Size Matters

Matching Externalities and the Advantages of Large Labor Markets

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Abstract. Economists have long hypothesized that large and thick labor markets facilitate the matching between workers and firms. We use administrative data from the LEHD to compare the job search outcomes of workers originally in large and small markets who lost their jobs due to a firm closure. We define a labor market as the Commuting Zone×industry pair in the quarter before the closure. To account for the possible sorting of high-quality workers into larger markets, the effect of market size is identified by comparing workers in large and small markets within the same CZ, conditional on workers fixed effects. In the six quarters before their firm's closure, workers in small and large markets have a similar probability of employment and quarterly earnings. Following the closure, workers in larger markets experience significantly shorter non-employment spells and smaller earning losses than workers in smaller markets, indicating that larger markets partially insure workers against idiosyncratic employment shocks. A 1 percent increase in market size results in a 0.014 and 0.023 percentage points increase in the 1-year re-employment probability of high school and college graduates, respectively. Displaced workers in larger markets also experience a significantly lower need for relocation to a different CZ. Conditional on finding a new job, the quality of the new worker-firm match is higher in larger markets, as proxied by a higher probability that the new match lasts more than one year; the new industry is the same as the old one; and the new industry is a "good fit" for the worker's college major. Consistent with the notion that market size should be particularly consequential for more specialized workers, we find that the effects are larger in industries where human capital is more specialized and less portable. Our findings may help explain the geographical agglomeration of industries--especially those that make intensive use of highly specialized workers--and validate one of the mechanisms that urban economists have proposed for the existence of agglomeration economies.

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1. Introduction

In this paper, we study the job search outcomes of job seekers in large and small labor markets. We focus on workers who lost their jobs due to an exogenous shock and investigate whether involuntarily displaced workers originally in large markets have better search outcomes compared to workers originally in small markets.

Economists have long hypothesized that large and thick labor markets facilitate the matching between workers and firms (Marshall, 1920). In urban economics models, labor pooling and matching externalities have often been assumed to be a potentially important advantage of large cities (Duranton and Puga, 2004). The idea is that in a large and thick market, there are many vacancies for workers to choose from and many job seekers for firms to choose from. If workers have heterogeneous human capital and firms have heterogeneous job requirements, in a large and thick market it should be more likely that job seekers find a job suitable to their human capital.

As a concrete example of this hypothesis, consider a computer scientist specializing in Artificial Intelligence looking for a job in San Francisco vs. Chicago. Because in San Francisco there is a large cluster of high-tech firms while in Chicago the high-tech cluster is small, we define San Francisco as a "large labor market" for computer scientists and Chicago as a "small labor market". Assume that the ratio of job openings for computer scientists to job seekers is the same in the two cities so that labor market tightness is comparable. Due to the market size difference, the overall number of job openings for computer scientists in San Francisco in any given month tends to be larger than in Chicago. Thus, the probability that in a given month one of the employers is looking not just for a computer scientist but specifically for a computer scientist who specializes in AI should be higher in San Francisco on average. This implies that if our job seeker decides to locate in San Francisco, the probability that she finds not just a job as a computer scientist but one with a firm that needs and values her AI specialization is higher. If the same person decides to locate in Chicago, she might have to wait longer for a suitable match or settle for a job in an area of computer science that is a worse fit for her human capital, or both.

In this example, the benefit of market size does not arise because San Francisco has a stronger local economy than Chicago, or more labor demand in the high-tech sector relative to labor supply—labor demand and supply are assumed to be balanced. The benefit of market size stems from the presence of heterogeneity in workers' skills and firms' job requirements. The wider the heterogeneity, the bigger the scope for differences in match quality across employer-employee pairs, and therefore the bigger the expected benefits of large and thick markets. Compare the computer scientist to a janitor. The janitor's human capital is less specialized in the sense that the quality of her output is not as sensitive to the specific employer that hires her. Since variation in match quality is more limited, the ease of finding a suitable job should be less dependent on market size for janitors and, by extension, for other workers whose human capital is not specialized.[1]

This notion implies that large labor markets are attractive to workers—because of the many potential employers—and to employers—because of the many potential employees. In principle, this can potentially lead to self-sustaining spatial agglomeration of workers and firms (Helsley and Strange, 1990). This notion is not just a theoretical curiosity. It has potentially important

[1] Worker heterogeneity is not necessarily limited to skills—it could also reflect their idiosyncratic tastes over employers.

implications for our understanding of key features of the economic geography of the United States and other industrialized countries. For example, it can help explain why in most countries firms and workers display a tendency to cluster geographically by industry. Despite the potential importance of this hypothesis, the empirical evidence is still limited. While there is evidence that is indirectly consistent with this hypothesis, *direct* empirical tests have been less common (with some notable exceptions discussed below). This is surprising because the matching-based theory of urban agglomeration represents one of the three theoretical mechanisms proposed for the existence of agglomeration economies (Duranton and Puga, 2004).

We use administrative longitudinal data from the LEHD matched to the American Community Survey and the 2010 Decennial Census to compare the job search outcomes of workers in large and small markets. We focus on workers who lost their jobs due to a firm closure. Our data include 531,000 workers who lost their jobs in 158,000 firm closures between 2010 and 2017. By focusing on firm closures, we focus on job searches that are presumably caused by an exogenous separation, as opposed to a choice on the part of the worker. We define a labor market as the Commuting Zone×industry pair in which the focal worker is observed in the quarter before the closure and its size as the mean employment in the relevant commuting zone-industry pair over the sample period.

Our models relate labor market size to several post-displacement outcomes: the 1-year reemployment probability; the 1-year percent change in earnings; the probability of relocation to a different CZ; three measures of quality of the new worker-firm match; and the change in spousal employment. We first test the hypothesis that job seekers have better reemployment outcomes if they are originally in a large labor market compared to otherwise similar workers in a small market. We then test the hypothesis that the effects of market size are larger for workers whose human capital is more specialized and less portable across industries. Our models condition on commuting zone fixed effects, estimated worker fixed effects, and a granular vector of local labor market controls.

A key concern is the possibility of positive selection. If large markets offer advantages to job seekers over small markets, as we hypothesize, it is plausible to expect that high-ability workers disproportionally sort into large markets. Comparing workers in large CZs to workers in small CZs is unlikely to yield credible estimates of the effect of market size as there is evidence based on data similar to ours that high-quality workers sort into larger CZs (Card et al., 2023). For this reason, in our models, the effect of market size is not identified by comparing workers in large CZs to workers in small CZs. It is identified by comparing workers in large and small markets who in the quarter before displacement reside *in the same CZ*. The sorting of workers across CZs does not pose a threat in our context because the CZ effects absorb geographical differences in worker quality. There could still be a selection of workers within a CZ across markets of different sizes. If workers employed in large markets have better unobservable characteristics than workers in the same CZ employed in small markets, we would expect to see that they have a higher probability of employment and higher quarterly earnings before displacement, or that employment and quarterly earnings are growing at a different rate.

We begin by presenting a simple visual analysis where we follow the displaced workers over time and examine their employment status, earnings, and mobility in the 6 quarters before the firm closure and the 7 quarters after closure, comparing workers who in the quarter before closure are in a large labor market to those who in the quarter before closure are in a small labor market. Empirically, we find that in the six quarters before displacement, workers in small and large markets have a similar probability of employment and quarterly earnings, both in levels and in trends. As an additional way to evaluate the extent of worker sorting across markets, we investigate the sensitivity of our estimates to controlling for worker fixed effects. While we cannot completely rule out selection, the failure to find significant differences in pre-displacement outcomes and the robustness of our estimates to the inclusion of worker fixed effects indicates that the selection of higher-quality workers into large markets within a CZ, if it exists, is unlikely to be the main driver of our estimates.

Following a firm closure, workers in larger markets experience significantly shorter non-employment spells and smaller earning losses than workers in smaller markets. A 1 percent increase in market size results in a 0.014 and 0.023 percentage points increase in the 1-year re-employment probability of high school and college graduates, respectively. To help interpret the magnitude of this effect, compare the labor market at the 90th percentile of the size distribution with the one at the 10th percentile. Our estimates imply that high school and college graduates originally located in the former enjoy a 6.77 and 10.42 percentage points higher probability of finding a job within 12 months of displacement compared to similar workers originally located in the latter. For earnings, the corresponding 90-10 difference indicates that high school and college graduates originally located in the large market enjoy 7.125% and 12.51% larger changes in earnings 12 months after displacement compared to similar workers originally located in the small market. Relative to the baseline probability of employment and mean earnings, these are economically large effects.

One way in which displaced workers can increase the probability of finding a new suitable job is by moving to a different CZ. Relocation, however, is costly. If before displacement workers tend to be located in the CZ that maximizes their utility given their constraints at that time, a move to a different CZ requires living after displacement in a place that was originally considered sub-optimal. We find that after displacement, workers originally in larger markets experience a lower need for relocation to a different CZ than workers originally in smaller markets. The 90-10 differences in the probability of relocation are -22.75 and -25.89 percentage points for high school and college graduates, respectively.

For displaced workers who find a new job within one year, we test whether the quality of the post-displacement worker-firm match is higher in larger markets. Since we do not directly observe match quality, we employ three indirect proxies. The first is the probability that a worker-firm match lasts more than one year. This measure is based on the assumption that good matches last longer than bad matches. The second measure is the probability that the new employer is in the same 2-digit industry as the old one (Wheeler, 2008; Bleakley and Lin, 2012). The third one measures whether the new employer's 2-digit industry is a "good fit" for the worker's college major. We uncover significant effects of market size on all three measures. High school and college graduates in the market at the 90th percentile are found to be 4.66 (0.021) and 9.41 (0.035) percentage points more likely to find a job that lasts more than one year compared to workers in the market at the 10th percentile. We find a similar effect on the probability of finding a job in the previous industry; and in an industry that is a good fit for the worker's college major, consistent with the hypothesis that jobseekers in large markets are more likely to find employers that value their human capital.

Our last outcome is the change in employment status experienced by the spouse of the focal worker. In large markers, the displaced worker's spouse is found to experience a larger increase in the probability of employment 12 months after the displaced worker's firm closure compared to small markets.

For all of our outcomes but one, the estimated effects are larger for college graduates than high school graduates, possibly because the latter have more specialized human capital. If our hypothesis is true, we should also observe that, for a given level of education, the effect of market size is larger for workers in industries where the average worker has more industry-specific human capital. We classify 4-digit industries based on the nationwide share of workers within a given education group who, following a firm closure, switch to a different industry. Those in low-share industries have a human capital that is, on average, more industry-specific. Since they are tied to one industry, its size should be relatively more consequential for their post-displacement outcomes. By contrast, workers in industries where the share is high have a human capital that is portable across industries, so market size should be relatively less consequential. For example, General Medical and Surgical Hospitals (NAICS 6221) and Scheduled Air Transportation (NAICS 4811) are low-share industries, reflecting the fact that the human capital of surgeons, nurses, pilots, and air traffic controllers is not very portable across industries. We expect the benefits of market size to be larger for them compared to other college graduates with more portable human capital. Empirically, we find that for most (although not all) of our outcomes the effect of labor market size following an involuntary displacement is larger for workers originally in low-share industries compared to workers with the same education originally employed in high-share industries.

We complete our analysis by asking whether industries for which we estimate the benefits of market size to be larger are more spatially agglomerated. For college graduates, we find a positive correlation between the industry-specific effect of market size on the 12-month reemployment probability and the degree of industry agglomeration. We find no significant correlation for less educated workers. While this evidence is descriptive and should be interpreted as merely suggestive, it is consistent with the notion that industries where market size offers the largest benefits to college graduates tend to agglomerate more.

Overall, we conclude that labor market size provides insurance against idiosyncratic shocks to one's employer. Larger city-industry pairs insure workers against idiosyncratic employment shocks by offering a larger pool of potential new employers to choose from. After involuntary displacement, job seekers in large markets find new jobs in a shorter amount of time, experience lower earning losses, and experience less need to move to a different city. Conditional on reemployment, they end up with jobs that last longer and seem a better fit for their human capital. This insurance is particularly valuable to highly educated workers, possibly because their human capital is more specialized. Within an education group, this insurance is particularly valuable for workers in industries where human capital is more specialized and less portable.

In most countries, industries tend to spatially agglomerate, with the amount of agglomeration particularly large in high-tech sectors (Ellison and Glaeser, 1997; Ellison et al. 2010; Duranton et al. 2010; Klepper, 2010; Kerr, 2018; Moretti, 2021). Spatial clustering is typically assumed to arise from three possible forms of agglomeration economies: human capital spillovers, a wider variety of input suppliers, or matching externalities/labor pooling. The evidence in this paper is consistent with the third channel. It is a tangible and intuitive concept—probably more tangible and intuitive than the notion of human capital spillovers, which has received more empirical scrutiny—and it has the potential to explain why workers and firms may find it advantageous to agglomerate geographically. Our findings could be particularly relevant for the clustering of industries that make intensive use of highly educated workers with industry-specific human capital—for example: the financial sector in New York, the high-tech sector in Silicon Valley, Seattle, and Austin; the biotech clusters in Boston, San Diego, and San Francisco; and the aerospace industry in Los Angeles. Despite the high costs of living, highly specialized workers whose human capital is tied to one industry may find these clusters attractive because they raise the probability of finding good matches faster and insure them against employment shocks.[2]

The remainder of the paper is organized as follows. In Section 2 we describe the conceptual framework and summarize the existing empirical literature. In Section 3 we describe the data. In Sections 4 and 5 we present the graphical evidence and discuss identification concerns. Estimates are in Sections 6 to 8. Section 9 concludes.

2. Conceptual Framework and Existing Evidence

2.1 Conceptual Framework

Matching externalities occur if an increase in the number of agents trying to match improves the probability that a match occurs or its expected quality. The intuition can be found in Diamond's (1982) barter model—where the probability of finding a trading partner depends on the number of potential partners available so that an increase in the size of the market makes trade easier—and Salop's (1979) model—where retail establishments locate on a circle and their distance to consumers decreases with their number.[3]

In a model that is closer to our empirical setting, Helsley and Strange (1990) apply this notion to local labor markets with two-sided heterogeneity. Workers have heterogeneous skills described by a point y_i on the unit circle representing the job for which they are best suited. Firms have heterogeneous job requirements described by a point x_j on the unit circle. The output of a worker-firm pair (i,j) is assumed to decline in the distance between worker i's skills and firm j's job requirements:

$$Output_{ij} = \alpha - \beta \, |x_i - y_j| \qquad (1)$$

Where the parameter β is the loss per unit distance caused by the mismatch.[4] Intuitively, a worker-firm pair where the worker skills are close to the employer's requirements is more productive than a pair where skills and requirements are further apart. Thus, the same worker may be highly productive at one firm and completely unproductive at another firm—a key feature of models with two-sided heterogeneity. Workers are perfectly mobile and choose the

[2] An additional implication is that the incentive to spatially agglomerate should be particularly strong for high-tech start-ups, whose employees face particularly high risk of failure and uncertainty. By locating in large markets like Silicon Valley, high-tech start-ups essentially offer a form of insurance to their employees: in case of failure, they can expect to find a new job sooner without having to relocate to a different city.

