Skill Mismatch and the Costs of Job Displacement*

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Abstract

We study whether earning losses after job displacement can be attributed to the skill mismatch that arises when workers' human capital is underutilized at the new job. Using detailed task data, we create asymmetric measures of skill mismatch between occupations. We use these measures to study the effect of worker displacement in plant closures and mass-layoffs in Germany, exploiting these events as exogenous job separations. To control for observed and unobserved worker heterogeneity, we use propensity-score matching and estimate difference-in-differences models. We find that displacement increases occupational switching and skill mismatch, primarily because displaced workers move to less skill-demanding occupations. The negative earning effects associated with displacement are mostly driven by these moves, while workers moving to more skill-demanding occupations have similar earning losses as stayers.

JEL Code: J24, J31, J63, J65

Keywords: job displacement, human capital, skill mismatch, occupational change

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1 Introduction

An increasing number of studies evidence large and persistent earning losses by displaced workers. The majority of these studies agree that, 15 or more years after displacement, the earnings and wages of displaced workers are 10–15% below their expected levels (e.g., Jacobson, LaLonde and Sullivan, 1993; Eliason and Storrie, 2006; Couch and Placzek, 2010; Hijzen, Upward and Wright, 2010; Schmieder, von Wachter and Bender, 2010; Bonikowska and Morissette, 2012; Seim, 2012). Moreover, involuntary job loss is also associated with nonmonetary costs in terms of lower life expectancy and fertility rates (Frey and Stutzer, 2002; Sullivan and von Wachter, 2009; Del Bono, Weber and Winter-Ebmer, 2012). Job displacement even seems to burden future generations, as the job-loss of parents adversely affects children's schooling achievements and their future careers (Oreopolous, Page and Stevens, 2008; Kalil and Wightman, 2011). A reason for this may be that displacement forces workers into unfavorable changes of occupation. This suggests that we need to move beyond the recently proposed symmetric occupational distance measures towards characterizing occupational switches as having both a distance and a direction. In this paper, we develop such measures and study whether the direction of occupational change is indeed an important channel through which the marked earning losses of displaced workers materialize.

Theoretically, there are at least four reasons why displaced workers experience difficult transitions: (i) the skills specific to the old job may not be useful in the new one (Becker, 1962; Neal, 1995; Parent, 2000; Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010); (ii) incentive contracts that raised earnings beyond market wages are lost with a job separation (Lazear, 1979); (iii) there are search costs involved with finding a new job (Topel and Ward, 1992); and (iv) workers who were laid off may be stigmatized in the labor market (Vishwanath, 1989; Biewen and Steffes, 2010).[1]

Several studies find support for the theory of specific human capital, which predicts that job switching causes wage penalties proportional to the loss of specific human capital (Podgursky and Swaim, 1987; Carrington, 1993; Jacobson, LaLonde and Sullivan, 1993; Neal, 1995; Parent, 2000; Burda and Mertens, 2001; Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010). This work finds that the relative earning losses of displaced workers are higher for industry switchers, occupational switchers, or workers who switch skill portfolios.[2]

[1] Stevens (1997) shows that serially correlated displacement spells explain much of the persistence and magnitude of lowered earnings after job displacement in the United States. Providing further empirical support for a stigma effect, Kroft, Lange and Notowidigdo (2013) find in a large-scale field experiment that the likelihood of being asked to a job interview significantly decreases with the length of a worker's unemployment spell.

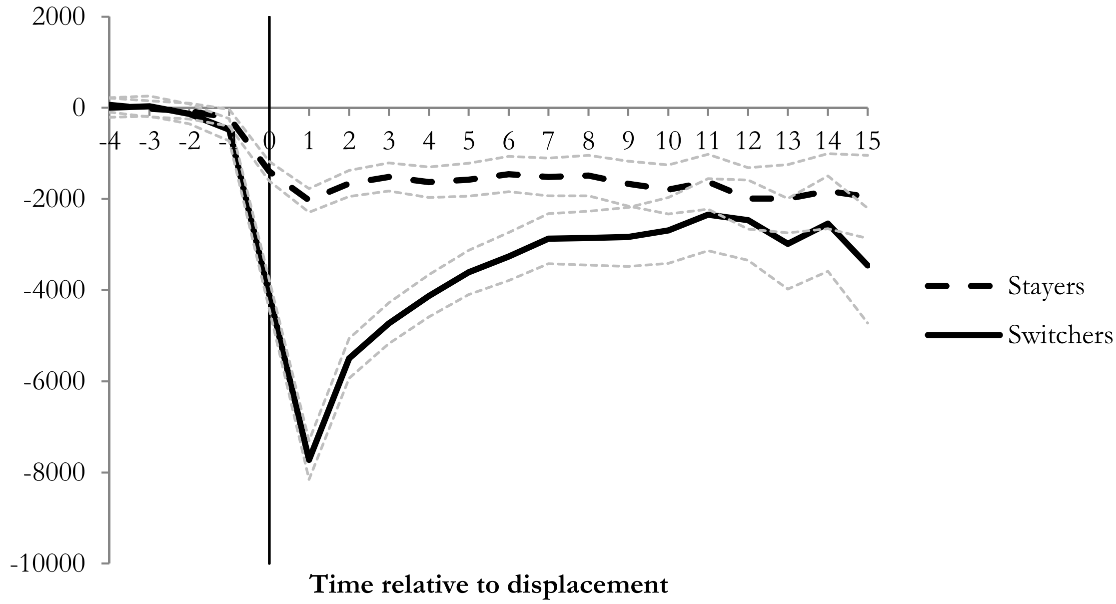
[2] See Gibbons and Waldman (2004) for a theoretical discussion of the concept of task-specific human capital, that is, human capital that is not narrowly specific to occupations, but rather to basic tasks

None of these studies, however, documents whether the differential losses are persistent or temporary. Moreover, they reveal little about the nature of the occupational switch. It is not clear whether any larger losses of displaced switchers are driven by occupational mobility in general or by moving to "worse" jobs, that is, jobs that leave a worker's human capital unused (as opposed to switches that require the worker to acquire new skills). This paper addresses these questions.

To motivate the analysis, we compare the earning losses of displaced occupational stayers and switchers, respectively, relative to their non-displaced peers in Germany in the period 1981–2006 (see Figure 1). The graph shows that switchers experience larger immediate earning losses after displacement than do stayers. The initial difference in displacement costs also persists in later periods. In the 15 years following displacement, stayers lose on average €1,700 per year relative to their non-displaced controls, while switchers' relative earnings losses are more than twice as high (€3,600). The difference in displacement costs between stayers and switchers is most persistent in the first nine years following displacement.

performed in these occupations.

Figure 1: Displacement Costs of Occupational Stayers and Switchers



Note: The figure plots the coefficients from the difference-in-differences model detailed in Section 6. The dependent variable is annual earnings in €2005. Sample: workers displaced in the period 1981–2006 in Germany and their matched controls, selected from among non-displaced workers using exact and non-exact matching techniques (Section 4 provides information on the matching approach). *Stayers* still work in their pre-displacement occupation in their first post-displacement job; *Switchers* move to another occupation. Confidence intervals are defined at the 90% level and derived from standard errors clustered at the individual level. *Data source:* SIAB 1975–2010.

The observed differences in the earning patterns of occupational stayers vs. switchers cannot be explained by lost incentive contracts because both groups lose these contracts. Moreover, the stigmatization theory suggests that potential employers view displacement as a negative signal for worker performance. However, if such stigma equally affects all displaced workers, this theory does not provide a good explanation for the observed differences in earning losses between occupational switchers and stayers.

It could be that search costs are higher for occupational switchers than for stayers. However, a theory based on search costs would predict only a temporary adverse effect on the earnings and employment of occupational switchers after displacement. We argue, and provide evidence, that the most likely explanation of the persistent displacement cost differences between stayers and switchers is the theory of specific human capital.

Our paper puts forward a number of novel research questions. First, does displacement increase the likelihood of occupational change? If so, what kind of occupational change does displacement induce? In particular, switching from one occupation to another may involve leaving skills unused, acquiring new skills, or both, depending on the direction of the switch. After establishing whether a relationship exists between displacement and the direction of occupational change, we ask whether earning losses are mitigated by workers who avoid certain types of switches. In particular, switching to occupations that require new skills may be more attractive than switching to occupations that leave previously acquired skills unused. Finally, we ask whether differences in displacement costs between occupational stayers and switchers are mainly due to differential productivity declines or to decreases in employment.

To answer these questions, we use German administrative data with longitudinal information on workers and their employers covering more than 30 years of labor market history. However, when studying occupational mobility, one has to address a number of selection problems. First, some job separations occur when workers are laid off. When potential employers believe that a worker has lost his or her job due to poor performance or incompetence, such job separations convey an adverse signal. At the same time, previous research has shown that a worker's skill set directly affects her job mobility.[3] Second, occupational switching is often part of a worker's career path. Indeed, some occupational switching deliberately aims at acquiring and/or utilizing certain skills, making the decision to change occupations endogenous to the worker's skill portfolio. A typical example is a promotion to a managerial position after acquiring sufficient competence to perform managerial tasks. Moreover, a voluntary occupational switch reflects an increase in the value of the new job relative to the old one. Consequently, voluntary occupational switches are unlikely to involve human capital losses. These selection issues can be addressed by concentrating on job changes that are unrelated to individual worker performance and career plans. To identify job separations that can be considered as exogenous, we use information on plant closures and mass-layoffs in Germany.

We supplement the data on workers' job histories with information about task and skill profiles of occupations using a representative employee survey. From this survey we construct measures of skill mismatch, which take into account both *distance* and *direction* of occupational moves. These measures allow us to characterize occupational moves by the amount of human capital that can be transferred from the old to the new occupation. Specifically, we distinguish among workers who, compared to their previous job, move to an occupation that predominantly requires new skills (*upskilling*), to an occupation that predominantly leaves existing skills unused (*downskilling*), to an occupation that requires few new skills and leaves few existing skills unused (*lateral*), and to an occupation that both requires new skills and

[3] For instance, Bergmann and Mertens (2011) find that, in accordance with the technological change hypothesis, men performing non-routine interactive tasks face a decreasing risk of layoff.

leaves many existing skills unused (*reskilling*).

Displaced workers do not switch occupations randomly. We therefore use a combination of exact and propensity score matching to obtain an appropriate counterfactual of the evolution of earnings and labor supply that displaced switchers would have experienced had they not been displaced and had they not switched occupations. Among other characteristics, we match on daily wages and days worked in several pre-displacement periods as well as on the pre-displacement occupation. We then estimate the effect of skill mismatch on displacement costs using difference-in-differences estimation to control for pre-displacement heterogeneity.

We find that displaced workers are 17 percentage points more likely to change their occupation than their non-displaced counterparts in the first year after displacement. The occupational mobility of displaced workers remains larger than that of their peers even 15 years after displacement. Conditional on occupational change, displacement decreases the probability of entering an occupation that requires new skills (upskilling) and also decreases the probability to switch over long skill distances (reskilling).

