The Impact of Skill Mismatch on Earnings Losses after Job Displacement*

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Abstract

The long-term earnings losses of displaced workers are substantial. We investigate to what extent these losses are due to skill mismatch at the post-displacement job. We combine German administrative data on the work history of displaced workers with information on the task content of more than 260 occupations, providing a measure of skill mismatch between a worker's pre- and post-displacement occupation. We find evidence that being displaced increases the probability of occupational change substantially. It particularly increases the probability of taking a job where one is over-skilled. The cost of job displacement varies by the type of skill mismatch. The costs are highest for those who are over-skilled at the new job. The results suggest that skill mismatch is an important mechanism through which the long lasting earnings losses of displaced workers are realized.

JEL Code: J24, J31, J63, J65

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

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1 Introduction

A growing number of empirical studies evidence large and persistent earnings losses of displaced workers. The majority of these studies agree that earnings and wages of displaced workers remain 10–15% below their expected levels 15 or more years after displacement (Jacobson, LaLonde and Sullivan (1993); Couch and Placzek (2010); Schmieder, von Wachter and Bender (2010); Eliason and Storrie (2006); Seim (2012); Bonikowska and Morissette (2012); Hijzen, Upward and Wright (2010)). Recent literature also highlights additional non-monetary cost associated with involuntary job losses, suggesting that both life expectancy and fertility are negatively affected by displacements (Del Bono, Weber and Winter-Ebmer (2012); Frey and Stutzer (2002); Sullivan and von Wachter (2009)). Job displacement even seems to entail inter-generational cost, as parental job loss appears to be related to adverse impacts on children including poorer schooling outcomes and worse labor market outcomes as adults (Oreopolous, Page and Stevens, 2008; Kalil and Wightman, 2011). This paper investigates occupational switching and skill mismatch after displacement as possible channels through which the sharp earnings losses of displaced workers materialize.

Figure 1 shows the daily wage losses in 2005 EUR of displaced workers compared to a group of non-displaced statistical twins in the period 1981–2004.[1] If we take the gross daily wage as an indicator of productivity at the job, Figure 1 suggests that the productivity of displaced workers drops by 6.1% in the post-displacement period. [2] One interpretation of this finding is that displaced workers are on average re-matched to jobs where they cannot realize their pre-displacement levels of productivity.

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

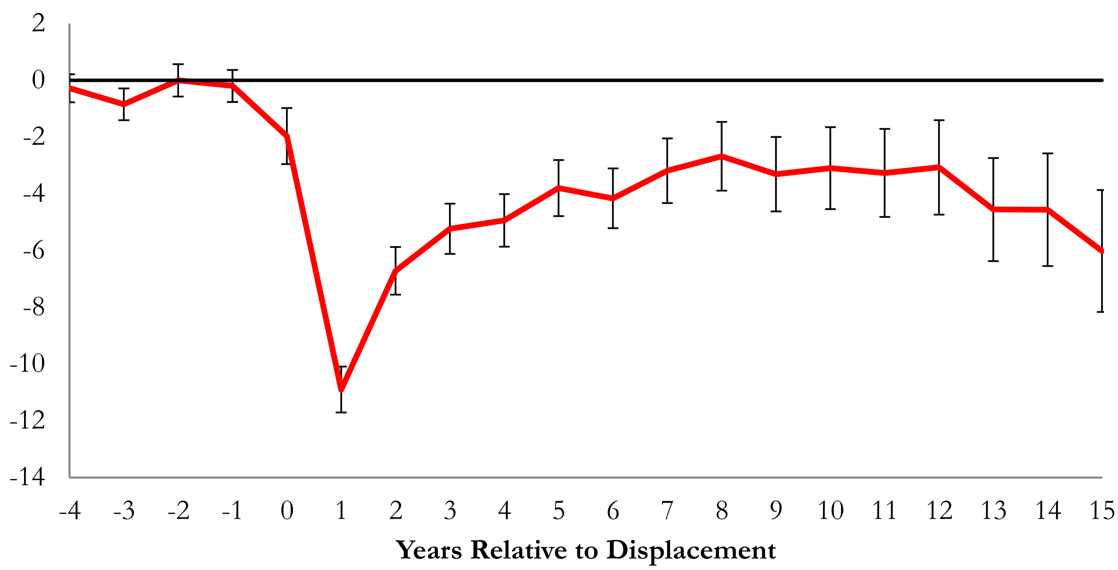
Several empirical studies find support for the theory of specific human capital, which predicts that job switching causes wage penalties proportional to the loss of specific human capital (Podgursky and Swaim, 1987; Carrington, 1993; Jacobson, LaLonde and Sullivan, 1993; Neal, 1995; Parent, 2000; Burda and Mertens, 2001; Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010). They find that the relative earnings losses of displaced workers are higher for industry switchers, occupational switchers, or those who switch skill portfolios but have not shown yet to what extent such changes are more frequent among displaced workers. The differences in the earnings patterns of occupational stayers and switchers cannot be explained by a theory of lost incentive contracts. It is also not clear why occupational stayers should be stigmatized less than occupational switchers. Moreover, while

[1] Figure 1 is constructed using the econometric approach by Jacobson, LaLonde and Sullivan (1993), which combines a fixed-effects model with a control group of never-displaced workers also used in (Stevens, 1997; Couch and Placzek, 2010; Schmieder, von Wachter and Bender, 2010; Davis and Von Wachter, 2011).

[2] These results are in line with those presented in Schmieder, von Wachter and Bender (2010), who investigate the earnings losses of high-tenure workers in Germany who lost their jobs in mass lay-offs in the 1982 recession.

it is reasonable to believe that search costs are higher for occupational switchers than stayers, a theory based on differential search costs cannot explain why there are persistent differences in the productivity after the workers have found new jobs. Our study complements the insights of the theory of specific human capital, by putting forward a number of novel research question. Does displacement cause skill mismatch? Are displaced workers more likely to be matched to new jobs where they are (a) under-qualified, (b) overqualified, (c) similarly qualified, or (d) fully switch their skill set? How do groups with different skill mismatch fare in terms of productivity, attachment to the job, and consequently total earnings?

Figure 1: Effects of Displacement on Wages



Note: The figure plots the coefficients from a dynamic difference-in-difference model. See section 6 for details. Confidence intervals are defined at the 90% level and derived from robust standard error. Data source: SIAB 1975–2008.

To shed light on these questions, we use German administrative data with longitudinal information on workers and their employers covering more than 30 years of labor market history. Following Hethey and Schmieder (2010) and Schmieder, von Wachter and Bender (2010), we take plant closures as an indicator for exogenous job separations, so we can neglect within-firm selection of workers being laid-off. We supplement these data with information about the occupation-specific tasks and skills from a representative worker survey. This allows us to describe skill transitions of displaced workers with far higher precision than in previous studies.

We use propensity score matching to create statistically identical groups of displaced and non-displaced workers. Among other characteristics, we match on pre-displacement productivity, labor market attachment and occupation. We then use difference-in-difference method in combination with demeaning to come as close as possible to a causal statement about the effect of skill mismatch on the earnings losses of displaced.

We find that displacement increases the probability of occupational change by over 30%. Conditional on occupational change, it also increases the probability of becoming overqualified at the new job by 8% and decreases the probability of finding a job that is similar in terms of skills by 10%. Furthermore, displaced occupational switchers have earnings losses that are more than double of those experienced by occupational stayers. The largest losses of about 22% are experienced by those who are overqualified at the new job. Those who are under-qualified at the new job, which is the case with about 32% of all displaced occupational switchers, experience average annual earnings losses of about 15%. The findings highlight skill mismatch as one important mechanism though which the substantial and persistent wage losses of displaced workers are realized.

The remainder of the paper is organized as follows: In Section 2, we introduce the data and describe the sample restrictions and the propensity score matching procedure. We then construct measures of skill transferability between occupations (Section 3) and show descriptive evidence on the role of occupation-specific skills in explaining the cost of job displacement (Section 4). Section 5 shows the results on our analysis on the effect of displacement on the probability of becoming skill mismatched. The econometric framework is presented in Section 6. Section 7 contains the empirical results. Section 8 discusses the implications of our findings for policy and research.

2 Data and Matching Strategy

2.1 SIAB

The Sample of Integrated Labor Market Biographies (SIAB), provided by the Institute for Employment Research (IAB), allows us to track workers' employment and unemployment histories. These data are a 2% random sample of all German social security records, being available for the years 1975 to 2008 (Dorner et al., 2010).[3] Because employers are required by law to report the exact beginning and the end of any employment relationship that is subject to social security contributions, the SIAB is the largest and most reliable source of employment information in Germany. Moreover, misreporting of earnings is punishable by law, which ensures high reliability of the earnings information.

