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Abstract

Establishment closures leave many workers unemployed. Based on employment histories of 20 million German workers, we find that workers often cope with their displacement by moving to different regions and industries. However, which of these coping strategies is chosen depends on the local industry mix. A large local presence of predisplacement or related industries strongly reduces the rate at which workers leave the region. Moreover, our findings suggest that a large local presence of the predisplacement industry induces workers to shift search efforts toward this industry, reducing the spatial scope of search for jobs in alternative industries and vice versa.

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Keywords

Displacement, local industry mix, agglomeration externalities, matching, mobility

JEL codes

J24, J61, J64, R12

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1 Introduction

The loss of a job often has a detrimental impact on people's careers and their well-being, ranging 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 kind of jobs a region has to offer. In particular, the decision to change industries or move to another region (or both) and the time it takes to find a new job will depend on which jobs currently exist in the region. That is, it depends (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 geographical concentrations of local industries, relatively little is known about how they affect the postdisplacement 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 and of 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 66% more likely to change industries and 32% 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 41%, this drop is reduced to only 35% in regions where the industry from which workers were displaced has a high employment share. A high availability of local jobs in the predisplacement industry also affects workers' mobility, reducing industry switching by 27% percent and region switching by 9%. In contrast, high local employment shares of industries related to the predisplacement industry do not offer much protection against wage drops. However, related industries help keep workers in the region: although displaced workers in such regions are 10% more likely to change industries, they are 21% less likely to move out of the area.[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 displacement 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 given to local specialization and diversity in the literature on Marshallian and Jacobs externalities (e.g., Glaeser et al., 1992; Henderson et al., 1995; Porter, 2003). In particular, although Marshallian labor market pooling effects in cities 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

[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, respectively, their predisplacement industries' local employment shares and the local employment shares of industries related to the predisplacement industry.

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 as they progress in 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 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 being close to dense concentrations of suitable jobs makes a difference, even for workers who live 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 are 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 a local economy is its 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). In this literature, benefits that arise in large concentrations of firms belonging to one and the same industry, so-called Marshallian externalities, are often attributed to, among other things, the benefits of labor market pooling, because regions with large concentrations of industries that require similar skills offer implicit protection against protracted unemployment.[3]

Although evidence on the existence of Marshallian externalities is mixed (e.g., Groot et al., 2015), recent studies using identification strategies based on employment shocks created by the entry of large manufacturing plants (Greenstone et al., 2010) or government investment programs (Kline and Moretti, 2013) suggest such benefits do exist. Similarly, in a study the aftermath of plant closures, Gathmann et al. (2014) conclude that such plant closures lead to a prolonged decline in employment of the affected local industry. Indeed, the authors report long-run employment declines that go far beyond the workers that were displaced. However, local workers who had not been affected directly by the closure seemed relatively untouched. In spite of this recent work on how the opening and closures of establishments affect local industries, so far little research exists on how the industry mix of a local economy (as opposed to local growth or unemployment rates) affects displaced workers. To shed light on this issue, we seek to understand how the local concentrations of both the predisplacement industry and of related industries impact the further careers of

[2]These 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 non-entry level placements in the accounting firm Ernst & Young came from employee recommendations. Likewise, Deloitte gets 49% of its experienced hires from referrals (Schwartz, 2013).

[3]Indeed, Marshall (1890) himself already pointed out the importance of local specialization in reducing unemployment risk:

> ... a localized industry gains a great advantage from the fact that it offers a constant market for skill. 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)

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?

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 $F_s(w)$. As in Fallick (1992), search effort increases the job offer arrival rate and involves costs, $C = c\left(\sum_s e_s\right)$, that are a function of the summed search efforts, e_s, in the two sectors. 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 non-zero effort is required and marginal returns to search effort 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 derived from searching for jobs:

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

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:

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

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

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

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

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:

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

Because, by assumption, σ' is positive and monotonically decreasing, optimal search efforts will shift from sector A to sector B when the distribution of wage offers in sector A or their arrival rates 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:

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

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 and B at time u, respectively v, after displacement. 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:

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

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:

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

Let h_s be the likelihood that an acceptable job offer arrives in sector s before the end of the period.[4] The second part of equation (5) now simplifies to:

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

$$= h_A(1 - h_B)$$

Let $S_s(x)$ be the survival function for sector s, i.e., the likelihood that no acceptable offer has arrived from sector s until time x. Because the hazard functions are constant over time, the first part of equation (5) can now be written as:[5]

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

Where h represents the likelihood that the worker finds a job in either of the two sectors before the end of the time period and θ_s the instantaneous hazard of finding a job in sector s.[6] Putting both pieces together, equation (5) becomes:

[4] 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.

[5] See Appendix A for a full derivation.

[6] 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.

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

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

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 of sector s. In particular, holding local conditions for sector B constant, more favorable local 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 workers divide their search efforts between the two sectors. Equation (2) shows that this effect is 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? We propose that, among other things, search efforts increase the geographical scope of search. That is, an increased effort allows workers to identify wage offers in locations that are farther away. This would imply that higher effort levels should be reflected in greater geographical mobility. We incorporate this into the model by modifying equation (1) to make offer arrival rates and wage offer distributions location-specific. In particular, offers from sector s originate from outside the worker's home region with probability $\rho(e_s|X_s)$, where ρ follows a monotonically increasing function of X_s, a vector that captures how favorable local conditions are for sector s, that maps e_s onto the interval $(0,1)$. The hazard of exiting unemployment through sector s in the home region, h_{0s}, now becomes:

$$h_0 s = \lambda_s \sigma(e_s)\left(1 - F_s\left(w^*\right)\right)\left[1 - \rho(e_s|X_s)\right] \tag{7}$$

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

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

Because we can without loss of generality think of wages net of commuting and/or relocation costs, the optimization problem of the worker is unaffected. However, we can now infer how workers allocate search efforts between the two sectors from their geographical mobility. That is, first of all, all else equal, better local conditions will increase local job-offer arrival rates. As a consequence, the likelihood that workers who exit unemployment through a given sector change regions will directly and negatively depend on the local conditions in that sector. That is $\frac{\partial \rho}{\partial X_s} < 0$. However, local conditions in sector A should have no direct effect on the ratio of non-local to local job offers in sector B and vice versa. Such cross-effects nevertheless will occur because favorable conditions in sector A will draw search efforts from sector B to sector A. This in turn reduces the geographical scope of search in sector B. As a consequence, the hazard rate ratio of exiting unemployment through non-local jobs versus local jobs in sector B, i.e., $\frac{h_{1B}}{h_{0B}}$, will decrease as a function of the ease with which jobs are found in sector A. This approach is similar in spirit to Fallick (1993), who uses the dependence of search duration in one sector on macro-economic conditions in the other sector as an indication of strategic shifts in search efforts. We will test our hypothesis explicitly at the end of section 6.