Further, our results identify skill mismatch as an important mechanism for the substantial and persistent earning losses of displaced workers. While occupational switchers lose more than stayers in general, we document a remarkable heterogeneity in displacement costs among switcher types. Switchers who are downskilled at the new job suffer the largest displacement costs, experiencing annual earning losses that are about twice as large as those incurred by upskilled switchers. Moreover, the annual earnings of downskilled switchers show no sign of recovery over almost the entire period of observation. Upskilled switchers, on the other hand, recover quickly from the displacement-induced loss in earnings. Those among them who find new jobs even gain from switching. However, these gains are modest considering the investments in education and training associated with upskilling moves. The displacement costs of reskilled and lateral switchers are somewhat in between those incurred by upskilled and downskilled switchers, respectively. The earning differences between switcher types are mainly caused by differential wage developments, which underscores the importance of skills mismatch (affecting worker productivity and thus wages) for displacement costs. The number of annual days worked is very similar across switcher types.

The remainder of the paper is organized as follows. Section 2 embeds our paper in the previous literature. In Section 3 we construct measures of skill transferability between occupations. In Section 4, we introduce the data and describe the sample restrictions and the matching procedure. Section 5 shows the results of our analysis of the effect of displacement on occupational mobility and on the probability of incurring skill mismatch. Section 6 contains our results on the relationship between skill mismatch and displacement costs in terms of earnings, wages, and employment. Section 7 discusses the implications of our findings for policy and research.

2 Previous Literature on Occupational Mismatch

Our work is related to a small but quickly growing literature that develops measures of the "distance" between occupations depending on the similarity of the skills used (or tasks performed) by the workers in the occupations.[4] The work of Shaw (1984, 1987) is perhaps the first attempt to define a measure of occupational distance which proxies the skill transferability across occupations. Here, the skill transferability between two occupations is assumed to be highly correlated with the probability of switching between these occupations. A similar approach is pursued by Neffke and Henning (2009), who regard excess labor flows between narrowly-defined industries as an indicator of the skill-relatedness of these industries.

Availability of detailed data that characterize occupations by their task or skill content—like the U.S. O*NET or the German Qualification and Career Survey (QCS)—recently enabled a more direct approach of measuring occupational distance. These newer measures incorporate the fact that different occupations report similar bundles of tasks or skills. The higher the overlap in the task or skill portfolio of two occupations, the more related the occupations are considered to be. Among such measures are those proposed by Poletaev and Robinson (2008) and Gathmann and Schönberg (2010).[5]

Gathmann and Schönberg (2010) use the QCS to place occupations in a 19-dimensional skill space. Each occupation can be thought of as a skill vector whose position is determined by the presence or absence of skills. Some occupations require the mastery of skills at higher levels than other occupations. To depict this fact, the length of the skill vectors can be interpreted as the level or intensity of skills. However, Gathmann and Schönberg (2010) normalize this length to unity, and only use the angle between the skill vectors to

[4] See Acemoglu and Autor (2011) and Robinson (2011) for insightful discussions of the differences between skills and tasks.

[5] More recent examples of measures of occupational distance are Geel and Backes-Gellner (2011), Yamaguchi (2012), Firpo, Fortin and Lemieux (2013), Summerfield (2013), and Cortes and Gallipoli (2014). Based on cluster analysis of job tasks, Geel and Backes-Gellner (2011) group occupations in skill-related clusters. The resulting measure is discrete, as occupations can either belong or not belong to the same skill cluster. Yamaguchi (2012) estimates a structural model of occupational choice to explore the evolution of tasks over a career. Firpo, Fortin and Lemieux (2013) attempt to identify the occupational tasks that are most vulnerable to offshoring. Summerfield (2013) simultaneously considers education mismatch and skill mismatch of occupational switchers to investigate how returns to schooling change when accounting for human capital heterogeneity within a given level of education. Finally, Cortes and Gallipoli (2014) use a gravity-model-type approach to estimate costs of occupational mobility, which in their model depend on the similarity of tasks performed in these occupations. However, none of the measures proposed in these papers incorporates asymmetries in the transferability of skills when comparing a move between two occupations in one versus the other direction. See Section 3 for details.

define distance (angular separation). The angle is a symmetric distance measure, which only contains information on the relative importance of a skill in an occupation. As a consequence, a switch, for instance, from a sales person to a professional negotiator assumes identical skill transferability as does a switch from a negotiator to a sales person. Nevertheless, although the relative importance of social-interaction skills for an ordinary sales person and for a professional negotiator may be similar, the absolute level required is likely to be far greater in the latter than in the former occupation because the negotiator's job is substantially more complex.

Unlike Gathmann and Schönberg (2010), Poletaev and Robinson (2008) propose two distance measures that use information about the length of the skill vectors. Here, the length of each skill vector is proportional to the self-reported average occupational skill intensity, derived from the U.S. Dictionary of Occupational Titles (DOT), a predecessor of O*NET. An occupational switch where the new occupation employs the previous occupation's "main skill" with much lower or much higher intensity is regarded as a distant switch.[6] Therefore, although Poletaev and Robinson (2008) consider the skill intensity, they employ the Euclidean distance, or the distance between the tips of the occupations' skill vectors, which, similar to the angular distance, produces a symmetric skill-transferability measure. We argue that, by suggesting a symmetric relation in the skill transferability between occupations, previous work on the similarity (or better, dissimilarity) of occupations obscures the fact that there are strong asymmetries in the transferability of skills when comparing a move from occupation i to j to a move from occupation j to i.

Another stream of literature aims at measuring the qualification asymmetries between jobs or, more often, between workers and jobs. At the worker-job level, the measures of over- and underqualification capture mismatch the educational attainment of a worker and the educational requirements of a job. Some of these measures are based on self-reporting (Hartog and Oosterbeek, 1988; Alba-Ramirez, 1993; Galasi, 2008), others are based on an analysis of job tasks (Eckaus, 1964; Hartog, 2000), and a third set is based on realized job-person matches (Verdugo and Verdugo, 1989; Kiker, Santos and de Oliveira, 1997; Quinn and Rubb, 2006).[7] A major shortcoming of many of these measures is that they often focus on the education or skill levels as opposed to skill content.

We develop measures of skill mismatch that combine the strengths of both the symmetric occupational distance and educational mismatch measures. We use the German QCS to derive the occupations-specific skill mix and use the average years of schooling and vocational

[6] The main occupational skill is the one with highest average intensity of use among the four derived general skills.

[7] See Leuven and Oosterbeek (2011) for a detailed overview.

training of workers in an occupation to proxy the complexity of the skilled needed in this occupation. Combining both types of information, we

measure skill transferability in terms of skill redundancies and skill shortages involved in occupational switches to reveal the asymmetry in skill transferability.

Our work is most closely related to Robinson (2011), who also accounts for both the distance and direction of an occupational switch. Using occupational task information from the DOT matched with workers' job histories from the Displaced Workers Survey (DWS) in the U.S., he finds that occupational switching is very frequent after job displacement, and that displaced workers mostly switch downward immediately after displacement. While similar in spirit, our study differs in a number of key points. First, our skill-mismatch measure has an intuitive interpretation: the number of years of schooling and training (a) needed to develop the newly required skills or (b) that remain unused in the new occupation. Second, our estimation strategy addresses the endogeneity in occupational mobility. Third, we do not just investigate the transition to the first post-displacement job, but follows workers for up to 15 years after displacement to assess the long-term effects of job displacement.

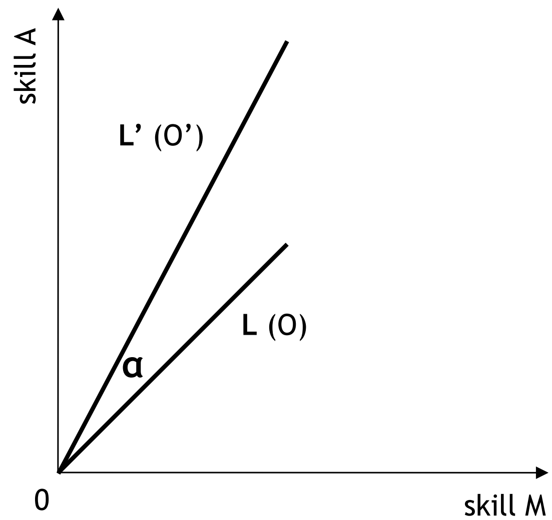
3 Skill Mismatch

We attempt to contribute to the understanding of the consequences of human capital specificity for the patterns of occupational switching and for the development of individual earnings after displacement by developing asymmetric measures of skill transferability between occupations.

3.1 Measuring Skill Mismatch

We assume that each occupation has a specific skill profile. A skill profile expresses the level of mastery required to accomplish the tasks associated with a job in each of k skills. Accordingly, an occupation's skill profile can be depicted as a k - dimensional skill vector. Figure 2 shows an example of two different occupations, O' and O, which use $k = 2$ different skills. As seen from the positions of the skill vectors, L' and L, both occupations require similar levels of skill M, but occupation O' demands about twice as much of skill A as occupation O. In other words, O not only involves a different skill mix than O', but also different skill levels. This difference in skill levels between jobs introduces asymmetries in the transferability of human capital between occupations.

Figure 2: Skill Profiles of Occupations O' and O in a Two-Dimensional Skill Space



The angle between the two vectors indicates whether occupations are similar in their skill compositions. For instance, Gathmann and Schönberg (2010) use the angular separation between skill vectors as a measure of occupational distance. However, some occupations require that skills are mastered at higher levels than other occupations. Thus, the relative importance of a task (and its required skills) provides only limited information about the skill similarity of two occupations. In the example in Section 2 we compared ordinary salespersons with professional negotiators. Both use the same skill mix, but negotiators have to master each skill at a much higher level. This introduces an asymmetry in the relation between negotiators and salespeople. That is, whereas it is relatively easy for a negotiator to become a salesperson, the reverse switch is much harder. Indeed, some of the negotiator's skills will be redundant when the negotiator works as a salesperson, whereas the salesperson will need to boost each of her skills to become an effective negotiator.

Each occupational switch can be characterized by two quantities: skill redundancy and skill shortage. Skill shortage consists of skills that are required in the new occupation but that were not needed in the old one. It is expressed in the number of years of schooling that it would typically take to master these new skills. Skill redundancy is analogously defined as the skills that are required in the old occupation, but remain unused in the new one. It is expressed in the number of years of schooling that remain unused when moving from one occupation to the other.

To measure skill redundancy and skill shortage, we use the 2005/2006 wave of the German QCS. This survey is conducted by the Federal Institute for Vocational Education and Training (BIBB), the Institute for Employment Research (IAB), and the Federal Institute for Occupational Safety and Health (BAuA). One of its purposes is to measure the task, skill, and knowledge requirements of occupations in Germany. The data cover individuals aged 16–65 who were employed in Germany at the time of the survey. The survey has been used extensively for labor-market research (for instance, DiNardo and Pischke (1997), Spitz-Oener (2006), Dustmann, Ludsteck and Schönberg (2009), Black and Spitz-Oener (2010), and Gathmann and Schönberg (2010)) because of its rich information about work tasks and employees' skills, education, and training. Due to limited comparability of survey questions over time, we consider only the 2005/2006 wave, which samples 20,000 individuals in 263 occupations. We transform the Likert-scaled answers on 46 survey questions on individual worker tasks, knowledge, and work conditions to binary variables that reflect whether or not a worker has a skill (or carries out a task).[8] We then construct occupation-level skill-profiles by calculating the share of workers in an occupation with a particular skill or task.