2.2 BIBB/IAB and BIBB/BAuA Surveys

The BIBB/IAB and BIBB/BAuA Surveys of the Working Population (BIBB/IAB and BIBB/BAuA Surveys) are conducted by the Federal Institute for Vocational Education and Training (BIBB), the IAB, and the Federal Institute for Occupational Safety and Health (BAuA). Its purpose, among others, is to measure task, skill, and knowledge requirements of occupations in Germany. It is a repeated cross-section carried out in seven-year intervals, starting in 1979. The data cover individuals aged 16–65, who are employed in Germany at the time of the survey. The survey is a rich source of information about the types of tasks employees execute at their jobs and builds a detailed account of their general and specific

[3] East Germany enters the sample in 1992.

education and training.[4] For the purpose of this study, we only consider the most recent wave of the survey, 2005/06, which constitutes a sample of 20,000 individual observations.

To reduce measurement error, we drop all occupations that have less than 3 observations. This leaves us with 266 occupations. We merge the information about skill mismatch derived from the BIBB/BAuA Survey with the SIAB at the level of occupational pairs.

2.3 Defining Job Displacement

We define a job displacement as the event where a tenured worker is laid off in the course of a plant closure. We use the definition by Hethey and Schmieder (2010) to identify plant closures.[5] In addition to workers employed in a plant at the period of closure, we also include 'early leavers' in the sample of displaced, that is, workers who leave the plant one year before it shuts down. This is in line with previous literature Davis and Von Wachter (for instance, 2011) and reflects the fact that many workers leave closing plants already some time before the official closure.[6]

The sample contains workers displaced due to plant closure who fulfill the following conditions: (i) Workers whose pre-displacement establishment employed at least 10 workers two years prior to the closure, to avoid cases where single workers significantly contribute to the bad fortune of the establishment. (ii) Workers between 18 and 55 years of age. (iii) Workers with at least six years of labor market experience prior to the displacement. (iv) Workers with at least three years of occupational tenure before displacement. (v) Workers having at minimum one year of tenure at the closing firm prior to its closure. (vi) Workers who were displaced at least once in the period 1981–2004. This allows us to observe the workers 6 years prior to potential plant closure and for at least 5 years afterward. (vii) Workers without left-censored labor market histories.[7]

We only consider the first displacement.[8] Further, our sample includes both male and

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[4] The survey has extensively been used for labor-market research, for instance, by DiNardo and Pischke (1997), Spitz-Oener (2006), Dustmann, Ludsteck and Schönberg (2009), Black and Spitz-Oener (2010), and Gathmann and Schönberg (2010).

[5] That is, we restrict the sample of displaced workers to only include displacement events where more than 80% of all workers were laid off in a given year, requiring that not more than 20% of the leaving workers were re-employed together in the following year.

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

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

[8] 85% of all displaced workers are displaced only once in their work history. Thus, serially correlated displacement spells (Stevens, 1997) seem not to play a major role in explaining the prolonged earnings losses of displaced workers in Germany. Similar to previous studies (e.g., Schmieder, von Wachter and

female workers. We exclude marginally employed workers, because we can only observe them from 1999 on. The employment histories in the SIAB often have gaps. During these gaps, among other reasons, people can be in education, in the military, or on parental leave. For these gap periods we assign zeros to the earnings and working days variables. We drop people with gaps longer than six years. We allow for gaps up to 6 years because these may coincide with periods spent in university education, which are possibly required for re-qualification after displacement.

2.4 Matching

With the sample restrictions described in the previous section, we obtain a sample of 9,060 workers displaced due to a plant closure. We observe these individuals each year, 6 years prior to displacement and up to 15 years following displacement. We rely on propensity-score matching to obtain an appropriate counterfactual representing the earnings and working days development displaced workers would have faced had they not been displaced.[9] We construct this counterfactual using workers from firms not being closed between 1981 and 2004, while we impose the same age and tenure requirements as for our sample of displaced workers.

We perform matching between displaced and non-displaced workers on the following variables: gender, location of the firm (East or West Germany), age, year of (virtual) displacement, work status (full-time or part-time), occupational tenure, industry (4 sectors), and occupation (9 occupations). In particular, it is important that the composition of industries and occupations is similar among displaced and non-displaced workers to account for the possibility that declining industries or occupations force workers to leave due to vanishing employment opportunities.

However, it is well known that matching on observables does not provide a proper identification if relevant variables are unobserved and therefore omitted (for a discussion, see Angrist and Pischke, 2008). We thus use propensity score matching on pre-displacement wages to select an appropriate control group for displaced workers. Assuming that wages capture productivity differences across workers[10], matching on pre-treatment outcomes controls for omitted variable bias from selection.[11] Our matching procedure is implemented by selecting for each displaced worker the closest control in terms of the estimated propensity score, while treated and control subjects are identical in several pre-displacement attributes. We employ a one-to-one nearest neighbor matching (without replacement) routine.[12]

Bender, 2010) we make the assumption that the second or any further displacement are endogenous to the first one.

9 Eliason and Storrie (2006) and Leombruni, Razzolini and Serti (2013) also perform non-exact (nearest neighbor) matching to eliminate differences in observables between displaced and non-displaced workers.

10 Since we only use persons with at least 6 years labor-market experience, wages before (virtual) displacement are likely to be a function of worker skills.

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

12 Kernel matching (see Biewen et al., Forthcoming) yields qualitatively similar results.

Applying this matching procedure, we obtain a statistical twin in the sample of non-displaced subjects for each displaced subject. Table 1 shows the matching variables and their distributions by groups of displaced and non-displaced[13].

2.5 Defining Switchers

Within the sample of displaced workers, we distinguish between occupational switchers and occupational stayers. An occupational switch occurs if a worker moves between any of the 263 3-digit occupations following displacement.[14] We refer to these switchers as 'simple switchers.'[15] We define occupational switchers in two additional ways. First, 'robust switchers' recategorize as stayers those switchers who return to the occupation they had at the point of displacement within one year at the post-displacement occupation. In this definition, those who return to the old occupation later than this are left out of the sample, which reduces the sample by 4.2%.

Second, in the sample of 'stable switchers' all those simple switchers that stay at the post-displacement occupation for less than a year are dropped. The rationale here is that skill mismatch between the occupations before and after displacement would be mismeasured if the first post-displacement occupation is only a stepping stone toward a more stable occupation. Imposing this restriction reduces the sample of displaced by 10.8%. However, one main caveat with restricting the analysis to stable switchers is that more able workers have a higher probability of accumulating occupational tenure. Besides this selection issue, another problem is that only those workers who expect growing earnings will remain in their occupation, which downward-biases differences in earnings losses between stable switchers and other types of displaced.

The sample counts 9,060 displaced workers whose employment, unemployment, and non-participation history we can follow for 20 years on average. Out of the sample of displaced workers, 6,090 stay in the same 3-digit occupation after displacement, while 2,970 workers change occupations. Within the group of switchers, 962 subjects move to occupations where they are under-qualified, and 1,167 individuals switch to occupations where they are overqualified (see Section 3 for details).

3 Skill Mismatch

Thus far in the literature there are two types of measures of skill mismatch. The first type captures the skill distance between jobs or occupations, but is symmetric in nature.That is, a move from job A to job B is equally skill-distant as a move from B to A. This symmetry is empirically problematic when dealing with moves between jobs with different qualification or skill levels. Symmetric measures do not capture the fact that while a move from job A to

[13] For brevity we did not include year of displacement and detailed occupational groups. These results are available from the authors on request.

[14] This is the number of occupations we obtain after merging the SIAB with the BIBB/IAB, BIBB/BAuA data.

[15] Switchers can have an unemployment or non-participation spells in between the pre- and post-displacement employment spells. We only restrict switchers to be working in an occupation other than the pre-displacement occupation in their first job after displacement.

Table 1: Descriptive Statistics

	Displaced	Non-Displaced	Displaced		Switchers			
			Stayers	Switchers	Down-skilling	Up-skilling	Lateral	Re-skilling
Observations (individuals)	9,060	9,060	6,090	2,970	1167	962	470	371
% Male	62.47	62.77	60.94	65.62	68.12	62.99	60.64	70.89
% West	85.63	85.54	86.45	83.94	83.12	85.97	82.98	82.48
Age at point of displacement	37.03	37.02	37.12	36.84	36.96	36.59	36.80	37.02
% University graduates	10.07	10.18	10.20	9.79	12.00	6.64	6.51	14.63
% Primary+secondary sector	50.05	50.82	46.56	58.45	57.50	56.44	60.64	63.34
Median annual earnings (€)	26,815	27,316	27,515	25,523	25,873	25,909	23,158	26,697
Median daily wage (€)	73,85	75,47	75,83	70,28	70,98	71,04	64,37	73,04
Median occupational tenure	5.98	5.99	6.06	5.37	5.50	5.28	5.24	5.41
% Full time employed	89.93	89.39	0.88	0.92	0.92	0.92	0.91	0.94
Skill shortage				0.62				
Skill redundancy				0.66				

Note: Wages, occupational tenure and full-time indicator are measured two years prior to displacement.

B may be characterized by, for instance, overqualification, a move in the opposite direction may not incur overqualification. Measures of this kind have been proposed by Poletaev and Robinson (2008) and Gathmann and Schönberg (2010).

