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

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Abstract

Does the local industry mix matter for how job-seekers trade off geographical against skill distance? To investigate this, we study how workers who lose their employment in establishment closures in Germany cope with their job loss. About a fifth of these displaced workers do not return to social-security covered employment within the next three years. Of the others, about two thirds leave their old industry, whereas one third move out of their region. Being in a location with a large concentration of one's old industry makes finding new jobs easier: in regions where the predisplacement industry is large, displaced workers suffer relatively small earnings losses and find new work faster. In contrast, a strong local presence of industries skill-related to the predisplacement industry increases earnings losses and the time it takes to find a new job. However, having skill-related industries in a region reduces the rate at which workers leave the region by 15%, and increases the rate at which they switch industries by 8%. When analyzing these spatial and industrial job-switching patterns through the lens of a job-search model, we find that workers take Marshallian externalities into consideration when they decide how to allocate search efforts between 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., the benefits afforded by dense concentrations of economic activity in a specific sector, are often linked to local labor markets. Accordingly, firms benefit from locating in such concentrations, because this facilitates finding workers who have the specialized skills these firms require. Moreover, also workers are supposed to benefit from Marshallian externalities. The argument is that if workers were to lose their jobs, a large local concentration of employers in their industry would make it easier to find new work that matches these workers' skills and work experience. However, in spite of ample research on Marshallian benefits to firms, the associated (re)employment benefits to workers have so far received comparatively little attention in the urban economics literature. In this paper, we focus on the latter question by studying the careers of workers who lose their jobs when establishments close down. In particular, we ask whether the consequences of such job displacement on workers' wages, unemployment durations and mobility decisions depend on the exact mix of industries that exists in a local economy.

Job displacement often has a detrimental impact on people's careers and their well-being. Consequences range from reduced wages and un- or underemployment, to health-related problems and depressions. These issues have been well-documented in a large and growing literature that focuses on workers who get displaced from their jobs when entire establishments close down. Such establishment closures leave workers looking for jobs when they neither planned on, nor contributed to, the termination of their employment and therefore are relatively unaffected by the self-selection problems that arise when job loss is an endogenous outcome of the interactions between workers and their employers. However, although, in this context, job loss itself may be plausibly exogenous to a worker's career plans, her or his response to it isn't. After all, workers have several alternatives when it comes to dealing with unemployment. For instance, they can search for jobs in their old industry or try to move to another industry. Similarly, workers can search for local jobs or consider relocating to other regions. Which strategy workers choose, and the likelihood of success of this strategy, will depend on which kinds of jobs a region has to offer. In particular, the decision to change industries or to move to another region (or both), as well as the time it takes to find a new job, will depend on which jobs currently exist in the region. That is, they depend (among other things) on the exact industry mix of the local economy. In spite of ample attention urban economists have spent on the importance of the geographical agglomeration of industries, relatively little is known about how industrial agglomeration affects the post-displacement careers of displaced workers. In particular, we have incomplete answers to questions such as: Do displaced workers find jobs faster when there are large local concentrations of the predisplacement or related industries? And do local concentrations of the predisplacement and related industries affect the way workers cope with displacement? Do they increase or decrease workers' geographical mobility? Do they lead to more or less industry switching?

To provide a framework for answering such questions, we propose a search model along the lines of Fallick (1992, 1993) in which workers divide their search efforts between two sectors: their own industry and a sector composed of suitable alternative (i.e., related) industries. Furthermore, we assume that search effort translates into a widening of the geographical search radius. A consequence of this assumption is that the geographical mobility of workers contains information about workers' (unobserved) allocation of search effort between the two sectors. Taking this into consideration, the model predicts that favorable local conditions in a sector increase the likelihood that workers find new jobs in that sector, both inside and outside the region. Moreover, and more interestingly, the model predicts that favorable local conditions in one sector reduce the spatial scope of search in the other sector, a prediction for which we find support in the data.

We test these hypotheses by applying a combination of matching techniques and regression models to a dataset that covers the employment history of over 20 million German workers. Using difference-in-differences techniques, we show that workers who are displaced in establishment closures not only experience significant earnings losses and are less likely to return to jobs covered by social security, but those who do return are also 65% more likely to change industries and 33% more likely to change regions than their statistical twins. However, the size of these effects depends to some extent on the local industry mix. Whereas, on average, earnings drop by 39%, this drop is reduced to 33% in regions where the industry from which workers were displaced has a high employment share. The availability of local jobs in the predisplacement industry furthermore reduces industry switching rates by 27% percent, while leaving region switching rates more or less unchanged. In contrast, high local employment shares of industries *related* to the predisplacement industry help prevent that workers leave the region, while increasing industry switching rates: although displaced workers in such regions are 15% *less likely* to move out of the region, they are 8% *more likely* to change industries.[1]

By focusing on how workers cope with their employment loss in terms of their industry and geographical mobility, this study contributes to the job dis-

[1]The reported percentages reflect the difference in the displacement effect on industry and region switching rates between displaced workers in the highest vis-à-vis the lowest third of our sample in terms of their predisplacement industries' local employment shares or of industries related to the predisplacement industry.

placement literature, which has predominantly dealt with wage and employment effects. Moreover, by studying how this coping strategy depends on the composition of the local economy, we connect the issue of job displacement to debates on agglomeration externalities in economic geography. Indeed, although numerous studies have shown that macro-economic as well as local conditions determine the severity of displacement effects, relatively little is known about the role of the local industry mix therein. This is surprising, given the ample attention that the literature on Marshallian and Jacobs externalities (e.g., Glaeser et al., 1992; Henderson et al., 1995; Porter, 2003) has given to the importance of the industrial specialization and diversity of regional economies. In particular, although Marshallian labor market pooling effects are often proposed to lead to smoother job search in urban economics models (Helsley and Strange, 1990; Duranton and Puga, 2004), direct empirical evidence on this issue is scarce. Finally, 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). In particular, the finding that skill-related employment induces workers to change industries instead of regions, shows that clusters of related activities not only create agglomeration externalities for local firms (Porter, 2003; Neffke et al., 2011; Delgado et al., 2010) but also help anchor talent and avoid an erosion of the region's skill base.

2 Literature Review

Establishment closures can have a profound impact on the lives of the workers who get caught up in them. Apart from pecuniary losses, displaced workers are also more likely to suffer addiction problems and a deterioration of their health. For instance, Black et al. (2015) show that displacement increased smoking habits in a sample of Norwegian workers, leading to cardiovascular health problems. Likewise, Eliason and Storrie (2009) document a 44% increase in mortality rates among male displaced workers in Sweden, which the authors ascribe to increased suicides and alcohol related deaths.

Most of the literature (see Carrington and Fallick (2015) for a recent review), however, has focused on displacement-related income losses. Establishment closures cause drastic reductions in earnings that are often long-lived, depressing incomes of those affected for periods of 10 years or longer (e.g. Jacobson et al., 1993; Couch and Placzek, 2010; Davis and von Wachter, 2011). These income losses are attributed to a variety of causes. First, because displaced workers are forced to find a new employer, firm-specific human capital becomes redundant (Becker, 1962). Second, some employment contracts back-load wage payments to provide incentives for more durable employment relations and to protect against shirking (Lazear, 1979). Such back-loaded payments are lost when a firm closes down. Third, wage losses will depend on how easy it is for a worker to find a new job that matches her current skill set. If workers get progressively better matched over the course of their careers, this accumulated "match capital" (Jacobson et al., 1993, p. 686) will be lost in the unanticipated employment termination that occurs in displacement events.

Whether these earnings losses materialize through protracted unemployment spells or through a reduction in daily wages varies from one country to another (Carrington and Fallick, 2015). In Germany, the focus of this study, unemployment has been shown to be a major factor in displacement-related income losses (Burda and Mertens, 2001; Nedelkoska et al., 2015), especially in the first years after displacement (Schmieder et al., 2010). This raises the question of what determines how displaced workers search and find new jobs. Previous research has highlighted that the economic conditions under which displacement takes place play an important role herein. In particular, the adverse effects of displacement are more severe in periods of macro-economic downturns (Davis and von Wachter, 2011) and in declining industries (Howland and Peterson, 1988; Fallick, 1993). However, also *local* economic conditions matter. For instance, workers suffer more severe displacement effects in declining local economies (Jacobson et al., 1993) and in declining local industries (Carrington, 1993). Moreover, Andersson et al. (2014) show that dense concentrations of suitable jobs decrease joblessness, even when looking at different locations in the same city.

