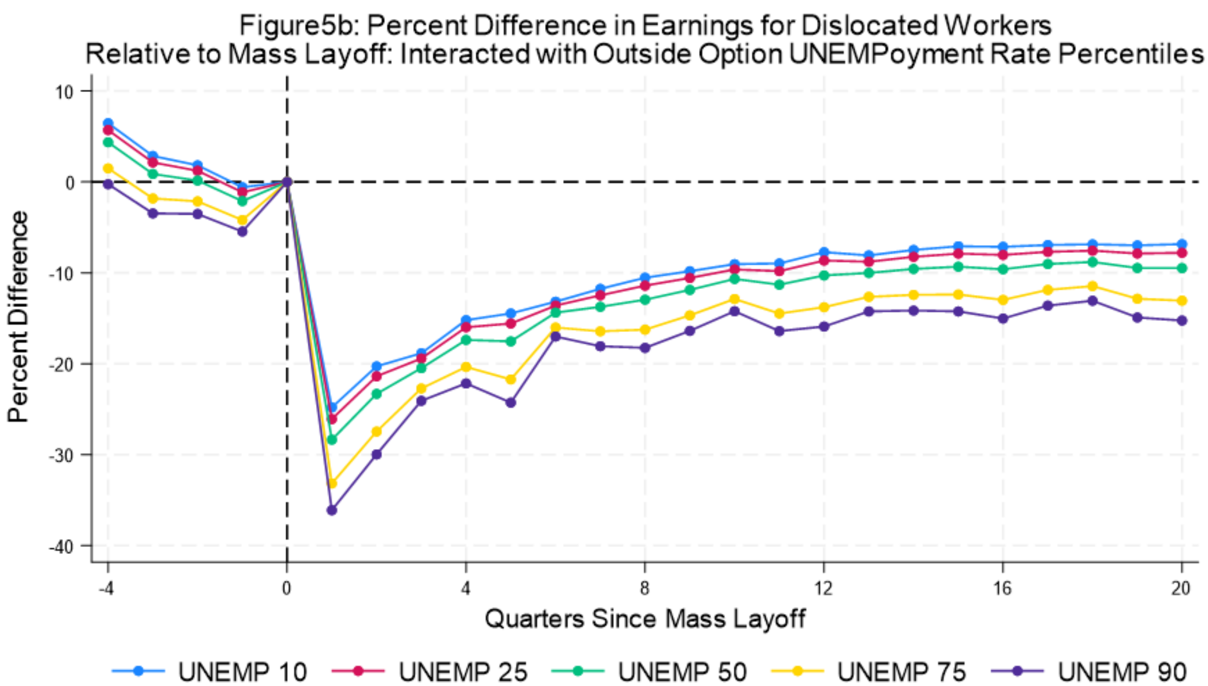
Notes: Calculations from LEHD data. Includes all individuals experiencing mass layoffs for whom we can identify earnings. Differences are relative to earnings in the quarter prior to Mass Layoff. Differences are relative to Comparison Group B in the same industry. Comparison Group B represents workers who were not employed in mass layoff establishments.

Figure 4: Percent Difference in Earnings: Relative to Mass Layoff
Dislocated Workers Based on Re-employment Location



Notes: Calculations from LEHD data. Includes all individuals experiencing mass layoffs for whom we can identify earnings. Differences are relative to earnings in the quarter prior to Mass Layoff. Differences are calculated relative to Comparison Group B. Comparison Group B represents workers who were not employed in mass layoff establishments.





Notes: Calculations from LEHD data. Includes all individuals experiencing mass layoffs for whom we can identify earnings. Differences are relative to earnings in the quarter prior to Mass Layoff and relative to Comparison Group B. Comparison Group B represents workers who were not employed in mass layoff establishments. The underlying regression controls for JOI and HCI.

