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Skill Mismatch and the Costs of Job Displacement*

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Abstract

When workers are displaced from their jobs in mass layoffs or firm closures, they experience lasting adverse labor market consequences. We study how these consequences vary with the amount of skill mismatch that workers experience when returning to the labor market. Using novel measures of skill redundancy and skill shortage, we analyze individuals' work histories in Germany between 1975 and 2010. We estimate difference-in-differences models, using a sample in which we match displaced workers to statistically similar non-displaced workers. We find that displacements increase the probability of occupational change eleven fold, and that the type of skill mismatch after displacement is strongly associated with the magnitude of post-displacement earnings losses. Whereas skill shortages are associated with relatively quick returns to the counterfactual earnings trajectories that displaced workers would have experienced absent displacement, skill redundancy sets displaced workers on paths with permanently lower earnings.

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1 Introduction

When workers are displaced from their jobs in firm or establishment closures, they often face large and persistent earnings losses. Fifteen years after displacement, average earnings and wages can fall ten to fifteen percent below the levels that would have been projected absent such a career interruption (Ruhm, 1991; Jacobson et al., 1993; Eliason and Storrie, 2006; Couch and Placzek, 2010; Hijzen et al., 2010; Schmieder et al., 2010; Morissette et al., 2012). Explanations for this economic hardship range from human capital mismatches (Neal, 1995; Parent, 2000; Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010), the loss of pre-displacement employment contracts that had raised earnings beyond workers' marginal productivity (Lazear, 1979), search costs (Topel and Ward, 1992) and stigmatization (Vishwanath, 1989; Biewen and Steffes, 2010). However, the average effect of displacement reported in this literature conceals the wide heterogeneity in outcomes that workers face. Using a German sample of displaced workers between 1975 and 2010, we find that, ten years after displacement, the interquartile range for earnings losses runs from 17% to just 4% below projected counterfactual wages without displacement. In this paper, we focus on the skill mismatch that displaced workers experience between their pre-displacement and post-displacement occupations as a source of heterogeneity. To do so, we propose new measures of occupational mismatch that take into consideration not only the amount of mismatch in job switches, but also its direction. This allows us to quantify both qualitative (i.e., differences in the kind of skills) and quantitative (differences in the level of skills) aspects of skill mismatches. Using these measures, we show that a substantial part of the heterogeneity in displacement outcomes is related to differences in the type and direction of job switches after displacement.

Our paper builds on prior work that uses skill and task profiles of occupations to measure occupational mismatch (Poletaev and Robinson, 2008; Gathmann and Schönberg, 2010). These measures are typically symmetric, presuming that the consequences of job switches do not depend on the direction in which workers move. That is, they assume, for instance, that salespeople who become professional negotiators experience the same human capital mismatch as workers who move in the reverse direction. However, although professional negotiators and salespeople may require similar skills, negotiations require more of these skills than sales activities. We relax this implicit assumption of symmetry and instead propose that the skill mismatch between two jobs has a gradient or *direction*.

To test this framework, we combine two different data sets. First, we extract information about the task content, education and training for 263 different occupations from a representative survey of 20,000 German employees (Zopf and Tiemann, 2010). We use these data to create directed (i.e., asymmetric) occupational skill distances. These skill distances are captured by a pair of variables: one measuring skill shortage – the amount of additional skills that a worker would have to acquire to meet the requirements of the new job – and skill redundancy – the amount of skills that remain unused in the new job. Next, we reconstruct employment histories in a 2 percent longitudinal sample of German workers drawn from Germany's social security records. The resulting dataset provides information on these individuals' employment, unemployment and earnings histories between 1975 and 2010. We then use our occupational mismatch variables to characterize the nature of job switches in this sample.

At the macro level, we find that the direction of job switches is pro-cyclical. In periods of economic growth, workers move more often into new jobs that are more demanding than their old jobs. That is, these jobs tend to require more new skills than they leave redundant. In recessions, this tendency reverses. Moreover, we find that young workers are more likely to move to more demanding jobs than older workers. Finally, net skill redundancy is highest for workers who change jobs involuntarily (i.e., with an unemployment spell in-between two employment spells) and lowest for workers who do so voluntarily (i.e., job-to-job transitions), with displaced workers finding themselves in between these two groups. The latter finding supports Gibbons and Katz's (1991) contention that samples of displaced workers avoid the selection biases that plague most observational samples of job switchers: having been displaced neither signals that workers were perceived as low ability by their old employer – as in the case of layoffs – nor as high ability by their new employer – as in the case of voluntary career moves.

Following the displacement literature, we regard job displacements as employment terminations that are exogenous to individual worker characteristics, such as performance, continuation value or outside options. We can identify over 12,000 displaced workers in our administrative data, whom we match to non-displaced statistical twins using a combination of exact and propensity score matching. In this matched sample, we find that displacement causes workers to switch occupations: displaced workers do so at a rate that is eleven to twelve times higher than for non-displaced workers. However, displacements do not lead to a specific *direction* in job switches.

Next, we divide displaced workers into five distinct groups based on their post-displacement occupation: (1) *occupation stayers* (workers find new work in their pre-displacement occupations), (2) *upskillers* (the new occupation mostly requires new skills with little skill redundancy), (3) *downskillers* (the new occupation leaves many old skills unused but does not require many new ones), (4) *reskillers* (the new occupation requires many new skills and makes many old skills redundant) and (5) *lateral switchers* (the new occupation requires more or less the same skills as the old occupation). For each group of displaced workers we then estimate the costs of job displacement separately.

Our identification strategy assumes that – conditional on observable characteristics – displacement events are exogenous. As long as this assumption holds, estimated effects of displacement are causal in the sense that they compare what happens to displaced workers to counterfactual career paths without displacement. This holds true *regardless of how we group workers*. Therefore, if displacement effects differ between groups of workers who make different post-displacement career choices, these differences summarize effect heterogeneity. However, they do not necessarily answer the question what would have happened to displaced workers had they chosen different post-displacement jobs. That is, these differences may be due to intrinsic characteristics of workers who choose certain types of skill mismatch, not to the skill mismatch itself. Our results should therefore be interpreted with caution when it comes to policy implications related to post-displacement job switching. Nevertheless, we believe that documenting the heterogeneity of displacement costs by type of switch offers important clues regarding the mechanisms of how job displacement affects workers' future careers.

Our analysis shows that differences in the nature and amount of skill mismatch that displaced workers face in their new jobs are indeed associated with substantial heterogeneity in displacement outcomes. Occupation switchers tend to experience longer-lived and substantially larger displacement-related earnings losses than occupation stayers: fifteen years after displacement, annual earnings of occupation switchers still trail their counterfactuals by 15.6 percent, whereas for occupation stayers, losses are limited to 7.6 percent. However, some occupation switchers manage to outperform occupation stayers, a fact that, *prima facie*, is puzzling from a skill mismatch point of view. The explanation lies in the direction of post-displacement switches. Most displaced occupation switchers either skill down (35 percent) or up (36 percent). However, these two groups experience markedly different earnings losses: across the first fifteen years after displacement, downskilling occupation switchers earn on average 22.7 percent below their pre-displacement wages, compared to 7.6 percent for upskilling occupation switchers. Moreover, upskilling switchers catch up with their counterfactual wage curves within seven years, whereas downskilling switchers still fall short of their counterfactual wages fifteen years after having been displaced. These differences are mainly due to differences in pay rates, not days worked, suggesting that they are related to differences in productivity.

Looking at the evolution of skill mismatch, we find that displaced workers tend to return to jobs that require similar skills to the ones they held prior to displacement. However, they do so in an asymmetric way: they steadily reduce the skill redundancy to their pre-displacement jobs, but maintain the skill shortage. This suggests that workers with large skill shortages, i.e., upskilling and reskilling workers, utilize their displacement to first move to more demanding jobs and then, with time, recover some of the skills they had left unused. This would explain why in the long run, these workers who fare better than those who chose an equally distant, yet less demanding occupation.

Our work adds to two areas of research. First, it contributes to the debate on the long-term consequences of job displacement (Kletzer, 1989; Seim, 2012). In particular, it documents a causal effect of displacement on the propensity of workers to change occupations and then describes how different post-displacement career choices are associated with drastically different consequences of displacement. We reveal significant heterogeneity in the displacement outcomes that we relate to the match between one's occupation-specific skills and the skills required at the post-displacement job. Compared to their counterfactuals, downskilled workers suffer long-term losses that are twice as large as the average displacement-related loss of earnings, and their scarring is permanent. Upskilled workers, on the other hand, suffer smaller losses that are comparable to those of occupational stayers and they eventually manage to catch up with the earnings of their counterfactuals.

Second, we contribute to the literature on the measurement of skill mismatch (Nordin et al., 2010; Leuven and Oosterbeek, 2011; Groot and Van Den Brink, 2000; Hartog, 2000; McGuinness, 2006; Tsang and Levin, 1985; De Grip and Van Loo, 2002; De Grip et al., 2008; Perry et al., 2014), offering a novel measure that describes occupational skill mismatch in a way that preserves a notion of directedness and is expressed in units that can be interpreted as years of required (re)education. In this regard, our paper is most closely related to Robinson (2018), who was the first to document patterns of distance and direction of occupational switchers.[1] We also

[1]However, our study differs from and innovates on Robinson's work in several respects. First, Robinson relies on wage differences between occupations to infer skill directionality in job switches. Because this approach risks circularity in variable definitions when analyzing post-displacement wages, we avoid using wage information in the measurement of skill mismatch. Second, the units of our mismatch measures have a clear interpretation in terms of years of educational requirements. Third, we allow workers to simultaneously experience skill redundancy and skill shortage. As a result, we distinguish between job switches between occupations with very similar skill requirements and switches between distant occupations in which skill redundancies and skill shortages cancel out. Furthermore, we rely on a different estimation approach in our empirical application, by first balancing the observable characteristics of displaced and non-displaced workers using a matching

discuss how our results for Germany differ from Robinson's results for the US (see Section 4).

The remainder of the paper is organized as follows. In Section 2, we construct measures of skill mismatch between occupations and define types of occupational switches. In Section 3, we introduce the data and derive some stylized facts about skill mismatch in the German labor market. Section 4 shows the relevance of skill mismatch in explaining the costs of of job displacement. We start by outlining the sample restrictions and the matching procedure. We then show the effect of displacement on occupational mobility and on the probability of incurring skill mismatch. Afterwards, we discuss the event-study framework that we use to investigate the relationship between skill mismatch and displacement costs in terms of earnings, wages, and employment, and present the respective results. Section 5 discusses the implications of our findings for policy and research.