4 Data

We use data from the Historic Employment and Establishment Statistics (HES) database.[7] The HES database is based on Germany's social security records. Our version of these data provides yearly information on an individual's daily wage[8], 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 "non-employment" instead of unemployment to refer to workers who leave jobs with social security coverage.

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 unambiguously as 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 workers for the period starting six years before and ending three years after the

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

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

closure. These conditions limit us to establishment closures between the years of 2003 and 2005.

5 Empirical strategy

Local conditions

In the empirical analyses, we equate one of the two sectors in the model of Section 3 with the 5-digit industry from which workers are displaced. Henceforth, we will refer to this industry as worker's "old" industry. The other sector consists of other suitable industries, namely those that are related to the old industry. As a measure of industry relatedness, 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.[9] 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:

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

Moreover, by definition, we impose that industries are not skill-related to themselves: $R_{ii} \equiv 0$. Because the 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. 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) is stable over time and very similar across workers in different occupations and wage groups.

We calculate an R-matrix for each year between 1999 and 2008 and average these matrices across all years. Furthermore, we symmetrize the elements of the resulting matrix by averaging its elements with those of its transpose. We refer to this averaged and symmetrized matrix as $\bar{R}$.[10] We then use this matrix to determine the total employment in the local economy that belongs to industries for which the skill-relatedness with the worker's old industry i exceeds a given skill-relatedness threshold:

$$E^{rel}_{irt} = \sum_{j\neq i} E_{jrt} I\left(\bar{R}_{ij} > \xi\right) \tag{10}$$

[9] 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.

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

Where E_{jrt} is the employment in industry j and region r at time t. We use a threshold value of $\xi = 3$, meaning that the observed labor flows between an industry and the worker's old industry are at least three times as large as the random benchmark. At this threshold, the average related employment that displaced workers find in their regions is about 5% of total local employment and about 40% of all industry switchers are moving to industries deemed related.

Estimation strategy

Typically, job separations occur when a worker prefers to pursue career opportunities elsewhere, or when the employer prefers to part ways. This makes job separations often endogenous to the expectations about a worker's career prospects in her firm. An exception are job separations that follow from establishment closures. As argued before, such separations are typically unrelated to the performance and career aspirations of individual workers and are, therefore, often considered to be exogenous from a worker's perspective (e.g., Gibbons and Katz, 1991; Jacobson et al., 1993; Couch and Placzek, 2010; Schwerdt, 2011). Using a sample of displaced workers should thus mitigate concerns about workers self-selecting into career changes as long as displacement is uncorrelated with worker characteristics.

To increase the plausibility of this exogeneity assumption, we compare displaced to nondisplaced, yet otherwise observationally similar, workers using a combination of propensity-score matching and regression analysis. To be more precise, we use matching as a prescreening method to reduce the dependence of the treatment variable (in our case, displacement) on worker characteristics as proposed by Ho et al. (2007). Such prescreening has several advantages. Firstly, because the procedure is based only on predisplacement covariates, it does not introduce selection biases. Secondly, prescreening avoids inference that is based on inter- or extrapolation by ensuring a common support of treated and untreated observations. Thirdly, because the preprocessing ensures that displacement is orthogonal to the exogenous covariates, parametric assumptions about how such covariates enter the data-generating process matter less. As a consequence, prescreening mitigates the problem of finding the right functional form for these covariates in the regression analyses (Ho et al., 2007). However, the cost of preprocessing the data is that the estimated effects represent average effects for a subset of workers instead of for the population as a whole.

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 amplify the effect of displacement. For each displaced worker who meets the tenure and other criteria listed in Section 4, we try to find a statistical twin among the nondisplaced workers.[11] We use a combi-

[11] Given that our total dataset contains over 20 million workers a year, we limit this search to a 10% random sample to reduce the computational burden.

nation of exact matching on establishment tenure and displacement year and propensity-score matching. Workers' propensity to experience a displacement event is predicted by a probit model. In as far as wages reflect workers' productivity, the predisplacement wage development of workers should help control for unobserved worker quality. Therefore, to calculate the propensity score, we use lags 6 to 2 of predisplacement wages and the logarithm of wage growth between 5 and 2 years before the displacement event, together with year and education dummies and age, years of work experience, industry experience, establishment tenure and work experience in the region. Age and experience variables enter as dummy groups, to allow for flexibility in the functional form. To control for regional economic conditions, we also add the predisplacement regional employment shares and squared values thereof for the old industry and for industries skill-related to the old industry. Next, we use nearest-neighbor matching, keeping only displaced workers with exactly one nearest neighbor and dropping all observations that are not on the support. This leaves a sample of 44,850 worker pairs.

Table 1 shows that predisplacement characteristics of displaced and nondisplaced workers are much more closely aligned than in the population as a whole. Differences in the means for displaced and nondisplaced workers of these variables are all well below 5%. In particular, predisplacement wages are well-balanced, with biases below 1%. To the extent that predisplacement wages reflect a worker's productivity, this strong balance suggests that there is little reason to be concerned about biases that are due to unobserved worker quality.