Such local economic conditions may matter for a number of reasons. First, the size and growth rates of local economies will affect the arrival rate and the distribution of wage offers, both of which affect reservation (and, consequently, accepted) wages in standard search models (e.g., Mortensen, 1986). Second, urban economists have argued that a greater number of available jobs in a city allow for better matches between the skill endowments of workers and the skill requirements of jobs (Helsley and Strange, 1990). Third, economic sociologists have pointed to the role that social networks - which are often very local - play in finding new jobs. For instance, in his landmark study of the labor market of the Boston suburb of Newton, Granovetter (1973) not only showed that a large fraction of jobs is found through social networks, but also, that the best jobs (that is, the highest paid and most creative jobs) are assigned through social networks (see also, Granovetter, 1995). Subsequent studies have confirmed these findings. For instance, the Panel Study of Income Dynamics, which followed 5,000 American families, found that in 1978, 52% of white men, 47% of white women, 59% of black men, and 43% of black women found their current jobs through friends and relatives (Putnam, 2001).[2]

One widely studied aspect of local economies is their industrial composition, i.e., the diversity and concentration of industries in a location (e.g. Glaeser et al., 1992; Henderson et al., 1995; Frenken et al., 2007). Evidence on benefits that supposedly arise when firms of the same industry colocate, so-called Marshallian externalities, is mixed (e.g., Groot et al., 2015). Recently, however, a number of studies have investigated the existence of Marshallian externalities using identification strategies based on employment shocks created by the entry or exit of large economic establishments. These studies find significant agglom-

[2]Effects of social networks do not seem to have diminished with the rise of online job-search platforms: the New York Times recently reported that 45% of nonentry level placements in the accounting firm Ernst & Young came from employee recommendations. Likewise, Deloitte gets 49% of its experienced hires from referrals (Schwartz, 2013).

eration effects. For instance, Greenstone et al. (2010) find that the opening of large new manufacturing plants leads to productivity spillovers to local incumbents and Gathmann et al. (2014) find that establishment closures lead to a prolonged decline in employment of the affected local industry that goes well beyond the initial jobs lost in the closure itself. These Marshallian externalities are attributed to, among other things, the benefits of labor market pooling. Accordingly, large local concentrations of firms with similar skill requirements reduce the costs of job search and, therewith, offer an implicit protection against protracted unemployment. However, to the best of our knowledge, whether the local industry mix indeed plays a role in moderating the effects of establishment closures has not yet been assessed empirically. In this paper, we, therefore, study how the local concentrations of the predisplacement and related industries impact the further careers of displaced workers. Do they affect the earnings drop associated with displacement? Do they affect the length of unemployment spells? Do they change the extent to which workers deal with displacement by switching industries or moving to other regions? Moreover, we will show evidence that suggests that workers search strategically by taking the local industry mix into account when allocating search efforts among industries.

3 Model

To structure our empirical analyses we draw on a job search model 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 predisplacement industry. However, we adjust Fallick's (1992) model to give an explicitly spatial dimension to job search.

Let there be two sectors $s \in \{A, B\}$, which are characterized by an offer arrival parameter λ_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 also involve costs, $C = c\left(\sum_s e_s\right)$. 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 λ_s and the search intensity in sector s:

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

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

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

$$rV = \max_{s\geq 0}\left[b - c\left(\sum_s e_s\right) + \sum_s \lambda_s \sigma\left(e_s\right)\left\{\int_0^\infty \max\left[0, W(x) - V\right]\,\mathrm{d}F_s\left(x\right)\right\}\right]$$

where, b represents the value of leisure, r a discount rate and $W(x)$ the NPV of accepting a wage offer of x. rV can be interpreted as the "rental income" derived from the expected NPV of next period's search process. Under the assumption of optimal search now and in the future, this equals the value a worker derives from leisure net of the costs of search, $b - c\left(\sum_s e_s\right)$, plus how much search increases the expected NPV of future incomes. This search-related increase in future incomes equals the sector-specific offer arrival rate, multiplied by the expected increase in NPV associated with the wage offer: $W(x) - V = x/r - V$.

For simplicity, we assume that the costs of search are the same regardless of whether a worker is employed or unemployed. Because, under this scenario, workers can continue their search while working, they have no incentive to wait after an offer arrives that exceeds the value of leisure. Consequently, the reservation wage is the same in both sectors: $V = w_A^*/r = w_B^*/r = w^*/r$. Given that a worker could enjoy leisure valued at b by not searching at all, w^* must exceed b for the worker to participate in the labor market (i.e., search). The constrained maximization problem above now becomes:

$$\max_{s\geq 0}\left[b - c\left(\sum_s e_s\right) + \sum_s \frac{\lambda_s}{r}\sigma\left(e_s\right)\left\{\int_{w^*}^\infty \left(x - w^*\right)\,\mathrm{d}F_s\left(x\right)\right\} - \phi\left(\sum_s e_s - 1\right)\right]$$

for $w^* \geq b$. As long as marginal costs are nondecreasing (or, at least, not decreasing too fast), concavity is ensured by the assumption that $\sigma''\left(e_s\right) < 0$. Optimal search is now determined by the following first-order conditions:

$$-c'\left(\sum_s e_s\right) + \frac{\lambda_A}{r}\sigma'\left(e_A^*\right)\left\{\int_{w^*}^\infty \left(x - w^*\right)\,\mathrm{d}F_A\left(x\right)\right\} - \phi = 0,\ w^* \geq b$$

$$-c'\left(\sum_s e_s\right) + \frac{\lambda_B}{r}\sigma'\left(e_B^*\right)\left\{\int_{w^*}^\infty \left(x - w^*\right)\,\mathrm{d}F_B\left(x\right)\right\} - \phi = 0,\ w^* \geq b$$

That is, optimal search equalizes the marginal returns to search in both sectors. Consequently, at optimal effort levels, e_A^* and e_B^*, the following must hold:

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

Because, by assumption, σ' is positive and monotonically decreasing, optimal search will shift efforts from sector A to sector B when the distribution of wage offers or arrival rates in sector A deteriorate compared to those in sector B. Whenever a sector offers a job with a wage above the reservation wage of

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-specific hazard rate for sector s is constant and equal to:

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

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, making standard continuous-time competing-risk models less well-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 approximately estimated by using 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 and 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 the likelihood that an acceptable job offer arrives in sector s before the end of the period.[3] The second part of equation (5) now simplifies to:

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

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. Because the hazard functions are constant over time, the first part of equation (5) can now be written as:[4]

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

[3] h_s can be thought of as a discrete-time hazard rate, whereas θ_s is a continuous-time hazard rate. Because there is only one period in our setting, the discrete-time hazard rate is the complement of the survival function evaluated at the end of the period.

[4] See Appendix A for a full derivation.

where h represents the likelihood that the worker finds a job in either of the two sectors before the end of the time period and θ_s the instantaneous hazard of finding a job in sector s.[5] 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:

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

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

The geography of search

In order to add a spatial dimension to the search process, we assume that the sector-specific intrinsic offer rates, λ_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 h_A, but not h_B. However, h_B will still depend on the local conditions in A because these conditions affect the way

[5] We have used that $h = 1 - S_A(1)\,S_B(1) = 1 - S(1)$, where $S(\tau)$ represents the joint survival function for the hazards of finding a job in A or B.

workers divide their search efforts between the two sectors. Equation (2) shows that this effect will be negative: the better the local conditions for sector A are, the less a worker will search in sector B. This in turn decreases h_B, the likelihood of exiting unemployment through sector B.

How would these search efforts be reflected in observable characteristics of workers' careers? Increasing search efforts means that workers sample jobs from a wider sets of firms. We propose that one of the ways in which workers do this is by increasing the geographical scope of their search. For instance, workers could attend job interviews outside the region. Likewise, because social networks tend to be local, reaching out to friends and acquaintances to learn about jobs elsewhere would require greater efforts.[6]

We incorporate this reasoning into the model by modifying equation (1) to make the arrival rates of suitable wage offers location-specific. 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, h_{0s}, now becomes:

$$h_{0s} = \lambda_s \sigma(e_s)\left(1 - F_s\left(w^*\right)\right)\left[1 - \rho(e_s|X_s)\right] \tag{7}$$

The arrival rate of offers from outside the region, h_{1s}, equals:

$$h_{1s} = \lambda_s \sigma(e_s)\left(1 - F_s\left(w^*\right)\right)\rho(e_s|X_s) \tag{8}$$

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 for 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 instead of from outside the region. Moreover ρ is assumed to *increases* ine_s, reflecting that acceptable job offers from outside the region require more intensive search.[7]

As mentioned before, 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 "predisplacement 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 predisplacement industry. In particular, we will choose a set of related industries such that they, together, absorb about the same number of displaced workers as the predisplacement industry itself.[8] The upshot of equations (7) and (8) is that we can now infer how

[6]Note that this introduces an asymmetry in job search between industries and locations. That is, I will assume that efforts are *directed* at finding jobs in a sector, not in a region. In other words, workers know what kind of job they are looking for, but they may be less sure where to find it.

[7]Note that we do not specify whether efforts and favorable local conditions increase job offer arrival rates or lead to better job 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 does not change qualitatively.

