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Skill mismatch and the costs of job displacement

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Skill Mismatch and the Costs of Job Displacement

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Skill Mismatch and the Costs of Job Displacement*

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Abstract

Establishment closures have lasting negative consequences for the workers they displace from their jobs. We study how these consequences vary with the amount of skill mismatch that workers experience after job displacement. Developing new measures of occupational skill redundancy and skill shortage, we analyze the work histories of individuals in Germany between 1975 and 2010. We estimate difference-in-differences models, using a sample of displaced workers who are matched to statistically similar non-displaced workers. We find that displacements increase the probability of occupational change eleven-fold. Moreover, the magnitude of post-displacement earnings losses strongly depends on the type of skill mismatch that workers experience in such job switches. 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. We show that these differences can be attributed to differences in mismatch after displacement, and not to intrinsic differences between workers making different post-displacement career choices.

Keywords: difference-in-differences, job displacement, occupational change, skill mismatch

JEL classification: J24, J31, J63, O33

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1 Introduction

Downsizing and closures of firms in an economy are integral to Schumpeter's description of structural transformation as a process creative destruction and establishment closures often are ultimately the consequence of technological change, organizational change, or the geographic reallocation of an industry (Kriechel, 2010; Autor et al., 2013; Schröder and Sørensen, 2012; Eriksson et al., 2016; Holm et al., 2017; Andersson et al., 2020). These closures have profound impacts on workers. When workers are displaced from their jobs in firm or establishment closures, they typically face large and persistent earnings losses. Fifteen years after displacement, average earnings and wages fall ten to fifteen percent below the levels expected 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; Raposo et al., 2021), the loss of firm wage premiums (Lazear, 1979; Lachowska et al., 2020; Fackler et al., 2021; Schmieder et al., 2023), search costs (Topel and Ward, 1992), stigmatization (Vishwanath, 1989; Biewen and Steffes, 2010; Kroft et al., 2013; Eriksson and Rooth, 2014), and technological change that changes the value of certain skills (Blien et al., 2018; Goos et al., 2021).

The average effect of displacement that is reported in the literature on displacement-related earnings losses conceals that individual workers may experience a wide variation in outcomes. 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 had workers not been displaced. 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 this variation in career outcomes. 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 con-

sequences of job switches are the same, regardless of the direction in which workers move. For instance, salespeople becoming professional negotiators are assumed to experience the same human capital mismatch as professional negotiators becoming salespeople. 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 described 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 economic expansions, workers tend to switch to more skill-demanding job. That is, workers tend to move to jobs that require more new skills than the amount of skills that they used in their old jobs, but that are now left redundant. In recessions, this tendency reverses. We also find that young workers are more likely to move to more demanding jobs than older workers. Finally, net skill redundancy is the highest for workers who change jobs involuntarily (i.e., job-unemployment-job transitions) and the 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 that affect their performance, continuation value or outside options. We identify over 12,000 displaced workers in the administrative data, whom we match to non-displaced sta-

tistical twins using a combination of exact and propensity score matching. Using this matched sample, we find that displacement causes workers to switch occupations: displaced workers are eleven to twelve times more likely to switch occupations than non-displaced workers. However, displacements do not significantly change the *direction* of skill mismatch in job switches.

Next, we divide displaced workers into five 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 new skills and makes 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.

Our identification strategy assumes that – conditional on observable characteristics and worker fixed effects – displacement events are exogenous. As long as this assumption holds, the estimated effects of displacement are causal in the sense that they compare the paths of displaced workers to counterfactual career paths without displacement. Moreover, any differences in displacement effects across the above-defined groups would reflect effect heterogeneity. However, it is unclear whether this heterogeneity in causal effects can be attributed to the differences in postdisplacement job mismatch, or to differences in the composition of different groups.[1] To examine this, we identify weights that align the samples of all five groups of displaced workers in terms of their predisplacement characteristics using entropy balancing. If differences in displacement effects are due to the fact that displaced workers that make different career choices are *intrinsically* different from one another, we would expect that effect heterogeneity is substantially reduced in these reweighted samples.

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: on average, in the 15 years post-displacement, occupational switchers experience 16.5 percent lower annual earnings compared to their earnings two years

[1] Yi et al. (2017, 2023) propose an instrumental variable approach to exogenize sectoral choices after displacement. Their instrument is based on the number of past coworkers present in each potential destination sector at the time of a worker's displacement. The underlying rationale is that past coworkers can inform about job openings in their firms and industries, thereby influencing the likelihood to choose that particular sector. However, constructing such instrument would require access to the entire population of workers in Germany, not only the 2 percent sample.

prior to displacement, while for occupational stayers these losses are limited to 8.7 percent. However, some occupation switchers manage to, if not outperform occupation stayers, at least draw even with them. This finding is, *prima facie*, puzzling from a skill mismatch point of view. The main explanation lies in the direction of post-displacement switches. Most displaced occupation switchers either make downskilling (35 percent) or upskilling (36 percent) job switches. However, these two groups experience markedly different earnings losses: across the first fifteen years after displacement, downskilling switchers earn on average 22.4 percent below their pre-displacement wages, compared to 8.9 percent for upskilling 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. Furthermore, using our reweighted samples that balance predisplacement characteristics, we find that only a small part of the heterogeneity in displacement effects across displaced worker groups can be attributed to compositional differences. This suggests that most of the observed effect heterogeneity reflects not intrinsic differences among workers, but differences in the level and type of occupational mismatch that these workers face after displacement.

Turning to the evolution of skill mismatch, all displaced worker groups and their counterfactuals tend to accumulate skill shortage and skill redundancy over time. The main difference across gorups is that reskillers, upskillers and downskillers all experience significant immediate shifts in one or two of these mismatch dimensions shortly after displacement. Over time, these three groups gradually converge towards their counterfactuals. Nevertheless, a gap in mismatch between actual and counterfactual career paths remains even 15 years after displacement. This means that displacement-induced skill mismatch is very persistent: although the groups that make the largest jumps in their skills right after displacement make relatively smaller jumps afterwards, within our period of observation, they do not converge to what their mismatch would have been absent displacement.

Our work adds to two areas of research. First, it contributes to the literature on the long-term consequences of job displacement, which has estimated the effects of displacements on workers' career developments (see Carrington and Fallick, 2017 for a review), their geographic mobility (Eriksson et al., 2016), the regional re-utilization of their skills (Holm et al., 2017; Andersson et al., 2020), their health outcomes and life expectancy (Sullivan and Von Wachter, 2009; Black et al., 2015), marriage and fertility outcomes (Del Bono et al., 2012; Eliason, 2012), as well as the health, educational and labor market outcomes of their children (Oreopoulos et al., 2008; Rege et al., 2011; Lindo, 2011; Hilger, 2016). We add to this literature by documenting a

causal effect of displacement on the propensity of workers to change occupations and shows how different post-displacement career choices are associated with drastically different post-displacement outcomes.

Second, we contribute to the literature on the measurement of skill mismatch (Tsang and Levin, 1985; Groot and Van Den Brink, 2000; Hartog, 2000; De Grip and Van Loo, 2002; McGuinness, 2006; De Grip et al., 2008; Nordin et al., 2010; Leuven and Oosterbeek, 2011; Perry et al., 2014; Addison et al., 2020; Guvenen et al., 2020), by offering a novel measure that describes occupational skill mismatch in a way that preserves a notion of directedness and is expressed in years of required (re)education. For this, we rely on the now widely-used task-based approach (Autor et al., 2003; Spitz-Oener, 2006; Autor and Handel, 2013; Consoli et al., 2016; Deming, 2017; Cirillo et al., 2021; Ciarli et al., 2021). Within this literature, our paper is most closely related to Robinson (2018), who document the patterns of distance and direction of occupational switchers in the United States. However, we differ from this work in several important ways.[2] We highlight these differences in the relevant sections of this paper.