Figure 6a: Percent Difference in Earnings for Dislocated Workers
Relative to Mass Layoff: Interacted with JOI Percentiles

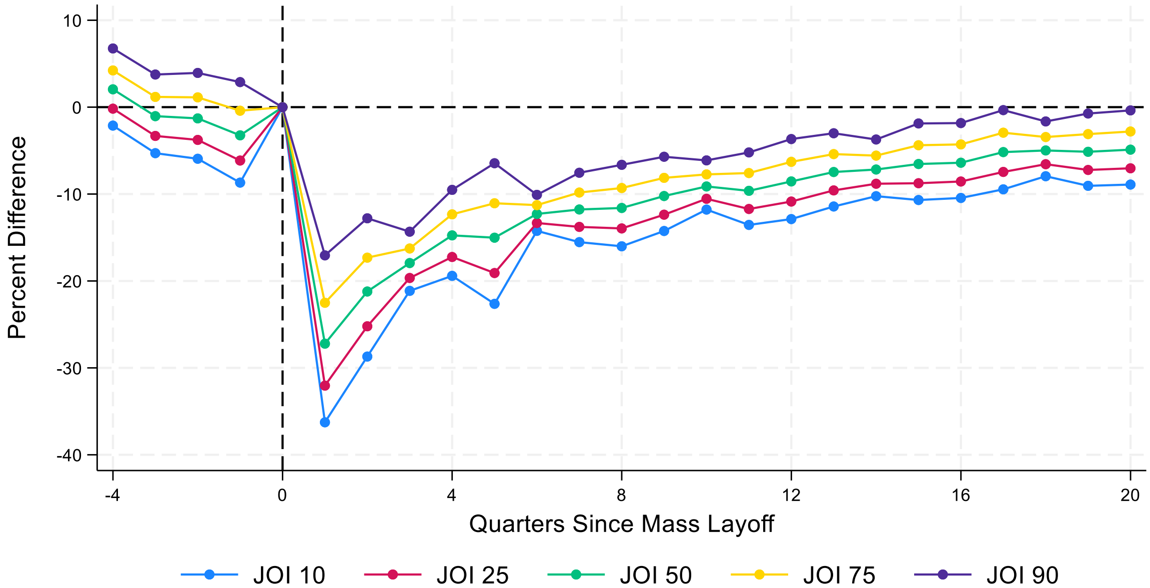


Figure 6b: Percent Difference in Earnings for Dislocated Workers
Relative to Mass Layoff: Interacted with Outside Option JOI Percentiles

Notes: Calculations from LEHD data. Includes all individuals experiencing mass layoffs for whom we can identify earnings. Differences are relative to earnings in the quarter prior to Mass Layoff and relative to Comparison Group B. Comparison Group B represents workers who were not employed in mass layoff establishments. The underlying regression controls for UNEMP and HCI.

Figure 7a: Percent Difference in Earnings for Dislocated Workers
Relative to Mass Layoff: Interacted with HCI Percentiles