The second type of measures, aims at measuring the skill and qualification asymmetries between jobs or, more often, between jobs and persons. At the job-person level, the measures of over- and underqualification or over- and underskilling try to capture whether there is a mismatch between the qualifications and skills a person has acquired and those required for the job. Some of these measures are based on self-reporting of the job-person mismatch (Hartog and Oosterbeek, 1988; Alba-Ramirez, 1993; Galasi, 2008), others are based on the analysis of job tasks (Eckaus, 1964; Hartog, 2000), and a third set is based on realized job-person matches (Verdugo and Verdugo, 1989; Kiker, Santos and de Oliveira, 1997; Quinn and Rubb, 2006).[16]

For the purpose of our analysis, we develop measures of over- and underqualification that are in the tradition of the second type of skill mismatch measures. However, instead of relying on self-reported mismatch, we exploit detailed information on occupation-specific job task requirements and workers' occupational histories that our data provide. Thus, our skill mismatch measures are based on the realized skill utilization when people switch occupations. In addition to the differences in the educational requirements of occupations, our approach takes into account the qualitative differences in skills. This means that we also capture skill mismatch between occupations that need the same years of formal education but require different sets of skills.[17] In what follows, we explain the construction of these measures in detail.

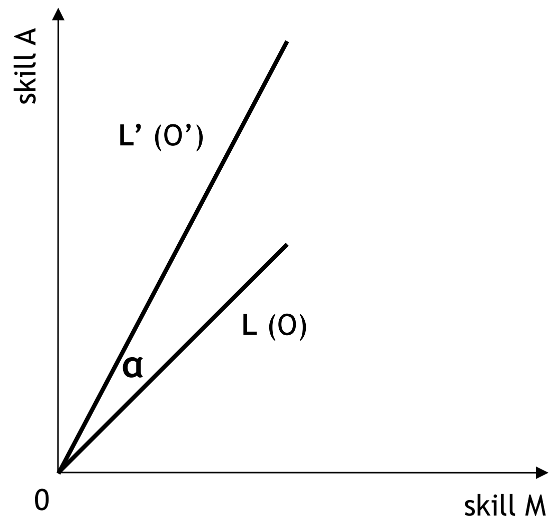
3.1 Measuring Skill Mismatch

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

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

[17] Since the quality of the education variable in the SIAB is rather poor, we do not design educational mismatch measures using the individual-level data. First, the education variable in the SIAB consists of only six coarse categories: (a) secondary education, (b) secondary education with vocational training, (c) upper secondary education, (d) upper secondary with vocational training, (e) university of applied sciences, and (f) university. Moreover, the quality of the reporting is poor (14.6% of the persons in our sample have missing education) and even deteriorates over time (Fitzenberger, Osikominu and Völter, 2006).

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



The angle between the two vectors indicates whether occupations have similar relative task structures. For instance, Gathmann and Schönberg (2010) use the angular separation between skill vectors as a measure of occupational distance. However, some occupations require skill mastery at higher levels than other occupations. As such, the relative importance of a task (and its required skills) gives only limited information about the skill similarity of two occupations. For instance, although the relative importance of interactive skills may be similar for ordinary sales persons and professional negotiators, the latter will require a much higher absolute level of this skill. The reason is that, in this example, negotiators are assumed to be advanced sales persons. That is, they use the same skill mix, but they have to master each skill at a much higher level. This introduces an asymmetry in the relation between negotiators and sales people. For instance, whereas it is relatively easy for a negotiator to become a sales person, the reverse is much harder. Indeed, the negotiator would have to leave some of his skills idle, whereas the sales person will need to learn how to master each of his skills at a higher level.

We propose that each occupational switch can be characterized by two numbers: skill redundancy and skill shortage. Both numbers will depend on the direction of the switch, highlighting the asymmetry of occupational 'distance.' Skill redundancy is defined as the total amount of skills, expressed in units of years of schooling that are typically associated with learning this amount of skills, that the old occupation uses, but that remain idle in the new occupation. The reverse we call skill shortage, or the amount of skills that are required in the new job, but were not in the old

To measure skill redundancy and skill shortage, we draw on data on occupational skill profiles provided in the 2005/2006 wave of the BIBB/IAB and BIBB/BAuA Surveys (see Section 2). In particular, we use 46 questions about job tasks, knowledge, and work conditions. We aggregate individual answers to the level of occupations. Variables that are given on a Likert scale are transformed into a binary scale, because we are only interested in whether a particular task is present or absent, irrespective of the intensity of use.[18] Within these 46 questions, we expect to find much overlap in terms of broad underlying skills. Therefore, we run a factor analysis that results in a total of 5 broad skill factors with eigenvalues above 1.[19]

Based on the results of the factor analysis, we characterize each occupation by its factor scores on these 5 factors, which can roughly be classified as (1) managerial / cognitive skills, (2) R&D / science skills, (3) technical skills, (4) sales / negotiation skills and (5) medical skills.[20] Following Poletaev and Robinson (2008), these factors are rescaled to start at zero, such that they compose a five-dimensional coordinate system. This provides us with vectors whose elements contain the percentile positions of an occupation on each skill factor. We also use a different set of 14 questions on the conditions under which workers have to do their jobs. These questions all load on one factor that quantifies a job's disutility. People are likely to take their own job as a frame of reference when reporting their job tasks. Thus, we interpret the task intensities relative to the intensity of other tasks in the job, and not relative to how intensely the task is used in other occupations. We therefore normalize the vectors to have unit length.

A second piece of information that is provided in the task survey is a detailed account of the schooling history of each worker.[21] By calculating the mean number of years of schooling of all workers in a given occupation, we arrive at an estimate of the schooling requirements of that occupation. This reflects the complexity of an occupation's task profile. We now assume that workers in an occupation use this schooling to acquire the skills of their skill profile. We will also assume that the years of schooling required to acquire different skills is strictly additive. That is, we can arrive at the total schooling for an occupation by adding up the amount of schooling used to acquire each individual skill up to the level indicated by the corresponding factor loadings. That is, we assume that total schooling can be written as a linear combination of the factor loadings of skills:

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

where S_O is the average number of years of schooling in occupation O and s_O^i is the factor score of the occupation on skill factor i, measured in standard deviations. Our analysis rests on the assumption that it is possible to calculate how much schooling is required to achieve a one standard deviation increase in each skill by using the estimated coefficients from a regression of schooling on skill-factor loadings. However, it may be that some skills

[18] Intensities of job tasks are self-reported in the BIBB/IAB and BIBB/BAuA data. Closer inspection of these data reveals that people seem to make erroneous judgments. This is due to the fact that most individuals are unaware of the true task distribution in the population; they mainly compare the tasks they fulfill with the tasks in jobs they know of.

[19] There are in fact two other relevant factors. However, both of them do not seem to capture any skills, but rather the disutility workers derive from their jobs, such as physical strain or work safety issues

[20] Previous work that uses the task-based approach to capture the relevant dimensions of the task content of jobs typically identifies three to four groups of tasks. Autor, Levy and Murnane (2003) and Spitz-Oener (2006) distinguish between routine cognitive, routine manual, non-routine cognitive, and non-routine manual. Goos, Manning and Salomons (2009) and Gathmann and Schönberg (2010) differentiate between abstract, routine/manual, and service tasks.

[21] The BIBB/IAB and BIBB/BAuA Survey not only provides information on the highest educational attainment, but also on the time workers spend on up to 7 episodes of post-secondary schooling.

are associated with worse work conditions. Therefore, we run the regression above, adding the disutility factor loadings as controls. The resulting regression analysis has a surprisingly good fit, with an R-squared of 0.74.[22] We will interpret the coefficients of this regression analysis as the number of years of schooling it requires to acquire a one standard deviation increase in the factor loading of the corresponding skill.

In the final step, we use the regression coefficients for each skill to derive the amount of skill redundancy and skill shortage associated with a move from one occupation to another. For this, we calculate for each skill the difference in factor loadings between the two occupations, O and O', and multiply this with the corresponding coefficient of the schooling regression. Finally, we arrive at the following equations for skill redundancy and skill shortage, that express the number of years of schooling that are required (or remain idle) when moving from one occupation to the other.

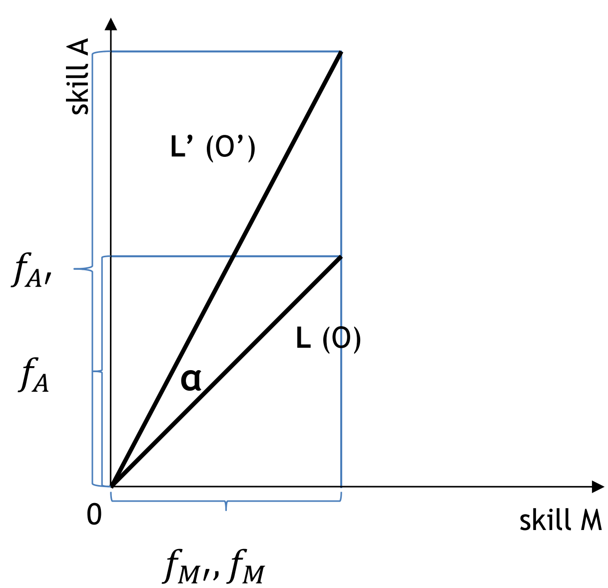
$$shortage_{OO'} = \sum_{i=1}^{5} \beta_i \times (f_{iO'} - f_{iO}) \times I(f_{iO'} > f_{iO})$$

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

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

We use Figure 3 to illustrate an example. A job move from O' to O will on average incur a skill shortage of zero, because employees in O' are at least as qualified as those in O in both skills. At the same time, the skill redundancy of such move will equal $f_{A'} - f_A$. In contrast, a move from O to O' results in a skill shortage of $f_{A'} - f_A$, with zero redundancy.