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 first outline the sample restrictions and the matching procedure. We then report on the estimated effect of displacement on occupational mobility and on the probability of incurring skill mismatch. Next, we present results obtained with an event-study framework to investigate the relationship between skill mismatch and displacement costs in terms of annual earnings, daily wages, and levels of employment. Lastly, we study to what extent the observed effect heterogeneity can be attributed to compositional

[2]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 employ a more rigorous estimation approach, by first balancing the observable characteristics of displaced and non-displaced workers using a matching approach and then estimating difference-in-differences models. As we will show, this pre-processing step is important. 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.

differences across displaced worker samples. Section 5 concludes and 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). More recently, Addison et al. (2020) and Guvenen et al. (2020) have measured such mismatch as the discrepancy between the skills required by an occupation and the worker's measured abilities for learning those skills.

Human capital mismatch between jobs – typically between occupations – has 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 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.

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

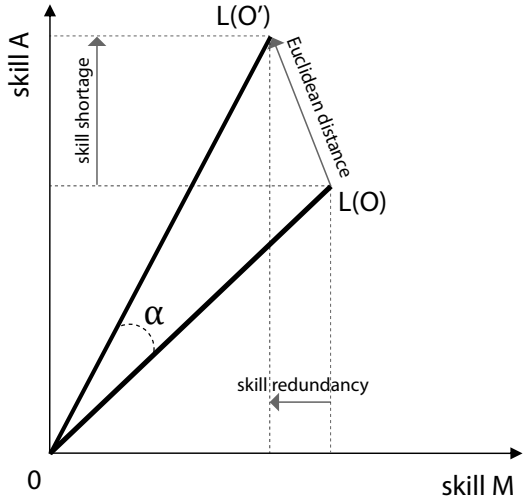


Figure 1: **Occupational Skill Profiles in a Two-dimensional Space**
Notes: Skill requirement vectors for two fictitious occupations, occupation O and O', and different measures of skill mismatch between them.

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 more 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.[3]

To do so, we use data from the BIBB survey. The dataset randomly samples

[3]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 robustness checks weight differences by the extent to which skills are associated with high wages. However, when used to analyze wage dynamics, this approach may result in asking whether moving to better paid occupations is associated with increased wages, raising concerns of circular reasoning.

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. We provide a more detailed description of the task and knowledge measures in the BIBB Survey in Appendix A, and in Appendix B, we provide more details in the construction of the skill vectors.

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 a factor analysis[4] 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 experiencing 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 a given 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 programs. Schooling therefore does not just refer to formal education, but includes training over the course of a worker's career.[5] Next, we try to estimate the years of schooling that each skill requires by regressing the average years of schooling in an

[4]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.

[5]Alternatively, one could try to explain occupational wages from skill factors as in Robinson (2018). However, this would express occupational distances in terms of differences in expected wages, that is, in terms of the market's valuation of skills. Using years of schooling emphasizes, instead, the *costs* of moving from one occupation to another. Moreover, using wages runs the risk of reaching somewhat tautological conclusions, such as that moving to better paid occupations is associated with more favorable post-displacement wage trajectories.

occupation on the occupation's 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.[6] Moreover, to safeguard against confounding certain skill requirements (e.g., of manual skills) 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 amount of skill mismatch 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 are 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* switches. 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

[6] We also experimented with more complex regression equations, adding control variables or bilateral interactions between all five skill factors. The resulting mismatch variables are highly correlated (between 0.88 and 0.99) with the ones used in the analysis of section 4 and using different specifications does not radically change our classification of job switchers.

change their skill profiles and are said to make *lateral* switches. Table 1 summarizes these definitions.[7]

Table 1: Types of Occupational Switchers

		Shortage	
		Above Median	Below Median
Redundancy	Above Median	Reskilled	Downskilled
	Below Median	Upskilled	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. Upskilling 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 C.1 in Appendix C 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.

[7]Given that the skill shortage and skill redundancy variables are derived from parameters estimated in a regression analysis, some uncertainty may exist about this classification. To explore this, we repeat this classification 1,000 times for all occupational pairs, each time drawing parameter estimates from a normal distribution that is centered on the point estimates of eq. (1) with a standard deviation equal to the corresponding standard errors. On average, this leads to reclassification of 7.4% of occupational pairs. However, most of these occur between adjacent classes. In fact, only 0.05% of occupational pairs are reclassified from upskillers to downskillers or vice versa and 0.04% of reclassifications occur between reskillers and lateral switches

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 coverage 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. Doing so, we distinguish between three types of job changes. First, *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. Second, workers can decide to change jobs themselves to pursue better career opportunities elsewhere. We identify such *voluntary* switches as job-to-job transitions that were uninterrupted by unemployment spells. Note, however, that, because in reality some workers who are laid off immediately find new jobs or refrain from applying for unemployment benefits, we may erroneously also classify some layoffs as voluntary job switches. Third, workers can get displaced from their jobs in the course of establishment closures. We define job separations due to such establishment closures as *job displacements*. To identify establishment closures, we rely on the definitions in Hethey-Maier and Schmieder (2013).

Hethey-Maier and Schmieder (2013) develop a method that uses worker flows between establishments to distinguish real openings and closures of establishments from mere changes in establishment identifiers. They construct variables that mark the entry or exit of an establishment that we can merge to our SIAB dataset at the level of individuals, using an establishment identifier.[8] Next, we keep workers in establish-

[8]In particular, we use the variable *austritt* (exit), categories 4, 5 and 6 to define plant closures. The variable is discussed in Ganzer et al. (2020), and in the original paper of Hethey-Maier and Schmieder (2013). The *austritt* (exit) variable helps us identify workers (in SIAB) who are employed

ments with at least 10 employees in the year before their closure, in order to reduce the possibility that individual workers may have had a great impact on the establishments' productivity and exit. Furthermore, we include in the group of displaced workers those who leave the establishment in the year leading up to the closure. The reason is that employees who anticipate trouble may leave a closing establishment before the closure. Often these "early leavers" include an establishment's best workers (Fallick, 1993; Gathmann and Schönberg, 2010; Davis and Von Wachter, 2011). Finally, whenever we cannot unambiguously determine that a job switch represents a layoff or a displacement, we label the switch involuntary or voluntary depending on whether or not we observe an unemployment-benefit spell between jobs.

The German Labor Market, 1975–2010

The German economy underwent a number of important changes during our period of observation, making this an interesting period to study. The aspects most relevant for our analysis are a secular increase in the unemployment rate (for a discussion, see Franz, 2013, ch. 1, p. 9) and the ensuing labor market reforms (Jacobi and Kluve, 2007; Möller, 2014; Burda and Seele, 2020), as well as the reunification of East and West Germany (Card et al., 2013; Dustmann et al., 2014).

First, while West Germany experienced a period of full employment in the 1960s and the first half of the 1970s, with unemployment rates of around one percent, unemployment became a persistent phenomenon after the first oil crisis in 1974. Only after around 30 years, the situation began to reverse. Around 2005, with West Germany's unemployment rate having reached peak levels of about 10 percent, labor market conditions started to improve both cyclically and in terms of long-term trends.

The rise of unemployment in Germany prompted a series of labor market reforms, starting in the mid-1990s, which generally made unemployment benefits less generous and increased the attractiveness of low-wage jobs. The resulting increase in the cost of unemployment and the corresponding decrease in the reservation wage may have led job seekers to accept jobs for which they were less suited. Some support for this conjecture is offered in Figure 4 below, which shows that skill mismatch starts increasing after 1995.

Second, the reunification of East and West Germany in 1990 led to substantial structural transformation and creative destruction. East German firms were often less productive than their West German counterparts and thus went bankrupt or

in an establishment on June 30 of a given year that exits between that date and June 30th of the following year.

had to downsize considerably. In fact, in the first decade of the re-unification, the number of employees in East Germany decreased from 8.8 million to 6.1 million, a drop by almost one-third (Franz 2013, Table 9.6). This rapid structural change is also reflected in our sample, as a disproportionate share of displaced workers come from East Germany (see Table 2 below). Moreover, Findeisen et al. (2021) show that workers (especially older ones) in East Germany are affected by "misallocation" at the beginning of reunification, which would offer a further explanation for the overall increase in skill mismatch after 1995 in Figure 4.

Some General Patterns of Skill Mismatch

Moving to job switches, we find that 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 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 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).[9] We find that this 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.