6 Findings

Displacement effects

To assess how displacement affects earnings, wages, non-employment and mobility decisions, we use the approach followed by Schwerdt (2011) and combine matching with the difference-in-differences framework that Jacobson et al. (1993) introduced to the displacement literature. That is, we estimate the following equation:

$$y_{mt} = \sum_{k=-3}^{3} \tau_1^k T_{mt}^k + \sum_{k=-3}^{3} \tau_2^k T_{mt}^k D_{mt} + X_{mt}\beta + \alpha_m + \delta_t + \epsilon_{mt} \tag{11}$$

Where α_m and δ_t represent individual and year fixed effects and the vector X_{mt} contains the workers age and age-squared. y_{mt} is daily earnings, the logarithm of daily wage, or a dummy variable for the event a worker is non-employed, changes industries, or changes regions. 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 further job switches, not delayed reemployment. T_{mt}^k is a dummy variable

Table 1: Balance of matched sample

	selected population			matched sample			
	treated	control	% bias	treated	control	% bias	t-test
share rel. emp.	4.70%	5.07%	-10.2	4.71%	4.68%	0.8	1.1
share old ind. emp.	0.70%	1.34%	-31.2	0.69%	0.67%	3.4	5.2
age	39.8	39.7	1.6	39.9	39.9	0.2	0.3
edu (ND)	10.05%	10.48%	-1.4	10.20%	10.58%	-1.2	-1.9
edu (VT)	63.93%	65.26%	-2.8	65.53%	65.73%	-0.4	-0.6
edu (HS)	0.52%	0.64%	-1.6	0.52%	0.53%	-0.1	-0.2
edu (HS+VT)	2.46%	3.99%	-8.7	2.46%	2.45%	0.0	0.0
edu (C)	2.96%	4.64%	-8.8	3.04%	3.00%	0.2	0.3
edu (U)	3.09%	6.32%	-15.3	3.16%	3.25%	-0.5	-0.7
edu (miss.)	17.00%	8.67%	25.1	15.09%	14.45%	1.8	2.7
log(reg. size)	14.8	15.7	-15.0	15.2	15.3	-0.2	-0.3
industry experience	9.2	10.6	-23.3	9.7	9.7	0.3	0.5
regional experience	12.5	13.8	-19.8	13.0	13.0	0.4	0.7
plant tenure	7.9	9.6	-28.8	8.4	8.4	0.0	0.0
year: 2005	0.4	0.3	11.0	0.4	0.4	0.0	0.0
year: 2006	0.4	0.3	3.4	0.4	0.4	0.0	0.0
year: 2007	0.3	0.3	-15.1	0.3	0.3	0.0	0.0
wage (4 yrs pre-D.)	83.7	100.4	-32.4	88.6	88.5	0.4	0.6
wage (3 yrs pre-D.)	86.2	104.8	-34.6	90.1	89.8	0.6	0.9
wage (2 yrs pre-D.)	89.4	109.1	-35.3	94.2	94.1	0.1	0.2
wage (1 yr pre-D.)	90.8	111.9	-35.9	93.2	95.6	-4.7	-7.1
wage (at D.)	91.8	114.3	-36.8	93.9	97.2	-6.2	-9.2
wage (1 yr post-D.)	49.7	110.4	-89.3	51.8	92.8	-67.4	-101.0
wage (2 yrs post-D.)	58.8	108.3	-72.4	61.2	90.5	-48.4	-72.4
wage (3 yrs post-D.)	61.2	106.3	-65.8	63.6	88.8	-41.2	-61.8

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 (10). "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. t-test refers to an equality-of-means test between displaced and nondisplaced workers for the variable in question.

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 given by the vector τ_2. This vector collects the difference between displaced and nondisplaced workers $|k|$ years away from the displacement event. This vector, which we graph for each of the dependent variables in Figure 1, shows how the effects of displacement on each of the dependent variables fade over time.

Displacement strongly affects all of our dependent variables, with most of the effects taking place within the first year after displacement. Displacement reduces daily earnings by about 41 EUR and keeps them depressed for the entire postdisplacement window. Much of this is due to the large reduction in employment rates that reaches 39.9 pp in the first postdisplacement year. However, for those who return to work within a year, daily wages are also typically reduced by 8.0%. Displacement furthermore affects which jobs workers choose. Displaced workers are much more likely than their statistical twins to change planning regions (31.0 pp) or 5-digit industries (65.3 pp) right after they are displaced. Moreover, although they do fade out, switching rates remain elevated for at least the two years after the displacement event for which we observe them. This suggests that displaced workers do not immediately find well-matching jobs. Given the parallel predisplacement trends for displaced and nondisplaced workers, it is plausible that the effects depicted in Figure 1 are causal.[12]

Local conditions as moderators of displacement effects

How does the local industry mix change the effect of D_{mt}? To study this, we categorize industry-region combinations once by the regional employment share of the old industry itself and once by the regional employment share of industries that are skill related to the old industry. We start by dividing locations into three types: those with small, moderate and large amounts of employment in the old industry (O). To do so, we define the following dummy group for a worker who got displaced from industry i in region r:

$$O_{irt}^{L} = I\left(\frac{E_{irt}}{\sum_j E_{jrt}}\right) \leq \zeta_1 \tag{12}$$

$$O_{irt}^{M} = \zeta_1 < I\left(\frac{E_{irt}}{\sum_j E_{jrt}}\right) \leq \zeta_2 \tag{13}$$

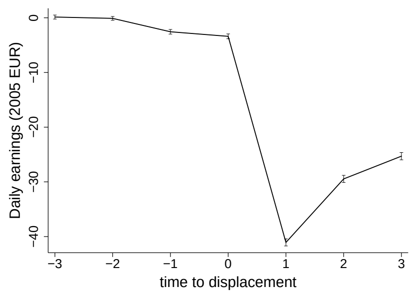
$$O_{irt}^{H} = I\left(\frac{E_{irt}}{\sum_j E_{jrt}}\right) > \zeta_2 \tag{14}$$

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

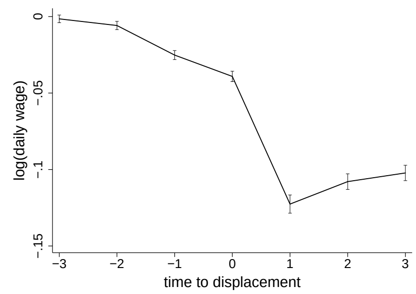
[12]The small dip in earnings in the two predisplacement years and the larger reduction in wages is quite common and is usually attributed to early signs of distress of establishments that are about to close.