2 Measuring Occupational Mismatch

Human capital mismatch is typically either identified for worker-job pairs, that is, as mismatch between a worker and a job, or for job-job pairs, i.e., as mismatch between two jobs. The former is often described in terms of the mismatch between the worker's educational attainment and the job's educational requirements. To quantify this mismatch, scholars have relied on self-reported mismatches (Hartog and Oosterbeek, 1988; Alba-Ramirez, 1993), assessments of educational requirements by professional job analysts (Eckaus, 1964; Hartog, 2000), or statistical benchmarks that compare a worker's educational attainment to the average or median educational attainment of workers with the same job (Verdugo and Verdugo, 1989; Kiker et al., 1997; Quinn and Rubb, 2006). Human capital mismatches between jobs – typically between occupations – have been derived from the network of labor flows in the economy. For instance, Neffke and Henning (2013) analyze the extent to which job switches between industries exceed a random benchmark. Similarly, Shaw (1984, 1987) measures the distance between two occupations by analyzing the extent to which they exchange workers with the same set of other occupations. Alternatively, job-to-job human capital mismatch can be derived directly from data on skill requirements or job tasks. These approaches rely on datasets that are either

approach and then estimating difference-in-differences models. As we will show below, this preprocessing step matters. Finally, the longitudinal character of our analysis allows us to follow displaced workers for up to fifteen years into their post-displacement careers, offering insights into who manages to catch up with their counterfactual career paths and who faces permanent income losses.

collected at the level of occupations or through worker surveys. Examples of the former are the US Dictionary of Occupational Titles DOT (Cain and Treiman, 1981) and its successor, O*NET (Peterson et al., 1999). Examples of worker surveys are the German BIBB/BAuA and BIBB/IAB Employment Surveys (henceforth, "BIBB survey") (Zopf and Tiemann, 2010).

Skill-survey based measures of mismatch typically cast human capital requirements as k-dimensional skill vectors that express the level of mastery that occupations require for each of k skills. Figure 1 uses this representation to show a stylized example with two occupations, O' and O, that use $k = 2$ different skills: Manual (M) and Analytic (A) skills.

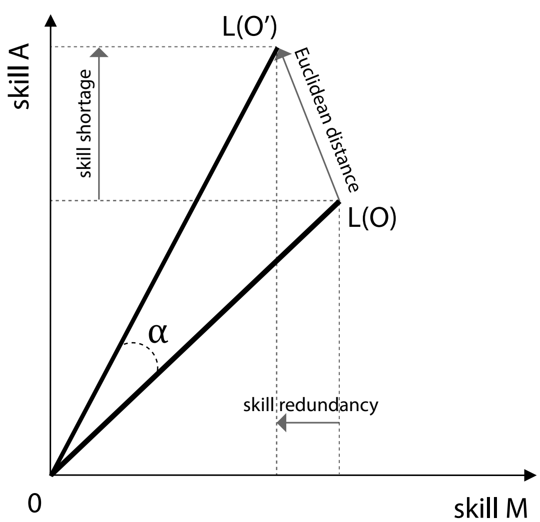

Figure 1: **Occupational Skill Profiles in a Two-dimensional Space**
Notes: Skill requirement vectors for two fictitious occupations, occupation O and O', and different measures of skill mismatch between them.

Skill mismatch can now be quantified in a variety of ways. For instance, one can measure the angular separation between two occupational vectors, α, as in Gathmann and Schönberg (2010), or their Euclidean distance, as in Poletaev and Robinson (2008). However, both measures have two shortcomings. First, they are symmetric. Therefore, they do not account for the fact that workers who switch from occupation O to O' experience a different skill mismatch from workers who switch in the opposite direction. Second, they do not account for the fact that workers can be simultaneously over- and underskilled: switching from O to O' leaves some manual skills unused, but also forces the worker to obtain higher levels of analytic skills.

We propose that both shortcomings can be addressed by using a variable pair that describes the skill shortages and skill redundancies that we would expect a worker to experience when switching from one occupation to another.[2]

To do so, we use data from the BIBB survey. The dataset randomly samples individuals aged 16–65 who were employed in Germany at the time of the survey. It has been used extensively in labor market research (Gathmann and Schönberg, 2010; DiNardo and Pischke, 1997; Spitz-Oener, 2006; Dustmann et al., 2009; Black and Spitz-Oener, 2010). Due to limited comparability of survey questions over time, we only work with the 2005/2006 wave, which sampled 20,000 employed Germans in 263 occupations. Below, we provide a sketch of how we use this dataset to construct mismatch variables and provide further details in Appendix A.

To construct skill vectors, we aggregate the answers of workers to 46 survey questions on knowledge requirements and job tasks to the level of occupations. Next, we reduce the dimensionality of these skill descriptions for occupations, using factor analysis[3] that identifies five broad skill factors. Together, these factors account for over three quarters of the variance in the average survey responses. Furthermore, we use 14 questions that aim to understand unfavorable working conditions, such as physical discomfort, working with dangerous substances or being exposed to heat or loud noises. 69% of the variation in these 14 working conditions is captured by a single factor, which we interpret as the disutility associated with working in the occupation.

The intensity with which an occupation requires each of the five broad skills is expressed in units of standard deviations. However, it is unclear how we should sum differences in these requirement scores across skills. Therefore, we develop weights that allow us to compare skill mismatch in different skills. To do so, we use the detailed information about the average years of schooling of workers in each occupation that the BIBB offers: apart from reporting workers' formal schooling, the survey also collects information on up to seven different episodes of work training

[2]Herein, we go further than Robinson (2018), who only addresses asymmetries in occupational distances, not the simultaneous skill shortages and redundancies that workers experience when changing jobs. Robinson uses factor analysis to convert 49 job characteristics in the 1992 DOT into four broad skills and then calculates for each pair of occupations the net difference in skill intensity across these four skills. If this net difference is positive, workers move "up the career ladder", if it is negative, they move down. This net difference is in the main analyses generated without weights, but in robustness checks by the extent to which skills are associated with high wages, raising concerns of circular reasoning when using these metrics to analyze wage dynamics.

[3]Herein, we deviate from the approach of Gathmann and Schönberg (2010), who work with raw 19-dimensional vectors. This, however, leads, conceptually to double-counting skills that are very similar and, empirically, to a bimodal distribution of occupational distances. The factor analysis ensures that skills are sufficiently distinct and avoids this bimodality.

programs. Schooling therefore does not just refer to formal education, but includes training over the course of a worker's career. Next, we try to estimate the years of schooling that each skill requires by regressing the average years of schooling in an occupation on its loading on the five skill factors, f_o^i:

$$S_o = \alpha + \sum_{i=1}^{5} \beta_i f_o^i + \gamma d_o + \varepsilon_o \tag{1}$$

Note that this approach assumes that schooling requirements are additive. Moreover, to safeguard against confounding certain skill requirements (e.g., manual) with poor working conditions, Eq. (1) also contains the occupation's loading on the disutility factor, d_o.

The estimated coefficients in Eq. (1) can be interpreted as the years of education that are needed to acquire an additional standard deviation of each skill. Consequently, we can calculate for each pair of occupations, (o, o'), the skill redundancies or shortages in terms of the years of schooling that are left unused, because some skills have become redundant, or that must be acquired to meet the new job's skill requirements. In particular, we define the *amount of skills* that is made redundant when a worker switches from occupation o to o' as the sum of all positive differences between the skill vectors of o and o', weighted by a skill's estimated coefficient in Eq. (1), $\hat{\beta}_i$:

$$redundancy_{oo'} = \sum_{i=1}^{5} \hat{\beta}_i (f_{io} - f_{io'}) I(f_{io} > f_{io'}), \tag{2}$$

where $I(.)$ is an indicator function that evaluates to one if its argument is true. Similarly, we estimate the expected skill shortage for workers moving from o to o' as:

$$shortage_{oo'} = \sum_{i=1}^{5} \hat{\beta}_i (f_{io} - f_{io'}) I(f_{io'} < f_{io}). \tag{3}$$

Next, we divide occupation switches into four groups, using the population medians of skill shortage (0.7 school years) and skill redundancy (0.6 school years) as thresholds. We refer to job switches that involve high skill redundancies and low skill shortages as *downskilling* and the opposite, switches with low redundancies and high shortages, as *upskilling*. If redundancies and shortages are both high, workers have to change their skill sets completely. We will call such switching *reskilling*. When both redundancies and shortages are low, workers barely have to change their skill profiles and are said to make *lateral* switches. Table 1 summarizes these definitions.

Table 1: Types of Occupational Switchers

		Shortage	
		Above Median	Below Median
Redundancy	Above Median	Re-skilled	Down-skilled
	Below Median	Up-skilled	Lateral

Notes: Workers are divided into different groups depending on the amount of skill shortage and skill redundancy they experience when changing occupations.

On average, reskilling switchers need to acquire new skills that represent 1.6 years of education, and leave skills unused representing 1.5 years of education. Up-skilling is, on average, associated with skill upgrading of 1.9 years and skill redundancy of 0.2 years. In contrast, downskilling is associated with an average of 1.7 years of skill redundancy and only 0.2 years of skill upgrading. Finally, lateral switches entail on average 0.4 years of skill acquisition and 0.3 years of skill redundancy.

Table B.1 in Appendix B shows the most common job switches by type. The most common reskilling switch is office clerks who become social workers. The most frequent upskilling switch is a salesperson becoming an office clerk, whereas the most common downskilling switch is the reverse (office clerks becoming salespersons). The most common lateral switch is typists who become office clerks.

Below, we use the measures of skill redundancy and skill shortage to derive some stylized facts about skill mismatch in the German labor market. To do so, it will be convenient to define the following composite measure:

$$mismatch_{oo'} = redundancy_{oo'} + shortage_{oo'}. \tag{4}$$

Note that, because shortage is by definition negative and redundancy positive, *mismatch* expresses the years of skill redundancy, net of the years of skill shortage.

