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The mobility of displaced workers: How the local industry mix affects job search

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Abstract

Are there Marshallian externalities in job search? We study how workers who lose their jobs in establishment closures in Germany cope with their loss of employment. About a fifth of these displaced workers do not return to social-security covered employment within the next three years. Among those who do get re-employed, about two-thirds leave their old industry and one-third move out of their region. However, which of these two types of mobility responses workers will choose depends on the local industry mix in ways that are suggestive of Marshallian benefits to job search. In particular, large concentrations of one's old industry make finding new jobs easier: in regions where the pre-displacement industry is large, displaced workers suffer relatively small earnings losses and find new work faster. In contrast, large local industries skill-related to the pre-displacement industry increase earnings losses but also protect against long-term unemployment. Analyzed through the lens of a job-search model, the exact spatial and industrial job-switching patterns reveal that workers take these Marshallian externalities into account when deciding how to allocate search efforts among industries. Keywords: Displacement, agglomeration externalities, matching, mobility. JEL codes: J24/J61/J64/R12.

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> Employers are apt to resort to any place where they are likely to find a good choice of workers with the special skill which they require; while men seeking employment naturally go to places where there are many employers who need such skill as theirs and where therefore it is likely to find a good market. The owner of an isolated factory, even if he has access to a plentiful supply of general labour, is often put to great shifts for want of some special skilled labour; and a skilled workman, when thrown out of employment in it, has no easy refuge. (Marshall, 1890, IV.X.9)

1 Introduction

Marshallian externalities, i.e., benefits afforded by dense concentrations of firms in the same economic activity, are sometimes associated with the thickness of local labor markets. Traditionally, the importance of local labor markets has been attributed to two separate, yet related, mechanisms. First, firms benefit from locating close to other firms in their industry as it would help them find workers with specialist skills. Second, specialist workers are attracted to such geographical clusters, because, if they were to lose their job, a local concentration of employers in their industry would make it easier to find new work that matches their skill profiles. However, in spite of ample research on Marshallian benefits that accrue to *firms*, the (re)employment benefits for *workers* have received comparatively little attention in the urban economics literature. In this paper, we aim to shed light on the existence of Marshallian externalities in job search by studying the careers of workers who lose their jobs when establishments close down. In particular, we pose two questions. First, do the career consequences of job displacement depend on the exact mix of industries that exists in a local economy? We show that Marshallian externalities manifest themselves in high re-employment rates and low wage losses. And second, are workers aware of the existence of such Marshallian externalities when they decide how to allocate search efforts among different industries? Building on a model of job search, we find that this is indeed the case: spatial patterns of new job matches suggest that workers adjust their search strategies in ways that would allow them to take better advantage of Marshallian job-search externalities.

In answering these questions, the paper connects debates on agglomeration economies to a large and growing literature in labor economics that focuses on workers who lose their jobs in establishment closures. Studying samples of these so-called "displaced" workers is attractive because establishment closures leave workers looking for new jobs when they neither planned on, nor contributed to, the termination of their current employment. As a consequence, such workers are relatively unaffected by the self-selection problems that arise when job loss is an endogenous outcome of interactions between workers and their employers. The literature on establishment closures has amply documented how detrimental job displacement can be to people's careers and well-being, with consequences ranging from wage reductions and un- or underemployment, to physical and

mental health issues.

However, although displacement-related job-loss itself may plausibly be exogenous to workers' career plans, their response to it isn't. After all, workers can deal with unemployment in several ways. For instance, they can search for jobs in their old industry or try their luck in another industry. Similarly, workers can search for local jobs or move to other regions. Which strategy they choose, and the likelihood of its success, will depend on the kind of jobs a region has to offer. Consequently, the rate at which workers change industries or move to other regions or both, as well as the time it takes to find new jobs, will depend on which jobs currently exist in the region. That is, they will depend on the local mix of industries.

The importance of local labor markets is widely acknowledged in the urban economics literature that deals with agglomeration externalities, both in theoretical models and in empirical studies. For instance, Helsley and Strange (1990) develop a model in which larger cities allow for a better fit between a worker's skills and an employer's skill requirements. Such matching externalities are not limited to the quality of the match. Duranton and Puga (2004) show that in matching models with search frictions also the probability of successful matches will increase as cities grow larger. That is, as the pools of potential employers and employees grow, the likelihood that a worker remains unemployed goes down. Indirect empirical evidence for such Marshallian labor market pooling benefits have been found in local industries' growth rates (e.g., Dauth, 2010) and productivity (e.g., Feser, 2002), as well as in industries' overall spatial concentration (Rosenthal and Strange, 2001) and coagglomeration patterns (Ellison et al., 2010). However, relatively little is known about the validity of Marshall's (1890) original claim that industrial agglomerations help unemployed workers find new jobs. In particular, we have incomplete answers to questions such as: Do unemployed workers find jobs faster in regions with large local concentrations of their prior industry? Do they suffer smaller wage losses in such regions? And, finally, does the local industry mix affect the way workers cope with unemployment in terms of industrial or geographical mobility?

The first contribution of this paper is to provide answers that address the causal mechanisms these questions imply by exploiting data on displaced workers. To do so, we apply a combination of matching techniques and regression models to a dataset that covers the employment history of over 20 million workers in Germany. Using difference-in-differences estimation, we first show the causal effects of job displacement on post-displacement wages and careers. Here, we find that workers who are displaced in establishment closures are not only less likely to return to jobs covered by social security and more likely to experience significant earnings losses. Those who do return to such jobs are also 66 percentage points (pp) more likely to change industries and 33 pp more likely to change regions than their statistical twins. Next, we show that there is substantial heterogeneity in these displacement effects that can be attributed to Marshallian externalities. First, we find that a strong local presence of the pre-displacement industry – i.e., its share of regional employment is in the top instead of the bottom third of all local industries – reduces post-displacement industry and

region switching rates by 31 percent, respectively 12 percent. In contrast, high shares of local employment in industries *related* to the pre-displacement industry increase industry switching rates substantially, but do not prevent workers from leaving the region. Turning to wages and re-employment rates, we find substantial moderating effects of the local industry mix. Whereas, on average, earnings drop by 39%, this drop is reduced to 32% in regions with large concentrations of the pre-displacement industry. Moreover, with 24% and 7% lower long-run nonemployment rates, having high instead of low concentrations of the pre-displacement and related industries in the region offers some protection against long-term nonemployment.

Having shown that Marshallian effects play a role in whether and where unemployed workers find new jobs, next we ask: Do job searchers take advantage of such Marshallian externalities? To provide a framework for answering this question, we build on a search model by Fallick (1992, 1993) in which unemployed workers divide their search efforts between two sectors: their own industry and a sector composed of suitable alternative (i.e., related) industries. We repurpose this model for the above question by assuming that greater search efforts translate into a widening of the geographical search radius.

As a consequence, we can learn about shifts in the (unobserved) allocation of search effort between the two sectors by looking at the geographical mobility of workers. The model predicts that favorable local conditions in a particular sector not only increase the likelihood of finding a job in this sector, but also induce workers to allocate most of their search efforts to this sector, at the expense of the other sector. As a consequence, favorable conditions in one sector will reduce the spatial scope of search in the other sector. This prediction finds strong support in the data.

Through our findings, we contribute to the debate on industrial specialization and diversity in regions (e.g., Glaeser et al., 1992; Henderson et al., 1995; Porter, 2003) by placing the issue of agglomeration externalities in the context of job displacement. Our findings also shed light on the importance of inter-industry relatedness, a topic of increasing interest in economic geography (Delgado et al., 2010; Ellison et al., 2010; Florida et al., 2011; Diodato et al., 2018). In particular, the finding that skill-related employment induces workers to change industries, while decreasing the likelihood of protracted nonemployment spells, shows that clusters of related activities not only create agglomeration externalities for local firms (Delgado et al., 2010; Neffke et al., 2012) but also for workers. Finally, our finding that workers take Marshallian externalities into account when deciding how to divide search efforts provides further (and more robust) support beyond Fallick (1993) for strategic search in wage search theory (e.g., Mortensen, 1986).

2 Literature Review

Establishment closures have a profound impact on workers' lives (see Carrington and Fallick (2015) for a recent review). Apart from pecuniary losses, displaced

workers suffer increased addiction problems and a deterioration of their health (Black et al., 2015; Eliason and Storrie, 2009). Income losses after displacement can be severe and long-lived, depressing incomes for periods of ten years or longer (e.g. Jacobson et al., 1993; Couch and Placzek, 2010; Davis and von Wachter, 2011). These income losses have been attributed to the loss of firm-specific human capital (Becker, 1962), of back-loaded wage payments designed to disincentivize shirking (Lazear, 1979), and of the "match capital" (Jacobson et al., 1993, p. 686) workers have accumulated through finding progressively better matching jobs over the course of their careers.

Earnings losses can materialize through protracted unemployment spells and a reduction in daily wages (Carrington and Fallick, 2015). In Germany, a major contributing factor to the loss of earnings is unemployment (Burda and Mertens, 2001; Nedelkoska et al., 2015), especially immediately following displacement (Schmieder et al., 2010). What determines how quickly displaced workers find new jobs? Previous research has pointed to national-level economic conditions: adverse effects of displacement are more severe in macroeconomic downturns (Davis and von Wachter, 2011) and in declining industries (Howland and Peterson, 1988; Fallick, 1993). However, also local economic conditions matter. First, the size and growth of local economies will affect the arrival rate and the distribution of wage offers, both of which determine reservation wages in standard search models (e.g., Mortensen, 1986). Second, urban models predict that cities with more employers and workers allow for better matches between the skill endowments of workers and the skill requirements of jobs (Helsley and Strange, 1990). Third, economic sociologists have stressed that social networks – which are often local – are important in finding new jobs. In line with this, proximity to suitable jobs decreases joblessness, even within a single city (Andersson et al., 2014) and displacement effects are more severe in declining local economies (Jacobson et al., 1993) and industries (Carrington, 1993).

Marshall's original argument for what are now known as Marshallian externalities was that a large local concentration of an industry in a region reduces the risk of protracted unemployment for the specialized workers employed in that industry. This suggests that displacement will depend on how many local jobs exist that utilize a displaced worker's skills. Interestingly, although authors have studied the exit (Gathmann et al., 2014) and entry (Greenstone et al., 2010) of large economic establishments to identify causal effects of Marshallian externalities through the employment shocks these events create, this work has focused on labor market pooling benefits to *firms*, not *workers*. Moreover, recent research in economic geography has studied how workers switch industries and regions in the aftermath of shipyard closures in Denmark (Holm et al., 2017), Germany and Sweden (Eriksson et al., 2016) but this has no implications regarding whether Marshallian externalities *change* the effects of establishment closures.

To address this issue, we study how the local concentrations of the pre-displacement and related industries impact the careers of displaced workers. Do such concentrations affect the earnings drop after displacement? Do they affect the length of unemployment spells? Do they change whether workers

deal with displacement by switching industries or by moving to other regions? Moreover, do displaced workers respond to the Marshallian externalities offered by these local industry concentrations by aligning their search efforts with these externalities?

3 Model

To structure our empirical analyses, we build on a model of job search developed by Fallick (1992, 1993). In this model, unemployed workers divide their search efforts between two sectors. As in Fallick (1993), we will think of the first sector as the industry from which the worker was displaced and the second sector as consisting of other suitable industries, i.e., industries that require similar skills as the pre-displacement industry. We then proceed to give this model an explicitly spatial dimension, by assuming that search efforts translate into – among other things – a widening of the geographical scope of the search.

Let there be two sectors $s \in \{A, B\}$, which are characterized by an offer-arrival parameter ψ_s and a cumulative wage-offer distribution $F_s(w)$. Search efforts, e_s, are sector-specific and increase the job-offer arrival-rate in a sector but are also costly, $C = c\left(\sum_s e_s\right)$. The arrival rate of job offers is assumed to follow a Poisson distribution with an arrival rate α_s that depends on the intrinsic, sector-specific offer-arrival parameter ψ_s and the search intensity in sector s:

$$\alpha_s = \psi_s \sigma(e_s) \tag{1}$$

The function $\sigma(e_s)$ links offer arrival rates to search efforts. Each worker has a total search budget of one unit of effort: $\sum_s e_s \leq 1$. To receive job offers, a non-zero effort is required and beyond this initial effort, job offer arrival rates increase monotonically with effort but marginal returns are diminishing in each sector: $\sigma(0) = 0, \sigma'(e_s) > 0, \sigma''(e_s) < 0$.

While unemployed, workers maximize the net present value (NPV) of searching for a job in the next period, V, by deciding how much search effort they want to dedicate to each sector and on a reservation wage, w_s^*, at which they will accept a job and stop searching. From standard continuous-time wage-search theory (e.g., Mortensen, 1986), it follows that the worker maximizes the expected net income stream when:

$$rV = \max_{e_A, e_B} \left[b - c(e_A + e_B) + \sum_{s \in \{A,B\}} \psi_s \sigma(e_s) \left\{ \int_0^\infty \max[0, W(x) - V] \, \mathrm{d}F_s(x) \right\} \right]$$

subject to $e_A \geq 0$, $e_B \geq 0$ and $e_A + e_B \leq 1$ and where b represents the value of leisure, r a discount rate, $W(x)$ the NPV of accepting a wage offer of x and then staying in this job indefinitely, and $F_s(x)$ the likelihood of being offered a wage of x or less. rV can be interpreted as the "rental income" derived from the expected NPV of future search processes. Assuming optimal search now and in the future, this equals the value a worker derives from leisure, b, minus the costs

of search, $c(e_A + e_B)$, plus the increase of expected NPV of future incomes due to search.[1]

The reservation wage is the same in both sectors: $V = w_A^*/r = w_B^*/r = w^*/r$.[2] Given that a worker could enjoy leisure valued at b by not searching at all, w^* must be at least equal to b for the worker to participate in the labor market (i.e., search). The constrained maximization problem above now becomes:

$$\max_{e_A, e_B} \left[b - c(e_A + e_B) + \sum_{s \in \{A,B\}} \frac{\psi_s}{r} \sigma(e_s) \int_{w^*}^{\infty} (x - w^*) \, \mathrm{d}F_s(x) - \lambda(e_A + e_B - 1) \right]$$

for $w^* \geq b$, $e_A \geq 0$, $e_B \geq 0$ and λ a Lagrangian multiplier. Optimal search is now determined by the following first-order conditions:[3]

$$-\frac{\partial c(e_A^* + e_B^*)}{\partial(e_A^* + e_B^*)} + \frac{\partial \sigma(e_A^*)}{\partial e_A} \frac{\psi_A}{r} \left\{ \int_{w^*}^{\infty} (x - w^*) \, \mathrm{d}F_A(x) \right\} - \lambda = 0, \; w^* \geq b$$

$$-\frac{\partial c(e_A^* + e_B^*)}{\partial(e_A^* + e_B^*)} + \frac{\partial \sigma(e_B^*)}{\partial e_B} \frac{\psi_B}{r} \left\{ \int_{w^*}^{\infty} (x - w^*) \, \mathrm{d}F_B(x) \right\} - \lambda = 0, \; w^* \geq b$$

Optimal search thus equalizes the marginal returns to search in both sectors. Consequently, at optimal effort levels, e_A^* and e_B^*, the following must hold:[4]

$$\frac{\sigma'(e_A^*)}{\sigma'(e_B^*)} = \frac{\psi_B \int_{w^*}^{\infty} (x - w^*) \, \mathrm{d}F_B(x)}{\psi_A \int_{w^*}^{\infty} (x - w^*) \, \mathrm{d}F_A(x)}, \; w^* \geq b \tag{2}$$

When the distribution of wage offers or arrival rates in sector A deteriorate compared to those in sector B, the right-hand side ratio increases. By assumption, σ' is positive and monotonically decreasing. Therefore, to increase the left-hand side ratio, under optimal search, efforts will shift from sector A to sector B. Moreover, given that $\frac{\sigma'(e_A^*)}{\sigma'(e_B^*)}$ is monotonically decreasing in e_A^*, the

[1] If a worker finds a job that pays a wage of x in each period, the present value of this job offer equals $W(x) = x/r$, representing an increase of $W(x) - V = x/r - V$ over the NPV of engaging in search. Because the instantaneous offer arrival rate equals $\psi_s \sigma(e_s)$, the expected net present value of searching with effort levels e_s equals $\sum_s \psi_s \sigma(e_s) \left\{ \int_0^{\infty} \max[0, W(x) - V] \, \mathrm{d}F_s(x) \right\}$.