[8]To be precise, whereas 27% of reemployed displaced workers manage to find jobs in the predisplacement industry (constituting the first sector), 29% end up in related industries (constituting the second sector).

workers allocate search efforts between these two sectors from their geographic mobility. In fact, the model has the following testable predictions:

1. Favorable local conditions in the predisplacement 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 the predisplacement industry*), favorable local conditions in the predisplacement industry (*in related industries*) will decrease the relative risk of finding jobs *outside* the predisplacement industry (*in the predisplacement industry*) compared to staying unemployed.

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

Prediction 1 derives from the fact that, as a direct effect of better local conditions in a sector, the quality of local job-offers and/or arrival rates increase in that sector. This effect is augmented by the fact that better local conditions will also induce greater search efforts in the sector, which raises the likelihood of receiving acceptable local or nonlocal job offers.[9] However, local conditions in sector A should neither directly affect the relative risk of workers finding a job in sector B vis-à-vis remaining unemployed, nor on the ratio of nonlocal to local job offers in sector B. Such cross-effects nevertheless arise, because favorable conditions in sector A will draw search efforts from sector B to sector A as implied in equation (2). This in turn reduces the relative risk of staying unemployed instead of finding a job in sector B, i.e., h_b, as implied by prediction 2. Moreover, the geographical scope of search in sector B will decrease, because $\frac{\partial \rho}{\partial e_B} > 0$. As a consequence, the relative risk of exiting unemployment through nonlocal instead of local jobs in sector B, i.e., $\frac{h_{1B}}{h_{0B}}$, will decrease as local conditions in sector A improve. In other words, the mobility of workers will reveal evidence of strategic search if the distance over which workers find jobs in one sector depends on the local conditions in the other sector. We will test for such dependencies explicitly at the end of section 6.

4 Data

We use data from the Historic Employment and Establishment Statistics (HES) database.[10] The HES database is based on Germany's social security records. Our version of these data provides yearly information on an individual's daily

[9] Note that 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.

[10] See Bender et al. (2000) for a detailed description of this database.

wage[11], occupation, work status (i.e., full-time employed, part-time employed, in apprenticeship), gender, and age. The HES also contains anonymized identifiers that allow us to follow individuals over time. Moreover, the HES 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.

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 reason individuals drop out of the data is that they become unemployed or inactive, some may also have returned to school, received civil servant status, started their own businesses, etc.. We therefore use the term "nonemployment" instead of unemployment to refer to workers who leave jobs with social security coverage.[12]

To identify displaced workers, we select those workers who lose their jobs in establishment closures that involve at least 10 employees and that according to the criteria of Hethey and Schmieder (2010) can be considered unambiguous closures (as opposed to mere administrative changes in establishment identifiers). The lower bound of 10 employees helps avoid selecting spurious closures and, at the same time, makes it less likely that the performance of individual workers would have precipitated the closure. We then gather all workers who left one of these establishments in the year it 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, ensuring 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

[11]Throughout the paper, wages and earnings reflect real daily wages (earnings) denominated in 2005 EUR.

[12]One potential concern is that nonemployed workers find jobs as civil servants. Given that such jobs are unequally distributed across regions, this may affect our nonemployment estimates in section 6. However, civil servant status is often only acquired after a qualifying period in which workers can be 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 indeed exit the dataset through jobs as civil servants, we regressed a dummy that tags permanent disappearances on a set of dummies that identify the capital, Berlin, West Germany's former administrative center, 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 percentage point higher rate), we find the opposite effect for Bonn (a 1 percentage point lower rate), and no such effects for the regional capitals. This suggests that any biases that arise from the missing data coverage will be minor.

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.

5 Empirical strategy

Related industries

In the model of section 3, we have assumed that workers divide search efforts between two sectors: the predisplacement industry and a second sector consisting of industries that are closely related to the predisplacement 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. (2013). This index is calculated as the observed labor flows between two industries, divided by the labor flows that would be expected had workers switched industries randomly.[13] 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:

$$R_{ij} = \frac{F_{ij}}{\sum_{k \neq j} F_{kj} \sum_{l \neq i} F_{il}} \sum_{k'} \sum_{l' \neq k'} F_{k'l'} \tag{9}$$

Moreover, by definition, we impose that industries are not skill-related to themselves: $R_{ii} \equiv 0$. Because inter-industry labor-flow connections are extremely sparse – about 90% of industry pairs display no labor flows at all – this method provides clearly delineated labor markets. We calculate this R-matrix for each year between 1999 and 2008 and then take its average across all years. Furthermore, we symmetrize the resulting matrix by averaging its elements with those of its transpose.[14] We refer to this averaged and symmetrized matrix as $\bar{R}$.[15]

Local conditions

Our main interest is in the role Marshallian externalities play in the post-displacement careers of workers who lose their job in establishment closures.

[13]To increase the precision with which we establish relatedness of industries, we use information for these labor flows for all full time employed men and women between an age of 18 and 65. However, we drop all workers that are at some point displaced in our data to avoid any circularity in the way the measure is constructed.

[14]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 extreme outliers in the right tail. The threshold value of 3 we use in this paper for R corresponds to a transformed value, R^*, of 3/4.

[15]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). Moreover, Neffke et al. (2013) show that the index defined in equation (9) does neither change much over time, nor across workers in different occupations and wage groups.

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 predisplacement 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: regions where the worker's old (O) industry represents a small, moderate or large share of a region's total 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:

$$\begin{aligned} O_{irt}^{L} &= I\left(\frac{E_{irt}}{\sum_j E_{jrt}} \leq \zeta_1\right) \\ O_{irt}^{M} &= I\left(\zeta_1 < \frac{E_{irt}}{\sum_j E_{jrt}} \leq \zeta_2\right) \\ O_{irt}^{H} &= I\left(\frac{E_{irt}}{\sum_j E_{jrt}} > \zeta_2\right) \end{aligned} \tag{10}$$

where $\frac{E_{irt}}{\sum_j E_{jrt}}$ is the regional employment share of the worker's old industry in the (real or virtual) displacement 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 predisplacement industry (i.e., of Alternative industries):

$$\begin{aligned} A_{irt}^{L} &= I\left(\frac{E_{irt}^{rel}}{\sum_j E_{jrt}} \leq \zeta_1^{'}\right) \\ A_{irt}^{M} &= I\left(\zeta_1^{'} < \frac{E_{irt}^{rel}}{\sum_j E_{jrt}} \leq \zeta_2^{'}\right) \\ A_{irt}^{H} &= I\left(\frac{E_{irt}^{rel}}{\sum_j E_{jrt}}\right) > \zeta_2^{'} \end{aligned} \tag{11}$$

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:

$$E_{irt}^{rel} = \sum_{k \neq i} E_{krt} I\left(\bar{R}_{ik} > \xi\right) \tag{12}$$

Employment in equations (11) and (12) 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 predisplacement industry are at least three times as large as the random benchmark. At this threshold, related industries represent on average about 5% of local employment. Moreover, according to this definition, about 29% of displaced workers (40% of all displaced industry switchers) move to related industries, which is similar to the 27% of displaced workers who return to their predisplacement industry. Finally, $\zeta_1^{'}$ and $\zeta_2^{'}$ once again divide workers into equally sized groups.

Estimation strategy

Most job separations occur when a worker decides to pursue career opportunities elsewhere, or when the employer makes this decision in her stead. As a consequence, job separations are often endogenous to the expectations about a worker's career prospects at her firm. An exception are job separations that follow from establishment closures. Such separations are typically unrelated to the performance and career aspirations of individual workers and have, therefore, been considered 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 this exogeneity assumption, we compare displaced to observationally similar nondisplaced 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 prescreening method to reduce the dependence of the treatment variable (in our case, displacement) on worker characteristics. Such prescreening has several advantages. Firstly, because the procedure is based on only predisplacement covariates, it does not introduce selection biases. Secondly, by ensuring a common support of treated and untreated observations, prescreening avoids inference that is based on inter- or extrapolation to parts of the covariate space where no displaced (or nondisplaced) workers are observed. Thirdly, because the preprocessing 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.[16] As a consequence, prescreening mitigates misspecification issues related to the exact functional form through which these covariates enter the regression equation (Ho et al., 2007). However, the cost of preprocessing the data is that the estimated effects represent average effects for the subset of displaced workers instead of for the population as a whole.

[16]For instance, mobility decisions will depend on a worker's age. However, because it is nigh impossible to know the functional relation between mobility and age, it is hard to correct for this by simply controlling for worker age. By matching displaced to nondisplaced workers, we preselect 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, regardless of the exact functional form through which mobility depends on age.