[9]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

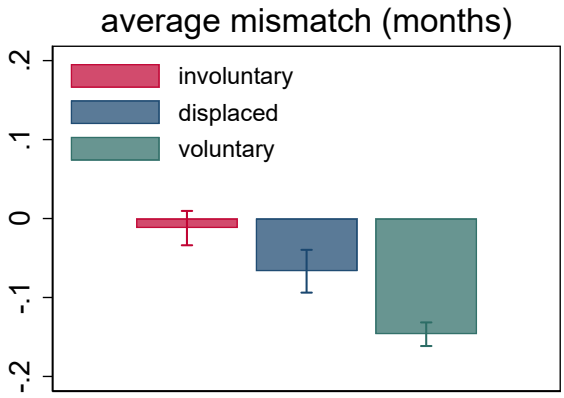


Figure 2: **Skill Mismatch by Type of Job Switch.**
Notes: Bars indicate the average skill mismatch (skill redundancy net of skill shortage) between 1978 and 2008 in months of educational requirements for voluntary, involuntary and displaced job switchers. The whiskers show 90% confidence intervals. 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 4 shows how skill mismatch changes over the period of observation. Contrary to Robinson's (2018) analysis of the US labor market, 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 linearly.

It is difficult to speculate what drives these temporal patterns. Macro conditions, technological conditions, cohort effects, among others, may all play a role. However, to provide an interpretation of this temporal mismatch pattern, we relate skill mismatch to the business cycle.[10] Figure 5 shows coefficients from regressing average skill mismatch on unemployment rates over time. Intriguingly, we find that the association between skill mismatch and economic conditions depends on whether workers

our sample.

[10]Some authors have recently suggested that the direction of job switches depends on the business cycle. 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 tightening, the trend turned towards reduced skill demands. These patterns of job switches may have implications for the size of displacement costs, which have been found to be substantially higher in recessions (e.g., Davis and Von Wachter, 2011; Schmieder et al., 2023).

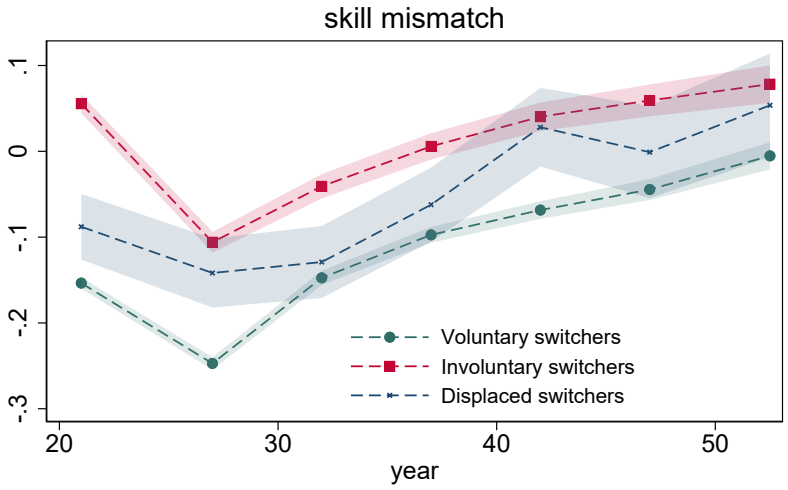


Figure 3: **Skill Mismatch by Age.**
Notes: Average skill mismatch (skill redundancy net of skill shortage) by age bracket between 1978 and 2008, in months of educational requirements for voluntary, involuntary and displaced job switchers. Age brackets (in years): 18-24, 25-29, 30-34, 35-39, 40-44, 45-49, 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.

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, or 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.

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

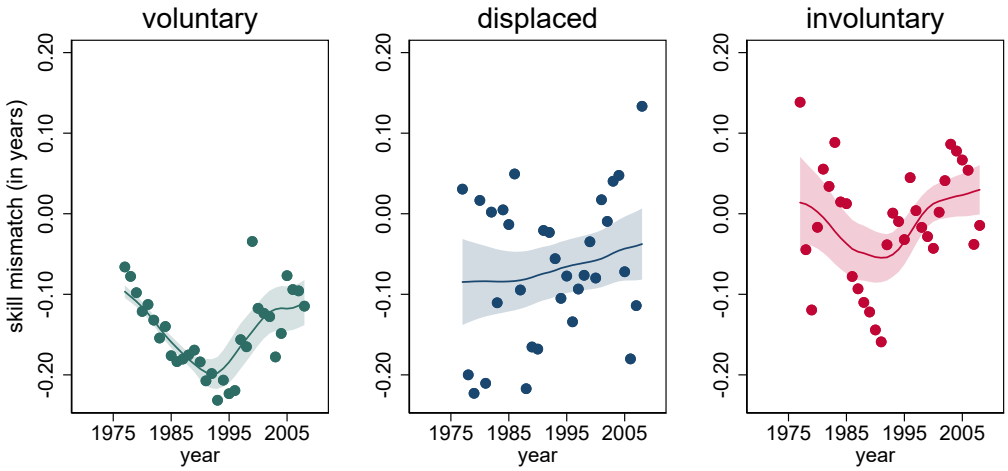


Figure 4: **Skill Mismatch over Time**
Notes: Yearly average skill mismatch (skill redundancy net of skill shortage) between 1978 and 2008 for voluntary, involuntary and displaced job switchers. Mismatch is expressed in months of educational requirements. Curves are locally mean-smoothed and the shaded 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.

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 how much time workers 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, had at least five years of labor market experience, of which at least three years 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 that closes down.[11]

[11] 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

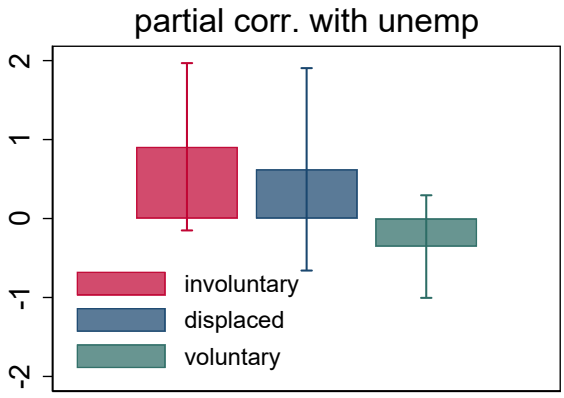


Figure 5: **Skill Mismatch and the Business Cycle.**
Notes: Bars show regression coefficients of average skill mismatch (months of skill redundancy net of skill shortage) in a year on unemployment rates over the period 1978 and 2008 by type of switch. The whiskers correspond to 90% confidence intervals. 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.

Furthermore, we limit the analysis to workers between 18 and 55 years and exclude workers with left-censored labor market histories.[12] 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.

workers and therewith its statistical power. All reported results also hold in this larger sample.

[12]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.

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.[13] 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. Conditional on the parallel trends assumption holding, 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-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.[14] As mentioned before, displaced workers tend to be older and less educated than the overall population. Moreover, they work more often in East Ger-

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

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

many and in the primary & construction or manufacturing sectors. Finally, among displaced workers, men are overrepresented compared to women. Matching improves the balance on these variables substantially (see Appendix D 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. Among the matched non-displaced sample, fewer than 3 percent change occupations. Table 3 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 displacement increases 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 control for observed and unobserved differences in worker quality, these estimates are likely to have a causal interpretation.

Conditional on having changed occupations, 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 displaced and non-displaced workers by the *type* of switch – upskilling, downskilling, lateral or reskilling – they make. Note that the sample now only contains occupation switchers, which may introduce some selection concerns.

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

Table 2: Worker Characteristics

	Population	Displaced
% West Germany	72.08	35.21
% Primary and secondary sector	27.06	46.6
% Female	46.04	38.4
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	6.8
% Other	12.55	5.28
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*). We apply some of the sample restrictions used in the *displaced* column and described in this section also to the *population* column: the population column only 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 labor market experience and its squared term 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.

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.[15]

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

[15]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.