[2] This holds even in models where sectors have different layoff rates (Fallick, 1992). The reason is that, at the reservation wage, workers are indifferent between unemployed search and employment. Furthermore, if search costs are the same when employed or unemployed, workers can continue their search while working. In this case, the reservation wage equals the value of leisure.

[3] We use the fact that $\frac{\partial c(e_A + e_B)}{\partial e_A} = \frac{\partial c(e_A + e_B)}{\partial(e_A + e_B)} \frac{\partial(e_A + e_B)}{\partial e_A} = \frac{\partial c(e_A + e_B)}{\partial(e_A + e_B)} = \frac{\partial c(e_A + e_B)}{\partial e_B}$.

[4] Denoting $c'' = \frac{\partial c^2(e_A^* + e_B^*)}{\partial(e_A^* + e_B^*)\partial(e_A^* + e_B^*)}$, $\sigma_s'' = \frac{\partial^2 \sigma(e_s^*)}{\partial e_s^2}$ and $k_s = \frac{\psi_s}{r} \left\{ \int_{w^*}^{\infty} (x - w^*) \, \mathrm{d}F_s(x) \right\}$ the bordered Hessian is given by $\begin{bmatrix} 0 & 1 & 1 \\ 1 & -c'' + k_A \sigma_A'' & -c'' \\ 1 & -c'' & -c'' + k_B \sigma_B'' \end{bmatrix}$, which – by the assumption of decreasing marginal benefits to search efforts ($\sigma_s'' < 0$) – ensures that the interior solution is a maximum, as long as marginal costs of search are increasing, constant or decreasing sufficiently slowly (i.e., $c'' > k_B \sigma_B''$).

ratio of sector A to sector B's attractiveness has a one-to-one mapping to e_A^*, guaranteeing that (2) has a unique solution.[5]

Whenever a sector offers a job with a wage above the reservation wage, w^*, search ends and workers exit unemployment through this sector. Because the likelihood of such an event is independent of the time a worker has spent searching, the destination-sector-specific hazard rate is constant and equal to:

$$\theta_s = \sigma\left(e_s^*\right)\psi_s\left[1 - F_s\left(w^*\right)\right],\ w^* \geq b \tag{3}$$

In principle, one could use a competing-risks model to approach this problem empirically. However, we observe workers only once a year, for up to to three years after displacement. Consequently, our data on survival are in discrete time. Standard continuous-time competing-risk models are therefore less suited. Below, we adapt the derivations in Jenkins (2005, pp. 103-105) to the context of the hazard rate in (3) to show that the determinants of a worker's hazard to exit unemployment through sector A or through sector B can be estimated approximately by a multinomial logit model.

Let $f(u,v)$ be the joint probability density function for the probability that acceptable job offers arrive in sector A at time u and in sector B at time v. The hazard of exiting unemployment through sector A, i.e., the probability that a worker will have accepted a job in sector A by the end of a one time-unit period, is given by:

$$P\left(u < \min\left(v,1\right)\right) = \int_0^1 \int_u^\infty f\left(u,v\right)\,\mathrm{d}v\,\mathrm{d}u \tag{4}$$

As common in competing risks models, we assume that, conditional on observables, the destination specific continuous hazard rate functions are independent. Equation (4) can then be rewritten as:

$$P\left(u < \min\left(v,1\right)\right) = \int_0^1 \left\{ \int_u^1 f_A\left(u\right) f_B\left(v\right)\,\mathrm{d}\nu + \int_1^\infty f_A\left(u\right) f_B\left(v\right)\,\mathrm{d}\nu \right\} \mathrm{d}u \tag{5}$$

Let h_s be a discrete hazard rate for exiting unemployment through sector s, i.e., the likelihood that an acceptable job offer arrives in sector s before the end of the period. The second part of equation (5) now simplifies to:

$$\int_0^1 \int_1^\infty f_A\left(u\right) f_B\left(v\right)\,\mathrm{d}\nu\,\mathrm{d}u = \left(1 - h_B\right) \int_0^1 f_A\left(u\right)\,\mathrm{d}u$$

$$= h_A(1 - h_B)$$

Let $S_s(x)$ be the survival function for sector s, i.e., the likelihood that no acceptable offer has arrived from sector s until time x. Given that the hazard

[5] This follows from the fact that, given that $\sigma'' < 0$ and the first-order condition related to the budget constraint implies that $e_A^* + e_B^* = 1$, the derivative of $\log \frac{\sigma'(e_A^*)}{\sigma'(1-e_A^*)}$ with respect to e_A^* is negative for any $0 \leq e_A^* \leq 1$.

functions are constant over time, the first part of equation (5) can now be written as:[6]

$$\int_0^1 \int_u^1 f_A(u) f_B(v) \, \mathrm{d}\nu \, \mathrm{d}u = \frac{\theta_A}{\theta_A + \theta_B} h - (1 - h_B) h_A \tag{6}$$

where h represents the likelihood that the worker finds a job in either of the two sectors before the end of the period and θ_s the instantaneous hazard of finding a job in sector s. Furthermore, we have used that with only one time period, the discrete hazard rate is the complement of the survival function at the end of that period: $h = 1 - S_A(1) S_B(1) = 1 - S(1)$, where $S(.)$ represents the joint survival function for the hazards of finding a job in A or B. Putting both pieces together, equation (5) becomes:

$$\int_0^1 f_A(u) \left\{ \int_u^1 S_B(v) \theta_B \, \mathrm{d}v \right\} \mathrm{d}u = h_A (1 - h_B) + \frac{\theta_A}{\theta_A + \theta_B} h - (1 - h_B) h_A$$

$$= \frac{\theta_A}{\theta_A + \theta_B} h$$

The probability that the worker receives an acceptable offer from sector B first is analogous. Finally, the probability of receiving no acceptable offer at all before the end of the period is simply $1 - h$. Consequently, the likelihood of observing δ_A individuals accepting job offers in sector A and δ_B individuals accepting offers in sector B is:

$$L = (1 - h)^{1 - \delta_A - \delta_B} \left(\frac{\theta_A}{\theta_A + \theta_B} h \right)^{\delta_A} \left(\frac{\theta_B}{\theta_A + \theta_B} h \right)^{\delta_B}$$

$$L = h^{\delta_A + \delta_B} (1 - h)^{1 - \delta_A - \delta_B} \left(\frac{\theta_A}{\theta_A + \theta_B} \right)^{\delta_A} \left(\frac{\theta_B}{\theta_A + \theta_B} \right)^{\delta_B}$$

Approximating $h = 1 - e^{-(\theta_A + \theta_B)}$ by $\theta_A + \theta_B$:

$$L \approxeq (\theta_A + \theta_B)^{\delta_A + \delta_B} (1 - \theta_A - \theta_B)^{1 - \delta_A - \delta_B} \left(\frac{\theta_A}{\theta_A + \theta_B} \right)^{\delta_A} \left(\frac{\theta_B}{\theta_A + \theta_B} \right)^{\delta_B}$$

$$L \approxeq (1 - \theta_A - \theta_B)^{1 - \delta_A - \delta_B} \theta_A^{\delta_A} \theta_B^{\delta_B}$$

If we choose a logistic function to relate hazard rates to observables, i.e. $\theta_s = \frac{e^{X\beta_s}}{1 + e^{X\beta_A} + e^{X\beta_B}}$, we obtain the likelihood function associated with a multinomial logit model:

$$L \approxeq \left(1 - \frac{e^{X\beta_A} + e^{X\beta_B}}{1 + e^{X\beta_A} + e^{X\beta_B}} \right)^{1 - \delta_A - \delta_B} \left(\frac{e^{X\beta_A}}{1 + e^{X\beta_A} + e^{X\beta_B}} \right)^{\delta_A} \left(\frac{e^{X\beta_B}}{1 + e^{X\beta_A} + e^{X\beta_B}} \right)^{\delta_B}$$

$$L \approxeq \left(\frac{1}{1 + e^{X\beta_A} + e^{X\beta_B}} \right)^{1 - \delta_A - \delta_B} \left(\frac{e^{X\beta_A}}{1 + e^{X\beta_A} + e^{X\beta_B}} \right)^{\delta_A} \left(\frac{e^{X\beta_B}}{1 + e^{X\beta_A} + e^{X\beta_B}} \right)^{\delta_B} \tag{7}$$

[6] See Online Appendix A for a full derivation.

The geography of search

In order to add a spatial dimension to the search process, we assume that the sector-specific intrinsic offer rates, ψ_s, or the wage-offer distributions, $F_s(w)$, or both, depend on the local labor market conditions in sector s. In particular, holding local conditions for sector B constant, more favorable conditions for sector A will directly and positively effect θ_A, but not θ_B. However, the improvement in local conditions in sector A will induce workers to reallocate search efforts from sector B to sector A. Consequently, local conditions in A will still *indirectly* affect θ_B, namely, through the way workers divide search efforts. Equation (2) shows that this effect will be negative: the better the local conditions in sector A are, the less a worker will search in sector B. This, in turn, decreases θ_B, the hazard of exiting unemployment through sector B.

How would these search efforts be reflected in observable characteristics of workers' careers? By increasing search efforts, workers can sample jobs from a wider sets of firms. We propose that one of the ways in which this manifests itself is through the increase in the geographical scope of search. For instance, workers could spend extra time to attend job interviews outside the region. Similarly, social networks may help identify job opportunities outside the region. However, given that these networks are often local, this may involve reaching out to friends and acquaintances that are somewhat removed in one's social network. As a consequence, identifying nonlocal, as opposed to local jobs, will typically require more effort. Note that we assume that workers predominantly direct their search efforts at sectors, not regions. In Online Appendix B, we provide some empirical results that show that this is a plausible assumption.

We incorporate this reasoning into the model by modifying equation (1) to add a geographical dimension to the arrival rates of suitable wage offers. In particular, let offers from sector s originate from outside the worker's home region with probability $\rho(e_s|X_s)$. The hazard of exiting unemployment through sector s in the home region, θ_{0s}, now becomes:

$$\theta_{0s} = \psi_s \sigma(e_s) \left(1 - F_s\left(w^*\right)\right) \left[1 - \rho(e_s|X_s)\right] \tag{8}$$

and the hazard of exiting through jobs in sector s outside the home region, θ_{1s}, equals:

$$\theta_{1s} = \psi_s \sigma(e_s) \left(1 - F_s\left(w^*\right)\right) \rho(e_s|X_s) \tag{9}$$

ρ thus maps search efforts onto the interval $(0, 1)$. We will assume that ρ *decreases* monotonically in X_s, a vector that captures how favorable local conditions are in sector s. That is, we will assume that $\frac{\partial \rho}{\partial X_s} < 0$, such that favorable local conditions raise the likelihood that acceptable offers will arrive from *within* the region as opposed to from *outside* the region. Moreover ρ is assumed to *increase* in e_s to reflect the greater efforts that job offers from outside the region require.[7]

[7]Note that we do not specify whether efforts and favorable local conditions increase job offer arrival rates or lead to better wage-offer distributions. Because, without loss of generality, we can think of wages net of commuting and/or relocation costs, the optimization problem of the worker remains unaffected by the fact that some jobs are located outside the region.

In the empirical analyses, we will equate one of the two sectors in the model with the 5-digit industry from which workers are displaced. Henceforth, we will refer to this industry as the "pre-displacement industry" or a worker's "old industry." The other sector consists of other industries that provide suitable jobs, namely those that are related to the pre-displacement industry. The upshot of equations (8) and (9) is that we can infer how workers allocate search efforts between these two sectors from workers' geographic mobility. In particular, the model has the following testable predictions:

1. Favorable local conditions in the pre-displacement industry (*in related industries*) will increase the likelihood of finding jobs in this industry (*in these industries*).

2. Conditional on the local conditions in related industries (*in pre-displacement industries*), favorable local conditions in the pre-displacement industry (*in related industries*) will decrease the relative risk of finding nonlocal jobs compared to local jobs *outside* the pre-displacement industry (*in the pre-displacement industry*).

3. Conditional on the local conditions in related industries (*in pre-displacement industries*), favorable local conditions in the pre-displacement industry (*in related industries*) will increase the likelihood of finding *nonlocal jobs outside* the pre-displacement industry (*in the pre-displacement industry*) compared to staying unemployed.

Prediction 1 derives from the fact that the quality of local job-offers and/or arrival rates increase in a sector as a direct effect of better local conditions in that sector. This effect is augmented by the fact that better local conditions will also spur greater efforts to search in the sector, which raises the likelihood of receiving acceptable job offers. The effect on whether acceptable offers will be local or nonlocal is ambiguous, because ρ decreases due to better local conditions, but increases because of greater efforts. However, local conditions in sector A should neither directly affect the ratio of nonlocal to local job-finding hazards in sector B nor of the ratio of finding a job in sector B to remaining unemployed. Such cross-over effects nevertheless arise, because favorable conditions in sector A will draw search efforts from sector B to sector A as implied by equation (2).

To see this, consider that the model specification in (7) implies the following log-odds for exiting unemployment through nonlocal instead of local jobs in sector A:

$$\log \frac{\theta_{1A}}{\theta_{0A}} \approx X_A \beta_A^{1A} + X_B \beta_B^{1A}, \tag{10}$$

where X_s quantifies the quality of local conditions in sector s and parameters are subscripted by this sector and superscripted by the hazard rate to which they refer (0 codes exits through local, 1 through nonlocal jobs and A and B code the sector in which the job was found). Furthermore, the coefficients of the reference category (local exits through sector A), β_A^{0A} and β_B^{0A}, are normalized

to zero and $\approx$ indicates an equality by assumption of the logistic functional form. Using (8) and (9), (10) implies:

$$\log \frac{\rho\left(e_A\left(X_A, X_B\right), X_A\right)}{1-\rho\left(e_A\left(X_A, X_B\right), X_A\right)} \approx X_A \beta_A^{1A} + X_B \beta_B^{1A}.$$

The derivative of this expression with respect to local conditions in sector B is given by:

$$\partial \log \frac{\rho\left(e_A\left(X_A, X_B\right), X_A\right)}{1-\rho\left(e_A\left(X_A, X_B\right), X_A\right)} / \partial X_B \approx \partial \left(X_A \beta_A^{1A} + X_B \beta_B^{1A}\right) / \partial X_B,$$

which evaluates to:

$$\frac{1}{\rho\left(e_A\left(X_A, X_B\right), X_A\right)\left(1-\rho\left(e_A\left(X_A, X_B\right), X_A\right)\right)} \frac{\partial \rho\left(e_A\left(X_A, X_B\right), X_A\right)}{\partial e_A\left(X_A, X_B\right)} \frac{\partial e_A\left(X_A, X_B\right)}{\partial X_B} \approx \beta_B^{1A}$$

Given that the first ratio is always positive, and the second is positive by assumption, a significant and *negative* estimate for β_B^{1A} implies $\frac{\partial e_A(X_A, X_B)}{\partial X_B} < 0$. Therefore, if we find that favorable local conditions in sector B *reduce* the log-odds of exiting through nonlocal instead of local jobs in sector A, we can infer that these favorable local conditions must have *negatively* impacted the efforts workers dedicated to search in sector A.

