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Human Capital Mismatches along the Career Path[1]

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Abstract

Human capital is transferable across occupations, but only to a limited extent because of differences in occupational skill-profiles. Higher skill overlap between occupations renders less of individuals' human capital useless in occupational switches. Current occupational distance measures neglect that differences in skill complexities between occupations yield skill mismatch asymmetric in nature. We propose characterizing occupational switches in terms of human capital shortages and redundancies. This results in superior predictions of individual wages and occupational switches. It also allows identifying career movements up and down an occupational complexity ladder, and assessing the usefulness of accumulated skill-profiles at an individual's current job.

JEL Classification: J24, J30, J63
Keywords: skill mismatch, skill transferability, occupational change, human capital, wages

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1. Introduction

Human capital is widely regarded as the most important source of economic wealth. The human capital of an individual, his or her skills and knowledge, is what the individual, in essence, is remunerated for in the form of wages. Traditionally, economics has stressed that human capital is to a large extent specific to an individual's job and has focused among other things on the consequences of this human capital specificity in terms of incentives of firms and employees to invest in education. More recent research, however, shows that human capital is more general than previously thought. In particular, some jobs require rather similar skills and knowledge. As a consequence, staying within occupations with high task/skill overlap has been shown to be a significant source of individual wage growth. So far however, this literature has tended to use the metaphor of occupational distance to describe the similarity (or better, dissimilarity) between jobs in different occupations.

We will argue that the distance metaphor, which suggests a symmetric relation, obscures the fact that there are non-negligible asymmetries in the transferability of human capital when comparing a job move from occupation *i* to *j* to a job move from *j* to *i*. By complementing existing measures of occupational distance with the measurement of such asymmetries, we aim to further contribute to the understanding of inter-occupational human capital similarities and their consequences for people's occupational switching patterns and earnings' differences. At the level of the individual, this should lead to a better estimate of the costs of moving to a new job. Similarly, at the country level, taking these asymmetries into consideration should lead to more accurate estimates of the costs of human capital destruction involved in structural change in the economy.

Understanding the degree of specificity of human capital is relevant from several management and policy perspectives. First, the more general human capital is the less costly are job displacements in the event of firm closures or the down-sizing of firms (Topel 1991, p. 147). After all, human capital generality means that the skills used at the pre-displacement job remain useful in alternative jobs. Countries with more portable skills across jobs should therefore exhibit smoother labor market adjustments in times of technological and structural change. Second, the more general human capital is, the more transferable it is across jobs and occupations. As a consequence, firm investments in training might be less effective means of binding employees to their firms as often claimed (Becker 1962, Hashimoto 1981).

Empirical work on this issue has tried to identify the sources of human capital specificity. For instance, Neal (1995) and Parent (2000) investigate the relative importance of firm-specific versus industry-specific human capital and argue in favor of industry-specificity. Pavan (2009), however, argues that firm-specificity has been understated in Neal and Parent’s work. Kambourov and Manovskii (2009), in turn, provide ample evidence that human capital is strongly occupation-specific. Gathmann and Schönberg (2010) show that human capital is more general than previously thought and use the concept of task-specificity based on the idea that different occupations use similar tasks[4]. Poletaev and Robinson (2008) provide similar evidence to Gathmann and Schönberg, and as analogue to the concept of task-specificity put forward the notion of skill-specificity. Both, Poletaev and

[4] To our knowledge the first article that theoretically elaborates the concept of task-specific human capital is Gibbons and Waldman (2004)

Robinson (2008) and Gathmann and Schönberg (2010) develop measures of distance between occupations based on the information about the overlap in the skills and tasks across occupations. Geel and Backes-Gelner (2009) follow this approach as well. The common idea incorporated in these articles is to measure distance between occupations as the degree of the skill or task mismatch between pairs of occupations.

We show how the concept of "occupational distance" fails to appreciate the asymmetry inherent in pairwise comparisons of occupations. In particular, occupations that require similar *types* of skills may differ in their skill *complexity*. An electrical engineer may use similar skills as an electrical engineering technician, however, the first job will involve tasks that are more complex and require a higher level of these skills than the latter one. As a consequence, moving from a job as an electrical engineer to a job as an electrical engineering technician is quite different from moving in the reverse direction. In this light, people can move parallel and upward the occupational complexity ladder, but downward movements are also common. We therefore propose a measure of occupational distance that is asymmetric. In particular, we typify a combination of occupations by two different measures: human capital redundancy and human capital shortage. Human capital redundancy measures the amount of human capital associated with the first job that becomes idle in the second job. Human capital shortage quantifies how much human capital an employee requires in the second job that had not yet been acquired in the first job.

We find that the human capital mismatch has implications for the mobility decisions and the wage offer at the new occupation. People change occupations in a manner that reduces the amount of human capital that would remain idle at the new job. Moreover, they also move to occupations where the amount of new skills they need to acquire is small. Exceptions are employees with few years of labor market experience who change occupations voluntarily. Such employees do not minimize the amount of skills that need to be learnt when changing occupations. We propose that this reflects movements upward the career ladder aimed at long-term maximization of earnings. We further find that employers penalize new employees for having a shortage of skills by giving them lower wage offers and reward employees for having redundant human capital through somewhat higher wage offers. These results also hold after sample selection and endogeneity corrections. Interestingly, the analysis of the wage growth at the new job (occupation) reveals that the initial wage offer penalty gets compensated through higher wage growth for employees with initial skill shortage. We speculate that this reflects productivity increases resulting from on-the-job learning. The finding is in line with our expectation that job-hopping is used by young employees to acquire new skills and increase lifetime earnings.

The article further develops a measure of skill experience that captures the individual accumulation of skills along a labor market experience path. Similar to Gathmann and Schönberg (2010) we show that skill-experience is an important component of a person's human capital, more so than firm- and occupation-specific human capital. We additionally propose a distinction between skill experience that is useful in the current job and skill experience that is useless. Useful skill experience indeed has a vastly stronger positive effect on wages than the seemingly useless one. However, also useless skill experience raises wages, though only moderately, indicating that skills that do not match the typical skill profile of an occupation may still have some value. In the remainder of this study, we will first explain the construction of our human capital similarity measures (section 2) and we will introduce our data and basic descriptives in section 3. Then we will test the predictive power of the measures of human capital asymmetries on the frequency of moves between occupations in section 4 and on the wage dynamics in section 5. Section 6 introduces the definitions of useful and useless skill experience and tests them empirically. Section 7 concludes.

2. Human capital redundancy and human capital shortage

In what follows we will assume that each occupation has a specific skill-profile. A skill-profile expresses the intensity with which each of k different broad skill categories that exist in the economy are required to fulfill the tasks associated with a job in the occupation. As an example, one may think of such categories as cognitive skills, manual dexterity, or social interaction skills. In this light, an occupation's skill-profile can be depicted as a k-dimensional skill-vector. In Figure 1, we show an example of two different occupations, with k equal to 2.

- Figure 1 around here-

In principle, the angle between the two vectors indicates whether occupations have similar relative task structures. For instance, Gathmann and Schoenberg (2010) use the angular separation between skill-vectors as a measure of occupational distance.[5] However, some occupations require more complex skills than other occupations. As such, the relative importance of a task (and its required skills) does not give much information about the human capital similarity between two occupations. For instance, the relative importance of social interaction skills may be similar for an ordinary sales person and for a professional

[5] In the empirical section, we will deviate to some degree from their design in the way we use the information from the German survey that investigates which tasks employees use in their job.

negotiator. However, the absolute intensity of this skill factor is likely to be far greater for the latter than for the former. The reason is that although the negotiator can be thought of as an advanced sales person, his job is vastly more complex. In the example of Figures 2a and 2b, people working in OCC1 require a relatively high amount of skill 2, whereas OCC2 relies more heavily on skill 1. However, the length of OCC1's skill-vector is greater than the length of OCC2's skill vector. In fact, although OCC1 requires relatively less of skill 1 than does OCC2, the absolute skill requirements for skill 1 are about the same in both jobs. The reason for this is that OCC1 is more complex than OCC2. In other words, OCC1 does not only involve a different skill-mix, but also different skill-intensities. Because the complexity of a job is likely to be reflected in the number of years of education that it requires, in section 3, we will use the average educational attainment of employees in an occupation to define the length of the skill-vector.

This difference in skill-intensity between jobs introduces asymmetries in the job switches between two occupations. Figures 2a and 2b show the human capital implications for the case that a person moves from OCC1 to OCC2 and vice versa.

The pivotal quantity for our analyses is the amount of skills that a person required for his old job remains useful in his new job. To this end, we decompose the old occupation's skill-vector into two components: one parallel to the new occupation's skill-vector and one perpendicular to it. In Figures 2a and 2b, this is illustrated by projecting the skill-vector of the previous occupation of the job switcher onto the

- Figures 2a and 2b around here-skill-vector of his new occupation. This projection shows to what extent the skills required in the old occupation are also useful in the new occupation. If we subtract the length of this projection from the length of the old occupation's skill-vector, we get the amount of the job switcher's human capital that remains idle in the new occupation. In the graphs, this is depicted by rotating the projection back onto the old occupation's skill-vector. We call this idle human capital the *human capital redundancy* that is involved in a job switch. When comparing Figure 2a to Figure 2b, it is interesting to note that, although OCC2 is less complex than OCC1, human capital redundancies arise in both, a job move from OCC1 to OCC2 and from OCC2 to OCC1.

If instead of comparing the projection to the old occupation's skill-vector, we compare it to the new occupation's skill vector, we get an indication of how well equipped the job switcher is for his new job. By subtracting the length of the projection from the new occupation's skill-vector we can quantify the *human capital shortage* the job switcher incurs in his new job. As shown in Figure 2b, a job switcher from OCC2 to OCC1 faces large human capital shortages due to the fact that OCC1's skill-vector is far longer than the projection of OCC2's skill-vector. However, in Figure 2a, depicting a move from OCC1 to OCC2, the projection of the relatively complex skill-vector of OCC1 exceeds the length of the skill-vector of OCC2. In this situation, there is in fact a negative human capital shortage, in other words, there is a human capital surplus.