3 Skill Mismatch in Germany

Data

To study job switches, we rely on administrative labor market records for Germany from the Sample of Integrated Labor Market Biographies (*SIAB*) provided by the Institute for Employment Research (IAB) (vom Berge et al., 2013). SIAB documents the employment and unemployment histories of some 1.6 million people subject to social security between 1975 and 2010, approximately 2 percent of the workforce included in the social security system. The German social security system covers about 80 percent of the total German workforce, but excludes self-employed individuals and civil servants. Furthermore, employers have a legal obligation to report the exact beginning and end of any employment relation, and misreporting individual earnings is punishable by law. As a result, the SIAB is the largest and most reliable source of employment information in Germany, offering a highly accurate depiction of workers' career trajectories.

Within these work histories, we identify all instances in which workers change occupations. We distinguish between three types of job changes. First, workers can change jobs voluntarily to pursue better career opportunities elsewhere. We identify voluntary switches as job-to-job transitions, uninterrupted by unemployment spells. Second, involuntary switches occur when employees are laid off by their employers. Because workers only qualify for unemployment benefits after a layoff, we identify involuntary switches as transitions between occupations with an unemployment benefit spell in between. Third, workers can get displaced from their jobs in establishments closures or mass layoffs. Following the definitions in Hethey-Maier and Schmieder (2013), we define job displacements as job separations due to establishment closures or mass-layoffs.[4] In this definition, we include workers who left their establishment in the year prior to such events to reduce sample selection issues due to some workers' anticipating of the closure (Fallick, 1993; Gathmann and Schönberg, 2010; Davis and Von Wachter, 2011). If we cannot unambiguously determine that a job switch followed a layoff or a displacement, we label the switch *voluntary*. Note that, because in reality some workers who are laid off immediately find new jobs or refrain from applying for unemployment benefits, we may erroneously classify some layoffs as voluntary job switches.

Some General Patterns of Skill Mismatch

Skill mismatch differs markedly between workers who change jobs voluntarily and those who don't. Figure 2 shows that in voluntary switches, skill shortage dominates skill redundancy by 1.7 months of schooling. That is, workers who change jobs voluntarily tend to move to jobs in which they need to acquire more skills than they

[4] Adding mass-layoffs reduces systematic bias in the firm-size distribution from which our sample of displaced workers is drawn, given that closures more often affect small establishments (Schmieder, 2010). However, we exclude closures of establishments with fewer than ten workers two years prior to the closure, because they have high turnover rates and because their workers may individually have significantly contributed to the plant's failure.

leave redundant. In involuntary switches, in contrast, workers tend to incur about equal amounts of skill shortage and skill redundancy. Finally, displaced workers display a net skill shortage of 0.75 months of schooling, roughly halfway between the other two types. These findings corroborate a hypothesis posited by Gibbons and Katz (1991) about self-selection biases in samples of job switchers. They argue that, because a worker's old employer has better information about the performance of the worker than prospective employers do, the type of job separation – voluntary or involuntary – will be endogenous to a worker's performance. Accordingly, involuntary job separations signal low performance, whereas voluntary job separations signal high performance. Displacements, in contrast, should be unrelated to workers' performance and can therewith be considered exogenous to worker characteristics.

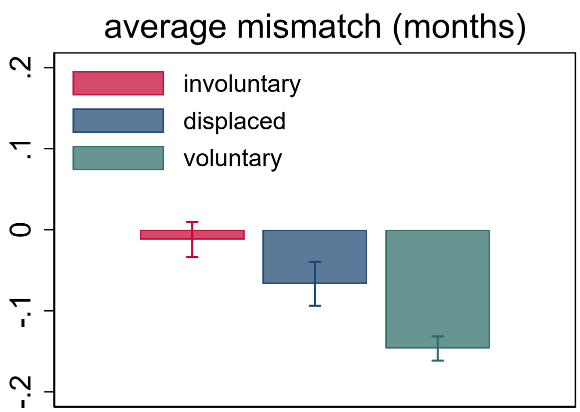

Figure 2: **Skill Mismatch by Type of Job Switch.**
Notes: Bars indicate the average skill mismatch (skill redundancy net of skill shortage) between 1978 and 2008 in months of educational requirements for voluntary, involuntary and displaced job switchers. The whiskers show 90% confidence intervals. Voluntary switches are occupational changes without an unemployment spell in between. Involuntary switches are occupational changes after an unemployment spell. Source: The occupational mobility data come from SIAB 1975-2010, the data on skill mismatch from BIBB/BAuA 2006.

Figure 3 shows that skill mismatch varies by worker age. This is to be expected: young workers have most incentives to invest in new skills. Therefore, they may try to move to more demanding jobs (Topel and Ward, 1992).[5] We find that this

[5]The particularly high net redundancy at age 18-25 is, from this perspective, unexpected. We suspect this to be a result of misclassification: the assignment of occupational titles to workers who enter the labor market may not properly reflect their level of skill or experience. It suggests that our measures may not work well for this group. However, most of these very young workers will be excluded from the displaced worker analysis below due to further restrictions that we impose on our sample.

prediction holds regardless of whether switches are voluntary or not. However, at any given age, displaced workers exhibit net skill shortages between the levels observed for voluntary and involuntary switchers.

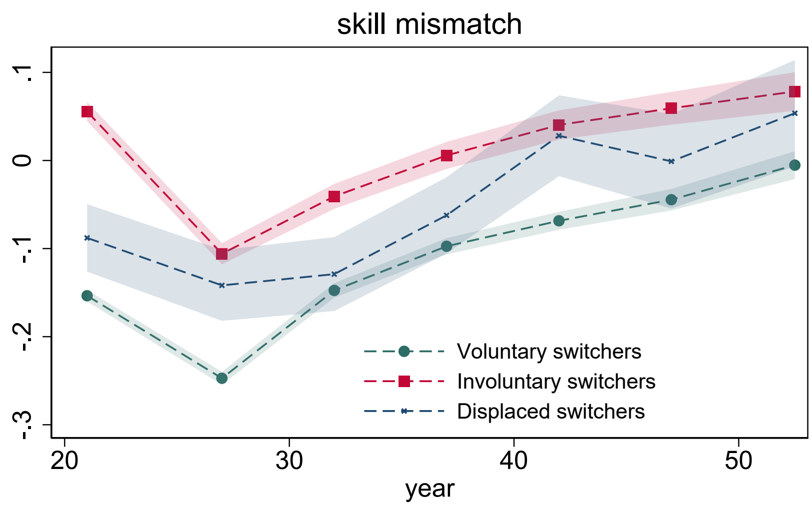

Figure 3: **Skill Mismatch by Age.**
Notes: Average skill mismatch (skill redundancy net of skill shortage) by age bracket between 1978 and 2008, in months of educational requirements for voluntary, involuntary and displaced job switchers. Age brackets (in years): 18-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-55. Shaded areas correspond to 90% confidence intervals. Voluntary switches are occupational changes without an unemployment spell in between. Involuntary switches are occupational changes after an unemployment spell. Source: The occupational mobility data come from SIAB 1975-2010, the data on skill mismatch from BIBB/BAuA 2006.

Figure 4 shows how skill mismatch changes over the period of observation. Contrary to Robinson (2018), we do not find evidence of a secular decline in skill mismatch in Germany. That is not to say that there are no temporal patterns. Skill mismatch for both voluntary and involuntary switchers follows a U-shaped pattern over time, whereas mismatch for displaced workers increases rather linearly. It is difficult to speculate what drives these temporal patterns. Macro conditions, technological conditions, cohort effects, among others, may all play a role. Finally, to provide an interpretation of this temporal mismatch pattern, we relate skill mismatch to the business cycle. Some authors have recently suggested that the direction of job switches depends on the business cycle.[6] Figure 5 shows coefficients from regress-

[6]For instance, Modestino et al. (2020) provide evidence that, facing excess labor supply during the Great Recession, employers in the U.S. started raising educational and experience requirements. Similarly, Modestino et al. (2016) show that in the recovery thereafter, as the labor market was

ing average skill mismatch on unemployment rates over time. Intriguingly, we find that the association between skill mismatch and economic conditions depends on whether workers change jobs voluntarily or not. For involuntary switchers, high unemployment rates are associated with higher net skill redundancy (or lower net skill shortage), presumably reflecting the difficulty of finding better jobs in a recession. Although less pronounced, the same holds for displaced workers. For voluntary job switches, there is no, and if anything, a negative relation between skill mismatch and the business cycle. The difference between the estimated coefficients for voluntary and involuntary switchers is statistically significant at the 5 percent level (p=0.015). One explanation for this difference in the business cycle dependence of mismatch is that workers who change jobs voluntarily do so conditional on finding a *better* job. This selection effect reduces the statistical association between mismatch and the unemployment rate.

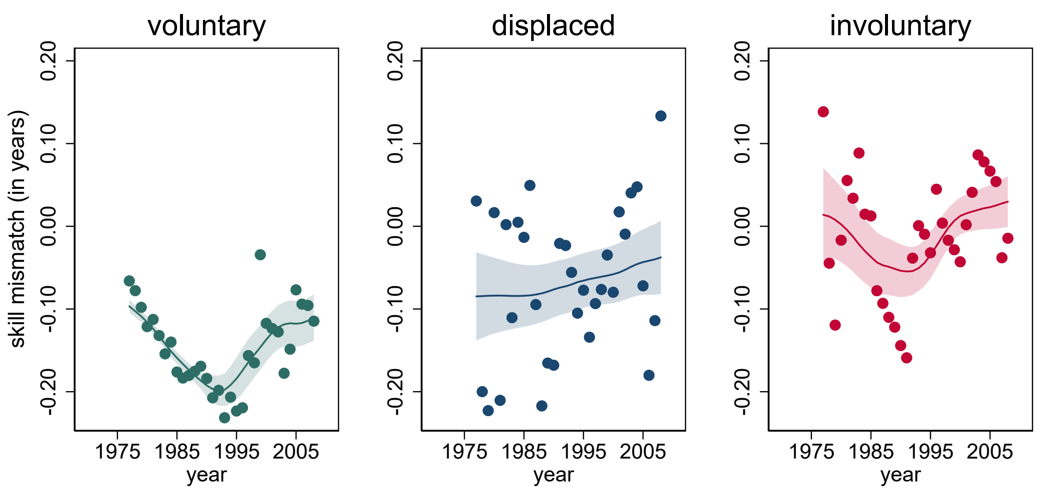

Figure 4: **Skill Mismatch over Time**

Notes: Yearly average skill mismatch (skill redundancy net of skill shortage) between 1978 and 2008 for voluntary, involuntary and displaced job switchers. Mismatch is expressed in months of educational requirements. Curves are locally mean-smoothed and the shaded areas correspond to the 90% confidence intervals. Voluntary switches are occupational changes without an unemployment spell in between. Involuntary switches are occupational changes after an unemployment spell. Source: The occupational mobility data come from SIAB 1975-2010, the data on skill mismatch from BIBB/BAuA 2006.