Figure 3: Skill Shortage and Skill Redundancy



[22] See Table A.1 for the results.

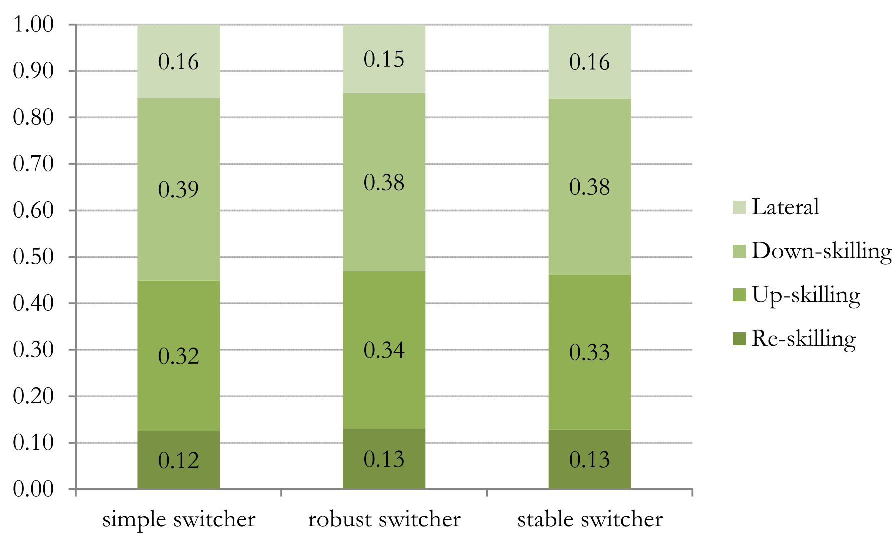
There are some obvious limitations to this decomposition of an occupation's schooling. For instance, it is not immediately clear that the schooling requirements of skills should be additive. For instance, there may be interaction effects that make it particularly easy to learn a combination of skills. Moreover, workers do not just acquire skills in schooling, but also through work experience. However, given the relatively good fit of the schooling regression, we believe that the created indicators can serve as a first approximation of an asymmetric notion of skill distance among occupations.

3.2 Types of Occupational Switches

People are seldom only overqualified or only under-qualified when switching occupations. Most often, they are skilled in areas that are not needed for the job, and under-skilled in areas relevant for the job. To capture this, our measures of skill mismatch between occupations depend on both, skill shortage and skill redundancy. We use the population medians of skill shortage and skill redundancy as cutoff points to distinguish between 4 different types of occupational moves: when both shortage and redundancy are above the median, a worker switches her skill set completely (re-skilling). If a worker incurs a high redundancy but only a low shortage, we call this a downward switch. Put differently, a worker who switches downward is overqualified for the new job. An upward switch occurs if the shortage in the new job is high, but the worker can still use a lot of her previously acquired skills. This is similar to saying that a worker is under-qualified. Finally, a lateral switch occurs if both shortage and redundancy in the new occupation are low.

Figure 4 shows the distribution of the four types of occupational switchers using the definitions of simple switchers, robust switchers, and stable switchers, respectively. It is apparent that most of the switchers are either upward- or downward-movers, while it is rather uncommon to change the skill portfolio completely or to move laterally. This holds for all definitions of switchers.

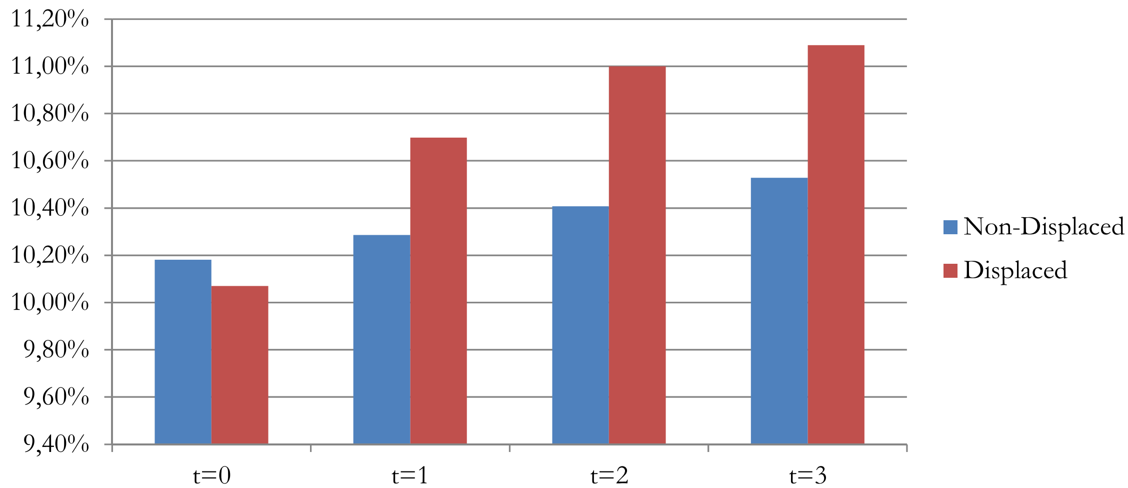
Figure 4: Switcher Types



4 Descriptive Evidence

We now shed some light on the structural dynamics of displaced workers in terms of the industries they transit from and to. We also document the educational investments that they are making following displacement. In Figure 5, we compare the share of workers with at least a college degree at the point of displacement (in $t = 0$) with the attained education in the first three post-displacement periods. It is apparent that the average displaced worker upgrades her education before entering a new job, which suggests that new jobs are actually more skill intensive than the old ones.

Figure 5: Share of Workers with at least a College Degree Before and After Displacement



In Figure 6, we compare the share of college-educated workers separately by the type of switch. We observe that educational upgrading is mainly driven by upward switchers. The share of tertiary educated workers increases most strongly in the group of upward switchers, from 6.6 to 9.4%. Other types of switchers also invest in their human capital, but do so more moderately.

Figure 6: Share of Workers with at least a College Degree by Type of Switch

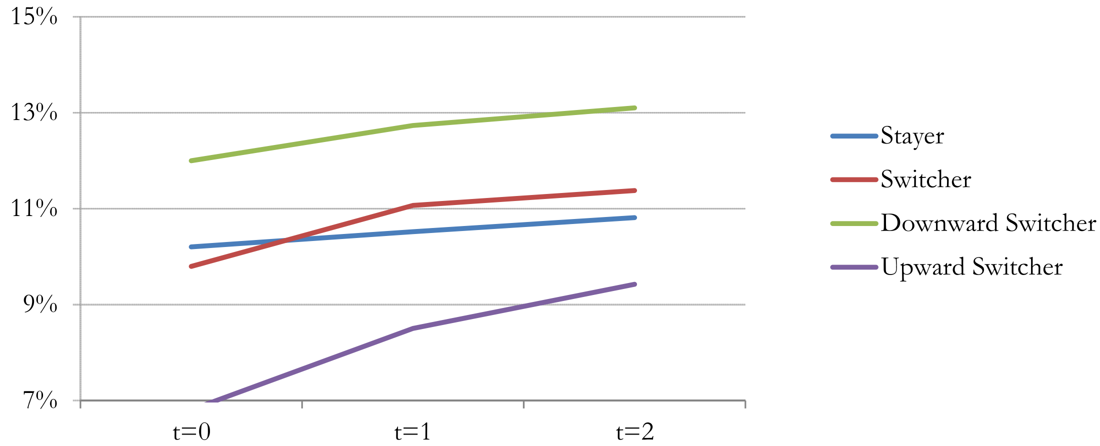
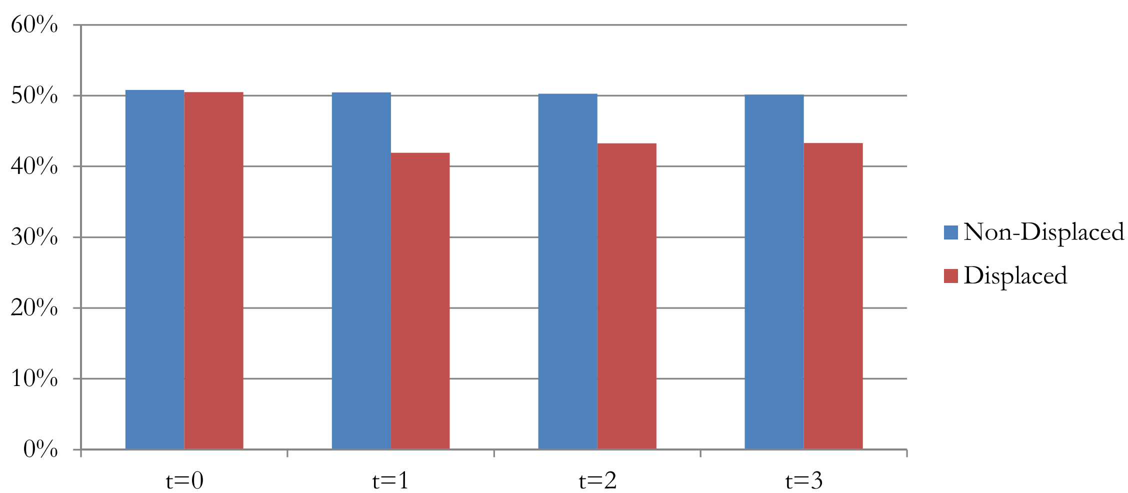