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 occupation switchers. Model 1 only includes labor market experience and its squared 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.

characteristics, displacement is an exogenous event. If this is the case, the careers 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:

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

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. D_i is a displacement dummy that denotes whether worker i is a displaced worker or a statistical twin. $S^{\sigma}_{p(i)}$ is an occupation-switching dummy. It takes a value of one if the displaced worker in pair $p(i)$ makes a job switch of type σ. Depending on the specification, σ can refer to stayers and switchers, or to stayers and specific types of occupational switches that the pair's displaced worker undertakes: upskilling, downskilling, lateral, or reskilling.

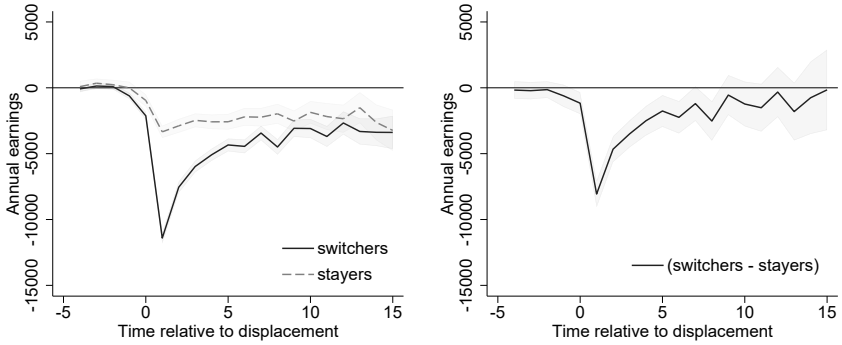
The coefficients β_2^k describe how the average difference in outcomes between displaced and non-displaced workers evolves for displaced workers who remain in their pre-displacement occupation. For displaced workers who make a job switch of type σ after displacement, the average difference in outcomes vis-à-vis their counterfactual career paths is captured by $\beta_2^k + \beta_4^{k,\sigma}$. $\beta_4^{k,\sigma}$ thus provides an estimate of the difference in displacement effects between workers who make a particular type of occupation switch and those who remain in the same occupation.

This setup allows for heterogeneity in the 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, 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 undertaking different job switches or of differences in observed and unobserved characteristics of the workers making these choices, is harder to assess. We will return to this issue later, but now, with this caveat in mind, proceed to the results.

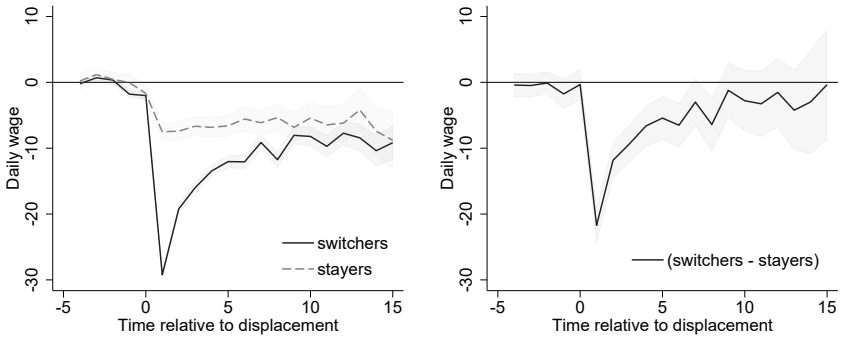
Results

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 occupation switchers and occupation stayers separately, whereas the right panel shows the difference between the two groups, i.e., it plots $\hat{\beta}_4^{k,\sigma}$ of eq. (5).

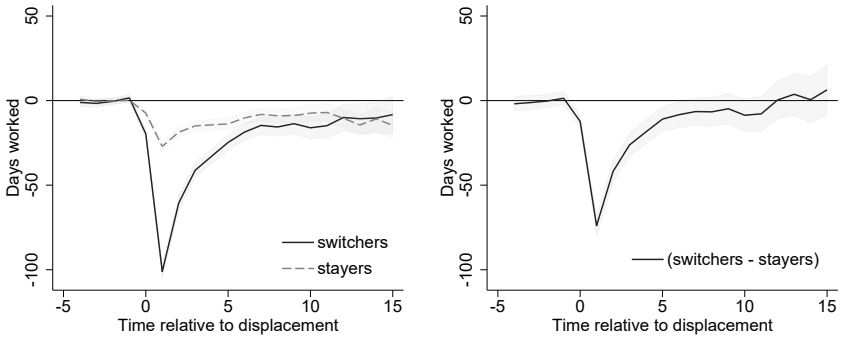
Apart from a dip in days worked right before displacement – possibly related to early leaving or distress signals – displaced workers' pre-displacement trends run parallel to those of their non-displaced counterparts. This holds for both displaced workers who change occupations after displacement and 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.



(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 eq. (5) with potential work experience, potential work experience squared, year 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.

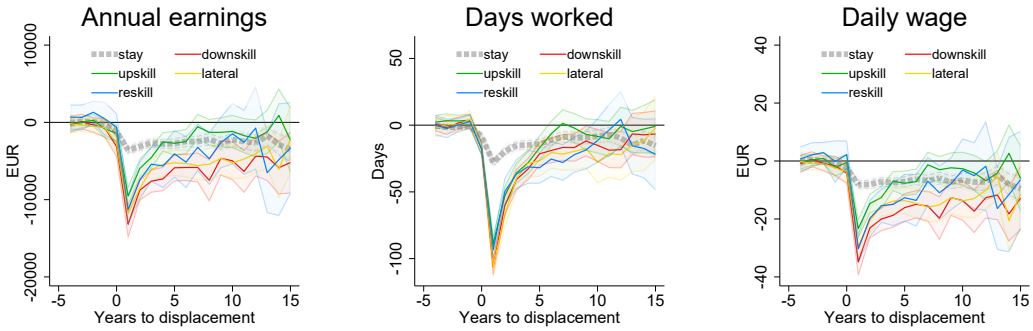


Figure 7: **Displacement Costs by Switch Type**
Notes: Panels show displacement effects experienced by different types of occupation switchers (solid lines) and occupation stayers (dashed lines). Displacement effects are based on a specification of eq. (5) with potential work experience, potential work experience squared, year effects 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.

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, close to €2,700, or 8.7 percent of their pre-displacement annual earnings, occupation switchers lose close to €4,800, or 16.5 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 11.6 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 years 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 role in displacement-induced 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, all four groups experience large drops in earnings in the first post-displacement year. Downskillers and lateral switchers experience the largest drops, 45.4 and 45.2 percent respectively, while upskillers and re-skillers experience somewhat milder drops of 33.1 and 33.5 percent. Second, upskilling workers are the only group who manage to eventually fully catch up with their counterfactual career paths. This happens about seven years after displacement. None of the other occupation switchers achieve this, nor 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, although the differences between these two groups are unlikely to be statistically significant.

Interestingly, these differences in earnings paths among the four groups 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 substantially worsens 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. 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. 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 F, 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. This is likely to be an underestimate of the true amount of schooling these workers take: given Germany's extensive system of con-

tinuing 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 worker's pre-displacement job changes over the years. We do so using the same difference-in-differences framework as before, but now estimate the following regression specification:

$$M_{it} = \tilde{\alpha}_i + \tilde{\gamma}_t + X'_{it}\tilde{\delta} + \sum_{k=-4}^{15} \tilde{\beta}_1^k T_{p(i)t}^k + \sum_{k=-4}^{15} \tilde{\beta}_2^k T_{p(i)t}^k D_i + \sum_{\sigma} \sum_{k=-4}^{15} \tilde{\beta}_3^{k,\sigma} T_{p(i)t}^k S_{p(i)}^{\sigma} + \sum_{\sigma} \sum_{k=-4}^{15} \tilde{\beta}_4^{k,\sigma} T_{p(i)t}^k D_i S_{p(i)}^{\sigma} + \tilde{\epsilon}_{it}, \quad (6)$$

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.

Figure 8 plots the results for our four different types of job switchers. The thick dashed lines display the career paths for displaced workers ($\tilde{\beta}_1^k + \tilde{\beta}_2^k + \tilde{\beta}_3^{k,\sigma} + \tilde{\beta}_4^{k,\sigma}$), the thin solid lines the counterfactual career paths of their statistical twins ($\tilde{\beta}_1^k + \tilde{\beta}_3^{k,\sigma}$). The graphs compare the skill shortage and skill redundancy of both displaced and non-displaced workers with respect to their pre-displacement occupations.