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tightening, the trend turned towards reduced skill demands.

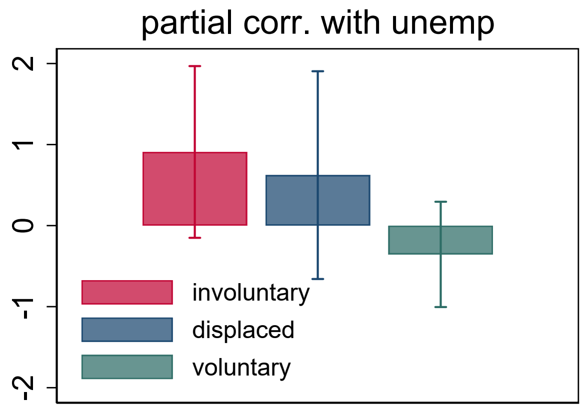


Figure 5: **Skill Mismatch and the Business Cycle.**
Notes: Bars show regression coefficients of average skill mismatch (months of skill redundancy net of skill shortage) in a year on unemployment rates over the period 1978 and 2008 by type of switch. The whiskers correspond to 90% confidence intervals. Voluntary switches are occupational changes without an unemployment spell in between. Involuntary switches are occupational changes after an unemployment spell. Source: The occupational mobility and unemployment data come from SIAB 1975-2010, the data on skill mismatch from BIBB/BAuA 2006.

4 The Consequences of Job Displacement

We now turn to the careers of displaced workers. We are particularly interested in how the consequences of displacement vary with the skill mismatch that workers experience when they become reemployed. Note that our mismatch variables implicitly assume that the skill requirements of workers' pre-displacement jobs are reasonable proxies for workers' skill endowments. To increase the likelihood that this is indeed the case, we impose some additional restrictions on the sample that we will analyze.

4.1 Sample Criteria

First, we expect that the correspondence between skill requirements and skill endowments increases with the time that workers have had to find jobs that match their skills. Furthermore, the quality of the worker-job match will also increase with tenure (Jovanovic, 1979). Therefore, we restrict our sample to workers who, at the time of displacement, have had at least five years of labor market experience, of which at least three years were outside unemployment, two years of experience in their pre-displacement occupation and, to limit the impact of short-term churn around the time of the establishment's closure, one year uninterrupted employment at the establishment.[7]

Furthermore, we limit the analysis to workers between 18 and 55 years and exclude workers with left-censored labor market histories.[8] Because the SIAB did not include marginal employment spells until 1999, we also drop workers who at some point in their careers had marginal employment contracts.

Finally, the employment histories in the SIAB often contain gaps. This happens, for instance, when individuals join the military, or take parental leave, but also when they go back to school or undertake other types of retraining. To allow for extensive requalification periods, we retain individuals with gaps of up to six years, but drop individuals with longer gaps. The above restrictions yield a sample of about 25,000 displaced individuals, whom we observe in each year on June 30, starting five years prior to displacement and for up to fifteen years after displacement.

4.2 Matching

Using a sample of displaced workers addresses self-selection concerns when studying how job changes affect future careers. However, although workers do not choose to be displaced, displacement is not randomly distributed across workers. On the contrary, as we will show, displaced workers tend to be older, more often male, less educated and they work less often in the tertiary sector than the general working age population. To balance the characteristics of displaced and non-displaced workers, we preprocess our data using a combination of exact and nearest neighbor propensity score matching with replacement.[9] That is, for each displaced worker, we select a "statistical twin" with very similar characteristics. After having selected non-displaced workers who are observationally equivalent to displaced workers, we use difference-in-differences models to analyze how displacement affects workers' careers. Given that the parallel trends assumption holds, the career paths of these statistical twins can be regarded as counterfactual paths that displaced workers would have followed had they not been displaced.

The matching proceeds as follows. First, we match displaced workers to groups of non-displaced workers who exactly mimic them in the following characteristics: pre-

[7] As a robustness check, we repeated the complete analysis using a sample of workers who had at least four years of labor market experience. This increases the sample size to 13,693 displaced workers and therewith its statistical power. All results we report here also hold in this larger sample.

[8] Our dataset starts in 1975 for West Germany and in 1991 for East Germany. Large shares of workers who appear for the first time in 1975 (West Germany) or 1991 (East Germany) and are older than 21 have left-censored labor market histories. We therefore exclude these workers from the sample.

[9] See Ho et al. (2007) for a discussion of this empirical strategy.

displacement occupation (263 codes), level of education (six categories), economic sector (four categories), gender and region of work (East or West Germany). Next, we estimate propensity scores for the event that a worker becomes displaced, using information on the worker's age and occupational tenure. To allow for the possibility that women and men have different returns to occupational experience, we interact the latter variable with gender. Finally, we also match on the pre-displacement number of days worked, real daily pay and the growth rates of both variables from five to two years before displacement. The latter variables ensure that workers were on similar wage trajectories, which should capture both observable and unobservable aspects of a worker's performance. Finally, within each group, we select the non-displaced worker whose propensity score is most similar to the one of the displaced worker.

Imposing a common support for displaced and non-displaced workers yields a sample of 12,160 displaced workers and an equal number of non-displaced matches. Table 2 shows that our sample of displaced workers differs markedly from the general population.[10] As mentioned before, displaced workers tend to be older and less educated than the overall population. Moreover, they work more often in East Germany and in the primary & construction or manufacturing sectors. Finally, men are overrepresented compared to women among the displaced. Matching improves the balance on these variables substantially (see Appendix C for details). Along most variables, the displaced and non-displaced samples are statistically indistinguishable. If differences are statistically significant, they are typically economically small. However, it is important to note that we do not use matching as an identification strategy, but to prescreen our data. Such prescreening can substantially improve estimates of standard regression models, because it limits the amount of extrapolation that the statistical models have to undertake (Angrist and Pischke, 2008). Moreover, the matching procedure ensures that the parallel trend assumption of our difference-in-difference models is more likely to be met.

4.3 Job Displacement and Occupational Change

Job displacement has a strong effect on the likelihood that workers change occupations. The average displaced worker in our sample has close to nine years of occupational experience. Yet, 25 percent of the displaced workers switch occupations right after their careers are disrupted by an establishment closure or a mass layoff. Among the matched non-displaced sample, fewer than 3 percent change occupations. Table 3

[10] This is also indicated by the fact that only 48.6 percent of the initial sample of 25,000 displaced workers could be matched.

Table 2: Worker Characteristics

	Population	Displaced
% West Germany	72.08	64.79
% Primary and secondary sector	27.06	33.23
% Female	46.04	38.45
Mean age	34.26	38.26
Occupational distribution		
Overrepresented occupations among the displaced		
% Extractive industry workers & construction	7.59	9.82
% Metal workers	14.72	18.72
% Engineers & technicians	5.86	6.28
% Trading & selling occupations	13.04	16.76
% Office clerks	15.58	19.80
Underrepresented occupations		
% Chemicals, paper, textile & food manufacturing	6.24	4.84
% Low skilled services, drivers	18.37	13.76
% Managers & professionals	5.67	4.79
% Health & education	12.93	5.24
Educational distribution		
% Volksschule/Hauptschule without voc train	14.50	4.64
% Volksschule/Hauptschule with voc train	67.43	83.28
% Hochschule/University	5.52	4.19
% Other	12.55	7.89
Number of Observations	10.372,309	12,160

Notes: Worker characteristics in the SIAB sample (*Population*) and the sample of displaced workers that meet all sample restrictions (*Displaced*). Some of the sample restrictions applicable to the *displaced* and described in this section also apply to the *population*. The population includes employees between 1978 and 2008, age 15-55, without missing values on the depicted variables, and without left-censored labor market histories. Source: SIAB 1975-2010.

Table 3: Impact of Job Displacements on Changing Occupations

	(1)	(2)
Displaced	11.279***	11.574***
	(0.6583)	(0.6809)
LM Experience	1.035**	1.027*
	(0.0142)	(0.0145)
LM Experience^2	0.999***	0.999***
	(0.0003)	(0.0003)
Matching variables	No	Yes
Number of observations	24,320	24,320
Wald chi2	1,759	1,928
Log pseudolikelihood	-8,384	-8,225
Pseudo R2	0.1437	0.1599

Notes: Estimated relative risk ratios using logit regressions. The sample includes 12,160 displaced workers and their non-displaced statistical twins. Column (1) only includes a quadratic polynomial in labor market experience as control, while Column (2) includes all matching variables as controls. Standard errors are clustered by individual. Significance levels: *** $p < .01$; ** $p < .05$; * $p < .10$. Source: SIAB 1975-2010.

further illustrates this difference by means of logit regressions, where the probability of occupational change in the first post-displacement job is modeled as a function of the displacement event. The model in Column (1) relies purely on matching to mitigate confounding, whereas Column (2) also adds all variables that were used in the matching procedure as control variables. The results suggest that displacements increase the relative risk of changing an occupation by a factor of around 11. The estimated effects in the two models are statistically indistinguishable, suggesting that the matching exercise managed to balance worker characteristics well. Given that the matching variables include the pre-displacement wage trajectories, which should encompass observed and unobserved differences in worker quality, these estimates are likely to have a causal interpretation.

Conditional on having changed an occupation, does the direction in which workers change jobs differ between the displaced and the non-displaced? To answer this, we estimate a multinomial logit regression model in which we study the differences between the displaced and the non-displaced by the *type* of switch – upskilling, downskilling, lateral or reskilling – that workers make. Note that the sample now only contains occupation switchers, which may introduce some selection concerns.