Hypotheses 3 can be derived from an inspection of the log-odds for exiting unemployment through nonlocal jobs in sector A instead of staying unemployed:

$$\log \frac{\theta_{1A}}{1-\theta_{0A}-\theta_{1A}-\theta_{0B}-\theta_{1B}} \approx X_A \widetilde{\beta}_A^{1A} + X_B \widetilde{\beta}_B^{1A},$$

where coefficients $\widetilde{\beta}_A^{1A}$ and $\widetilde{\beta}_B^{1A}$ have been normalized against the coefficients of the hazard to remain unemployed. Using equations (8) and (9), the derivative of this expression with respect to local conditions in sector B can be written as:

$$\Psi_1 \frac{\partial e_A\left(X_A, X_B\right)}{\partial X_B} + \frac{\Psi_2 \frac{\partial e_A(X_A, X_B)}{\partial X_B} - \Psi_3 \frac{\partial e_A(X_A, X_B)}{\partial X_B} + \frac{\partial k_B(X_B)}{\partial X_B} \sigma\left(e_B\left(X_A, X_B\right)\right)}{\Psi_4} \approx \widetilde{\beta}_B^{1A}$$

where:

$k_s\left(X_s\right) = \psi_s\left(1 - F_s\left(w^*\right)\right)$

$\Psi_1 = \frac{1}{\sigma(e_A(X_A, X_B))} \frac{\partial \sigma(e_A(X_A, X_B))}{\partial e_A(X_A, X_B)} + \frac{1}{\rho(e_A(X_A, X_B))} \frac{\partial \rho(e_A(X_A, X_B), X_B)}{\partial e_A(X_A, X_B)}$

$\Psi_2 = k_A\left(X_A\right) \frac{\partial \sigma(e_A(X_A, X_B))}{\partial e_A(X_A, X_B)}$

$\Psi_3 = -k_B\left(X_B\right) \frac{\partial \sigma(1-e_A(X_A, X_B))}{\partial (1-e_A(X_A, X_B))} \frac{\partial (1-e_A(X_A, X_B))}{\partial e_A(X_A, X_B)} = k_B\left(X_B\right) \frac{\partial \sigma(e_B(X_A, X_B))}{\partial e_B(X_A, X_B)}$

$\Psi_4 = 1 - k_A\left(X_A\right) \sigma\left(e_A\left(X_A, X_B\right)\right) - k_B\left(X_B\right) \sigma\left(e_B\left(X_A, X_B\right)\right)$

If search efforts were not responsive to local conditions, i.e., $\frac{\partial e_A(X_A, X_B)}{\partial X_B} = 0$, $\widetilde{\beta}_B^{1A}$ should have the same sign as $\frac{\partial k_B(X_B)}{\partial X_B}$ and therefore be positive. Finding a negative effect of conditions in sector B on the relative risk of finding

nonlocal jobs in sector A vis-à-vis remaining unemployed, therefore, would imply that $\frac{\partial e_A(X_A,X_B)}{\partial X_B} < 0$.[8] Note, that a similar observation can be made for the effects on the relative risk of finding *local* jobs in sector A instead of remaining unemployed. In this case, the second term in Ψ_1 is replaced by $-\frac{1}{1-\rho(e_A(X_A,X_B))}\frac{\partial \rho(e_A(X_A,X_B),X_B)}{\partial e_A(X_A,X_B)}$, dampening the negative effect of effort reallocation. Intuitively, this happens, because decreasing search efforts will reduce the spatial scope of search in sector A, which, in turn, will increase *local* job-finding rates. We will test whether the cross-dependencies predicted in hypotheses 2 and 3 exist in reality at the end of section 6.

4 Data

Our data are taken from the German Employee History database (Beschäftigtenhistorik, EH, see Bender et al. (2000) for details). The EH database is based on Germany's social security records. Our version of these data provides yearly information on an individual's daily wage, deflated to 2005 EUR, occupation, work status (i.e., full-time employed, part-time employed, or in apprenticeship), gender, and age. The EH also contains anonymized identifiers that allow us to follow individuals over time. Moreover, the EH contains information about the industry and location of each establishment. Because of changes in the industry classification system, we limit our analyses to the years 1999 to 2008. Furthermore, we focus on male, full-time employees between the ages of 25 and 50 and drop apprentices. To ensure a uniform definition of success in post-displacement job-search across workers, we ignore part-time jobs. Because this strategy may lead to overstated wage losses for displaced workers, we rerun our analyses while including all post-displacement part-time jobs. Apart from some reductions in the effect of displacement on wages and nonemployment rates, these estimations yield virtually the same results as those presented hereafter (see Online Appendix D).

A drawback of social security records is that they do not cover individuals who are exempt from social security contributions, such as civil servants, soldiers, self-employed workers, entrepreneurs and unpaid family workers. In total, these workers constitute about 20 percent of the German labor force (Herberger and Becker, 1983). When we use the term "employed", we therefore refer to people employed in jobs with social security coverage. Similarly, although the main

[8] In principle, this finding could also imply that $(\Psi_3 - \Psi_2)\frac{\partial e_A(X_A,X_B)}{\partial X_B} > \frac{\partial k_B(X_B)}{\partial X_B}\sigma\left(e_B\left(X_A,X_B\right)\right)$, requiring that the indirect effect of the shift in search efforts due to better local conditions in sector B on *total* job finding rates is negative and in excess of the positive direct effect on job-offers. This would mean that the derivative of the entire denominator of the log-odds were negative. That is, better conditions in a sector would have to lead to an *increase* in the likelihood that workers remain unemployed. This is not impossible: if the sector in which search conditions improve offers much higher wages but much worse job arrival rates, workers might be tempted to shift search efforts to this sector because of higher expected wages (but lower employment chances) in a way that outdoes the improved conditions. However, we believe such an outcome to be unlikely in general.

reason individuals drop out of the data is because they have become unemployed or inactive, some may also have returned to school, received civil servant status, started their own businesses, and so on. We therefore use the term "nonemployment" instead of unemployment to refer to workers who leave jobs with social security coverage. Appendix F addresses some issues arising from this definition in further detail.

As displaced workers, we select all workers who have lost their jobs in establishment closures. Closures are identified with the help of a variable created by Hethey and Schmieder (2010). These authors marked each disappearance of an establishment identifier from the EH as a potential closure event. However, when analyzing the labor outflows from these establishments, they found that only about 40% of establishments of four employees or larger with a disappearing identifier can be regarded unambiguously as closures rather than mere administrative changes in establishment identifiers. In the remaining 60%, large shares of the disappearing establishment's workforce move to the same new employer, which suggests that some kind of corporate connection (such as take-overs or identifier recodings) exists between the old and the new establishment. In what follows, we will consider establishment-identifier disappearances to signal closure events, if the establishment had at least 10 employees in the year before the closure, and if fewer than 30% of its workers move to the same other establishment in the year after the closure (see Online Appendix F for a discussion of alternative definitions of closure events). We then gather all workers who left one of these establishments during the year they closed down. Of these workers, we select those who, prior to the displacement event, (a) had at least six years of work experience, (b) three years of industry experience and (c) one year of establishment tenure. These three conditions ensure that workers have had enough time to find well-matching jobs and gain relevant work experience, such that their industry affiliation is a good reflection of their (industry-specific) skills. Moreover, insisting on over one year of establishment tenure avoids selecting workers who were hired for reasons directly related to the closure. We then follow these workers for the period starting six years before and ending three years after the closure. These conditions limit us to establishment closures between 2003 and 2005.

The empirical analyses are divided into two parts. First, we will estimate the causal effects of job displacement on workers' career trajectories and to what extent the local industry mix moderates these effects. In particular, we will quantify the effect of displacement events, not just on employment rates and wages, but also on workers' geographical and industrial mobility. This will help determine whether there is evidence for the existence of Marshallian benefits in job search. We describe these analyses in section 5.

Second, we will explore whether displaced workers internalize these Marshallian benefits in their search strategies. In particular, we will test the hypotheses formulated in section 3 using a multinomial logit estimation. The core of these hypotheses is that, all else equal, workers should reduce search efforts in one sector when the Marshallian externalities in the other sector increase. These reductions in search efforts, in turn, should manifest themselves in a contraction

of the spatial scope of search. The second part of the empirics – summarized in section 6 – tests this prediction.

5 Displacement effects

Related industries

In the model of section 3, workers divide search efforts between two sectors: the pre-displacement industry and a second sector consisting of industries that are closely related to the pre-displacement sector in terms of their skill requirements. To define the set of related industries that constitute this second sector, we use the skill-relatedness index proposed by Neffke et al. (2017). This index is calculated as the observed labor flows between two industries, divided by the labor flows that would have been expected had workers switched industries randomly. That is, let F_{ij} be the number of workers who change jobs from establishments in industry i to establishments in industry j. The relatedness between i and j is now defined as:

$$R_{ij} = \frac{F_{ij}}{\sum_{k \neq j} F_{kj} \sum_{l \neq i} F_{il}} \sum_{k'} \sum_{l' \neq k'} F_{k'l'} \tag{11}$$

and $R_{ii} \equiv 0$: industries are by definition not skill-related to themselves. To enhance the precision of the index, we construct these labor flows using information on all full-time employed men and women between the age of 18 and 65. Similar inter-industry relatedness indices have been used in a variety of studies (Greenstone et al., 2010; Dauth, 2010; Baptista and Costa, 2012; Neffke and Henning, 2013; Timmermans and Boschma, 2013; Csáfordi et al., 2018)

Because inter-industry labor-flow connections are extremely sparse – in any given year, over 80% of industry pairs display no labor flows at all – this method provides clearly delineated labor markets. To avoid mechanical relations between the R-matrix and the careers of displaced workers, we remove from F_{ij} all workers who at any point between 1999 and 2008 had been employed in an establishment that closes down in this same period.[9] Finally, we calculate this R-matrix for each year between 1999 and 2008, take its average across years, and symmetrize the resulting matrix by averaging its elements with those of its transpose.[10] We refer to this averaged and symmetrized matrix as $\bar{R}$.

[9] Neffke et al. (2017) show that these matrices are all but invariant across years and highly similar across a number of broad occupational and wage groupings. Moreover, flows of workers who change jobs over long or short distances yield all but indistinguishable R-matrices. This suggests that the patterns expressed in these matrices express some fundamental, non-idiosyncratic similarities in job tasks across industries.

[10] To be precise, we first use the following transformation to reduce skew: $R^* = \frac{R}{R+1}$, which maps the values of R from the interval $[0, \infty)$ onto the interval $[0, 1)$. This ensures that the averages are not overly affected by right-tail outliers. The threshold value for R of 3 we use in this paper corresponds to a threshold of $3/4$ for R^*.

Local conditions

Our main interest is the role Marshallian externalities play in the post-displacement careers of workers who lose their job in establishment closures. Therefore, we define the local conditions in the model of section 3 in terms of local industrial concentration patterns. In particular, we use the local employment shares of the pre-displacement and of related industries to categorize industry-region combinations into different classes.

As regional units, we use Germany's 141 labor market areas as defined by Kosfeld and Werner (2012). We start by dividing locations into three types, reflecting regions where the worker's old (O) industry represents a small, moderate or large share of regional employment. To do so, we define the following dummy group for a worker who got displaced from industry i in region r and year t:

$$\begin{aligned} O_{irt}^{L} &= I\left(\frac{E_{irt}}{\sum_j E_{jrt}} \leq \zeta_1\right) \\ O_{irt}^{M} &= I\left(\zeta_1 < \frac{E_{irt}}{\sum_j E_{jrt}} \leq \zeta_2\right) \\ O_{irt}^{H} &= I\left(\frac{E_{irt}}{\sum_j E_{jrt}} > \zeta_2\right) \end{aligned} \tag{12}$$

where $\frac{E_{irt}}{\sum_j E_{jrt}}$ is the regional employment share of the worker's old industry in year t (not counting the employment in the establishments that close down). Furthermore $I(.)$ is an indicator function that evaluates to 1 if its argument is true. Finally, ζ_1 and ζ_2 are chosen such that all categories represent an equal number of observations in our sample.

Analogously, we group region-industry cells by the local employment share of industries related to the pre-displacement industry ("Alternative" industries):

$$\begin{aligned} A_{irt}^{L} &= I\left(\frac{E_{irt}^{rel}}{\sum_j E_{jrt}} \leq \zeta_1^{'}\right) \\ A_{irt}^{M} &= I\left(\zeta_1^{'} < \frac{E_{irt}^{rel}}{\sum_j E_{jrt}} \leq \zeta_2^{'}\right) \\ A_{irt}^{H} &= I\left(\frac{E_{irt}^{rel}}{\sum_j E_{jrt}}\right) > \zeta_2^{'} \end{aligned} \tag{13}$$

$\zeta_1^{'}$ and $\zeta_2^{'}$ once again divide workers into equally sized groups and E_{irt}^{rel} represents the employment in region r and year t in industries closely related to industry i, where "closely related" refers to industries for which the skill-relatedness to the worker's old industry i exceeds a threshold, ξ. That is:

$$E_{irt}^{rel} = \sum_{k \neq i} E_{krt} I\left(\bar{R}_{ik} > \xi\right) \tag{14}$$

Employment in equations (13) and (14) is again measured in the displacement year, excluding employment in establishments that close down. We use a threshold value of $\xi = 3$, which implies that the observed labor flows between an industry and the pre-displacement industry are at least three times as large as the random benchmark. The reason for this choice is that, at this threshold, related industries absorb about the same share of displaced workers (29%) as the pre-displacement industry itself (27%). Consequently, the two sectors we distinguish (the old industry and related industries) represent similarly important reservoirs of new jobs. Variations of this threshold and definitions analogous to equations (12) and (13) based on employment levels, instead of shares, yield similar results (available on request).

Estimation strategy

Most job separations occur when workers decide it is time to pursue career opportunities elsewhere, or when their employers make this decision in their stead. As a consequence, job separations are often endogenous to the expectations about a workers' career prospects at their current firm. An exception are job separations due to establishment closures. Such separations are typically unrelated to the performance and career aspirations of individual workers and have, therefore, been considered to be exogenous from a worker's perspective (e.g., Gibbons and Katz, 1991; Jacobson et al., 1993; Couch and Placzek, 2010; Schwerdt, 2011). Using a sample of displaced workers should thus mitigate concerns about workers self-selecting into career changes as long as displacement is uncorrelated with worker characteristics.

To enhance the plausibility of the exogeneity assumption, we compare displaced to observationally similar non-displaced workers, using a combination of propensity-score matching and regression analysis. To be precise, we follow Ho et al. (2007) and use matching as a pre-screening method to reduce the dependence of the treatment variable (in our case, displacement) on worker characteristics. Such pre-screening has several advantages. Firstly, because the procedure is based on only pre-displacement covariates, it does not introduce selection biases. Secondly, by ensuring a common support of treated and untreated individuals, pre-screening avoids inference that is based on inter- or extrapolation to parts of the covariate space where we do not observe any displaced (or nondisplaced) workers. Thirdly, because the pre-screening ensures that displacement is orthogonal to the exogenous covariates, we don't need to make any parametric assumptions about how such covariates enter the data-generating process.[11] As a consequence, pre-screening mitigates misspecification issues related to the exact functional form through which these covariates enter

[11] For instance, mobility decisions will depend on a worker's age. However, because the functional relation between mobility and age may be complex, it is hard to correct for this by simply controlling for worker age. By matching displaced to nondisplaced workers, we select a sample of workers in which displacement is orthogonal to age. Consequently, in this sample, a worker's age cannot confound the estimated displacement effect, irrespective of the exact functional form through which mobility depends on age.

the regression equation (Ho et al., 2007). The cost of pre-screening the data is that the estimated effects represent average effects for the subset of displaced workers instead of for the population as a whole.

Matching

Our matching strategy closely follows the one in Nedelkoska et al. (2015).[12] For each displaced worker who meets the criteria listed in Section 4, we try to find a statistical twin among the non-displaced workers by means of propensity-score matching. Statistical twins are drawn from a donor pool that observes the same pre-displacement restrictions as the ones imposed on displaced workers, with the additional requirement that they do not experience any displacement events in the 1999-2008 period.[13] We estimate workers' propensity to experience a displacement event with a probit model that uses as explanatory variables a worker's education, age, years of general, industry, and regional work experience, as well as establishment tenure. To avoid parametric assumptions, age and experience variables enter as dummy groups. Furthermore, we control for regional economic conditions by adding the regional employment shares and squared values thereof in the pre-displacement and in related industries in the year before the establishment closes down. Most importantly, however, we use lags 6 to 2 of pre-displacement wages and the logarithm of wage growth between 5 and 2 years before the displacement event to capture a worker's pre-displacement wage curve. Because this curve reflects rewards for both observed and unobserved worker characteristics, it helps control for unobserved characteristics that might affect post-displacement wage dynamics and mobility decisions. Matching workers with similar pre-event wage curves, therefore, allows us to establish plausible counterfactual careers for displaced workers. Finally, we match exactly on establishment tenure and displacement year. After using nearest-neighbor matching and dropping all observations that are not on the support, we are left with a sample of 45,344 worker pairs.