This 46-dimensional skill profile contains a lot of redundant information. We therefore use factor analysis to reduce the dimensionality of the skill profiles, which results in a total of five broad factors whose eigenvalues exceed one and two significant factors that seem to capture the disutility of certain jobs like physical strain and work safety issues. Next, we rotate these factors such that most loadings are either close to one or zero, which allows us to characterize each occupation by its scores on the five skill factors, which can roughly be classified as (1) managerial/cognitive skills, (2) R&D/science skills, (3) technical skills, (4) sales/negotiation skills, and (5) medical skills. This classification deviates from the by-now-standard distinctions introduced by Autor, Levy and Murnane (2003) along the cognitive-manual and routine-non-routine dimensions. The reason for this is that Autor et al.'s classifications have the specific purpose of analyzing the effect of automation and computer-use on the labor market. In contrast, we are interested in the human capital distances among occupations and therefore prefer to remain agnostic about specific contents of skill profiles. Apart from the skill profile, we also calculate a disutility score for each occupation, which is based on 14 questions on the conditions under which workers perform their jobs; all of these questions load on one factor that quantifies a job's disutility.

The QCS also provides a detailed account of each worker's schooling history. The survey not only provides information on the highest educational attainment, but also on the time workers spent in up to seven episodes of postsecondary schooling and training. We use this information to calculate the average number of years of cumulative schooling of workers in a given occupation and assume that workers used this schooling to acquire the skills of their

[8] Intensities of job tasks are self-reported in the QCS. Close inspection of these data reveals that people seem to make erroneous judgments. This is due to the fact that most individuals are unaware of the true task distribution in the population; they mainly compare the tasks they perform with the tasks in jobs with which they are familiar.

occupation's skill profile. If schooling requirements for different skills are additive, total schooling requirements can be written as a linear combination of skill factors:

$$S_O = \alpha + \beta_1 s_O^1 + \beta_2 s_O^2 + \beta_3 s_O^3 + \beta_4 s_O^4 + \beta_5 s_O^5 + \varepsilon_O, \tag{1}$$

where S_O is the average number of years of schooling in occupation O and s_O^i is the factor score of the occupation for skill factor i, which is measured in standard deviations. We also add the occupation's disutility score as a control variable to avoid that some skills have negative estimates due to their correlation with poor working conditions. The resulting regression has a surprisingly good fit, with an R-squared of 0.74 and positive regression coefficients for all skill factors (see Table A.1 in the Appendix). The coefficients of this regression analysis can be interpreted as the number of years of schooling it takes to acquire a one standard deviation increase in the corresponding skill.

In the final step, we use the regression coefficients for each skill to derive the skill redundancy and skill shortage associated with occupational switches. For each skill, we calculate the difference in factor scores between two occupations, O and $O^{'}$, and multiply this by the corresponding coefficient of the schooling regression, yielding the following expressions for skill redundancy and skill shortage.

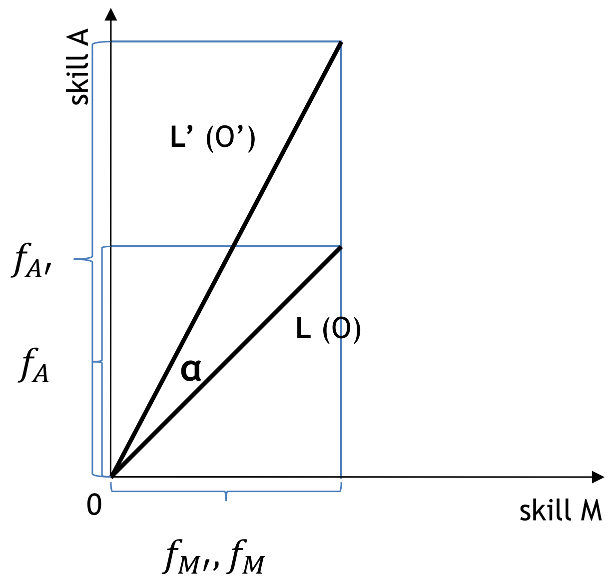
$$shortage_{OO'} = \sum_{i=1}^{5} \beta_i (f_{iO'} - f_{iO}) I(f_{iO'} > f_{iO})$$

$$redundancy_{OO'} = \sum_{i=1}^{5} \beta_i (f_{iO} - f_{iO'}) I(f_{iO'} < f_{iO}),$$

where f_{iO} is occupation O's factor score for skill i, β_i is the coefficient on skill i in the schooling regression (1), and $I(.)$ is an indicator function that equals 1 if its argument is true.

This procedure is illustrated in Figure 3. A job move from O' to O yields a skill shortage of zero because employees in O' are at least as qualified as those in O in both skills. At the same time, the skill redundancy of such a move will equal $\beta_A(f_{A'} - f_A)$. In contrast, a move from O to O' results in a skill shortage of $\beta_A(f_{A'} - f_A)$, with zero redundancy.

Figure 3: Skill Shortage and Skill Redundancy



There are some obvious limitations to this decomposition of an occupation's schooling requirements. For instance, schooling requirements for skills would not be additiveif it is particularly easy (or hard) to learn certain combinations of skills. However, including all possible interactions of skill factors increases the R-squared of the model to 0.78, a gain of just four percentage points at the cost of ten extra parameters. Another objection is that workers do not only acquire skills through schooling, but also through work experience. However, given the relatively good fit of the schooling regression, we believe that our method yields a good approximation to the skill redundancies and shortages in that arise in occupational switches.

3.2 Types of Occupational Switches

People are seldom only over- or underskilled when switching occupations; often they possess some skills that are not needed for the new job, and lack some that are. We therefore classify occupational skill mismatch in a two-by-two grid, using the population medians of skill shortage (0.7 school years) and skill redundancy (0.6 school years) as cutoff points to distinguish between four types of occupational moves (see Table 1). We call moves that involve high skill redundancies and low skill shortages "downskilling" moves. The opposite moves with low redundancies and high shortages are called "upskilling" moves. Workers who switch at high redundancies and high shortages have to change their skill sets completely.

Table 1: Types of Occupational Switchers

		Shortage	
		Above Median	Below Median
Redundancy	Above Median	Reskilled	Downskilled
	Below Median	Upskilled	Lateral

We call such switching “reskilling" moves. When both redundancies and shortages are low, moves are “lateral" and workers barely have to change their skill profiles.

On average, reskilled switchers upgrade their skills for the new job with an extra 1.6 years of education, and leave skills unused representing 1.5 years of education. Upskilling is associated with skill upgrading of 1.9 years on average and skill redundancy of 0.2 years. In contrast, downskilling is associated with 1.7 years of skill redundancy and only 0.2 years of skill upgrading. Finally, lateral switches entail 0.4 years of skill acquisition and 0.3 years of skill redundancy.

Table 2 shows the most common occupational moves by type of occupational switch. Switching from a job as an office clerk to a job as a social worker is the most common move among reskilled switchers. A salesperson becoming an office clerk (office clerk becoming a salesperson) is the most frequent upskilling (downskilling) move. Among the lateral movers, a switch from typist to office clerk is the most commonly observed.

We merge these skill-mismatch measures with data on workers' job histories in Germany (see below) at the level of occupational pairs.

4 Data and Matching Strategy

4.1 Worker Labor-Market History

The Sample of Integrated Labor Market Biographies (SIAB), provided by the IAB, documents workers' employment and unemployment histories. These data are a 2% random sample of all German social security records and are available for the years 1975 to 2010 (Dorner et al., 2010). Because employers are required by law to report the exact beginning and end of any employment relationship that is subject to social security contributions, the SIAB is the largest and most reliable source of employment information in Germany. Moreover, misreporting of earnings is punishable by law, which ensures high reliability of the earnings information. Wages are right-censored, which affects about 7% of our sample.

Table 2: Most Common Occupational Moves by Type of Occupational Switch

Reskilled		Upskilled	
Office clerks	Social workers	Salespersons	Office clerks
Social workers	Office clerks	Office clerks	Buyers, wholesale and retail
Technical draughtspersons	Office clerks	Salespersons	Buyers, wholesale and retail
Salespersons	Office assistants	Office assistants	Office clerks
Cooks	Office clerks	Assistants, laborers	Gardeners, garden workers
Nursery teachers, child nurses	Office clerks	Assistants, laborers	Motor vehicle drivers
Office clerks	Home wardens	Assistants, laborers	Salespersons
Restaurant and hotelkeepers	Office clerks	Cashiers	Salespersons
Office clerks	Watchmen, custodians	Household cleaners	Cooks
Metal workers	Salespersons	Nursing assistants	Social workers
Downskilled, all moves		**Lateral, all moves**	
Office clerks	Salespersons	Typists	Office clerks
Office clerks	Typists	Stores, transport workers	Assistants, laborers
Buyers, wholesale and retail	Office clerks	Assistants, laborers	Stores, transport workers
Buyers, wholesale and retail	Salespersons	Accountants	Office clerks
Office clerks	Office assistants	Office clerks	Accountants
Gardeners, garden workers	Assistants, laborers	Stores, transport workers	Motor vehicle drivers
Salespersons	Household cleaners	Motor vehicle drivers	Stores, transport workers
Salespersons	Assistants, laborers	Building laborers	Assistants, laborers
Entrepreneurs, managers	Office clerks	Warehousemen and managers	Stores, transport workers
Salespersons	Cashiers	Guest attendants	Waiters, stewards

Data source: QCS 2005/2006.

Similar to Dustmann, Ludsteck and Schönberg (2009) and Card, Heining and Kline (2013), we use the method proposed by Gartner (2005) to impute wages for these cases.

4.2 Job Displacement

We define job displacement as the layoff of a tenured worker due to a plant closure or a mass-layoff. We do not consider all layoffs because workers may have been laid-off because of a relatively low productivity, making the layoff endogenous to the worker's expected future performance. Indeed, such layoffs may act as signals for otherwise hard-to-observe performance characteristics (Gibbons and Katz, 1991, 1992; Fox, 1994). Using only plant closures to identify displaced workers has the advantage that employers do not select whose contracts are terminated. However, this comes at the cost of oversampling small plants, which typically have higher failure rates, but also tend to pay lower wages. To circumvent introducing systematic bias in the firm-size distribution from which our sample of displaced workers is drawn, we therefore also consider workers displaced in the course of mass-layoffs (see also Schmieder, von Wachter and Bender, 2010). We use the definition by Hethey-Maier and Schmieder (2013) to identify exogenous displacement events.[9] Because many workers leave closing plants some time before the official closure(for instance, Gathmann and Schönberg, 2010; Davis and Von Wachter, 2011), we include "early leavers" in the sample of displaced, that is, workers who leave the plant one year before the displacement event.[10]

Furthermore, we impose a number of additional conditions. (i) Pre-displacement establishments must have employed at least 10 workers two years prior to the closure, to avoid cases where single workers significantly contribute to the establishment's closure. (ii) Workers must be between 18 and 55 years of age at the time of displacement. (iii) Workers must have at least six years of labor market experience prior to the displacement. Using only workers with at least six years of labor market experience makes pre-displacement wages

[9] That is, we restrict the sample of workers displaced due to a plant closure to include only those displacement events in which more than 80% of all workers were laid off in a given year, with the additional requirement that not more than 20% of the laid-off workers were reemployed at the same plant in the following year. Likewise, workers displaced in a mass-layoff come from firms whose employment declined from one year to the next by thirty percent or more excluding events where blocks of 20% or more workers moved to the same establishment in the subsequent year.