We find that all four counterfactual groups move slowly away from the skill mix of their (virtual) pre-displacement occupations, and they do so in a similar fashion across groups. However, the actual career paths of the groups of displaced workers that experience substantial skill mismatch (upskillers, downskillers and reskillers) are very different from these counterfactual paths. These three groups of workers experience a large shift in their mismatch immediately following their displacement. Afterwards, they slowly converge to the level of mismatch of their counterfactuals. However, this convergence is not the result of displaced workers moving closer to their predisplacement occupations, but rather due to the steady increase in mismatch on their counterfactual paths. Moreover, none of the displaced worker groups converge with their counterfactual career paths within the period of 15 years that we follow them. This suggests that displacement forces workers on skill paths that are quite

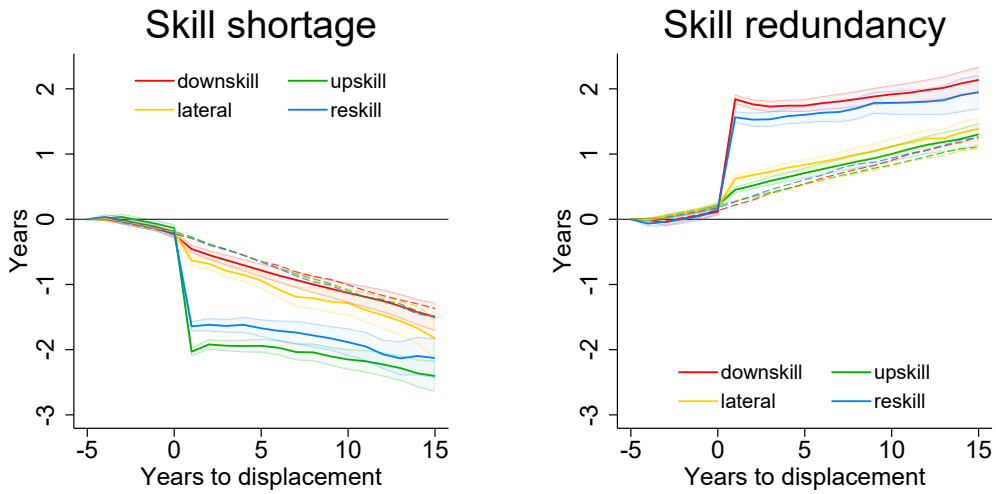


Figure 8: **Evolution of Mismatch to Pre-Displacement Job**
Notes: Graphs show the average skill shortage (left panel) and skill redundancy (right panel) to pre-displacement jobs for displaced workers (solid lines) and their statistical twins (dashed lines) in years of required schooling, controlling for potential work experience, potential work experience squared, year effects and individual fixed effects. These conditional averages are calculated as $\hat{\beta}_1^k + \hat{\beta}_2^k + \hat{\beta}_3^{k,\sigma} + \hat{\beta}_4^{k,\sigma}$ for displaced workers and $\hat{\beta}_1^k + \hat{\beta}_3^{k,\sigma}$ for their non-displaced statistical twins in eq. (6). Error bands reflect 95% confidence intervals. Source: SIAB 1975-2010 and BIBB/BAuA 2006.

distinct from the ones they would have chosen had they not been displaced, and they remain distinct even 15 years after displacement.

Analyzing Compositional Effects

In as far as our combination of matching and difference-in-differences analysis manages to identify plausible counterfactual career paths for workers in each switcher group, the estimated displacement effects have a causal explanation for each group of displaced workers. However, should we attribute the observed heterogeneity in causal effects across these groups to the differences in postdisplacement job mismatch, or to differences in the composition of these groups? For instance, occupation stayers may be inherently different from occupation switchers, and among occupation switchers, downskillers may be different from upskillers. Such differences indeed sometimes exist. For instance, stayers are more often women, worked more often in services, and had slightly steeper earnings growth pre-displacement. As a consequence, the

observation that some groups experience less severe consequences of displacement may have more to do with the workers in these groups than with the occupational choices they made when they got displaced. To analyze the importance of such compositional differences across displaced worker groups, we balance the different displaced worker samples in terms of their observable characteristics. To do so, we rely on entropy balancing (Hainmueller, 2012).

Entropy balancing uses (a variant of) maximum entropy estimation to identify weights that balance two samples. In particular, it aims to find weights that ensure that the distributions of a prespecified set of variables have approximately equal moments in both samples, while keeping these weights as close as possible to uniform. Entropy balancing can therewith be seen as an alternative to propensity score matching. However, unlike propensity score matching, which typically requires a large donor pool of untreated individuals, entropy balancing retains the entire donor pool of statistical control individuals, but weights individuals in this pool differently. As a consequence, it can typically achieve balance with far smaller control samples.

We use entropy balancing to balance the samples of displaced workers. To do so, we estimate weights for each subsample of displayed workers, such that the weighted samples mimic the characteristics of the group of stayers (the group with the lowest cumulative losses). As characteristics that we try to balance, we choose the most important variables that we used to match displaced to non-displaced workers. We balance these characteristics in terms of the first two moments of their distributions, i.e., their means and variances. Next, we clone the derived weights and copy them to the non-displaced statistical twins of the displaced workers. This ensures that we also retain the balance between displaced and non-displaced workers. The end result is weights that render switch-type specific samples of displaced workers similar in terms of predisplacement demographic and career characteristics. Appendix E provides further details of how we implemented the entropy balancing.

The most striking differences before balancing can be observed between occupation stayers and occupation switchers in general (see Appendix E, Table E.1). Stayers tend to be half a year older, with one year more experience in their occupation, a daily wage before displacement that was almost 5 percent higher, and 2.5 percentage points steeper pre-displacement wage growth. They also include more women (41 percent vs. 31 percent among switchers) and workers in the service sector (47 percent vs. 32.5 percent among switchers). After applying weights, however, all switcher groups match these characteristics in terms of their means almost perfectly.

We use these weights to estimate a weighted version of the difference-in-differences model of eq. (5). First, we reevaluate the differences in displacement effects between stayers and switchers (Figure 9). Although differences are not statistically significant

in any given year, cumulatively, the earnings and wage losses of occupation switchers are significantly larger in the reweighted sample compared to our original estimates. One way to interpret this finding is that occupation switchers had less to lose from changing occupations than occupation stayers, providing some explanation for why these workers chose to change occupations.

It is important to note that compositional differences between the switcher and stayer groups can only explain a small part of the heterogeneity in displacement effects. In fact, had switchers looked just like stayers, their cumulative earnings losses would have been 22 percent larger. To put this into perspective, switchers incur 78 percent greater cumulative losses than stayers. Note, moreover, that accounting for worker heterogeneity actually widens, not narrows, the gap between the displacement effects of occupation stayers and occupation switchers. Finally, these differences only accrue over time: in the first year after displacement, reweighted coefficients amount to just 9 percent greater losses than unweighted coefficients. That is, the compositional differences only become manifest with time, presumably as worker quality differences start to become reflected in career outcomes. However, worker heterogeneity seems to account for little in terms of how workers cope with the initial shock of displacement.

To explore the role of compositional effects further, we turn to the different switcher groups. Occupation switchers are mostly either upskillers or downskillers, together accounting for over 70 percent of all occupation switchers. Moreover, these two groups of switchers make radically different post-displacement occupational choices, and display the most pronounced differences in post-displacement consequences. For these reasons, we focus on a comparison of upskillers and downskillers.[16] To do so, we balance the samples of upskillers to match the characteristics of downskillers and vice versa.

Table 5 shows the alignment of the balancing variables for displaced upskillers and downskillers.[17] Even before balancing the samples, upskillers and downskillers have very similiar characteristics. After balancing, the samples have practically identically distributed characteristics.