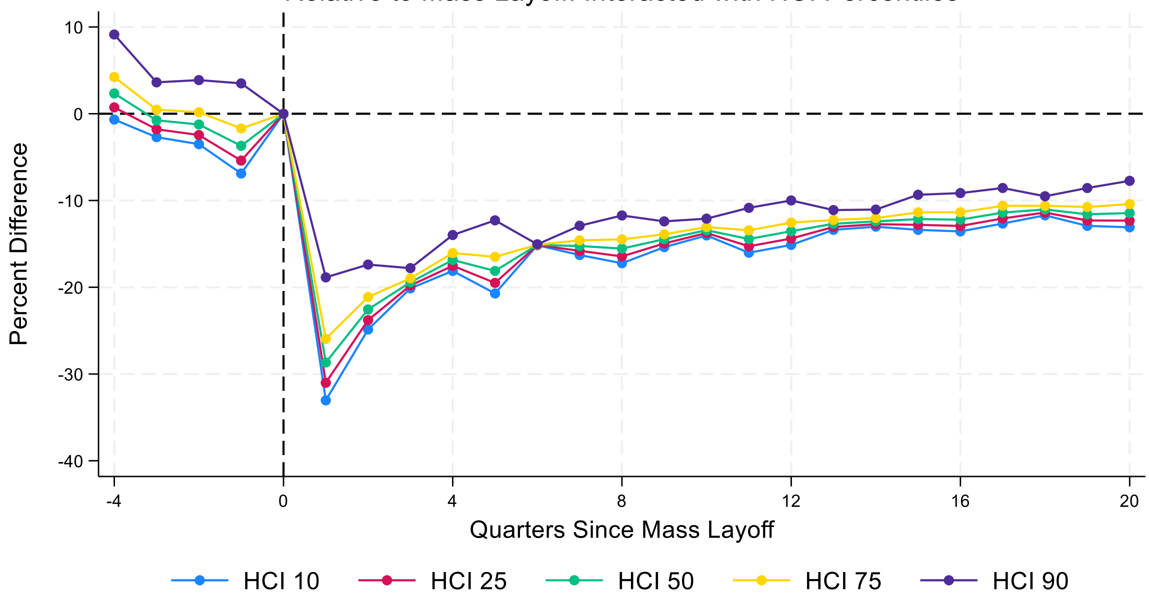
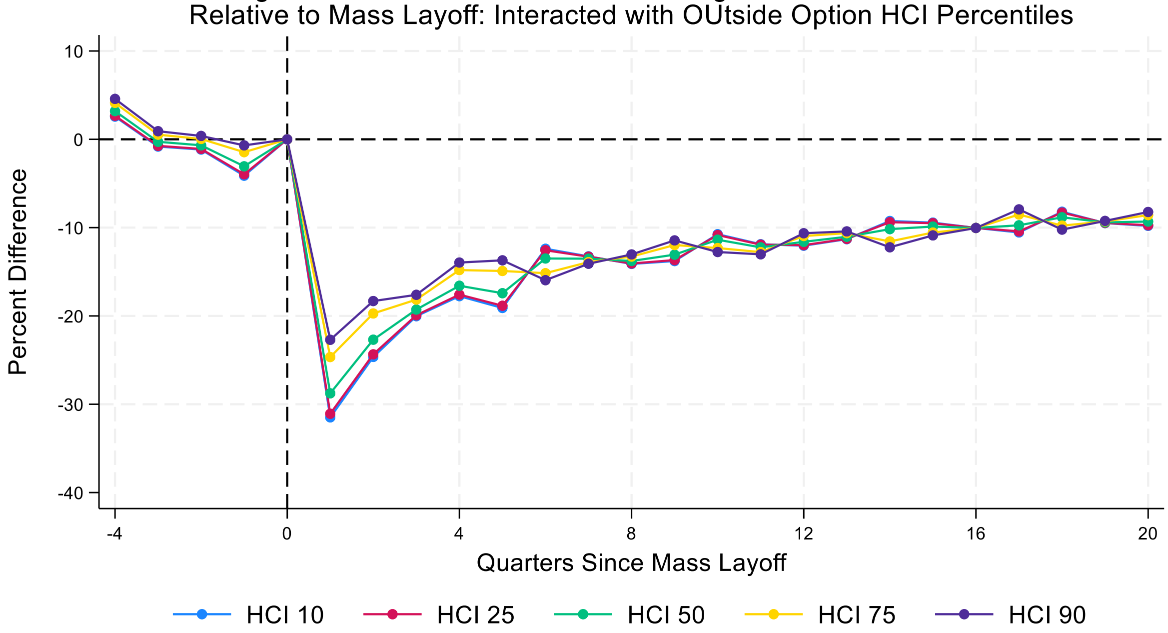
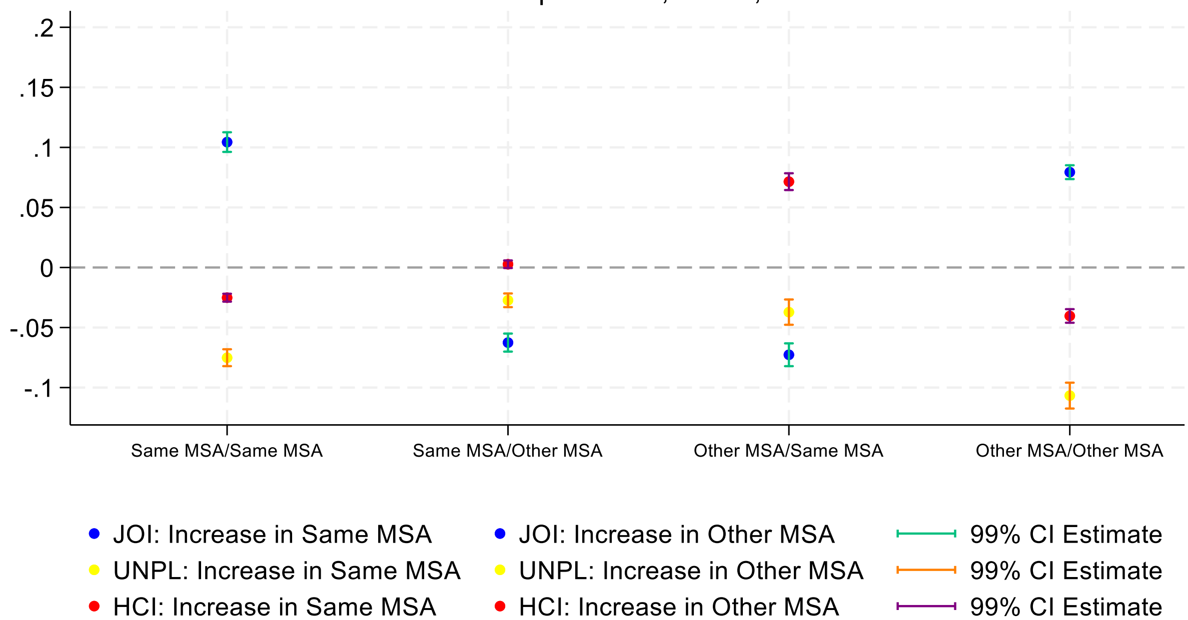