Table 4: Job Displacement and Type of Skill Mismatch

Occupation-switch type	(1)	(2)
Upskilled	0.853	0.852
	(0.117)	(0.117)
Reskilled	0.748	0.74
	(0.137)	(0.136)
Lateral	0.901	0.915
	(0.155)	(0.159)
Number of observations	3,373	3,373
Log pseudolikelihood	-4,346	-4,273
Pseudo R2	0.0023	0.0191

Notes: Estimated relative risk ratios using multinomial logit models, with downskilling switches as a baseline. The sample only includes occupational switchers. Model 1 only includes labor market experience and its square term as controls, while Model 2 includes all matching variables as controls. Standard errors are in parentheses and clustered by individual. Significance levels: *** $p < .01$; ** $p < .05$; * $p < .10$. Source: SIAB 1975-2010 and BIBB/BAuA 2006.

Table 4 shows results (base category: downskilling switches). Contrary to the correlational patterns we described in section 3, we do not find any evidence that displaced workers make relatively more downskilling career switches than their non-displaced peers. That is, once we align samples of displaced and non-displaced workers on observable characteristics and pre-displacement outcomes, the differences in terms of the direction of occupational changes between displaced and non-displaced job switchers disappear.[11]

4.4 Labor Market Consequences of Displacement

Displacement events lead to drastic drops in earnings, wages and the number of days that workers are employed in a year. We investigate displacement costs using difference-in-differences estimations. Our identifying assumption is that, conditional on pre-displacement outcomes, worker fixed effects and further observable worker characteristics, displacement is an exogenous event. If this is the case, the careers

[11] Note that this finding diverges from Robinson's (2018) findings for the US. He reports that displacements cause downskilling career switches. However, because Robinson (2018) does not balance the displaced and non-displaced samples, we cannot rule out that these findings for the US are confounding worker heterogeneity with displacement effects, in the same way as our initial results in section 3 did.

of non-displaced workers provide appropriate counterfactuals for the careers of their displaced peers.

However, not all workers experience equally poor post-displacement outcomes. To assess the heterogeneity in displacement effects, we split workers by the type of job switch they undertake after displacement. In particular, we estimate variants of the following regression:

$$Y_{it} = \alpha_i + \gamma_t + X_{it}'\delta + \sum_{k=-4}^{15} \beta_1^k T_{p(i)t}^k + \sum_{k=-4}^{15} \beta_2^k T_{p(i)t}^k D_i + \sum_{k=-4}^{15} \beta_3^k T_{p(i)t}^k S_{p(i)} + \sum_{k=-4}^{15} \beta_4^k T_{p(i)t}^k D_i S_{p(i)} + \epsilon_{it} \quad (5)$$

where Y_{it} is the outcome of interest (annual earnings, daily wage or days worked) for individual i in year t. α_i are worker fixed effects, γ_t are calendar year fixed effects, and the vector X_{it} includes a quadratic polynomial of years of labor market experience.

The subscript $p(i)$ denotes the matched worker-pair to which worker i belongs. $T_{p(i)t}^k$ are dummy variables that code event time: they are equal to one k years after the establishment of the displaced worker in pair $p(i)$ closed down or had a mass-layoff. D_i is a displacement dummy that denotes whether worker i is the displaced worker or the statistical twin.

$S_{p(i)}$ is an occupation-switching dummy. It takes a value of one if the displaced worker in pair $p(i)$ has a first post-displacement occupation that is different from her or his pre-displacement occupation. Depending on the specification, we let the dummy variable $S_{p(i)}$ refer to specific types of occupational switches that the pair's displaced worker undertakes: upskilling, downskilling, lateral, or reskilling. This dummy is meant to capture heterogeneity in effects of displacement across different worker groups. The preconditions under which these effects have a causal interpretation, i.e., reflect the difference between workers' observed and counterfactual career trajectories in which they had not been displaced, remain the same as before. However, workers choose themselves which type of post-displacement job switch they make. Therefore, the extent to which differences in displacement effects are the result of making a specific type of job switch, as opposed to of differences in observed and unobserved characteristics of workers who make different post-displacement career choices, is harder to assess. With this caveat in mind, we proceed to the results.

The β_2^k coefficients describe how the average difference in outcomes between displaced and non-displaced workers evolves if displaced workers remain in their pre-displacement occupation. For displaced workers who change occupations after displacement, the average difference in outcomes to non-displaced is captured by $\beta_2^k + \beta_4^k$. β_4^k thus provides an estimate of the difference in displacement effects between workers who switch occupations and those who don't.

Results

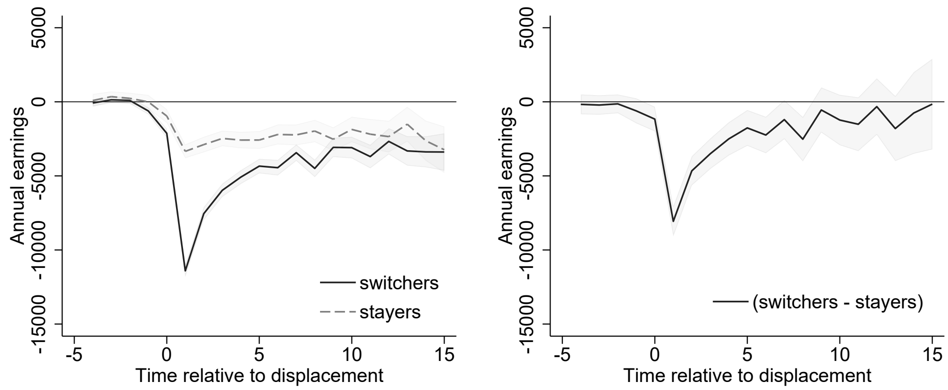
Figure 6 plots the estimated coefficients for different outcomes. Figure 6(a) shows the effect on annual earnings, 6(b) on daily wages and 6(c) on days worked, where wages and earnings are expressed in constant 2005 €. In each subfigure, the left panel shows the displacement effects for occupational switchers and occupational stayers separately, whereas the right panel shows the difference between the two groups, i.e., it plots $\hat{\beta}_4^k$ of eq. (5).

Apart from a dip in days worked right before displacement – possibly related to early leaving or distress signals – displaced workers' pre-displacement trends run parallel to those of their non-displaced counterparts. This holds for both displaced workers who change occupations after displacement and those who do not. That is, the parallel trends before displacement suggest that the matching procedure was able to control for all relevant observed and unobserved worker characteristics.

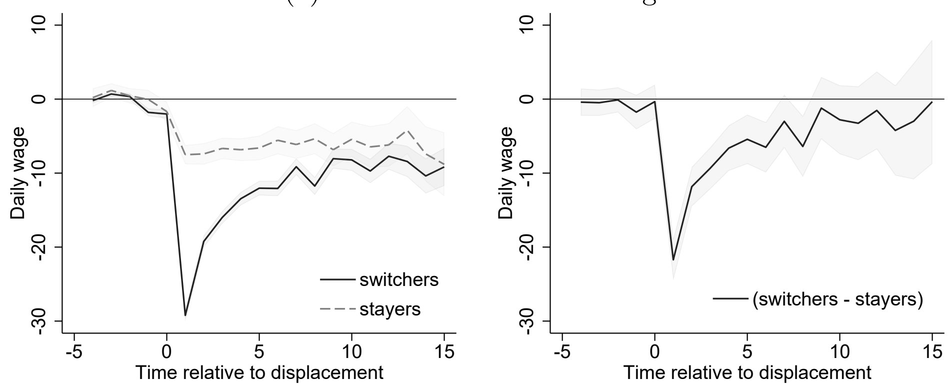
Both, occupation stayers and occupation switchers, suffer losses throughout the post-displacement period. However, these losses are substantially larger for occupation switchers. While occupation stayers lose, on average, over €2,300, or 7.6 percent of their pre-displacement annual earnings, occupation switchers lose about twice as much, close to €4,500, or 15.6 percent of their pre-displacement earnings.

These differences are mainly driven by the collapse in earnings right after displacement. For occupation stayers, the immediate drop in earnings is small at 11 percent of pre-displacement earnings. In contrast, for occupation switchers this drop amounts to 40 percent of their pre-displacement earnings. Neither group manages to catch up with its counterfactual earnings trajectory, even fifteen years after displacement. Moreover, it takes occupation switchers nine year until they have caught up to occupation stayers in terms of displacement-induced earnings losses.

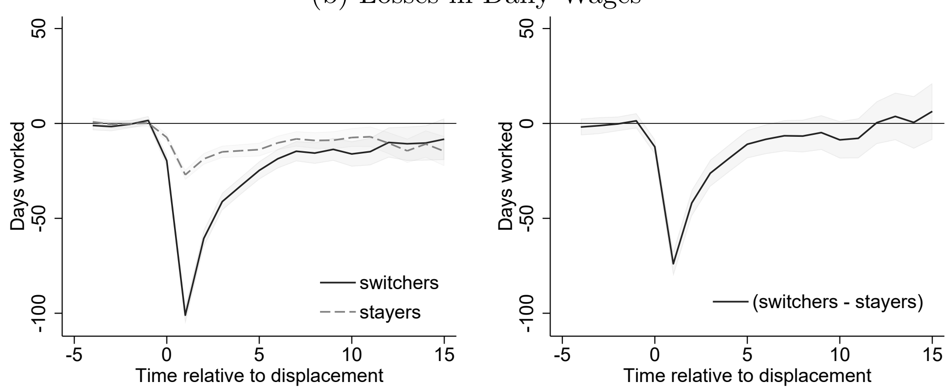
The differences in post-displacement experience between workers who change occupations and those who don't are not only visible in the reduction in days worked (i.e., unemployment spells), but also in the reduction in daily pay. Displaced workers who change occupations suffer much larger drops in their daily pay than those who don't. Moreover, it takes this group very long before they bounce back as much as workers who manage to find work in their pre-displacement occupations. This suggests that productivity-related aspects, such as skill mismatch, play an important



(a) Losses in Annual Earnings

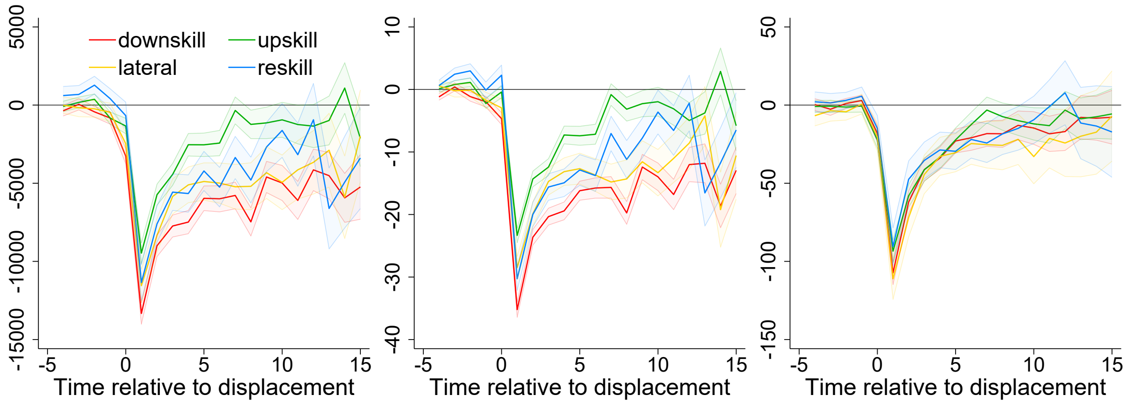


(b) Losses in Daily Wages



(c) Losses in Days Worked

Figure 6: **Displacement Costs: Stayers vs. Switchers**
Notes: Left panels show estimated displacement effects for occupation switchers (solid lines) and occupation stayers (dashed lines) for different dependent variables before and after displacement; right panels show differences in effects between these two categories. Displacement effects are based on a specification of equation (5) with potential work experience, potential work experience squared and worker fixed effects as control variables. Error bands refer to 95% confidence intervals, with standard errors clustered by individual. In the annual earnings results missing wages are treated as zeros. The daily wage results are conditional on being employed. Source: SIAB 1975-2010 and BIBB/BAuA 2006.