Matching

Our matching strategy closely follows the one in Nedelkoska et al. (2015), who study occupational mobility of displaced workers and the extent to which the need for skill-adjustments amplifies the effect of displacement. For each displaced worker who meets the criteria listed in Section 4, we try to find a statistical twin among the nondisplaced workers my means of propensity-score matching.[17] We estimate workers' propensity to experience a displacement event with a probit model that uses a worker's education, age, years of general, industry, and regional work experience, as well as establishment tenure as explanatory variables. To avoid parametric assumptions, age and experience variables enter as dummy groups. Furthermore, we control for regional economic conditions by adding the predisplacement regional employment shares and squared values thereof of the predisplacement and of related industries. Most importantly, however, we use lags 6 to 2 of predisplacement wages and the logarithm of wage growth between 5 and 2 years before the displacement event to capture a worker's predisplacement wage curve. Because this curve reflects rewards for both observed and unobserved worker characteristics, matching workers with similar pre-event wage curves helps establishing counterfactual careers for displaced workers. That is, the predisplacement wage curves help control for unobserved characteristics that might affect postdisplacement wage dynamics and mobility decisions. 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 44,922 worker pairs.

Table 1 compares means for the matching variables and wage paths of displaced and nondisplaced workers in the overall population with the ones in the selected sample. Individual characteristics of displaced and nondisplaced workers are much more closely aligned in the sample than in the population as a whole. For all predisplacement variables, differences in means between displaced and nondisplaced are well below 5%. Note that predisplacement wages are particularly well-balanced, with biases below 1%.[18] 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 introduce biases.

6 Findings

Displacement effects

To assess the overall effects of displacement on earnings, wages, nonemployment and mobility decisions, we follow Schwerdt (2011) and combine matching with

[17]Given that our total dataset contains over 20 million workers a year, we search in a 10% random sample of nondisplaced workers to reduce the computational burden.

[18]The small dip in earnings of displaced workers a year before displacement is quite 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.	4.73%	5.17%	-11.4	4.75%	4.71%	1.1
share old ind. emp.	0.72%	1.54%	-28.8	0.72%	0.69%	2.8
age	39.8	39.7	1.6	39.9	39.8	0.9
edu (ND)	10.05%	10.47%	-1.4	10.19%	10.38%	-0.6
edu (VT)	63.93%	65.17%	-2.6	65.47%	65.83%	-0.8
edu (HS)	0.52%	0.63%	-1.5	0.51%	0.48%	0.5
edu (HS+VT)	2.46%	4.00%	-8.7	2.46%	2.48%	-0.2
edu (C)	2.96%	4.64%	-8.8	3.03%	3.03%	0.0
edu (U)	3.09%	6.36%	-15.5	3.16%	3.20%	-0.2
edu (miss.)	17.00%	8.72%	24.9	15.17%	14.60%	1.6
log(reg. size)	14.8	15.7	-14.7	15.3	15.2	0.9
industry experience	9.2	10.6	-23.0	9.7	9.7	0.4
regional experience	12.4	13.7	-19.5	12.9	12.9	0.4
establishment tenure	7.9	9.6	-28.5	8.4	8.4	0.0
year: 2005	38.87%	33.66%	10.9	38.50%	38.50%	0.0
year: 2006	35.04%	33.41%	3.5	35.11%	35.11%	0.0
year: 2007	26.09%	32.94%	-15.1	26.39%	26.39%	0.0
wage (4 yrs pre-D.)	83.8	100.4	-32.2	88.8	88.4	0.9
wage (3 yrs pre-D.)	86.1	104.9	-35.1	90.0	89.7	0.5
wage (2 yrs pre-D.)	89.5	109.2	-35.2	94.2	94.2	0.1
wage (1 yr pre-D.)	90.7	112.0	-36.2	93.1	95.6	-4.8
wage (at D.)	91.8	114.4	-36.7	94.0	97.4	-6.4
wage (1 yr post-D.)	49.6	110.4	-89.6	51.7	92.7	-68.0
wage (2 yrs post-D.)	58.7	108.4	-73.0	61.0	90.9	-49.3
wage (3 yrs post-D.)	61.1	106.4	-66.3	63.4	89.2	-42.2

The selected population refers to all individuals that meet the criteria outlined in Section 4: full-time employees with (1) at least six years of work experience, (2) three years of industry experience and (3) one year of establishment tenure. “Share rel. emp.” refers to the share of skill-related employment in the region at the time of (virtual) displacement as defined in equation (12). “Share own ind. emp.” refers to the regional employment share of the industry of the closing establishment. 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.

the difference-in-differences framework introduced to the displacement literature by Jacobson et al. (1993). That is, we estimate the following equation:

$$y_{mt} = \sum_{k=-3}^{3} \tau_1^k T_{mt}^k + \sum_{k=-3}^{3} \tau_2^k T_{mt}^k D_{mt} + X_{mt}\beta + \alpha_m + \delta_t + \epsilon_{mt} \tag{13}$$

where α_m and δ_t represent individual and year fixed effects and the vector X_{mt} contains a worker's age and age-squared. y_{mt} can be one of the following dependent variables: daily earnings, the logarithm of daily wage, or a dummy variable for the event a worker is nonemployed, changes industries, or changes regions.[19] 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 displacement year t.

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. This vector, graphed in Figure 1, shows how the effects of displacement on each of the dependent variables fade over time.

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 38 EUR and keeps them depressed for the entire postdisplacement window. Much of this reduction is due to the large drop in employment rates, which reaches 39.7 percentage points (pp) in the first postdisplacement year. However, also workers who get reemployed within a year, face a fall in daily wages (on average, of 8.0%).

Displacement also affects which jobs workers choose. Displaced workers are much more likely than their statistical twins to move out of a labor market area (32.9 pp) or to change 5-digit industries (65.5 pp) right after they are displaced. Moreover, switching rates remain elevated for at least two years after the displacement event. This suggests that displaced workers do not immediately find well-matching jobs. Given the parallel predisplacement trends for displaced and nondisplaced workers, the effects depicted in Figure 1 are plausibly causal.

Local conditions as moderators of displacement effects

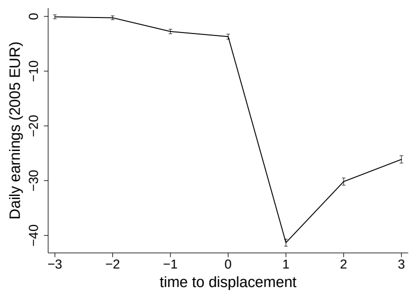
How does the local industry mix change the effect of D_{mt}? To study this, we interact the dummy groups created in equations (10) and (11).[20] Ideally, we would integrate these interaction terms in the difference-in-differences estimations of equation (13). However, this set-up would yield complicated and hard-to-estimate interaction effects. Instead, we estimate cross-sectional models

[19] Region and industry switches are registered in the last year of the old job, regardless of when exactly the new job starts (provided it starts before the end of the observation window). Therefore, industry and region switching after the displacement year $t = 0$ reflect repeated job switches, not delayed reemployment.

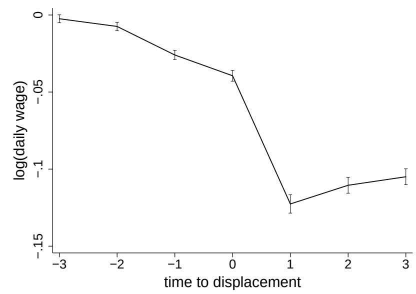
[20] The highly skewed distribution of the employment shares of the predisplacement and of related industries makes interacting the displacement dummy with these shares themselves problematic.

Figure 1: Difference-in-differences in postdisplacement careers

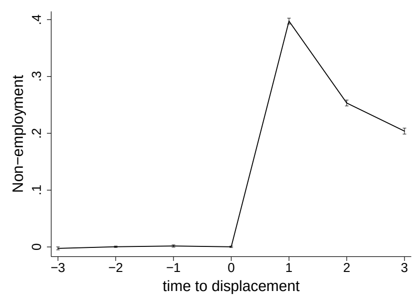
(a) Daily earnings (2005 EUR)



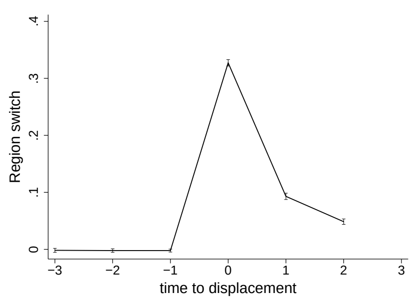
(b) log(daily wage)



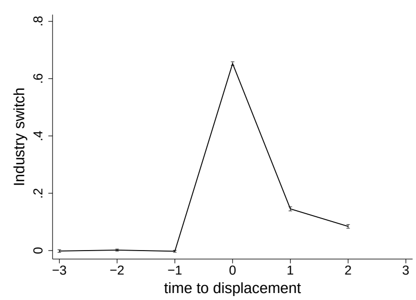
(c) Nonemployment



(d) Relocation



(e) Industry switching



Graphs report the difference-in-differences estimates using equation (13), 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 is 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 $t = 1$ and $t = 2$ are switches from one postdisplacement job to another.

of the following form:

$$y_{mt} = \kappa D_{mt} + \Pi_{irt}\gamma_0 + D_{mt}\Pi_{irt}\gamma_1 + X_{mt}\beta + \eta_{it} + \rho_{rt} + \epsilon_{mt} \tag{14}$$

where Π_{irt} collects the dummy groups defined in equations (10) and (11). η_{it} and ρ_{rt} are industry-year and region-year fixed effects at the time of displacement (for nondisplaced workers, these refer to the industry, region and year in which their statistical twin got displaced). X_{mt} is a set of worker characteristics, including age, age^2, and a seven-category dummy group for the worker's educational attainment.[21] The dependent variable, y_{mt}, can be one of six variables: (1) the change in earnings worker m experiences 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 postdisplacement 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 reports four different model specifications for one of the dependent variables. 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 model 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 model, 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 the models in these fourth columns in the section on robustness checks.