Let L_1 and L_2 be the length of OCC1's and OCC2's skill-vectors. The length of the projection of OCC1's skill-vector onto OCC2's skill-vector (i.e., the line segment indicated by "hum.cap. of OCC1 useful in OCC2"), $P_{1,2}$, can be calculated as follows:[6]

[6] The first term of the right hand side expression is the angular separation, i.e., the arccosine of the angle between $\vec{v}_1$ and $\vec{v}_2$. Equation (1) now follows from using simple trigonometry and canceling out the functions *cos(arccos)*.

(1) $$P_{1,2} = \frac{\vec{v}_1 \cdot \vec{v}_2}{L_1 L_2} L_1$$

Where $\vec{v}_1$ and $\vec{v}_2$ are the skill-vectors of OCC1 and OCC2 and $\cdot$ is used for the dot-product. Human capital redundancies involved in a move from OCC1 to OCC2 are now defined as:

(2) $$redun_{1,2} = L_1 - P_{1,2}$$

Human capital shortage involved in the move depicted in Figure 2a is the relative human capital deficit that the job switcher faces in his new job. We can calculate this as follows:

(3) $$short_{1,2} = L_2 - P_{1,2}$$

To summarize, we use the skill profiles of occupations to express a job switch in an occupational pair by two different variables. The first variable, human capital redundancy, measures how much of the human capital associated with the old job is rendered idle by moving to the new job. The second variable, human capital shortage, measures how much of the human capital required in the new job still needs to be acquired given the human capital requirements in the old job. This results in an asymmetric description of the job switches in an occupational pair. The set of measures is considerably richer than corresponding symmetric distances like the angle between the skill-vectors of OCC1 and OCC2 or the Euclidian distance between the tips of the skill-vectors of OCC1 and OCC2, which takes into account the complexity of occupations, but does not yield asymmetric measures.

3. Data and descriptive statistics

We use two datasets for our analyses: the Qualification and Career Survey and the IAB Employment Samples (IABS). The first dataset is our source of occupational task and knowledge information and is used for construction of the occupational skill profiles and the measures of human capital mismatch, while the second dataset contains the individual level employment histories including occupational mobility and wages. The information from the first dataset is merged with the IABS at the occupational level.

3.1. Qualification and Career Survey

The Qualification and Career Survey was started in 1979 and has been repeated every 7-years afterwards. It is constructed cross-sectionally and in each wave draws a random sample from the German working population. The survey is administered by the Federal Institute for Vocational Education and Training (BIBB) and the Institute for Employment (IAB). Its purpose, among others, is to track skill requirements of occupations. We use the 2005/2006 survey because of its detailed educational information which we need to assess the level of complexity of an occupation's set of tasks. We focus on the answers to 52 questions that shed light on the task and knowledge structure of the respondent's job and on his or her education. As we are interested in the skill structure associated with particular occupations, we calculate averages of the scores on the questions and of the individual's schooling for each occupation. After dropping all observations from Eastern Germany and all occupations with fewer than 10 respondents we obtain a sample of 16,037 respondents in 118 different occupations.

Factor analysis

Although we selected 52 questions we are likely to identify a smaller number of broad tasks (or skills needed to carry out these tasks). Some of the tasks referred to in the 52 questions might be rather similar in the skills they require and it should be possible to carry them out with the same human capital. In fact, the average absolute cross-correlation between the answers to the 52 questions is 37%. Therefore, we chose to deviate from the approach used by Gathmann and Schönberg who treat each question as corresponding to a separate task. Instead we use factor analysis to extract 6 factors that account for 85% of total variation. The resulting factors could be labeled (1) cognitive, (2) manual, (3) engineering, (4) interactive, (5) commercial and (6) security[7].

For each occupation, we now have factor loadings representing the intensity with which a task is used in an occupation. Factor loadings can be both positive and negative, but it is hard to interpret what it means that an occupation uses a specific skill with a negative intensity. Therefore, following Polataev and Robinson (2008), for each factor, we rank scores across occupations. This provides us with vectors whose elements contain percentile positions of an occupation on a skill-factor that range from 0 to 1. As we believe that people take their own job as a frame of reference and less so the tasks in the economy at large, we assume that task intensities should be interpret relative to the intensity of other tasks in the job and not relative to how intense the task is used in other occupations. We therefore normalize the vectors to have unit length. As a last step, we add information on the complexity of an occupation's task profile by multiplying the vectors with the average number of years of schooling of employees in the occupation.[8] As a

[7] Table A2 in the appendix contains the factor loadings on each of the 52 questions listed in table A1.

[8] We have information on the exact number of months an individual spent on tertiary and university education. To that, we add the number of years that correspond to the

result, the units in which human capital shortages and redundancies that characterize an occupation switch are measured reflect the number of years of schooling that are lacking or remain idle.

To illustrate this, consider an electrical engineer (“Elektroingenieur”) that becomes a mechanic (“Maschinenbautechniker”). This person would render 0.48 years of his human capital redundant and have 2.97 years of human capital surplus in his new job. The reason is that, although the electrical engineer uses quite similar skills as compared to the mechanic (the angle between the task vectors is only 15.1°) his education is typically 3.45 years longer. The reverse move, from mechanic to electrical engineer, would involve about the same human capital redundancies: 0.36 years of the mechanic’s human capital is rendered idle. However, the mechanic would face major problems in acquiring the skills needed for his new job: the human capital shortage for this move is 3.81 years of schooling.

Broadly, the asymmetries that arise conform to intuition. For instance, university professors experience more human capital redundancies when they become high school professors than vice versa, and the same holds for medical doctors that become nurses. However, this information is lost in currently available distance measures. For instance, regardless of the direction of the move, the Angular distance between an electrical engineer and a mechanic is about 15.1°. In the next section, we show that these asymmetries indeed add to our understanding of cross-occupational labor mobility and the wage dynamics involved.

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highest level of secondary education the individual acquired, excluding primary school. That is, Hauptschule and Realschule are both counted as yielding 5 years of education and Abitur represents 9 years of education.

Table 1 lists the occupational movements with (a) highest and (b) lowest human capital redundancies, and with (c) highest, and (d) lowest human capital shortages. The human capital variables are expressed in years of education. Of all possible occupation switches in the economy, a mechanical engineer that becomes a household cleaner would incur the highest human capital redundancy. Skills representing over 13 years of education would become idle. The movement with lowest human capital redundancy is from a sheet metal presser to a generator machinist. The largest shortage in skills in an occupation switch occurs if a household cleaner becomes a mechanical engineer, while the largest surplus occurs if a physician would become a sheet metal presser.

- Table 1 around here -

3.2. IAB Employment Samples

The IAB Employment Samples (IABS) is a 2% random sample of the German population subject to social security, and is available for the period 1975-2004. This sample is explained in detail in Drews (2008), therefore we will only rehearse its most important features.
IABS stems from administrative data and can be used to follow individuals' complete work histories for over a period of up to 30 years. This includes information on occupational, industrial and regional attachment, daily earnings, several demographic characteristics, unemployment incidence and duration, and job changes. The data does not contain information on employees who are not subject to social security such as civil servants and self-employed. However, for the rest of the employees it is the largest and probably the most reliable source

of employment information in Germany. Furthermore, the social security wage data is the most accurate information on wages in Germany because non-reporting or false-reporting is punishable by law. However, wages are right-censored and this affects yearly between 9% and 16% of all observations. When appropriate (e.g. sample of occupational pairs) we impute the wages using the method offered by Gartner (2005). The IABS and the Qualification and Career Survey are matched at the occupational level[9]. The matching results in 118 occupations.

3.3. Final samples

We restrict our analyses to all male employees in West Germany for the period 1976-2004. Furthermore, we drop all observations that entered the sample in 1975 to avoid problems with incomplete (i.e. left censored) work histories, which would prohibit the construction of reliable experience measures. We also drop individuals that enter the labor market for the first time at an age of 35 or older. Turning to job switches, we distinguish between a sample of direct (job-job) and indirect (job-unemployment-job) job switches[10]. While the direct job switches may be both, voluntary (quits) and involuntary (layoffs), the indirect job switches are a sample of layoffs. To guarantee that we select a sample of layoffs, we exclude from the indirect job switches all individuals whose unemployment spell starts later than 84 days after their last employment

[9] Although the Qualification and Career Survey contains more detailed occupational categories, this matching forces us to use the occupational classification used in the IABS, which lies between the 2- and the 3-digit level.

[10] Previous studies (e.g. Gathmann and Schönberg 2010) use plant closures identified through the last record of an establishment in the administrative data. Hethey and Schmieder (2010) show that the administrative establishment ID changes in the iABS are severely misleading. “Only about 35 to 40 percent of new and disappearing IDs with more than 3 employees correspond unambiguously to real establishment entries and exits”.

date, because this is typical for quits.[11] From the samples we also exclude moves that follow a non-participation period of more than 2 years. Periods shorter than that are common because individuals often interrupt their labor market participation to obtain additional schooling. Each move that we consider is a move that includes occupational change.

Individual-level samples

The sample of direct occupational switchers has 132,795[12] observations involving 74,194 different individuals. 31.7% of these individuals have changed their occupation only once, while the rest 68.3% have two or more occupational changes. The sample of indirect movements contains 58,961 observations involving 38,949 individuals. Here 45.1% have one indirect occupational change record, while the rest 54.9% have been laid off two or more times. The distributions of the relevant variables in the direct and the indirect sample vary significantly. Tables 2a and 2b show some descriptive statistics on the variables of interest in both samples. Note that wages are converted and deflated in 1995 DM and present the daily earnings. All experience variables (general, occupational, plant, and skill experience) are expressed in years. Unemployment length is also expressed in years. Education takes the following values: (1) no formal education, (2) high-school without A-levels (Abitur), (3) A-levels without vocational training. (4) A-levels with occupational training, (5) technical college, and (6) university. Occupational distance is measured as in Gathmann and Schönberg: one minus the angular separation, where we take the angular separation between the skill-vectors from our factor analysis.