[3] See also Shapley and Shubik (1971) for one of the first two-sided matching models with transfers.

[4] Alternatively, β can be interpreted as the cost of training a worker to perform a task that requires skills different from her own.

city that maximizes their expected utility. When selecting a city, workers form expectations about the quality of the potential matches that are available in each city based on the number of employers in that city. Similarly, firms form expectations about profits based on the number of workers in each city. In each city c, there are n_c workers employed by m_c firms. In equilibrium, the n_c workers and m_c firms are spread out uniformly on the circle and firms employ the n_c/m_c workers that are closest to their location on the circle.

The key implication of the model is that as more workers or firms enter a labor market, the average distance between firms and workers declines and the output of the mean worker-firm pair rises. This is illustrated in Figure 1. The market on the left has 3 workers and 3 firms and therefore is smaller than the one on the right, which has 10 workers and 10 firms. It is clear that in the latter worker skills are closer to firm requirements and therefore the output of each match is larger. (Like for the example of the computer scientist in the introduction, the figure shows a case where $n_c=m_c$ so that the ratio of workers to employers is the same in the two markets.)

This is the source of agglomeration economies in this setting: in large markets, workers have many potential employers to choose from and employers have many potential employees to choose from and therefore they form matches where worker skills are on average a good fit for firm requirements. By contrast, in small markets workers and firms have fewer options to choose from, and they form matches where worker skills are on average a worse fit for firm requirements. Thus, workers and firms find large cities more attractive, and in equilibrium, land is more expensive in large cities. The agglomeration economy has the characteristics of a local public good. "A firm entering a city improves the expected quality of the match for all workers. No worker can be excluded from the benefits of a better expected match; such benefits are also non-rival" (Helsley and Strange, 1990). Wheeler (2001) develops a model with similar implications.[5]

In this class of models, the benefits of market size crucially depend on the presence of heterogeneity in workers' skills and firms' job requirements. The larger the heterogeneity, the larger the scope for match effects, and therefore the more important the size of the market. Intuitively, if workers and firms are homogenous, there is no scope for match effects. This point is easy to see in Equation 1: if all workers have the same skills ($y_i = \bar{y}\ \forall i$) and all firms have the same job requirements ($x_j = \bar{x}\ \forall j$), the output of each match becomes a constant α - $\beta\ |\bar{x}\text{-}\bar{y}|$, implying that it does not depend on which worker is matched with which firm. In this case, market size does not matter. This insight is testable and will be relevant for our empirical analysis, where we investigate whether the benefits of market size are larger for workers with more specialized human capital and smaller for workers with more homogeneous human capital.

More recently, Lazear (2009) formalizes a result similar to the one in Helsley and Strange (1990) using a completely different setting. In his model, workers have a variety of general skills, and firms vary in their weighting of the different skills so that the skills are firm-specific in the combination demanded. Consider two skills, A and B, which workers can invest in. Worker i with skill set (A_i,B_i) employed at firm j generates output equal to

[5] Duranton and Jayet (2011) propose a model of how the division of labor varies across cities as a function of market size. See also Wasmer and Zenou (2002 and 2006), Caldwell and Danieli (forthcoming), and Hall and Schulhofer Wohl (2018). Duranton and Puga (2004) have a review of the early urban literature on matching, while Chiappori and Salanié (2016) have a review of the literature on matching models outside urban economics.

(2) $$Output_{ij} = \lambda_j A_i + (1- \lambda_j) B_i$$

where $0 \leq \lambda_j \leq 1$ is a firm-specific random variable that reflects how firm *j* weighs the two skills. Just like in Equation 1, here too a worker's output varies depending on the specific employer that hires her. When the market is thin, a skill can be used only by a limited number of firms and thereby it is firm-specific. "As the market thickens, the same skill takes on a general nature", because there are many firms that can use the skill to the same extent as *j*. Lazear's model is not about cities, but it does have implications similar to the Helsley and Strange (1990) model. The expected joint surplus increases in size due to better matching. Moreover, Lazear's model predicts that the earnings loss from involuntary separation is smaller in large markets than in small markets: laid-off workers in large markets are more likely to find a suitable match because more firms are looking for workers with their skills—a prediction that is relevant for our empirical analysis. See also Kim (1989 and 1990).

Krugman's (1991) model of labor pooling is based on a different advantage of large markets, namely the fact that when firms face idiosyncratic shocks, each firm benefits from sharing its labor market with more firms. Idiosyncratic demand shocks do not affect equilibrium wages in large markets, while in small markets wages are higher when firms seek to expand in response to a positive shock, limiting their ability to increase their employment. Since Krugman's model is based on a frictionless labor market, market size benefits firms but not workers. Introducing labor market frictions and unemployment in his setting extends the benefits of labor pooling to workers, a point originally made by Duranton and Puga (2004).

This point is particularly relevant for our empirical application as it implies that workers in large labor markets who lose their jobs due to an idiosyncratic shock to their employer have a higher chance of finding a new job than workers in small markets. Workers have an "incentive to agglomerate to minimize the risk of being unemployed and thus receiving zero income." (Duranton and Puga, 2004). Put differently, in a model of labor pooling with unemployment, market size provides insurance to workers against idiosyncratic shocks to their employer. Losing one's job due to a firm closure is predicted to result in a shorter unemployment spell in a large market than in a small market, a hypothesis that is testable and is central to our empirical analysis where we investigate the length of non-employment duration after a firm closure.

The match effects of the type modeled by Helsley and Strange (1990) and Lazear (2009)—where an increase in the number of agents trying to match improves the expected quality of each match—and the version of the labor pooling model with unemployment—where an increase in the number of agents trying to match improves the probability or speed of matching—are not mutually exclusive. In practice, they can both exist at the same time, so that an increase in the number of agents trying to match increases the probability/speed of matching and, given a match, the average quality of matches. For example, Berliant and Konishi (2000) propose a model that combines both effects and therefore is a useful reference for our purposes.

To sum up: the models discussed here predict that, compared to small markets, large markets should make it easier for workers to find firms that value their specific human capital and for firms to find workers with the human capital that they need. The models yield three testable hypotheses. First, in comparing involuntarily displaced workers in small and large labor markets, those in large markets are expected to have a higher probability of reemployment within a set period of time. Second, conditional on reemployment, the resulting new employer-employee match is expected to be of higher average quality in large markets. Third, market size is expected to matter more for groups of workers with human capital that is specialized and/or specific to a firm or industry than groups of workers whose human capital is undifferentiated.

2.2 Existing Empirical Literature

While there is a wealth of indirect evidence on labor pooling and the effects of large cities, direct empirical evidence on the benefits of labor market size for job seekers is less extensive. Even less extensive is direct evidence based on jobseekers who are involuntarily displaced and therefore did not choose to look for a new job.

In the literature on agglomeration economies, the seminal study—and the study closest to ours—is the paper by Bleakley and Lin (2012). They focus on the frequency of industry and occupation switching and find that workers in denser cities are more likely to change occupation or industry when they are young—presumably because denser cities make it easier to search—but less likely to change when they are old—presumably because they have found a good match. Below, we compare our findings on industry switching to theirs.[6] More recently, Dauth et al. (2022) focus on the relationship between market size and the average quality of the employer-employee match and find that the degree of assortative matching increases in labor market size so that the match between high-quality workers and high-quality plants is significantly tighter in large markets. Unlike this paper, which focuses on two-sided heterogeneity and horizontal matching, they focus on vertical matching. Papageorgiou (2022) finds that workers in larger cities have more occupational options and, consequently, they form better occupational matches.[7] Baum-Snow and Pavan (2012) use an on-the-job search model with endogenous mobility to decompose the city size wage gap into the effect of search frictions and the distributions of the firm-worker match component of wages; sorting; wage-level effects; and returns to experience and find that differences in search frictions and distributions of firm-worker match quality play a limited role.

In the labor economics literature, there is a large literature that studies worker outcomes after a layoff. Existing studies have typically focused on how wage losses vary as a function of the characteristics of the worker, the firm, the industry, or the phase of the business cycle but have mostly ignored the role played by the size of the local labor market.[8] One exception is the

[6] See also the related study by Wheeler (2008).

[7] Duranton and Jayet (2011) show that scarce occupations tend to be over-represented in large cities. Atalay et al. (2022) find that workers in larger markets are more specialized within occupations. Strange et al. (2006) find that firms that face greater difficulty in matching tend to locate in larger markets. Andini et al. (2013) use survey questions that ask Italian workers to assess their current match and find only modest benefits of density. Andersson et al. (2007) and Orefice and Peri (2020) find evidence of a positive relationship between assortative matching and market size, while Mion and Naticchioni (2009) and Figueiredo et al. (2014) find limited support for it in Italy and Portugal. Overman and Puga (2010) find that industries with more idiosyncratic shocks are more spatially concentrated. Marinescu and Rathelot (2018) study spatial mismatch caused by a difference in the location of job openings and job seekers. See also Rosenthal and Strange (2001, 2003 and 2004).

[8] Examples include but are not limited to Jacobson, Lalonde, and Sullivan, 1993; Farber, 1993; Von Wachter, Song and Manchester, 2009; Schmieder and von Wachter, 2010; Couch and Placzek 2010; Hijzen, Upward and Wright, 2010; Davis and von Wachter, 2011; Krolikowski, 2017; Huckfeldt, 2022; Lachowska, Mas, and Woodbury, 2020;

study by Haller and Heuermann (2019), who examine whether the positive effects of urban density are offset by more intense competition between workers and conclude that in Germany the effect of job competition dominates.

This paper is also related to the literature on scale effects in matching functions, where a common (although not universal) finding is that the matching function has constant returns to scale. For example, Layard et al. (1991); Berman (1997) and Yashiv (2000) focus on scale effects at the level of a national labor market. Warren (1996); Anderson and Burgess (2000); and Şahin et al. (2012) focus on industries or occupations. Coles and Smith (1996); Burgess and Profit (2001); Hynninen (2005); Fahr and Sunde (2006); Petrongolo and Pissarides (2006); and Di Addario (2011) focus on cities. While the question in the matching function literature is related to ours, the underlying economic mechanism that links market size to outcomes is different. The econometric models, the outcomes of interest, and the definition of labor market are also different, making its findings difficult to directly compare to ours.

Within the literature on imperfect competition in labor markets, recent studies have focused on the link between labor market concentration and wages (for example, Azar et al., 2022; Benmelech et al., 2022; Hershbein et al. 2018; Rinz, 2022; Qiu and Sojourner 2022; and Arnold, 2021). While our measure of market size may be correlated with measures of employer market power, our paper focuses on a different economic mechanism and different outcomes.

3. Data and Definition of Labor Market Size

Our main data source is the Longitudinal Employer-Household Dynamics (LEHD), which is an administrative dataset derived from quarterly earnings reports provided by employers to state unemployment insurance agencies. The data are at the worker-employer-quarter level. It provides information on the earnings paid by a given employer to a given worker in a given quarter, as well as the employer's location and industry. Except for federal employees and self-employed workers, nearly all employees in the US are included. The main advantage of the LEHD is that it is a longitudinal sample that allows us to follow workers over time. Since it is an administrative dataset, the quality is good, and its sample size is large enough to allow for a detailed geographical analysis. However, it has limited information on worker characteristics. We augment it with information on worker education from the American Community Survey (ACS) and family structure from the Decennial Census. We use unique person identifiers (Personal Identification Keys - PIKs) to link workers who are part of the ACS at some point during the 2001–2017 period or part of the 2010 Decennial Census.

We include LEHD observations from the first quarter of 2010 to the second quarter of 2018. We focus on workers who are 22–62 when first observed in the data and drop workers who are observed for fewer than 8 quarters in the 2010Q1–2018Q2 period. To ensure we capture only full-quarter earnings, we exclude observations in transitional quarters—the first quarter of a "job spell" where the employment relationship may have begun midway through the quarter, and the last quarter of such a spell, where the relationship may have ended mid-quarter. We exclude observations with missing location, industry, education, and demographics. We also exclude

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Schmieder, von Wachter and Heining, 2023; Bertheau et al., 2023; Helm, Kügler and Schönberg, 2022; Rose and Shem-Tov, 2023.

observations where earnings are less than $3,800 as they are below the earnings from a full-time job at the federal minimum wage and observations with multiple employers in a quarter.

Two important limitations of our data are that we cannot distinguish between unemployment and non-participation and we observe only quarterly earnings, not the number of hours worked within the quarter nor the start and end date of an employment spell. Our exclusion of observations with quarterly earnings below $3,800 of quarters with multiple jobs, and transitional quarters should eliminate many but not all part-time and partial-quarter employment spells (Card et al., 2023).

We conduct our analysis on the sample of workers who lost their jobs due to a firm closure occurring in the period 2010 Q1 to 2017 Q3. Since our data include the period 2010 Q1 to 2018 Q2, this allows us to observe a worker's outcomes for at least 4 quarters after her firm closure. To identify closures, we use the State Employer Identification Numbers (SEINs) and look for cases where a firm SEINs disappears. One important issue in this respect is represented by administrative changes of SEINs. In some instances, firms are assigned different SEINs for administrative reasons. To avoid incorrectly classifying administrative changes in SEINs as closures, we exclude cases in which 80% or more of the existing workers are observed being employed together in a different SEIN in the following quarter.[9]

In total, our sample includes 158,000 firm closures and 531,000 displaced workers. (The numbers are rounded due to confidentiality requirements). Since we observe all closures but include in the sample only the subset of workers who are matched to the ACS and Census, the average firm size is not the ratio of these two numbers. The mean of the total number of employees of the firms that close (including all the workers, irrespective of whether they are matched to ACS and Census) is 63.06 and the median is 12.

Appendix Table 1 shows the number of firm closures by year during the period under consideration and the corresponding number of displaced workers in our sample. (The exact numbers are rounded due to the Census' confidentiality policy). Our sample period is one of expansion of the US economy and labor market. The number of closures ranges from 17,500 in 2011 to 24,500 in 2014. The numbers for 2017 are low because our data only include the first two quarters.