Figure 1: Difference-in-differences in postdisplacement careers

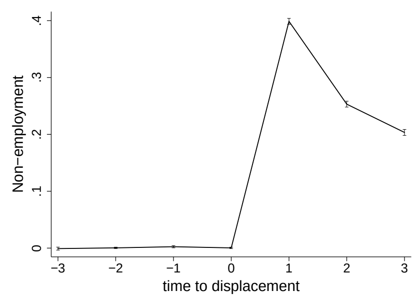
(a) Daily earnings (2005 EUR)



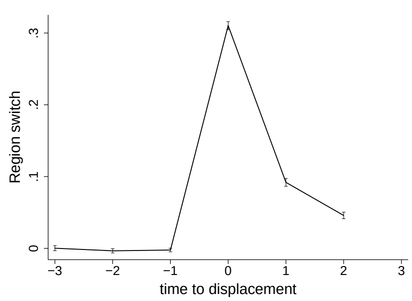
(b) log(daily wage)



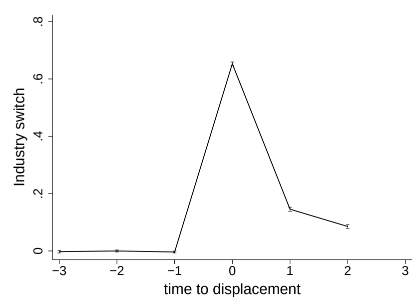
(c) Non-employment



(d) Relocation



(e) Industry switching



Graphs report the difference-in-differences estimates using equation (11) with age and age^2 as time-varying control variables. The dependent variables are daily earnings (in 2005 EUR, 1a), log(daily wage) (1b) and dummy variables for being non-employed (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.

establishment that closes down). ζ_1 and ζ_2 are chosen such that all categories have equal numbers of observations. Analogously, we define dummy variables that group region-industry cells by the local employment share of industries related to the old industry, which represent local employment alternatives (A):

$$A^L_{irt} = I\left(\frac{E^{rel}_{irt}}{\sum_j E_{jrt}}\right) \leq \zeta_1^{'} \tag{15}$$

$$A^M_{irt} = \zeta_1^{'} < I\left(\frac{E^{rel}_{irt}}{\sum_j E_{jrt}}\right) \leq \zeta_2^{'} \tag{16}$$

$$A^H_{irt} = I\left(\frac{E^{rel}_{irt}}{\sum_j E_{jrrt}}\right) > \zeta_2^{'} \tag{17}$$

E^{rel}_{irt} is defined as in equation (10). Again, regional employment is measured in the displacement year, but excludes the employment of the establishments that close down. $\zeta_1^{'}$ and $\zeta_2^{'}$ once more divide workers into equally sized groups.

Ideally, we would interact these dummy groups with the displacement dummy in the difference-in-differences estimations of equation (11). However, this set-up would yield complicated and hard-to-estimate interaction effects. Instead, we estimate cross-sectional models of the following form:

$$y_{mt} = \kappa D_{mt} + \Pi_{irt}\gamma_0 + D_{mt}\Pi_{irt}\gamma_1 + X_{mt}\beta + \eta_i + \rho_r + \delta_t + \epsilon_{mt} \tag{18}$$

where Π_{irt} collects the dummy groups defined in equations (12) to (17). η_i, ρ_r and δ_t are fixed effects for the industry, region and year in which worker m got displaced (for nondisplaced workers, this is the year in which their statistical twin got displaced) and X_{mt} is a set of worker characteristics, including age, age-squared, gender and a seven-category dummy group for the worker's educational attainment.[13] 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 those who immediately find new jobs; a dummy variable that indicates whether or not worker m remains non-employed (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. Vector γ_1 contains the parameter estimates of interest, namely those for the interactions of the local industry share dummy groups with the displacement dummy.

Once again, the devastating effects of displacement on earnings are clearly visible. On average (see Table 2, Column 1), in the first year after being displaced from their jobs, workers lose about 38 EUR in daily earnings (over 40% of their predisplacement earnings). Table 4 shows that this is largely due to an increase in the non-employment hazard of around 40 pp. By contrast, for workers who find a new job immediately, the effects on the loss in log(daily

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

wages) are limited to a wage reduction of 7.6% (Column 1, Table 1b).[14] These estimates are very close to the difference-in-differences estimates in Figure 1. However, effects vary with the industry mix of the location in which a worker is displaced. Displacement-induced earnings losses and non-employment risk are lower in locations with high employment shares of the old industry. The reduction amounts to 6.0 EUR (16%) for the earnings effect (Column 3 of Table 2) where the old industry's employment shares are high compared to where they are low. This is not mainly due to changes in the effect on wages: for those who find new jobs, the presence of the old industry in the region does not significantly affect the drop in log(daily wage) (Table 3). However, the effect of displacement on non-employment incidence (Column 3 of Table 4) depends markedly on the industry mix of a region. In regions with intermediate employment shares of the old industry, displacement effects on non-employment rates are reduced by 2.4 pp (6%). Where the old industry is large, the effect reduction rises to even 6.5 pp (or by 16%). Moreover, high local employment shares in the old industry reduce long-term non-employment rates among displaced workers by about 4.3 pp, a 21% reduction (Column 3 of Table 5), compared to regions with low employment shares in the old industry. In contrast, large shares of skill-related employment in the region neither significantly reduce displacement-related non-employment nor immediate losses in daily wages.[15]

However, related employment does affect the mobility decisions of workers. To study the effect of displacement on workers' mobility, we drop all worker pairs for which at least one worker does not regain employment with social security coverage within our observation window of three years after displacement.[16] Once again, the main effects are all but indistinguishable from the ones in our difference-in-differences estimates. Displacement increases the likelihood of moving to another region by about 32 pp (Table 6) and of switching 5-digit industries by about 66 pp (Table 7). The exact mobility choices do, however, depend on the local industry mix. Compared to regions where the old industry is relatively small, regions with a high employment share in the old industry show a 3.1 pp. decrease in displacement related region switching. This is a modest change in effect size when compared to the 20 pp. reduction in industry switching after displacement (see columns 3 of Tables 6 and 7). By contrast, high shares of related industries reduce region switching by more than twice as much (7.5 pp), but increase, instead of decrease, industry switching by 7.5 pp. In other words, whereas a presence of the old industry is a more important factor in reducing effects on earnings and non-employment, related industries are more important when it comes to keeping displaced workers from moving out of the region.