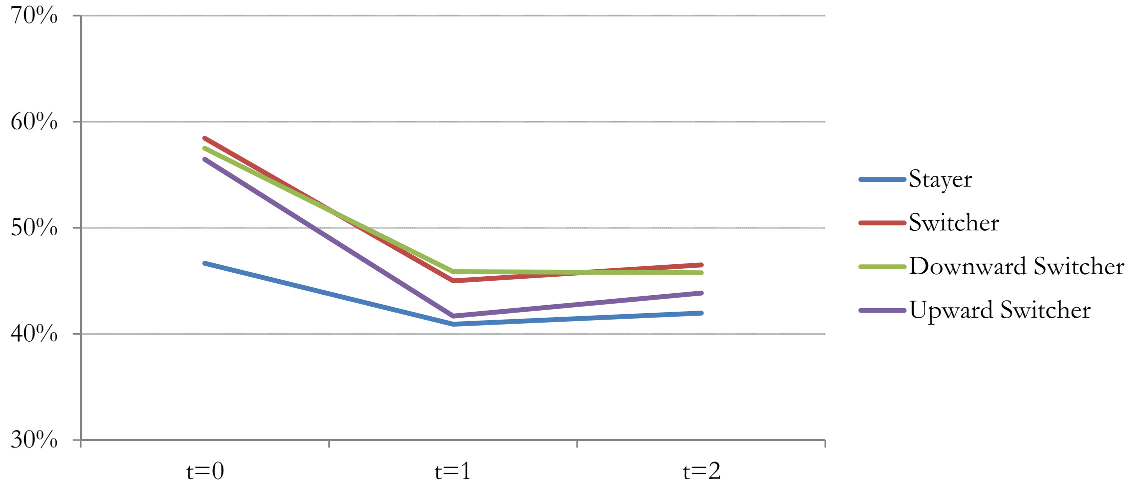
Figure 7 shows a major post-displacement employment shift from extractive industries, including construction, and manufacturing toward services and public services (including healthcare and education). As indicated by Figure 7three years after displacement, the share of persons working either in the primary or secondary sector decreases from 51% to 43% for the group of displaced. For the group of non-displaced workers, this share remains quite stable over time at about 50%.

Figure 7: Share of Workers in Primary or Secondary Sector Before and After Displacement



Perhaps not surprisingly, the shift in industries is more pronounced for occupational switchers than for stayers. Comparing upward and downward switchers, the figure suggests that upward switchers are somewhat more likely to leave the primary or secondary sector. However, structural change seems to be important driving force of post-displacement occupational switching for both switcher types.

Figure 8: Share of Workers in Primary or Secondary Sector Before and After Displacement



5 The Effect of Displacement on the Switching Probability

Next, we ask whether displacement has an effect on the probability to switch occupations as well as on the direction of the switch. Table 3 shows results from Probit regressions of the outcome in the left-hand side column on a displacement dummy, controlling for all matching variables (see Section 2). The estimates are transformed into predicted probabilities. First, we observe that displaced workers are much more likely to switch occupations than their non-displaced counterparts. In fact, about 68% of displaced workers stay in the same occupation after displacement, while non-displaced workers almost never change their occupation after their virtual displacement.[23] The difference between both groups is obviously highly significant. When distinguishing between the types of switches, we observe that the overall difference between displaced and non-displaced is largest for downward switches. These are switches where workers leave most of their previously acquired human capital idle.

[23] This result lends support to our argument presented above that displaced would not have changed the occupation voluntarily, given that they have a minimum occupational tenure of 3 years.

Table 2: Predicted Probabilities from Probit Estimations: Matching Sample

Outcome		Displaced	Non-Displaced	Difference
Stay		67.52	98.10	-30.58***
Switch	Downward	12.87	0.60	12.27***
	Upward	10.42	0.56	9.86***
	Lateral	5.15	0.50	4.65***
	Re-Skilled	4.05	0.25	3.80***

Notes: This table shows predicted probabilities, obtained from Probit estimations. The dependent variable is indicated in the LHS column. All regressions control for gender, age, occupational tenure, location of the firm (East or West Germany), industry (4 sectors), detailed occupation (263 occupations), displacement year, as well as daily wages and days worked in years 6 to 2 before (virtual) displacement. Sample: 17134 observations. *** p<0.01, ** p<0.05, * p<0.1.

When conditioning on occupational switching, we find evidence that displacement significantly increases the chances to be over-qualified at the new job by about 8%, while it decreases the probability of skill-related or lateral switches by more than 10% (see Table 3). These results suggest that displacement alters the probability of occupational change, and as a result the skill mismatch. But displacement also changes the direction of the switch, meaning that involuntary switchers (displaced) incur larger mismatch than voluntary switchers (non-displaced). In the next section, we investigate the wage and employment consequences of occupational switching after displacement.

Table 3: Predicted Probabilities from Probit Estimations: Switchers Only

Outcome		Displaced	Non-Displaced	Difference
Switch	Downward	39.62	31.58	8.04**
	Upward	32.08	29.47	2.61
	Lateral	15.86	26.32	-10.46***
	Re-Skilled	12.47	13.16	-0.69

Notes: This table shows results from regressions analogous to those underlying Table 3 for the sample of occupational switchers (2947 observations). *** p<0.01, ** p<0.05, * p<0.1.

6 Empirical Strategy

To gauge the role of occupational switching in explaining displacement costs, we employ a difference-in-differences approach. Our identification strategy rests on the assumption that, conditional on pre-displacement outcomes, worker fixed effects, and further observable worker characteristics, workers in the control group (non-displaced) are equivalent to those in the treatment group (displaced). Moreover, if both occupational stayers and switchers are on average remunerated according to their productivity, pre-displacement wages should appropriately reflect their overall earnings potential. Matching on days worked before displacement additionally captures preferences for being active on the labor market. Our difference-in-differences strategy in combination with matching on pre-displacement outcomes then controls for unobserved selection into occupations and yields a valid estimate of the differential effect of displacement on occupational stayers vis-à-vis switchers.[24]

We estimate variants of the following regression:

$$Y_{it} = \alpha_i + \gamma_t + X_{it}^{'}\delta + \sum_{k \geq -4}^{15} \beta_1^k T_{it}^k + \sum_{k \geq -4}^{15} \beta_2^k T_{it}^k D_i + \varepsilon_{it} \tag{2}$$

where Y_{it} is the outcome of interest (annual earnings, daily wage, or days worked) of individual i in year t. The inclusion of worker fixed effects, denoted by α_i, controls for heterogeneity between displaced and non-displaced workers that remains after applying our matching procedure. Accounting for worker fixed effects also allows the selection into occupational switching to depend on time-invariant characteristics.[25] γ_t are calendar time effects, which account for economy-wide changes in the outcome over time, e.g., business cycle effects. The vector X_{it} consists of the observed, time-varying characteristics of the worker, such as age and age squared.

The dummy variables T_{it}^k take the value 1 if worker i is observed in year t at a distance of k years from plant closure, with 0 denoting the year of plant closure. This term identifies the time path of earnings of non-displaced workers 4 periods before up to 15 periods after virtual displacement. D_i is a dummy variable taking the value 1 if i is displaced in a plant closure for the first time in the period 1981–2004. Depending on the specification, the dummy variable D_i, instead of identifying all displaced workers, can also refer to displaced stayers, displaced switchers, and the several various types of switchers (downward, upward, lateral, re-skilled). When we estimate these other versions of the model, we only keep in the sample non-displaced workers who are matched to the group of displaced we are looking at. ε_{it} is the error term, which captures unobservables of i in year t.

The β-coefficients in equation (2) measure the time path of the outcome of displaced and non-displaced workers from 4 periods prior to displacement to the period 15 after displacement. Inter alia, our difference-in-differences specification captures the fact that earnings of displaced workers may begin to deteriorate prior to the actual displacement, as the competitive abilities of the employers worsen. The coefficients of primary interest are β_2^k, which measure displacement costs.