[11] By law en employee who quits a job is not eligible for unemployment benefits within the first three months after the quit. Therefore, those whose unemployment spell starts shortly after the last employment must be layoffs.
[12] The number of observations decreases when estimating the wage growth at the new occupation because fewer persons can be followed over longer time periods.

- Tables 2a and 2b around here -

Involuntary occupational switchers receive significantly lower wage offers relative to their previous wage than direct occupational switchers. In fact, except for the group of occupational switchers who change jobs very early in their career, on average, involuntary switchers move to occupations where they undergo wage losses. In contrast for the sample of direct moves occupational switching usually results in wage increases. Figure 3 graphs the average wage growth calculated as the difference between the immediate wage at the new occupation and the last wage earned before the switch (instantaneous wage growth) for different experience categories. This is presented for both, for the sample of direct and the sample of indirect occupational moves.

- Figure 3 around here -

It is evident from Figure 3 that our two samples are inherently different. For example, indirect occupational switchers who change occupation in a period of 6 to 8 years of labor market experience on average undergo real wage losses of around 5.5%, while direct occupational switchers in the same experience category undergo an average real wage growth of around 4.6%. Moreover, the wage losses are larger (respectively, the wage increases are smaller) the more experienced people are. This may reflect the greater stock of occupation specific skills of experienced employees that are turned idle in the new job.

The discrepancies in the two samples are also evident in the human capital mismatch variables. Figures 4a, 4b, and 4c plot the densities of occupational distance, human capital redundancy and human capital shortage distributions for the two samples. These graphs show that indirect moves have (1) significantly *higher* occupational distance, (2) significantly *higher* redundancy of human capital and (3) significantly *lower* human capital shortage when compared to the sample of direct moves. This is confirmed by both t-tests and median tests.

- Figure 4a, 4b, and 4c around here -

Occupational pairs samples

We create a sample at the level of the occupational pair. That is, the sample consists of all possible combinations of two occupations, excluding same-occupation combinations (118^2-118=13,806). We use this sample for the occupational switching estimations. The dependent variable is the count of moves (direct or indirect) between occupations, distinguishing movements from OCC1 to OCC2 from those from OCC2 to OCC1.

- Table 3 around here -

4. Movements upward and downward the occupational complexity

In this section, we analyze the relationships between occupational switching and our measures of human capital mismatch. We are interested in answering three questions: first, do our measures have explanatory power beyond a measure of occupational distance, second, do the patterns we see in these relationships differ between our two samples, and third, do the observed patterns differ by labor market experience groups? To tackle the first question we conduct an analysis of variance (ANOVA). The partial sum of squares and F statistics in Table 4 show that human capital redundancy is the variable that has most explanatory power. Therefore, we can conclude that our measures are superior to occupational distance in explaining occupational changes.

- Table 4 around here -

To answer the second and the third question, we estimate negative binomial models[13] which predict the movement count between occupational pairs. We distinguish between two labor market experience categories: people with up to 5 years of general experience and people with over 5 years of general experience. Table 6 presents the results for both experience groups and for both, direct moves and layoffs.

- Table 5 around here -

In all models but in Model Ia, people tend to move to occupations where they incur relatively small shortages of human capital. Human capital shortage does not seem to affect moves of less experienced people in the direct moves sample, while one standard deviation higher human capital shortage between occupations corresponds to a 10.5% decrease in the between-occupational direct moves for people with over 5 years of general experience. Hence, while people in general avoid moving to occupations where they incur human capital shortage, this is not so for the young employees who move directly from one job to another. This result fits the reasoning that among the young direct occupational switchers there are individuals who switch to more ambitious occupations where they incur high human capital shortages and move upward on the career ladder. In line with this reasoning, a person should be less likely to move to a relatively complex occupation (one where he incurs high human capital shortage) if he has been laid off than if he has moved voluntarily. This is indeed supported by the empirical evidence:

[13] Our dependent variables are right-skewed and over-dispersed.

estimates of human capital shortage for indirect occupational switchers (layoffs) are always more negative than for direct occupational switchers.

People furthermore move more frequently to occupations where less human capital is left redundant. As in the case of human capital shortage, the correlations between the number of observed moves and the human capital redundancy intensify for the more experienced groups. One interpretation is that more experienced labor is better positioned to protect their human capital from becoming redundant than less experienced labor. The results are also in line with earlier observations that more experienced people move to shorter occupational distances (Gathmann and Schönberg 2010). Similarly, those who move directly are in a better position to prevent their human capital from remaining idle than those who were laid off from their previous occupation (i.e., compare coefficients of human capital redundancy between models Ia and Ib, and between IIa and IIb).

5. Predicting the wage offer and the wage growth on the new job

In this section we explore whether human capital shortage and redundancy can predict the wage offered to employees who switch occupations, as well as the wage development in the new occupation.

5.1. Wage offers

For the purpose of illustration, let us frame the initial wage offer as the outcome of a wage bargaining situation where both the employer and the job candidate observe the candidate’s qualifications, experience, ability, and (if applicable) his unemployment duration. If the candidate bargains for a position in an occupation that is simpler than his background occupation he would try to negotiate a starting salary above the average starting wage in that occupation. This is because he has qualifications that are richer than what is usually required for the position. If the employer finds these qualifications redundant, he would offer him the same starting salary that he would offer to a person, who, all else equal, comes from the same occupation as the one the candidate is applying for. Therefore, the effect of human capital redundancy on the instantaneous wage growth should be non-negative. In contrast, if the candidate applies for an occupation in relation to which he shows human capital shortage, the employer would opt for offering such candidate a lower starting salary than he would offer to a candidate coming from the same occupation, because of costs associated with on-the-job learning. Hence, we expect that the effect of human capital shortage on the wage offer is negative. In order to evaluate this, we estimate a model where we regress our measures of human capital mismatch on the deviation of the individual's wage offer from the occupational mean wage offer received by first-time occupational entrants. We control for experience, age, education, unemployment length and year effects. We also include individual fixed effects regressions to control for ability-related biases. This approach is expressed in equation (4).

$$(4) \qquad w_{iot} - \bar{w}_{ot} = \beta_1 short_p + \beta_2 redun_p + X_{it} + u_i + \varepsilon_{iot}$$

In (4), the left-hand side measures the individual wage offer to occupational switchers as a deviation from the mean occupational wage offer given to people who enter the occupation without any labor market experience ($\bar{w}_{ot}$). The wage is observed for each person i who switches occupation *o*, at time *t*. On the right-hand side we have the human capital shortage and human capital redundancy that vary by occupational pair *p*. X_{it} stands for individual-specific time variant variables and u_i for individual-specific time-invariant effects. Table 6 presents the OLS and the fixed effects results for the direct and the involuntary occupational moves.

- Table 6 around here -

In table 6 one can identify few overarching patterns that match our expectations outlined above. First, independent of the type of move, human capital shortage is associated with lower wage offer at the job after the occupational switch. Second, human capital redundancy is consistently associated with a higher wage offer in all specifications. The inclusion of fixed effects does not reveal any substantial biases in the OLS coefficients.

5.2. Analysis of biases in the wage offer models

Ideally, we would like to work with a sample of plant closures because this type of presumably exogenous event results in employee displacement that comes as close as empirically possible to experimentally dislocated labor (see e.g. Gibbons and Katz 1991). Unfortunately, to this end there is no reliable identification of plant closures in the IABS. In fact, Hethey and Schmieder (2010) and Brixy and Fritsch (2004) show that the common strategy of taking the exit date of a plant in our administrative data as a plant closure is severely misleading. Therefore, in the analysis of wage offers we mainly focus on the sample of involuntary mobile. This is because we know that this is a sample of people who have been laid off from their last job.[14] In such a sample one expects that people accept the wage offer that exceeds the unemployment benefits. In contrast, voluntary movements reflect improvement in the value of the new job relative to the old one. Therefore, there should be strong self-selection into better job matches in our sample of direct moves. However, we also recognize that our sample of involuntary mobile is a sample that deviates from the general population. Layoffs may be of lower average ability than the general population. Furthermore, persons who manage to stay in the same occupation may be different from those who change occupations. For example, Neal (1995) argues that industrial switchers probably have less industry- specific skills than industrial stayers. A parallel can be made to the occupational dimension.

Moreover, people who move to similar occupations in terms of human capital shortage and redundancy may be systematically different from people who move to more distant occupations in terms of these measures.[15] In particular, we must address two selection problems: (1) among job switchers, occupational switchers may have less occupation-specific skills than occupational stayers, and (2) among occupational switchers, those who move to occupations where they incur higher human capital shortage (redundancy) may be of higher (lower) ability than those who move to more similar occupations on these two dimensions. This is because we expect that high-ability people will tend to move to more demanding occupations-those where they face skill shortages, and low-ability people will tend to move to less demanding occupations-those for which they may even be over-qualified.
To solve the first selection problem we need to identify factors that affect the probability of switching occupations, but which do not affect the

[14] This includes many people who were laid off due to plant closures.
[15] For a comparable line of reasoning see Gathmann and Schönberg (2010, p. 24)

individual wage offer at the new job. Neal (1995) deals with a similar situation (p.660). He argues that the total number of jobs in an industry (in our case occupation) and the industrial (in our case occupational) employment growth of the pre-displacement industry (occupation) in the year of individual displacement are valid instruments in a wage growth regression. The rationale behind these instruments is that the search costs for laid off workers decrease with the employment size and the employment growth of an occupation making job switching within the same occupation easier. At the same time, in a competitive labor market, size and growth of an industry are unlikely to affect wages as they should reflect the marginal productivity of labor. Since job search tends to be geographically bounded, we define these measures for occupations in the individual's commuting area (see Gathmann and Schönberg 2010, p. 27 for such approach).