Wages

Table 2 illustrates the devastating effects of displacement on earnings. On average, workers lose about 38 EUR in daily earnings in the first year after being displaced (almost 40% of their predisplacement earnings, see column 1). Table 4 shows that this is largely due to an increase in the nonemployment hazard of around 40 pp. By contrast, for workers who find a new job immediately, the effects on the loss in log(daily wages) are limited to a wage reduction of 7.5% (column 1, Table 3).[22]

As expected, these estimates are very close to the difference-in-differences estimates in Figure 1. However, effects vary with the industry mix of the region in which a worker is displaced. Displacement-induced earnings losses and nonemployment risk are lower in locations with high employment shares of the

[21] The HES distinguishes among six different levels of education. The seventh category is missing education codes.

[22] This estimate is based on worker pairs for which both nondisplaced and displaced workers are employed in the year immediately following the displacement event.

predisplacement industry. Taking locations with low shares of the predisplacement and of related industries as a benchmark, the reduction amounts to 7.0 EUR (16%) for the earnings effect (column 3 of Table 2) when the old industry's employment shares are high. This is not mainly due to changes in the effect on daily wages: for workers who find new jobs, the presence of the old industry in the region affects the drop in log(daily wage) only marginally (Table 3). However, the effect of displacement on nonemployment incidence (Table 4) depends markedly on a region's industry mix. In places with intermediate employment shares of the old industry, the effect of displacement on nonemployment rates is reduced by 2.1 pp (8%). Where the old industry is large, the effect is reduced by even 5.3 pp (or by 17%). Moreover, high local employment shares in the old industry reduce displacement effects on long-term nonemployment rates by about 3.9 pp, a 19% reduction (Table 5), compared to regions with low employment shares in the old industry.

Skill-related employment in the region has much less of an effect on wages and nonemployment rates. It neither significantly reduces displacement-related nonemployment nor the immediate losses in earnings. If anything, high shares of related industries *increase* earnings losses after displacement. At 3.3 EUR, their impact is modest, however. Moreover, a presence of related industries seems to influence the drop in daily wages, not nonemployment durations. Possibly, jobs in related industries represent a less than ideal match compared to jobs in the predisplacement industry. As a consequence, the availability of related employment in a location allows workers to stay in their regions, This is evidenced in the reduction in geographical mobility in locations with much related employment reported in Table 6. However, this reduced geographical mobility comes at the cost of a slight mismatch between workers' prior experience and their new tasks.

Mobility

To study the effect of displacement on workers' mobility, we drop all worker pairs for which at least one worker does not return to the social security data within three years after displacement.[23] For these workers, displacement increases the likelihood of moving to another region by about 33 pp (Table 6) and of switching 5-digit industries by about 66 pp (Table 7).

The exact mobility choices, however, depend on the local industry mix. Once again, we use regions with low shares of the predisplacement and of related industries as a benchmark. Against this benchmark, regions with a moderate employment share in the old industry show a 2.6 pp decrease in displacement related region switching (see column 3 of Table 6). This is a modest change in effect size when compared to the 20 pp reduction in industry switching after displacement (Table 7). By contrast, high shares of related industries reduce region switching by more than twice as much (5.3 pp), but increase, instead of decrease, industry switching by 5.9 pp. These findings support our earlier

[23]Due to attrition, this sometimes happens to statistical twins as well.

Table 2: The effect of regional conditions on earnings losses upon displacement

dep. var.: earnings increase (EUR)	(1)	(2)	(3)	(4)
D	-37.598***	-39.471***	-38.237***	-26.942
	(0.582)	(1.187)	(0.872)	(27.603)
$D \times O^M_{i,r}$		3.121**	2.970***	2.887***
		(1.470)	(1.116)	(1.110)
$D \times O^H_{i,r}$		7.003***	6.379***	5.715***
		(1.395)	(1.172)	(1.159)
$D \times A^M_{i,r}$		-1.442	-1.653	-1.229
		(1.379)	(1.087)	(1.061)
$D \times A^H_{i,r}$		-3.412**	-3.321***	-3.340***
		(1.485)	(1.226)	(1.234)
$O^M_{i,r}$		-0.247	-0.259	-0.109
		(0.452)	(0.583)	(0.576)
$O^H_{i,r}$		0.793	-0.253	0.168
		(0.493)	(0.791)	(0.786)
$A^M_{i,r}$		0.274	-0.101	-0.348
		(0.441)	(0.582)	(0.574)
$A^H_{i,r}$		1.056**	0.144	-0.257
		(0.459)	(0.736)	(0.726)
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	0.131	0.133	0.178	0.185
# obs.	89,844	89,844	89,844	89,844

***: 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 predisplacement 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 at least 3 to the predisplacement 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 time-dummies for the displacement year. Standard errors are clustered at the region-industry level.

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

dep. var.: log(wage gain)	(1)	(2)	(3)	(4)
D	-0.078***	-0.078***	-0.069***	-0.162
	(0.004)	(0.008)	(0.008)	(0.236)
$D \times O_{i,r}^{M}$		0.011	0.013	0.012
		(0.011)	(0.012)	(0.012)
$D \times O_{i,r}^{H}$		0.017*	0.018*	0.016*
		(0.010)	(0.009)	(0.009)
$D \times A_{i,r}^{M}$		-0.018*	-0.025***	-0.024***
		(0.009)	(0.009)	(0.009)
$D \times A_{i,r}^{H}$		-0.009	-0.010	-0.012
		(0.011)	(0.012)	(0.012)
$O_{i,r}^{M}$		0.003	0.006	0.007
		(0.003)	(0.005)	(0.005)
$O_{i,r}^{H}$		0.004	0.007	0.008
		(0.003)	(0.006)	(0.006)
$A_{i,r}^{M}$		0.006**	0.003	0.002
		(0.003)	(0.005)	(0.005)
$A_{i,r}^{H}$		0.008**	-0.002	-0.002
		(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	0.015	0.015	0.064	0.066
# obs.	46,104	46,104	46,104	46,104

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

Table 4: The effect of regional conditions on short-term nonemployment

dep. var.: non-employed (y/n)	(1)	(2)	(3)	(4)
D	0.397***	0.411***	0.413***	0.979***
	(0.006)	(0.013)	(0.007)	(0.208)
$D \times O_{i,r}^M$		-0.014	-0.021**	-0.019**
		(0.013)	(0.009)	(0.009)
$D \times O_{i,r}^H$		-0.055***	-0.053***	-0.050***
		(0.015)	(0.009)	(0.009)
$D \times A_{i,r}^M$		0.001	-0.002	-0.000
		(0.015)	(0.009)	(0.009)
$D \times A_{i,r}^H$		0.029**	0.010	0.016*
		(0.013)	(0.010)	(0.010)
$O_{i,r}^M$		-0.006**	-0.005	-0.005
		(0.003)	(0.004)	(0.004)
$O_{i,r}^H$		-0.014***	-0.004	-0.004
		(0.003)	(0.005)	(0.005)
$A_{i,r}^M$		0.002	-0.002	-0.003
		(0.003)	(0.004)	(0.004)
$A_{i,r}^H$		0.002	-0.001	-0.002
		(0.003)	(0.005)	(0.005)
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	0.217	0.220	0.268	0.274
# obs.	89,844	89,844	89,844	89,844

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

Table 5: The effect of regional conditions on long-term nonemployment

dep. var.: non-employed after 3 yrs (y/n)	(1)	(2)	(3)	(4)
D	0.190***	0.203***	0.206***	0.800***
	(0.004)	(0.008)	(0.005)	(0.176)
$D \times O^M_{i,r}$		-0.002	-0.005	-0.004
		(0.009)	(0.007)	(0.007)
$D \times O^H_{i,r}$		-0.041***	-0.039***	-0.036***
		(0.009)	(0.007)	(0.007)
$D \times A^M_{i,r}$		-0.001	-0.003	-0.003
		(0.009)	(0.007)	(0.007)
$D \times A^H_{i,r}$		0.007	-0.001	0.002
		(0.008)	(0.007)	(0.007)
$O^M_{i,r}$		-0.003	-0.003	-0.004
		(0.002)	(0.003)	(0.003)
$O^H_{i,r}$		-0.008***	-0.000	-0.002
		(0.002)	(0.004)	(0.004)
$A^M_{i,r}$		0.001	-0.001	-0.001
		(0.002)	(0.003)	(0.003)
$A^H_{i,r}$		-0.001	0.004	0.004
		(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	0.091	0.093	0.135	0.140
# obs.	89,844	89,844	89,844	89,844

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

conjecture that the presence of related industries lower postdisplacement wages by persuading workers to remain in the region and settle for a slightly worse-matching local job. Overall, Tables 2 to 7 lead us to conclude that, whereas a presence of the old industry is a more important factor in reducing displacement effects on earnings and nonemployment, related industries are more important when it comes to keeping displaced workers from moving out of the region.