Figure 7b: Percent Difference in Earnings for Dislocated Workers
Relative to Mass Layoff: Interacted with OUtside Option HCI Percentiles



Notes: Calculations from LEHD data. Includes all individuals experiencing mass layoffs for whom we can identify earnings. Differences are relative to earnings in the quarter prior to Mass Layoff and relative to Comparison Group B. Comparison Group B represents workers who were not employed in mass layoff establishments. The underlying regression controls for UNEMP and JOI.

Figure 8
Standardized Coefficients for the Imapct of JOI, UNPL, and HCI on Exit from Joblessness



Notes: Values in this table are resutls from estimating the competing risks model of jobless duration and mobility (equations 2 and 3) using the LEHD data (see Table 3). Indicators on the X axis refer to – (the source of the change)/(the location of the impact). The capped lines around the point estimates are the 99% confidence interval estimates.

Appendix A: Constructing the Job Opportunity Index

We construct the Job Opportunity Index with the publicly available data from the Job-to-Job Flows (J2J) data. The J2J provides the number of hires, separations, total employment, and earnings at the MSA-level for 383 MSAs. Subtotals for these variables can be filtered by 20 hiring firms' NAICS sectors and by 3 categories of worker education level. These subtotals can be used to compute separate job opportunity indices for different industry and education cells of workers.

The Job Opportunity Index is the product of the average wage and the likelihood of getting a job for workers in each MSA in aggregate or in skill (education) cell. The expected wage is the average earnings of J2J job switchers who get a new job in that MSA. We consider four potential ways of calculating the likelihood of getting a job; 1) the number of hires, 2) the number of net hires equal to the number of hires less the number of separations for a given MSA-year, 3) the hiring rate equal to the number of hires divided by employment and 4) the net hiring rate equal to the number of net hires divided by employment.

While the number of new hires alone captures the number of potential new jobs, net hires better captures stable employment as it accounts for separations. As net hires rise with fewer separations, the net hiring rate better indicates hiring that is less likely to be shortly followed by a separation. The net hiring rate provides a gauge of market tightness for workers in each MSA and provides predictive power for wage gains of new jobs in the MSA. The net hiring rate is a better indicator of job opportunity than total net hiring because cities with a greater level of net hiring also are likely to have more competition for the available jobs. By applying to MSAs with larger proportions of net new jobs available compared to total employment, any prospective workers are more likely to find employment.

All this said, what matters is what individuals take into consideration when deciding to move to another MSA. While new hires are likely to be information that individuals can obtain, net hires might be more difficult to do so. The same holds for hires versus the hire rate. Hence, we look at the J2J data to see what measure is better from an empirical standpoint. To gauge their effectiveness, we look at how these measures are correlated with the average change in earnings for workers who are hired in new jobs, an output variable of interest.

Table A1 provides summary statistics for hires, separations, employment, hire rates, net hire rates, and the average percent change in earnings for workers switching jobs in the 383 MSAs from 2001 to 2017. Next, we run regressions of this latter variable on the four potential job opportunity indices. We standardize all variables, so the slope estimates are standardized coefficients. Columns (1), (3), (5), and (7) of Table A2 are results from simple bivariate OLS regressions. Then the coefficient estimates are the sample correlations between the two variables. The even numbered columns include MSA and year fixed effects. Column (9) includes all four measures as explanatory variables.