[10] Pfann (2006) and Schwerdt (2011) show that ignoring early leavers biases estimates of displacement costs, although both papers suggest different directions for this bias. Pfann (2006) finds that during the downsizing process prior to closure, the firm displaces workers with low firing costs, low expected future productivity growth, and low lay-off option values. He uses personnel records from a Dutch aircraft building company that went bankrupt in 1996 and shows that high-productivity workers are most likely to be retained. Schwerdt (2011), however, comes to the exact opposite conclusion. Using Austrian administrative data, he finds that early leavers are associated with significantly lower costs of job loss due to plant closure. He further proposes that separations up to two quarters before plant closure should be included in the sample of displaced workers.

better proxies for worker productivity (Altonji and Pierret, 2001; Hanushek et al., Forthcoming) and also allows us to observe workers six years before displacement. (iv) Workers must not have switched occupations in the three years before displacement. On the one hand, this makes it more likely that our (occupation-based) measures adequately describe the true skills of a worker. Thus, being mismatched in the old occupation is unlikely to drive the reemployment decision (Phelan, 2011). On the other hand, it ensures a strong occupational attachment (workers will have a minimum of three years occupational tenure), which makes it less likely that these workers would have left their occupations voluntarily (we report some evidence for this in section 5).[11] (v) Workers must have a minimum of one year of tenure in the closing plant (Fallick, 1993). (vi) Workers must have been displaced only once in the period 1981–2006 because any further displacement can be regarded as endogenous to the first one (e.g., Schmieder, von Wachter and Bender, 2010).[12] (vii) Workers must not have left-censored labor market histories.[13]

We exclude marginally employed workers because we can observe them only from 1999 onward. There are often gaps in the SIAB employment histories, which occur, for example, due to the individual being in further education or retraining, in the military, or on parental leave. For these gap periods we assign zeros to the earnings and working days variables. We allow for gaps up to six years because these may coincide with periods spent obtaining a university education as part of their requalification after displacement, but drop people with gaps longer than six years.

4.3 Matching

Our final sample is comprised of 18,748 workers who were displaced due to a plant closure or a mass-layoff. We observe these individuals each year, starting six years prior to displacement and for as many as 15 years after displacement. For each of these workers, we construct a counterfactual career that these workers would have had had they not been displaced.[14] We construct this counterfactual by matching workers to observationally similar

[11] It is well established in the empirical labor-market literature that the probability of job change is generally declining with tenure. For instance, Topel and Ward (1992) find that for men, two-thirds of all job changes happen in the first 10 years after entering the labor market. Farber (1994) shows that the job hazard rate peaks after three months of employment, and declines afterward. Abraham and Farber (1987) estimate a Weibull hazard model for job change transitions, finding that the hazard declines sharply with tenure.

[12] 85% of all displaced workers are displaced only once in their work history.

[13] Our dataset starts in 1975 for West Germany and in 1991 for East Germany. The largest share of the individuals in 1975 and East Germans in 1991 have left-censored labor market histories. We therefore delete all those who appear for the first time in 1975 in West Germany or in 1991 in East Germany and who are older than 21.

[14] Biewen et al. (2014) use a combination of exact and non-exact matching techniques to investigate the effectiveness of public sponsored training. Ichino et al. (2013) compare differences in the transitions of

workers in a sample of workers who have never been displaced and who meet the experience and tenure requirements imposed on our sample of displaced workers.

To do so, we perform exact matching between displaced and non-displaced workers on gender, education (six categories), firm location (East or West Germany), sector (four categories), and detailed occupation (263 categories).[15] By construction, displaced and non-displaced subjects are exactly aligned along these criteria. Since we are investigating the role of occupational switching in explaining displacement costs, it is especially important that workers in the control group are in the same occupation as displaced workers at the point of (virtual) displacement. Moreover, worker gender, educational degree, region, and sector are also highly relevant for labor-market outcomes, which underlines the importance to match on these variables.

However, it is well known that matching solely on observables can be inadequate if relevant variables are unobserved and therefore omitted (for a discussion, see Angrist and Pischke, 2008). We thus additionally employ propensity score matching on pre-displacement outcomes, namely, daily wages, and days worked. Assuming that wages capture productivity differences across workers[16] and that working days reflect individual preferences for labor market activity, matching on pre-treatment outcomes controls for selection into occupational switching.[17] To ensure that workers in the treatment and control groups follow the same trends before (virtual) displacement, we also match on the simple growth rate from $t-6$ until $t-3$ of both wages and days worked, with t being the year of (virtual) displacement. We also include age and occupational tenure into the calculations of the propensity score. Finally, we add an interaction term between gender and occupational tenure to account for the possibility that employers value the same occupational experience differently for men and women. For each displaced worker, we select the closest control in terms of the estimated propensity score from those workers who also meet the exact-matching requirements, using

old and young workers who lost their jobs due to a plant closure. The authors select a control group out of the sample of non-displaced workers by matching exactly on a broad set of pre-displacement worker characteristics and job attributes. They perform non-exact matching on daily wages and firm size. Eliason and Storrie (2006) and Leombruni, Razzolini and Serti (2013) perform non-exact (nearest neighbor) matching to eliminate differences in observables between displaced and non-displaced workers.

[15] We also match exactly on the year of (virtual) displacement. For non-displaced workers, the virtual displacement year is chosen at random provided that the sample restrictions are fulfilled.

[16] Among others, Hendricks (2002) argues that observed earnings of migrants are a suitable measure of their human capital endowment.

[17] Ashenfelter and Card (1985) account for pre-training earnings to correct for the fact that participants in training programs experience a decline in earnings prior to the training period. In the context of sorting induced by redistribution policies, Abramitzky (2009) argues that wages well capture individual characteristics that influence selection. McKenzie, Gibson and Stillman (2010) control for pre-migration wages to investigate earning gains from migration. They find that results from the difference-in-differences specification are reasonably close to the results obtained from using experimental data.

one-to-one nearest neighbor matching (without replacement).[18]

Although we apply a highly demanding matching procedure, we obtain a close "statistical twin" in the sample of non-displaced subjects for 13,724 (73.2%) displaced subjects. Table 3 shows the matching variables and their distributions by groups of displaced and non-displaced workers. After our matching procedure, the means of the pre-treatment variables look similar for the two groups of workers (Column 1) and are exactly the same for the variables on which we match exactly (not shown). This observation is confirmed by the results of a standard t-test for the equality of means (Column 2). The only significant differences between displaced and non-displaced workers arise for days worked in $t-6$, growth in days worked between $t-6$ and $t-3$, and age. However, although significant, the magnitudes of the differences are very small.

Table 3: Quality of Matching

	Mean		t-test	
Variable	Non-displaced	Displaced	t	p < |t|
Daily wage in $t-2$	80.51	80.93	-1.11	0.268
Daily wage in $t-3$	78.32	78.77	-1.17	0.244
Daily wage in $t-4$	76.42	77.02	-1.57	0.116
Daily wage in $t-5$	74.40	74.86	-1.22	0.221
Daily wage in $t-6$	72.80	73.26	-1.32	0.189
Day worked in $t-2$	362	362	-0.06	0.953
Day worked in $t-3$	358	358	0.92	0.357
Day worked in $t-4$	357	356	0.82	0.413
Day worked in $t-5$	356	355	1.34	0.179
Day worked in $t-6$	358	356	2.15	0.032
Daily wage growth $t-6$ to $t-3$	0.13	0.14	-1.52	0.128
Days worked growth $t-6$ to $t-3$	0.06	0.10	-3.02	0.003
Age	38.57	38.26	3.42	0.000
Occupational experience in $t-2$	9.16	9.11	0.74	0.457

Notes: Days worked include weekends, holidays, short sick leaves, and vacation days. For the ease of exposition, days worked are rounded to the next integer. *Data source:* SIAB 1975–2010.

[18] Kernel matching (see Biewen et al., 2014) yields qualitatively similar results.

4.4 Final Sample

The final sample includes 13,724 displaced workers and an equal number of matched non-displaced workers whose employment, unemployment, and non-participation history we follow for 15 years after (virtual) displacement. Within the sample of displaced workers, we distinguish between occupational switchers and occupational stayers. An occupational switch occurs if a worker moves between any of the 263 three-digit occupations.[19]

Out of the sample of displaced workers, 9,823 (71.6%) stay in the same three-digit occupation after displacement, while 3,901 (28.4%) workers change occupations. Table 4 sets out descriptive statistics for the sample of all displaced workers, as well as occupational stayers and switchers, and their statistical twins among the non-displaced. Both stayers and switchers are mostly male and primarily work in West Germany. They also have similar working days and age. However, switchers have somewhat lower earnings than stayers. They also have less occupational tenure and more often work in the primary or secondary sector than do stayers. However, the non-displaced controls are similar to the displaced in all variables, so any differences between displaced stayers and switchers will not affect our estimates of differential displacement costs.[20]

In our sample of displaced occupational switchers, 521 (13%) workers are reskilled, 1,435 (37%) are upskilled, 1,470 (38%) are downskilled, and 475 (12%) are lateral switchers. Table 5 provides descriptive statistics for the four types of displaced occupational switches and their matched controls. We observe that the matching exercise evened out almost all differences between switcher types and their controls; only the differences in age and occupational experience are significant for upskilled switchers. Displaced workers appear to be somewhat younger and less experienced than their counterfactuals. However, to ensure that these differences are not affecting our results in a systematic fashion, we control for a quadratic polynomial in age in the regressions (see Section 6).

5 The Effect of Displacement on Occupational Moves

Does displacement affect the probability of switching occupations? And if so, does it also affect the direction of the switch? Unlike workers who change jobs voluntarily, choices of displaced workers will be more limited, especially if workers are displaced in regions with no

[19] To check whether our results are sensitive to the definition of occupational switcher, we used two other definitions. In the first (second) definition, we drop workers who leave the post-displacement occupation for a third occupation within one year (two years). Since our results are not sensitive to these definitional changes, we report only the results based on the broadest definition of occupational switching.

[20] The only significant difference between displaced and non-displaced workers emerges for age; this difference, however, appears small in magnitude.

Table 4: Descriptive Statistics

	Matched Sample			Switchers		
	ND	D	$p < \|t\|$	ND	D	$p < \|t\|$
Number of individuals	13,724	13,724		3,901	3,901	
Mean annual earnings in $t-2$ (€)	29,372	29,471		28,348	28,259	
Mean real daily wage in $t-2$ (€)	80.51	80.93	0.268	77.83	77.84	0.990
Mean days worked in $t-2$	362	362	0.953	362	361	0.252
% Women	35.80	35.80	1.000	30.33	30.33	1.000
% East Germany	14.60	14.60	1.000	16.23	16.23	1.000
% Primary and secondary sector	49.01	49.01	1.000	58.14	58.14	1.000
Age	38.57	38.26	0.000	38.30	37.63	0.000
Occupational experience	9.16	9.11	0.457	8.43	8.29	0.191

Notes: Earnings, wages, days worked, and occupational experience are measured two years prior to displacement. Days worked contain weekends, holidays, short sick leaves, and vacation days. For the ease of exposition, days worked are rounded to the next integer. *Data source:* SIAB 1975–2010.