One caveat to the above results is that, in spite of the matching efforts, workers may differ from one another in some unobserved characteristics, such as unobserved ability. In that case, we would expect some sorting of workers into regions and industries based on these unobserved characteristics. It is therefore interesting to note that, although neither region nor industry fixed effects were used in the matching procedure, adding them in column 3 of Tables 2 to 7 does not change the point estimates of the displacement or of interaction effects noticeably. However, because their explanatory power reduces the standard error of regression, adding these fixed effects does yield efficiency gains (i.e., smaller standard errors) in all models. This shows that the matching procedure successfully removed any correlation between displacement and unobserved confounding variables at the region and industry level. This is reassuring. After all, had there been any confounders, we would have expected them to have some relation to the regions and industries of workers. Therefore, the scope for ability-related confounding *beyond* what is captured by (unobserved) region and industry effects would seem limited.

Robustness: effect heterogeneity

Worker characteristics may yet be problematic in a different way. So far, we have interpreted our findings as evidence that displacement effects are heterogeneous across local industries. However, this effect heterogeneity may also be driven by characteristics that are not inherent to the local industries themselves, but to the workers attracted to them. For instance, firms in local clusters may attract more highly educated workers than their peers outside those clusters do. In that case, the more modest earnings drop and lower nonemployment incidence we attributed to a concentration of the old industry may instead be due to the specific type of workers found in these places. A similar problem occurs if our local industry groupings pick up differences in a local economy's size. 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, education or region-size, not in local industry composition.[24]

To find out whether such differences could explain the results presented

[24]Table B1 in Appendix B shows that different local conditions are indeed associated with different kinds of workers. In particular, although the average age of workers is very similar across industry-region combinations, average education levels vary somewhat. For instance, locations with high shares of the old industry tend to have a somewhat higher educated workforce. Furthermore, there are some small differences in the average size of the regions in which these local industries are found.

Table 6: The effect of regional conditions on relocation upon displacement

dep. var.: region switch (y/n)	(1)	(2)	(3)	(4)
D	0.331***	0.370***	0.358***	0.409***
	(0.006)	(0.011)	(0.009)	(0.152)
$D \times O^M_{i,r}$		-0.031**	-0.026**	-0.025**
		(0.014)	(0.011)	(0.011)
$D \times O^H_{i,r}$		-0.015	-0.018	-0.022*
		(0.015)	(0.011)	(0.012)
$D \times A^M_{i,r}$		-0.024	-0.028**	-0.027**
		(0.015)	(0.012)	(0.012)
$D \times A^H_{i,r}$		-0.048***	-0.053***	-0.062***
		(0.014)	(0.012)	(0.012)
$O^M_{i,r}$		-0.004*	-0.009**	-0.007*
		(0.003)	(0.004)	(0.004)
$O^H_{i,r}$		-0.005*	-0.020***	-0.015**
		(0.003)	(0.006)	(0.006)
$A^M_{i,r}$		0.002	0.006	0.004
		(0.003)	(0.004)	(0.004)
$A^H_{i,r}$		-0.003	0.009	0.011*
		(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	0.178	0.180	0.245	0.248
# obs.	70,456	70,456	70,456	70,456

Idem Table 2, with as a dependent variable a dummy for whether the worker changed labor market regions in the first job after the displacement event. If a worker or his matched twin remains nonemployed this observation is dropped.

Table 7: The effect of regional conditions on switching industries upon displacement

dep. var.: industry switch (y/n)	(1)	(2)	(3)	(4)
D	0.656***	0.759***	0.739***	0.594**
	(0.007)	(0.011)	(0.008)	(0.273)
$D \times O^M_{i,r}$		-0.157***	-0.128***	-0.127***
		(0.014)	(0.011)	(0.010)
$D \times O^H_{i,r}$		-0.215***	-0.199***	-0.201***
		(0.015)	(0.010)	(0.010)
$D \times A^M_{i,r}$		-0.001	-0.000	0.003
		(0.015)	(0.011)	(0.011)
$D \times A^H_{i,r}$		0.066***	0.059***	0.056***
		(0.016)	(0.011)	(0.011)
$O^M_{i,r}$		-0.012***	0.011**	0.012**
		(0.004)	(0.005)	(0.005)
$O^H_{i,r}$		-0.018***	0.014**	0.017***
		(0.004)	(0.007)	(0.007)
$A^M_{i,r}$		0.008**	0.011**	0.009*
		(0.004)	(0.005)	(0.005)
$A^H_{i,r}$		0.004	-0.007	-0.007
		(0.004)	(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	0.449	0.469	0.515	0.516
# obs.	70,448	70,448	70,448	70,448

Idem Table 2, with a dummy as a dependent variable for whether the worker changed industries in the first job after the displacement event. If a worker or his matched twin remains nonemployed, this observation is dropped.

above, we explore how much of our findings 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 heterogeneity drive our results. To investigate this, we rerun the analyses of column 3 of Tables 2 to 7, but now add interactions of the displacement dummy with educational attainment dummies, worker age and the logarithm of total employment in a 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 Appendix B, Table B2.

Many of the new interaction effects are significant and interesting in their own right. For instance, earnings losses tend to increase with educational attainment (column 1, Table B2). However, this simply reflects that *absolute* earnings drops are higher for the higher predisplacement earnings of highly educated workers. Instead, the *relative* drop in daily wages for reemployed workers (column 2) follows a different ordering. Here, workers with high school and vocational training (HS+VT), as well as workers with a degree from Germany's - mostly vocational - technical colleges (C) experience lower reductions in daily wages. This suggests that what matters is *how applied* an education is, not its length. Similar patterns emerge in the incidence of displacement-induced short- or long-term nonemployment (columns 3 and 4), where vocational training (VT and HS+VT) and degrees from technical colleges are associated with shorter nonemployment post-displacement spells. Moreover, a degree from a technical college protects better against nonemployment spells than university degrees. Apparently, workers with applied educations are more easily reemployed and face less severe wage losses. Similarly, these applied educations are 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 also change with age, although the statistical evidence for this is weaker.[25] The size of a region is an important moderator as well, in particular of the effects of displacement on region and industry switching: doubling the region size cuts either switching rate by about 2 pp. Overall, the findings in Table B2 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 the interaction effects of displacement with local conditions.[26] This suggests that, although displacement effects do depend on observable worker characteristics, this dependence does not explain any of the moderating effects we attributed to the local industry mix. Although we cannot be sure that the same holds for *unobservable* worker characteristics, this would be remarkable given that important markers of individual productivity such as age and education do not

[25]The implied effect curves suggest that, except for very young workers, displacement-related nonemployment rates go up with age. In other models, age-effects are insignificant.

[26]Note that the main effect of displacement changes drastically in all tables. However, this simply reflects that the new interaction terms modify the meaning of the reference category.

seem to be part of the explanation.

Marshallian externalities and strategic search

A central prediction in search theory is that workers will search more intensively when job prospects are better. Testing this prediction is hard, because search efforts are unobserved. After all, the fact that unemployment spells are shorter when labor markets are tight does not necessarily imply higher 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 through search efforts can be isolated from their direct effects on job offers' quality and arrival rate 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 other industries 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 from other industries to the old industry. Fallick (1993) shows that these effects indeed exist.[27]

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 on agglomeration externalities, which has identified easier job search as one of the channels through which Marshallian agglomeration externalities operate (e.g., Duranton and Puga, 2004). Moreover, we control for regional size to make sure these effects are not just driven by the local labor market's size but rather by its composition.

In this new 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 first prediction derives from a combination of two effects: suitable job offers will arrive at higher rates when local conditions in a sector are favorable, which induces workers to redirect their search efforts toward this sector, raising arrival rates even further. The latter shift in search efforts leads to two further indirect effects. Take a region in which the predisplacement sector is relatively large. The Marshallian externalities in this region should shift efforts to the predisplacement 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. Therefore, the second prediction is that a large local presence of the predisplacement industry leads to a drop in the relative risk of finding a job in related industries vis-à-vis staying nonemployed.[28] Finally, because a reduction in search efforts will also limit the

[27]Fallick's evidence for strategic search is not very robust, emerging only when labor market conditions in the old industry are approximated by the (national) employment growth in the industry, but not for other measures of the industries' success.