Second, the decision of switching to a more or less complex, or more or less related occupation is also endogenous. Therefore, we need to instrument our measures of human capital shortage and redundancy. In doing so, we follow Gathmann and Schönberg (2010) and, for each occupation of departure, we measure (a) the average human capital shortage in the commuting area based on the occupational structure in that commuting area and (b) the average human capital redundancy in the commuting area. Formally these measures are:

$$ADshort_{rto} = \sum_{o'} \frac{empl_{o'rt}}{empl_{rt}} \cdot short_{oo'} \text{ and}$$

$$ADredun_{rto} = \sum_{o'} \frac{empl_{o'rt}}{empl_{rt}} \cdot redun_{oo'}$$

Here, $empl$ indicates the employment size r is a region identifier, o is the occupation of departure o' the occupation of arrival and t is a year identifier. The intuition behind these measures is that due to the fact that search and reallocation costs increase with distance, people prefer to remain in the same commuting area. People living in areas offering a wide choice of related occupations will not have to make large jumps in terms of occupational shortage or redundancy. If an area has scarcity of related occupations people will be pressured to also choose among occupations that fit their skill profile worse.

Our identification strategy involves a combination of a Heckman (1979) and a 2SLS model (see e.g. Wooldridge 2002b, p. 567). In the first stage of the Heckman procedure we predict the occurrence of an involuntary occupational move as a function of a number of variables that are considered as exogenous in the wage offer regression[16] and all our instrumental variables. Using the prediction from the first stage we calculate the inverse Mills ratio. We then include the inverse Mills ratio in the 2SLS model (that is estimated only for occupational switchers) as an additional exogenous variable. Let us rewrite the model of interest (4) as:

(5) $$y_1 = \mathbf{z}_i \delta_1 + \alpha_1 y_2 + \alpha_2 y_3 + u_1$$

where y_1 is the deviation from the mean occupational entrants' wage offer, and y_2 and y_3 are our measures of human capital shortage and redundancy. $\mathbf{z}_1$ is a set of variables considered exogenous in the wage offer estimation. To this model we add a selection equation specified as:

[16] This means that we include all variable that appeared in the wage offer regression with exception of human capital shortage and human capital redundancy.

(6) $y_4 = 1(\mathbf{z}\delta_4 + \nu_3 \geq o)$

where in our case with three instruments $\mathbf{z}\delta_4$ consists of the size of the occupation of departure in the commuting area[17], $ADshort_{rto}$, and $ADredun_{rto}$. y_4 takes value of 1 if a person changes the occupation and zero if a person changes job but not the occupation. Therefore, we estimate equation (6) for the full population of job switchers using a probit model. After obtaining $\hat{y}_4$, we calculate the inverse Mills ratio as $\hat{\lambda}_{i4} = \lambda(\mathbf{z}_i\hat{\delta}_3)$, which is a monotone decreasing function of the probability that an observation is selected into the sample. As a next step we estimate:

(7) $y_{i1} = \mathbf{z}_{i1}\delta_1 + \alpha_1 y_{i2} + \alpha_2 y_{i3} + \gamma_1\hat{\lambda}_{i4} + e_i$

By 2SLS where $\mathbf{z}_i$ and $\hat{\lambda}_{i3}$ are instruments.

Table 7 presents the endogeneity-corrected models for layoffs. The dependent variable is the deviation from the mean occupational entrants' wage offer.

- Table 7 around here -

Compared to the original OLS model (table 6, Model Ia) the human capital shortage coefficient is larger, and the human capital redundancy coefficient becomes insignificant. This means that the OLS overstated the effect of human capital redundancy and understated the one of human capital shortage. However, the endogeneity corrected estimates

[17] The area growth of an occupation was not significant in the first stage probit model so we do not include it in our estimations.

still point out in the direction of the expectations outlined at the beginning of section 5.1. The effect of human capital shortage on the wage offer at the new job/occupation is negative; one standard deviation increase of human capital shortage results in 4% lower wage offer. Furthermore, after the bias correction the effect of human capital redundancy is close to zero and is statistically insignificant. Therefore, the results suggest that employers do not reward employees for having skills that are not necessary for the job.

Since we have three instruments for three sources of bias we cannot test for overidentifying restrictions. However, we did test whether our instruments are weak. The partial R^2 of the first stage 2SLS estimations are .21 for human capital shortage and .17 for human capital redundancy. Therefore, we do not face weak instrument problem. Also, the *t* statistic of the coefficient of the size of the occupation in the commuting area in the first stage Heckman model is 4.53. Moreover, as evident in table 7, the inverse Mills ratio is significant in the 2SLS specification. The complete tables of the first stage Heckman and first stage 2SLS models can be found in the appendix, tables A2 and A3.

5.3. Wage development at the new job

The initial human capital shortages and redundancies one brings from the old job may also affect the earnings development at the new job/occupation. Already in section 4 we noted that people may consciously move to occupations where they incur human capital shortage as part of their career path (see discussion of Table 5, Model Ia). In such cases the human capital shortage measure may measure the learning potential implicit in the move to the new job. If higher shortages translate into more learning, the coefficient of human capital shortage may reverse and exhibit a positive effect on the wage growth in the job after the occupational change. To investigate this possibility we estimate equation (8):

$$(8) \qquad \left(\ln w_{io,t+n} - \ln w_{iot}\right)/t = \beta_1 short_o + \beta_2 redun_o + \varepsilon_{iot}$$

Equation (8) indicates that we estimate the annual wage growth as a function of the measures of human capital asymmetries and a set of controls[18] (not noted in (8)). We study the annualized wage growth after 1, 3 and 5 years at the new occupation. We focus on the sample of direct occupational switchers because this is where we expect that people intentionally move to more ambitious occupations as a part of their career progression. Moreover, we expect that these types of moves are more common in the early years on the labor market and therefore we distinguish between a sample of those who change occupations within the first 5 years on the labor market and those who change occupations later. Table 8 contains the results of these estimations.
As suspected, human capital shortage does reverse the sign in the prediction of the wage development at the new occupation. This is evident in models IIa, IIIa IIb, and IIIb. Moreover, the coefficients of human capital shortage are larger for the sample of less experienced labor than those in the sample of more experienced labor (0.003 vs. 0.002).
The effects noted in table 8 diminish once we control for individual fixed effects. One possible interpretation of this is that if our claim that human capital shortage captures learning at the new job is correct, such learning only pays off through wage growth for high-ability people. One direct implication of such a result would be that moves to more ambitious occupations are only justified for people of sufficient ability

[18] The controls include: age, experience, education and a set of year dummies.

and if there is an ability-ambition mismatch this will also be reflected in the wage development at the job.

- Table 8 around here -

6. Skill-experience and wages

6.1. Construction of skill experience

Until now, we have used the skill-vectors only to characterize occupational pairs. However, we can also use them to construct an experience vector that reflects an employee's complete work history. For this purpose, we add up all skill-vectors corresponding to the jobs an individual held in the past. Let $e_{t,o}$ represent the length in years of an individual's *t*'th employment spell in occupation *o*. We can now recursively define the total skill-experience of the individual at the end of this *t*'th spell as:

$$\overrightarrow{SE}_t = \overrightarrow{SE}_{t-1} + e_{t,o}\vec{v}_o^n \tag{8}$$

where we normalized the skill-vector of occupation *o* by the average length of all occupational skill-vectors $\vec{v}_o$ to arrive at the normalized $\vec{v}_o^n$. As a consequence, the length of the skill-experience vector is the total experience acquired in past jobs weighted by the complexity of the occupation in which experience was acquired. That is, the unit of measurement is complexity weighted years, where one unit represents the experience one would acquire in an occupation of average complexity. This means that the skill-experience vector will grow fastest in complex occupations, which require much education.

The skill-experience vector can now be compared to the skill-profile required in the individual's current job. As before, we will use vector decomposition to derive a component parallel to the current occupation's skill-vector and a component perpendicular to it. We label the former component "useful human capital" and the latter "useless human capital." Figure 5 depicts this decomposition graphically.

- Figure 5 around here -

The skill-experience variables at spell t can now be formally defined. Using the same trigonometry as in equation (1), an individual's useful human capital at spell t is:

$$HC_{useful_t} = \frac{\overrightarrow{SE} \cdot \vec{v}_o}{\left\|\overrightarrow{SE_t}\right\| \left\|\vec{v}_o\right\|} \left\|\overrightarrow{SE_t}\right\| \tag{9}$$

where $\|\vec{x}\|$ represents the length of a vector $\vec{x}$ and $\vec{v}_o$ is the current occupation's skill-vector. Using Pythagoras, we obtain the useless component of human capital:

$$HC_{useless_t} = \sqrt{\left\|\overrightarrow{SE_t}\right\|^2 - HC_{useful_t}{}^2} \tag{10}$$

6.2. Returns to skill-experience

In what follows, we will use the variables constructed in subsection 6.1. to estimate the returns to useful and useless skill-experience. As here we only want to sketch how the skill-experience variables could be used, we will use OLS and fixed effects estimates and ignore endogeneity and censoring issues.

Based on educational attainment, we split up the sample into low-skilled, medium-skilled and high-skilled sub-samples[19]. The problem of censoring is relevant for the high-skill sample, where censored wages account for about 25% of all spells. For the low-skill and medium-skill subsamples, censoring is under 5% and can therefore be ignored. For this reason, we will focus our discussion on the findings in these two samples.

The outcomes of the regression analyses are reported in Tables 9a and 9b. Models Ia shows the baseline OLS estimates where the log of wage is regressed on experience, experience squared, occupational experience (i.e., the number of years an employee spent in his current occupation), and plant experience (i.e., the number of years an employee spent in his current plant). The specification also includes occupation and year dummies.

Our analyses confirm Gathmann and Schoenberg's (2010) findings in the sense that there are significant returns to useful skill-experience. These returns easily surpass those of occupational tenure and of plant tenure. However, in the low-skill sample, OLS overestimates these returns by some 20% compared to fixed effects estimates. It is plausible that this is due a positive correlation between skill-experience and unobserved ability. After all, high ability individuals are more likely to choose complex occupations and thus build up skill-experience faster than do low ability individuals.

[19] Low-skilled employees are those with no formal education; medium-skilled are employees with secondary education including those with vocational training. High-skilled employees have college or university education.