Appendix Table 2 reports the mean of the main variables in the quarter before the relevant worker's displacement. The first row shows that all individuals in our sample are employed in the quarter before displacement. This is true by construction: to be included in our sample, workers need to experience displacement at $t = 0$ and therefore are required to have a job at $t =-1$. The average worker has mean quarterly earnings equal to $20,670 and is 46 years old; 44.1% of workers are female, 7.5% are Black and 10.3% are Hispanic. In our analysis, we estimate separate models for workers with a high school degree or less, and workers with a college degree or more. The former group represents 48% of the sample, while the latter represents 52% of the sample.[10]

The geographical unit of analysis is the commuting zone (CZ). We observe both the establishment address and the worker's residential address. The latter comes from the residential files, and is based on tax records, but it is only available at the yearly level. The former is available quarterly. Since we need to assign geographical location in each quarter, we use the location of the establishment to assign workers to a CZ in each quarter. The establishment

[9] See Flaaen, Shapiro and Sorkin (2019) and Schmieder, von Wachter and Heining (2023) for similar sample restrictions based on worker flows.

[10] We do not include workers with some college in our analysis.

address should be a good approximation because CZs are defined precisely so that most residents who live in one also work in it. We restrict our analysis to the 688 CZs that can be identified in the ACS, omitting a small number of very small CZs. The sample includes all U.S. states, although observations for Alaska, South Dakota, and Maine are included only up to 2016Q2, 2017Q1, and 2018Q1, respectively, due to lapsing agreements with the LEHD program.

We define a labor market as a commuting zone×2-digit industry pair and assign it to a worker based on her CZ-industry in the quarter before the firm closure. Consider the case where worker *i* is laid off because of a firm closure in quarter *t*. Let *c* be worker *i*'s CZ at time *t -1* and *j* be *i*'s 2-digit industry at *t-1*. Labor market size S_{cj} is defined as the mean employment over the 2010–2018 period in the commuting zone *c*×2-digit industry *j* pair. Conceptually, the commuting zone×industry pair is probably a better definition of the labor market that is relevant for a displaced worker than the entire commuting zone. For many workers who become involuntarily displaced, a natural starting point for a job search is likely to be the previous industry. In practice, the modal 2-digit industry of the new employer is the same as the 2-digit industry of the previous employer for displaced workers in our sample, likely reflecting a combination of worker preferences, industry-specific training in the previous job, and specialized human capital.[11]

There are 10,500 labor markets in our sample. Table 1 shows the distribution of market size. The mean and median markets have sizes of 20,510 and 3,466, respectively. The 10th, 25th, 75th, and 90th percentiles are 398, 1,103, 12,410 and 43,230. The log difference in size between the 90th and 10th percentiles, which in the rest of the paper we will refer to as the 90-10 difference, is 4.7.

The typical firm closure in our sample period is small compared to the size of its market. In particular, the average firm that closes has employment in the quarter before closure which amounts to 0.3% of its market's total employment. This implies that the direct effect of the average firm closure on local labor market conditions is limited – a point that we will come back to when we discuss the identification of our models.

To illustrate the difference in the number of potential employers that are located near displaced workers in small and large markets, Appendix Table 3 shows the number of firms within a 20-mile radius of the focal worker, by market size. To create the table, we take each displaced worker's residential address in the year before closure, draw a 20-mile radius around it, and count how many firms exist in the industry where she was employed before her employer closure.[12] Throughout the paper, we define large markets as markets in the top 3 deciles of the size distribution and small markets as those in the bottom 3 deciles of the size distribution. The first row indicates that the median number of firms in the same 2-digit industry located within 20 miles of a displaced worker's residence is 640.6 in large markets and 9.3 in small markets. The second and third rows show corresponding figures conditioning on the same 3-digit or 4-digit industry, respectively. The entries in the third row suggest that a displaced worker in a large CZ lives within 20 miles of 62.2 firms in the same 4-digit industry, while the corresponding number for a displaced worker in a small CZ is only 2.0. Overall, the differences in the number of potential employers appear large. While not all firms are necessarily hiring at any moment in

[11] Dauth et al. (2022), find that the benefits of labor market size on match quality are larger when labor markets are defined as city-industry than when they are defined as cities.

[12] This is the only case where we use residential address.

time, the universe of potential employers within 20 miles in a large market is 30 to 70 times larger than in a small market, depending on the level of industry detail.

4 Graphical Evidence

We begin by presenting a simple graphical analysis that compares the evolution over time of our three main outcomes for workers originally in large and small markets. Specifically, we examine the displaced worker's employment status, quarterly earnings, and mobility in the 6 quarters before involuntary displacement and the 7 quarters after displacement. By focusing on firm closures, we focus on job searches that are presumably caused by an exogenous and involuntary separation, as opposed to a potentially endogenous decision on the part of the worker (Jacobson, LaLonde and Sullivan, 1993).

In the literature on worker displacement, a key concern has traditionally been the selection into displacement, namely the possibility that workers who are laid off have worse unobservable characteristics than workers who retain their jobs. In our setting, this is not an issue, since all the workers in the sample are displaced. In our setting, a key concern is selection across labor markets of different sizes. If large markets offer advantages to job seekers over small markets, as we hypothesize, it is plausible to expect that high-ability workers disproportionally select into large markets. The finding that workers in large markets tend to find a new job sooner after displacement or experience smaller earning losses than workers in small markets could simply reflect the fact that workers in large markets are of higher unobserved quality and/or more motivated, rather than the causal effect of market size.

In particular, comparing workers in large CZs to workers in small CZs is unlikely to yield credible estimates of the effect of market size. Using the same data that we use, Card et al. (2023) document that in the U.S. high-quality workers do sort into larger CZs: Using an AKM model that includes worker and firm effects, they find that worker effects tend to be higher in large CZs than in small CZs, suggesting that worker unobserved ability is higher in large CZs—a phenomenon that also has been observed in other countries in previous studies. Furthermore, even if worker unobserved ability was balanced in large and small CZs, a comparison of job search outcomes of workers in large and small CZs is likely to be confounded by the fact that large CZs tend to have a higher cost of living, increasing the incentives for laid-off workers to find and accept a new job sooner rather than later.

Our analysis does not compare workers in large and small CZs because our models condition on CZ effects. The effect of market size is identified by comparing post-displacement outcomes of workers in large and small markets who at the time of displacement reside *in the same CZ*. The sorting of workers across CZs does not pose a threat in our context because the CZ effects absorb all systematic differences in worker quality across commuting zones. Differences in the cost of living are also accounted for.

Of course, there could still be selection of workers within a CZ across markets of different sizes if workers employed in large markets have better unobservable characteristics than workers in the same CZ employed in small markets. In this case we would overestimate the effect of market size because we would attribute the effect of worker quality to market size. To begin assessing this possibility, we compare pre-displacement outcomes in small and large markets. If workers in large markets are positively selected and have better unobservables than workers in small markets in the same CZ, we would expect to observe differences in the probability of employment or quarterly earnings in the quarters leading up to displacement. We will come back to the issue of selection in the next section where we discuss an alternative approach.

We estimate the following model, separately by education group *e*:

$$(3) \quad Y_{it}^{e} = \alpha_e + \sum_{\tau=-6}^{-2} \beta_{e\tau}^{S} D_{\tau}^{S} + \sum_{\tau=1}^{7} \beta_{e\tau}^{S} D_{\tau}^{S} + \sum_{\tau=-6}^{-1} \beta_{e\tau}^{L} D_{\tau}^{L} + \sum_{\tau=1}^{7} \beta_{e\tau}^{L} D_{\tau}^{L} + X_i' \delta_e + d_{ec} + d_{ej} + d_{et} + u_{it}$$

where D_{τ}^{S} is an indicator for whether worker *i* is observed in a small market at t = *-1* interacted with an indicator for time relative to closure, and D_{τ}^{L} is an analogous indicator for large markets. The interaction of the indicators for small market and t = *-1* is excluded. Recall that large and small markets are defined as the ones in the top and bottom three deciles of the size distribution and this definition is time-invariant: we do not use variation over time in market size to identify its effects. The terms $\beta_{e\tau}^{L}$ and $\beta_{e\tau}^{S}$ are the conditional means of the dependent variable in the 6 quarters before the firm closure and the 7 quarters after closure for workers in education group *e* who at *t =-1* are in a large and small labor market, respectively. The vector X_i is a vector of individual controls that includes age, age^2, gender, six indicators for race, Hispanic status, and foreign-born status. The term d_{ec} represents a vector of education-specific indicators for the CZ of residence at t = *-1*. Its inclusion implies that identification of the βs for a given education group is based on *within-CZ* variation in market size. The term d_{ej} represents a vector of education-specific indicators for the industry of employment at *t = -1* which absorbs nationwide education-specific industry differences in post-displacement outcomes. The term d_{et} is a set of education-time dummies defined by the quarter-year of closure.

Throughout the paper, we report standard errors clustered at the commuting zone level, based on the CZ of residence at *t = -1*.

Employment and Earnings. Figure 2 plots the conditional probability of employment before and after closure. The shaded area identifies the quarter when the relevant closure occurs and by construction has no data point. Because our data are at the quarter level, we do not observe the exact calendar day of the closure: It can occur at any point in time within the shaded area. Three features of the figure are worth highlighting.

First, the figure reveals that in the 6 quarters before the closure, the conditional probability of employment in large and small markets is similar, both in levels and in trends. The probability of employment in small and large markets is mechanically balanced at t = *-1* due to the fact that all the workers in our sample are employed at *-1* by construction. (The small difference displayed in the graph at t = *-1* is due to the presence of controls.) In thinking about selection, this implies that there cannot be any significant heterogeneity across workers in the propensity to be employed at t = *-1*. There is no similar constraint in the period between *t = -6* and *t = -2*. A statistical test fails to reject that the estimates for small markets between *t = -6* and *t = -2* are jointly equal to those for large markets, indicating that the probabilities of employment are balanced. The p-values are .541 for high school graduates and .149 for college graduates. The upward trend between *-6* and *-2* reflects the fact that all workers are employed at t = *-1* but they are not necessarily employed in the quarters before *-1*.

A second feature of the figure that is worth highlighting is that, in the first quarter after displacement (*t=+1*) the employment probabilities in small and large markets drop by a similar amount. For high school graduates, the drop in employment probabilities is 88 percentage points in small markets and 89 percentage points in large markets. For college graduates, the corresponding figures are 83 and 82 percentage points.

A third feature is that, in the following quarters, the employment probabilities start to recover, and the pace of recovery is different depending on market size. Workers originally in large markets experience higher reemployment probabilities, indicating that they find new jobs faster, compared to workers originally in small markets. The gap between large and small markets appears larger for college graduates than for high school graduates.[13]

In Figure 3, we turn to quarterly earnings in the 6 quarters before the firm's closure and in the 7 quarters after its closure. The dependent variable in a given quarter is the ratio of the focal worker's quarterly earnings divided by her quarterly earnings at *t=-1*. Thus, the figure compares the within-worker change in earnings in small and large markets.[14]

As before, the similarity of the conditional earnings in large and small markets at t = *-1* is due to the fact that the dependent variable is equal to 1 by definition but the earnings between *t=-6* and *t=-2* are not mechanically balanced. The figure shows that before the closure of the focal worker's firm, workers in large and small markets have similar pre-trends. A statistical test fails to reject that the estimates for small markets between *t = -6* and *t= -2* are jointly equal to those for large markets. The p-values are .218 for high school graduates and .793 for college graduates. Between t = *0* and t = *+1* mean quarterly earnings decline by a comparable magnitude in small and large markets. For high school graduates, they drop by 87-89 percentage points in both large and small markets; for college graduates, they drop by 79-81 percentage points. Staring at t = *+2*, quarterly earnings begin their recovery. Notably, the recovery appears faster in large markets compared to small markets. The difference between large and small markets is more pronounced for college graduates than high school graduates.

Taken together, Figures 2 and 3 provide a useful diagnostic of the hypothesis that, within a CZ, workers in large markets are positively selected. If workers in large markets have better unobservable characteristics than workers in small markets in the same CZ, we would expect to observe *steeper* pre-trends in small markets between *t=-6* and *t=-2*. (Note that this is the opposite of the usual intuition: Since the outcomes at *t=-1* are balanced by construction, better unobserved quality of workers in large markets would imply that workers in small markets have to improve their outcomes at a faster pace between *t=-6* and *t=-2*.) The fact that we do not observe differences in employment or quarterly earnings between *t=-6* and *t=-2* indicates that positive selection into large markets, if it exists, is not quantitatively large. The fact that the

[13] In both large and small markets, the probability of reemployment is lower than what is typically observed in the existing literature on displacement. This reflects the fact that we do not condition on a minimum tenure, so workers in our sample tend to be less attached to the labor force than those in previous studies. In addition, our firm closures involve mostly small firms and are not concentrated in manufacturing.

[14] We cannot use log earnings because log(0) is undefined. We estimated the same model using the inverse hyperbolic sine of quarterly earnings as dependent variable. While the results are qualitatively unchanged, the magnitudes are quite different (available on request). We do not use this transformation as our preferred one because a growing number of studies highlight its limitations in identifying the correct scale of the effect (Bellemare and Wichman, 2020; Mullahy and Norton, 2022; Chen and Roth, 2023).

immediate effect of displacement in the first quarter after closure is comparable in small and large markets is further evidence that worker quality is likely balanced.

We reiterate that this conclusion applies when comparing workers within a CZ and it does not necessarily imply that the probability of employment or quarterly earnings are the same when comparing workers in CZs of different sizes. We also stress that our findings are based on a selected sample of workers who, by construction, are all employed at t = *-1* and therefore are more homogeneous than the population of U.S. workers as a whole. For identification purposes, our sample selection is advantageous because it reduces worker heterogeneity at t = *-1*, making workers in large and small markets more comparable. The disadvantage is that our results only apply to the subset of workers who are employed at *-1* and are displaced due to a firm closure. Their external validity is unknown.

Relocation. One way in which laid-off workers can increase the probability of finding a new suitable job is by searching not just locally but also in other CZs. Relocation, however, can be costly, both economically and psychologically. Moving to a different CZ after displacement requires living in a place that before displacement was considered sub-optimal. If large markets increase the probability of finding a suitable job, we expect to see that displaced workers originally in large markets experience a lower need for relocation than workers originally in small markets.