[28]Note that this is not the same as a drop in the *probability* of finding jobs in related

spatial scope of search, a large local presence of the predisplacement industry leads 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 three predictions hold with the roles of predisplacement and related industries reversed. In total, we therefore have six empirical implications.

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 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.

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 regional employment shares of the old and of related industries, the relative risk of finding a local job in the old industry 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 predisplacement industry by factors of 1.1 and 1.2, respectively (third column). These findings provide some first evidence that Marshallian externalities directly affect offer arrival rates (and/or offer quality).

The model furthermore predicts that local conditions affect job-finding rates indirectly, through the reallocation of search efforts. In line with this prediction, we find that intermediate local employment shares 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 (see the third and fourth column in Table 8).[29] Similarly, intermediate and high shares of related industries in the region decrease the likelihood of finding nonlocal jobs in the old indus-

industries. This probability will drop because more workers exit nonemployment through jobs in the predisplacement industry. However, the higher job-finding rate in the predisplacement industry will also lower the likelihood of staying nonemployed. As a consequence, it is not obvious how a local concentration of jobs in the predisplacement will affect the *relative* risk of accepting jobs in related industries instead of remaining nonemployed.

[29]For high employment shares in the predisplacement industry, outcomes are statistically insignificant, but have the right sign.

Table 8: Multinomial postdisplacement regression

	Outcome:			
	stay ind. & reg.	switch reg.	switch ind.	switch ind. & reg.
$O^M_{i,r}$	2.280***	1.752***	0.876***	0.745***
	(0.189)	(0.181)	(0.043)	(0.047)
$O^H_{i,r}$	3.444***	2.515***	0.995	0.921
	(0.300)	(0.299)	(0.052)	(0.066)
$A^M_{i,r}$	0.905	0.802*	1.091*	1.061
	(0.072)	(0.093)	(0.058)	(0.071)
$A^H_{i,r}$	0.884	0.539***	1.173***	1.080
	(0.080)	(0.067)	(0.065)	(0.077)
log(reg. size)	1.053	0.988	1.006	0.906***
	(0.041)	(0.065)	(0.025)	(0.032)
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)	-64,437	-64,437	-64,437	-64,437
# obs.	44,919	44,919	44,919	44,919
# clust.	5,029	5,029	5,029	5,029
partial R^2	0.044	0.044	0.044	0.044

***: $p<.01$, **: $p<.05$, *: $p<.1$. 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.

Table 9: Multinomial postdisplacement regression, cross-effects

	outcome: switch reg. base: stay ind. & reg.	outcome: switch ind. & reg. base: switch ind.
$O_{i,r}^M$	0.769**	0.850***
	(0.093)	(0.051)
$O_{i,r}^H$	0.730**	0.925
	(0.098)	(0.061)
$A_{i,r}^M$	0.887	0.972
	(0.115)	(0.059)
$A_{i,r}^H$	0.610***	0.921
	(0.081)	(0.065)

Rendering of selected coefficients from Table 8 against the base outcomes stated in the column headers.

try compared to staying nonemployed (second column of Table 8). Although point estimates suggest that the likelihood of finding *local* jobs in the old industry (first column) is affected in the same way, these effects are not statistically significant.

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. That is, a large local presence of one sector reduces search efforts in the other sector, which limits 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 such a way that they refer to how regressors affect the relative risk that workers accept nonlocal jobs in the predisplacement industry (first column) or in other industries (second column) against the baseline that they accept *local* jobs in these industries. In line with predictions, intermediate (high) shares of the old industry reduce the relative risk of finding nonlocal instead of local jobs in other industries by 23.1% (27.0%). In contrast, the effects of intermediate and high local shares of related industries on workers' finding nonlocal instead of local jobs in the predisplacement industry are statistically insignificant, although they do have the right sign.

A potential concern is that our findings are confounded by the fact that the local conditions of a sector correlate with conditions in nearby regions. To explore this, we also run these analyses while controlling for the conditions in regions that are at most 90 minutes driving distance away. Results, reported in Appendix C, show that, if anything, evidence for strategic search becomes even more pronounced after adding these variables. Furthermore, so far, we have calculated the employment shares that define local conditions as shares of total employment reported in the social security data. However, the prevalence of employment that is not covered by social security may differ by region. Therefore, we redo all analyses using predisplacement and related industry employment as a share of a region's population to define local conditions. Also with this adjustment, the substance of outcomes does not change (see Appendix D).

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 find evidence for Marshallian externalities in how a region's industry mix affects the postdisplacement careers of workers who lose their jobs in establishment closures. High concentrations of the predisplacement industry reduce the earnings losses experienced by these workers, predominantly by reducing the time it takes workers to find a new job. In contrast, high concentrations of industries that are related to the predisplacement industry are associated with higher earnings losses and longer job search. In places where these related industries are abundant, workers move out of the region less frequently and opt instead to change industries. Interestingly, we find evidence that suggests that workers take these Marshallian externalities into consideration when allocating search efforts. Large concentrations of the predisplacement industry not only lead to reductions in the relative risk of finding a job in related industries instead of remaining nonemployed, they also reduce the relative risk of finding nonlocal instead of local jobs in these related industries.

These results prove to be highly robust against 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. Worker-level heterogeneity is indeed reflected in displacement effects. For instance, workers with applied educations suffer relatively low displacement-induced wage losses and manage to find new jobs more readily. Moreover, such workers are less likely to resort to industry mobility to cope with their job loss. However, accounting for such worker-level heterogeneity does not change any of our estimates regarding Marshallian externalities.

Overall, the careers of displaced workers proved to provide a useful lens through which the labor market effects of agglomeration externalities can be studied. 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 has been shown to affect workers in different countries in different ways (Carrington and Fallick, 2015). Repeating the analyses of this paper in different regions of the world might therefore reveal interesting disparities across countries in how Marshallian externalities affect job search.

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Appendix 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:

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

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

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

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

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

Appendix B Worker characteristics

This appendix provides summary statistics of worker-level characteristics in region-industry combinations with different concentrations of the old and related industries (Table B1) and the interaction effects of worker characteristics, as well as a region's size, with the displacement dummy for the models in columns (4) of Tables 2-7.

Table B1: Group averages of individual level characteristics

	employment share old ind.			employment share related ind.		
	low	medium	high	low	medium	high
age	39.9	39.8	39.9	39.9	39.9	39.8
edu (ND)	11.59%	10.41%	8.86%	8.25%	10.75%	10.54%
edu (VT)	64.39%	63.70%	68.85%	68.16%	64.18%	66.32%
edu (HS)	0.47%	0.63%	0.39%	0.62%	0.48%	0.47%
edu (HS+VT)	2.69%	2.41%	2.32%	2.32%	2.33%	2.66%
edu (C)	2.21%	3.23%	3.66%	3.70%	2.64%	3.30%
edu (U)	2.47%	3.14%	3.93%	3.43%	2.64%	3.23%
edu (miss.)	16.18%	16.48%	12.00%	13.53%	16.99%	13.49%
log(reg. size)	12.3	12.4	12.0	12.0	12.4	12.3

Averages of age and share 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). Furthermore, the last row of the table reports the natural log of average region-size.

Appendix C Local conditions in neighboring regions

In this appendix, we repeat the analyses in Tables 8 and 9 while controlling for local conditions in neighboring regions. Neighboring regions are defined as labor market areas whose central agglomeration is not more than 90 minutes driving distance away from the focal labor market area's central agglomeration.

The results for the focal region's local conditions are surprisingly similar to those reported in the main text. If anything, the evidence for strategic search is even stronger in the regression analyses reported in this appendix. In particular, we now also find statistically significant evidence that a large local share of related industries reduces the spatial scope of search in the predisplacement industry.