Table 5: Descriptive Statistics by Type of Occupational Switch

	Reskilled Switchers			Upskilled Switchers			Downskilled Switchers			Lateral Switchers		
	ND	D	p < |t|	ND	D	p < |t|	ND	D	p < |t|	ND	D	p < |t|
Number of individuals	521	521		1,435	1,435		1,470	1,470		475	475	
Mean annual earnings in $t-2$ (€)	29,642	29,723		27,252	27,772		29,641	28,910		26,236	26,111	
Mean real daily wage in $t-2$ (€)	81.67	81.66	0.993	74.82	76.55	0.108	81.22	79.67	0.175	72.24	71.90	0.838
Mean days worked in $t-2$	362	362	0.603	362	361	0.516	363	361	0.098	361	362	0.642
% Women	18.81	18.81	1.000	14.56	14.56	1.000	17.28	17.28	1.000	15.16	15.16	1.000
% East Germany	24.18	24.18	1.000	31.71	31.71	1.000	29.80	29.80	1.000	34.53	34.53	1.000
% Primary and secondary sector	60.65	60.65	1.000	55.68	55.68	1.000	59.86	59.86	1.000	57.47	57.47	1.000
Age	38.02	37.61	0.348	38.50	37.20	0.000	38.25	37.90	0.197	38.12	38.14	0.968
Occupational experience	8.32	8.20	0.667	8.66	8.32	0.045	8.36	8.36	0.986	8.03	8.11	0.807

Notes: Earnings, wages, days worked, and occupational experience are measured two years prior to displacement. Days worked contain weekends, holidays, short sick leaves, and vacation days. For the ease of exposition, days worked are rounded to the next integer. *Data sources:* QCS 2005/2006, SIAB 1975–2010.

job vacancies in the same or related occupations of if work in these occupations is becoming scarce because of a secular shift in technology.[21] In such cases, workers may decide to switch occupations, and job displacement will increase the probability of occupational change.

Figure 4 shows that displacement indeed substantially increases occupational mobility.[22] In the first year after (virtual) displacement, 20.7% of the displaced workers are employed in an occupation other than their pre-displacement occupation, while only 3.2% of the non-displaced workers change occupations. (Note that due to our sample restrictions neither displaced nor non-displaced workers change occupations in the three periods before displacement.) Occupational mobility of displaced workers only slowly converges to that of non-displaced workers; in fact, the share of occupational switchers among displaced workers is significantly larger than the corresponding share for non-displaced workers up to 15 years after displacement.[23] This substantial increase for displaced workers in the hazard of occupational change translates into a higher risk of incurring any type of skill mismatch.

Core to this study is the notion that occupational change has a direction in terms of whether workers face skill redundancies or shortages at the new job. In the short run, occupational changes that do not require the acquisition of additional skills (lateral and downskilled) are less costly than those that do (reskilled and upskilled). However, the latter types of occupational switches will most likely have long-term payoffs. Therefore, the decision to invest in up- or reskilling depends on workers' remaining years of working life. The average age of displaced workers in our sample is 38.3 years, which means that a typical worker will stay in the labor market for 25 more years. However, compared to non-displaced workers (who do not have to leave their current employer), displaced workers have substantially less negotiation power when searching for new jobs. Employers will in general avoid workers who lack all required skills, but have no reason to reward redundant skills. Therefore, displacement may increase the probability of switching to occupations for which a worker has all necessary skills, that is, it may increase downskilling and lateral moves.

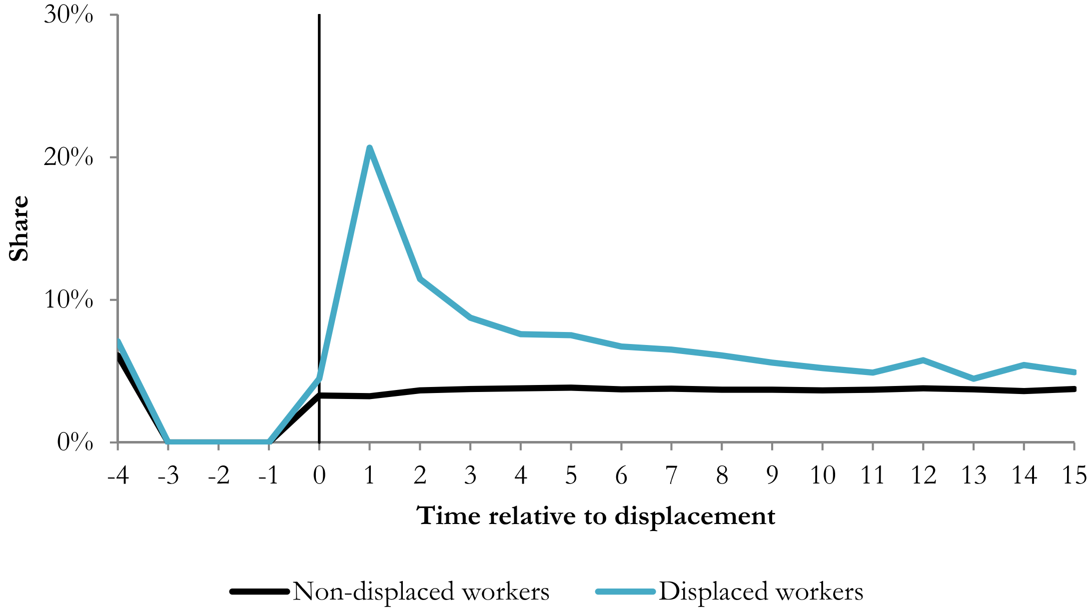
Table 6 shows the results from a multinomial logistic regression that models occupational choice as a function of displacement. Workers choose between staying in the same occupation (which is our baseline group) and the four types of occupational switches defined in Section 3.

[21] Nedelkoska (2013) finds that German workers employed in occupations that are prone to technological substitution and outsourcing have a significantly higher hazard of occupational change.

[22] Note that for this analysis we extended the samples of both non-displaced and displaced workers beyond those obtained after matching primarily because non-displaced workers hardly ever change their occupation, rendering the groups of upskilled, downskilled, reskilled, and lateral occupational switchers too small to allow for meaningful comparisons between displaced and non-displaced switchers. We thus used a 5% random sample of non-displaced workers. To remain consistent, we also use all 18,748 displaced workers, so displaced and non-displaced workers were subject to the same sample selection criteria described in Section 4. We add all matching variables (see Section 4) as controls in the multinomial logit estimations.

[23] Results are available on request.

Figure 4: Job Displacement Induces Occupational Moves



Notes: The figure plots the share of workers who change occupations (263 categories) in a given year. The sample includes all displaced workers who meet the selection criteria explained in 4.2 (18,748 workers in $t = 0$) and a 5% random sample of non-displaced workers who meet the same criteria (80,462 workers in $t = 0$). (Virtual) displacement takes place in year zero. *Data source:* SIAB 1975–2010.

The regression controls for all the matching variables described in Section 4.3. Coefficients are reported as relative risk ratios. The results show that, compared to non-displaced workers, displaced workers are 8.6 times more likely to switch to an occupation with very similar skill requirements (lateral switches) and 8.2 times more likely to switch to an occupation that leaves a substantial part of the previously acquired skills idle (downskilled switches). On the other hand, switches that require workers to learn new skills, but keep most of the previously acquired skills in use (upskilled switches) and switches that require obtaining a completely different skill set (reskilled switches) are only about 7.5 times more likely among displaced vis-à-vis non-displaced workers. These differences in coefficients already indicate that displacement alters the direction of occupational switching.

Table 6: The Effect of Job Displacement on Skill Mismatch, Full Sample

Independent variable →	Displacement
Reskilled	7.472***
	(34.36)
Upskilled	7.465***
	(50.89)
Downskilled	8.213***
	(53.21)
Lateral	8.649***
	(30.96)
Observations	89,962
χ^2(df=212)	11183.71
Pseudo R^2	0.14

Notes: The sample includes all displaced workers who meet the selection criteria explained in 4.2 and a 5% random sample of non-displaced workers who meet the same criteria. All matching variables are used as controls (see Section 4.3). Occupational stayers are the base category. The reported coefficients are relative risk ratios (RRR). z statistics are reported in parentheses. *Data sources:* QCS 2005/2006, SIAB 1975–2010. *** p<0.01, ** p<0.05, * p<0.1.

The results in Table 7, where we condition on occupational switching, support this conclusion. We observe that displaced workers clearly exhibit different switching patterns than do non-displaced workers. Relative to workers who downskill, displacement decreases the probability of upskilling and reskilling, respectively, where the coefficient on upskilling is just shy of statistical significance ($p = 0.124$). At the same time, the relative probability of lateral moves is very similar for displaced and non-displaced workers ($p = 0.753$). These findings are in line with the hypothesis put forward above that displaced workers lack negotiation power and must accept that their previously acquired skills are left unused rather than employers having to accept skill deficits.

Table 7: The Effect of Job Displacement on Skill Mismatch, Occupational Switchers

Independent variable →	Displacement
Reskilled	0.886*
	(-1.70)
Upskilled	0.916
	(-1.54)
Lateral	1.026
	(0.31)
Observations	8,672
χ^2(df=156)	1513.10
Pseudo R^2	0.07

Notes: The tables shows regressions analogous to those in Table 6 for the sample of occupational switchers. All matching variables are used as controls (see Section 4.3). Downskilled switchers are the base category. The reported coefficients are relative risk ratios (RRR). z statistics are reported in parentheses. *Data sources:* QCS 2005/2006, SIAB 1975–2010. *** p<0.01, ** p<0.05, * p<0.1.

6 Skill Mismatch and the Cost of Displacement

6.1 Estimation Strategy: Event-Study Framework

In the previous section, we established differential switching patterns of displaced vis-à-vis non-displaced workers. We now analyze whether these differences can explain why switchers experience such difficult transitions after displacement by investigating displacement costs by switcher type. To gauge the role of occupational switching in explaining displacement costs, we employ a difference-in-differences approach, in combination with matching on pre-displacement outcomes and controlling for unobserved selection into occupations based on time-invariant characteristics. Our identification strategy rests on the assumption that, conditional on pre-displacement outcomes, worker fixed effects, and further observable worker characteristics, workers in the control group (non-displaced) provide appropriate counterfactuals for those in the treatment group (displaced).

We estimate variants of the following regression:

$$
\begin{aligned}
Y_{it} &= \alpha_i + \gamma_t + X_{it}^{'}\delta \\
&+ \sum_{k\geq -4}^{15} \beta_1^k T_{it}^k + \sum_{k\geq -4}^{15} \beta_2^k T_{it}^k D_i \\
&+ \sum_{k\geq -4}^{15} \beta_3^k T_{it}^k Switcher_i + \sum_{k\geq -4}^{15} \beta_4^k T_{it}^k D_i Switcher_i \\
&+ \varepsilon_{it},
\end{aligned} \tag{2}
$$

where Y_{it} is the outcome of interest (annual earnings, daily wage, or days worked) of individual i in year t. The inclusion of worker fixed effects, denoted by α_i, controls for any differences between displaced and non-displaced workers that remain after applying our matching procedure. Accounting for worker fixed effects also allows the selection into occupational switching to depend on time-invariant characteristics.[24] γ_t are calendar time effects, which account for economy-wide changes in the outcome over time, for instance, business cycle effects. The vector X_{it} consists of observed, time-varying characteristics of the worker, namely, age and age squared.