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

[15]Indeed, earnings losses are somewhat higher in regions with much related employment. A possible explanation is that workers in such regions accept jobs that do not fully match their work experience to avoid having to move to another region, which is in line with the reduction in geographical mobility in locations with much related employment we report in Table 6.

[16]Due to attrition, in some cases, this 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	-37.689***	-38.973***	-38.244***	32.238**
	(0.617)	(1.433)	(0.937)	(14.862)
DxOir(M)		1.087	1.665	1.726
		(1.566)	(1.236)	(1.233)
DxOir(H)		5.852***	6.014***	5.502***
		(1.467)	(1.320)	(1.309)
DxAir(M)		-0.811	-0.688	-0.604
		(1.525)	(1.207)	(1.192)
DxAir(H)		-2.544	-2.819**	-2.793**
		(1.585)	(1.350)	(1.367)
Oir(M)		0.240	-0.157	-0.057
		(0.440)	(0.600)	(0.596)
Oir(H)		0.657	-0.708	-0.514
		(0.462)	(0.836)	(0.833)
Air(M)		-0.492	-0.448	-0.679
		(0.439)	(0.613)	(0.606)
Air(H)		0.278	0.111	-0.281
		(0.466)	(0.770)	(0.771)
other interaction terms?	no	no	no	yes
age controls?	yes	yes	yes	yes
year dummies?	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes
industry dummies?	no	no	yes	yes
region dummies?	no	no	yes	yes
R-squared	0.129	0.130	0.156	0.162
# obs.	89,706	89,706	89,706	89,706

***: p<.01, **: p<.05, *: p<.1. The dependent variable measures a worker's change in real daily earnings (measured 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). Oir(M) and Oir(H) form a dummy group that captures whether the old industry has a moderate (M) or high (H) employment share in the region in which the worker was displaced. Air(M) and Air(H) form an analogous dummy group for the regional employment share of industries with a skill-relatedness of at least 3 to the old industry. Age controls are the worker's age and squared age in the year of displacement. Education dummies group workers into one of seven education classes. Industry dummies refer to the 5-digit industry and region dummies to the spatial planning region (Raumordnungsregion) in 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	-0.079***	-0.077***	-0.074***	-0.022
	(0.004)	(0.009)	(0.007)	(0.126)
DxOir(M)		-0.002	0.002	0.002
		(0.012)	(0.011)	(0.011)
DxOir(H)		0.004	0.009	0.007
		(0.010)	(0.009)	(0.009)
DxAir(M)		-0.003	-0.007	-0.007
		(0.011)	(0.010)	(0.010)
DxAir(H)		-0.005	-0.002	-0.004
		(0.011)	(0.010)	(0.011)
Oir(M)		0.002	0.003	0.004
		(0.003)	(0.004)	(0.004)
Oir(H)		0.005	0.006	0.006
		(0.003)	(0.006)	(0.006)
Air(M)		-0.006*	-0.004	-0.005
		(0.003)	(0.004)	(0.004)
Air(H)		0.002	-0.003	-0.004
		(0.003)	(0.006)	(0.006)
other interaction terms?	no	no	no	yes
age controls?	yes	yes	yes	yes
year dummies?	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes
industry dummies?	no	no	yes	yes
region dummies?	no	no	yes	yes
R-squared	0.015	0.015	0.038	0.039
# obs.	46,216	46,216	46,216	46,216

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 non-employment

dep. var.: non-employed (y/n)	(1)	(2)	(3)	(4)
D	0.398***	0.418***	0.416***	0.726***
	(0.006)	(0.012)	(0.008)	(0.128)
DxOir(M)		-0.012	-0.024**	-0.022**
		(0.014)	(0.011)	(0.010)
DxOir(H)		-0.060***	-0.065***	-0.062***
		(0.015)	(0.011)	(0.011)
DxAir(M)		0.001	-0.002	0.001
		(0.014)	(0.010)	(0.010)
DxAir(H)		0.015	0.008	0.014
		(0.016)	(0.011)	(0.011)
Oir(M)		-0.006**	-0.001	-0.001
		(0.003)	(0.004)	(0.004)
Oir(H)		-0.006*	0.009	0.009
		(0.003)	(0.006)	(0.006)
Air(M)		0.008***	0.004	0.003
		(0.003)	(0.005)	(0.005)
Air(H)		0.006*	0.002	0.001
		(0.003)	(0.006)	(0.006)
other interaction terms?	no	no	no	yes
age controls?	yes	yes	yes	yes
year dummies?	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes
industry dummies?	no	no	yes	yes
region dummies?	no	no	yes	yes
R-squared	0.217	0.219	0.247	0.252
# obs.	89,706	89,706	89,706	89,706

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

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

dep. var.: non-employed after 3 yrs (y/n)	(1)	(2)	(3)	(4)
D	0.190***	0.207***	0.208***	0.211**
	(0.004)	(0.008)	(0.006)	(0.097)
DxOir(M)		-0.003	-0.009	-0.008
		(0.009)	(0.008)	(0.008)
DxOir(H)		-0.041***	-0.043***	-0.041***
		(0.009)	(0.008)	(0.008)
DxAir(M)		-0.003	-0.004	-0.003
		(0.009)	(0.008)	(0.007)
DxAir(H)		-0.000	-0.002	0.002
		(0.010)	(0.008)	(0.008)
Oir(M)		-0.005**	-0.001	-0.002
		(0.002)	(0.003)	(0.003)
Oir(H)		-0.006**	0.006	0.005
		(0.002)	(0.005)	(0.005)
Air(M)		0.005**	0.003	0.003
		(0.002)	(0.003)	(0.003)
Air(H)		0.002	0.005	0.005
		(0.002)	(0.004)	(0.004)
other interaction terms?	no	no	no	yes
age controls?	yes	yes	yes	yes
year dummies?	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes
industry dummies?	no	no	yes	yes
region dummies?	no	no	yes	yes
R-squared	0.088	0.090	0.113	0.116
# obs.	89,706	89,706	89,706	89,706