Table 1 compares the means of the matching variables and wage paths between displaced and non-displaced workers in the overall population and in the selected sample. Individual characteristics of displaced and non-displaced workers are much more closely aligned in the sample than in the population as a whole. For all pre-displacement variables, differences in means between displaced and non-displaced are well below 5%. Note that pre-displacement wages

[12] Nedelkoska et al. (2015) study occupational mobility of displaced workers and the extent to which the need for skill-adjustments amplifies the effect of displacement.

[13] Note that this means that we do not impose any further restrictions on the post-displacement careers of the donor pool. As a consequence, most statistical twins will not change employer in the year of displacement. An alternative would be to match displaced workers to nondisplaced job-separators. However, this design would not estimate the treatment effect of job displacement, i.e., the difference between a displaced worker's observed career path and her (counterfactual) career path, had she not been displaced. Instead, we would end up estimating the difference between two treatments: the (exogenous) displacement event on the one hand and (a most likely endogenous) regular job separation on the other hand.

are particularly well-balanced, with biases below 1%.[14] In as far as prior wages reflect a worker's productivity, the strong balance on these variables suggests that there is little cause for concern that unobserved worker quality will bias our results.

Findings

To assess the overall effects of displacement on earnings, wages, non-employment and mobility decisions, we follow Schwerdt (2011) and combine matching with the difference-in-differences framework introduced to the displacement literature by Jacobson et al. (1993). That is, we estimate the following equation:

$$y_{mt} = \sum_{k=-3}^{3} \tau_1^k T_{mt}^k + \sum_{k=-3}^{3} \tau_2^k T_{mt}^k D_{mt} + X_{mt}\beta + \alpha_m + \delta_{t^*(m)} + \epsilon_{mt} \tag{15}$$

where the subscript t refers to the (calendar) year and $t^*(m)$ to the year of the establishment closure. D_{mt} is a dummy variable that assumes a value of one if year t equals the year in which individual m's establishment closed down. α_m and $\delta_{t^*(m)}$ represent individual, respectively, displacement-year fixed effects and the vector X_{mt} contains a worker's age and age-squared in year t. y_{mt} can be any of the following dependent variables: daily earnings, the logarithm of daily wages, or a dummy variable for the event that a worker is nonemployed, changes industries, or changes regions. T_{mt}^k is a dummy variable encoding event time. That is, it takes the value one in observations that take place k years after the (real or matched) displacement year (i.e., when $t = t^*(m) + k$).

The parameters of interest are collected in vector τ_2. These point estimates can be interpreted as the difference between displaced and nondisplaced workers $|k|$ years before or after the displacement event. Figure 1 graphs this vector, showing how the effects of displacement on each of the dependent variables fade over time. First, note that pre-displacement trends displaced and nondisplaced workers are very similar, suggesting that it is justifiable to interpret the effects depicted in the figures as causal. Second, all of our dependent variables are strongly affected by displacement, with most of the effects taking place in the first year after displacement. Displacement reduces daily earnings by about 37 EUR and keeps them depressed for the entire post-displacement observation-window. Much of this reduction is due to the large drop in employment rates, which reaches 38.4 percentage points (pp) in the first post-displacement year. However, workers who get re-employed within a year, face a fall in daily wages as well, of on average, 8.7%. Note that these wage effects do not take into consideration any unemployment or other benefits that displaced workers may receive. As a consequence, the *income* effects of job-displacement will be less pronounced than the reduction in *earnings* reported here (see Schmieder et al. (2010) for a treatment of unemployment benefits after job displacement in Germany).

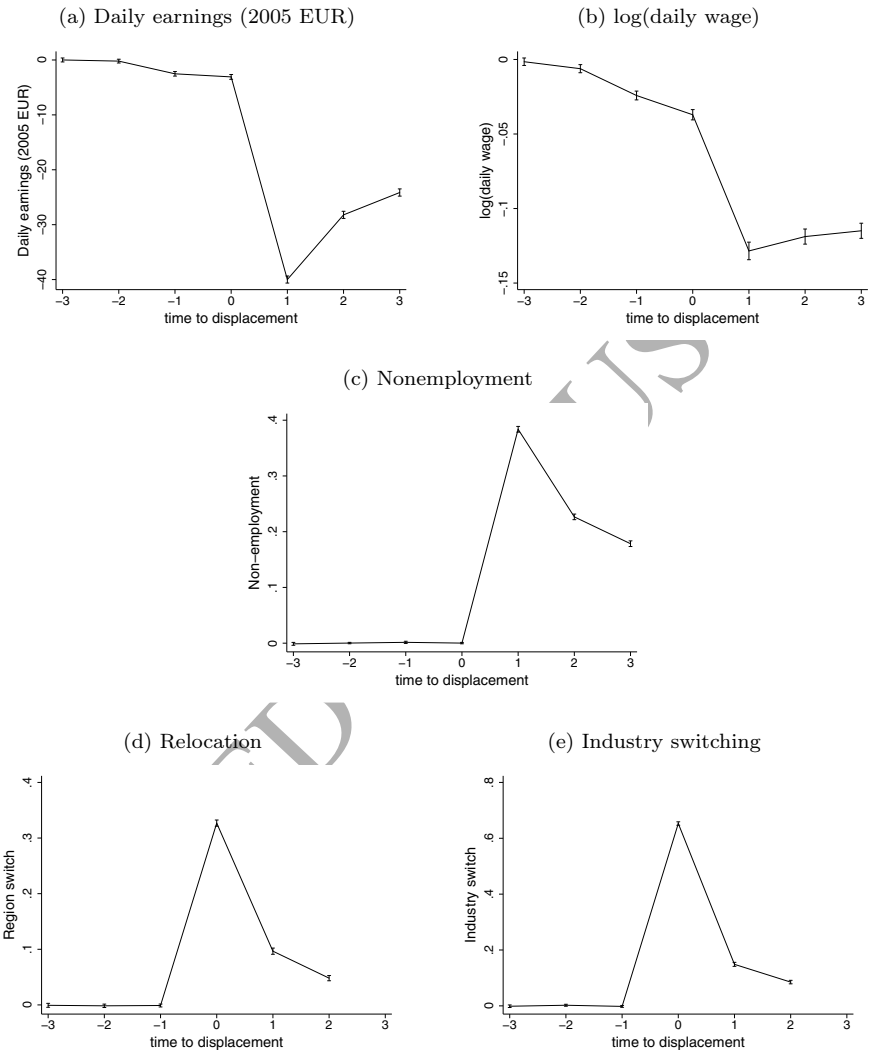
[14] The small dip in earnings of displaced workers a year before displacement is common and usually attributed to early signs of distress in establishments that are about to close.

Table 1: Balance of matched sample

	selected population			matched sample		
	treated	control	% bias	treated	control	% bias
share rel. emp.	4.04%	4.62%	-13.9	4.08%	4.07%	0.3
share old ind. emp.	0.72%	1.54%	-28.8	0.72%	0.69%	3.3
age	39.8	39.7	1.7	39.8	39.8	0.8
edu (ND)	10.05%	10.47%	-1.4	10.20%	10.35%	-0.5
edu (VT)	63.93%	65.20%	-2.7	65.35%	65.81%	-1.0
edu (HS)	0.52%	0.65%	-1.7	0.52%	0.46%	0.8
edu (HS+VT)	2.46%	4.01%	-8.7	2.47%	2.43%	0.3
edu (C)	2.96%	4.60%	-8.6	3.03%	3.02%	0.1
edu (U)	3.09%	6.39%	-15.6	3.16%	3.21%	-0.3
edu (miss.)	17.00%	8.69%	25.0	15.27%	14.72%	1.5
log(reg. size)	14.8	15.7	-14.7	15.2	15.2	-0.3
industry experience	9.2	10.6	-23.0	9.7	9.6	1.2
regional experience	12.4	13.7	-19.5	12.9	12.9	-0.5
establishment tenure	7.9	9.6	-28.6	8.3	8.3	0.0
year: 2005	38.86%	33.65%	10.8	38.50%	38.50%	0.0
year: 2006	35.06%	33.42%	3.5	35.13%	35.13%	0.0
year: 2007	26.09%	32.93%	-15.0	26.38%	26.38%	0.0
wage (4 yrs pre-D.)	84.2	100.7	-32.1	88.7	88.4	0.5
wage (3 yrs pre-D.)	86.4	105.0	-34.7	90.0	89.6	0.8
wage (2 yrs pre-D.)	89.5	109.1	-35.2	94.0	94.1	-0.2
wage (1 yr pre-D.)	90.7	111.9	-36.0	93.0	95.5	-4.9
wage (at D.)	91.9	114.3	-36.5	93.9	97.4	-6.5
wage (1 yr post-D.)	50.8	110.4	-87.8	52.7	92.9	-66.7
wage (2 yrs post-D.)	60.5	108.5	-70.5	62.6	90.8	-46.6
wage (3 yrs post-D.)	63.0	106.6	-64.0	65.1	89.4	-40.0

The selected population refers to all individuals that meet the criteria outlined in Section 4: full-time employees with at least (1) six years of work experience, (2) three years of industry experience and (3) one year of establishment tenure. For matched nondisplaced workers, we also require that they are not displaced at any time in the 1999-2008 period. "Share rel. emp." refers to the share of skill-related employment in the region at the time of (virtual) displacement as defined in equation (14). "Share old ind. emp." refers to the regional employment share of the pre-displacement industry. Wages are real wages, denominated in 2005 EUR, at the specified number of years before or after the displacement event (D.). Age, experience and tenure are measured in years.

Figure 1: Difference-in-differences in post-displacement careers



Difference-in-differences estimates using equation (15), controlling for age, age^2, education, year and worker fixed effects. The dependent variables are daily earnings (in 2005 EUR, 1a), log(daily wage) (1b) and dummy variables for being nonemployed (1c), switching regions (1d) and switching industries (1e). Region and industry switching are recorded in the last year in which a person worked in the job from which the switch took place. As a consequence, switches recorded at $t = t^*(m) + 1$ and $t = t^*(m) + 2$ represent switches from one post-displacement job to another, not delayed reemployment.

Displacement also affects which jobs workers will choose. Displaced workers are much more likely than their statistical twins to move out of a labor market area (32.8 pp) or to change 5-digit industries (65.5 pp) right after they were displaced. Moreover, switching rates remain elevated for at least two years after displacement occurs. This suggests that displaced workers do not immediately find well-matching jobs.

Local conditions as moderators of displacement effects

How does the local industry mix change the effect of D_{mt}? To study this, we interact the displacement dummy with information on the employment shares of the pre-displacement and related industries in the region. However, these shares have strongly right-skewed distributions. Therefore, we interact the displacement dummy with the dummy groups created in equations (12) and (13), which are robust to outliers. Ideally, we would integrate these interaction terms in the difference-in-differences estimations of equation (15). However, given that this would quintuple the number of parameters in the model, this set-up would yield complex and hard-to-estimate interaction effects. Instead, we collapse the data to cross-sections (one for each displacement year), where we observe workers at the time of displacement, t^*. Next, we pool the data from these three cross-sections to estimate models of the following form:

$$y_{mt^*} = \kappa D_{mt^*} + \Pi_{irt^*-1}\gamma_0 + D_{mt^*}\Pi_{irt^*-1}\gamma_1 + X_{mt^*}\beta + \eta_{it^*} + \rho_{rt^*} + \epsilon_{mt^*} \quad (16)$$

where Π_{irt^*-1} collects the dummy groups defined in the year before the displacement using equations (12) and (13). η_{it^*} and ρ_{rt^*} are industry-displacement-year and region-displacement-year fixed effects (for nondisplaced workers, these refer to the year in which their statistical twin was displaced). X_{mt^*} is a set of worker characteristics, including age, age^2, nationality dummies and a dummy group for the worker's educational attainment in the displacement year. The dependent variable, y_{mt^*}, can be one of six variables: (1) worker m's change in earnings in the first year after displacement; (2) the change in daily wages for workers who immediately find new jobs; a dummy variable that indicates whether or not worker m remains nonemployed (3) for one year or (4) for three years after displacement; (5) a dummy for whether his first post-displacement job was in a different industry or (6) in a different region than the job from which he was displaced.

The main parameters of interest - the interactions of local conditions with the displacement dummy - are collected in γ_1 and reported in Tables 2 to 7. Each table refers to one of the dependent variables and reports four different model specifications. The first column in these tables reports the overall effect of displacement, while controlling for a worker's age, education and nationality. These estimates should be similar to the ones depicted in Figure 1. The second column adds interactions with local conditions. The third column adds industry-year and region-year fixed effects. This is our preferred specification and most of the discussion below will refer to this column. Finally, in the fourth column,

we consider additional interactions of the displacement dummy with a range of worker characteristics, as well as with a region's size. We will discuss these models at the end of this section.

Wages

Table 2 illustrates the adverse effects of displacement on earnings. On average, workers lose about 37 EUR in daily earnings in the first year after having been displaced (about 36% of their pre-displacement earnings, see column 1). Table 4 shows that this is largely due to an about 38 pp increase in nonemployment hazard. By contrast, for workers who immediately find a new job, the loss in log(daily wages) is limited to an 8.2% reduction (column 1, Table 3).[15]

As expected, these estimates are very close to the difference-in-differences estimates in Figure 1. However, effects vary with the local industry mix. Displacement-induced earnings-losses and nonemployment-risks are lower in locations with high employment shares of the pre-displacement industry. Taking locations with low shares of the pre-displacement and of related industries as a benchmark and referring to our preferred specification (column 3), the reduction in the earnings-effect (see Table 2) of having high employment shares of the old industry amounts to 6.7 EUR (18%). This reduction is in part due to changes in the effect on daily wages: for workers who find new jobs, a large presence of the old industry in the region reduces the drop in log(daily wage) by 0.023 log points (25%) (Table 3). Another part of the reduction in earnings drop is due to lower rates of displacement-related nonemployment. Having high instead of low local employment shares of the old industry reduces the effect of displacement on short-term nonemployment (Table 4) by 5.9 pp (or 15%) and on long-term nonemployment rates by about 4.0 pp, a 21% reduction (Table 5).

The impact of skill-related employment in the region on wages and nonemployment rates is somewhat different: it neither significantly reduces displacement-related nonemployment nor earnings losses. On the contrary, high shares of related industries *increase* displacement-related earnings losses by 4.9 EUR. At the same time, however, a large presence of related industries protects workers from long-term nonemployment, reducing the displacement effect by 1.1 pp.[16] A potential explanation for these findings is that jobs in related industries represent a lower quality match compared to jobs in the pre-displacement industry. As a consequence, skill-related employment opportunities in a region help workers return to social-security covered employment faster, but they do so at the expense of the quality of the skill match.[17]

To study the effect of displacement on workers' mobility, we drop all displaced workers who disappear from the data for the entire 3-year post-displacement

[15] To keep the pairs balanced in these estimations, we require that not only the displaced worker but also her statistical twin is employed in the year immediately after the displacement event.

[16] At 1.5 pp, the interaction effect with intermediate shares of related industries is even higher, although this difference is not statistically significant.

[17] In line with this, we find (not shown) that high local shares of related employment are associated with a *reduced* skill-relatedness between pre- and post-displacement jobs.