In Figure 4, the dependent variable is set equal to 1 if the focal worker is observed in a CZ different from the one in which she is observed at t = *-1*. In the quarters before closure, the line for large markets is above the line for small markets, indicating that workers originally in large markets have a higher propensity to relocate compared to workers originally in small markets in the same CZ. By contrast, the opposite pattern emerges after the firm's closure. In the quarters after *t =+2*, workers originally in large markets experience a significantly lower probability of relocation to a new CZ than workers originally in small markets. The difference between large and small markets appears more pronounced for college graduates.

The estimates for quarters *t =-6* to *t =-1* point to the possibility of selection for this outcome. The fact that workers in larger markets display a *higher* probability of mobility before displacement suggests that for this outcome the selection may go against finding an effect of market size. Thus, the estimates of the effect of market size on mobility presented below should be considered as a lower bound (in absolute value).

In the figure, the probability of mobility appears visually very high, especially after displacement, but it is difficult to precisely infer average mobility rates from the Figure due to the inclusion of controls and the difference in sample sizes. The majority of our sample is in large markets and the presence of controls shifts up the line for this group.[15] In this respect, we note that the amount of mobility in our raw data is in line with other sources. For example, in the four quarters before displacement, the unconditional share of workers who are observed changing CZ is 1.93% for high school graduates and 3.06% for college graduates. These

[15] In models that do not include any controls, estimates for the *t-1* period for large markets are mechanically equal to 0 in Figures 2 to 4 (due to the definition of the dependent variable). The inclusion of controls captures the difference in mean covariates between small and large markets and appears to have a negligible impact of the *t-1* estimate for large markets in Figures 2 and 3, but a much larger impact in Figure 4.

numbers are roughly in line with the mobility rates observed in the CPS for the general population.[16] Not surprisingly, mobility in our data increases significantly after displacement, as workers who lose their jobs are more likely to relocate. In the 4 quarters after displacement, the unconditional share of workers who are observed changing CZ is 20.3% for high school graduates and 19.16 for college graduates. These numbers seem generally consistent with the high mobility rates documented in the same period by Card et al (2023), who find that among workers who switch employers (not necessarily due to a firm closure), 33% relocate to a different CZ.

5 Econometric Models and Identification

With this background in mind, we now quantify the magnitude of the effect of market size. We estimate the following model, separately by education group:

$$(4) \qquad Y_i = \beta_e \ln(S_{cj}) + X'_i \delta_e + Z'_{cjet} \alpha_e + d_{ec} + d_{ej} + d_{et} + \gamma_e \hat{d}_i + u_i$$

Our main outcomes are the probability of re-employment at time t = *+4* (one year after displacement); the percent change in quarterly earnings between t = *-1* and t = *+4*; and the probability of relocation to a different CZ between t = *-1* and t = *+4*. Additional outcomes include three measures of the quality of the new worker-firm match at t = *+4*; and the change in employment status of worker *i* 's spouse between t = *-1* and t = *+4*.

Market size S_{cj} and the vector of individual controls X_i are defined above; the vector Z_{cjet} includes time-varying local labor market controls that seek to hold constant the local business cycle and the relevant share of other displaced workers in the market: the BLS unemployment rate in *c* at t = *-1* and its change between t = *-4* and *-1* (the year leading up to the closure); the employment-to-population ratio in *c* at t = *-1* and its *-4* to *-1* change; the share of displaced workers in the relevant CZ-industry-education cell at t = *-1* computed *excluding the focal worker*, and its *-4* to *-1* change.

The term $\hat{d}_i$ is worker *i*'s fixed effect estimated from an AKM model. We use the AKM model in equation (1) of Card et al (2023) and estimate it including all the workers in the LEHD in our sample period—not just workers affected by firm closures.[17] To avoid any mechanical correlation, the subset of workers affected by firm closures is only included in the estimation of the AKM model in the quarters *before* the closure (namely *t=-1* or earlier). The quarters following the closure—which is the period of analysis—do not contribute to the estimation of the fixed effects of our focal workers. Workers who are not involved in firm closures contribute to the estimation of the AKM model because they help identify the firm effects and the coefficients on the individual controls, but their fixed effects are not used in the estimation of Equation 4, since only workers who experience a firm closure are included.

[16] The shares of CPS respondents over age 24 who reported changing counties in 2015 are 3.72% and 3.90% (for High school and College graduates, respectively). The share of employed workers who reported changing counties during the same period was 3.82%. (https://www.census.gov/data/tables/2015/demo/geographic-mobility/cps-2015.html). The comparison is not perfect because counties are smaller than CZs.

[17] It seems a reasonable model to use given that their paper's main identification concern (just like ours) is the possibility of systematic sorting of workers into different labor markets.

We were unable to estimate the standard version of a worker fixed effect model—one that includes worker dummies in Equation 4. There are too few workers in our sample that are observed in multiple labor markets. It is rare for U.S. workers to experience a firm closure, and the number of those who experience two or more closures during our sample period is too small to yield meaningful estimates. Even if their number was larger, it is unclear whether such a sample would be helpful, as it seems questionable that a sample made of workers who experience multiple firm closures is representative.

Because $\hat{d}_i$ is an estimate, OLS standard errors are downward biased since they fail to take into account its sampling variability. For specifications that include $\hat{d}_i$ we report standard errors obtained by bootstrapping.[18]

5.1 Threats to Identification

The assumption needed to ensure that ordinary least squares applied to equation 4 yield unbiased estimates of β_e is that the error term u_i is orthogonal to labor market size S_{cj}. As discussed above S_{cj} is defined as the mean employment over the sample period in the relevant commuting zone-industry pair. Thus, we focus on long-term differences in size and do not use year-to-year variation. The main concerns are the presence of (1) unobserved heterogeneity in worker quality and (2) unobserved heterogeneity in local labor market conditions.

(1) Worker Heterogeneity. If workers are heterogenous in their quality, there are at least two reasons for why the error term u_i could be systematically correlated with market size.

(a) Sorting Across Markets. First, there is the possibility of sorting of higher-quality workers into larger markets, as we discussed in Section 4. Such a threat would be revealed in Figures 2 to 4. The failure to find clear pre-displacement differences in Figures 2 and 3 seems reassuring. Figure 4 indicates that if anything, selection may bias our estimates for mobility against finding an effect of market size.

As an additional way to assess the extent of sorting, we compare estimates of equation (4) that condition on worker fixed effects $\hat{d}_i$ with estimates that do not. If our estimates are mostly driven by the sorting of high-quality workers into large markets within a CZ, we expect to see that models that condition on worker fixed effects yield estimates of the effect of market size that are significantly lower than models that do not. We caution that $\hat{d}_i$ is an estimate, not the true worker effect. While the dataset used to estimate $\hat{d}_i$ is large—as it includes virtually all private sector workers in the US and all their employment spells—$\hat{d}_i$ inevitably measures worker *i*'s quality with error and as such it accounts for worker heterogeneity only imperfectly.

(b) *Differential Attrition.* Another possible source of bias is the differential attrition in the months leading up to the firm's closure. Recall that our baseline sample includes the displaced

[18] For each bootstrap replication, we first estimate the AKM person effects using 100% of the non-displaced worker job spells and an 80% random sample without replacement of displaced worker job spells. We then estimate the effect of market size using each of the bootstrapped person effects and compute the variance of these estimates and sum the variance of the bootstrapped estimates to the variance of the main estimates.

workers who are employed by the closing firm at *t =-1*. We don't require displaced workers to be employed by the closing firm at *t =-2* or earlier. We chose to define our baseline sample this way in order to study differences in pre-trends. Not constraining employment in quarters before -*1* has the advantage that it allows us to test whether the probability of employment in large and small markets is similar.

However, if workers with the best unobservable characteristics anticipate the forthcoming closure and leave in quarters *t =-2* or earlier, those who stay are negatively selected. To see if this is an important source of bias, in a robustness analysis we re-estimated our models using a sample that includes any individual employed at the firm at any moment in time during the four quarters before the firm closure (from *t = -4* to *t = -1*). Our estimates are generally robust, indicating that this type of attrition is not significant, or, at least, it is not correlated with market size.[19]

(2) Heterogeneity in Local Labor Market Conditions. A displaced worker in a labor market where there are many other displaced workers looking for work arguably faces a more challenging task in finding a new job than one in a market with few other displaced workers. The closure of a large employer in a market may raise the number of workers looking for jobs in that market, making it harder for job seekers to find a suitable job, especially if the market is small to begin with. Moreover, firm closures do not necessarily happen in isolation. The contemporaneous closure of several employers in a market may make it even harder for job seekers to find new jobs.

The typical firm closure in our sample is not very large compared to the size of the market. Recall that the average firm that closes in our sample period has employment at *-1* which amounts to 0.3% of its market's total employment. The share of workers involved in all firm closures combined in the average market in the average quarter amounts to 1.31% of total employment, arguably too small to create large negative general equilibrium effects on job seekers. What matters for identification, however, are differences across markets of different sizes: if small markets experience more closures than large markets relative to their size and end up with a higher share of displaced workers, then estimates of the coefficient β_e would confound the effect of market size with the effect of the closures, leading us to overestimate the effect of market size. The opposite bias would arise if large markets experience more closures relative to their size.

To isolate the effect of market size on post-displacement outcomes for workers laid off due to firm closures, it is critical that the share of displaced workers—and, more broadly, the local business cycle—is balanced in small and large markets. Since in our data we observe virtually all the firm closures and the displaced workers in the U.S., we can control for differences across markets in a very granular way. To this end, we have included in the vector Z_{cjet} the share of displaced workers in each CZ-industry-education cell, with the goal of controlling for the presence of other unemployed workers who might be directly competing with the focal worker because they are in the same CZ, have the same level of schooling and were previously employed in the same industry. We have also included the change in such share between *t=-4* and *t=-1*, with the goal to control for its trend over time in the year before the focal

[19] For attrition to introduce bias, it needs to vary systematically as a function of market size, as would be the case if attrition of high-quality workers is more pronounced in smaller markets than in larger markets.

worker is displaced. Z_{cjet} also includes the CZ-level unemployment rate and the employment-to-population ratio, with the aim to control for the overall strength of a commuting zone's labor market at the time when the focal worker is displaced and its trend in the year before. (We include the E/Pop in addition to the unemployment rate because we are concerned that the unemployment rate may be measured with error in small CZs. While the BLS estimates the unemployment rate from a survey, which has a necessarily small sample size in small CZs, our administrative data allow us to see the number of employed workers with precision.)

To further assess the role played by heterogeneity in labor market conditions, in a robustness analysis we investigate what happens to our estimates when we drop labor markets hit by very large negative employment shocks. Specifically, we drop displaced workers who at $t = -1$ are in a labor market where the total number of all displaced workers is particularly large relative to the initial size of the market. Our estimates appear insensitive to this change, suggesting that they are not driven by small markets experiencing a disproportionate share of large negative shocks.

5.2 Industry-Based Measure of Specialization

In additional specifications, we test whether, for a given level of education, our estimates are larger for workers in industries where the average worker has more industry-specific human capital. We classify industries based on how common it is for workers to switch to other industries after involuntary displacement. For each 4-digit industry *j*, we compute the leave-out probability that following a firm closure, workers originally employed in *j* at $t = -1$ are observed employed in a different 4-digit industry in their first job after displacement. For this classification, we use the nationwide sample of workers who are involuntarily displaced in the U.S. due to a firm closure, leaving out worker *i*. We implement this classification separately by education level.

Workers in industries with a high out-mobility share have a human capital that is arguably more portable across industries. Those in industries with a low out-mobility share have a human capital that is more industry-specific (Arnold, 2022; Jäger and Heining, 2022; and Yi et al., forthcoming). Since workers in low-share industries are more tied to their previous industry, the local size of their previous industry should be relatively more consequential for their post-displacement outcomes. By contrast, workers originally employed in high-share industries can more easily look for a job in other industries, and the local size of their original industry should be relatively less consequential.

As examples, consider industries like Offices of Dentists (NAICS 6212); Legal Services (NAICS 5411); Scheduled Air Transportation (NAICS 4811); or General Medical and Surgical Hospitals (NAICS 6221). College graduates in these industries have a low probability of moving to other industries following a firm closure. The probabilities are 15%, 27%, 14%, and 18%, respectively, significantly lower than the average for all workers (40%). Presumably, this reflects the fact that the human capital of dentists, lawyers, pilots, and surgeons is not very portable across industries, in the sense that it has a high return in one industry and a low return in most other industries. We expect the benefits of labor market size to be larger for dentists, lawyers, pilots, and surgeons compared to other college graduates with more portable human capital. More generally, we expect that if our hypothesis is true, the effects of labor market size are larger for workers originally employed in low-share industries than workers with the same education originally employed in high-share industries. Finding otherwise would cast doubt on our interpretation of the rest of the evidence and raise the probability that it may reflect spurious correlations rather than causal effects.

For each education group, we divide industries into quartiles of the out-mobility share—$Q1_{ej}$, $Q2_{ej}$, $Q3_{ej}$, and $Q4_{ej}$—and estimate education-specific models similar to equation (4) where market size is interacted with quartile indicators.

6 Effect of Market Size on Changes in Employment, Earnings and Location

6.1 Employment

In the top panel of Table 2, the outcome variable is an indicator for employment at *t =+4*. The entries in columns 1 and 2 are from models that condition on education-specific CZ effects, industry effects, year-quarter effects, and the vector X_i of individual controls. The coefficients are positive, suggesting that the 12-month probability of reemployment is higher in larger markets. The entries in columns 3 and 4 are from a model that also includes the vector of market-level controls Z'_{cjet}. The estimated coefficients are 0.0177 (0.0038) and 0.0231 (0.0049) for high school and college graduates, respectively. The entries in columns 5 and 6 show the corresponding coefficients from our preferred specification, which includes the estimated worker fixed effect. The sample size is smaller, because the AKM fixed effects are not identified for some workers.[20] The estimated coefficients are 0.0144 (0.0037) and 0.0222 (0.0052), smaller than the corresponding estimates in columns 3 and 4, indicating that the estimates in columns 3 and 4 are slightly upward biased, likely due to the sorting of high-quality workers into larger markets. The entries in columns 4 and 6 are statistically different from each other, while the entries in columns 3 and 5 are not. In both cases the difference in the estimates is not economically large, suggesting that conditional on CZ effects and the other controls, the amount of residual worker sorting is limited.