The estimate in column (1) of Table A2 indicates that a standard deviation increase in an MSA's net hiring rate is associated with a 0.223 standard deviation increase in the percent earnings change for J2J workers in that MSA, on average. When MSA and year fixed effects are included, the estimate is 0.221. The estimate in column (3) of Table A2 indicates that the hiring rate is negatively correlated with the percent earnings change for J2J workers in that MSA, but this coefficient becomes positive and large when the MSA and year fixed effects are included; 0.433. The number of net hires and hires do not show as strong a relationship with the percent earnings change for J2J workers in that MSA. Hence, we limit further analysis to the hiring and net hiring rates.

Table A1: Descriptive Statistics for J2J Data

Variable	Mean	Std. Dev.	Min	Max
Hires (thousands)	30.622	65.05	1.047	876.804
Separations (thousands)	29.485	62.259	0.971	858.367
Net Hire (thousands)	1.138	4.391	-45.627	65.034
Employed (thousands)	276.52	619.426	7.284	8760.782
Hire Rate	.116	0.020	0.058	0.236
Net Hire Rate	.004	0.007	-0.138	0.051
Average % Change in Earnings for J2J Workers	7.311	4.206	-30.777	50.757

Notes: Data drawn from Job-to-Job (J2J) aggregate LEHD data for 2001.

Table A2: Regression results:
Dependent Variable: Standardized Average Change in Earnings for J2J Switchers to MSA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Net Hire Rate	0.315***	0.221***							0.173***
	(0.021)	(0.023)							(0.023)
Hire Rate			-0.012	0.430***					0.241***
			(0.014)	(0.032)					(0.040)
Net Hires					0.091***	0.042***			-0.048***
					(0.013)	(0.013)			(0.015)
Hires							-0.046***	0.333***	0.220***
							(0.010)	(0.061)	(0.070)
MSA Effects	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Year Effects	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Obs.	6879	6879	6879	6879	6879	6879	6879	6879	6789
R-squared	0.099	0.530	0.000	0.525	0.008	0.501	0.002	0.501	0.538
Mean of Dep. Var	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073

Notes: Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Dependent variable in all columns is standardized average change in earnings for J2J workers switching to job in destination MSA. All explanatory variables are standardized so that the coefficient estimates can be interpreted as the number of standard deviations in the dependent variable that are associated with a one standard deviation change in the explanatory variables.

Appendix B: Procedure for Assigning Workers to Establishments

We provide details of the procedure we used to allocate workers to establishments when there are multiple establishments in a firm. This is needed to carry out our analysis at the establishment level since the LEHD only provides worker-level data at the firm level. For multi-establishment firms, we must determine the establishment in the firm where the workers are employed. We rely on the probabilistic method to allocate specific workers to establishments within the firm that was developed by the Census Bureau using results from Minnesota, where unemployment insurance data are reported at both the firm and establishment level (Abowd et al. 2009). The Census provides 10 "imputed establishments" for each worker. These imputations are based on a linear spline in the distance between the worker's residence and the physical location of each establishment in the firm. Thus, an establishment that is a great distance from the firm's other establishments would have 10 identical imputes, and we will be certain that it is the correct one for a given worker. However, in a very high-density urban setting where the firm may have several nearby establishments a worker may have several "imputed" establishments. However, it is important to recall that we only consider establishments with at least 50 workers; thus, we do not have cases with many relatively small establishments. After exploration, we have chosen a cautious approach to minimize measurement error in identifying an appropriate establishment for a given displaced worker: we require seven or more imputes to a given establishment. Workers that have fewer than seven imputes to the same establishment are dropped from our analysis. We believe that this introduces minimal error and is considerably better than carrying out our analysis at the firm level.