However, also “useless human capital” generates positive returns. In the low-skilled sample, these returns are only about a fifth of the returns to useful human capital. In the medium-skill sample, the returns are more substantial and sum up to 44% of those of ’useful human capital.’ The positive effect of useless human capital might be caused by the fact that our skill-experience variables partly reflect the complexity of pervious jobs. When we replace the useless human capital and useful human capital variables by the ratio of useless-to-useful human capital (Models IVa and IVb), we find a negative effect in all specifications. This indicates that useless human capital is indeed less valuable than is useful human capital. Employees who have cumulated related skills relative to the current occupation are paid higher wages than those who have acquired skills in less-related occupations.

- Tables 9a and 9b around here –

In summary, we find that skill-experience indeed is an important component of a person’s human capital next to the traditional components of firm and occupation specific human capital and an overall component reflecting general work experience. Moreover, the useful and useless components of a skill-vector both have significantly positive effects on wages. Still, wages are higher the larger the useful component is compared to the useless component.

7. Conclusions

We provide empirical evidence that there are considerable asymmetries to be reckoned with when studying human capital transferability in job switches. We construct a set of asymmetric measures of cross-occupational human capital or skill mismatches and use these to study job switching across occupations. These measures provide information above and beyond existing symmetric measures of occupational distance. We additionally propose a measure of skill experience that captures the cumulative skill formation over the course of individuals' occupational history. The measure of skill experience further allows us to disentangle accumulated skills that are useful from those that are useless in the current occupation.

Our measures show superior predictive power with respect to between-occupational moves compared to existing measures. Furthermore, their asymmetric nature allows us to shed light on a hitherto neglected aspect of occupational switches: the direction of the switch. Occupations do not only differ from one another in terms of their skill profiles, but they also require these skills at different degrees of complexity. As such, occupations can share a similar set of skills, but may differ in their position on what could be termed as an occupational complexity ladder. We show that this asymmetry has profound effects on between-occupational moves and wage dynamics. First, people sort into jobs that limit their human capital losses, especially in voluntary or, to be more precise, job-to-job movements. At the same time, few cross-occupational job switches are observed that are associated with high human capital shortages. This effect holds for both, involuntary and voluntary occupational switchers with an exception of people with few years of labor market experience that voluntarily change occupations. This group seems to choose higher levels of human capital shortage than other groups. That behavior is punished in the short term: having a human capital shortage results in a lower wage offer at the new job. However, this initial wage loss associated with an ambitious career path is compensated by above average wage growth at the new job, which suggests that learning curves are steeper in such careers.

Second, using our proposed measure of skill experience, we show that even after controlling for plant, occupation, and general experience, skill experience remains the dominant predictor of wages. Additionally, although both the useful and the useless component of the skill experience correlate positively with wages, wages are lower the larger the ratio between the useless and the useful component. In future research, this detailed representation of individual's life-time accumulated skills might help us gain understanding of how some individuals build up skill portfolios to the benefit of lifetime earnings and others do not.

Skill-experience vectors may have a number of applications that support policy makers in dealing with changes in the economic structure of countries. For instance, they could be used to investigate the effects of structural change on the economy-wide destruction of human capital. That is, it is possible to construct a vector that captures the current labor force's skill profile and compare this to a vector that represents the required skills in a hypothetical, post-structural change economy. This would allow identifying which parts of the labor force that are most likely to suffer from changing skill-requirements and which are best positioned to benefit from them. Further application of the measures proposed here is an evaluation of various requalification programs which also advice individuals about the choice of occupations for which they may requalify. From what was said before we learn that requalifying individuals for occupations where much of their previously cumulated human capital would be rendered redundant will harm their long-term earnings. Instead of requalifying individuals for such occupations, they should be assisted in overcoming skill shortages for occupations where they can make maximum usage of their past skill experience.

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Appendix

- Table A1 around here -

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Figures and Tables

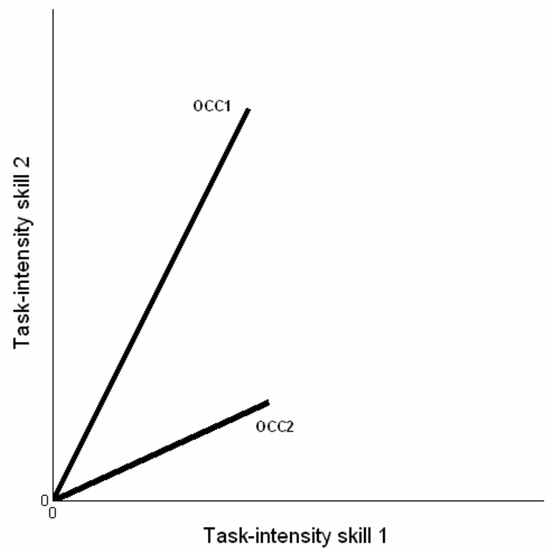

Figure 1: Skill-profiles occupations OCC1 and OCC2 in two-dimensional skill-space

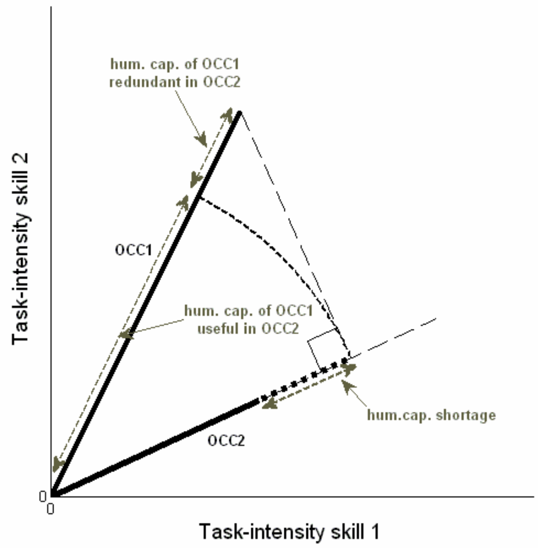

Figure 2a: Move from OCC1 to OCC2

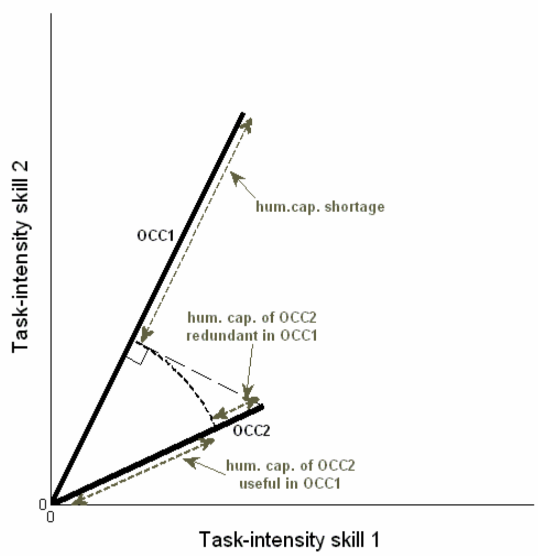

Figure 2b: Move from OCC2 to OCC1

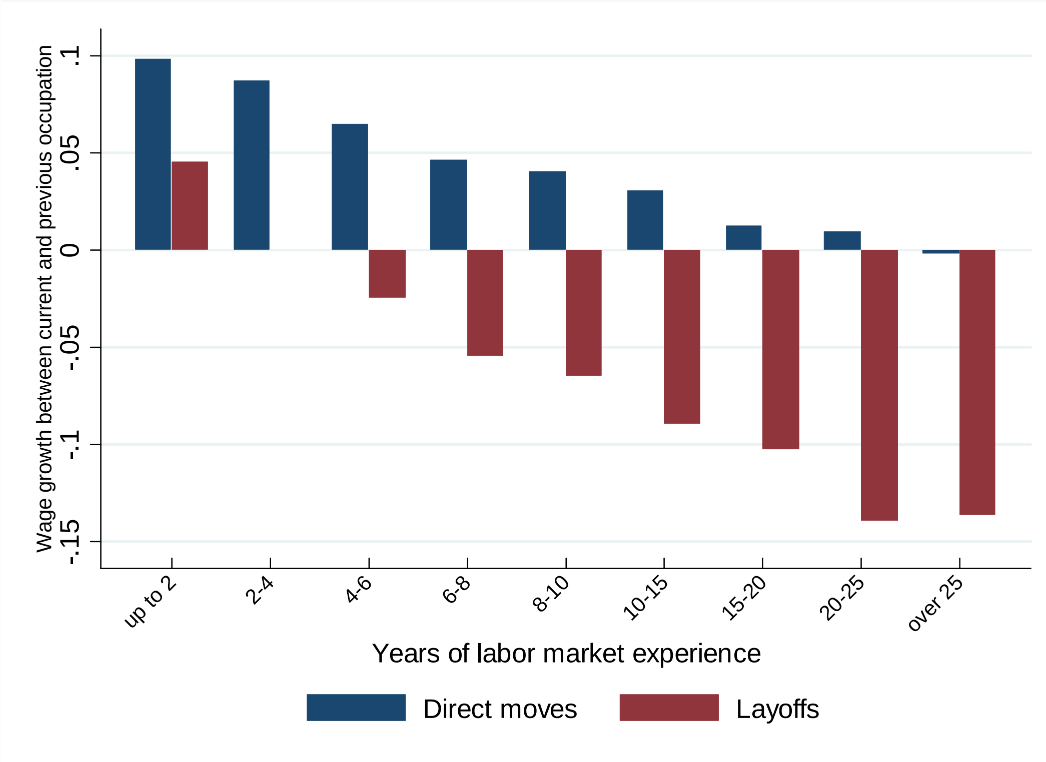

Figure 3: Instantaneous wage growth for different labor market experience categories