7 Occupational Switching and Displacement Costs

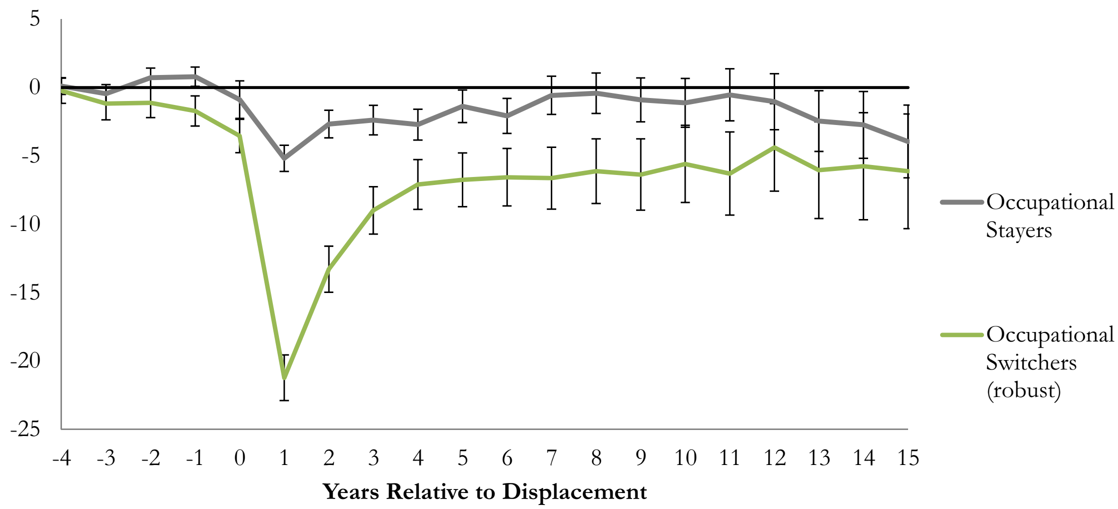
Figure 9 shows the results of estimating equation 2 once for the sample of occupational switchers and their statistical non-displaced twins (green line) and once for the sample of stayers and their twins (gray line). The outcome variable is gross daily wages. On the axis we see the time relative to displacement and on the ordinate the differences in daily wages between the treatment and the control group. The occupational stayers have relatively low

[24] We further tackle the potential endogeneity of occupational switching by considering only workers with a strong occupational attachment in the estimations (see Section (2)). These workers would not have left the occupation voluntarily. Another virtue of focusing on tenured workers is that being mismatched in the old occupation is unlikely to drive the re-employment decision (Phelan, 2011).

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

productivity losses of 2.6% following displacement and they manage to catch up to their pre-displacement levels of daily earnings between the 5th and the 7th year following displacement. On contrary, occupational stayers have substantially higher daily wage losses of 13.8% and never manage to catch up to their pre-displacement levels of daily wages. [26]

Figure 9: Daily Wage Losses of Displaced Switchers and Stayers



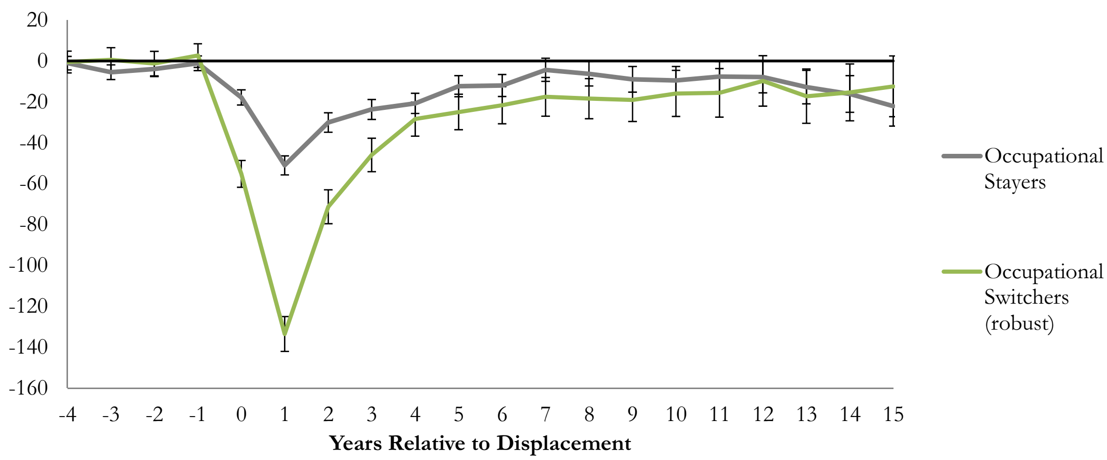
Notes: The confidence intervals are defined at the 90% level, derived from robust standard errors.

Occupational switchers additionally experience more severe detachments from the labour market following displacement, as measured by the differences in the annual number of days worked in Figure 10. While stayers have an average post-displacement drop of 4.5%, the number of days worked in the case of switchers drops by 11.3%. The average annual earnings losses of occupational switchers that result from these dynamics are 19.5%. In the case of occupational stayers, the earnings losses are only 7.5%. This result is in line with the results of Kambourov and Manovskii (2009), who find that displaced workers in the U.S. who switch occupations experience 12% larger losses than those who stay in the same occupation. As evident from Figures 9 and 10 the drop in the daily wage is the driving force behind the persistence of the earnings losses.

Figure 11 shows the wage losses of workers who are employed in occupations where they are overqualified (downward switchers) or under-qualified (upward switchers) following displacement. Despite the large variance in daily earnings as visible by the wide confidence intervals, on average those overqualified at the new job lose more than the under-qualified at the new job. While this is not surprising, what is surprising is that the upward switchers who between displacement and the post-displacement job likely upgraded their education (see Figure 6) do not see returns to their investment in skills. Figure 12 additionally shows

[26] The wages of occupational switchers exhibit a slight downward trend already before displacement. Jacobson, LaLonde and Sullivan (1993), Schmieder, von Wachter and Bender (2010), and Davis and Von Wachter (2011) find a similar pattern when comparing annual wages of displaced and non-displaced workers.

Figure 10: Reductions in Annual Days Worked of Displaced Switchers and Stayers



the trends in the labour market attachment once for the upward and once for the downward switchers. Compared to their statistical non-displaced counterparts, both groups undergo equally severe detachments from work.[27] The result is a drop in the mean annual earnings following displacement of 22.7% for the group of downward switchers and of 15.4% for the group of upward switchers.

These findings suggest that the loss of occupation-specific human capital is one important mechanism behind the large and persistent earnings losses of displaced workers. The ones that lose most in terms of earnings and productivity are the ones who are over-skilled at the post-displacement job, followed by those under-skilled at the new job.

[27] Not shown here are the results for those who switch to unrelated jobs (those where both skill shortage and skill redundancy are high). This group behaves very similarly to the downward switchers. For the group of lateral switchers (about 16% of all displaced occupational switchers) we fail to find a proper control group among the non-displaced.

Figure 11: Daily Wage Losses of Upward and Downward Occupational Switchers

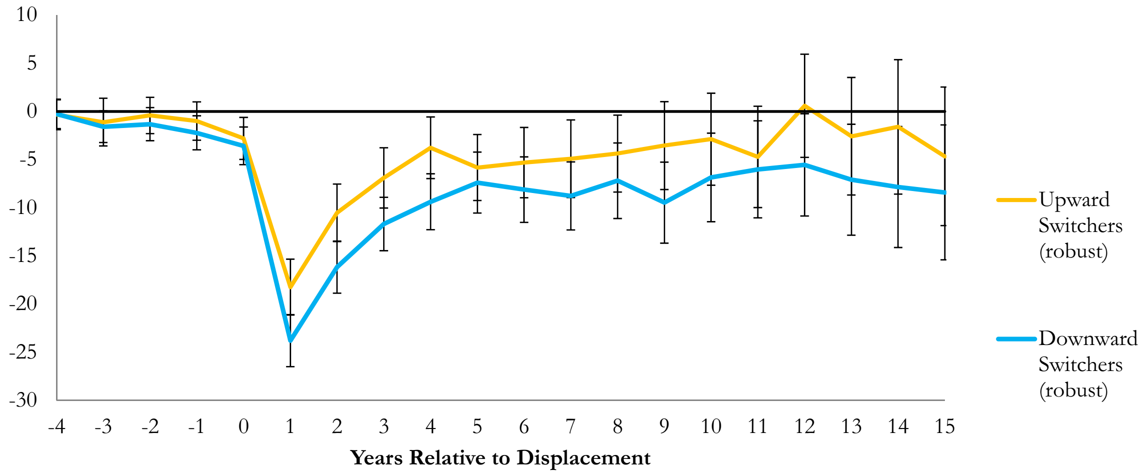
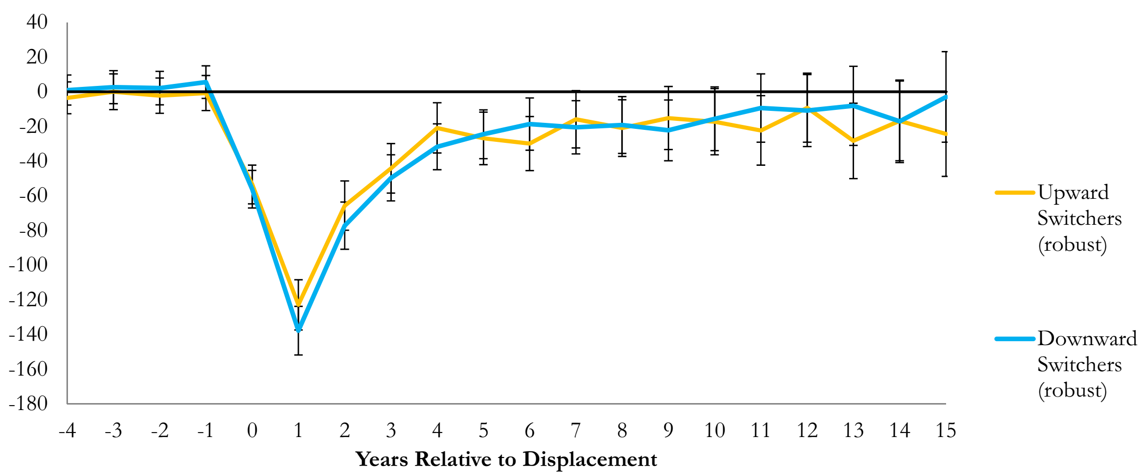