Figure 10 shows the reweighted difference-in-differences graphs in the dashed lines, along with their original, unweighted estimates in the solid lines. That is,

[16]We also estimate the difference between weighted and unweighted difference-in-differences estimates for all switcher groups, using the weights that balance all samples with the sample of occupation stayers. Fig. E.1 in Appendix E plots the results.

[17]The first and third columns show the means of variables before entropy balancing, the second column shows weighted means using entropy balancing weights that align the upskiller to the downskiller sample and the fourth column shows weighted means that align the downskiller sample to the upskiller sample.

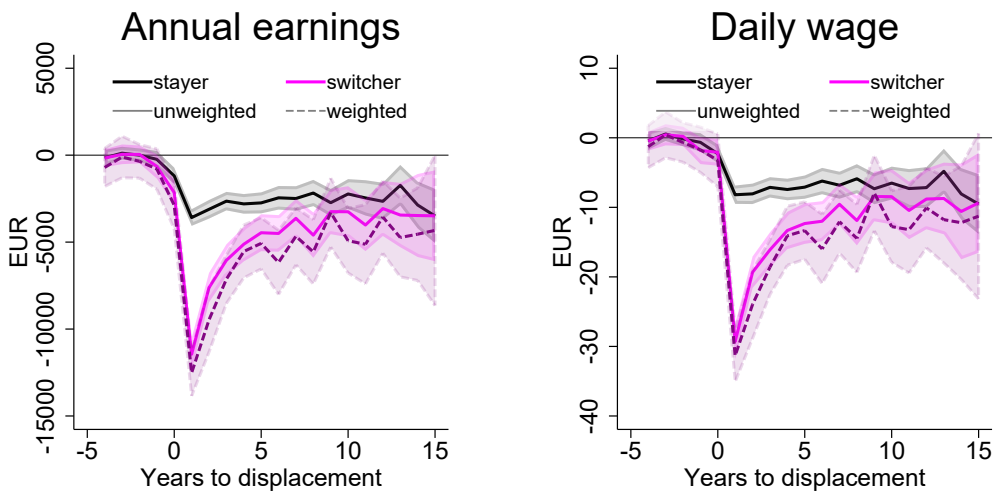


Figure 9: **Comparison of Unweighted and Weighted Regression Results**
Notes: Graphs show the difference-in-differences results in terms of average earnings losses (left panel) and losses of daily pay (right panel) for occupation stayers (black lines), occupation switchers from unweighted regressions (full purple lines) and, for occupation switchers, from the re-weighted regression using entropy balancing weights (dashed purple lines). The estimates are based on eq 5. Error bands reflect 95% confidence intervals. Source: SIAB 1975-2010.

Table 5: Entropy Balancing Quality: Upskillers weighted as Downskillers, Downskillers as Upskillers

	Upskillers		Downskillers	
	UW	W Dwn	UW	W Up
Age	37.20	37.79	37.79	37.20
Real daily wage t-2	79.25	80.19	80.19	79.25
% change, real daily wage t-5 to t-2	0.14	0.14	0.14	0.14
Occupational experience t-2	7.99	7.82	7.82	7.99
Year of displacement	1999.00	1999.00	1999.00	1999.00
%Women	0.33	0.27	0.27	0.33
%Primary and secondary sector	0.55	0.61	0.61	0.55
%West	0.34	0.34	0.34	0.34
%Less than Abitur	0.92	0.90	0.90	0.92
%Tertiary educated	0.04	0.07	0.07	0.04

Note: Means of worker characteristics. UW stands for unweighted, W Dwn for weighted to align with the composition of the downskillers, W Up for weighted to align with the composition of the upskillers. Means are calculated for the samples of displaced workers.

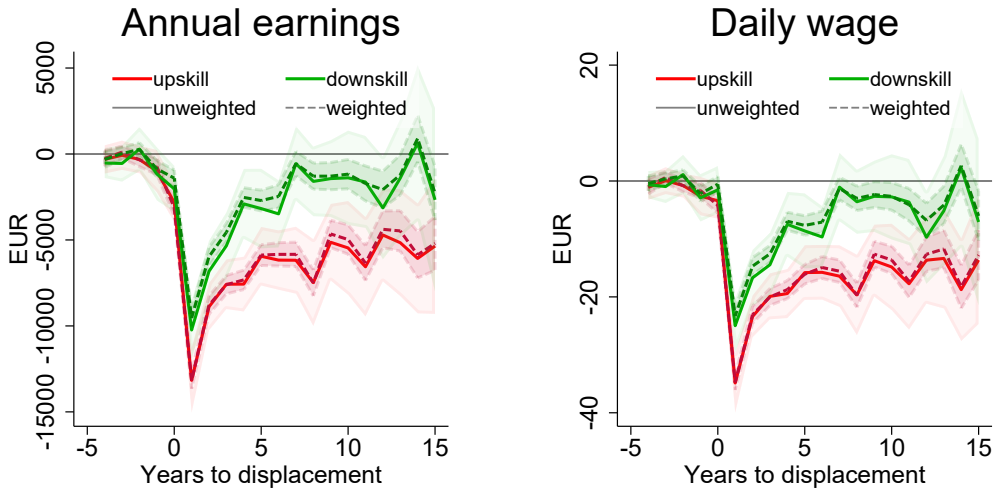


Figure 10: **Comparison of Unweighted and Weighted Regression Results**
Notes: Graphs show the difference-in-difference results in terms of average earnings losses (left panel) and losses of daily pay (right panel) for occupational stayers (black lines), occupational switchers from unweighted regressions (full purple lines) and occupational switchers from the reweighted regression using the entropy weights (dashed purple lines). The estimates are based on eq 5. Error bands reflect 95% confidence intervals. Source: SIAB 1975-2010.

it shows how upskillers would have fared, had they had similar characteristics as downskillers and vice versa. The figure shows that unweighted and reweighted effect estimates are more or less identical, suggesting that compositional effects do not play a significant role in the observed differences between upskillers and downskillers.[18] It is therefore likely that the radically different displacement effects experienced by these two groups are related to differences in the type of postdisplacement skill mismatch they face.

In principle, it could still be the case that the various switcher groups and stayers differ in some important unobserved characteristics. However, note that, although we balance characteristics that include many important determinants of wages such as age, experience and gender, these characteristics do not explain much of the difference in displacement effects. It would therefore be surprising if any unobserved characteristic would have a much greater impact on these effects. Moreover, our

[18]In light of the fact that upskillers and downskillers have fairly similar predisplacement characteristics, it is less surprising that the reweighting does not lead to radically different displacement effects than in the comparison of switchers and stayers.

observed variables include predisplacement wages and wage growth, which should capture important information about observed, as well as unobserved worker quality. The results from our reweighted analyses therefore offer substantial further support for our hypothesis that occupational and skill mismatch are important sources of heterogeneity in displacement-related earnings losses. Moreover, they suggest that workers may have relatively little control over their post-displacement job choices: otherwise, we would have expected that accounting for worker heterogeneity would lead to large and immediate shifts in the effects of displacement.

5 Conclusion

When workers change jobs, they typically leave some of their old skills unused, while at the same time acquiring new ones. In this paper, we propose measures of human capital mismatch that quantify 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 between mismatch and the business cycle.

However, our most important finding is that the earnings losses caused by job displacements vary substantially with the kind of skill mismatch displaced workers experience. 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 displaced workers who move to more skill-demanding jobs barely manage to completely close the gap in earnings to the counterfactual career paths, but at least in the medium run, they do not fare worse than workers who manage to remain

in their old occupation.

The differences across workers who experience different post-displacement skill mismatch are unlikely to be due to intrinsic differences among these workers. To show this, we reweight the different samples of displaced workers so that they all mimic the sample of the displaced workers who remain in their predisplacement occupation. When we re-estimate our models in these weighted samples, we find that accounting for compositional effects would widen, not narrow the gap between stayers and switchers. Given that we include information on important demographic characteristics and on predisplacement wage trajectories – which should reflect both observed and unobserved differences in worker quality – we conjecture that most of the observed effect heterogeneity is indeed due to differences in postdisplacement mismatch, not intrinsic differences between workers. We conclude therefore that skill mismatch is an important contributor to the earnings losses of displaced workers.