The dummy variables T_{it}^k take the value 1 if worker i is observed in year t at a distance of k years from (virtual) plant closure or mass-layoff, with $k = 0$ denoting the year of (virtual) displacement. D_i is a dummy variable taking the value 1 if i is displaced in a plant closure or a mass-layoff in the period 1981–2006. $Switcher_i$ takes the value 1 if the *displaced* worker changes occupations. That is, the dummy is one if (a) i is displaced and observed in an occupation different from the pre-displacement occupation when he or she re-appears in the labor market; or (b) i is a matched control to a displaced switcher. These matched controls do not necessarily switch occupations, but are otherwise statistically identical to the displaced switchers and thus provide a counterfactual outcome path for displaced switchers. Depending on the specification, the dummy variable $Switcher_i$ can also refer to underskilling, overskilling, lateral, or reskilling switchers and their matched controls. ε_{it} is an error term for unexplained person-year variation in the dependent variable..

Taken together, the β-coefficients in Equation (2) separately describe the time path of the outcome of displaced and non-displaced workers from four periods prior to displacement to 15 periods after displacement for occupational stayers and switchers separately. The difference in the outcome between displaced and non-displaced workers for stayers is:
$E(Y_{it} \,|\, Switcher_i = 0,\ D_i = 1,\ T_{it}^k = 1) - E(Y_{it} \,|\, Switcher_i = 0,\ D_i = 0,\ T_{it}^k = 1) = \beta_2^k$.

[24] The fixed effects are identified by the variation in the outcome in years 5 and 6 before displacement.

For switchers, the within-group difference reads:

$$E(Y_{it} \,|\, Switcher_i = 1,\ D_i = 1,\ T_{it}^k = 1) - E(Y_{it} \,|\, Switcher_i = 1,\ D_i = 0,\ T_{it}^k = 1) = \beta_2^k + \beta_4^k.$$

The time path of the difference between both within-group differences, that is, the difference-in-differences estimate, is given by β_4^k. This estimate measures any additional effect of being an occupational switcher (or any type thereof) beyond the common effect of job displacement.

6.2 Results

Figure 5 shows the results of estimating Equation (2) for each of the four groups of occupational switchers (that is, downskilled, upskilled, lateral and reskilled), with annual earnings as the outcome variable. The left-hand side figures compare the effect of being displaced for occupational stayers with the combined effect of being displaced and mismatched. The right-hand side figures plot the empirical counterpart of the difference-in-differences estimate, β_4^k, in Equation (2).

The first observation is that the pre-displacement trends are flat for both stayers and switchers.[25] Apparently, conditional on using worker fixed effects, the matching exercise achieves a very good balance in earnings trends even within the different switcher groups. If switching behavior had been driven by (unobserved) productivity differences beyond what our estimation strategy controls for, we would not have expected these trends to be flat. For instance, assume that upskilled workers have a higher productivity than downskilled workers, but that this productivity differential is not picked up by the matching. In that case, pre-displacement earnings, which are a proxy for worker productivity, would not have been well-balanced between displaced and non-displaced workers. Second, stayers and switchers suffer displacement costs in almost every period.[26] Put differently, neither staying in the pre-displacement occupation nor switching occupations can shield displaced workers against experiencing earning losses. However, the post-displacement earning development of switchers *relative* to that of stayers differs remarkably by switcher type, which is indicated by the difference-in-differences graphs. We focus on these relative outcomes of switchers in the remainder of this section.

[25] An exception is the last pre-displacement year, in which we already find a modest drop in annual earnings of displaced workers (see Jacobson, LaLonde and Sullivan, 1993, Schmieder, von Wachter and Bender, 2010, and Davis and Von Wachter, 2011 for a similar result). Commonly, this is interpreted as an early sign of distress of the plants that are closing down.

[26] One may argue that annual earnings overestimate the true displacement costs, given the generous German welfare system. However, our results are similar when we use workers' disposable income, that is, earnings plus unemployment insurance benefit, as the outcome variable. This is in line with Schmieder, von Wachter and Bender (2010), who find that using annual earnings or annual income leads to comparable estimates of displacement costs.

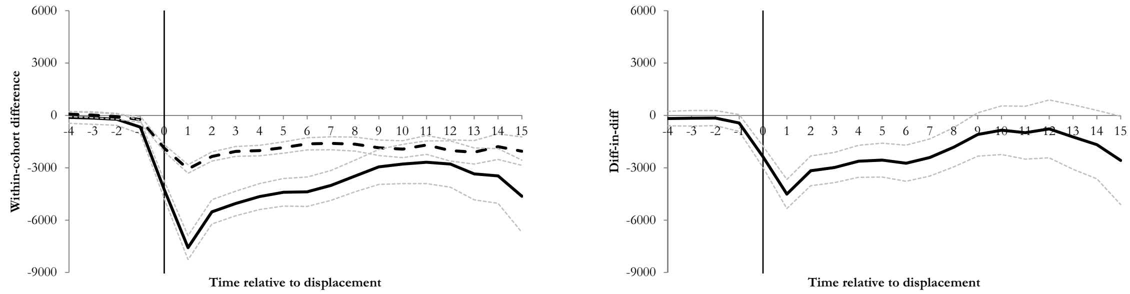
Compared to stayers and relative to the control group, downskilled occupational switchers experience the largest earning losses. One year after displacement, the relative earnings of downskilled switchers drop sharply by roughly €4,500, or 16.3% of pre-displacement earnings. These immediate losses are calculated as the difference-in-differences estimate (that is, β_4^k) in period $t+1$ net of the corresponding estimate in $t-2$, where insignificant difference-in-differences estimates are set to zero. We chose $t-2$ as period for comparison because it is unlikely that future displacement affects outcomes two periods before actual displacement. To express immediate losses relative to pre-displacement earnings, we divide these losses by the average earnings in periods $t-6$ to $t-2$. Recovery is very slow, and only nine years after displacement the earning losses relative to stayers become insignificant. In the 15 years after displacement, the additional average earning losses of downskilled switchers amount to 6.3% of pre-displacement earnings per year. These losses are calculated by taking the mean of the difference-in-differences estimates in periods $t=0$ to $t=15$ and then subtracting the mean of these estimates prior to displacement, that is, in periods $t=-4$ to $t-2$, setting insignificant difference-in-differences estimates once again to zero.

In contrast, the adverse earning effects for reskilled, lateral, and especially upskilled switching after displacement are more temporary in nature. Specifically, upskilling switchers close the earning gap to stayers very quickly; however, they never overtake them. While upskilled switchers incur immediate earnings losses upon displacement of about €2,100 relative to stayers, or 8.0% of pre-displacement earnings, their earnings recover almost immediately and show a clear upward trend. On average, upskilled switchers lose a modest €184 or 0.7% of pre-displacement earnings per year more than stayers over 15 post-displacement years. Total earnings losses of downskilled switchers are about twice as large as those incurred by upskilled switchers, highlighting the asymmetry of occupation switches. However, if upkilled switchers incurred costs in terms of education taken to acquire new skills, the net benefits of such moves are uncertain.

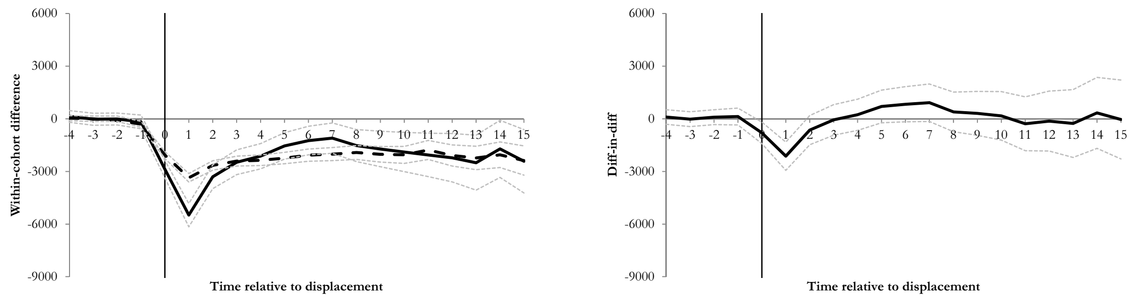
The earnings of reskilled and lateral switchers also recover quickly after displacement, although the positive earning development for these groups is not as pronounced as it is for the upskilled switchers. Moreover, because of the small sample size for these switcher groups, it is less precisely estimated. In most periods we therefore cannot reject that either of these two switcher types experience the same evolution of their earnings as stayers do.

Figure 5: Effects of Skill Mismatch on Annual Earnings

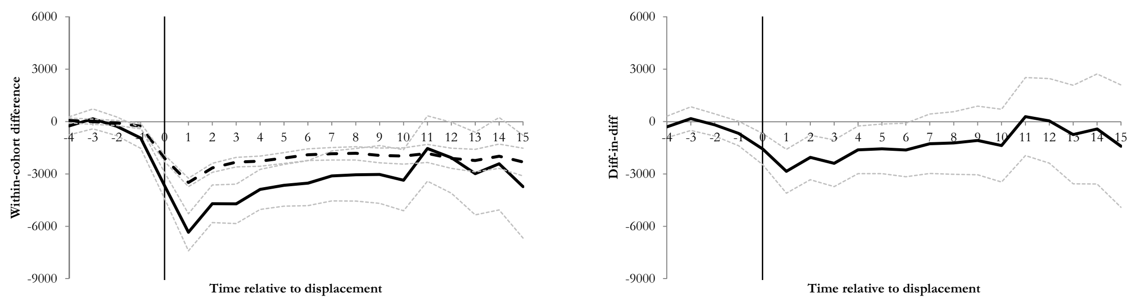
(a) Stayers vs. Downskilled Switchers



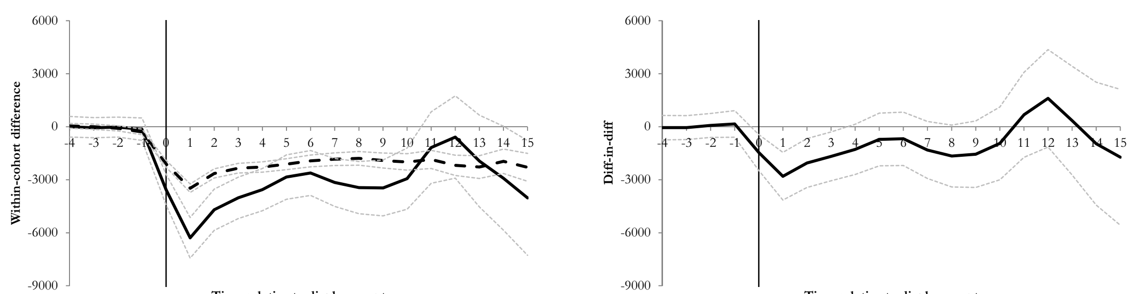
(b) Stayers vs. Upskilled Switchers



(c) Stayers vs. Lateral Switchers



(d) Stayers vs. Reskilled Switchers



Notes: The figure plots coefficients from estimating Equation (2) with annual earnings (in real €2005) as the dependent variable. Controls include calendar time and individual fixed effects, as well as age and age squared. In each left-hand side panel, the straight line represents displaced stayers; the dashed line represents displaced switchers. The 90% confidence intervals are derived from standard errors clustered by individual. *Data sources:* QCS 2005/2006, SIAB 1975–2010.