The estimates in columns 5 and 6 indicate that a 1 percent increase in market size results in a 0.014 and 0.022 percentage points increase in the 12-month probability of reemployment. To help interpret the magnitude of the estimated effect, the next row reports the implied difference in re-employment probability between a labor market at the 10th and 90th percentile of the size distribution. The 90-10 difference in column 5 is 0.0676 (0.0172), indicating that high school graduates in a labor market at the 90th percentile of size—i.e. a very large market—enjoy 6.76 percentage points higher probability of reemployment compared to high school graduates in a labor market at the 10th percentile of size—i.e. a very small market. The 90-10 difference for college graduates in column 6 is larger: 10.42 percentage points. We consider these magnitudes not just statistically but also economically significant. To put these estimates in perspective, we also report the nationwide means of the dependent variable. The 90-10 differences amount to 8.54% and 12.55% of these means.

[20] In particular, we lose roughly 29,000 and 32,000 observations, respectively. The AKM model only estimates firm and worker effects for the largest set of connected firms. Workers can only have person effects estimated if they have observed job spells in connected firms. Since we drop any post-displacement spell for workers in our sample, young displaced workers who started their careers in unconnected firms will likely not have estimated worker effects.

The second panel focuses on the length of the post-displacement non-employment spell, measured in log of quarters. The estimated coefficients are negative, indicating that workers in larger markets experience shorter non-employment spells. The 90-10 differences in columns 3 and 4 indicate that high school and college graduates in a market at the 90th percentile of size experience non-employment spells that are 14.4% and 20.5% shorter compared to similar workers in a market at the 10th percentile of size. The entries in columns 5 and 6 imply smaller effects of 11.2% and 16.5%, respectively.

This is not our preferred specification because the true length of non-employment spells is only observed for workers who find a new job before the end of the sample period. For the others, it is censored and set equal to the number of quarters between $t=-1$ and the end of the sample period. Because of censoring, these estimates are biased. If smaller markets have longer non-employment spells, on average —as indicated by the top panel—the gap between true and observed non-employment spells should be larger in smaller cities. Thus, the estimates based on the censored data should be considered a lower bound (in absolute value). To get a sense of the magnitude of the bias, we have re-estimated our model including only closures that occur in the period 2010 Q1 to 2016 Q2. This sample allows us to observe workers' outcomes for at least 8 quarters after displacement, as opposed to 4 quarters in the baseline sample. We find coefficients that are 10%–11% larger (in absolute value), confirming that the estimates in the bottom panel are biased toward zero.[21]

Overall, Table 2 suggests that large labor markets provide insurance against the risk of non-employment caused by an idiosyncratic shock to one's employer. This insurance comes in the form of faster reemployment and therefore shorter non-employment spells.[22]

Industry Specialization. We expect that, within each education group, the effect of market size is larger for workers in industries where workers tend to have more specialized human capital. We divide industries into 4 quartiles based on the share of workers who switch to a different industry following a firm closure, as described in Section 5.2. In Table 3 we estimate models where the effect of market size is allowed to vary by quartile. The excluded quartile is the first quartile, which includes workers originally in industries with the lowest probability of switching after displacement. The coefficients on the interactions between market size and the identifiers for the second, third, and fourth quartiles are the additional effects for workers originally in industries in the second, third, and fourth quartile and are all negative. Their magnitude indicates that the higher the quartile, the smaller the effect of market size. This appears to be true both in the models without worker fixed effects (columns 1 and 2) and those with fixed effects (columns 3 and 4).

Thus, consistent with our hypothesis, the effect of labor market size seems to be largest for workers originally in industries with the lowest probability of out-mobility, and it declines

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[21] For example, the coefficients for the models in columns 3 and 4 are -0.033 (0.008) and -0.048 (0.011), respectively.

[22] In additional specifications, we have further subdivided the college graduates into those with just a 4-year college education and those with a post-graduate education, such as a master's degree or a Ph.D. We find that the estimates for workers with a post-graduate education tend to be significantly larger than those for workers with a 4-year college education. For example, in models where the dependent variable is the 12-month probability of re-employment, the coefficients are 0.0180 (0.0050) and 0.0361 (0.0060), respectively. In models where the dependent variable is the length of non-employment, the coefficients are -0.0325 (0.0102) and -0.0737 (0.0143). This finding likely reflects the fact that the human capital of workers with a master's or Ph.D. is on average more specialized than the human capital of workers with a college degree.

monotonically as the probability of out-mobility increases. We stress that this is true within a given schooling level and for a given market size. In columns 2 and 4, for example, we are comparing college graduates with more industry-specific human capital to college graduates in a market of similar size with less industry-specific human capital.[23]

Functional Form. An interesting question is what is the functional form that relates reemployment probability to market size. Equation 4 assumes that the effect is a linear function of the logarithm of market size, implying that the probability increases in market size at a declining rate (a concave relationship). To visually see the amount of concavity implied by our estimates, Figure 5 plots the predicted probability of reemployment in 12 months against market size, when size is measured in number of workers in a market (as opposed to its logarithm), using the estimates in columns 5 and 6 of Table 2 (top panel). For reference, the three vertical lines mark the 25th, 50th and 75th percentiles of the size distribution. The lines are helpful in seeing where the bulk of the sample is located.

Both for high school graduates and college graduates the slope of the curve declines with market size. In particular, the concavity appears quite pronounced for sizes below the 75th percentile, which is the range of market size where most of the sample is located. The slope is still positive for the largest markets in the observed range, but it is considerably smaller than the slope for the markets below the 75th percentile.

6.2 Earnings

In Table 4, we focus on changes in quarterly earnings after displacement. The dependent variable is the percent change in the quarterly earnings between $t = -1$ and $t = 4$ measured as $(Y_4 - Y_{-1}) / Y_{-1}$. Thus, the dependent variable is the within-worker change in earnings experienced one year after displacement relative to before displacement. The coefficients in columns 3 and 4 are 0.0211 (0.0054) and 0.0500 (0.0153) for high school and college graduates, respectively. The corresponding coefficients in columns 5 and 6 are smaller but remain economically sizable: 0.0152 (0.0054) and 0.0267 (0.0105). These estimates can be interpreted as elasticities and indicate that a 1 percent increase in market size is associated with a 0.015 and 0.027 percent increase in post-displacement earnings for high school graduates and college graduates, respectively. The 90-10 differences are economically large: In columns 5 and 6 they are 7.12% and 12.51%, respectively.

Table 5 reports the estimates by quartile of industry specialization. For high school graduates the magnitude of the effect on earnings increases monotonically as a function of the quartile. The coefficients on the interaction between market size and the identifiers for the second, third, and fourth quartiles are all negative, and their magnitude indicates that the higher the quartile, the smaller the benefits of market size. However, contrary to our hypothesis, this does not seem to be true for college graduates, for whom the interactions terms are not statistically different from zero.

[23] These findings are consistent with Jäger and Heining (2022) and Sauvagnat and Schivardi (2024) who show that the cost of replacing a worker who dies is larger in thin markets when their skills are specialized; and Yi et al. (forthcoming), who show that workers adjust better to negative shocks when located in labor markets that value their industry-specific human capital.

Conceptually, the length of non-employment and the quarterly earning loss are jointly determined, as jobseekers trade off the length of non-employment and earnings. For example, a worker may decide to accept a less-than-ideal salary over the expectation of a better salary later, while another worker may decide to turn down a less-than-ideal salary at the cost of remaining non-employed for longer. Our approach is to study each outcome in isolation, for a given time horizon. This choice does not compromise the internal validity of our estimates, but it does affect their interpretation and it is important to keep in mind when thinking about the magnitude of our estimated parameters.

Market size affects quarterly earnings either because it affects the speed of reemployment, or because it changes the salary conditional on reemployment. To see which of these two channels is responsible for the overall effect uncovered in the top panel, we estimate the same models dropping workers who are non-employed by $t = 4$. Entries are small and not distinguishable from 0, indicating that market size does not affect the post-displacement change in quarterly earnings for workers who find a new job. For example, the entries corresponding to the models in columns 3 to 6 are 0.0028 (0.0037), 0.0170 (0.0189), 0.0017 (0.0036) and 0.0006 (0.0148). This implies that most of the effect of market size on quarterly earnings uncovered in Table 4 is due to changes in the probability of reemployment within four quarters, rather than changes in quarterly earnings conditional on reemployment. (This finding is consistent with the similarity of Figures 2 and 3 above). Since the dependent variable is the within-worker earnings *change*, this is not surprising. Our hypothesis is that a large market allows displaced workers to find a new job sooner after displacement and, conditional on finding a job, it may result in an employer-employee match of higher quality. While a high-quality match may imply a higher salary in larger markets on average, the same logic suggests that the initial match before displacement is also of higher quality in larger markets. Our hypothesis does not have specific predictions for how the within-worker change in earnings conditional on employment should vary as a function of market size. While the reservation wage should depend on market size (Petrongolo and Pissarides, 2006), there is no expectation that the change in reservation wage should necessarily depend on market size.[24]

6.3 Relocation

In Table 6, we quantify the effect of market size on the probability of relocation after displacement. The dependent variable is an indicator for whether at $t = +4$ the focal worker is observed in a CZ different from the CZ she was observed at $t = -1$.[25] The coefficients are negative, confirming that the probability of relocation after displacement is lower in large markets. The entries in columns 3 and 4 are -0.0476 (0.0044) and -0.0541 (0.0057) for high school and college graduates, respectively. The corresponding coefficients in columns 5 and 6 are slightly larger, but economically quite similar: -.0484 (0.0047) and -0.055 (0.0062).

[24] If we estimate the models in columns 5 and 6 using log quarterly earnings one year after displacement as a dependent variable (the level, not the change) we uncover positive estimates: 0.031 (0.005) and 0.038 (0.008) for high school and college graduates, respectively, indicating that one year after their firm closure, displaced workers in large markets who find a new job have a higher level of quarterly earnings than those in small markets.

[25] We exclude workers who are never reemployed after displacement, since employment is needed to observe location.

The 90-10 differences indicate that, quantitatively, these are large effects. Based on columns 5 and 6, high school and college graduates in markets at the 90th percentile are estimated to have 22.8 and 25.9 percentage points lower probability of having to relocate to a new CZ after displacement compared to high school and college graduates in markets at the 10th percentile, respectively.

Table 7 reports the estimates by quartile of industry specialization. We find that the estimated effect of market size on relocation in absolute value is largest for the industries in the first quartile and smallest for industries in the fourth quartile. This is true both for workers in the high school group and workers in the college group. However, the coefficients for industries in the second and third quartiles are not statistically different from the ones for industries in the first quartile.

In principle, mobility can be particularly costly for married workers, since changing cities may be disruptive of spousal employment, although it is not obvious that this additional cost should necessarily vary by market size. To explore whether it does, we estimated a model where we added the interaction between market size and an indicator for being married. We find that the effect of market size does not appear to be particularly sensitive to marital status.[26] We caution, however, that our measure of marital status contains a non-trivial amount of measurement error because we observe marital status only in 2010. For most of the sample, this information is stale due to divorces and separations. Thus, this finding is difficult to interpret, as it may reflect attenuation bias.

A limitation of our data is that Alaska, South Dakota, and Maine are included only up to 2016Q2, 2017Q1, and 2018Q1, respectively, as discussed in the Data Section. This introduces measurement error in our measure of mobility, because we miss mobility to CZs in states not included in our data. In 2015, these three states account for only 1.2% of displaced workers, arguably too small of a share to make a large difference. Empirically, our results are robust to dropping states contiguous to these three states.

6.4 Robustness

Differential Attrition. To deal with the possibility of differential attrition in the months before closure, in columns 3 and 4 of Appendix Table 4, we report estimates based on a sample that includes among the set of displaced workers all individuals who worked at the closing firm at any point in time in the four quarters before closure. Our estimates are generally similar to the ones from the baseline sample in columns 1 and 2, which include workers who were employed at the closing firm in the quarter before closure. We infer that differential attrition is not an important source of bias.

Dropping Cells with Large Share of Displaced Workers. In columns 5 and 6 of Appendix Table 4, we drop observations in markets with a particularly large share of displaced workers. Specifically, we drop displaced workers who at $t = -1$ belong to a CZ-industry cell where the ratio of the number of displaced workers over initial total employment is in the top 5 percent of

[26]The coefficients on the interaction are 0.0003 (0.00019) and -0.0006 (0.00019) for high school and college graduates, respectively.

the distribution. Results are similar to our baseline estimates in columns 1 and 2, suggesting that our estimates are not driven by labor markets that experience particularly large negative shocks.

7 Additional Outcomes

7.1 Match Quality

The LEHD contains no variable that directly measures the quality of an employer-employee match. We employ three indirect proxies.

(A) Match Lasts More than 1 Year. In Panel A of Table 8, we study the probability that within one year of closure, the displaced worker finds a job that ultimately lasts more than 12 months. This measure has an intuitive appeal because the length of an employer-employee match is presumably correlated with job satisfaction on the part of the worker and with satisfaction on the part of the employer. Matches where the employee or the employer is unhappy are likely to be short. At the same time, this measure is not perfect because the length of a match depends not just on the match quality, but also on the availability of outside opportunities that a worker faces. If larger markets offer more outside opportunities than smaller markets—as we hypothesize—then the probability that a match lasts at least 12 months will be smaller in large markets for a given level of job satisfaction. Thus, estimates in Panel A need to be interpreted as a lower bound of the true effect of market size.

We find that after involuntary separation, workers originally in large markets are more likely to find a job that lasts more than one year compared to workers originally in small markets. The coefficients in columns 3 and 4 are 0.0147 (0.0045) and 0.0270 (0.0076). The ones in columns 5 and 6 are significantly smaller: 0.0099 (0.0045) and 0.0201 (0.0075). The corresponding 90-10 differences are 4.66 and 9.41 percentage points. When scaled relative to the means of the dependent variable, these differences are 8.7% and 17.1% respectively, arguably large effects.

(B) Same Industry. The dependent variable in Panel B is an indicator for whether a focal worker finds a job within 1 year of displacement that is in the same 2-digit industry as the one at $t = -1$. As pointed out by Wheeler (2008) and Bleakley and Lin (2012), if workers accumulate industry-specific human capital, finding a job in the same industry may be desirable. Consistent with the hypothesis that market size increases the probability of finding a job in the previous industry, the coefficients in columns 3 and 4 are 0.0487 (0.0062) and 0.0299 (0.0078). The coefficients in columns 5 and 6 are not too different—0.0452 (0.0062) and 0.0331 (0.0075), respectively—and the corresponding 90-10 differences are 21.2 and 15.5 percentage points. This is the only case where the estimated benefit of market size is found to be larger for high school graduates than for college graduates, and we do not have a clear intuition for why it may be the case.