Table 2: Effects of regional conditions on earnings losses upon displacement

dep. var.: earnings increase (EUR)	(1)	(2)	(3)	(4)
D	-36.872***	-37.872***	-37.127***	-90.431***
	(0.658)	(1.857)	(0.916)	(19.135)
$D \times O^M_{i,r}$		0.883	1.690	1.625
		(1.613)	(1.083)	(1.076)
$D \times O^H_{i,r}$		6.355***	6.666***	5.889***
		(1.537)	(1.133)	(1.126)
$D \times A^M_{i,r}$		-0.102	-0.696	-0.165
		(1.573)	(1.036)	(1.020)
$D \times A^H_{i,r}$		-4.478***	-4.925***	-4.220***
		(1.667)	(1.191)	(1.170)
$O^M_{i,r}$		0.438	0.463	0.558
		(0.433)	(0.569)	(0.562)
$O^H_{i,r}$		-0.040	-0.504	-0.076
		(0.449)	(0.736)	(0.729)
$A^M_{i,r}$		0.236	0.130	-0.203
		(0.435)	(0.617)	(0.604)
$A^H_{i,r}$		1.543***	1.454*	0.825
		(0.463)	(0.857)	(0.837)
other interaction terms?	no	no	no	yes
age controls?	yes	yes	yes	yes
year dummies?	yes	yes		
education dummies?	yes	yes	yes	yes
industry-year dummies?	no	no	yes	yes
region-year dummies?	no	no	yes	yes
R^2	0.127	0.128	0.175	0.183
# obs.	90,688	90,688	90,688	90,688

***: p<.01, **: p<.05, *: p<.1. The dependent variable measures a worker's change in real daily earnings (in 2005 EUR), which is calculated as the (possibly zero) wage in the year directly after the displacement event minus the wage in the last year in which the worker is observed in the establishment that closes down. D is a displacement dummy (1 for a displaced worker, 0 for a statistical twin). O^M_{ir} and O^H_{ir} form a dummy group that captures whether the pre-displacement industry has a moderate (M) or high (H) employment share in the region in which the worker was displaced. A^M_{ir} and A^H_{ir} form an analogous dummy group for the regional employment share of industries with a skill-relatedness of 3 or higher to the pre-displacement industry. Age controls are the worker's age and squared age in the year of displacement. Education dummies group workers into seven education classes. Industry dummies refer to the 5-digit industry and region dummies to the labor market area in the displacement year. Both industry and region dummies are interacted with displacement-year dummies. Standard errors are clustered at the region-industry level.

Table 3: Effects of regional conditions on log(daily wage) upon displacement

dep. var.: log(wage gain)	(1)	(2)	(3)	(4)
D	-0.085***	-0.097***	-0.092***	0.145
	(0.005)	(0.011)	(0.009)	(0.099)
$D \times O^M_{i,r}$		0.014	0.017	0.017
		(0.012)	(0.012)	(0.012)
$D \times O^H_{i,r}$		0.020*	0.023**	0.019*
		(0.010)	(0.009)	(0.010)
$D \times A^M_{i,r}$		0.005	0.002	0.002
		(0.011)	(0.010)	(0.010)
$D \times A^H_{i,r}$		-0.006	-0.008	-0.010
		(0.012)	(0.012)	(0.012)
$O^M_{i,r}$		0.001	0.006	0.007
		(0.003)	(0.004)	(0.004)
$O^H_{i,r}$		-0.001	0.008	0.010*
		(0.003)	(0.006)	(0.006)
$A^M_{i,r}$		0.000	-0.002	-0.003
		(0.003)	(0.005)	(0.005)
$A^H_{i,r}$		0.007**	-0.003	-0.004
		(0.003)	(0.006)	(0.006)
other interaction terms?	no	no	no	yes
age controls?	yes	yes	yes	yes
year dummies?	yes	yes		
education dummies?	yes	yes	yes	yes
industry-year dummies?	no	no	yes	yes
region-year dummies?	no	no	yes	yes
R^2	0.017	0.017	0.067	0.069
# obs.	48,020	48,020	48,020	48,020

Idem Table 2, with as dependent variable the change in log(daily wages) in the first job after the displacement event. We only keep worker pairs for which both displaced worker and matched twin are employed in the year immediately after displacement.

Table 4: Effects of regional conditions on short-term nonemployment

dep. var.: non-employed (y/n)	(1)	(2)	(3)	(4)
D	0.383***	0.405***	0.405***	0.839***
	(0.006)	(0.013)	(0.008)	(0.138)
$D \times O^M_{i,r}$		-0.001	-0.015	-0.012
		(0.013)	(0.009)	(0.009)
$D \times O^H_{i,r}$		-0.055***	-0.059***	-0.055***
		(0.015)	(0.009)	(0.009)
$D \times A^M_{i,r}$		-0.017	-0.008	-0.008
		(0.015)	(0.009)	(0.009)
$D \times A^H_{i,r}$		0.010	0.006	0.008
		(0.013)	(0.009)	(0.009)
$O^M_{i,r}$		-0.006**	-0.001	-0.002
		(0.003)	(0.004)	(0.004)
$O^H_{i,r}$		-0.002	0.009*	0.008
		(0.003)	(0.005)	(0.005)
$A^M_{i,r}$		-0.004	-0.001	-0.001
		(0.003)	(0.005)	(0.005)
$A^H_{i,r}$		-0.008***	-0.007	-0.006
		(0.003)	(0.006)	(0.006)
other interaction terms?	no	no	no	yes
age controls?	yes	yes	yes	yes
year dummies?	yes	yes		
education dummies?	yes	yes	yes	yes
industry-year dummies?	no	no	yes	yes
region-year dummies?	no	no	yes	yes
R^2	0.210	0.212	0.260	0.266
# obs.	90,688	90,688	90,688	90,688

Idem Table 2, with as dependent variable a dummy for whether the worker was nonemployed in the year following the displacement event.

Table 5: Effects of regional conditions on long-term nonemployment

dep. var.: non-employed after 3 yrs (y/n)	(1)	(2)	(3)	(4)
D	0.166***	0.187***	0.191***	0.673***
	(0.004)	(0.008)	(0.006)	(0.189)
$D \times O^M_{i,r}$		0.006	-0.003	-0.002
		(0.008)	(0.006)	(0.006)
$D \times O^H_{i,r}$		-0.034***	-0.040***	-0.037***
		(0.008)	(0.006)	(0.006)
$D \times A^M_{i,r}$		-0.019**	-0.015**	-0.016**
		(0.008)	(0.006)	(0.006)
$D \times A^H_{i,r}$		-0.011	-0.011*	-0.010
		(0.008)	(0.007)	(0.007)
$O^M_{i,r}$		-0.005**	0.000	-0.000
		(0.002)	(0.003)	(0.003)
$O^H_{i,r}$		-0.003	0.009**	0.007**
		(0.002)	(0.004)	(0.004)
$A^M_{i,r}$		-0.002	-0.001	0.000
		(0.002)	(0.003)	(0.003)
$A^H_{i,r}$		-0.005**	0.000	0.002
		(0.002)	(0.004)	(0.004)
other interaction terms?	no	no	no	yes
age controls?	yes	yes	yes	yes
year dummies?	yes	yes		
education dummies?	yes	yes	yes	yes
industry-year dummies?	no	no	yes	yes
region-year dummies?	no	no	yes	yes
R^2	0.079	0.081	0.123	0.127
# obs.	90,688	90,688	90,688	90,688

Idem Table 2, with as dependent variable a dummy for whether the worker was nonemployed for at least three years after the displacement event.

observation window.[18] For these workers, displacement increases the likelihood of moving to another region by about 33 pp (column 1, Table 6) and of switching 5-digit industries by about 66 pp (column 1, Table 7).

The exact mobility choices, however, depend on the local industry mix. Again, we use regions with low shares of the pre-displacement and of related industries as a benchmark. Against this benchmark, we observe a 4.1 pp decrease in displacement-related region switching in regions with a moderate employment share of the old industry (column 3 of Table 7) and a slightly lower (yet statistically indistinguishable) 3.9 pp decrease in regions with a high share of employment in the old industry. This is a modest change when compared to the 21 pp reduction in post-displacement industry-switching rates (Table 7) caused by the same variable. By contrast, high shares of *related* industries *increase* industry switching by 17 pp. These findings support our earlier conjecture that the presence of related industries helps workers find jobs faster in alternative industries, which represent relatively bad matches and therefore pay somewhat lower wages.

Overall, Tables 2 to 7 lead us to conclude that, whereas a presence of the old industry helps reduce displacement effects on earnings and nonemployment, related industries only help displaced workers getting re-employed. However, a potential caveat is that, in spite of the matching efforts, workers may differ from one another in some unobserved (e.g., ability-related) characteristics. In that case, we would expect some sorting of workers across regions and industries based on these characteristics. It is therefore interesting that, although neither region nor industry fixed effects were used in the matching procedure, adding them (columns 3 of Tables 2 to 7) or not (columns 2) neither changes the point estimates of displacement nor of the interaction effects much. However, because their explanatory power reduces the standard error of regression, adding these fixed effects typically yields efficiency gains, which manifest themselves in smaller standard errors. This is reassuring. After all, had there been any confounders, we would have expected that they would exhibit at least some regional or industry variation. The combination of an absence of notable shifts in point estimates and a tightening of confidence intervals suggests that the matching procedure successfully removes any correlation between displacement and confounders at the region or industry level. Therefore, the scope for ability-related confounding *beyond* what is captured by (unobserved) region and industry effects would seem limited.

[18] As in the case of log(wage gain), we impose the same requirement on statistical twins (who may disappear due to attrition) to keep samples balanced. Given that a worker's willingness to change regions or industries may depend on her likelihood of finding a new job, this design choice may lead to some sample selection bias in the current analyses. However, this attrition does not affect the tests in later multinomial logit models for the cross-over effects predicted by our model.

Table 6: Effects of regional conditions on relocation upon displacement

dep. var.: region switch (y/n)	(1)	(2)	(3)	(4)
D	0.330***	0.364***	0.349***	0.208***
	(0.006)	(0.013)	(0.010)	(0.069)
$D \times O^M_{i,r}$		-0.049***	-0.041***	-0.041***
		(0.013)	(0.011)	(0.011)
$D \times O^H_{i,r}$		-0.034**	-0.039***	-0.044***
		(0.014)	(0.011)	(0.011)
$D \times A^M_{i,r}$		-0.008	-0.011	-0.015
		(0.015)	(0.012)	(0.012)
$D \times A^H_{i,r}$		-0.011	-0.009	-0.021*
		(0.014)	(0.012)	(0.011)
$O^M_{i,r}$		0.002	-0.001	-0.001
		(0.002)	(0.004)	(0.004)
$O^H_{i,r}$		0.003	-0.009	-0.005
		(0.003)	(0.006)	(0.006)
$A^M_{i,r}$		-0.002	0.002	0.003
		(0.003)	(0.005)	(0.005)
$A^H_{i,r}$		-0.014***	-0.008	-0.005
		(0.002)	(0.007)	(0.007)
other interaction terms?	no	no	no	yes
age controls?	yes	yes	yes	yes
year dummies?	yes	yes		
education dummies?	yes	yes	yes	yes
industry-year dummies?	no	no	yes	yes
region-year dummies?	no	no	yes	yes
R^2	0.176	0.178	0.242	0.246
# obs.	71,108	71,108	71,108	71,108

Idem Table 2, with as dependent variable a dummy for whether a worker's first post-displacement job is in a different labor market region than the pre-displacement job. If a worker or his matched twin remains nonemployed, this observation is dropped.

Table 7: Effects of regional conditions on switching industries upon displacement

dep. var.: industry switch (y/n)	(1)	(2)	(3)	(4)
D	0.657***	0.718***	0.687***	0.885***
	(0.007)	(0.012)	(0.009)	(0.069)
$D \times O^M_{i,r}$		-0.161***	-0.134***	-0.133***
		(0.014)	(0.010)	(0.010)
$D \times O^H_{i,r}$		-0.219***	-0.207***	-0.207***
		(0.014)	(0.010)	(0.010)
$D \times A^M_{i,r}$		0.046***	0.067***	0.067***
		(0.015)	(0.011)	(0.011)
$D \times A^H_{i,r}$		0.152***	0.169***	0.167***
		(0.015)	(0.010)	(0.010)
$O^M_{i,r}$		-0.005	0.024***	0.024***
		(0.004)	(0.005)	(0.005)
$O^H_{i,r}$		-0.011***	0.026***	0.027***
		(0.004)	(0.006)	(0.006)
$A^M_{i,r}$		0.012***	-0.013**	-0.013**
		(0.004)	(0.006)	(0.006)
$A^H_{i,r}$		0.010***	-0.044***	-0.043***
		(0.004)	(0.007)	(0.007)
other interaction terms?	no	no	no	yes
age controls?	yes	yes	yes	yes
year dummies?	yes	yes		
education dummies?	yes	yes	yes	yes
industry-year dummies?	no	no	yes	yes
region-year dummies?	no	no	yes	yes
R^2	0.451	0.478	0.519	0.520
# obs.	71,102	71,102	71,102	71,102

Idem Table 2, with as dependent variable a dummy for whether a worker's first post-displacement job is in a different industry than the pre-displacement job. If a worker or his matched twin remains nonemployed, this observation is dropped.

Robustness: effect heterogeneity

Worker characteristics may yet be problematic in a different way. So far, we have interpreted the heterogeneity in displacement effects as evidence of Marshallian externalities. However, this effect-heterogeneity may not be driven as much by characteristics of local industries as of the workers attracted to these industries. For instance, firms in local clusters may attract more highly educated workers than their peers outside those clusters. In that case, the more modest earnings drop and lower nonemployment incidence we attributed to Marshallian externalities may instead be due to the specific type of workers that clusters attract. A similar problem occurs if our local industry groupings pick up differences in the size of the local economy. In that case, what matters is not the industry mix, but the total amount of employment in the region. In essence, the effects would still be causal, but the differences in these causal effects would arise from differences in, for instance, region-size or workers' education, not local industry mix.

Table A1 of the Appendix shows that different local conditions are indeed associated with different kinds of workers. Most saliently, locations where the pre-displacement and related industries have higher employment shares tend to also have a higher educated workforce. To find out whether this could explain the results presented above, we explore how much of the documented effect heterogeneity can be attributed to these worker characteristics (and to a region's size). If our findings are unaffected by accounting for these *observable* sources of heterogeneity, there is less cause for concern that *unobservable* sources of worker heterogeneity drive our results. Therefore, we rerun the analyses of column 3 of Tables 2 to 7, but now add interactions of the displacement dummy with a worker's educational attainment, age and the logarithm of total employment in the region. Results on the interactions with local conditions are reported in columns 4 of these tables. The estimated interaction effects of displacement with worker-level characteristics and region size are reported in Table A2 of the Appendix.

Many of the new interaction effects are significant and interesting in their own right. For instance, absolute earnings losses tend to increase with educational attainment (column 1, Table A2). However, this simply reflects that, for highly educated workers, earnings drop from higher pre-displacement levels. Instead, differences in the *relative* drop of daily wages (column 2) across education groups are barely statistically significant. However, point estimates suggest that the drop in daily wages is relatively modest for workers with vocational training (VT), high school *and* vocational training (HS+VT), or with a degree from Germany's - mostly vocational - technical colleges (C). This suggests that what matters is *how applied*, not *how long*, workers' education is. Similar patterns emerge for the incidence of displacement-induced short- and long-term nonemployment (columns 3 and 4), where vocational training (VT and HS+VT) and degrees from technical colleges are associated with shorter post-displacement nonemployment spells. Apparently, an applied education shields workers from some of the detrimental consequences of job displacement. Similarly, an applied

education is associated with lower post-displacement industry-switching rates. In contrast, the degree to which displaced workers leave their region increases monotonically with the level of education. Displacement effects furthermore change with age, although the statistical evidence for this is weaker. The size of a region is an important moderator as well: doubling a region's size cuts earnings losses by 2.9 EUR, daily wage losses by 1.1%, region-switching rates by 2 pp and industry-switching rates by 1 pp.

Overall, the findings in Table A2 imply substantial effect-heterogeneity across workers with different educational backgrounds and age. However, when comparing columns 4 to columns 3 in Tables 2 to 7, adding these interactions barely changes how displacement effects vary with local conditions.[19] This suggests that, although displacement effects do depend on observable worker characteristics, this dependence does not explain any of the moderating effects we have attributed to the local industry mix. We still cannot be certain that the same holds for *unobservable* worker characteristics. However, given that important markers of individual productivity such as age and education do not seem to be part of the explanation, this would be remarkable.