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

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

dep. var.: region switch (y/n)	(1)	(2)	(3)	(4)
D	0.315***	0.354***	0.358***	0.165
	(0.006)	(0.012)	(0.009)	(0.156)
DxOir(M)		-0.014	-0.012	-0.011
		(0.015)	(0.013)	(0.013)
DxOir(H)		-0.019	-0.031**	-0.032**
		(0.015)	(0.013)	(0.013)
DxAir(M)		-0.018	-0.025*	-0.026**
		(0.015)	(0.013)	(0.013)
DxAir(H)		-0.064***	-0.075***	-0.080***
		(0.015)	(0.013)	(0.013)
Oir(M)		-0.001	-0.003	-0.004
		(0.002)	(0.004)	(0.004)
Oir(H)		-0.001	-0.009	-0.008
		(0.003)	(0.007)	(0.008)
Air(M)		-0.003	0.005	0.006
		(0.003)	(0.005)	(0.005)
Air(H)		-0.013***	0.013*	0.015**
		(0.003)	(0.007)	(0.007)
other interaction terms?	no	no	no	yes
age controls?	yes	yes	yes	yes
year dummies?	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes
industry dummies?	no	no	yes	yes
region dummies?	no	no	yes	yes
R-squared	0.167	0.171	0.210	0.214
# obs.	70,320	70,320	70,320	70,320

Idem Table 2, with as a dependent variable a dummy for whether the worker changed spatial planning regions (Raumordnungsregionen) in the first job after the displacement event. If a worker or his matched twin remains non-employed 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	0.659***	0.760***	0.742***	0.738***
	(0.007)	(0.010)	(0.008)	(0.133)
DxOir(M)		-0.158***	-0.142***	-0.142***
		(0.015)	(0.011)	(0.011)
DxOir(H)		-0.215***	-0.203***	-0.202***
		(0.015)	(0.011)	(0.011)
DxAir(M)		0.002	0.010	0.011
		(0.014)	(0.011)	(0.011)
DxAir(H)		0.070***	0.075***	0.076***
		(0.017)	(0.012)	(0.012)
Oir(M)		-0.008**	0.025***	0.025***
		(0.004)	(0.005)	(0.005)
Oir(H)		-0.016***	0.035***	0.035***
		(0.004)	(0.008)	(0.008)
Air(M)		0.006*	0.014***	0.014***
		(0.004)	(0.006)	(0.006)
Air(H)		-0.002	-0.013*	-0.013*
		(0.004)	(0.007)	(0.007)
other interaction terms?	no	no	no	yes
age controls?	yes	yes	yes	yes
year dummies?	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes
industry dummies?	no	no	yes	yes
region dummies?	no	no	yes	yes
R-squared	0.454	0.473	0.503	0.503
# obs.	70,312	70,312	70,312	70,312

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 non-employed, this observation is dropped.

One caveat to the above results is that, in principle, 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 industry and region fixed effects in Column 3 of Tables 2 to 7 does not noticeably change the point estimates of the displacement effect or of its interactions. Adding these variables does, however, yield efficiency gains (i.e., smaller standard errors) by increasing the explained variance in the dependent variables and reducing the standard error of regression. This shows that, although region and industry effects do help explain earnings, wages, non-employment and mobility, the matching procedure successfully removes any correlation between displacement and unobserved confounding worker characteristics, at least at the region and industry level. Although this is no definite evidence against the existence of such confounders, it does give some confidence that the scope for ability-related confounding *beyond* what is captured by region and industry fixed effects will also be 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 non-employment 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 sizes of local economies. 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 the differences in these causal effects would arise from differences in education, not in local industry composition.

In Appendix B (Table B1), we show that workers indeed differ between regions with high or low shares of local employment in the old and related industries. In particular, although the average age of workers is very similar across different groups of local industries, average education levels differ somewhat across these groups. For instance, locations with high shares of the old industry tend to have a somewhat more highly educated workforce. Furthermore, there are also some small differences in the average size of the regions in which these local industries are found.

To find out whether such differences could explain our result, we explore how much of our findings can be attributed to *observed* worker characteristics and to a region's size. For this purpose, 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 the region. Results on the interactions with worker-level characteristics and region size are reported in Appendix B, Table B2.

Many of these interaction effects are indeed significant and interesting in their own right. For instance, earnings losses tend to increase with educational attainment. However, this simply reflects the higher predisplacement earnings associated with high levels of education, which yield higher absolute drops in earnings when workers become non-employed. Indeed, the relative wage drop for workers who find a job within the first year after being displaced (Column 2) shows that workers with a high school degree (HS) or with a university degree (U) do not experience displacement effects that are statistically different from those in the the omitted category (no degree). By contrast, we do find statistically significant evidence of less severe losses for workers with vocational training (VT) or with a high school degree *and* vocational training (HS+VT). Similarly, workers trained in Germany's (applied) colleges (C) also experience lower immediate wage drops. This pattern is reversed when looking at displacement-induced short- or long-term non-employment incidence. Here, vocational training and degrees from technical colleges are associated with relatively long non-employment post-displacement spells. That is, workers with more applied educations search longer for new jobs, but face less severe wage losses if they find one. A possible explanation is that vocational training and applied colleges provide skills that are more specific than those taught in high schools and universities. Such an interpretation is corroborated by the fact that workers with more applied educational backgrounds also tend to rely less on industry switching to cope with displacement. In contrast, the degree to which workers leave their region after displacement increases monotonically with the level of education.

Displacement effects also change with age, although the statistical evidence for this is weaker. The implied effect curves suggest that, except for very young workers, displacement-related non-employment rates go up with age, but older workers resort less often to regional mobility to cope with displacement than younger workers do. The size of a region is an even less important moderator. Only in workers' absolute earnings do we find a strong effect, but this may just reflect that wages are generally higher in large cities, where the same relative fall translates into much larger absolute earnings drops.

These findings imply substantial effect heterogeneity across workers with different educational backgrounds and age. However, when we turn to Columns 4 of Tables 2 to 7, we see that adding the interactions of these variables with the displacement dummy barely changes the interaction effects of displacement with the local industry mix that we reported in Columns 3. 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 individual characteristics such as age and education do not seem to be part of the explanation.