Our study has some limitations. First, although we allow for some effect heterogeneity, our estimated displacement effects are still averaged across larger groups of workers. In fact, as the confidence intervals illustrate, even within the same switcher category, we do not expect all individuals to experience equally large career impacts from displacement. Second, it is important to note that our study focuses on the German labor market and includes the period in which German reunification brought about massive structural transformation. However, its distinction between upskilling and downskilling workers may be relevant in many other economies that face challenges posed by technological advancements, international outsourcing and offshoring, and an evolving industrial organization — forcing workers to either adapt or face wage reductions. Nevertheless, the generalizability of our findings will depend on labor market structures, culture and norms, and policy environments. For instance, thicker and larger labor markets, as well as better developed adult learning institutions, should allow for less painful career transitions. In this light, it is, however, surprising to observe that even in Germany – where the labor market is relatively large, unemployment low in a global perspective, and adult learning institutions highly developed – the best strategy to maximize lifelong earnings appears to be to remain in the same occupation.

In terms of policy implications, our findings emphasize the importance of avoiding skill mismatch, and in particular, downskilling, which imposes the largest and most persistent costs on workers. Against this background, we see three main areas for policies that can help workers adapt to changing labor market demands and avoid skill losses. First, there is a growing need for continuous retraining throughout a person's career (for an overview, see EIU (2018)). The "Job 4.0" initiative of Germany, the "Lifelong Education Act" of South Korea and Singapore's "SkillsFu-

ture" initiative, which funds learning account that adults can use for training courses throughout their lives, are pioneering efforts in this direction. Second, strategies to expand workers' search space may produce large payoffs because they can mitigate skill mismatches. Examples of such strategies are the increasing use of online job postings, the provision of working from home options, and career counseling to improve the quality of job information or to make workers aware of job opportunities. Third, encouraging geographic mobility may be pivotal, because workers may face a trade-off between avoiding mismatch and avoiding to relocate. Previous evaluations of mobility subsidy programs are optimistic about their effectiveness. A prominent example is Caliendo et al. (2017), who evaluate a program in Germany that offered a subsidy to cover moving costs and incentivize unemployed job seekers to search for and accept jobs in distant regions. These authors show that the program helped workers access jobs that provide a better match to their skills, leading to higher earnings and greater job stability.

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Appendix

A Knowledge and Task Variables in the BIBB Survey

To construct the skill vectors, we start by selecting 46 survey questions from the BIBB survey that refer to individuals' tasks, knowledge and skills listed in Table A.1, part "Variables used in the construction of the skill factors". The answers to the original survey questions are coded using different Likert scales. To align the scales, we make the variables binary, reflecting whether or not a worker has a skill or carries out a task. For instance, the task variables 1 to 17 and 19 to 27 in the table, can take three values: never, sometimes and often. We re-code them to one if their value is "often", and zero otherwise. The knowledge variables 28 to 40 are coded 1 if one reports expert knowledge/skill, and zero otherwise. 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. The occupation that we use is the German 1988 Classification of Occupations (KldB 1988), with 263 occupational groups. We choose this classification among the few available ones in the BIBB Survey, to enable the merge of these occupational task and skill data with the SIAB 1975-2010 individual-level data.

Table A.1: Tasks, Knowledge and Work Conditions Variables

	Variable	Variable description
Variables used in the construction of the skill factors		
1	F303	Manufacturing, producing goods
2	F304	Measuring, testing, quality control
3	F305	Monitoring, controlling machines, systems, processes
4	F306	Repair
5	F307	Buy, procure, sell
6	F308	Transport, storage, shipping
7	F309	Advertising, marketing, PR
8	F310	Organizing, planning and preparing work processes
9	F311	R&D, engineering
10	F312	Educate, teach
11	F313	Gathering, researching, documenting information

Continued on next page

Table A.1 – continued from previous page

	Variable	Variable description
12	F314	Advising, informing
13	F315	Hosting, accommodating, preparing meals
14	F316	Care, heal
15	F317	Secure, protect, guard, monitor, regulate traffic
16	F318	Work with computers
17	F319A	Clean, dispose of waste, recycle
18	F320	Computer programming
19	F325_01	React to unforeseen problems and solve them
20	F325_02	Convey difficult facts in a generally understandable way
21	F325_03	Convince others and negotiate compromises
22	F325_04	Make difficult decisions independently
23	F325_05	Recognize and close your own knowledge gaps
24	F325_06	Give free speeches or lectures
25	F325_07	Have contact with customers, clients or patients
26	F325_08	Have a lot of different tasks to do
27	F325_09	Have a responsibility for the well-being of other people
28	F403_01_fach	Need scientific knowledge
29	F403_02_fach	Need craftsmanship knowledge
30	F403_03_fach	Need pedagogical knowledge
31	F403_04_fach	Need legal knowledge
32	F403_05_fach	Need project management skills
33	F403_06_fach	Need medical, nursing knowledge
34	F403_07_fach	Need layout, design, visualization knowledge
35	F403_08_fach	Need knowledge of mathematics, statistics
36	F403_09_fach	Need knowledge of German languag
37	F403_10_fach	Need knowledge of PC application programs
38	F403_11_fach	Need technical knowledge
39	F403_12_fach	Need commercial, business knowledge
40	F403_13_fach	Need language skills other than German
41	F411_01	Work under deadline, performance pressure
42	F411_03	The same operation is repeated down to the last detail
43	F411_04	New tasks that you first have to think your way through
44	F411_09	Has different types of work, processes at the same time
45	F411_11	Small mistakes result in great financial loss
46	F411_13	Work very fast

Continued on next page

Table A.1 – continued from previous page

	Variable	Variable description
Variables use in the construction of the disutility factor		
1	F600_01	Work standing
2	F600_02	Work sitting down
3	F600_03	Lift and carry heavy loads
4	F600_04	Work in smoke, dust or under gases, vapours
5	F600_05	Work in cold, heat, wet, damp or draft conditions
6	F600_06	Work with oil, grease, dirt, grime
7	F600_07	Work in awkward positions, work overhead
8	F600_08	Work with strong shocks, impacts and vibrations
9	F600_09	Work in bright light or poor or too weak lighting
10	F600_10	Handle hazardous substances, exposure to radiation
11	F600_11	Wear protective clothing or equipment
12	F600_12	Work in noise
13	F600_13	Deal with microorganisms
14	F600_14	Work in a place where people smoke
15	F700_02	Can plan and schedule your own work
16	F700_03	Have influence on the amount of work
17	F700_04	Job puts you in situations that affect you emotionally
18	F700_06	Can decide when to take a break
19	F700_07	Feel that what you do is important
20	F700_08	Not informed about drastic decisions, changes or plans
21	F700_09	Do not receive all the necessary information
22	F700_10	Feel part of a community in your workplace
23	F700_11	Good cooperation between you and your colleagues
24	F700_12	Get help and support from colleagues
25	F700_13	Get help and support from your line manager

Source: BIBB/BAuA Survey 2005/2006. See Hall (2009) for the full list of available variables.

B Construction of Skill Vectors

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:

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

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. 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.

Table B.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.

Therefore, we decide to drop them from the schooling regression in eq. (B.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 B.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 (B.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.

C 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 C.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.

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

Table D.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.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.

Table D.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 D.4 and D.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 D.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).

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

Table D.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 D.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 D.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								
% 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 D.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).

E Entropy Balancing Quality: Aligning with the Group of Stayers

To ensure that we compare across groups with similar demographic and socio-economic structure, and pre-displacement earnings trajectory, we took the structure of the displaced stayers as a base, and used entropy balancing (Hainmueller, 2012; Hainmueller and Xu, 2013) to re-weight the observations of all other displaced worker groups (upskillers, downskillers, reskillers and lateral switchers) to closely resemble this base group. Next, we copy for each displaced worker the identified weight to their statistical twin. This ensures that we the displaced and non-displaced worker samples remain balanced to one another as well.

We balance on the following matching variables: daily wages two years prior to displacement, wage growth between year five and year two prior to displacement, occupational experience, age, year of displacement, gender, East/West dummy, three dummies for educational achievement, and a dummy for being displaced from the primary or the secondary sector. Moreover, we balance both means and variances for these variables. Note, however, that for dummy variables, all higher order moments are fully determined by the means. Therefore, variances for these variables are automatically balanced as soon as their means are balanced.