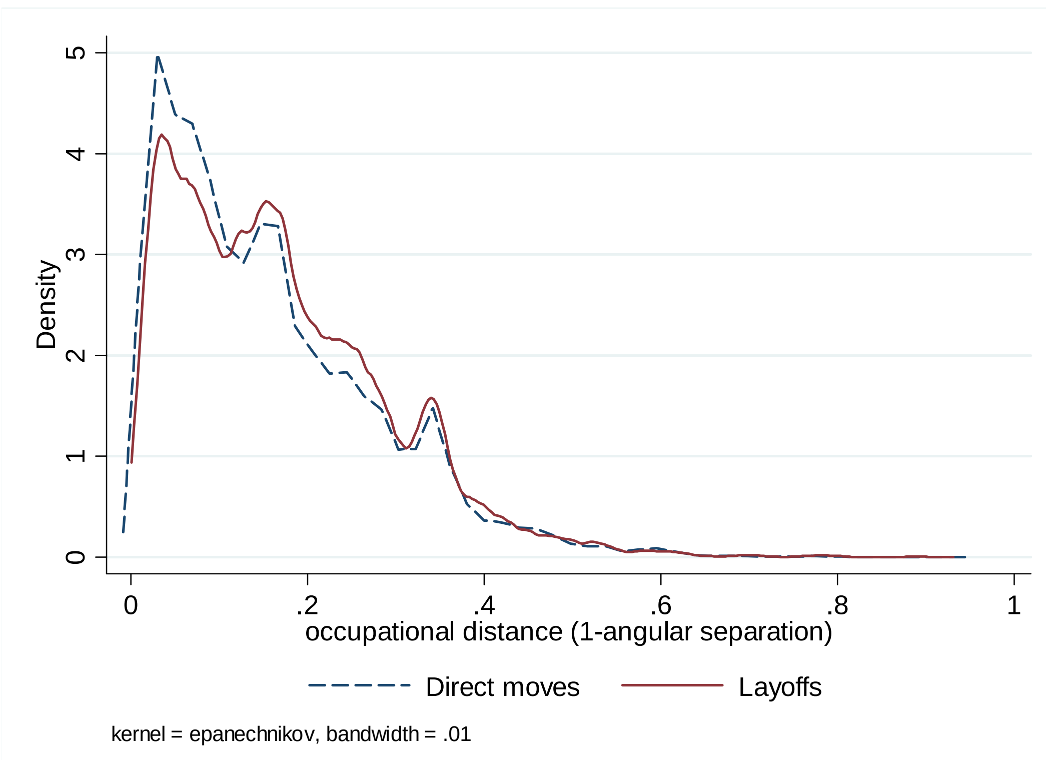

Figure 4a: Layoffs move to less similar occupations than direct occupational switchers

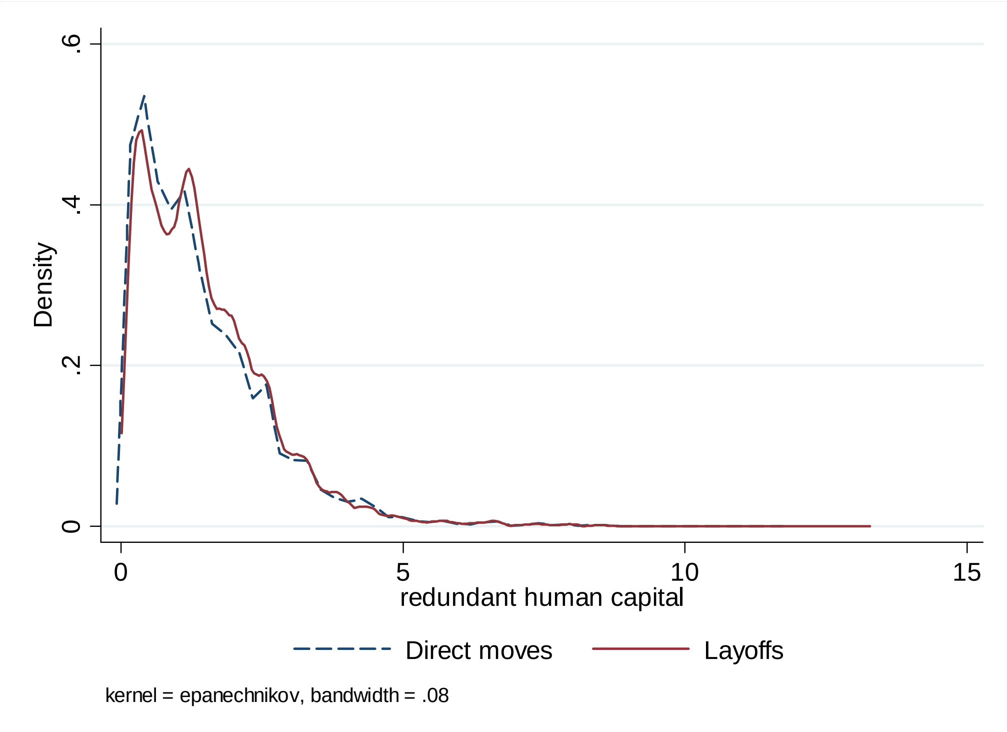

Figure 4b: Layoffs incur higher human capital redundancy than direct occupational switchers

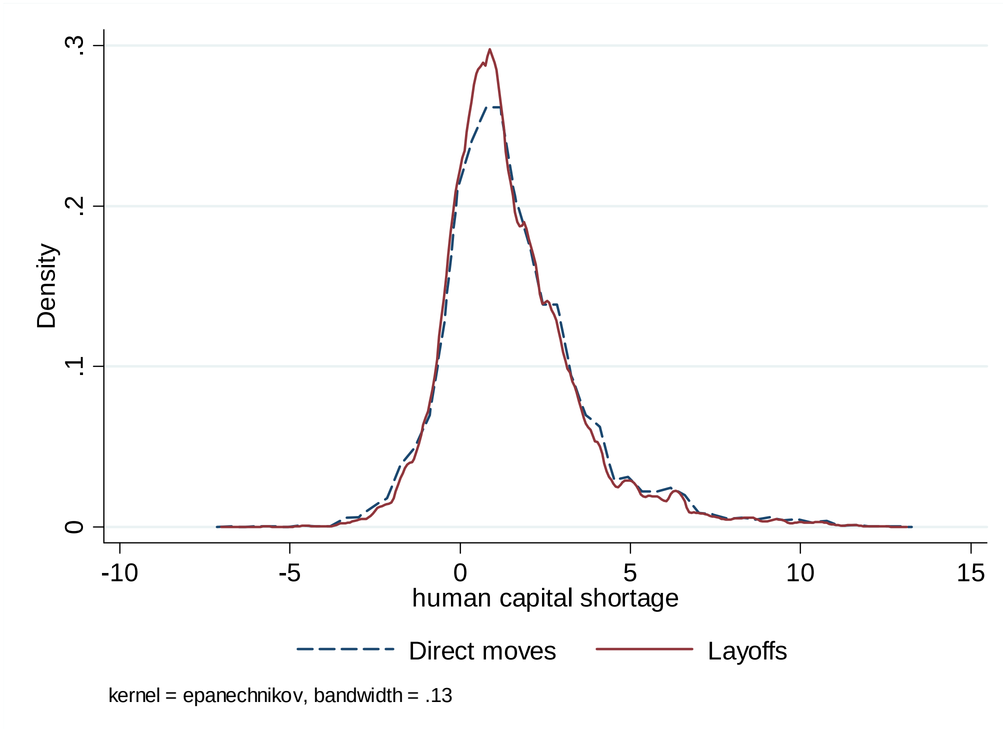

Figure 4c: Layoffs incur lower human capital shortage than direct occupational

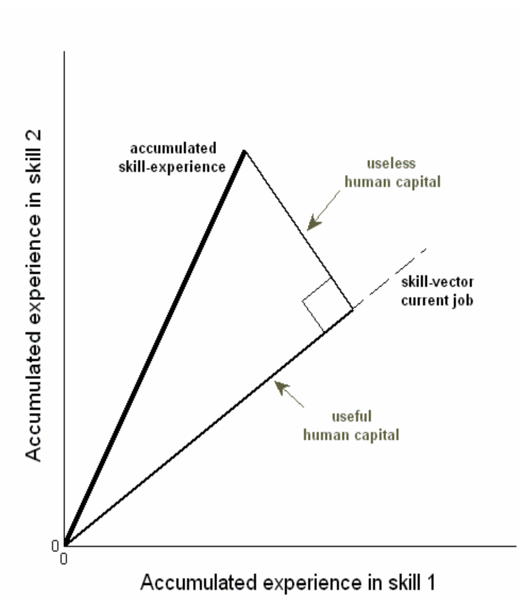

Figure 5: Decomposition of the skill-experience vector into a useful and a useless component.

Table 1: Human capital redundancies and shortages in extreme labor moves

a. Occupational switches with highest human capital redundancy		**HC redundancy**
Mechanical, motor engineers	Household cleaners	13.28
Electrical engineers	Household cleaners	11.65
Mechanical, motor engineers	Postal deliverers	11.54
Architects, civil engineers	Household cleaners	11.52
Mechanical, motor engineers	Motor vehicle drivers	11.34
b. Occupational switches with lowest human capital redundancy		**HC redundancy**
Sheet metal pressers, drawers, stampers	Generator machinists	0.01
Ceramics workers	Metal polishers	0.01
Generator machinists	Sheet metal pressers, drawers, stampers	0.01
Metal polishers	Ceramics workers	0.01
Ceramics workers	Paper, cellulose makers	0.02
c. Occupational switches with highest human capital shortage		**HC shortage**
Household cleaners	Mechanical, motor engineers	14.06
Postal deliverers	Mechanical, motor engineers	13.13
Household cleaners	Architects, civil engineers	12.98
Motor vehicle drivers	Mechanical, motor engineers	12.98
Glass, buildings cleaners	Mechanical, motor engineers	12.91
d. Occupational switches with lowest human capital shortage		**HC shortage**
Physicians	Sheet metal pressers, drawers, stampers	-8.68
Physicians	Iron, metal producers, melters	-7.90
Physicians	Ceramics workers	-7.07
Physicians	Moulders, coremakers	-7.01
Physicians	Metal workers (no further specification)	-7.01

Table 2a: Basic descriptive statistics: voluntary occupational moves

Variable	**Mean**	**Std. dev.**	**Min**	**Max**	**Obs.**

Deviation from occ. entrants' wage mean	0.51	0.44	-1.75	2.12	132,795
HC shortage	1.15	1.87	-6.59	11.51	132,795
HC redundancy	1.49	1.52	-0.31	15.01	132,795
Experience	5.87	4.65	1.00	29.02	132,795
Age	29.50	6.30	18	62	132,795
Education	2.23	1.23	1	6	132,795
Wage growth after 1 year at the job	0.037	0.11	-1.51	1.61	69,911
Wage growth after 3 years at the job	0.037	0.05	-0.43	0.62	35,678
Wage growth after 5 years at the job	0.030	0.04	-0.24	0.37	21,062