Search effort allocation and the spatial scope of search

A central prediction in search theory is that workers search more intensively when job prospects are better. Testing this prediction is hard, because search efforts are unobserved. After all, that unemployment spells are shorter when labor markets are tight does not necessarily mean that search efforts are higher in such episodes. Instead, the reduction in unemployment duration could just be due to an improvement in job arrival rates or wage offers. However, Fallick (1993) shows that the effect of labor market conditions on search 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 in Fallick (1993) predicts that the hazard of getting new jobs in other industries - while controlling for labor market conditions in these other industries - 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 shows that these effects indeed exist, at least 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.

We follow this framework, but adjust it in two important ways. First, we use the industry's local employment shares to measure labor market conditions. That is, we assume conditions are favorable in regions where industries represent a large share of regional employment. This is in line with the literature on agglomeration externalities that states that easier job search represents a channel through which Marshallian agglomeration externalities operate (e.g., Duranton and Puga, 2004). We also control for regional size to make sure these effects are not driven by the local labor market's size but rather by its composition. Second, we extended the search model to include workers' geographical scope of search. This provides testable implications, additional to the ones in Fallick (1993), concerning the geographical mobility of displaced workers.

To test these implications, we drop all nondisplaced workers and keep only the sample of displaced workers. Presumably, all of these workers were confronted with an exogenous shock that required them to start searching for jobs again, 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 results in terms of relative risk ratios vis-à-vis the base category of non-employment. As before we add age, age-squared, log(region size) and education dummies as controls. However due to the non-linearity of the multinomial logit model, we have to use industry and region dummies at an aggregated level of 15 broad sectors and the 16 German states (Bundesländer) respectively.

Because favorable local conditions should directly increase offer arrival rates (and/or qualities), we expect that they help workers find local jobs. That is, higher local employment shares of a sector should increase the likelihood of finding local jobs. We find that this is indeed the case. Compared to where the old industry has a low regional employment share, the relative risk of finding a local job in the old industry is about 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 likelihood of finding local jobs in another industry compared to remaining non-employed by factors of 1.1 and 1.2 (third column).

However, local conditions also have indirect effects through their impact on search efforts. The model predicts that favorable conditions in a sector - in our framework, a large relative local presence of the sector - will intensify search efforts and, therefore, increase the rate at which offers arrive from outside the region. Indeed, intermediate (high) shares of the old industry increase the relative risk of finding non-local jobs in that industry instead of remaining non-employed by a factor of 1.8 (2.4) (Column 2). However, intermediate and high local shares of related industries (Column 4) do not have any discernible effects on finding non-local jobs outside the region instead of remaining non-employed.

These findings could be interpreted as evidence that workers shift search efforts to sectors that are large in the region. An alternative explanation for the link between geographical mobility and the local employment mix is that regions have similar employment structures as their neighbors. In that case, what the model picks up in the second and fourth columns of Table 8 is not a reallocation of search efforts, but simply the fact that economic conditions in the region are mimicked in the surrounding regions. A more convincing proof for the shift in search efforts is that favorable conditions in one sector, decrease, ceteris paribus, search in the other sector. Such a shift in search effort should be visible in a reduction of the geographical scope, and therefore the likelihood of finding a job outside the region, in the other sector. To show that this is indeed happening, we re-express the relative risk ratios of Table 8 in Table 9 in such a way that the base category reflects the event in which workers accept local jobs in the old industry (first column) or in other industries (second column).[17]

The first column of this table shows that, for those who stay in the old industry, the risk of changing regions is decreased by (a statistically insignificant) 17 percent at intermediate shares and by 36 percent at high shares of related industry employment. Evidence that regional employment in the old industry makes industry switchers' search more local (second column) is weaker. Intermediate employment shares of the old industry reduce region switching among work-

[17]For instance, to analyze the effect of the old industry's employment share on search efforts, we look at the relative risk of changing industries *and* regions against the base category of changing only industries. Similarly, the effect of related industry employment is analyzed by calculating the relative risk ratio of changing regions *but not* industries against the risk of staying in the region and the old industry.

Table 8: Multinomial postdisplacement regression

	Outcome:			
	stay ind. & reg.	switch reg.	switch ind.	switch ind. & reg.
Oir(M)	2.243***	1.808***	0.874***	0.783***
	(0.186)	(0.205)	(0.042)	(0.051)
Oir(H)	3.176***	2.439***	0.980	0.896
	(0.272)	(0.294)	(0.050)	(0.066)
Air(M)	0.930	0.769**	1.096*	1.059
	(0.073)	(0.089)	(0.057)	(0.072)
Air(H)	0.861	0.548***	1.211***	0.996
	(0.082)	(0.074)	(0.070)	(0.069)
log(reg. size)	5.556	3.295	0.126	0.782
	(17.743)	(15.166)	(0.273)	(2.260)
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)	-63,535	-63,535	-63,535	-63,535
# obs.	44,850	44,850	44,850	44,850
# clust.	4,797	4,797	4,797	4,797
partial R2	0.051	0.051	0.051	0.051

***: 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 (non-employment). Coefficients are relative risk ratios, standard errors, clustered at industry-region level, in parentheses.

Table 9: Multinomial postdisplacement regression: Cross-effects

	outcome: switch reg. base: stay ind. & reg.	outcome: switch ind. & reg. base: switch ind.
Oir(M)	0.806*	0.896*
	(0.102)	(0.056)
Oir(H)	0.768*	0.914
	(0.104)	(0.060)
Air(M)	0.827	0.966
	(0.099)	(0.060)
Air(H)	0.636***	0.822***
	(0.086)	(0.056)

Rendering of selected coefficients from Table 8 against different base categories in column headers.

ers who also switch industries by a marginally significant 10 percent, whereas high shares of related employment have similarly sized negative, but statistically insignificant effects. Overall, however, in both cases we find that favorable conditions in one sector reduce the propensity to switch regions in the other sector.

The fact that search effort allocation responds to local conditions can also be inferred from Table 8 by emulating the approach in Fallick (1993). As explained above, Fallick (1993) shows that the old industry's (national) growth rate decreases search in alternative industries by showing that the duration of search in the other industries depends negatively on employment growth in the old industry. Similarly, we find that intermediate local employment shares in the old industry significantly decrease the odds ratio of finding a new job in other industries (be it local or non-local) vis-à-vis remaining non-employed (see the third and fourth column in Table 8). For high employment shares, outcomes are statistically insignificant, but have the right sign. Similarly, intermediate and high shares of related industries in the region decrease the likelihood of finding non-local jobs in the old industry compared to staying non-employed (second column of Table 8). Although point estimates suggest that the likelihood of finding *local* jobs in the old industry is affected in the same way, these effects are not statistically significant. In sum, whereas the results in Fallick (1993) are not very robust and somewhat contradictory, our findings all point in the same direction: namely, that a high concentration of jobs in one sector reduces search efforts in the other sector.