Our estimates are somewhat smaller than but generally consistent with the estimates by Bleakley and Lin (2012) for the case of workers with any experience.[27] In additional models,

[27] They estimate that a one-standard-deviation increase in density results in a decrease of one-third of a standard deviation in industry switching. Our estimates in columns 3 and 4 imply that a one-standard-deviation increase in market size results in a decrease of 0.18 and 0.11 of a standard deviation in the probability of being employed within a year of displacement in a different industry for high school graduates and college graduates, respectively.

Bleakley and Lin (2012) find that the effect of city size is positive for more experienced workers but negative for less experienced workers. On this point, our findings differ. If we interact market size with an indicator for whether the focal worker's potential experience is above 15 years, we find the coefficients on the interaction to be negative: -0.00498 (0.000520) for high school and -0.00171 (0.000426) for college. We find a similar result for the two other proxies. The difference with Bleakley and Lin on this point may reflect the difference in the specifications and the definitions of market size: They conduct their analysis at the MSA level and focus on metro area population density while we focus on employment in a CZ-industry cell and conduct the analysis within a CZ.

(C) College Major. The third proxy is a measure of how well the industry of the focal worker's new employer after displacement fits the focal worker's college major. Intuitively, one may expect that the Information industry (NAICS 51) is a good match for workers with a Computer Science major but not necessarily for those with a Library Science major; while the Educational Services industry (NAICS 61) is a good match for workers with a Library Science major but not necessarily for those with a Computer Science major. We classify a 2-digit industry *j* as a good fit for college major *m* if workers with that major employed in *j* are observed earning conditional quarterly earnings above the median for workers with major *m*. Specifically, we estimate the following regression: $\log(W_{imj}) = d_{mj} + b_m X_{imj} + e_{imj}$ where W_{imj} is quarterly earnings; X_{imj} is the vector of individual controls defined above; and d_{mj} is a vector of college major-industry interactions that identifies conditional quarterly earnings of workers with major *m* in industry *j*. We estimate this model separately by college major using all workers with a college degree or more in the LEHD-ACS sample (not just displaced workers) and define industry *j* to be a "good match" for major *m* if $d_{mj} > m$'s median.

In the bottom panel of Table 8, the dependent variable is a dummy equal one if the focal worker finds a job within 1 year of displacement that is a "good match" based on this definition. Obviously, estimates are only available for college graduates. The entries indicate a positive effect of market size on the probability of finding a job that is a good match. The coefficient in column 4 is 0.0256 (0.0053), while the one in column 6 is 0.0233 (0.0055). The 90-10 difference indicates that displaced workers in markets that are at the 90th percentile of the size distribution are 10.9 percentage points more likely to find a job that is a good match for their college major compared to workers in markets that are at the 10th percentile of the size distribution. This difference amounts to 18 percent of the mean of the dependent variable.

None of our three measures of match quality is a perfect measure, therefore we cannot draw definitive conclusions. But taken together, the estimates in Table 8 are at least consistent with the notion that employer-employee matches in larger markets are better than matches in smaller markets. Table 9 shows the estimates by quartile of industry specialization. The estimated effects are the largest for the industries in the first quartile, as expected. The bottom part of Appendix Table 4 shows the robustness analysis.

7.2 Change in Spousal Employment

The focal worker's dismissal can affect her spouse's employment status through at least two channels, both of which could depend on market size. First, the job of a spouse who at the time of the focal worker's displacement was employed could be disrupted if the family decides to relocate to a different CZ following the focal worker's layoff (Jayachandran et al., 2023). Since the probability of relocation was found to be lower in large markets compared to small markets, the risk of disruption of the trailing spouse's employment may be lower in large markets. Second, a spouse who at the time of the focal worker's displacement was not employed could decide to start working after the focal worker's displacement to offset the focal worker's earning losses. Because the probability of finding a job within a given time period was found to be higher for focal workers in large markets, it is conceivable that the probability that their spouses find a job within a time period is also higher in large markets. Both channels would imply that following the displacement of the focal worker we could observe a larger increase in the probability of spousal employment in large markets compared to small markets.

The dependent variable in Table 10 is the change in the employment status of the focal worker's spouse between $t = -1$ to $t = +4$ measured as $(E_{i+4}) - (E_{i-1})$ where E_{i+4} and E_{it-1} are indicators for whether the spouse of the focal worker *i* is employed 4 quarters after *i'*s displacement and the quarter before *i*'s displacement, respectively. Unlike the focal workers, their spouses are not necessarily employed at $t = -1$[28], thus the dependent variable can take values -1, 0, and +1. The Table shows that in large markets, the displaced worker's spouse experiences a larger increase in the probability of employment 12 months after the displaced worker's firm closure compared to small markets. The coefficients in columns 3 and 4 are 0.0047 (0.0016) and 0.0016 (0.0013) for high school and college graduates, respectively, where education is the education of the spouse, not the focal worker. The 90-10 differences are 2.19 and 0.74 percentage points, respectively. In results available on request, we find that the increase in the probability of spousal employment in large markets is visible among movers and stayers, suggesting that both potential explanatory channels may play a role.

We stress that an important limitation of this analysis is that the identity and employment status of the spouse are observed with considerable measurement error in our data. As mentioned above, the information on the identity of the spouse comes from the 2010 Decennial Census and therefore is precise only in 2010, which is the year in which the focal worker in the LEHD is matched with the Decennial Census responses. In later years, the information becomes stale due to divorces and separations.[29]

8. Market Size Effects and Industry Agglomeration

An interesting question is whether the benefits of market size that we have uncovered in our analysis lead workers and firms to agglomerate spatially in industry clusters. As a way to offer some preliminary, descriptive evidence on this question, we examine whether the industries

[28] We assign spouses to the industry in which they were last employed, as long as the spouse was last employed within 2 years of the time of the focal worker displacement.

[29] The longer the period between 2010 and the time of the focal worker's firm closure the more imprecise the information on the spouse becomes. To assess the effect of measurement error caused by divorces after 2010, we tried re-estimating our model on a sample of closures before 2013. In this sample, the identity of the focal worker's spouse is observed no more than 3 years before the focal worker's displacement. (By contrast, in the full sample, the identity of the focal worker's spouse is observed up to 8 years before the focal worker's displacement.) The estimates are too noisy to be informative.

for which we estimate the benefits of market size to be large tend to be more geographically agglomerated than industries for which we estimate the benefits of market size to be limited. Specifically, we re-estimate Equation 4 separately for each 2-digit industry and education group using the 1-year reemployment probability as an outcome and obtain industry-specific coefficients β_{ej} for each education group. We then correlate these estimates with a measure of spatial agglomeration, namely the share of industry employment that is concentrated in the top 5% of CZs by that industry employment. Industries, for which this share is high are more spatially concentrated than industries for which this share is low. If industries for which the benefits of market size are estimated to be larger tend to be more spatial agglomerated, we should expect to see a positive correlation. The correlation does not need to be the same for high school and college graduates. If industry agglomeration reflects the benefits of market size for college graduates more than high school graduates, the correlation may be stronger for the former group than the latter. For this analysis, we focus on tradable industries, since the localization of non-tradable industries likely reflects different economic forces.[30]

In Figure 6, we plot the estimated β_{ej} on the x-axis and the industry shares on the y-axis. The Figure shows a positive correlation for college graduates, with a slope equal to 5.07 (2.73); and a lack of significant correlation for high school graduates, with a slope equal to 1.46 (4.02). The evidence appears to be consistent with the hypothesis that tradable industries where college graduates enjoy larger post-displacement benefits from spatial agglomeration tend to be more geographically agglomerated than tradable industries where college graduates enjoy smaller post-displacement benefits. By contrast, there is little evidence that industry agglomeration is associated with post-displacement benefits for high school graduates.

This evidence needs to be interpreted as suggestive at best. For once, even for college graduates the slope is significant only at the 10% level. More importantly, the correlation could be spurious, in the sense that there could be unobserved industry characteristics that affect the relationship between market size and non-employment duration after displacement that are correlated with industry concentration. A causal analysis of the effect of the benefits of market size on industry agglomeration is an interesting question for future research.

9. Conclusions

In the six quarters before their firm's closure, future displaced workers in large markets have similar probabilities of employment, mean quarterly earnings and a higher propensity to relocate to a new CZ than displaced workers in small markets in the same CZ. But after their firm closes, displaced workers in larger markets experience a shorter non-employment spell, smaller earning losses and a lower probability of relocation than workers in smaller markets in the same CZ. The implied differences between large and small markets in non-employment duration, earning losses and probability of relocation are economically significant. Thus, labor market size appears to provide insurance against a negative shock to one's employer. This insurance appears more valuable to workers with more specialized human capital. We also find

[30] The twelve 2-digit NAICS industries considered tradable in this analysis are: 11 (Agriculture, Forestry, Fishing and Hunting), 21 (Mining, Quarrying, and Oil and Gas Extraction), 31-32-33 (Manufacturing), 42 (Wholesale Trade), 48-49 (Transportation and Warehousing), 51 (Information), 52 (Finance and Insurance), 54 (Professional, Scientific, and Technical Services), 55 (Management of Companies and Enterprises).

that conditional on finding a match, the quality of the new match is better in large markets when match quality is measured using whether the match lasts one year or more, the displaced worker is reemployed in the same industry, or the industry of the new employer is a good fit for the worker college major.

We conclude that large markets provide concrete economic advantages to job seekers in the form of improved likelihood of a match and increased quality of the match. These advantages are larger for groups of workers whose human capital is more differentiated and specialized and more limited for workers whose human capital is less specialized and more homogeneous. Overall, our evidence is consistent with the existence of self-reinforcing agglomeration economies stemming from matching externalities. Our findings empirically validate one of the three theoretical mechanisms that urban economists have long proposed for the existence of agglomeration economies but have not directly tested.

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Figure 1: An Example of a Large and a Small Labor Market

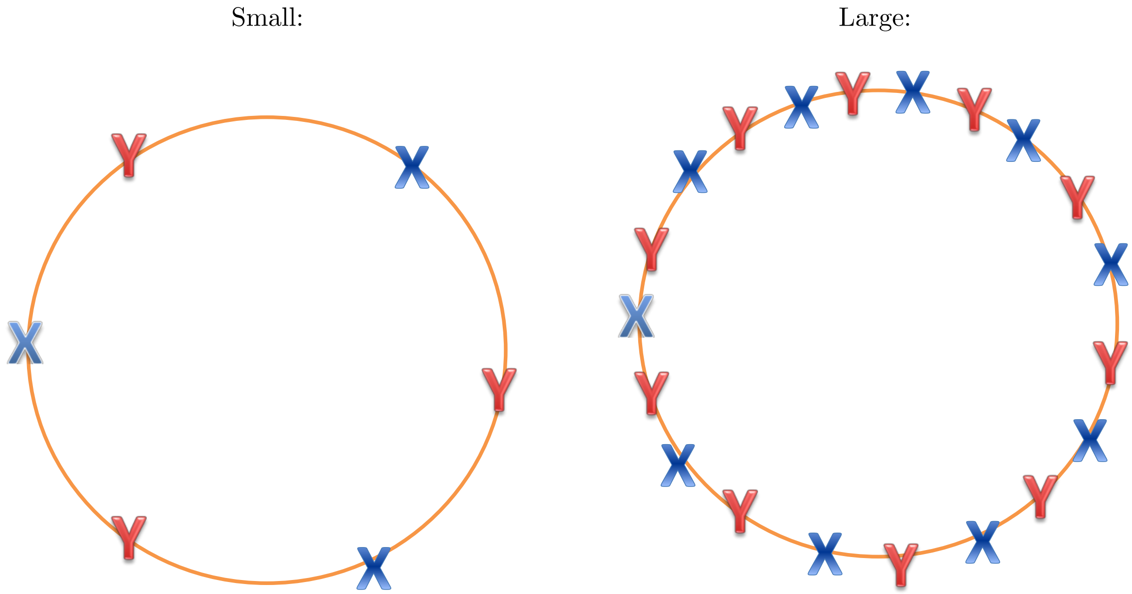
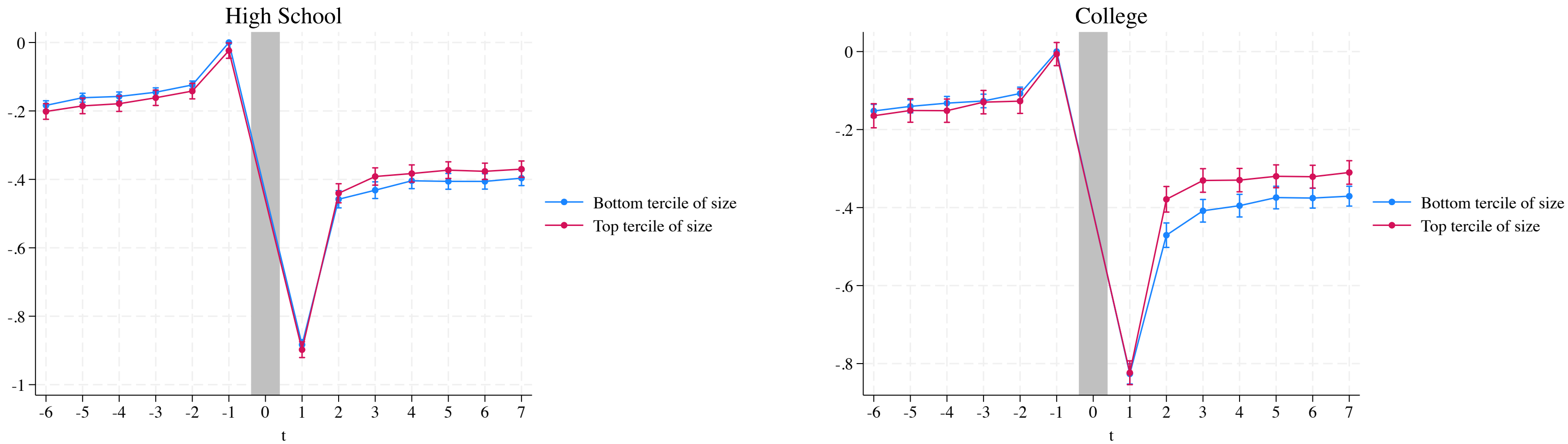


Figure 2: Employment

Panel A: High School　　　　Panel B: College

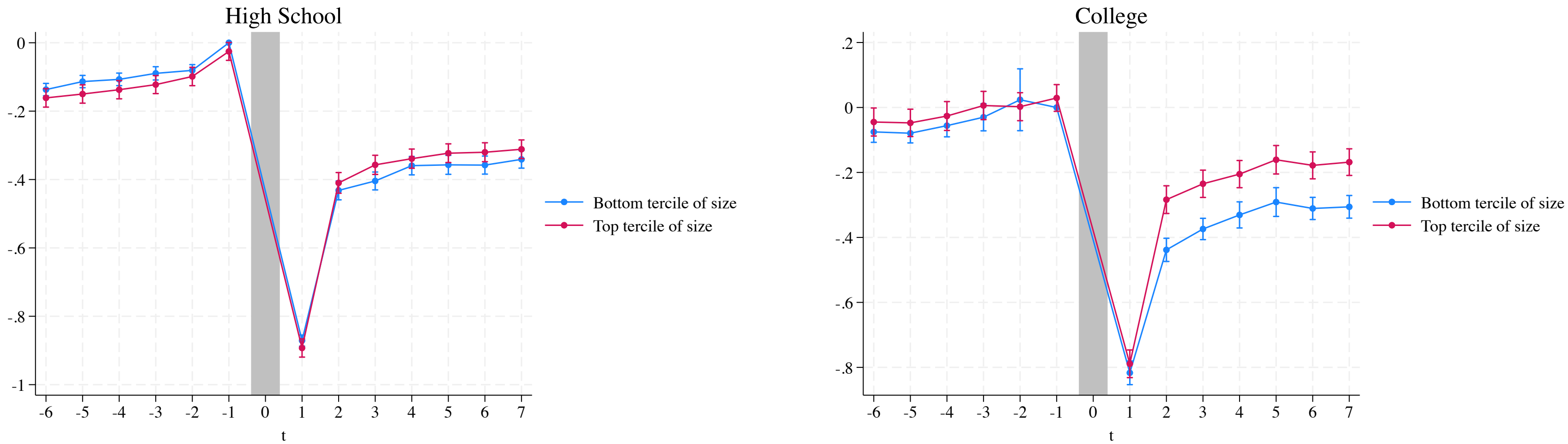


Notes: This figure plots the conditional probability of employment for a worker from 6 quarters before involuntary displacement to 7 quarters after displacement. The shaded area highlights the quarter when the relevant closure occurs. These estimates come from the specification in equation (3). Plot whiskers show 95% confidence intervals from standard errors clustered at the CZ-level based on CZ residence at $t = -1$.