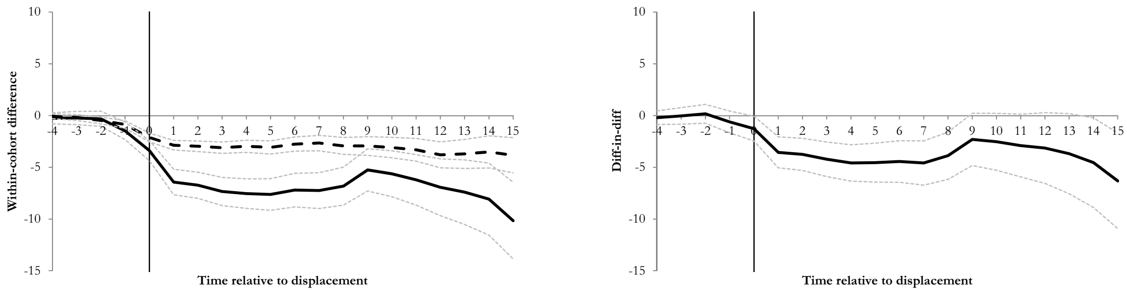
The displacement costs shown in Figure 5 occur from a combination of unemployment spells and reduced wages at the new job. If the differences in the displacement effect in terms of earning losses is due to differences in skill mismatch associated with each switching type, these differences should materialize through drops in daily wages, not lower re-employment rates. For instance, downskilled switchers should experience drops in pay rates, while upskilled switchers should gain in wage. Moreover, lateral switchers should have experiences similar to those of displaced occupational stayers, neither suffering a large drop nor enjoying a significant raise in pay rate. Because reskilled switchers, who move over large skill distances, lose and gain substantial amounts of skills at the same time, their wage development is harder to foresee.

Given that information on the exact number of hours worked is unavailable, we use daily instead of hourly wage rates for this analysis. Figure 6 shows difference-in-differences plots with daily wages as the dependent variable.[27] These graphs support the hypothesis that skill mismatch is a main driver of displacement costs. Downskilled workers lose an average of €3 in daily wages more than stayers, which corresponds to 3.6% of pre-displacement wages. There is no apparent tendency for recovery; only towards the end of the observation period do relative wage losses become (marginally) insignificant. The wage path of upskilled workers is markedly different. First, conditional on being employed, there are barely any immediate or long-term displacement costs. Second, the wage gap between upskilled workers and occupational stayers becomes larger over time and is positive in all but one post-displacement periods. On average, upskilled workers gain €3.4 or 4.4% of pre-displacement wages on stayers. Like the annual earnings development, the wage development for lateral and reskilled switchers is somewhat in between those of downskilled and upskilled switchers. The relative wage losses amount to a modest 0.6% for lateral switchers and are virtually non-existing for reskilled switchers.

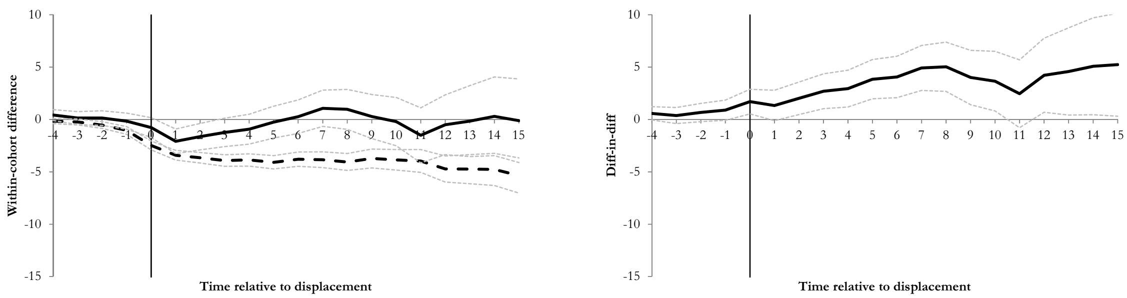
[27] In the daily-wage regressions, we restrict the sample to workers being full-time employed on June 30th of each year. Thus, these estimates can be interpreted as "intensive margin" effects. We use only full-time employees because daily wage is not a meaningful measure of productivity for part-time employees.

Figure 6: Effects of Skill Mismatch on Daily Wages

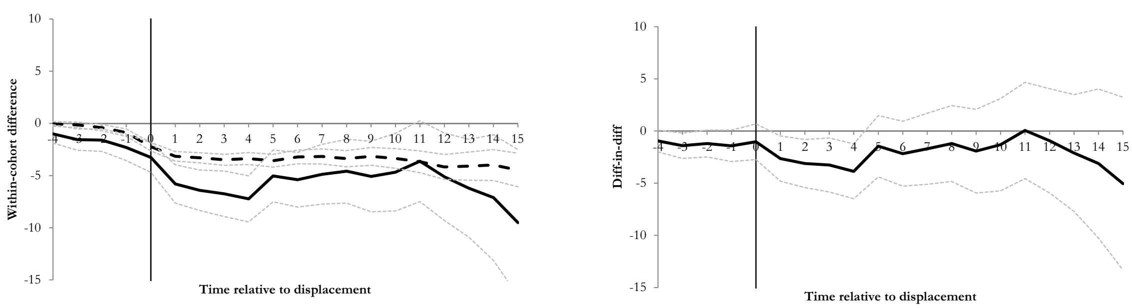
(a) Stayers vs. Downskilled Switchers



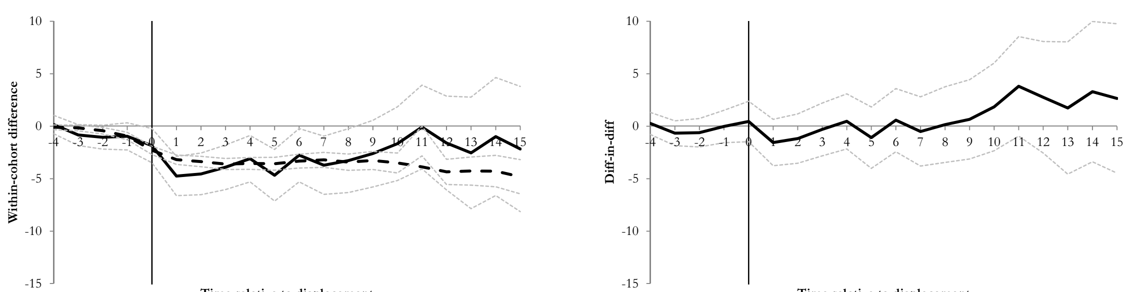
(b) Stayers vs. Upskilled Switchers



(c) Stayers vs. Lateral Switchers



(d) Stayers vs. Reskilled Switchers

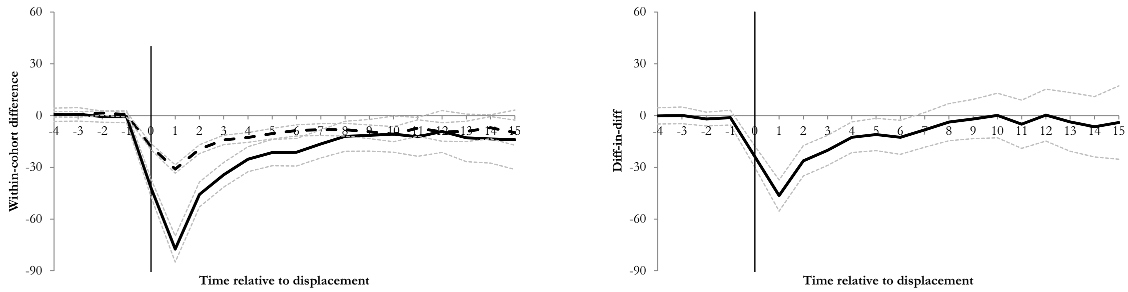


Notes: The figure plots coefficients from regressions analogous to those underlying Figure 5 with daily wages (in real €2005) as the dependent variable and conditional on being full-time employed on June 30th in a given year. In each left-hand side panel, the straight line represents displaced stayers; the dashed line represents displaced switchers. The confidence intervals are defined at the 90% level and are derived from standard errors clustered by individual. *Data sources:* QCS 2005/2006, SIAB 1975–2010.

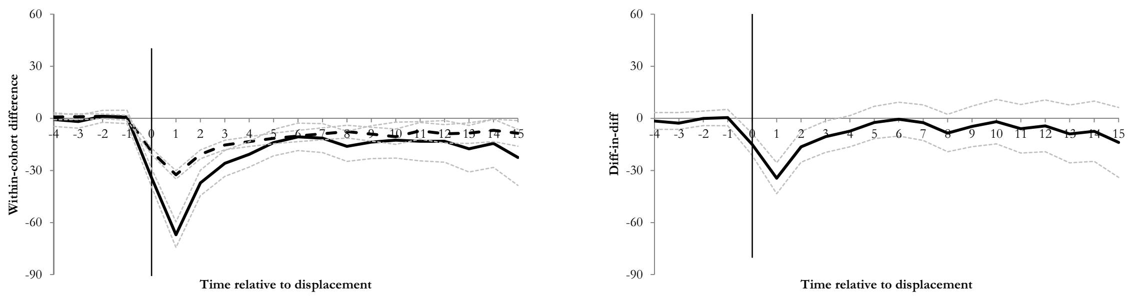
Figure 7 shows that the initial post-displacement losses and subsequent recovery in annual earnings are primarily due to changes in the number of days worked. Moreover, employment rates of displaced workers are already reduced in the year before displacement, which explains the decline in annual earnings prior to the displacement year. However, it is important to note that the evolution in days worked is similar for all four types of displaced switchers. Each type of occupational switcher initially experiences a severe detachment from the labor market in the first two to three years after displacement. However, employment recovers quickly in all groups, and trends look similar across groups. On average, downskilled switchers decrease their number of working days following displacement by 10 days more than stayers, a decline of 2.7% compared to their pre-displacement employment rates. Upskilled switchers experience reductions in employment of 5 days on average, which is a decline of 1.3%. Lateral (reskilled) switchers work 5 (12) days less after displacement, which corresponds to a drop of 1.3% (3.4%). Although modest, these differences in post-displacement labor-force attachment across switcher types make intuitively sense; for instance, workers who switch their skill portfolio completely (reskilled) have to invest more in training before entering a new occupation than laterals, who switch very close to their initial skill portfolio.