6 Marshallian externalities and strategic search

A central prediction in search theory is that workers will search harder when job prospects are better. Testing this prediction is difficult, because search efforts are unobserved. After all, the fact that unemployment spells are shorter when labor markets are tighter does not necessarily imply greater search efforts in such episodes. Instead, the reduction in unemployment duration could simply be due to an improvement in job arrival rates or wage offers. However, the model in section 3 showed that the indirect effect of labor market conditions on job-offer quality and arrival rates via search efforts can be isolated from their direct effects by studying not just *whether* workers find new jobs, but *where* they find these jobs. In particular, the model predicts that the hazard of getting new jobs in industries other than their old industry – holding labor market conditions in these other industries constant – decreases when job prospects in the old industry improve. Finding such effects would mean that workers strategically reallocate search efforts toward the old industry. Fallick (1993) shows that these effects indeed exist.[20]

We use this framework to explore whether workers also strategically adjust their search efforts to Marshallian externalities. We do so by interpreting what we have called "favorable local conditions" for a sector as a large presence of this sector in the region. Such an interpretation is in line with the literature

[19] Note that the main effect of displacement changes drastically in all tables. However, this simply reflects a change in reference category.

[20] Fallick does not use any spatial information in his tests. Moreover, his evidence for strategic search is not robust across specifications but only holds when proxying labor market conditions in the old industry by the (national) employment growth in the industry but not when using other measures of the industries' success.

on agglomeration externalities, which uses spatial concentration indices to identify Marshallian externalities (e.g., Glaeser et al. 1992; Henderson et al. 1995). Moreover, we control for a region's size to make sure these effects are not just driven by the local labor market's size but rather by its composition.

In this context, the model of section 3 predicts that job searchers are more likely to find a job in sectors that have a large local presence in the region. This prediction derives from a combination of two effects: first, suitable job offers will arrive at higher rates when local conditions in a sector are favorable, which, second, induces workers to redirect their search efforts toward this sector, raising arrival rates even further. To illustrate this, imagine a region in which the pre-displacement sector is relatively large. The Marshallian externalities in this region should shift efforts to the pre-displacement sector, but away from the alternative, skill-related sector. As a consequence, holding local conditions in these industries constant, the job-finding hazard in related industries should drop. This is comparable to Fallick's original prediction: favorable conditions in the pre-displacement industry should lead to a drop in the relative risk of finding a job in related industries vis-à-vis staying nonemployed.[21] Because a reduction in search efforts will also limit the spatial scope of search, we derived a further prediction, namely that a large local presence of the pre-displacement industry will lead to a drop in the relative risk of finding nonlocal jobs in related industries vis-à-vis finding local jobs in such industries. The same predictions hold with the roles of pre-displacement and related industries reversed.

To test these implications, we drop all nondisplaced workers and keep only the sample of displaced workers. Presumably, all of these workers have been confronted with an exogenous shock that requires them to start searching for jobs, making them an ideal group in which to test the predictions of our search model. To do so, we jointly estimate how local conditions affect each of the potential search outcomes. That is, we estimate the multinomial logit model proposed in section 3 with five potential outcomes. The first outcome is that the worker does not find a new job within three years after displacement. The other outcomes are that the first job the worker finds is (2) in the same industry and region, (3) in the same industry but in a different region, (4) in a different industry but the same region or (5) in a different industry *and* region than the job from which he was displaced. Table 8 reports how local conditions affect relative risk ratios vis-à-vis the base category of nonemployment. In this analysis, we control for age, age^2, log(region size) and education dummies. However, because of the nonlinearity of the multinomial logit model, we have to aggregate industry and region dummies to the level of 15 broad sectors and the 16 German states (Bundesländer) respectively.

We report the outcomes of these multinomial regressions in terms of relative

[21] Note that this is not the same as a drop in the *probability* of finding jobs in related industries. This probability will drop because more workers exit nonemployment through jobs in the pre-displacement industry. However, the higher job-finding rate in the pre-displacement industry will itself lower the likelihood of staying nonemployed. From this, it is not clear how a local concentration of jobs in the pre-displacement industry will affect the *relative* risk of accepting jobs in related industries instead of remaining nonemployed.

risk ratios. That is, parameter estimates reflect the increase in the ratio of the likelihood that the outcome reported in the columns materializes instead of the base-line outcome of nonemployment, for a one-unit increase in regressor value. Parameter estimates above one indicate a positive association with this ratio, below one a negative association. For instance, the parameter estimate of 1.41 for A_{ir}^{H} in the final column means that, when we compare workers in regions where the employment share of related industries is high instead of low, the ratio of the probability that a worker will find a job in a different region and industry to the probability that he will remain nonemployed increases by a factor 1.41.

Higher local employment shares in a sector increase the likelihood that workers find local jobs in that sector. Compared to the reference category of regions with low employment shares of the old and of related industries, the relative risk of finding a local job in the old industry vis-à-vis staying nonemployed is over twice (three times) as high in regions with intermediate (high) employment shares of the old industry (first column of Table 8). Similarly, higher local employment shares of related industries increase the relative risk of finding local jobs *outside* the pre-displacement industry by factors of 1.3 and 1.5, respectively (third column). These findings provide some first evidence that Marshallian externalities directly affect offer arrival rates (and/or offer quality).

Local conditions should also affect job-finding rates indirectly, through the reallocation of search efforts. In line with this, we find that high shares of related industries in the region decrease the likelihood of finding local (first column) and nonlocal jobs (second column) in the old industry compared to staying nonemployed. Similarly, the third and fourth columns of Table 8 show that favorable conditions in the old industry significantly decrease the relative risk of finding a new job in other industries (be it local or nonlocal) vis-à-vis remaining nonemployed, although we only find such effects when employment shares in the pre-displacement industry are intermediate, not when they are high.[22]

These indirect cross-over effects between the local conditions in one sector and job finding rates in the other sector are also visible when looking at spatial aspects of job search. In particular, a large local presence of one sector should reduce search efforts in the other sector, therewith limiting the spatial reach of search in this other sector. Table 9 confirms this prediction. The table re-expresses the relative risk ratios reported in Table 8 in a way that compares nonlocal to local job-finding rates in the pre-displacement (first column) and other industries (second column). As predicted, high local shares of related industries decrease the relative risk of finding nonlocal instead of local jobs in the old industry by 24.1% (first column). A similar effect is visible for jobs *outside* the pre-displacement industry: a presence of the old industry increases the relative risk of workers' finding such jobs outside instead of inside the region.

[22]Note that the effects on finding local jobs (third column) are smaller than effects on finding nonlocal jobs (fourth column). This aligns with our expectations that the reduction of search efforts not only decreases job-arrival rates, but also shifts the balance of job-finding rates towards local jobs. We will test this more formally below.

Table 8: Multinomial post-displacement regression

	Outcome:			
	stay ind. & reg.	switch reg.	switch ind.	switch ind. & reg.
$O^M_{i,r}$	2.265***	1.625***	0.876***	0.737***
	(0.193)	(0.160)	(0.042)	(0.043)
$O^H_{i,r}$	3.544***	2.437***	1.010	0.918
	(0.313)	(0.280)	(0.054)	(0.063)
$A^M_{i,r}$	0.925	0.868	1.329***	1.371***
	(0.065)	(0.090)	(0.066)	(0.088)
$A^H_{i,r}$	0.674***	0.511***	1.459***	1.412***
	(0.054)	(0.056)	(0.077)	(0.091)
log(reg. size)	1.027	0.981	1.007	0.899***
	(0.040)	(0.065)	(0.025)	(0.030)
age controls?	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes
sector-year dummies?	yes	yes	yes	yes
state-year dummies?	yes	yes	yes	yes
log(L)	-64,356	-64,356	-64,356	-64,356
# obs.	45,341	45,341	45,341	45,341
# clust.	5,042	5,042	5,042	5,042
partial R^2	0.049	0.049	0.049	0.049

***: p<.01, **: p<.05, *: p<.1. Multinomial regression of first job-switch within three years of displacement. Base category is composed of workers who do not return to social-security covered jobs (nonemployment). Coefficients represent relative risk ratios. Standard errors, clustered at industry-region level, are reported in parentheses.

Table 9: Multinomial cross-over effects

	outcome: switch reg. base: stay ind. & reg.	outcome: switch ind. & reg. base: switch ind.
$O^M_{i,r}$	0.717***	0.841***
	(0.085)	(0.047)
$O^H_{i,r}$	0.688***	0.909
	(0.091)	(0.057)
$A^M_{i,r}$	0.938	1.032
	(0.106)	(0.060)
$A^H_{i,r}$	0.759**	0.968
	(0.084)	(0.059)

Coefficients from Table 8, expressed against the base outcomes in the column headers.

However, here, we observe this effect only for intermediate employment shares of the old industry.

In Online Appendix B, we show that the substance of these results does not change when we add variables that describe the local conditions in neighboring regions. Moreover, so far, we have calculated employment shares as shares of total employment reported in the social security data. However, the amount of employment that is not covered by social security may differ by region. Therefore, as a robustness check we redefine local conditions based on shares that use a region's population as a denominator. This adjustment does not change the substance of our outcomes either (see Online Appendix C). Finally, we explore whether any of our results are strongly driven by a particular time period or region by splitting the sample of displaced workers into subsamples by displacement year and by the territories of former West and East Germany. Results are reported in Online Appendix E. Given the smaller sizes of these subsamples, point estimates tend to be less precisely estimated. However, although there is some variation in the magnitude of effects across these subsamples, our main conclusions on the existence of Marshallian externalities in job search, as well as their reflection in strategic search effort allocation, find support in each of the subsamples. Taken together, therefore, the findings in this subsection strongly support the notion that workers take Marshallian externalities into account when searching for jobs.

7 Conclusions

We have shown evidence for Marshallian externalities in how a region's industry mix affects the post-displacement careers of workers who lose their jobs in establishment closures. High concentrations of the pre-displacement industry reduce the earnings losses experienced by these workers, predominantly by reducing the time it takes workers to find new jobs. In contrast, high concentrations of industries that are related to the pre-displacement industry are

associated with higher earnings losses, but a lower long-term nonemployment incidence. In places where these related industries are abundant, workers tend to find re-employment faster by opting to change industries. Furthermore, we find evidence that suggests that workers take these Marshallian externalities into consideration when allocating search efforts. Large concentrations of related industries not only lead to reductions in the relative risk of finding a job in the pre-displacement industry instead of remaining nonemployed, they also increase the spatial scope of search, reducing the relative risk of finding nonlocal instead of local jobs in the pre-displacement industry. Similar cross-over effects are found in regions where the pre-displacement industry is large.

These results are robust to a number of changes in the model specification. For instance, adding the industrial composition of neighboring regions does not change any of the conclusions in the paper. Similarly, controlling for industry and region fixed effects does not lead to any significant changes in point estimates. Furthermore, we explored whether our findings are driven by the sorting of workers across locations. Although such sorting happens and although the characteristics of workers moderate displacement effects, accounting for worker-level heterogeneity in displacement effects does not alter the estimated effects of Marshallian externalities.

Our study can be extended in several ways. Our focus on Marshallian externalities made it natural to study the role of the local *industry* concentrations. However, workers' human capital is not just specific to an industry, but also to occupations. It would therefore be interesting to explore the relative importance of geographical clusters of occupations instead of industries as studied by, for instance, Bleakley and Lin (2012). Moreover, national labor market institutions vary markedly across countries. Consequently, displacement will have different consequences in different countries. Repeating the analyses of this paper in different regions of the world might therefore provide interesting lessons in how Marshallian labor market externalities operate in different national contexts.

Finally, the finding that a concentration of the displacement and related industries help displaced workers find new jobs may have useful implications for economic policy. Currently, cluster-based policies and local development programs like the European Union's Smart Specialization efforts often focus on innovation and the creation of new businesses. However, our findings suggest that clusters also benefit workers, offering alternative employment opportunities that protect against protracted unemployment. Taking industries' human capital requirements into account in cluster definitions could therefore increase the effectiveness of cluster policies.

Appendix: Summary statistics

Table A1 provides summary statistics for the EH of worker-level characteristics in region-industry combinations with different concentrations of the old and related industries. Table A2 displays the interaction effects of worker characteristics, as well as of a region's size, with the displacement dummy for the models in columns (4) of Tables 2-7.

Table A1: Group averages of individual level characteristics

	employment share old ind.			employment share related ind.		
	low	medium	high	low	medium	high
age	39.7	39.8	39.9	39.8	39.7	39.8
edu (ND)	11.27%	10.04%	9.49%	10.66%	10.72%	9.54%
edu (VT)	65.66%	64.39%	66.53%	64.17%	65.98%	67.06%
edu (HS)	0.54%	0.48%	0.41%	0.48%	0.49%	0.32%
edu (HS+VT)	2.64%	2.24%	2.66%	2.31%	2.69%	2.67%
edu (C)	1.97%	3.32%	3.75%	2.60%	3.13%	3.29%
edu (U)	2.23%	3.26%	4.13%	2.62%	3.30%	3.83%
edu (miss.)	15.71%	16.27%	13.02%	17.16%	13.69%	13.29%
log(reg. size)	12.3	12.3	12.1	12.4	12.3	12.1

Averages of a worker's age and the natural log of a region's total social-security-covered employment, as well as shares of each education type (ND: no degree, VT: vocational training, HS: high school, HS+VT: high school + vocational training, C: (applied) college, U: University) by group. Groups refer to categories based on the local employment share of the old industry (the three left-most columns) or of industries related to the old industry (the three right-most columns).

Table A2: Estimated interaction effects of individual level characteristics

	dependent variable:					
	earnings increase	log(wage gain)	nonemp. (short)	nonemp. (long)	reg. switch	ind. switch
D	-90.431***	0.145	0.839***	0.673***	0.208***	0.885***
	(19.135)	(0.099)	(0.138)	(0.189)	(0.069)	(0.069)
$D \times$ log(reg. size)	-2.950***	-0.011***	-0.001	0.006**	-0.020***	-0.009**
	(0.499)	(0.004)	(0.004)	(0.003)	(0.006)	(0.005)
$D \times$ age	-0.944***	-0.003***	0.008***	0.004***	0.001	0.002***
	(0.058)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
$D \times$ age^2	-0.0198**	-0.0000	0.0004***	0.0001	-0.0001	0.0000
	(0.0077)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$D \times$ edu(VT)	2.863***	0.022*	-0.104***	-0.043***	0.017	-0.048***
	(0.900)	(0.012)	(0.010)	(0.008)	(0.011)	(0.010)
$D \times$ edu(HS)	-25.352***	-0.003	0.035	0.111***	0.063	-0.000
	(8.514)	(0.057)	(0.037)	(0.041)	(0.047)	(0.041)
$D \times$ edu(HS+VT)	-22.740***	0.030	-0.085***	-0.004	0.135***	-0.032
	(3.613)	(0.021)	(0.019)	(0.015)	(0.022)	(0.020)
$D \times$ edu(C)	-13.132***	0.036	-0.157***	-0.020	0.144***	-0.099***
	(3.738)	(0.023)	(0.018)	(0.015)	(0.021)	(0.026)
$D \times$ edu(U)	-29.133***	0.015	-0.133***	-0.010	0.162***	-0.036*
	(5.088)	(0.023)	(0.017)	(0.015)	(0.022)	(0.019)
$D \times$ edu(miss.)	5.138***	0.028*	-0.093***	-0.037***	0.036***	-0.043***
	(1.140)	(0.016)	(0.012)	(0.010)	(0.013)	(0.013)
age controls?	yes	yes	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes	yes	yes
industry-year dummies?	yes	yes	yes	yes	yes	yes
region-year dummies?	yes	yes	yes	yes	yes	yes
R^2	0.183	0.069	0.266	0.127	0.246	0.520
# obs.	90,688	48,020	90,688	90,688	71,108	71,102

***: p<.01, **: p<.05, *: p<.1. Estimated interaction effects of age, age^2, education dummies and log(region size) with the displacement dummy for models 4 in Tables 2-7. Age and log(region size) are expressed in deviation of their sample means before creating interaction terms. The dependent variable for each column is indicated in the column headers.

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Supplementary Online Material

This document contains the supplementary online material to the paper:

The mobility of displaced workers:
How the local industry mix affects job search

by Frank Neffke, Anne Otto and César Hidalgo

The material is distributed over six sections. Section A contains additional derivations for the model presented in the main text in section 3. Section B explores the effect of economic conditions in local industries of neighboring regions. Sections C, D and E report robustness checks for different specifications and subsamples. Section F discusses some additional details on issues that arise when using the German EH database to study displaced workers and how we have addressed these issues.