7 Conclusions

Marshallian externalities are benefits that emerge in regions with a large employment concentration of a particular industry. One often proposed mechanism through which these benefits materialize is the thick local labor markets they provide to workers with industry-specific skills. By focusing on the job search of workers who lose their jobs exogenously in establishment closures, we provide evidence that these thick labor markets indeed help finding new jobs. In particular, we show that the detrimental effects of job displacement on earnings and employment, which are well-known and have been extensively documented in the growing academic literature on this topic, depend on the local economy's industry mix. In particular, high local employment shares in the old industry reduce displacement-related long-term non-employment incidence by up to 21% and immediate earnings drops by 16%, representing substantial agglomeration benefits to displaced workers.

When turning to workers' career choices after displacement, we find that the industry mix also changes the way in which workers cope with displacement. After losing their job, displaced workers often change industries and regions. However, in places with large shares of the old industry, industry switching rates among displaced workers are reduced by 27% and region switching rates by 9%. What matters even more for the geographical mobility of displaced workers is the presence of industries related to the old industry. By offering local employment alternatives, high shares of such related industries decrease postdisplacement region switching by up to 21%. This suggests that one of the benefits of local clusters of related industries that have recently been identified in the cluster and economic geography literatures is that such clusters help preserve talent and human capital for the region when one of its local firms is in distress.

We explored whether these findings could be driven by sorting of workers across locations. We indeed do find that worker-level heterogeneity is associated with differential displacement effects. For instance, we find that (more so than the level of education) it matters whether education is general or more applied. In particular, workers with vocational training or a degree from an applied college suffer relatively low displacement-induced wage losses (provided they find a new job immediately), but higher non-employment rates. They also are less likely to resort to industry mobility to cope with their job loss. However, accounting for such worker-level heterogeneity does not noticeably change our estimates of how the local industry mix moderates displacement effects.

Finally, we conducted a more in-depth analysis of displaced workers' mobility decisions to replicate Fallick's test of one of the central predictions of search theory: namely that workers increase search efforts when labor market conditions are favorable. In our paper, favorable labor market conditions arise from agglomeration benefits that emerge where an industry is relatively large. This strategy allows us to provide robust support for the earlier, somewhat ambiguous, results on strategic search behavior in Fallick (1993). In particular, we show that, given the local employment share of related industries, a significant local presence of the old industry lowers workers' job-finding hazards in other industries and vice versa. Moreover, for workers who still move to other industries, higher local employment shares of the old industry reduce the rate at which these workers switch regions (and vice versa), implying that job opportunities in one industry reduce the geographical scope of search in other industries.

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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

Table B1: Group averages of individual level characteristics

	employment share old ind.			employment share related ind.		
	low	medium	high	low	medium	high
age	40.0	39.8	39.9	39.9	39.9	39.8
edu (ND)	11.78%	10.61%	8.79%	7.84%	10.84%	10.80%
edu (VT)	63.80%	64.96%	68.13%	67.98%	64.23%	66.83%
edu (HS)	0.56%	0.62%	0.39%	0.62%	0.56%	0.53%
edu (HS+VT)	2.76%	2.35%	2.25%	2.41%	2.25%	2.60%
edu (C)	2.34%	2.35%	4.37%	3.75%	2.80%	2.90%
edu (U)	2.32%	2.92%	4.39%	3.44%	2.60%	3.15%
edu (miss.)	16.44%	16.19%	11.69%	13.96%	16.71%	13.19%
log(reg. size)	12.5	12.5	12.3	12.3	12.5	12.5

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 average region size in natural logs.

Table B2: Estimated interaction effects of individual level characteristics

	dependent variable:					
	earnings increase	log(wage gain)	non-emp. (short)	non-emp. (long)	reg. switch	ind. switch
D	32.238**	-0.022	0.726***	0.211**	0.165	0.738***
	(14.862)	(0.126)	(0.128)	(0.097)	(0.156)	(0.133)
DISPXlog(reg. size)	-4.111***	-0.009*	-0.003	0.007*	-0.008	-0.000
	(0.768)	(0.005)	(0.006)	(0.004)	(0.009)	(0.006)
DISPXage	-0.176	0.003	-0.017***	-0.006	0.013**	0.001
	(0.603)	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)
DISPXage2	-0.0092	-0.0001	0.0003***	0.0001**	-0.0002**	0.0000
	(0.0079)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
DISPXedu(VT)	4.334***	0.031**	-0.128***	-0.074***	0.029**	-0.046***
	(0.964)	(0.012)	(0.010)	(0.009)	(0.012)	(0.011)
DISPXedu(HS)	-17.460**	0.067	-0.038	0.019	0.143***	0.014
	(7.471)	(0.051)	(0.036)	(0.041)	(0.042)	(0.041)
DISPXedu(HS+VT)	-11.089***	0.046**	-0.143***	-0.059***	0.142***	-0.034
	(3.806)	(0.023)	(0.020)	(0.016)	(0.022)	(0.022)
DISPXedu(C)	-11.338***	0.048**	-0.209***	-0.090***	0.186***	-0.082**
	(4.152)	(0.023)	(0.020)	(0.017)	(0.021)	(0.032)
DISPXedu(U)	-21.643***	0.021	-0.185***	-0.071***	0.193***	-0.043*
	(4.949)	(0.024)	(0.019)	(0.016)	(0.022)	(0.023)
DISPXedu(miss.)	6.598***	0.036**	-0.111***	-0.061***	0.053***	-0.056***
	(1.297)	(0.016)	(0.013)	(0.011)	(0.014)	(0.013)
age controls?	yes	yes	yes	yes	yes	yes
year dummies?	yes	yes	yes	yes	yes	yes
education dummies?	yes	yes	yes	yes	yes	yes
industry dummies?	yes	yes	yes	yes	yes	yes
region dummies?	yes	yes	yes	yes	yes	yes

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