Table 2b: Basic descriptive statistics: layoffs

Variable	**Mean**	**Std. dev.**	**Min**	**Max**	**Obs.**
Deviation from occ. entrants' wage mean	0.37	0.40	-1.69	2.00	58,961
HC shortage	1.14	1.81	-6.59	11.64	58,961
HC redundancy	1.62	1.51	-0.31	17.32	58,961
Experience	4.94	4.10	1.00	28.69	58,961
Age	29.78	6.62	19	60	58,961
Education	2.04	1.09	1	6	58,961
Unemployment length	0.88	1.23	0.00	21.53	58,961
Wage growth after 1 year at the job	0.042	0.11	-1.32	1.34	32,431
Wage growth after 3 years at the job	0.042	0.05	-0.44	0.48	14,713
Wage growth after 5 years at the job	0.036	0.04	-0.30	0.31	8,842

Table 3: Basic descriptive statistics: moves between occupational pairs

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**
Direct moves (up to 5 yrs. of experience)	10.48	34.68	0	1163	13,806
Direct moves (over 5 yrs. of experience)	5.89	23.03	0	848	13,806
Indirect moves (up to 5 yrs. of experience)	5.90	17.90	0	444	13,806
Indirect moves (over 5 yrs. of experience)	2.03	6.74	0	173	13,806
HC shortage	2.28	2.92	-8.68	14.06	13,806
HC redundancy	2.28	1.51	0.01	13.28	13,806
Occupational distance	0.24	0.14	0.00	0.94	13,806
Log employment in OCC1	18.51	2.04	11.81	23.78	13,806
Log employment in OCC2	18.51	2.04	11.81	23.78	13,806

Table 4: Analysis of variance (ANOVA)

	Direct moves			**Layoffs**		
Source	**Partial SS**	**df**	**F**	**Partial SS**	**df**	**F**

Model	140.20	3	638.45	134.61	3	609.62
HC shortage	0.64	1	8.73	2.76	1	37.49
HC redundancy	12.85	1	175.53	26.86	1	364.93
Occupational distance	0.34	1	4.68	1.85	1	25.14
Residual	1,010.3	13802		1,015.89	13802	
Total	1,150.5	13805		1,150.5	13805	
R^2	0.12			0.12		
Observations	13,806			13,806		

Explained variable: rank of the count of moves between occupational pairs. Dependent variables are continuous and normalized with mean 0 and SD=1 for comparability.

Table 5: Explaining mobility between occupational pairs

	Direct moves		**Layoffs**	
	Model Ia	Model IIa	Model Ib	Model IIb
Dependent variable→	**up to 5 exp. years**	**over 5 exp. years**	**up to 5 exp. years**	**over 5 exp. years**
HC shortage	0.013	-0.105***	-0.116***	-0.142***
	(0.02)	(0.02)	(0.02)	(0.02)
HC redundancy	-0.633***	-0.686***	-0.594***	-0.652***
	(0.02)	(0.03)	(0.02)	(0.02)
Log employment of OCC1	0.374***	0.458***	0.384***	0.429***
	(0.01)	(0.01)	(0.01)	(0.01)
Log employment of OCC2	0.382***	0.465***	0.399***	0.442***
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-12.45***	-16.39***	-13.52***	-16.36***
	(0.28)	(0.32)	(0.24)	(0.31)
Ln(alpha)	0.482***	0.594***	0.408***	0.349***
	(0.02)	(0.02)	(0.02)	(0.03)
Log likelihood	-37,116.08	-28,046.09	-30,744.04	-19487.13
Observations	13,806	13,806	13,806	13,806

Coefficients are reported ; Robust standard errors in parentheses; Significant at *** 1%, ** 5%, * 10% level

Table 6: Human capital mismatch affects the wage offer at the new job: direct moves

Dependent variable→	**Deviation from occupational entrant's**

	wage offer			
	Layoffs		**Direct moves**	
	Model Ia	Model Iia	Model Ib	Model Iib
	OLS	**FE**	**OLS**	**FE**
HC shortage	-0.028***	-0.022***	-0.035***	-0.034***
	(0.00)	(0.00)	(0.00)	(0.00)
HC redundancy	0.009***	0.006**	0.014***	0.016***
	(0.00)	(0.00)	(0.00)	(0.00)
Experience	0.030***	0.042***	0.051***	0.057***
	(0.00)	(0.00)	(0.00)	(0.00)
Experience^2	-0.001***	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)
Age	-0.003***	-0.005**	-0.003***	0.0001
	(0.00)	(0.00)	(0.00)	(0.00)
Education	0.083***	0.032***	0.059***	0.004
	(0.00)	(0.00)	(0.00)	(0.00)
Unemployment length	-0.013***	-0.006**		
	(0.00)	(0.00)		
Constant	0.024	0.259***	0.100**	0.221*
	(0.02)	(0.08)	(0.04)	(0.11)
R^2	0.13	0.06	0.19	0.16
Observations	58,961	36,168	132,795	98,260
Number of persons		16,156		39,659

Robust standard errors in parentheses. Significant at ***1%, **5%, and *10% level. HC shortage and HC redundancy are standardized to have mean 0 and S.D. 1.

Table 7: Explaining the wage offer at the new occupation: bias-corrected sample of layoffs

Dependent variable→	**Dev. from the occ. entrants' wage offer**
HC shortage	-0.039***
	(0.00)
HC redundancy	-0.003
	(0.00)
Inverse Mills ratio	0.042***
	(0.01)
Experience	0.028***
	(0.00)
Experience^2	-0.001**
	(0.00)
Age	-0.002***
	(0.00)
Education	0.084***
	(0.00)
Unemployment length	0.003
	(0.00)
Constant	-0.011
	(0.024)
Observations	58,961

Results from a Heckman-2SLS model. Dependent variable: deviation from the occ. entrants' mean wage offer. Robust std. errors in parentheses. Significant at ***1%, **5% and *10% level.

Table 8: Predicting the wage development at the new occupation

	Direct moves with up to 5 yrs of experience			**Direct moves with over 5 yrs of experience**		
	Model Ia	Model IIa	Model IIIa	Model Ib	Model IIb	Model IIIb
Dependent variable →	**Wage growth after 1 yr**	**Wage growth after 3 yrs**	**Wage growth after 5 yrs**	**Wage growth after 1 yr**	**Wage growth after 3 yrs**	**Wage growth after 5 yrs**
HC shortage	0.000	0.003***	0.003***	0.000	0.002***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HC redundancy	0.001**	0.001	0.001**	0.001	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Education	0.002***	0.003***	0.003***	-0.001	0.001***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience	-0.004***	-0.004***	-0.003***	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year dummies	yes	yes	yes	yes	yes	Yes
Constant	0.055***	0.076***	0.060***	0.049***	0.033***	0.035***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
Observations	43,804	25,962	15,743	26,107	23,386	13,926
R^2	0.03	0.09	0.15	0.04	0.11	0.15

OLS, robust standard errors in parentheses, significant at: *** 1%, ** 5%, * 10% level

Table 9a: Returns to skill-experience of low-skilled

Dependent var. →	**ln(wage) of low-skilled employees**							
	Model Ia	Model IIa	Model IIIa	Model IVa	Model Ib	Model IIb	Model IIIb	Model IVb
Useful HC		0.032***	0.036***			0.027***	0.031***	
		(0.00)	(0.00)			(0.00)	(0.00)	
Useless HC			0.009***				0.008***	
			(0.00)				(0.00)	
Useless HC/useful HC				-0.125***				-0.039***
				(0.00)				(0.00)
Experience	0.048***	0.024***	0.017***	0.050***	0.050***	0.029***	0.023***	0.050***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience^2	-0.002***	-0.002***	-0.002***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Occ. Experience	0.005***	0.001***	0.004***	-0.0004*	0.001***	-0.002***	0.0003	-0.0003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Plant experience	0.010***	0.010***	0.010***	0.009***	0.003***	0.003***	0.003***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	4.236***	4.229***	4.230***	4.290***	4.358***	4.368***	4.371***	4.411***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
R^2	0.42	0.42	0.42	0.41	0.25	0.25	0.25	0.23
Observations[20]	375,849	375,849	375,849	345,396	375,849	375,849	375,849	345,396
Num. of persons					72,952	72,952	72,952	62,595

Robust standard errors in parentheses. Significant at ***1%, **5% and *10% level

[20] The drop in the observations in Models IVa and IVb is due to the fact that some employees do not have any useful skill experience relative to the current occupation.