Figure 12: Reductions in Annual Days Worked of Upward and Downward Occupational Switchers



8 Conclusions

Human capital is occupation-specific (Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009). This specificity means that wage losses are minimized by staying in the same occupation or in closely related ones (Gathmann and Schönberg (2010)). We investigate the role of skill specificity in explaining the size and the persistence of earnings losses of workers who were displaced in the course of a plant closure in Germany between 1981 and 2004.

We find that job displacements resulting from firm closures drastically increase the probability of changing one's occupation. Conditional on occupational switching, job displacements significantly increase the probability of becoming overqualified at the new job, and decrease the probability of finding a job in a highly skill-related one. Those who switch occupations experience annual earnings losses that are much higher than those of people who stay in the pre-displacement occupation (7.5% vs. 19.5%).

Using job tasks data, we introduce novel measures of skill mismatch between occupations that allow us to classify occupational switches into up-skilling, down-skilling, re-skilling and lateral-skill changes. Most of the individuals who switch occupations after displacement are either over or under-skilled at the post-displacement job. A smaller share of occupational switchers go to jobs that require a fully different skill set (re-skill) and another small share stay in highly related occupations (lateral switchers).

Those who are overqualified at the new job fare worse in terms of post-displacement earnings, losing on average 22.7% of their pre-displacement annual earnings. Re-skilled lose about 17% of their pre-displacement earnings, while under-skilled about 15.4%. We conclude that skill mismatch is one important mechanism behind the observed patterns of large and irreversible earnings losses of workers displaced due to plant closures. The losses depend on the extent to which the skills used in the pre-displacement occupation become redundant at the new one.

References

Abramitzky, R. 2009. "The effect of redistribution on migration: Evidence from the Israeli kibbutz." *Journal of Public Economics*, 93: 498–511.

Alba-Ramirez, A. 1993. "Mismatch in the Spanish Labor Market: Overeducation?" *Journal of Human Resources*, 28: 259–278.

Angrist, J., and S. Pischke. 2008. *Mostly Harmless Econometrics: An Empiricists' Companion.* Princeton, NJ: Princeton University Press.

Ashenfelter, O., and D. Card. 1985. "Using the Longitudinal Structure of Earnings to Estimate the Effects of Training Programs." *Review of Economics and Statistics*, 67: 648–660.

Autor, D. H., F. Levy, and R. J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics*, 118: 1279–1333.

Becker, G. S. 1962. "Investment in Human Capital: A Theoretical Analysis." *Journal of Political Economy*, 70: 9–49.

Biewen, M., and S. Steffes. 2010. "Unemployment persistence: Is there evidence for stigma effects?" *Economics Letters*, 106: 188–190.

Biewen, M., B. Fitzenberger, A. Osikominu, and M. Paul. Forthcoming. "Effectiveness of Public Sponsored Training Revisited: The Importance of Data and Methodological Choices." *Journal of Labor Economics.*

Black, S., and A. Spitz-Oener. 2010. "Technological Change and the Skill Content of Women's Work." *Review of Economics and Statistics*, 92: 187–194.

Bonikowska, A., and R. Morissette. 2012. "Earnings Losses of Displaced Workers with Stable Labour Market Attachment: Recent Evidence from Canada." *Statistics Canada Research Paper Series No. 346.*

Burda, M., and A. Mertens. 2001. "Estimating Wage Losses of Displaced Workers in Germany." *Labour Economics*, 8: 15–41.

Carrington, W. 1993. "Wage Losses for Displaced Workers: Is It Really the Firm That Matters?" *Journal of Human Resources*, 28: 493–496.

Couch, K., and D. Placzek. 2010. "Earnings Losses of Displaced Workers Revisited." *American Economic Review*, 100: 572–589.

Davis, S. J., and T. Von Wachter. 2011. "Recessions and the Costs of Job Loss." *Papers on Economic Activity*, 43: 1–72.

Del Bono, E., A. Weber, and R. Winter-Ebmer. 2012. "Clash Of Career And Family: Fertility Decisions After Job Displacement." *Journal of the European Economic Association*, 10: 659–683.

DiNardo, J. E., and J.-S. Pischke. 1997. "The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too." *Quarterly Journal of Economics*, 112: 291–303.

Dorner, M., J. Heining, P. Jacobebbinghaus, and S. Seth. 2010. "Sample of Integrated Labour Market Biographies (SIAB) 1975–2008." *FDZ-Methodenreport 09/2010.*

Dustmann, C., J. Ludsteck, and U. Schönberg. 2009. "Revisiting the German Wage Structure." *Quarterly Journal of Economics*, 124: 843–881.

Eckaus, R. 1964. "Economic Criteria for Education and Training." *Review of Economics and Statistics*, 46: 181–190.

Eliason, M., and D. Storrie. 2006. "Lasting or Latent Scars? Swedish Evidence on the Long-term Effects of Job Displacement." *Journal of Labor Economics*, 24: 831–856.

Fitzenberger, B., A. Osikominu, and R. Völter. 2006. "Imputation rules to improve the education variable in the IAB employment subsample." *Schmollers Jahrbuch. Zeitschrift für Wirtschafts- und Sozialwissenschaften*, 126: 405–436.

Frey, B. S., and A. Stutzer. 2002. "What Can Economists Learn from Happiness Research?" *Journal of Economic Literature*, 40: 402–435.

Galasi, P. 2008. "The Effect of Educational Mismatch on Wages for 25 Countries." *Budapest Working Papers on the Labour Market BWP-2008/8.*

Gathmann, C., and U. Schönberg. 2010. "How General is Human Capital? A Task-Based Approach." *Journal of Labor Economics*, 28: 1–50.

Goos, M., A. Manning, and A. Salomons. 2009. "Job Polarization in Europe." *American Economic Review Papers and Proceedings*, 99: 58–63.

Hartog, J. 2000. "Over-Education and Earnings: Where Are We, Where Should We Go?" *Economics of Education Review*, 19: 131–147.

Hartog, J., and H. Oosterbeek. 1988. "Education, Allocation and Earnings in the Netherlands: Overschooling?" *Economics of Education Review*, 7: 185–194.

Hethey, T., and J. Schmieder. 2010. "Using worker flows in the analysis of establishment turnover: evidence from German administrative data." *FDZ Method Report No. 201006.*

Hijzen, A., R. Upward, and P. Wright. 2010. "The Income Losses of Displaced Workers." *Journal of Human Resources*, 45: 243–269.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan. 1993. "Earnings Losses of Displaced Workers." *American Economic Review*, 83: 685–709.

Kalil, A., and P. Wightman. 2011. "Parental Job Loss and Children's Educational Attainment in Black and White Middle-Class Families." *Social Science Quarterly*, 92: 57–78.

Kambourov, G., and I. Manovskii. 2009. "Occupational specificity of human capital." *International Economic Review*, 50: 63–115.

Kiker, B., M. Santos, and M. de Oliveira. 1997. "Overeducation and Undereducation: Evidence for Portugal." *Economics of Education Review*, 16: 111–125.

Lazear, E. 1979. "Why is there Mandatory Retirement?" *Journal of Political Economy*, 87: 1261–1284.

Leombruni, R., T. Razzolini, and F. Serti. 2013. "The pecuniary and non-pecuniary costs of job displacement — The risky job of being back to work." *European Economic Review*, 61: 205–216.

Leuven, E., and H. Oosterbeek. 2011. "Overeducation and Mismatch in the Labor Market." In *Handbook of the Economics of Education.* , ed. E. Hanushek and F. Welch, 283–326. Elsevier Science.