Table B2: Estimated interaction effects of individual level characteristics

	dependent variable:					
	earnings increase	log(wage gain)	nonemp. (short)	nonemp. (long)	reg. switch	ind. switch
D	-26.942	-0.162	0.979***	0.800***	0.409***	0.594**
	(27.603)	(0.236)	(0.208)	(0.176)	(0.152)	(0.273)
$D \times$ log(reg. size)	-2.630***	-0.006	-0.001	0.006**	-0.022***	-0.017***
	(0.532)	(0.004)	(0.004)	(0.003)	(0.006)	(0.005)
$D \times$ age	0.218	0.004	-0.018***	-0.007	0.005	-0.000
	(0.618)	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)
$D \times \text{age}^2$	-0.0149*	-0.0001	0.0003***	0.0002***	-0.0001	0.0000
	(0.0080)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$D \times$ edu(VT)	2.381***	0.014	-0.097***	-0.051***	0.015	-0.048***
	(0.897)	(0.013)	(0.010)	(0.009)	(0.011)	(0.010)
$D \times$ edu(HS)	-15.610**	0.058	0.001	0.055	0.103**	0.055
	(7.052)	(0.059)	(0.035)	(0.040)	(0.045)	(0.041)
$D \times$ edu(HS+VT)	-14.917***	0.044*	-0.109***	-0.032**	0.108***	-0.034
	(3.727)	(0.023)	(0.019)	(0.016)	(0.022)	(0.021)
$D \times$ edu(C)	-7.764*	0.056**	-0.163***	-0.053***	0.137***	-0.092***
	(4.287)	(0.026)	(0.019)	(0.015)	(0.022)	(0.026)
$D \times$ edu(U)	-28.008***	0.004	-0.135***	-0.032**	0.166***	-0.013
	(4.693)	(0.024)	(0.018)	(0.016)	(0.021)	(0.019)
$D \times$ edu(miss.)	5.033***	0.013	-0.089***	-0.046***	0.031**	-0.054***
	(1.156)	(0.016)	(0.013)	(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

***: p<.01, **: p<.05, *: p<.1. Reported are the estimated interaction effects of age, age^2, education dummies and log(region size) with the displacement dummy for models 4 in Tables 2-7. The dependent variable for each column is indicated in the column headers.

Table C1: Multinomial postdisplacement regression

	Outcome:			
	stay ind. & reg.	switch reg.	switch ind.	switch ind. & reg.
$O^M_{i,r}$	1.808***	1.250**	0.880**	0.742***
	(0.179)	(0.135)	(0.048)	(0.056)
$O^H_{i,r}$	2.621***	1.562***	1.035	0.966
	(0.304)	(0.242)	(0.072)	(0.093)
$A^M_{i,r}$	0.865*	0.825	1.058	0.989
	(0.076)	(0.107)	(0.060)	(0.074)
$A^H_{i,r}$	0.939	0.583***	1.141*	0.923
	(0.100)	(0.089)	(0.078)	(0.081)
$O^M_{i,NB}$	1.589***	1.907***	1.007	0.993
	(0.166)	(0.236)	(0.057)	(0.075)
$O^H_{i,NB}$	1.550***	2.232***	0.937	0.907
	(0.191)	(0.309)	(0.066)	(0.086)
$A^M_{i,NB}$	1.209**	0.893	1.101	1.125
	(0.115)	(0.115)	(0.066)	(0.086)
$A^H_{i,NB}$	0.872	0.800	1.055	1.318***
	(0.097)	(0.132)	(0.072)	(0.117)
log(reg. size)	1.058	0.983	1.008	0.900***
	(0.040)	(0.065)	(0.026)	(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)	-64,284	-64,284	-64,284	-64,284
# obs.	44,919	44,919	44,919	44,919
# clust.	5,029	5,029	5,029	5,029
partial R^2	0.047	0.047	0.047	0.047

***: $p<.01$, **: $p<.05$, *: $p<.1$. 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. Subscript r refers to the focal region, subscript NB to neighboring regions.

Table C2: Multinomial postdisplacement regression, cross-effects

	outcome: switch reg. base: stay ind. & reg.	outcome: switch ind. & reg. base: switch ind.
$O_{i,r}^{M}$	0.691***	0.844**
	(0.096)	(0.059)
$O_{i,r}^{H}$	0.596***	0.933
	(0.106)	(0.084)
$A_{i,r}^{M}$	0.954	0.935
	(0.143)	(0.065)
$A_{i,r}^{H}$	0.621***	0.809**
	(0.106)	(0.070)
$O_{i,NB}^{M}$	1.200	0.986
	(0.175)	(0.070)
$O_{i,NB}^{H}$	1.441**	0.968
	(0.233)	(0.087)
$A_{i,NB}^{M}$	0.739**	1.022
	(0.104)	(0.071)
$A_{i,NB}^{H}$	0.918	1.249***
	(0.173)	(0.102)

Rendering of selected coefficients from Table C1 against the base outcomes stated in the column headers.

Appendix D Employment as a share of regional population

In this appendix, we repeat all empirical analyses reported in Tables 2 to 9, using the predisplacement 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 D1 reports our preferred specification (model 3) of Tables 2 to 7. Tables D2 and D3 repeat the analyses of Tables 8 and 9.

In spite of using a completely new sample of matched workers and having redefined the main variables of interest, there are few substantive changes in outcomes.[30]

[30]The only qualitative difference is that we do not find any negative interaction effect of related employment on the logarithm of daily wages.

Table D1: Displacement interactions with population shares

	dependent variable:					
	earnings increase	log(wage gain)	nonemp. (short)	nonemp. (long)	reg. switch	ind. switch
earnings increase (EUR)	earnings increase	log(wage gain)	nonemp. (short)	nonemp. (long)	reg. switch	ind. switch
D	-38.175***	-0.085***	0.422***	0.209***	0.359***	0.738***
	(0.849)	(0.008)	(0.007)	(0.006)	(0.008)	(0.008)
$D \times O_{i,r}^M$	0.773	0.016	-0.017*	0.001	-0.023**	-0.120***
	(1.093)	(0.012)	(0.010)	(0.007)	(0.011)	(0.011)
$D \times O_{i,r}^H$	5.553***	0.026***	-0.060***	-0.037***	-0.026**	-0.201***
	(1.190)	(0.010)	(0.009)	(0.007)	(0.011)	(0.010)
$D \times A_{i,r}^M$	0.423	-0.006	-0.019**	-0.014**	-0.031***	-0.008
	(1.070)	(0.010)	(0.009)	(0.007)	(0.011)	(0.011)
$D \times A_{i,r}^H$	-3.091**	-0.004	-0.000	-0.009	-0.049***	0.063***
	(1.241)	(0.011)	(0.010)	(0.007)	(0.011)	(0.011)
$O_{i,r}^M$	1.952***	0.007	-0.008*	-0.004	-0.008*	0.013***
	(0.565)	(0.005)	(0.004)	(0.003)	(0.004)	(0.005)
$O_{i,r}^H$	0.927	0.003	0.002	0.004	-0.014**	0.013*
	(0.773)	(0.007)	(0.006)	(0.004)	(0.006)	(0.007)
$A_{i,r}^M$	-1.122*	-0.005	0.008*	0.003	-0.002	0.011**
	(0.577)	(0.005)	(0.004)	(0.003)	(0.005)	(0.005)
$A_{i,r}^H$	-0.200	-0.010*	0.011**	0.007*	0.005	0.001
	(0.767)	(0.006)	(0.005)	(0.004)	(0.006)	(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	0.177	0.066	0.266	0.134	0.242	0.516
# obs.	89,808	46,060	89,808	89,808	70,340	70,332

***: p<.01, **: p<.05, *: p<.1. The columns repeat the specification of model 3 in Tables 2 to 7, using employment as a share of regional *population* to create the dummy groups for local conditions. That is, O_{ir}^M and O_{ir}^H are defined using $\frac{E_{irt}}{pop_{rt}}$ and A_{ir}^M and A_{ir}^H are defined using $\frac{E_{irt}^{rel}}{pop_{rt}}$, where pop_{rt} represents the population of labor market area r in year t.

Table D2: Multinomial postdisplacement regression using population shares

	Outcome: stay ind. & reg.	switch reg.	switch ind.	switch ind. & reg.
$O_{i,r}^M$	2.250***	1.621***	0.855***	0.749***
	(0.185)	(0.166)	(0.041)	(0.048)
$O_{i,r}^H$	3.496***	2.350***	0.966	0.894
	(0.306)	(0.268)	(0.051)	(0.064)
$A_{i,r}^M$	0.988	0.898	1.143**	1.114
	(0.077)	(0.091)	(0.061)	(0.074)
$A_{i,r}^H$	0.884	0.618***	1.263***	1.153**
	(0.080)	(0.067)	(0.073)	(0.083)
log(reg. size)	1.038	1.000	0.984	0.878***
	(0.043)	(0.071)	(0.027)	(0.033)
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)	-64,389	-64,389	-64,389	-64,389
# obs.	44,901	44,901	44,901	44,901
# clust.	5,023	5,023	5,023	5,023
partial R^2	0.045	0.045	0.045	0.045

***: 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_{ir}^M, O_{ir}^H, A_{ir}^M and A_{ir}^H are defined as in Table D1.

Table D3: Multinomial postdisplacement regression using population shares, cross-effects

	outcome: switch reg. base: stay ind. & reg.	outcome: switch ind. & reg. base: switch ind.
$O_{i,r}^M$	0.720***	0.876**
	(0.085)	(0.053)
$O_{i,r}^H$	0.672***	0.925
	(0.087)	(0.060)
$A_{i,r}^M$	0.909	0.974
	(0.097)	(0.062)
$A_{i,r}^H$	0.699***	0.913
	(0.081)	(0.061)

Rendering of selected coefficients from Table D2 against the base outcomes stated in the column headers.