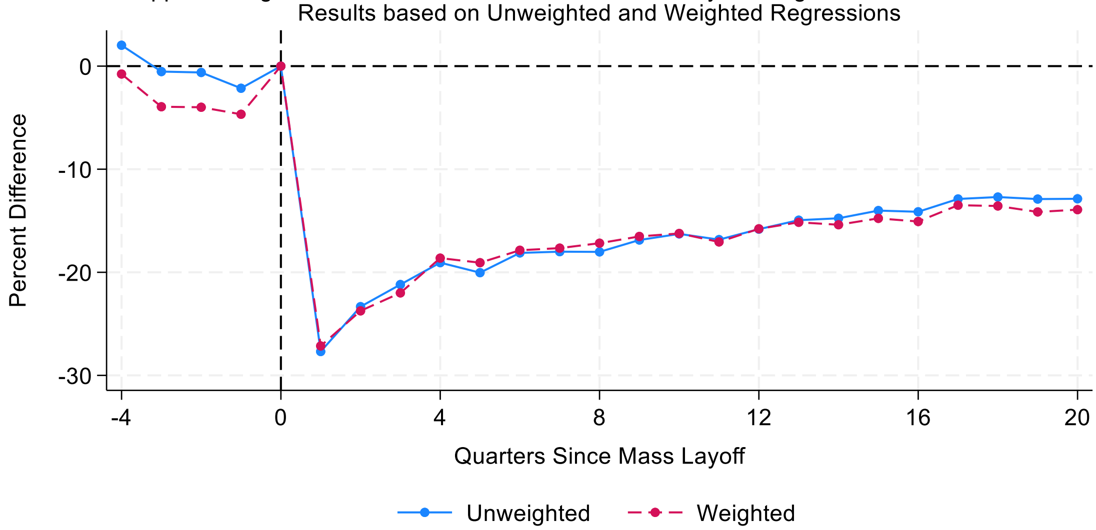
Appendix C: Additional Tables and Figures

Appendix C: Table 1. Characteristics of Workers Leaving before Mass Layoff Event

	All Workers (1)	Displaced Workers (2)	Early Leavers (1-4Q) (3)	Very Early Leavers (5-8Q) (4)
Age				
25-29	0.112	0.130	0.193	0.193
30-34	0.139	0.150	0.164	0.165
35-39	0.162	0.163	0.166	0.167
40-44	0.178	0.173	0.161	0.163
45-49	0.196	0.185	0.159	0.158
50-55	0.214	0.199	0.158	0.154
Earnings				
$15,000-$29,999	0.252	0.312	0.379	0.400
$30,000-$44,999	0.305	0.297	0.284	0.278
$45,000-$59,999	0.192	0.163	0.151	0.153
$60,000-$74,999	0.111	0.092	0.084	0.081
$75,000-$89,999	0.059	0.054	0.043	0.039
$90,000+	0.082	0.081	0.060	0.050
Tenure				
4 Quarters	0.242	0.292	0.480	0.507
5-8 Quarters	0.305	0.336	0.287	0.251
9-16 Quarters	0.162	0.143	0.095	0.118
16+ Quarters	0.292	0.230	0.139	0.124
Race/Ethnicity				
Non-Hispanic White	0.844	0.811	0.792	0.793
Black	0.088	0.111	0.127	0.127
Non-Black Hispanic	0.041	0.046	0.051	0.050
Other	0.028	0.032	0.030	0.030
Gender				
Male	0.641	0.597	0.604	0.599
Female	0.359	0.403	0.397	0.401
Industry				
Extraction/Utilities/Construction	0.092	0.062	0.091	0.093
Manufacturing	0.422	0.349	0.301	0.279
Wholesale Trade/Retail Trade/Transportation	0.139	0.186	0.134	0.144
Information/Finance/Real Estate/Professional	0.209	0.233	0.290	0.295
Education/Health	0.092	0.127	0.120	0.143
Arts/Entertainment/Accommodation/Food	0.022	0.030	0.046	0.032
Other Industry	0.024	0.013	0.017	0.015
Number of Observations	389,000	162,000	108,000	60,500

Notes: Calculations from LEHD data. Earnings are in 2000 dollars. Sample includes displaced workers, early leavers and very early leavers.

Appendix Figure 1: Percent Difference in Real Quarterly Earnings for Dislocated Workers
Results based on Unweighted and Weighted Regressions



Notes: Calculations from LEHD data. Includes all individuals experiencing mass layoffs for whom we can identify earnings. Differences are relative to earnings in the quarter prior to Mass Layoff and relative to Comparison Group B. Comparison Group B represents workers who were not employed in mass layoff establishments. Weighted results are based on inverse propensity score weights.