Figure 7: Effects of Skill Mismatch on Days Worked

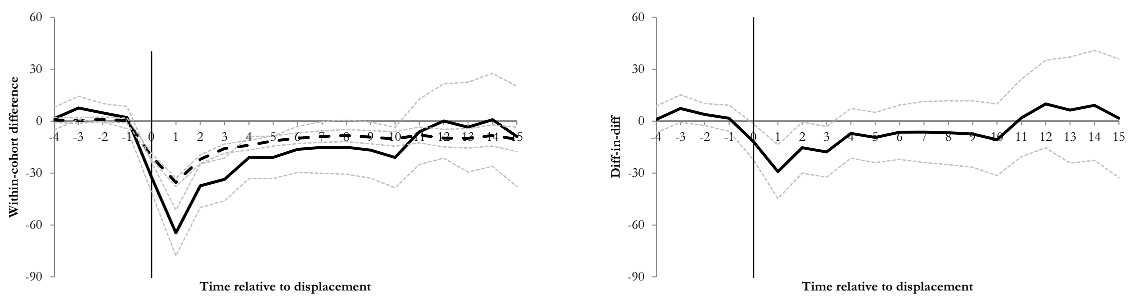
(a) Stayers vs. Downskilled Switchers



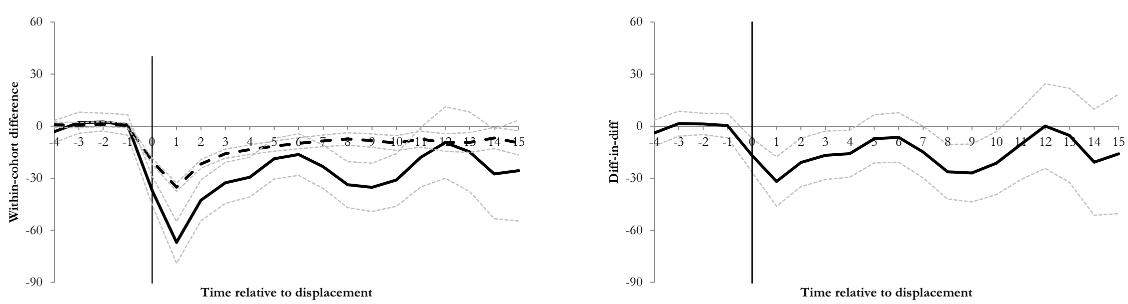
(b) Stayers vs. Upskilled Switchers



(c) Stayers vs. Lateral Switchers



(d) Stayers vs. Reskilled Switchers



Notes: The figure plots coefficients from regressions analogous to those underlying Figure 5 with days worked as the dependent variable. In each left-hand side panel, the straight line represents displaced stayers; the dashed line represents displaced switchers. The confidence intervals are defined at the 90% level and are derived from standard errors clustered by individual. *Data sources:* QCS 2005/2006, SIAB 1975–2010.

A large part of the losses that displaced workers experience are due to lower employment after displacement; irrespective of the switcher type, at least 40% of the total earning losses are due to unemployment periods or a decrease in working days after displacement. However, we observe that the relative contribution of decreases in labor supply (as compared to decreases in pay rate) to the displacement costs differs substantially between switcher types. In the case of downskilled workers, 41.1% of the annual earning losses result from fewer working days. In the case of upskilled switchers, however, more than 95.8% of the losses are due to lower employment. Reskilled switchers (74.7%) and lateral switchers (50.7%) are somewhat in between. This strongly suggests that the loss of specific human capital is an important mechanism behind the large and persistent earning losses of displaced workers.

7 Conclusions

We investigate the role of skill specificity in explaining the size and persistence of earnings losses of workers displaced due to a plant closure or mass-layoff in Germany between 1981 and 2006. We find that such job displacements drastically increase a worker's probability of changing occupations. Workers who switch occupations after displacement experience annual earnings losses that are considerably higher than those of people who stay in the pre-displacement occupation (6.0% vs. 13.5%).

We introduce measures of skill mismatch between occupations that allow us to classify occupational switches as upskilling, downskilling, reskilling, or lateral. Most individuals who switch occupations after displacement are either over- or under-skilled at the post-displacement job. A smaller share of occupational switchers moves to jobs that require a completely different skill set (reskill) and another small share stays in highly related occupations (lateral switchers). However, comparing occupational switching patterns between displaced and non-displaced workers, we find that job displacements significantly increase the probability of entering an occupation with lower skill requirements, and decreases the probability to switch over long skill distances.

Downskilled switchers fare worse in terms of post-displacement earnings than all other types of switchers, losing on average 14.9% of their pre-displacement earnings per year relative to their counterfactual. They also experience significantly larger displacement costs than stayers for up to year 9 after displacement. Workers moving to more skill-demanding occupations (upskilling) lose only a modest 0.7% of pre-displacement earnings more than stayers. When we consider daily wages as a more direct measure of a worker's productive human capital, differences in the transitions between upskilled and downskilled switchers become even more pronounced. While there is again no tendency toward recovery for downskilled workers, upskilled workers earn significantly more than stayers from the second year after displacement.

We conclude that skill mismatch is an important mechanism behind the observed pattern of large and irreversible earnings losses of displaced workers. These losses depend on the extent to which the skills used in the pre-displacement occupation become redundant at the new job.

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A Appendix

Table A.1: Schooling Regression

Independent variable->	Years of schooling
Factor1 (cognitive)	1.488***
	(0.0946)
Factor2 (science)	1.159***
	(0.111)
Factor3 (technical)	0.132
	(0.110)
Factor4 (sales)	0.0911
	(0.0959)
Factor5 (medical care)	0.325***
	(0.0900)
Factor6 (work disutility)	-0.556***
	(0.140)
Constant	12.42***
	(0.0830)
Observations (occupations)	263
R-squared	0.734

Note: Skills are measured in standard deviations.

Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

Table A.2: Factor loadings

	Cognitive	Technical	Interactive	Commercial	Production	Security
Tasks:						
Production of goods	-0.5164	0.2698	-0.1196	-0.0377	0.3062	0.0738
Measuring, checking, quality control	-0.312	0.5935	-0.0438	0.0193	0.3643	0.0257
Monitoring, operating of machines	-0.5159	0.4212	0.0008	-0.3061	0.2779	0.2664
Repair, maintenance	-0.3021	0.6288	0.085	0.1346	-0.132	-0.1604
Purchase, procurement, sales	0.2601	-0.0385	0.2298	0.7052	0.2117	0.1044
Transport, storage, distribution	-0.3692	0.1024	0.2355	0.2905	0.0343	0.2356
Advertising, marketing, PR	0.4479	-0.2334	0.0462	0.3349	-0.0826	0.1637
Organize, plan, prepare work processes	0.4884	0.2954	0.1703	0.1547	0.0591	0.0175
Develop, plan, design	0.4526	0.3081	-0.337	-0.0247	0.1527	-0.2592
Educate, teach, raise	0.5314	0.1002	0.4148	-0.1933	0.0636	-0.1936
Collect information, research, document	0.8232	0.0484	-0.0573	-0.0978	0.0701	0.0395
Consult, inform	0.7969	-0.0065	0.2251	0.1943	-0.0163	0.087
Serve, accommodate, prepare food	0.0107	-0.2165	0.4189	0.0806	0.2114	0.087
Care, parent, cure	0.3187	-0.0401	0.6343	-0.2007	0.3203	-0.1493
Secure, protect, guard, monitor, regulate traffic	-0.0369	0.2645	0.3327	-0.2895	0.0555	0.2705
Work with computers	0.667	0.04	-0.4008	-0.149	0.1888	0.2675
Cleaning, collect trash, recycle	-0.4842	0.0819	0.3889	0.0933	0.3212	0.0509
Computer programming	0.3586	0.2781	-0.3745	-0.1349	0.0983	0.0042
Solving unforeseen problems	0.59	0.3805	0.1762	-0.226	-0.1398	0.0845
Simple presentation of difficult situations	0.9021	0.0888	0.1412	-0.068	-0.0927	-0.0545
Persuade, negotiate compromise	0.8096	0.09	0.2235	0.0046	-0.194	0.0457

Independently making difficult decisions	0.644	0.3114	0.1941	0.0315	-0.1192	0.0844
Finding and closing own knowledge gaps	0.5921	0.1041	-0.0033	-0.2116	-0.1178	0.1389
Speeches, presentations	0.7495	-0.0656	0.1987	-0.2251	-0.1915	-0.1029
Contact with customers and patients	0.6734	-0.2105	0.3597	0.3826	-0.0384	-0.0129
Performing many different tasks	0.4873	0.3056	0.2288	0.1621	0.0412	0.1491
Responsibility for the welling of other people	0.5507	-0.0168	0.6344	-0.097	0.1156	0.0516
Knowledge:						
Natural sciences	0.4218	0.3805	0.0342	-0.0043	0.3545	-0.2249
Manual, technical	-0.3717	0.6251	0.0848	0.2968	-0.0607	-0.2711
Pedagogy	0.531	-0.0272	0.4433	-0.2232	0.0001	-0.2797
Law	0.5502	0.0014	0.1387	-0.1149	-0.1867	0.1607
Project management	0.6473	0.2478	-0.266	0.1097	0.0219	-0.0498
Medicine and healthcare	0.327	0.018	0.4789	-0.1245	0.4009	-0.1961
Layout, composition, visualization	0.3293	0.1031	-0.2628	0.1697	-0.013	0.0037
Mathematics, statistics	0.2784	0.5522	-0.2108	0.3086	0.0883	-0.1153
German, writing, spelling	0.7954	0.0057	-0.0979	0.0218	-0.1044	0.0609
PC applications	0.547	0.1487	-0.4747	0.1326	0.0789	0.0045
Technical	-0.0019	0.7723	-0.2245	0.1441	0.0918	-0.1558
Business administration	0.4854	-0.0177	0.0182	0.5393	0.0287	0.25
Foreign languages	0.5791	0.136	-0.2926	-0.074	0.0868	-0.0969
Working conditions:						
Work under time and performance pressure	0.179	0.395	-0.047	-0.0594	-0.2345	0.334
Repetitive work	-0.6199	-0.1837	0.1193	0.0096	0.2257	0.204
New tasks which require effort to understand	0.5647	0.3596	-0.2441	-0.1245	-0.1251	-0.0647

Multitask	0.4315	0.2389	0.1176	-0.1176	0.1783	0.4324
Can small mistake cause large financial losses?	-0.0804	0.4561	-0.0596	-0.1734	-0.077	0.4343
Work very fast	-0.2593	0.0883	0.1387	0.1687	-0.0319	0.3045
Carry weight of over 20kg?	-0.5378	0.2945	0.3754	0.1363	-0.2161	-0.0594
Work with smoke, dust, gas, vapor?	-0.5952	0.3626	0.1583	-0.1294	0.0003	0.1042
Work in cold, hot, wet, humid, drought?	-0.4879	0.2769	0.3402	0.0289	-0.3049	0.0332
Work with oil, fat, dirt?	-0.5405	0.4707	0.1884	-0.0837	-0.1158	-0.0468
Work bended, crouching, on the knees, horizontally?	-0.3321	0.3973	0.3313	0.1302	-0.2941	-0.2542
Work with strong commotions, kicks, vacillations?	-0.3388	0.2835	0.2342	-0.0683	-0.3474	0.0731

Notes: The table provides the factor loadings yielded by a principal component analysis of the 46 skill- and task-related questions in the BIBB/IAB and BIBB/BAuA Surveys (2005/2006 wave). Individual-level data was aggregated at the occupational level before performing the factor analysis. In total, there are 263 occupations. The factor analysis resulted in six orthogonal factors, displayed in Columns 2–7.