(a) Annual Earnings (b) Daily Wages (c) Days Worked

Figure 7: **Displacement Costs by Switch Type**

Notes: Panels show displacement effects experienced by different types of occupation switchers (green: upskilling switchers; blue: reskilling switchers; yellow: lateral switchers; red: downskilling switchers). Displacement effects are based on a specification of equation (5) with potential work experience, potential work experience squared and worker fixed effects as control variables. Error bands refer to 95% confidence intervals, with standard errors clustered by individual. In the annual earnings results missing wages are treated as zeros. The daily wage results are conditional on being employed. Source: SIAB 1975-2010 and BIBB/BAuA 2006.

role in displacement-related earnings losses.

We explore this further in Figure 7, which shows displacement effects for workers who make different types of occupation switches. Pre-displacement trajectories are once again reasonably similar between displaced and non-displaced workers. However, post-displacement career paths differ markedly. In particular, they depend on the type of occupation switch that displaced workers undertake.

First, there are large differences in the initial drop in earnings. Upskilling switchers are least affected by their displacement, losing only 33 percent in annual earnings immediately after displacement. This contrasts with the 46 percent reduction in annual earnings for downskilling workers, who experience the most severe immediate earnings losses. Immediate earnings losses for reskilling and lateral switchers lie somewhere in between these extremes.

Second, upskilling workers are the only group who manage to fully catch up with their counterfactual career paths. This happens about seven years after displacement. None of the other occupation switchers are able to achieve this and neither are workers who remained in their pre-displacement occupation. In fact, already after four years, upskilling workers surpass workers who don't switch occupations in terms of catching up with their counterfactual earnings paths.

Interestingly, these differences in earnings paths are fully driven by differences in daily wages, not days worked. That is, we do not find any evidence that workers whose switches are associated with lower earnings losses also differ in the extent to which they postpone accepting new jobs. Another noteworthy finding that emerges from Figure 7 is that lateral switchers fare much worse than occupation stayers. Apparently, even relatively minor occupational mismatch is associated with worse career outcomes. Yet, somewhat surprisingly, reskillers do not fare worse than lateral switchers, even though reskillers experience much greater skill redundancies and shortages than lateral switchers.

Overall, it seems that, although skill redundancies and skill shortages both measure skill mismatch, they have drastically different consequences. In particular, skill shortages are associated with much more benign displacement consequences than skill redundancies. This would explain why upskilling displaced workers do much better than their downskilling peers, in the long run, even managing to do better than occupation stayers. Moreover, it explains why reskilling displaced workers are not worse off than lateral switchers: although their skill redundancy suggests negative career prospects, these are counteracted by their skill shortage.

One explanation for these patterns is that skill shortages force workers to acquire valuable new skills. In Appendix D, we show corroborating evidence for this conjecture that shows that upskilling workers use their job loss as an opportunity to return to school and increase their educational attainment. That is, the share of upskilled workers with a tertiary degree increases from 6.2 to 9 percent over the course of the first three years after displacement. Given Germany's extensive system of continuing and adult education (Nuissl von Rein, 2008), the full extent of educational upgrading is likely to be greater than what we are able to capture with this coarse measure of educational attainment.

Evolution of Mismatch

Finally, we ask whether displaced workers embrace their new jobs or try to find their way back to their old careers. To answer this question, we study how the mismatch *to pre-displacement jobs* changes over the years after displacement. We do so using the same difference-in-differences framework as before, but now estimate the following regression specification:

$$M_{it} = \tilde{\gamma}_t + X'_{it}\tilde{\delta} + \sum_{k=-4}^{15} \tilde{\beta}_1^k T^k_{p(i)t} + \sum_{k=-4}^{15} \tilde{\beta}_2^k T^k_{p(i)t} D_i + \varepsilon_{it}, \tag{6}$$

where regressors are defined as in eq. (5). M_{it} now is either the skill-redundancy or the skill-shortage of worker i in year t to the job they held in year 0, the year in which the displaced worker in pair $p(i)$ was displaced. For ease of interpretation, we change the sign of skill-shortage so that both types of mismatch are expressed in (positive) years of schooling.

In other words, we compare the skill shortage and skill redundancy vis-à-vis the pre-displacement jobs that displaced workers experience to their counterfactual career paths without displacement. Figure 8 plots the results for our four different types of job switchers. The thick dashed lines display the career paths for displaced workers ($\tilde{\beta}_1^k + \tilde{\beta}_2^k$), the thin solid lines the counterfactual career paths of their statistical twins ($\tilde{\beta}_1^k$).

All four counterfactual groups move slowly away from the jobs they held in the year before their statistical twins had been displaced. Moreover, the counterfactual development paths are similar for all four types of occupation switchers, but very different from the actual career paths of displaced workers. This suggests that displacement forces workers on career paths that are quite distinct from the ones they would have chosen had they not been displaced.

Furthermore, whereas the control groups tend to slowly drift away from their old jobs, apart from lateral switchers, who move over very short skill distances, displaced workers tend to move back in the direction of their pre-displacement jobs. However, this process is slow: ten years after displacement, neither the group of upskillers nor the groups of downskillers or reskillers had managed to even halve the skill mismatch to their pre-displacement jobs.

Finally, displaced workers do not close the gap to their counterfactual career paths symmetrically. Instead, they reduce skill redundancies at a faster rate than skill shortages. For instance, upskilling displaced workers manage to reduce an average initial skill shortage of 1.7 years by about 22 percent, whereas downskilling displaced workers reduce an initial 1.5 years of skill redundancy by 42 percent.[12] Similarly, reskilled workers reduce the skill redundancy to their pre-displacement jobs by 40%, but their skill shortage by only 20%. In fact, upskillers and reskillers all but cease reducing skill shortages some five years after displacement. In contrast, downskillers and reskillers keep reducing skill redundancy for at least ten years.[13] Upskilling and

[12]This is based on the distance between the peak of mismatch in the first year and the average mismatch in the last five years after displacement: $\left(\tilde{\beta}_1^1 + \tilde{\beta}_2^1\right) - \frac{1}{5}\sum_{k=11}^{15}\left(\tilde{\beta}_1^k + \tilde{\beta}_2^k\right)$.

[13]Because the counterfactual groups tend to increase skill shortage faster than skill redundancy, the estimated displacement effects $\hat{\beta}_2^k$ are similar for skill redundancy and skill shortage. However, this symmetry is driven by asymmetries in the counterfactual career paths in the direction of jobs that are, net, more demanding.

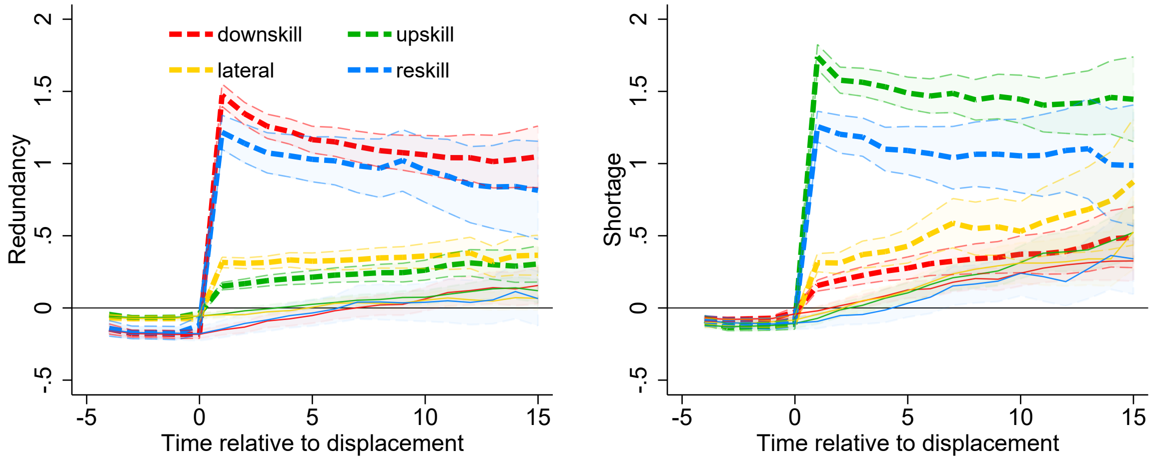


Figure 8: **Evolution of Mismatch to Pre-Displacement Job**
Notes: Graphs show the average skill redundancy (left panel) and skill shortage (right panel) to pre-displacement jobs for displaced workers (thick dashed lines) and their statistical twins (thin solid lines) in years of required schooling, controlling for work experience. These conditional averages are calculated as $\hat{\beta}_1^k + \hat{\beta}_2^k$ for displaced workers and $\hat{\beta}_1^k$ for their non-displaced statistical twins in eq. (6). The regression controls for year fixed effects and potential experience and the square of potential experience. Error bands reflect 95% confidence intervals. Source: SIAB 1975-2010 and BIBB/BAuA 2006.

reskilling workers thus seem to permanently move to more demanding jobs. This corroborates our earlier conjecture that the reason why upskilling displaced workers fare relatively well and why reskilling workers don't do worse than lateral switchers is that these workers use the displacement event to move up the career ladder.