A Derivation equation (6)

Equation (6) can be derived as follows:

$$\int_0^1 \int_u^1 f_A(u) f_B(v) \, \mathrm{d}\nu \, \mathrm{d}u = \int_0^1 f_A(u) \left\{ \int_u^1 S_B(v) \theta_B \, \mathrm{d}\nu \right\} \mathrm{d}u$$

Using the fact that $S_s(\tau) = e^{-\int_0^\tau \theta_s \, \mathrm{d}t} = e^{-\theta_s \tau}$

$$= \int_0^1 f_A(u) \left\{ \int_u^1 e^{-\theta_B v} \theta_B \, \mathrm{d}\nu \right\} \mathrm{d}u$$

$$= \int_0^1 f_A(u) \left\{ e^{-\theta_B u} - e^{-\theta_B} \right\} \mathrm{d}u$$

Given that the hazard rate can be expressed as $\theta_s = \frac{f_s(\tau)}{S_s(\tau)}$, we get:

$$= \int_0^1 S_A(u) \theta_A \left\{ e^{-\theta_B u} - e^{-\theta_B} \right\} \mathrm{d}u$$

$$= \int_0^1 e^{-\theta_A u} \theta_A \left\{ e^{-\theta_B u} - e^{-\theta_B} \right\} \mathrm{d}u$$

$$= \theta_A \int_0^1 e^{-(\theta_A + \theta_B)u} \, \mathrm{d}u - \theta_A \int_0^1 e^{-\theta_A u} e^{-\theta_B} \, \mathrm{d}u$$

$$= \frac{\theta_A}{\theta_A + \theta_B} \left(1 - e^{-(\theta_A + \theta_B)} \right) + e^{-\theta_B} \left(e^{-\theta_A} - 1 \right)$$

$$= \frac{\theta_A}{\theta_A + \theta_B} h - (1 - h_A) h_B$$

B Effect of conditions in neighboring regions

A potential concern regarding the findings in section 6 of the main paper is that the reported effects are confounded by the fact that the local conditions of a sector correlate with conditions in nearby regions. To explore this, we rerun our analyses while controlling for conditions in regions that are at most 90 minutes driving distance away. Results are reported in Tables SOM.B1 and SOM.B2.

The cross-over effects related to conditions inside the own region still provide evidence for strategic search. In fact, the relevant parameter estimates become even more statistically significant after controlling for the industry mix of neighboring regions. Turning to the effect of conditions in neighboring regions, we find that large shares of the pre-displacement industries (related industries) in these regions increase the relative risk that workers find jobs in the pre-displacement industry (in other industries) outside the region. However, this may simply reflect that there are many jobs in the pre-displacement (related) industries in neighboring regions.

We have argued that workers organize their search efforts along sectoral, not geographical lines. That is, workers choose how much effort to spend searching in a particular sector, not in a particular region. We believe this is a reasonable assumption, given that displaced workers are not looking for new jobs because of a desire to move to another region. In fact, such moves are typically costly. Consequently, workers will be searching primarily from within their current locations, and not preferentially in any other location. Furthermore, given that the suitability of job opportunities will depend on how well they match a worker's skill set, workers will concentrate their search in sectors where their current human capital is most valued.

The findings in Table SOM.B2 support this reasoning. In particular, favorable conditions in neighboring regions in one sector do not seem to reduce the spatial scope of search in the other sector: there are no cross-over effects visible that would suggest that workers shift search efforts between sectors to exploit job opportunities outside the region. If workers were to search strategically across regions, as opposed to across sectors, we would have expected that the conditions in nearby regions should result in a re-allocation of search efforts. The absence of such effects therefore validates our choice to model displaced workers' job search as primarily directed at industries, not regions.

C Employment as a share of regional population

In this section, we repeat the empirical analyses reported in Tables 2 to 9 of the main text, using the pre-displacement industry's and related industry's employment as a share of total *population* instead of as a share of total *social-security-covered employment* in a region. Table SOM.C1 reports results for our preferred specification (model 3) of Tables 2 to 7. Tables SOM.C2 and SOM.C3 repeat the analyses of Tables 8 and 9.

In spite of using a completely new sample of statistical twins and having

Table SOM.B1: Multinomial post-displacement regression, conditions in neighboring regions

	Outcome:			
	stay ind. & reg.	switch reg.	switch ind.	switch ind. & reg.
$O^M_{i,r}$	1.760***	1.156	0.884**	0.744***
	(0.188)	(0.125)	(0.049)	(0.053)
$O^H_{i,r}$	2.715***	1.586***	1.066	0.988
	(0.338)	(0.265)	(0.081)	(0.093)
$A^M_{i,r}$	1.048	0.978	1.250***	1.205**
	(0.081)	(0.095)	(0.070)	(0.093)
$A^H_{i,r}$	0.854	0.602***	1.343***	1.080
	(0.089)	(0.081)	(0.092)	(0.088)
$O^M_{i,NB}$	1.663***	1.838***	1.018	0.992
	(0.181)	(0.218)	(0.059)	(0.071)
$O^H_{i,NB}$	1.514***	1.965***	0.933	0.906
	(0.193)	(0.293)	(0.070)	(0.082)
$A^M_{i,NB}$	0.845**	0.805**	1.114**	1.173**
	(0.065)	(0.083)	(0.061)	(0.090)
$A^H_{i,NB}$	0.700***	0.799	1.122*	1.503***
	(0.076)	(0.127)	(0.078)	(0.128)
log(reg. size)	1.036	0.976	1.006	0.889***
	(0.039)	(0.064)	(0.025)	(0.029)
age controls?	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes
sector-year dummies?	yes	yes	yes	yes
state-year dummies?	yes	yes	yes	yes
log(L)	-64,189	-64,189	-64,189	-64,189
# obs.	45,341	45,341	45,341	45,341
# clust.	5,042	5,042	5,042	5,042
partial R^2	0.051	0.051	0.051	0.051

Idem Table 8 of the main text. Subscript r refers to the focal region, subscript NB to neighboring regions.

Table SOM.B2: Multinomial cross-over effects, conditions in neighboring regions

	outcome: switch reg. base: stay ind. & reg.	outcome: switch ind. & reg. base: switch ind.
$O^M_{i,r}$	0.657***	0.842***
	(0.096)	(0.056)
$O^H_{i,r}$	0.584***	0.927
	(0.115)	(0.081)
$A^M_{i,r}$	0.933	0.964
	(0.099)	(0.067)
$A^H_{i,r}$	0.705**	0.804***
	(0.109)	(0.064)
$O^M_{i,NB}$	1.105	0.975
	(0.164)	(0.065)
$O^H_{i,NB}$	1.298	0.971
	(0.232)	(0.085)
$A^M_{i,NB}$	0.953	1.052
	(0.108)	(0.074)
$A^H_{i,NB}$	1.141	1.339***
	(0.218)	(0.109)

Coefficients from Table SOM.B1 of the main text, expressed against the base outcomes in the column headers.

redefined the main variables of interest, there are few substantive changes in outcomes.

D Part-time post-displacement jobs

The analyses reported in the main text are based on a sample from which part-time jobs have been removed. Allowing workers with different hours worked in the sample would introduce unwanted heterogeneity among displaced workers. Moreover, because there is no information on the exact part-time rate, it would risk matching displaced workers to counterfactuals with the same daily, yet potentially very different hourly, wages. However, dropping part-time spells means that we do not account for successful job-search that ends in part-time employment. As a consequence, we may have misstated wage, nonemployment and mobility effects. To explore how our choice to drop part-time jobs affects results, we redo our analyses, but now focus on transitions to the first post-displacement job of a worker, regardless of whether this is a full-time or a part-time job. Note, however, that we still require all displaced workers (and their statistical twins) to be in full-time employment in the pre-displacement period. That is, we study the effects of displacement on full-time employed workers only. Table SOM.D1 reports the preferred specification of Tables 2-7 (column 3) for each dependent variable in a different column. Table SOM.D2

Table SOM.C1: Displacement effects with population shares

	dependent variable:					
	earnings increase	log(wage gain)	nonemp. (short)	nonemp. (long)	reg. switch	ind. switch
D	-36.101***	-0.083***	0.406***	0.191***	0.348***	0.688***
	(0.901)	(0.009)	(0.008)	(0.006)	(0.009)	(0.009)
$D \times O^M_{i,r}$	1.331	-0.001	-0.021**	-0.007	-0.035***	-0.126***
	(1.076)	(0.012)	(0.009)	(0.006)	(0.011)	(0.010)
$D \times O^H_{i,r}$	6.066***	0.017*	-0.065***	-0.041***	-0.042***	-0.216***
	(1.162)	(0.009)	(0.009)	(0.006)	(0.011)	(0.010)
$D \times A^M_{i,r}$	-2.173**	0.001	-0.001	-0.014**	-0.010	0.064***
	(1.023)	(0.010)	(0.009)	(0.006)	(0.011)	(0.011)
$D \times A^H_{i,r}$	-5.857***	-0.009	0.009	-0.009	-0.007	0.161***
	(1.173)	(0.012)	(0.009)	(0.007)	(0.011)	(0.010)
$O^M_{i,r}$	-0.109	0.017***	0.003	0.004	-0.001	0.019***
	(0.581)	(0.005)	(0.004)	(0.003)	(0.004)	(0.005)
$O^H_{i,r}$	-1.036	0.010*	0.013**	0.008**	-0.007	0.023***
	(0.775)	(0.006)	(0.005)	(0.004)	(0.006)	(0.006)
$A^M_{i,r}$	0.609	0.000	0.002	-0.003	-0.003	-0.007
	(0.643)	(0.005)	(0.005)	(0.003)	(0.005)	(0.006)
$A^H_{i,r}$	2.110**	0.001	-0.001	0.000	-0.006	-0.034***
	(0.875)	(0.008)	(0.006)	(0.004)	(0.007)	(0.007)
other interaction terms?	no	no	no	no	no	no
age controls?	yes	yes	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes	yes	yes
industry-year dummies?	yes	yes	yes	yes	yes	yes
region-year dummies?	yes	yes	yes	yes	yes	yes
R^2	0.173	0.068	0.260	0.122	0.244	0.521
# obs.	90,656	48,100	90,656	90,656	71,062	71,058

***: p<.01, **: p<.05, *: p<.1. The columns repeat the specification of model 3 in Tables 2 to 7 of the main text, using employment as a share of regional *population* (instead of total employment) to create the dummy groups for local conditions. That is, O^M_{ir} and O^H_{ir} are defined using $\frac{E_{irt}}{pop_{rt}}$ and A^M_{ir} and A^H_{ir} are defined using $\frac{E^{rel}_{irt}}{pop_{rt}}$, where pop_{rt} represents the population of labor market area r in year t.

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Table SOM.C2: Multinomial post-displacement regression using population shares

	Outcome:			
	stay ind. & reg.	switch reg.	switch ind.	switch ind. & reg.
$O^M_{i,r}$	2.261***	1.591***	0.874***	0.761***
	(0.190)	(0.160)	(0.041)	(0.045)
$O^H_{i,r}$	3.670***	2.441***	1.006	0.909
	(0.329)	(0.278)	(0.054)	(0.062)
$A^M_{i,r}$	0.850**	0.822**	1.389***	1.348***
	(0.060)	(0.081)	(0.069)	(0.083)
$A^H_{i,r}$	0.638***	0.527***	1.458***	1.432***
	(0.051)	(0.056)	(0.082)	(0.096)
log(reg. size)	1.036	0.992	0.978	0.862***
	(0.043)	(0.071)	(0.027)	(0.031)
age controls?	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes
sector-year dummies?	yes	yes	yes	yes
state-year dummies?	yes	yes	yes	yes
log(L)	-64,289	-64,289	-64,289	-64,289
# obs.	45,325	45,325	45,325	45,325
# clust.	5,041	5,041	5,041	5,041
partial R^2	0.049	0.049	0.049	0.049

***: p<.01, **: p<.05, *: p<.1. Multinomial regression of first job-switch within three years of displacement. Base category is composed of workers who do not return to social-security covered jobs (nonemployment). Coefficients are relative risk ratios. Standard errors, clustered at industry-region level, are reported in parentheses. O^M_{ir}, O^H_{ir}, A^M_{ir} and A^H_{ir} are defined as in Table SOM.C1 of the main text.

Table SOM.C3: Cross-over effects using population shares

	outcome: switch reg. base: stay ind. & reg.	outcome: switch ind. & reg. base: switch ind.
$O^M_{i,r}$	0.703***	0.870**
	(0.085)	(0.049)
$O^H_{i,r}$	0.665***	0.903
	(0.088)	(0.056)
$A^M_{i,r}$	0.966	0.971
	(0.101)	(0.055)
$A^H_{i,r}$	0.826*	0.982
	(0.087)	(0.061)

Coefficients from Table SOM.C2 of the main text, expressed against the base outcomes in the column headers.

contains the estimates for the cross-over effects reported in Table 9 of the main text.

Results differ little from those reported in the main text. The post-displacement short-term and long-term nonemployment rates are reduced by about 4 pp. As a consequence, the displacement-induced drop in daily wages is slightly reduced as well (by 40 Eurocent). However, when we turn to the log of daily wages (and therewith restrict ourselves to workers who manage to find jobs immediately after displacement), we find much stronger negative wage effects when part-time employment spells are included. Overall, this shows that a relatively small share of displaced workers find part-time jobs, which pay substantially less than their previous full-time jobs. More importantly, the interaction effects of displacement with the regional industry-mix dummies do not change significantly. The only exception is the effects on the log of daily wages. Here, the protection from large drops in daily wages offered by an intermediate or large presence of the pre-displacement industry strengthens significantly. However, including part-time spells neither alters displacement or interaction effects on industrial and geographical mobility, nor – turning to Table SOM.D2 – does it alter any of the cross-over effects reported in Table 9.

E Robustness across subsamples

In this section, we report results derived from splitting the sample of displaced workers into five subsamples. The first set of subsamples splits the data by year of displacement. The second set splits the data into the territories of former East and West Germany.

The outcomes are summarized in Tables SOM.E1-SOM.E4. The first table reports the displacement effect for each dependent variable without adding local industry mix interactions. That is, it replicates column (1) of Tables 2-7 of the main text for each subsample. The subsequent three tables replicate the results of the interaction models in column (3) of these same tables. The different panels refer to different dependent variables; columns within these panels refer to different subsamples. Finally, Table SOM.E5 contains the estimates of the cross-over effects of the multinomial regression model (Table 9 of the main text).

Although there are differences between subsamples, the general patterns reported in the paper remain unaltered. In the overall effects of displacement (Table SOM.E1), we find larger displacement effects on (Euro) earnings (but not on log(daily wages)) in the regions of former West Germany compared to those in former East Germany. Given that the effects on short- and long-term nonemployment rates are stronger in the east, this is most likely due to higher pre-displacement wages in the western regions. In terms of post-displacement mobility rates, we find that geographical mobility in the east is lower than in the west, whereas industrial mobility rates are similar.