Table 9b: Returns to skill-experience of medium-skilled

Dependent var. →	ln(wage) of medium-skilled employees							
	Model Ia	Model IIa	Model IIIa	Model IVa	Model Ib	Model IIb	Model IIIb	Model IVb
Useful HC		0.0275***	0.0320***			0.0354***	0.0432***	
		(0.00)	(0.00)			(0.00)	(0.00)	
Useless HC			0.013***				0.019***	
			(0.00)				(0.00)	
Useless HC/useful HC				-0.100***				-0.024***
				(0.00)				(0.00)
Experience	0.047***	0.026***	0.016***	0.050***	0.051***	0.022***	0.007***	0.053***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Occ. Experience	0.005***	0.001***	0.005***	0.001***	0.003***	-0.002***	0.005***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Plant experience	0.005***	0.005***	0.005***	0.005***	0.001***	0.001***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	4.271***	4.278***	4.281***	4.314***	4.375***	4.388***	4.399***	4.437***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
R^2	0.395	0.398	0.398	0.393	0.396	0.402	0.403	0.391
Observations	494,747	494,747	494,747	481,315	494,747	494,747	494,747	481,315
Num. of persons					137,123	137,123	137,123	131,707

Robust standard errors in parentheses. Significant at ***1%, **5% and *10% level

Table A1. List of variables used in the factor analysis

Original name	Variable	Original question
		Wie häufig kommt bei Ihrer Arbeit vor:
F303	Production	Herstellen, Produzieren von Waren und Gütern
F304	Measure, check, quality control	Herstellen, Produzieren von Waren und Gütern
F305	Monitoring and operating machines	Überwachen, Steuern von Maschinen, Anlagen, technischen Prozessen
F306	Repair (machines)	Reparieren, Instandsetzen
F307	Purchase, procure	Einkaufen, Beschaffen, Verkaufen
F308	Transport, stock, shipping	Transportieren, Lagern, Versenden
F309	Advertise, marketing, PR	Werben, Marketing, Öffentlichkeitsarbeit, PR
F310	Organize, plan	Organisieren, Planen und Vorbereiten von Arbeitsprozessen. Gemeint sind hier nicht die eigenen Arbeitsprozesse.
F311	Development, research, design	Entwickeln, Forschen, Konstruieren
F312	Teach, educate	Ausbilden, Lehren, Unterrichten, Erziehen
F313	Collecting, researching and documenting information	Informationen Sammeln, Recherchieren, Dokumentieren
F314	Advice and inform	Beraten und Informieren
F315	Serve, accomodate, meals preparation	Bewirten, Beherbergen, Speisen bereiten
F316	Taking care of, curing	Pflegen, Betreuen, Heilen
F317	Security, protection, monitoring, traffic regulation	Sichern, Schützen, Bewachen, Überwachen, Verkehr regeln
F318	Work with computers	Arbeiten mit Computern
F319A	Cleaning,trash collection, recycling	Reinigen, Abfall beseitigen, Recyceln
F325_01	Reacting on new situations	auf unvorhergesehene Probleme reagieren und diese lösen müssen?
F325_02	Explaining complex relationships	schwierige Sachverhalte allgemeinverständlich vermitteln müssen?
F325_03	Convincing others, reaching compromise	andere überzeugen und Kompromisse aushandeln müssen?
F325_04	Making difficult decisions	eigenständig und ohne Anleitung schwierige Entscheidungen treffen müssen?
F325_05	Knowledge upgrading	eigene Wissenslücken erkennen und schließen

		müssen?
F325_06	Presenting	freie Reden oder Vorträge halten?
F325_07	Contact with customers, clients, patients	Kontakt zu Kunden, Klienten oder Patienten haben?
F325_08	Variety of tasks	sehr viele verschiedene Aufgaben zu erledigen haben?
F325_09	Responsibility for others	besondere Verantwortung für das Wohlbefinden anderer Menschen haben, z.B. für Patienten, Kinder, Kunden, Mitarbeiter?
F411_01	Work under pressure	unter starkem Termin- oder Leistungsdruck arbeiten müssen?
F411_03	Repetitive work	dass sich ein und derselbe Arbeitsgang bis in alle Einzelheiten wiederholt?
F411_04	Challenging tasks	neue Aufgaben gestellt werden, in die Sie sich erst mal hineindenken und einarbeiten müssen?
F411_09	Multitasking	dass Sie verschiedenartige Arbeiten oder Vorgänge gleichzeitig im Auge behalten müssen?
F411_11	Responsibility	dass auch schon ein kleiner Fehler oder eine geringe Unaufmerksamkeit größere finanzielle Verluste zur Folge haben können?
F411_13	Speedy work	dass Sie sehr schnell arbeiten müssen?
F600_03	Heavy load	Lasten von mehr als < bei männl. Zpn: 20 Kg, bei weibl. 10 Kg einsetzen > heben und tragen
F600_04	Work near smoke, dust, gasas, vapor	Bei Rauch, Staub oder unter Gasen, Dämpfen arbeiten
F600_05	Work in cold, heat, humidity, infiltration	Unter Kälte, Hitze, Nässe, Feuchtigkeit oder Zugluft arbeiten
F600_06	Work with oil, dirt	Mit Öl, Fett, Schmutz, Dreck arbeiten
F600_07	Work in uncomfotable physical position	In gebückter, hockender, kniender oder liegender Stellung arbeiten, Arbeiten über Kopf
F600_08	Work with oscilations, vibrations, hits	Arbeit mit starken Erschütterungen, Stößen und Schwingungen, die man im Körper spürt
F320	Level of computer usage	Nutzen Sie Computer ausschließlich als Anwender oder geht Ihre Nutzung über die reine Anwendung hinaus?
		Bitte sagen Sie zu jedem Gebiet, ob Sie bei Ihrer derzeitigen Tätigkeit diese Kenntnisse benötigen und wenn ja, ob Grundkenntnisse oder Fachkenntnisse?
F403_01	Natural science knowledge	Naturwissenschaftliche Kenntnisse

F403_02	Manual (artisan) knowledge	Handwerkliche Kenntnisse
F403_03	Pedagogy	Pädagogische Kenntnisse
F403_04	Law knowledge	Rechtskenntnisse
F403_05	Project management knowledge	Kenntnisse im Bereich Projektmanagement
F403_06	Medical, care-related knowledge	Kenntnisse im medizinischen oder pflegerischen Bereich
F403_07	Construction, design, visualization knowledge	Kenntnisse im Bereich Layout, Gestaltung, Visualisierung
F403_08	Math, advanced calculus, statistics	Kenntnisse im Bereich Mathematik, Fachrechnen, Statistik
F403_09	German language knowledge	Kenntnisse in Deutsch, schriftlicher Ausdruck, Rechtschreibung
F403_10	Knowledge in computer programs	Benötigen Sie Grund- oder Fachkenntnisse in PC - Anwendungsprogrammen?
F403_11	Technical knowledge	Technische Kenntnisse
F403_12	Knowledge in business	Benötigen Sie kaufmännische bzw. betriebswirtschaftliche Grund- oder Fachkenntnisse?
F403_13	Foreign language knowledge	Benötigen Sie in Ihrer Tätigkeit Grund- oder Fachkenntnisse in Sprachen außer Deutsch?

The factor analysis of 52 tasks resulted in six factors that we refer to as skills. Although the list of resulting factors is much longer, only six of them had eigenvalues larger than one. Together these factors explain 85% of the total variance in the 52 tasks. Table A3 contains the factor loadings on each of the variables of interest.

Table A2. Factor loadings

Variable	Cognitive factor	Manual factor	Engineering factor	Interactive factor	Commercial factor	Security factor
Production			0.78			
Measure, check, quality control			0.87			
Monitoring and operating machines			0.76			
Repair (machines)		0.60	0.61			
Purchase, procure	0.43				0.52	
Transport, stock, shipping		0.55				
Advertise, marketing, PR	0.61		-0.54			
Organize, plan	0.78					
Development, research, design	0.65		0.46			
Teach, educate	0.65			0.53		
Collecting, researching and documenting information	0.77	-0.47				
Advice and inform	0.80					
Serve, accommodate, meals preparation				0.52	0.51	
Taking care of, curing				0.89		
Security, protection, monitoring, traffic regulation				0.44		0.61
Work with computers	0.46	-0.80				
Cleaning, trash collection, recycling		0.64				
Level of computer usage	0.44	-0.72				
Reacting on new situations	0.82					
Explaining complex relationships	0.87					
Convincing others, reaching compromise	0.87					
Making difficult decisions	0.89					
Knowledge upgrading	0.83					
Presenting	0.77					
Contact with customers, clients, patients	0.56		-0.60			

Variety of tasks	0.80					
Responsibility for others	0.43			0.74		
Natural science knowledge	0.63					
Manual (artisan) knowledge		0.60	0.68			
Pedagogy	0.59			0.68		
Law knowledge	0.70					
Project management knowledge	0.81					
Medical, care-related knowledge				0.83		
Construction, design, visualization knowledge	0.74					
Math, advanced calculus, statistics	0.69		0.41			
German language knowledge	0.74	-0.47				
Knowledge in computer programs	0.63	-0.49				
Technical knowledge	0.40		0.69			
Knowledge in business	0.57		-0.42			
Foreign language knowledge	0.62	-0.57				
Work under pressure	0.69					
Repetitive work	-0.72					
Challenging tasks	0.79					
Multitasking	0.70					
Responsibility			0.53	-0.42		0.49
Speedy work					0.68	
Heavy load		0.82				
Work near smoke, dust, gasas, vapor		0.65	0.55			
Work in cold, heat, humidity, infiltration		0.82				
Work with oil, dirt		0.65	0.57			
Work in uncomfotable physical position		0.85				
Work with oscilations, vibrations, hits		0.71				

Table A3. Heckman first stage: selection into occupational change

Dependent Variable→	Involuntary occupational change
Regional employment in occ. of departure	-0.002***
	(0.00)
HC shortage	0.062***
	(0.00)
HC redundancy	0.063***
	(0.00)
Experience	-0.060***
	(0.00)
Experience^2	0.001***
	(0.00)
Age	-0.008***
	(0.00)
Education	-0.089***
	(0.00)
Unemployment length	0.896***
	(0.02)
Constant	-6.151***
	(0.09)
Log pseudolikelihood	-113,878
Observations	262,914

Table A4. 2SLS first stage

Dependent variable →	HC shortage	HC redundancy
Regional employment in occ. of departure	-0.010***	-0.003***
	(0.00)	(0.00)
$ADredun_{rto}$	-0.071***	0.913***
	(0.01)	(0.01)
$ADshort_{rto}$	0.667***	-0.062***
	(0.01)	(0.01)
Inverse Mills ratio	-0.323***	-0.183***
	(0.03)	(0.03)
Experience	0.006	-0.017***
	(0.01)	(0.00)
Experience^2	-0.000	0.001***
	(0.00)	(0.00)
Age	0.010***	-0.001
	(0.00)	(0.00)
Education	0.586***	-0.038***
	(0.01)	(0.01)
Year dummies	yes	yes
Unemployment length	0.056***	0.044***
	(0.01)	'(0.01)
Constant	-1.538****	0.212
	(0.14)	(0.13)
Centered R2	0.262	0.197
Partial R2 of excluded instruments	0.207	0.168
Observations	58,961	58,961