5 Conclusion

When workers change jobs, they typically leave some of their old skills unused, and at the same time acquire new ones. In this paper, we propose measures of human capital mismatch that measure the skill shortage and skill redundancy that workers experience when moving from one job to another.

These measures allow us to uncover a number of general patterns of skill mismatch for the German labor market. First, the type of job switches that people undertake depends on whether or not they changed jobs voluntarily. Workers who are laid off tend to move to jobs that leave relatively much human capital redundant, whereas workers who voluntarily change jobs tend to move to jobs that require them to acquire new skills. Displaced workers lie somewhere in between these two groups, corroborating that different types of job switches are associated with different self-selection patterns. Furthermore, we show that young people tend to choose career switches with more skill shortage than older workers. Finally, for involuntary job switchers and displaced workers, skill shortages are negatively correlated with the business cycle: these workers tend to leave more of their skills redundant when unemployment rates are high than when they are low. In contrast, for workers who voluntarily change jobs, we do not find any relation with the business cycle.

Finally, we show that the earnings losses related to job displacements vary significantly with the type of skill mismatch. The largest losses are experienced by workers who choose new jobs in which they leave many of the skills they used in their pre-displacement occupation unused, and the mildest losses are experienced by those who move to jobs that require many additional skills compared to their pre-displacement occupation. Interestingly, however, even workers who move to more demanding jobs do not manage to completely close the gap in earnings to the counterfactual career paths on which displacement did not occur. But in the medium run they do not fare worse than workers who manage to remain in their old occupation after displacement. Overall, our results suggest that skill mismatch is an important contributor to the earnings losses that displaced workers face.

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Appendix

A Construction of Skill Vectors

To construct our skill vectors, we start by selecting 46 survey questions from the BIBB survey that refer to individuals' tasks, knowledge and skills. Answers are typically provided on an ordinal scale, which we turn into binary values which reflect whether or not a worker has a skill or carries out a task. Next, we average these binary values within an occupation to arrive at occupational vectors that express the share of workers in the occupation that use a skill, rely on a field of knowledge or perform a task.

These 46-dimensional skill profiles contain much redundant information. To reduce the dimensionality of the skill profiles, we use factor analysis. This a coordinate system consisting of seven axes that that together account for 86.5 percent of the overall variation in the data. However, the axes of this coordinate system do not necessarily map onto natural skill categories. A natural assumption is that the original survey questions correspond to more or less well-defined skill categories. Therefore, we rotate these factors such that most factor loadings are either large or close to zero, ensuring that our skill factors closely match the originally surveyed skill categories.

Apart from the 46 job questions related to job requirements, we also use 14 questions about different aspects of physical discomfort and exposure to dangerous working conditions. Factor analysis reveals that these questions have one dominant common factor. We interpret this factor as a measure of the disutility that workers experience in an occupation.

Finally, the BIBB survey also provides a detailed account of each worker's schooling history. It not only provides information on the highest educational attainment, but also on the time that workers have spent in up to seven episodes of post-secondary schooling and training. We use this information to calculate the average number of years of cumulative schooling of workers in a given occupation.

We will assume that workers used this schooling to acquire the skills that their current occupation requires. If schooling requirements for different skills are additive, total schooling requirements can be written as a linear combination of skill factors:

$$S_o = \alpha + \sum_{i=1}^{7} \beta_i s_o^i + \gamma d_o + \varepsilon_o \tag{A.1}$$

where S_o is the average number of years of schooling in occupation o and s_o^i the factor score of the occupation for skill factor i, measured in units of standard deviations.

Table A.1: Schooling Regression

Independent variable	Coefficients	Standard Errors
Factor 1 (cognitive)	1.488***	(0.095)
Factor 2 (science)	1.159***	(0.111)
Factor 3 (technical)	0.132	(0.110)
Factor 4 (sales)	0.091	(0.096)
Factor 5 (medical care)	0.325***	(0.090)
Factor D (work disutility)	-0.556***	(0.140)
Constant	12.420***	(0.083)
Observations (occupations)	263	
Adj. R-squared	0.727	

Notes: OLS regression analysis of required years of schooling for an occupation on the occupation's skill vector and disutility. Schooling requirements are defined as the average years of schooling and training that workers with a given in occupation report in the BIBB survey. Factors 1-5 are the rotated factors from the average share of workers that report a skill or task, Factor D is a disutility factor from a factor analysis of working conditions. Significance levels: *** $p < .01$; ** $p < .05$; * $p < .10$. Source: BIBB/BAuA 2006.

The term d_o controls for the disutility of working in occupation o. This control variable is important, because some skill requirements correlate with poor working conditions. Controlling for these working conditions ameliorates confounding such skills with poor working conditions.

If workers use education to acquire skills, all skills should have a positive effect on schooling requirements. This holds true for all but two out of the seven rotated skill factors. The first of these factors captures security related tasks (Secure/Protect/Guard/Monitor/Regulate traffic) and the second is related to working under time pressure (How often do you have to work under time/performance pressure? How often do you have to work very fast?). These two factors therefore do not seem to be closely associated to a specific type of schooling or training. Moreover, they contribute less than 6 percent to the variance explained in the factor analysis. Therefore, we decide to drop them from the schooling regression in eq. (A.1). The remaining factors all have positive effects on schooling. They 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.

Table A.1 summarizes the results of the schooling regression. The five skill factors can account for 73.4 percent of the variance in schooling requirements across occupations. We interpret the point estimates in this regression as the number of years of schooling that it takes to acquire a one standard-deviation increase in the corresponding skill. This allows us to calculate skill redundancy and skill shortage for each pair of occupations as:

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

and

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

where f_{io} is occupation o's factor score for skill i, β_i the coefficient on skill i in the schooling regression (A.1), and $I(.)$ an indicator function that evaluates to 1 if its argument is true. Note that skill shortage is expressed in negative years of schooling, whereas skill redundancy is expressed in positive years of schooling.

B Most Common Job Switches by Type

In the main text, we focus on workers who change occupations, arguing that different types of occupational switches may be associated with different displacement consequences. To give an idea of the level of granularity at which occupational change is recorded, as well as provide a sense of the different types of switches we observe Table B.1 tabulates the most common occupational moves in the SIAB sample. In particular, it records for each type of our four job switch types the five most common examples of directed occupational pairs. The most skill-similar occupations are found among the lateral moves, the most skill-dissimilar occupations among the reskilled moves. Furthermore, note that many of the common upskilled moves are also found among the the most common downskilled moves, albeit with workers moving in the opposite direction.

C Matching Results

The donor pool for matched workers is very large. For computational feasibility, we therefore match displaced workers year-by-year and then pool the resulting data sets. Note that the distinction between occupation stayers and different types of switchers only emerges after displacement and is the result of endogenous career choices. We therefore do not match these subsamples separately. That is, our matching procedure

Table B.1: Most Common Occupational Moves by Type

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		**Lateral**	
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

Source: SIAB 1975-2010. The sample includes all individuals aged 18-55 with non-missing occupational information and without left-censored labor market histories. Number of observations: 10.4 million.

does not take into account information about the job switches that may take place after displacement.

Table C.2 shows that, after matching, the means of pre-treatment variables are very similar in economic terms and mostly statistically indistinguishable between the displaced and non-displaced samples. However, there are differences in pre-displacement daily wages, with displaced workers earning slightly higher average wages than their matched counterparts. These differences are only statistically significant when we pool observations across years, as in the table shown here, and are modest in economic terms. Moreover, our evidence is consistent with the parallel trends assumption underlying our difference-in-differences framework: pre-displacement trends of daily wages and days worked are not significantly different between the displaced and non-displaced samples.

Table C.3 reports the balancing properties for the matched samples of occupation switchers and occupation stayers. To illustrate the differences between the two types of displaced workers, we also include variables on which we matched exactly, even though these are perfectly balanced by definition.

An occupation switch occurs if a worker moves between any of the 263 three-digit occupations in our sample. While 3,026 workers (24.9 percent) in the displaced sample change occupations, only 347 (2.9 percent) of non-displaced workers in the matched sample do so. In spite of this, the characteristics of displaced and non-displaced workers remain well balanced even within these subsamples. Moreover, although the differences in pre-trends for the two subsamples are somewhat larger than in the overall sample, our evidence is still consistent with the parallel trends assumption.

However, occupation stayers and switchers differ markedly from one another. For instance, occupation switchers tend to have about a year less of occupational experience, slightly lower pre-displacement pay, and slightly lower pre-displacement growth in pay. They are also more likely to be male and to work in the primary or secondary sector, than are occupational stayers.

We can further divide occupational switchers using our mismatch categories: 1,066 (35.2 percent) make downskilling, 1,087 (35.9 percent) upskilling, 357 (11.8 percent) reskilling, and 516 (17.1 percent) lateral moves. Tables C.4 and C.5 provide additional information on the balancing properties for each set of switchers. Differences in pre-displacement pay levels between displaced and non-displaced workers are somewhat more pronounced for some switcher types. However, most other differences (occupational experience, age, level of employment, and for the most part, the growth of pay) remain well balanced. In spite of workers' self-selecting into different types of occupation switches, the differences between displaced and non-displaced worker are small and pre-displacement trends are moving in parallel.

Moreover, note that the matching procedure is merely a pre-screening procedure. Any remaining imbalances are further addressed by the inclusion of fixed effects in the event analysis and the difference-in-differences estimation (see Ho et al., 2007).

Table C.1 reports the average level of skill shortage and skill redundancy (measured in years of schooling) for each of these four groups. For the non-displaced groups, the average level of skill mismatch is almost always negligible (half a month at most), while workers in the displaced groups exhibit substantial mismatch. The average upskilling worker lacks skills worth close to two years of schooling for their new job, and leaves two and a half months of schooling redundant. The average downskilling worker faces skill shortages of about three months, and 20 months of skill redundancies at the new job. Re-skilling workers incur 18 months of skill short-

Table C.1: Skill Shortage and Skill Redundancy by Type of Switch and Displacement Status

	Reskilled		Upskilled		Lateral		Downskilled	
	ND	D	ND	D	ND	D	ND	D
$\lvert SkillShortage \rvert$	0.02	1.50	0.04	1.88	0.05	0.39	0.03	0.22
$SkillRedundancy$	0.04	1.47	0.02	0.22	0.01	0.40	0.04	1.70

Notes: The measurement units are years of schooling. Skill shortage is measured in negative years of schooling, but here we show its absolute value. Source: SIAB 1975-2010 and BIBB/BAuA 2006 (matched sample).

ages as well as redundancies, whereas lateral movers experience only 5 months of skill shortages and skill redundancies.