As described in Hainmueller (2012), the balancing procedure may result in very large weights for some observations in the re-weighted group. This happens when there are only very few suitable observations among the re-weighted group that are similar to the observations in the base group. Such observations then receive large weights because they contribute most information about the population of interest. These large weights are problematic because they increase the variance in the subsequent analysis. Hainmueller therefore recommends an iterative trimming procedure to reduce the influence of large weights. In our case, only a handful of the 12,160 observations were assigned weights larger than four times the median of the weights, and these were trimmed accordingly.

Table E.1 shows the samples of the various types of occupation switchers, re-weighted to align them with the sample of displaced occupation stayers. After reweighting, means are virtually indistinguishable from one another and the same holds for the variables' variances (not shown).

Table E.1: Results from Entropy Balancing

	Before balancing						After balancing					
	St	Sw	Re	Up	Down	Lat	St	Sw	Re	Up	Down	Lat
Age	38.45	37.68	37.71	37.20	37.79	38.40	38.45	38.45	38.46	38.45	38.45	38.45
	(0.08)	(0.13)	(0.39)	(0.22)	(0.22)	(0.33)	(0.08)	(0.14)	(0.40)	(0.23)	(0.23)	(0.33)
Real wage t-2	84.76	79.29	86.89	79.25	80.19	72.32	84.76	84.77	84.79	84.76	84.76	84.78
	(0.52)	(0.75)	(2.57)	(1.15)	(1.37)	(1.40)	(0.52)	(0.90)	(2.63)	(1.51)	(1.52)	(2.19)
% chg. real wage	0.15	0.13	0.15	0.14	0.14	0.09	0.15	0.15	0.15	0.15	0.15	0.15
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)
Occ. exp.	9.16	7.89	7.81	7.99	7.82	7.91	9.16	9.16	9.16	9.16	9.16	9.16
	(0.05)	(0.08)	(0.23)	(0.14)	(0.14)	(0.21)	(0.05)	(0.10)	(0.28)	(0.16)	(0.16)	(0.23)
Year of disp.	1999	1997	1998	1997	1999	1999	1999	2000	2000	2000	2000	2000
	(0.05)	(0.09)	(0.29)	(0.15)	(0.16)	(0.24)	(0.05)	(0.09)	(0.27)	(0.16)	(0.16)	(0.23)
%Women	0.41	0.31	0.23	0.33	0.27	0.40	0.41	0.41	0.41	0.41	0.41	0.41
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)	(0.01)	(0.02)	(0.02)
%Prim./sec. sector	0.43	0.58	0.62	0.55	0.61	0.55	0.43	0.43	0.43	0.43	0.43	0.43
	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)
%West	0.36	0.34	0.31	0.34	0.34	0.35	0.36	0.36	0.36	0.36	0.36	0.36
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)
%Less than Abitur	0.87	0.91	0.85	0.92	0.90	0.96	0.87	0.87	0.87	0.87	0.87	0.87
	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
%Tertiary edu.	0.07	0.05	0.13	0.04	0.07	*	0.07	0.07	0.07	0.07	0.07	*
	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)		(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	

* 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).

F 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 F.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 F.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.

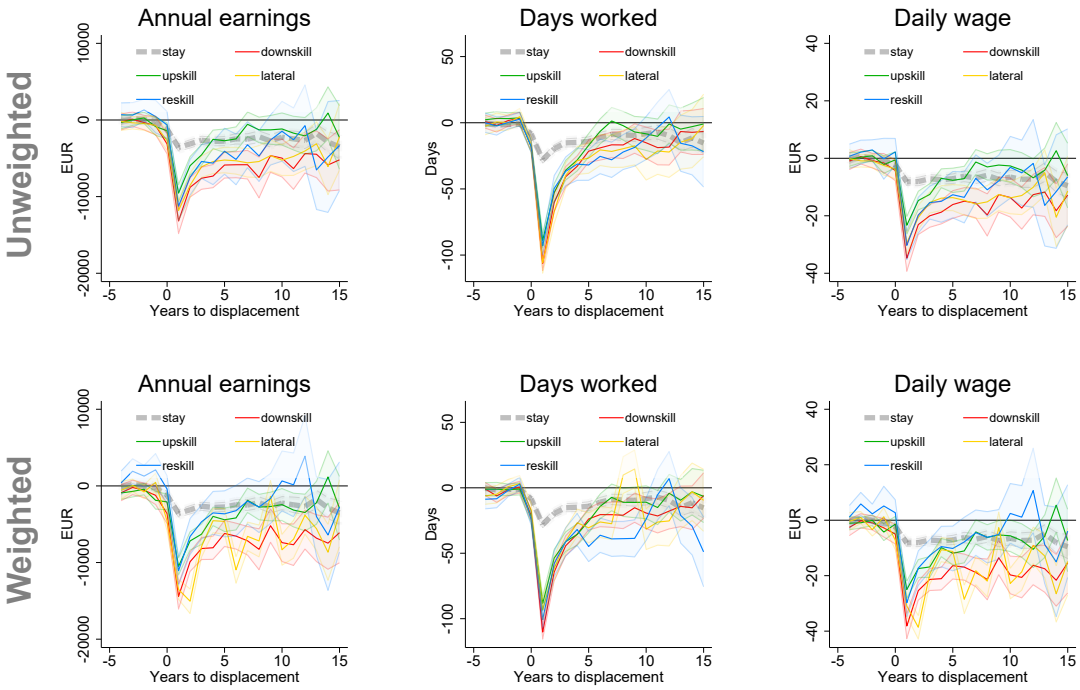

Figure E.1: **Comparison of Unweighted and Weighted Regression Results by Type of Switcher**

Notes: Graphs show the difference-in-differences results in terms of average earnings losses (left panel), days worked (middle panel) and losses of daily pay (right panel) for occupation stayers (thick dashed lines), and the four groups of occupation switchers (colored think lines), once calculated without weights (upper panel), and once from the re-weighted regression using the entropy balancing weights (lower panel). The estimates are based on eq 5. Error bands reflect 95% confidence intervals. Source: SIAB 1975-2010.

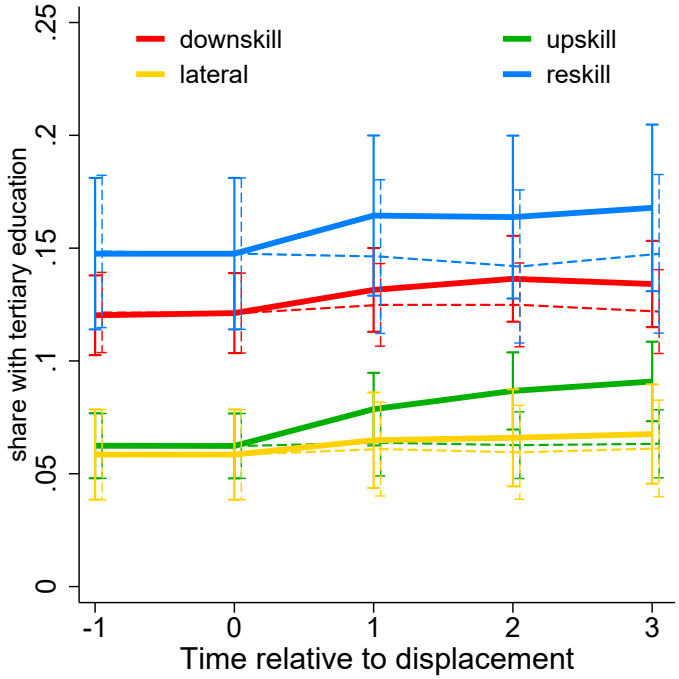

Figure F.1: **Educational Upgrading**
Notes: Evolution of shares of workers with tertiary degree. Solid lines refer to displaced workers, dashed lines to their matched non-displaced counterparts. Whiskers correspond to 90% confidence intervals. Source: SIAB 1975-2010 and BIBB/BAuA 2006 (matched sample).

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