Figure 3: Earnings

Panel A: High School

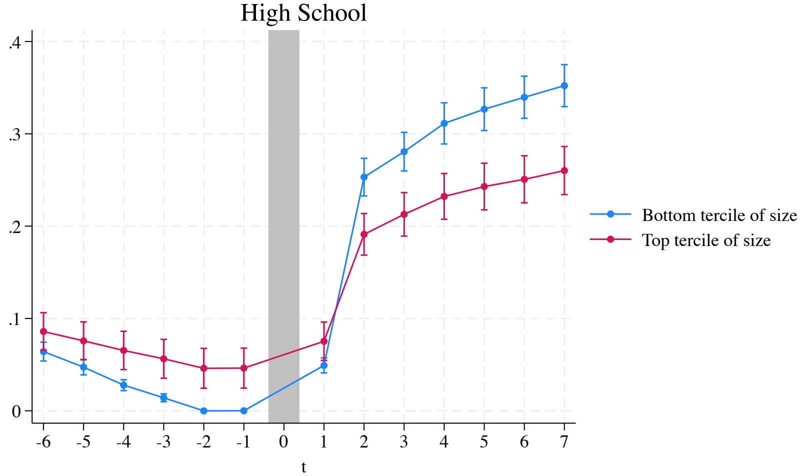
Panel B: College



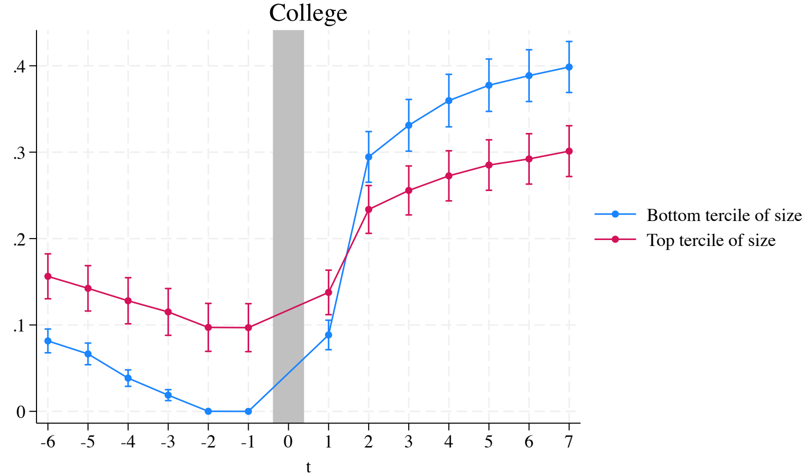
Notes: This figure plots the ratio of quarterly earnings for a worker divided by their earnings at $t = -1$ from 6 quarters before involuntary displacement to 7 quarters after displacement. The shaded area highlights the quarter when the relevant closure occurs. These estimates come from the specification in equation (3). Plot whiskers show 95% confidence intervals from standard errors clustered at the CZ-level based on CZ residence at $t = -1$.

Figure 4: Probability of Changing CZs

Panel A: High School

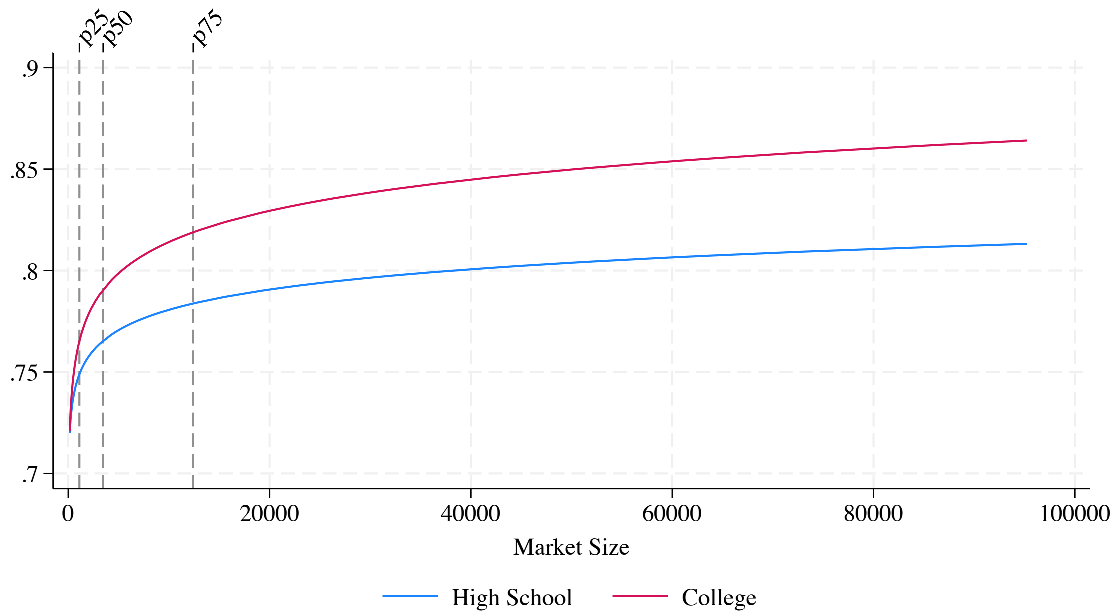


Panel B: College



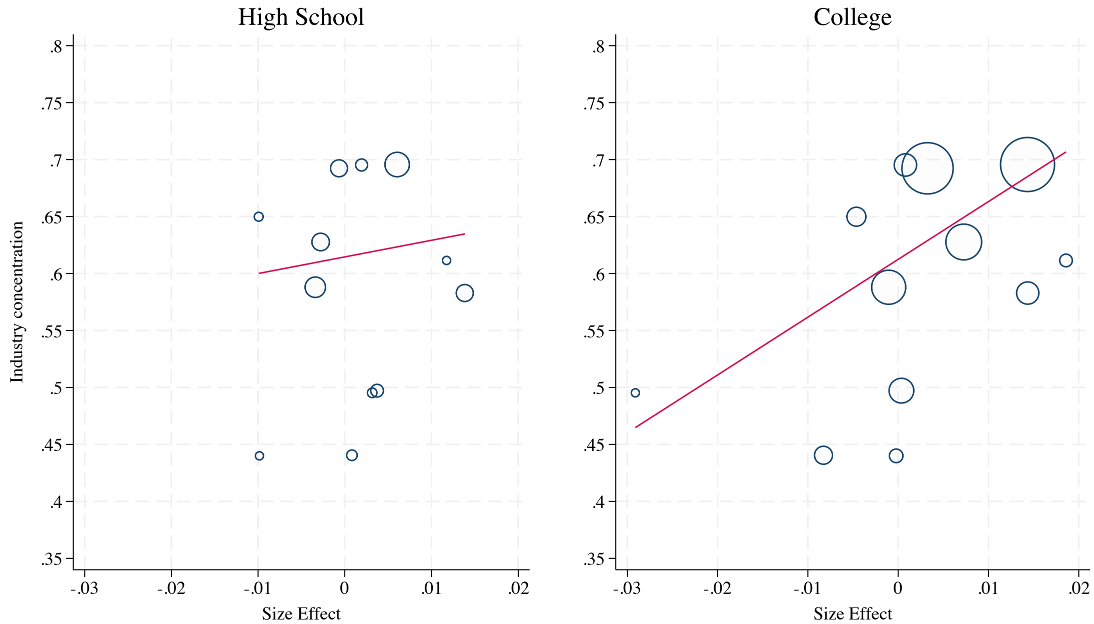
Notes: This figure plots the probability of changing CZs for a worker from 6 quarters before involuntary displacement to 7 quarters after displacement. The shaded area highlights the quarter when the relevant closure occurs. These estimates come from the specification in equation (3). Plot whiskers show 95% confidence intervals from standard errors clustered at the CZ-level based on CZ residence at $t = -1$.

Figure 5: Predicted Probability of Finding a Job in 12 Months



Notes: This figure plots the predicted probability of reemployment in 12 months against market size, where market size is measured in number of workers. The predicted values are calculated using coefficients from our preferred specification in Table 2, columns 5 and 6. The three vertical dashed lines show the 25^{th}, 50^{th}, and 75^{th} percentiles of the market size distribution. The Y-axis has been rescaled so that the predicted reemployment probability for workers in average-sized markets ($\sim 20,510$) corresponds to the unconditional reemployment probabilities shown in Table 2.

Figure 6: Industry Concentration



Notes: Each point represents a 2-digit industry. The size effects were estimated separately for each industry. The dependent variable was the probability of finding a job within 12 months after displacement. Linear fit is weighted by the inverse of the variance of the size coefficients.

Table 1: Distribution of Market Size at Time of Closure

	Mean	SD	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
Market size	20,510	67,570	398	1,103	3,466	12,410	43,230

Notes: Market is defined at the CZ by 2-digit NAICS industry level, summary statistics correspond to 10,500 CZ-industry cells in our estimation sample.

Table 2. Probability of Reemployment in 12 months and Non-Employment Duration

	HS (1)	College (2)	HS (3)	College (4)	HS (5)	College (6)
Dependent variable: Probability of reemployment in 12 months						
Market size	.02532***	.03419***	.01774***	.02309***	.01442***	.0222***
	(.003499)	(.004213)	(.003797)	(.004858)	(.00367)	(.00515)
90-10 difference	.1189***	.1605***	.08326***	.1084***	.06768***	.1042***
	(.01643)	(.01978)	(.01783)	(.0228)	(.0172)	(.0242)
Mean dependent variable	0.770	0.816	0.770	0.816	0.791	0.830
Dependent variable: Length of non-employment						
Market size	-.04103***	-.063***	-.03081***	-.04376***	-.02391***	-.03522***
	(.006657)	(.01079)	(.007039)	(.01059)	(.00674)	(.0109)
90-10 difference	-.1926***	-.2958***	-.1446***	-.2054***	-.1122***	-.1654***
	(.03125)	(.05065)	(.03304)	(.04971)	(.0316)	(.0510)
Mean dependent variable	1.042	0.914	1.042	0.914	1.013	0.899
CZ effects	x	x	x	x	x	x
Industry effects	x	x	x	x	x	x
Worker controls	x	x	x	x	x	x
Market controls			x	x	x	x
Worker effects					x	x

Notes: Standard errors clustered at the CZ level in parentheses. Each column is a separate regression, with dependent variable in the panel heading. The number of observations in the high school subgroup is 252,000 in columns 1–4, and 223,000 in columns 5–6; the number of observations in the college subgroup is 279,000 in coumns 1–4, and 247,000 in columns 5–6. Sample sizes are rounded for confidentiality purposes.

Table 3. Probability of Reemployment in 12 months and Non-Employment Duration

	HS (1)	College (2)	HS (3)	College (4)
<u>Dependent variable: Probability of reemployment in 12 months</u>				
Market Size	.02115***	.02594***	.01697***	.02451***
	(.003731)	(.004535)	(.00367)	(.00494)
Q2 X Market Size	-.002639***	-.001554***	-.002154***	-.001213**
	(.0004882)	(.0005258)	(.0004921)	(.0005388)
Q3 X Market Size	-.003096***	-.001928***	-.00264***	-.001709**
	(.0004623)	(.0007015)	(.0004723)	(.0007551)
Q4 X Market Size	-.008828***	-.006126***	-.006903***	-.004408***
	(.0005064)	(.0006877)	(.0005505)	(.0006491)
<u>Dependent variable: Length of non-employment</u>				
Market Size	-.03674***	-.04926***	-.02847***	-.04031***
	(.006919)	(.01024)	(.00673)	(.0105)
Q2 X Market Size	.004443***	.003036***	.004022***	.002616***
	(.001058)	(.001127)	(.00104)	(.0009575)
Q3 X Market Size	.005291***	.003729***	.004854***	.003996***
	(.0008217)	(.001278)	(.0007728)	(.001204)
Q4 X Market Size	.01552***	.01138***	.01207***	.008067***
	(.001012)	(.001306)	(.001107)	(.001243)
CZ effects	x	x	x	x
Industry effects	x	x	x	x
Worker controls	x	x	x	x
Market controls	x	x	x	x
Worker effects			x	x

Notes: Standard errors clustered at the CZ level in parentheses. Each column is a separate regression, with dependent variable in the panel heading. The number of observations in the high school subgroup is 252,000 in columns 1–2, and 223,000 in columns 3–4; the number of observations in the college subgroup is 279,000 in coumns 1–2, and 247,000 in columns 3–4. Sample sizes are rounded for confidentiality purposes.