Table C.2: Matching Quality: Displaced and Non-displaced Workers

	Mean		t-test	
	Non-displaced (ND)	Displaced (D)	t-test	$p > \|t\|$
Age	38.3	38.3	-0.08	0.939
Real daily wage t-2	81.8	83.4	2.49	0.013
Real daily wage t-3	78.5	80.6	3.52	0.000
Real daily wage t-4	77.1	78.2	1.62	0.104
Real daily wage t-5	74.3	75.8	2.89	0.004
Days worked t-2	363	363	-0.02	0.988
Days worked t-3	358	358	-0.85	0.394
Days worked t-4	357	357	0.61	0.543
Days worked t-5	357	358	0.77	0.444
% change, real daily wage t-5 to t-2	15.1%	14.8%	-0.37	0.710
% change, days worked t-5 to t-2	5.9%	5.0%	-1.14	0.254
Occupational experience t-2	8.8	8.8	1.19	0.235
Number of observations	12,160	12,160		
Exact matching variables				
% Women	38.4%			
% Primary and secondary sector	46.6%			
% Vocational training	88.5%			
% Tertiary educated	6.8%			
% West	35.2%			

Notes: Balance in average worker characteristics between the displaced and matched non-displaced samples. t-test reflects the null hypothesis that the two groups have equal means. The means of the exact matching variables are identical between the groups by definition. Source: SIAB 1975-2010.

Table C.3: Matching Quality: Occupational Stayers (St) and Occupational Switchers (Sw)

	Mean		t-test		Mean		t-test	
	ND St	D St	t	$p > \|t\|$	ND Sw	D Sw	t	$p > \|t\|$
Age	38.4	38.4	0.19	0.851	37.8	37.7	-0.49	0.624
Real daily wage t-2	82.4	84.7	3.12	0.002	80.0	79.2	-0.75	0.453
Real daily wage t-3	78.8	81.8	4.19	0.000	77.4	76.9	-0.44	0.657
Real daily wage t-4	77.6	79.6	2.32	0.020	75.4	74.0	-1.31	0.190
Real daily wage t-5	74.5	76.9	3.75	0.000	73.6	72.6	-1.07	0.286
Days worked t-2	363	363	0.79	0.430	363	362	-1.56	0.120
Days worked t-3	358	358	-0.01	0.993	359	357	-1.72	0.086
Days worked t-4	357	358	1.43	0.152	358	356	-1.24	0.215
Days worked t-5	357	358	1.93	0.053	359	356	-1.89	0.059
% change, real daily wage t-5 to t-2	15.9%	15.3%	-0.70	0.486	12.6%	13.4%	0.77	0.439
% change, days worked t-5 to t-2	6.1%	4.8%	-1.31	0.191	5.5%	5.5%	0.02	0.985
Occupational experience t-2	9.0	9.2	1.74	0.082	8.0	7.9	-0.80	0.422
Number of observations	9,134	9,134			3,026	3,026		

Exact matching variables		
% Women	40.9%	31.0%
% Primary and secondary sector	43.0%	57.5%
% Vocational training	88.4%	88.9%
% Tertiary educated	7.2%	5.6%
% West	35.6%	33.9%

Table C.4: Matching Quality: Reskilled (Re) and Upskilled (Up)

	Mean		t-test		Mean		t-test	
	ND Re	D Re	t	$p > \|t\|$	ND Up	D Up	t	$p > \|t\|$
Age	37.4	37.7	0.63	0.529	38.0	37.2	-2.43	0.015
Real daily wage t-2	88.4	86.9	-0.44	0.662	75.4	79.2	2.51	0.012
Real daily wage t-3	87.1	85.2	-0.47	0.637	72.9	76.2	2.14	0.032
Real daily wage t-4	84.4	80.7	-0.98	0.326	71.1	73.7	1.69	0.091
Real daily wage t-5	81.4	77.2	-1.37	0.171	69.8	72.7	2.04	0.042
Days worked t-2	362	363	0.25	0.806	363	363	-0.21	0.830
Days worked t-3	359	358	-0.28	0.782	359	359	0.06	0.952
Days worked t-4	355	355	-0.10	0.919	357	357	-0.04	0.966
Days worked t-5	358	358	0.17	0.862	359	356	-1.20	0.231
% change, real daily wage t-5 to t-2	14.2%	14.7%	0.17	0.863	11.9%	14.4%	1.48	0.139
% change, days worked t-5 to t-2	2.8%	3.5%	0.52	0.602	7.4%	8.5%	0.26	0.796
Occupational experience t-2	8.0	7.8	-0.51	0.612	8.2	8.0	-0.85	0.395
Number of observations	357	357			1,087	1,087		

Exact matching variables	Re	Up
% Women	22.7%	33.4%
% Primary and secondary sector	62.7%	54.4%
% Vocational training	*	89.9%
% Tertiary educated	12.6%	*
% West	30.8%	33.7%

*These values were suppressed in accordance with the data privacy regulations and data censoring rules by the Research Centre of the Institute for Employment Research (FDZ IAB).

Table C.5: Matching Quality: Lateral (Lat) and Downskilled (Down)

	Mean		t-test		Mean		t-test	
	ND Lat	D Lat	t	$p > \|t\|$	ND Down	D Down	t	$p > \|t\|$
Age	38.3	38.4	0.13	0.894	37.4	37.8	1.15	0.252
Real daily wage t-2	71.1	72.3	0.57	0.568	86.3	80.0	-3.07	0.002
Real daily wage t-3	69.2	70.5	0.58	0.563	82.8	78.0	-2.32	0.020
Real daily wage t-4	67.8	69.9	0.82	0.410	80.5	74.1	-3.30	0.001
Real daily wage t-5	65.8	67.9	1.21	0.226	78.6	73.2	-3.08	0.002
Days worked t-2	365	362	-1.60	0.109	362	361	-1.42	0.155
Days worked t-3	360	358	-0.57	0.570	360	354	-2.35	0.019
Days worked t-4	362	356	-1.58	0.115	357	354	-0.95	0.343
Days worked t-5	361	359	-0.59	0.554	358	355	-1.60	0.110
% change, real daily wage t-5 to t-2	10.9%	8.7%	-1.21	0.227	13.5%	14.2%	0.32	0.749
% change, days worked t-5 to t-2	5.5%	2.4%	-1.26	0.207	4.4%	4.6%	0.15	0.879
Occupational experience t-2	7.8	7.9	0.57	0.572	7.9	7.8	-0.60	0.548
Number of observations	516	516			1,066	1,066		

Exact matching variables		
% Women	39.9%	27.0%
% Primary and secondary sector	54.8%	60.6%
% Vocational training	*	93.4%
% Tertiary educated	*	6.6%
% West	35.3%	34.5%

*: values suppressed in accordance with the data privacy regulations and data censoring rules by the Research Centre of the Institute for Employment Research (FDZ IAB).

D Post-Displacement Educational Upgrading

In the main text, we speculate that upskilling and reskilling displaced workers may invest in the acquisition of new skills. Here, we explore whether we find some evidence in support of this claim.

Figure D.1 shows how reported educational attainment in the SIAB data changes over time. In particular, it shows how the percentage of displaced (solid lines) and non-displaced workers (dashed lines) with tertiary degrees changes.

Before displacement, there are no noticeable changes in the share of workers with tertiary education. However, after displacement, three out of four groups of displaced occupation switchers increase their educational attainment, while their non-displaced statistical twins do not. The exception is the group of lateral switchers, where both displaced and non-displaced do not seem to invest in education. Although most of the differences depicted in Figure D.1 are not estimated precisely enough to be statistically significant, we do find statistical evidence that the group of displaced upskilling workers acquire more education than their statistical twins after displacement. In particular, before displacement, 6.2 percent of upskilling displaced workers had a tertiary degree. This share increases to 9 percent three years after displacement, an increase of 46 percent that is significantly different at the 5 percent level from the change observed in the matched non-displaced sample. We should note that the change in the share of tertiary educated is a very crude measure of educational upgrading in the German context, and for our sample of displaced workers who tend to be older and highly experienced in a single occupation.

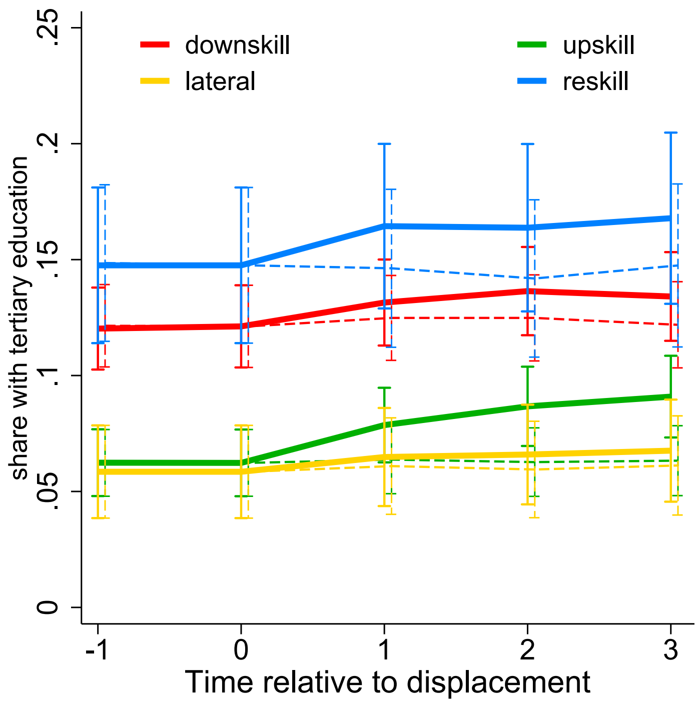

Figure D.1: **Educational Upgrading**
Notes: Evolution of shares of workers with tertiary degree. Solid lines refer to displaced workers, dashed lines to their matched non-displaced counterparts. Whiskers correspond to 90% confidence intervals. Source: SIAB 1975-2010 and BIBB/BAuA 2006 (matched sample).