McKenzie, D., J. Gibson, and S. Stillman. 2010. "How Important is Selection? Experimental VS. Non-Experimental Measures of the Income Gains from Migration." *Journal of the European Economic Association*, 8: 913–945.

Neal, D. 1995. "Industry-specific Human Capital: Evidence from Displaced Workers." *Journal of Labor Economics*, 13: 653–677.

Oreopolous, P., M. Page, and A. H. Stevens. 2008. "The Intergenerational Effects of Worker Displacement." *Journal of Labor Economics*, 26: 455–483.

Parent, D. 2000. "Industry-Specific Capital and the Wage Profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics." *Journal of Labor Economics*, 18: 306–323.

Pfann, G. A. 2006. "Downsizing." *Review of Economics and Statistics*, 88: 158–170.

Phelan, B. 2011. "Task Mismatch and the Reemployment of Displaced Workers." *Unpublished Manuscript.*

Podgursky, M., and P. Swaim. 1987. "Displacement and Earnings Loss: Evidence from the Displaced Worker Survey." *Industrial and Labor Relations Review*, 41: 17–29.

Poletaev, M., and C. Robinson. 2008. "Human capital specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys." *Journal of Labor Economics*, 26: 387–420.

Quinn, M., and S. Rubb. 2006. "Mexico's Labor Market: The Importance of Education-Occupation Matching on Wages and Productivity in Developing Countries." *Economics of Education Review*, 25: 147–156.

Schmieder, J., T. von Wachter, and S. Bender. 2010. "The Long-Term Impact of Job Displacement in Germany During the 1982 Recession on Earnings, Income, and Employment." *Columbia University, Department of Economics Discussion Paper Series DP0910-07.*

Schwerdt, G. 2011. "Labor turnover before plant closure: 'Leaving the sinking ship' vs. 'Captain throwing ballast overboard'." *Labour Economics*, 18: 93–101.

Seim, D. 2012. "Job Displacement and Labor Market Outcomes by Skill Level." *Bank of Estonia Working Paper Series No. 4/2012.*

Spitz-Oener, A. 2006. "Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure." *Journal of Labor Economics*, 24: 235–270.

Stevens, A. H. 1997. "Persistent Effects of Job Displacement: The Importance of Multiple Job Losses." *Journal of Labor Economics*, 15: 165–188.

Sullivan, D., and T. von Wachter. 2009. "Job Displacement and Mortality: An Analysis using Administrative Data." *Quarterly Journal of Economics*, 124: 1265–1306.

Topel, R., and M. Ward. 1992. "Job Mobility and the Careers of Young Men." *Quarterly Journal of Economics*, 107: 439–479.

Verdugo, R., and N. Verdugo. 1989. "The Impact of Surplus Schooling on Earnings: Some Additional Findings." *Journal of Human Resources*, 24: 629–643.

Vishwanath, T. 1989. "Job Search, Stigma Effect, and Escape Rate from Unemployment." *Journal of Labor Economics*, 7: 487–502.

A Appendix

Table A.1: Schooling Regression

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

Note: Skills are measured in standard deviations.
Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.2: Factor loadings

	Cognitive	Technical	Interactive	Commercial	Production	Security
Tasks:						
Production of goods	-0.5164	0.2698	-0.1196	-0.0377	0.3062	0.0738
Measuring, checking, quality control	-0.312	0.5935	-0.0438	0.0193	0.3643	0.0257
Monitoring, operating of machines	-0.5159	0.4212	0.0008	-0.3061	0.2779	0.2664
Repair, maintenance	-0.3021	0.6288	0.085	0.1346	-0.132	-0.1604
Purchase, procurement, sales	0.2601	-0.0385	0.2298	0.7052	0.2117	0.1044
Transport, storage, distribution	-0.3692	0.1024	0.2355	0.2905	0.0343	0.2356
Advertising, marketing, PR	0.4479	-0.2334	0.0462	0.3349	-0.0826	0.1637
Organize, plan, prepare work processes	0.4884	0.2954	0.1703	0.1547	0.0591	0.0175
Develop, plan, design	0.4526	0.3081	-0.337	-0.0247	0.1527	-0.2592
Educate, teach, raise	0.5314	0.1002	0.4148	-0.1933	0.0636	-0.1936
Collect information, research, document	0.8232	0.0484	-0.0573	-0.0978	0.0701	0.0395
Consult, inform	0.7969	-0.0065	0.2251	0.1943	-0.0163	0.087
Serve, accommodate, prepare food	0.0107	-0.2165	0.4189	0.0806	0.2114	0.087
Care, parent, cure	0.3187	-0.0401	0.6343	-0.2007	0.3203	-0.1493
Secure, protect, guard, monitor, regulate traffic	-0.0369	0.2645	0.3327	-0.2895	0.0555	0.2705
Work with computers	0.667	0.04	-0.4008	-0.149	0.1888	0.2675
Cleaning, collect trash, recycle	-0.4842	0.0819	0.3889	0.0933	0.3212	0.0509
Computer programming	0.3586	0.2781	-0.3745	-0.1349	0.0983	0.0042
Solving unforeseen problems	0.59	0.3805	0.1762	-0.226	-0.1398	0.0845
Simple presentation of difficult situations	0.9021	0.0888	0.1412	-0.068	-0.0927	-0.0545
Persuade, negotiate compromise	0.8096	0.09	0.2235	0.0046	-0.194	0.0457
Independently making difficult decisions	0.644	0.3114	0.1941	0.0315	-0.1192	0.0844
Finding and closing own knowledge gaps	0.5921	0.1041	-0.0033	-0.2116	-0.1178	0.1389
Speeches, presentations	0.7495	-0.0656	0.1987	-0.2251	-0.1915	-0.1029
Contact with customers and patients	0.6734	-0.2105	0.3597	0.3826	-0.0384	-0.0129
Performing many different tasks	0.4873	0.3056	0.2288	0.1621	0.0412	0.1491

Responsibility for the welling of other people	0.5507	-0.0168	0.6344	-0.097	0.1156	0.0516
Knowledge:						
Natural sciences	0.4218	0.3805	0.0342	-0.0043	0.3545	-0.2249
Manual, technical	-0.3717	0.6251	0.0848	0.2968	-0.0607	-0.2711
Pedagogy	0.531	-0.0272	0.4433	-0.2232	0.0001	-0.2797
Law	0.5502	0.0014	0.1387	-0.1149	-0.1867	0.1607
Project management	0.6473	0.2478	-0.266	0.1097	0.0219	-0.0498
Medicine and healthcare	0.327	0.018	0.4789	-0.1245	0.4009	-0.1961
Layout, composition, visualization	0.3293	0.1031	-0.2628	0.1697	-0.013	0.0037
Mathematics, statistics	0.2784	0.5522	-0.2108	0.3086	0.0883	-0.1153
German, writing, spelling	0.7954	0.0057	-0.0979	0.0218	-0.1044	0.0609
PC applications	0.547	0.1487	-0.4747	0.1326	0.0789	0.0045
Technical	-0.0019	0.7723	-0.2245	0.1441	0.0918	-0.1558
Business administration	0.4854	-0.0177	0.0182	0.5393	0.0287	0.25
Foreign languages	0.5791	0.136	-0.2926	-0.074	0.0868	-0.0969
Working conditions:						
Work under time and performance pressure	0.179	0.395	-0.047	-0.0594	-0.2345	0.334
Repetitive work	-0.6199	-0.1837	0.1193	0.0096	0.2257	0.204
New tasks which require effort to understand	0.5647	0.3596	-0.2441	-0.1245	-0.1251	-0.0647
Multitask	0.4315	0.2389	0.1176	-0.1176	0.1783	0.4324
Can small mistake cause large financial losses?	-0.0804	0.4561	-0.0596	-0.1734	-0.077	0.4343
Work very fast	-0.2593	0.0883	0.1387	0.1687	-0.0319	0.3045
Carry weight of over 20kg?	-0.5378	0.2945	0.3754	0.1363	-0.2161	-0.0594
Work with smoke, dust, gas, vapor?	-0.5952	0.3626	0.1583	-0.1294	0.0003	0.1042
Work in cold, hot, wet, humid, drought?	-0.4879	0.2769	0.3402	0.0289	-0.3049	0.0332
Work with oil, fat, dirt?	-0.5405	0.4707	0.1884	-0.0837	-0.1158	-0.0468
Work bended, crouching, on the knees, horizontally?	-0.3321	0.3973	0.3313	0.1302	-0.2941	-0.2542
Work with strong commotions, kicks, vacillations?	-0.3388	0.2835	0.2342	-0.0683	-0.3474	0.0731

Notes: The table provides the factor loadings yielded by a principal component analysis of the 53 task-related questions in the BIBB/IAB and BIBB/BAuA Surveys (2005/2006 wave). Individual-level data was aggregated at the occupational level before performing the factor analysis. In total, there are 266 occupations. The factor analysis resulted in six orthogonal factors, displayed in Columns 2–7.