Table 4. Percent Change in Quarterly Earnings

	HS (1)	College (2)	HS (3)	College (4)	HS (5)	College (6)
Market size	.02999***	.08216***	.02114***	.05004***	.01517***	.02666**
	(.00526)	(.02474)	(.005425)	(.01525)	(.00542)	(.0105)
90-10 difference	.1408***	.3857***	.09926***	.2349***	.07122***	.1251**
	(.02469)	(.1161)	(.02547)	(.07156)	(.0255)	(.0491)
Mean dependent variable	-0.317	-0.214	-0.317	-0.214	-0.308	-0.219
CZ effects	x	x	x	x	x	x
Industry effects	x	x	x	x	x	x
Worker controls	x	x	x	x	x	x
Market controls			x	x	x	x
Worker effects					x	x

Notes: Standard errors clustered at the CZ level in parentheses. Each column is a separate regression model, with dependent variable in the panel heading. The number of observations in the high school subgroup is 252,000 in columns 1–4, and 223,000 in columns 5–6; the number of observations in the college subgroup is 279,000 in coumns 1–4, and 247,000 in columns 5–6. Sample sizes are rounded for confidentiality purposes.

Table 5. Percent Change in Quarterly Earnings

	HS (1)	College (2)	HS (3)	College (4)
Market Size	.02423*** (.005378)	.04624*** (.01351)	.01768*** (.00542)	.02431** (.00997)
Q2 X Market Size	-.002365*** (.0005913)	-.0009639 (.001393)	-.001947*** (.0006299)	.00022 (.001391)
Q3 X Market Size	-.002853*** (.0006627)	.006557 (.004263)	-.002375*** (.0007158)	.003514 (.004361)
Q4 X Market Size	-.008008*** (.0006552)	-.003946* (.002181)	-.007028*** (.0006709)	-.002734 (.002166)
CZ effects	x	x	x	x
Industry effects	x	x	x	x
Worker controls	x	x	x	x
Market controls	x	x	x	x
Worker effects			x	x

Notes: Standard errors clustered at the CZ level in parentheses. Each column is a separate regression model, with the dependent variable in the panel heading. The number of observations in the high school subgroup is 252,000 in columns 1–2, and 223,000 in columns 3–4; the number of observations in the college subgroup is 279,000 in coumns 1–2, and 247,000 in columns 3–4. Sample sizes are rounded for confidentiality purposes.

Table 6. Change in CZ of Residence

	HS (1)	College (2)	HS (3)	College (4)	HS (5)	College (6)
Market size	-.04611***	-.06575***	-.0476***	-.05414***	-.04846***	-.05515***
	(.004549)	(.005815)	(.004412)	(.005709)	(.00474)	(.00615)
90-10 difference	-.2165***	-.3087***	-.2234***	-.2541***	-.2275***	-.2589***
	(.02135)	(.0273)	(.02071)	(.0268)	(.0222)	(.0289)
Mean dependent variable	0.278	0.243	0.278	0.243	0.276	0.239
CZ effects	x	x	x	x	x	x
Industry effects	x	x	x	x	x	x
Worker controls	x	x	x	x	x	x
Market controls			x	x	x	x
Worker effects					x	x

Notes: Standard errors clustered at the CZ level in parentheses. Each column is a separate regression model, with dependent variable in the panel heading. Sample restricted to displaced workers who are employed at any point after displacement. The number of observations in the high school subgroup is 227,000 in columns 1–4, and 202,000 in columns 5–6; the number of observations in the college subgroup is 229,000 in coumns 1–4, and 247,000 in columns 5–6. Sample sizes are rounded for confidentiality purposes.

Table 7. Change in CZ of Residence

	HS (1)	College (2)	HS (3)	College (4)
Market Size	-.04865***	-.05522***	-.04945***	-.05627***
	(.004519)	(.0058)	(.00486)	(.00618)
Q2 X Market Size	.0007909	.0004904	.001001*	.0008581*
	(.0005186)	(.0004473)	(.0005599)	(.0004465)
Q3 X Market Size	-.0000819	.0007422	.000172	.0005017
	(.0006387)	(.0008043)	(.0006934)	(.0006222)
Q4 X Market Size	.002619**	.003066***	.002339*	.002894***
	(.001214)	(.0006491)	(.001322)	(.0006705)
CZ effects	x	x	x	x
Industry effects	x	x	x	x
Worker controls	x	x	x	x
Market controls	x	x	x	x
Worker effects			x	x

Notes: Standard errors clustered at the CZ level in parentheses. Each column is a separate regression model, with the dependent variable in the panel heading. Sample restricted to displaced workers who are employed at any point after displacement. The number of observations in the high school subgroup is 227,000 in columns 1–2, and 202,000 in columns 3–4; the number of observations in the college subgroup is 229,000 in coumns 1–2, and 247,000 in columns 3–4. Sample sizes are rounded for confidentiality purposes.

Table 8. Proxies for Match Quality

	HS (1)	College (2)	HS (3)	College (4)	HS (5)	College (6)
Panel A						
Dependent variable: Probability of finding a job in 12 months that Lasts more than 12 months						
Market size	.02569***	.03641***	.01473***	.02707***	.009934**	.02006***
	(.004711)	(.007548)	(.004549)	(.007627)	(.00451)	(.00746)
90-10 difference	.1206***	.1709***	.06912***	.1271***	.04663**	.09414***
	(.02211)	(.03543)	(.02135)	(.0358)	(.0212)	(.0350)
Mean dependent variable	0.520	0.544	0.520	0.544	0.535	0.552
Panel B						
Dependent variable: Probability of reemployment in the same industry in 12 months						
Market size	.05709***	.05074***	.04878***	.02999***	.04516***	.0331***
	(.005269)	(.007342)	(.006222)	(.007833)	(.00616)	(.00754)
90-10 difference	.268***	.2382***	.229***	.1408***	.212***	.1554***
	(.02473)	(.03447)	(.02921)	(.03677)	(.0289)	(.0354)
Mean dependent variable	0.575	0.584	0.575	0.584	0.595	0.596
Panel C						
Dependent variable: Probability of reemployment in 12 months in a good major-industry match						
Market size		.03787***		.02561***		.02331***
		(.005131)		(.005384)		(.00548)
90-10 difference		.1778***		.1202***		.1094***
		(.02409)		(.02527)		(.0257)
Mean dependent variable		0.598		0.598		0.604
CZ effects	x	x	x	x	x	x
Industry effects	x	x	x	x	x	x
Worker controls	x	x	x	x	x	x
Market controls			x	x	x	x
Worker effects					x	x

Notes: Standard errors clustered at the CZ level in parentheses. Each column is a separate regression model, with dependent variable in the panel heading. Sample restricted to displaced workers who are employed at any point after displacement. The number of observations in the high school subgroup is 252,000 in columns 1–4, and 223,000 in columns 5–6; the number of observations in the college subgroup is 279,000 in coumns 1–4, and 247,000 in columns 5–6. Sample size for Panel C is 208,000 in columns 1–4 and 184,000 in column 6 due to limited college major availability in the ACS. Sample sizes are rounded for confidentiality purposes.

Table 9. Proxies for Match Quality

	HS (1)	College (2)	HS (3)	College (4)
Panel A				
Dependent variable: Probability of finding a job in 12 months that Lasts more than 12 months				
Market Size	.01807***	.03112***	.01269***	.02388***
	(.004519)	(.007399)	(.00456)	(.00716)
Q2 X Market Size	-.002377***	-.002611***	-.002048***	-.002131***
	(.0005754)	(.0006047)	(.0005934)	(.0007227)
Q3 X Market Size	-.003822***	-.002698***	-.00352***	-.00302***
	(.0006085)	(.0008071)	(.0006458)	(.000811)
Q4 X Market Size	-.008943***	-.005925***	-.007823***	-.00461***
	(.0004948)	(.0008027)	(.0005323)	(.000816)
Panel B				
Dependent variable: Probability of reemployment in the same industry in 12 months				
Market Size	.05781***	.04425***	.05345***	.0465***
	(.006001)	(.007386)	(.00601)	(.00754)
Q2 X Market Size	-.008081***	-.007524***	-.007713***	-.007574***
	(.0007735)	(.0006571)	(.0008378)	(.0006356)
Q3 X Market Size	-.01101***	-.01131***	-.01104***	-.01036***
	(.000811)	(.000765)	(.0008637)	(.0007025)
Q4 X Market Size	-.02206***	-.01767***	-.02114***	-.01692***
	(.001853)	(.0009173)	(.001921)	(.0009328)
Panel C				
Dependent variable: Probability of reemployment in 12 months in a good major-industry match				
Market Size		.03037***		.02814***
		(.004991)		(.00525)
Q2 X Market Size		-.003808***		-.003761***
		(.0005683)		(.0005672)
Q3 X Market Size		-.002433***		-.002693***
		(.0006948)		(.000744)
Q4 X Market Size		-.006744***		-.00586***
		(.000885)		(.0007555)
CZ effects	x	x	x	x
Industry effects	x	x	x	x
Worker controls	x	x	x	x
Market controls	x	x	x	x
Worker effects			x	x

Notes: Standard errors clustered at the CZ level in parentheses. Each column is a separate regression model, with the dependent variable in the panel heading. The number of observations in the high school subgroup is 252,000 in columns 1–2, and 223,000 in columns 3–4; the number of observations in the college subgroup is 279,000 in coumns 1–2, and 247,000 in columns 3–4. Sample size for Panel C is 208,000 in column 2 and 184,000 in column 4 due to limited college major availability in the ACS. Sample sizes are rounded for confidentiality purposes.

Table 10. Change in Spousal Employment

	HS (1)	College (2)	HS (3)	College (4)
Market size	0.00465***	0.00254*	.004662***	.00157
	(0.00157)	(0.00134)	(.001642)	(.001261)
Mean dependent variable	-0.0588	-0.0467	-0.0540	-0.0430
CZ effects	x	x	x	x
Industry effects	x	x	x	x
Worker controls	x	x	x	x
Market controls	x	x	x	x
Worker effects			x	x

Notes: Standard errors clustered at the CZ level in parentheses. Each column is a separate regression model, with dependent variable in the panel heading. Education, person effects controls and market size are based on the spouse (we use the last observed industry of employment for a spouse before the focal worker displacement). The number of observations in the high school subgroup is 46,000 in columns 1–2, and 44,500 in columns 3–4; the number of observations in the college subgroup is 72,000 in coumns 1–2, and 69,500 in columns 3–4. Sample sizes are rounded for confidentiality purposes.

Appendix Table 1: Number of Displaced Workers and Firm Closures Over Time

Year	Number of firm closures (1)	Number of displaced workers (2)
2010	21,500	82,500
2011	17,500	69,500
2012	21,000	74,500
2013	22,500	76,500
2014	24,500	70,000
2015	22,000	72,500
2016	20,500	64,500
2017	8,500	21,000

Notes: 2017 counts only include the first two quarters of 2017. Sample sizes are rounded for confidentiality purposes.

Appendix Table 2: Characteristics of Displaced Workers

	Sample Mean at t=-1
	(1)
Employed	1
	(0)
Quarterly earnings	20,670
	(113300)
Age	46.77
	(9.064)
Fraction Female	.4415
	(.4966)
Fraction Black	.07588
	(.2648)
Fraction Hispanic	.1037
	(.3048)
Fraction Foreign Born	.1754
	(.3803)
Fraction College	.5255
	(.4993)
Fraction High School	.4745
	(.)
Number of observations	531,000
Number of CZ-industries	10,500
Number of firm closures	158,000

Notes: Entries in this table refer to the last quarter of employment (t=-1). The sample includes all matched ACS-LEHD indivduals of age 22–62 with at least 8 quarters of employment in the LEHD 2010Q1 to 2018Q2. Quarterly observations for individuals with multiple employers are excluded, as are the first and last (transitional) quarters of any spell with the same employer, quarters for which industry or location information is missing, and quarters with earnings less than $3,800. Sample sizes are rounded for confidentiality purposes.

Appendix Table 3: Firm Counts by Distance and Industries

	Small Markets Bottm 3 Deciles (1)	Medium Markets (2)	Large Markets Top 3 Deciles (3)
Firms within 20 miles and in the same 2-digit industry	9.30	29.32	640.67
Firms within 20 miles and in the same 3-digit industry	4.00	9.66	179.28
Firms within 20 miles and in the same 4-digit industry	2.00	4.33	62.21

Notes: For each displaced worker, we took all firms present at the time of displacement in the last CZ of employment and all adjacent CZs. We then drew a radius of 20 miles around the displaced worker residential address. Counts includes firms (SEINS) with employment size 3 and above. Firms with multiple establishments are counted as a single firm. In those cases, we assign the industry of the establishment closest in distance to the displaced workers.

Appendix Table 4. Robustness

	Baseline		Adding early leavers		Excluding high displacement cells	
	HS	College	HS	College	HS	College
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Probability of reemployment in 12 months						
Market size	.01774***	.02309***	.01949***	.02368***	.02232***	.02772***
	(.003797)	(.004858)	(.002366)	(.00352)	(.004254)	(.004979)
Dependent variable: Length of non-employment						
Market size	-.03081***	-.04376***	-.03377***	-.04258***	-.03648***	-.05342***
	(.007039)	(.01059)	(.00443)	(.006826)	(.007824)	(.01051)
Dependent variable: Probability of changing CZs						
Market size	-.0476***	-.05414***	-.04321***	-.06039***	-.04359***	-.05699***
	(.004412)	(.005709)	(.003217)	(.004729)	(.004259)	(.005964)
Dependent variable: Probability of finding a job in 12 months that Lasts more than 12 months						
Market size	.01473***	.02707***	.01173***	.01107**	.01802***	.02426***
	(.004549)	(.007627)	(.003472)	(.005233)	(.004801)	(.006819)
Dependent variable: Probability of reemployment in the same industry in 12 months						
Market size	.04878***	.02999***	.05032***	.04125***	.04616***	.03812***
	(.006222)	(.007833)	(.003354)	(.005962)	(.00607)	(.007645)
Dependent variable: Probability of reemployment in 12 months in a good major-industry match						
Market size		.02561***		.028***		.03039***
		(.005384)		(.004367)		(.006003)
CZ effects	x	x	x	x	x	x
Industry effects	x	x	x	x	x	x
Worker controls	x	x	x	x	x	x
Market controls	x	x	x	x	x	x

Notes: Standard errors clustered at the CZ level in parentheses. Each column is a separate regression model, with dependent variable in the panel heading. Columns 1–2 present our baseline estimates. Columns 3–4 exclude CZ-industry cells in the top 5 percentile of the share of displaced workers (relative to employment). Columns 5–6 present results when adding workers who left a firm up to 4 quarters before the closure date.