Comparing across years, displacement-related absolute (i.e., Euro) earnings losses are smallest in the year 2005. This is not due to lower *relative* effects on daily wages (these are actually slightly higher), but rather due to a less severe

Table SOM.D1: Displacement effects with part-time post-displacement jobs

	dependent variable:					
	earnings increase	log(wage gain)	nonemp. (short)	nonemp. (long)	reg. switch	ind. switch
D	-36.727***	-0.288***	0.363***	0.155***	0.335***	0.685***
	(0.915)	(0.015)	(0.008)	(0.005)	(0.010)	(0.009)
$D \times O^M_{i,r}$	1.772	0.046***	-0.013	-0.003	-0.037***	-0.129***
	(1.081)	(0.017)	(0.009)	(0.006)	(0.010)	(0.010)
$D \times O^H_{i,r}$	6.597***	0.072***	-0.054***	-0.033***	-0.032***	-0.198***
	(1.129)	(0.016)	(0.009)	(0.006)	(0.011)	(0.009)
$D \times A^M_{i,r}$	-0.670	-0.002	-0.010	-0.013**	-0.007	0.068***
	(1.036)	(0.016)	(0.009)	(0.006)	(0.011)	(0.011)
$D \times A^H_{i,r}$	-5.097***	0.004	0.011	-0.002	-0.005	0.165***
	(1.189)	(0.017)	(0.009)	(0.006)	(0.011)	(0.010)
age controls?	yes	yes	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes	yes	yes
industry-year dummies?	yes	yes	yes	yes	yes	yes
region-year dummies?	yes	yes	yes	yes	yes	yes

Table SOM.D2: Cross-over effects with part-time post-displacement jobs

	outcome: switch reg. base: stay ind. & reg.	outcome: switch ind. & reg. base: switch ind.
$O^M_{i,r}$	0.730***	0.840***
	(0.086)	(0.046)
$O^H_{i,r}$	0.712***	0.913
	(0.093)	(0.055)
$A^M_{i,r}$	0.948	1.037
	(0.106)	(0.059)
$A^H_{i,r}$	0.759**	0.978
	(0.083)	(0.058)

Table SOM.E1: Average displacement effects by subsample

dep. var.:	EAST	WEST	2003	2004	2005
earnings increase (EUR)	-28.778***	-38.677***	-37.353***	-37.259***	-33.573***
	(0.796)	(0.616)	(0.731)	(0.859)	(0.854)
log(wage gain)	-0.080***	-0.079***	-0.078***	-0.074***	-0.092***
	(0.010)	(0.005)	(0.008)	(0.007)	(0.007)
non-employed (y/n)	0.403***	0.373***	0.390***	0.396***	0.344***
	(0.009)	(0.004)	(0.006)	(0.007)	(0.007)
non-employed after 3 yrs (y/n)	0.172***	0.166***	0.185***	0.167***	0.144***
	(0.006)	(0.003)	(0.004)	(0.005)	(0.005)
region switch (y/n)	0.287***	0.321***	0.301***	0.319***	0.336***
	(0.009)	(0.005)	(0.007)	(0.008)	(0.008)
industry switch (y/n)	0.643***	0.649***	0.659***	0.647***	0.652***
	(0.011)	(0.006)	(0.007)	(0.008)	(0.008)
other interaction terms?	no	no	no	no	no
industry-year dummies?	yes	yes	yes	yes	yes
region-year dummies?	yes	yes	yes	yes	yes

Table SOM.E2: Displacement effect by subsample: wages

dep. var.: earnings increase (EUR)	EAST	WEST	2003	2004	2005
D	-30.876***	-38.015***	-38.310***	-36.934***	-35.531***
	(1.627)	(1.144)	(1.419)	(1.605)	(1.636)
$D \times O^M_{i,r}$	-1.024	3.373***	0.340	0.717	4.498**
	(1.862)	(1.296)	(1.693)	(1.912)	(1.884)
$D \times O^H_{i,r}$	7.441***	5.392***	7.222***	3.719*	9.504***
	(1.655)	(1.425)	(1.696)	(2.033)	(1.969)
$D \times A^M_{i,r}$	-3.341**	-1.493	0.739	-1.020	-2.190
	(1.648)	(1.238)	(1.620)	(1.761)	(1.794)
$D \times A^H_{i,r}$	1.508	-8.861***	-4.646**	-4.322**	-6.039***
	(1.774)	(1.486)	(1.880)	(2.022)	(2.047)
other interaction terms?	no	no	no	no	no
age controls?	yes	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes	yes
industry-year dummies?	yes	yes	yes	yes	yes
region-year dummies?	yes	yes	yes	yes	yes

dep. var.: log(wage gain)	EAST	WEST	2003	2004	2005
D	-0.091***	-0.089***	-0.101***	-0.076***	-0.101***
	(0.021)	(0.010)	(0.016)	(0.016)	(0.016)
$D \times O^M_{i,r}$	-0.011	0.032**	0.015	0.006	0.035**
	(0.022)	(0.015)	(0.025)	(0.017)	(0.017)
$D \times O^H_{i,r}$	0.010	0.025**	0.031**	-0.001	0.042**
	(0.021)	(0.011)	(0.015)	(0.016)	(0.018)
$D \times A^M_{i,r}$	-0.009	0.002	0.012	0.007	-0.015
	(0.022)	(0.011)	(0.016)	(0.017)	(0.017)
$D \times A^H_{i,r}$	0.035	-0.028**	0.013	-0.005	-0.037*
	(0.021)	(0.014)	(0.023)	(0.017)	(0.020)
other interaction terms?	no	no	no	no	no
age controls?	yes	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes	yes
industry-year dummies?	yes	yes	yes	yes	yes
region-year dummies?	yes	yes	yes	yes	yes

Table SOM.E3: Displacement effect by subsample: nonemployment

dep. var.: non-employed (y/n)	EAST	WEST	2003	2004	2005
D	0.433***	0.397***	0.417***	0.403***	0.388***
	(0.017)	(0.009)	(0.012)	(0.015)	(0.014)
$D \times O^M_{i,r}$	0.001	-0.024**	-0.009	0.011	-0.051***
	(0.021)	(0.010)	(0.014)	(0.017)	(0.016)
$D \times O^H_{i,r}$	-0.084***	-0.059***	-0.063***	-0.028*	-0.087***
	(0.018)	(0.010)	(0.014)	(0.016)	(0.017)
$D \times A^M_{i,r}$	0.027	-0.006	-0.016	-0.014	0.007
	(0.020)	(0.010)	(0.014)	(0.017)	(0.016)
$D \times A^H_{i,r}$	-0.015	0.012	0.003	0.012	-0.001
	(0.019)	(0.011)	(0.015)	(0.017)	(0.016)
other interaction terms?	no	no	no	no	no
age controls?	yes	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes	yes
industry-year dummies?	yes	yes	yes	yes	yes
region-year dummies?	yes	yes	yes	yes	yes

dep. var.: non-employed after 3 yrs (y/n)	EAST	WEST	2003	2004	2005
D	0.201***	0.187***	0.216***	0.186***	0.158***
	(0.013)	(0.007)	(0.009)	(0.010)	(0.010)
$D \times O^M_{i,r}$	0.003	-0.009	-0.003	0.005	-0.010
	(0.013)	(0.007)	(0.010)	(0.011)	(0.011)
$D \times O^H_{i,r}$	-0.051***	-0.041***	-0.048***	-0.035***	-0.032***
	(0.013)	(0.007)	(0.010)	(0.011)	(0.011)
$D \times A^M_{i,r}$	-0.003	-0.009	-0.025**	-0.016	-0.001
	(0.013)	(0.007)	(0.010)	(0.011)	(0.012)
$D \times A^H_{i,r}$	-0.024*	-0.004	-0.018*	-0.011	-0.000
	(0.013)	(0.008)	(0.011)	(0.011)	(0.011)
other interaction terms?	no	no	no	no	no
age controls?	yes	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes	yes
industry-year dummies?	yes	yes	yes	yes	yes
region-year dummies?	yes	yes	yes	yes	yes

Table SOM.E4: Displacement effect by subsample: mobility

dep. var.: region switch (y/n)	EAST	WEST	2003	2004	2005
D	0.298***	0.369***	0.335***	0.348***	0.374***
	(0.019)	(0.011)	(0.015)	(0.019)	(0.016)
$D \times O^M_{i,r}$	-0.023	-0.050***	-0.058***	-0.056***	-0.003
	(0.021)	(0.012)	(0.015)	(0.021)	(0.019)
$D \times O^H_{i,r}$	0.013	-0.062***	-0.037**	-0.048**	-0.039**
	(0.020)	(0.013)	(0.016)	(0.020)	(0.018)
$D \times A^M_{i,r}$	0.007	-0.025*	-0.020	0.013	-0.028
	(0.022)	(0.014)	(0.018)	(0.022)	(0.019)
$D \times A^H_{i,r}$	-0.029	-0.008	0.010	0.001	-0.045**
	(0.021)	(0.013)	(0.017)	(0.020)	(0.019)
other interaction terms?	no	no	no	no	no
age controls?	yes	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes	yes
industry-year dummies?	yes	yes	yes	yes	yes
region-year dummies?	yes	yes	yes	yes	yes
dep. var.: industry switch (y/n)	EAST	WEST	2003	2004	2005
D	0.687***	0.693***	0.703***	0.683***	0.667***
	(0.020)	(0.010)	(0.014)	(0.015)	(0.016)
$D \times O^M_{i,r}$	-0.102***	-0.145***	-0.135***	-0.130***	-0.138***
	(0.021)	(0.011)	(0.015)	(0.017)	(0.019)
$D \times O^H_{i,r}$	-0.196***	-0.217***	-0.211***	-0.202***	-0.208***
	(0.019)	(0.011)	(0.016)	(0.017)	(0.018)
$D \times A^M_{i,r}$	0.069***	0.057***	0.056***	0.055***	0.100***
	(0.023)	(0.012)	(0.017)	(0.019)	(0.020)
$D \times A^H_{i,r}$	0.127***	0.172***	0.148***	0.163***	0.204***
	(0.022)	(0.012)	(0.017)	(0.018)	(0.019)
other interaction terms?	no	no	no	no	no
age controls?	yes	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes	yes
industry-year dummies?	yes	yes	yes	yes	yes
region-year dummies?	yes	yes	yes	yes	yes

Table SOM.E5: Multinomial cross-over effects effect by subsample

Sample: Germany, 2003

	outcome: switch reg base: stay ind & reg	outc.: sw. ind & reg base: switch ind
$O^M_{i,r}$	0.928	0.742***
	(0.158)	(0.066)
$O^H_{i,r}$	0.805	0.918
	(0.151)	(0.087)
$A^M_{i,r}$	0.786	0.986
	(0.131)	(0.105)
$A^H_{i,r}$	1.058	0.960
	(0.176)	(0.092)
# obs.	17,451	

Sample: Germany, 2004

	outcome: switch reg base: stay ind & reg	outc.: sw. ind & reg base: switch ind
$O^M_{i,r}$	0.578***	0.775**
	(0.121)	(0.080)
$O^H_{i,r}$	0.764	0.902
	(0.182)	(0.104)
$A^M_{i,r}$	1.044	1.026
	(0.202)	(0.108)
$A^H_{i,r}$	0.559***	0.922
	(0.101)	(0.101)
# obs.	15,919	

Sample: Germany, 2005

	outcome: switch reg base: stay ind & reg	outc.: sw. ind & reg base: switch ind
$O^M_{i,r}$	0.797	1.167
	(0.181)	(0.127)
$O^H_{i,r}$	0.635**	0.994
	(0.120)	(0.098)
$A^M_{i,r}$	0.668**	0.929
	(0.115)	(0.093)
$A^H_{i,r}$	0.545***	0.756**
	(0.117)	(0.083)
# obs.	11,971	

Sample: East-Germany, all years

	outcome: switch reg base: stay ind & reg	outc.: sw. ind & reg base: switch ind
$O^M_{i,r}$	0.718*	0.951
	(0.134)	(0.113)
$O^H_{i,r}$	0.760	1.072
	(0.131)	(0.127)
$A^M_{i,r}$	1.041	1.121
	(0.162)	(0.140)
$A^H_{i,r}$	0.739*	0.857
	(0.122)	(0.102)
# obs.	12,479	

Sample: West-Germany, all years

	outcome: switch reg base: stay ind & reg	outc.: sw. ind & reg base: switch ind
$O^M_{i,r}$	0.768*	0.837***
	(0.112)	(0.057)
$O^H_{i,r}$	0.740*	0.899
	(0.118)	(0.066)
$A^M_{i,r}$	0.784*	0.950
	(0.112)	(0.068)
$A^H_{i,r}$	0.661***	0.901
	(0.090)	(0.067)
# obs.	32,862	

impact on nonemployment rates in that year. Turning to mobility effects, we find that geographical mobility after displacement rises between 2003 and 2005, while industrial mobility stays constant.

In spite of the slight overall variation in displacement effects, we find little evidence that the industry mix moderates these displacement effects in different ways across subsamples. Due to the reduction in sample sizes, fewer of the interaction effects are statistically significant, although, in some instances, effects that were insignificant in the overall sample turn marginally significant in some of the subsamples.[23]

The estimated cross-over effects in the various subsample panels of Table SOM.E5 suffer from a loss in precision as well. However, in all samples, we find at least some of the predicted cross-over effects. That is, we find that the ratio of nonlocal to local job-finding rates in the pre-displacement industry is reduced by a presence of related industries or vice versa. The weakest evidence is found in 2003 and in the regions of former East Germany. The strongest evidence in favor of the hypotheses formulated in section 3 of the main text are found in the sample for western Germany. Overall, the general conclusions in the main paper seem not to be driven by a specific year or by differences between former East and West Germany.

F Data issues

The Employment History (EH) database covers about 80% of German employment. Because its entries are used to determine social security contributions, they are generally considered highly reliable. However, in the context of measuring displacement effects, some issues stand out.

F.1 Civil servants

Because civil servants are exempt from social security contributions, they are not covered in the EH database. In principle, this does not matter much: we are not focusing on job losses of civil servants. However, one potential concern is that private-sector workers who move into what we have labeled "nonemployment" do not remain unemployed, but find jobs as civil servants. Given that such jobs are unequally distributed across regions, this may affect our nonemployment estimates in section 5. However, civil servant status is often only acquired after a qualifying period in which workers are employed as regular employees. Displaced workers who would start such careers would therefore first be observed as regular employees in the social security data. To explore whether displaced workers may still exit the dataset through jobs as civil servants, we regress a dummy that tags permanent disappearances on a set of dummies that identify the capital,

[23] For instance, intermediate shares of the pre-displacement industry significantly lower short-term nonemployment rates and daily-wage drops in the subsamples of former West Germany and of the year 2005. Moreover, we find that a presence of related industries reduces region switching effects in these samples as well.

Berlin, the administrative center of former West Germany, Bonn, as well as the capitals of the German Bundesländer (the seats of regional governments). Although we do find some evidence that more workers disappear permanently from the data in Berlin (at a 1 pp higher rate), we find the opposite for Bonn (a 1 pp lower rate), and no effects for the regional capitals. This suggests that any biases that arise from missing civil service careers will be minor.

F.2 Establishment closures

Another shortcoming of the EH database are the problems related to defining establishment closures aluded to in section 4 of the main text. In order to use information on blocks of inter-establishment labor-flows to identify spurious establishment closures, we drop small establishments where small numbers of workers can form blocks that represent large shares of total employment. An additional advantage is that by focusing on larger establishments, it becomes less likely that the performance of individual workers would have precipitated the establishment's closure and thereby made closures endogenous responses to worker quality.

However, our strategy to use inter-establishment labor-flow information may risk some false positives and false negatives in the identification of establishment closures. The former could, for instance, occur when corporate take-overs do not move all employees from the old to the new organization at once, but in successive waves. The latter (false negatives) would contaminate the donor pool of nondisplaced workers if we failed to identify workers who are let go because their establishments downsize severely, without closing down. To mitigate the former problem, we require for a closure event to be counted as a real closure that there cannot be a single economic establishment that absorbs more than 30% of workers displaced in that closure over a time-horizon of, not one, but three years. To address the latter concern, we calculate one-, two- and three-year growth rates for all establishments in the economy. If any of these growth rates implies a 50% or worse contraction in employment, we drop this establishment and its workers from the donor pool. With these new sample definitions, results (available on request) are indistinguishable from the ones reported here.

Furthermore, if closure events are, to some extent, foreseeable, selective job separations may occur just prior to the closure. Schwerdt (2011) shows that workers who leave an establishment up to two quarters before the actual closure experience elevated wage losses vis-à-vis regular (i.e., not displacement-related) job switchers. This suggests that, ideally, we would include workers who leave a failing establishment up to two quarters before it closes down. Shorter time windows may lead to an endogenous sample, because the sampled workers may have self-selected into staying until the very end. However, longer time windows would not be desirable either: these would lead to the inclusion of regular job-switchers, which, as argued in section 5 of the main text, represent a selected sample as well. Given that we observe workers once a year, the average time between the date on which we observe workers and the closure event should be around the two-quarter window recommended by Schwerdt (2011). For that

reason, we require that workers stay with the establishment until the year in which it closes down.