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Occupational Mobility Within and Between Skill Clusters: An Empirical Analysis Based on the Skill-Weights Approach

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Abstract

Mobility and flexibility is increasingly demanded as structural change challenges established educational systems and traditional occupational demarcations. We use Lazear's skill-weights approach (2003) first to operationalize the degree of specificity of skill combinations in an innovative manner and second to derive hypotheses about the effects of occupation-specific skill combinations. In our empirical section, we find that the more specific an occupation, the smaller is the probability of an occupational change, as expected. Furthermore, we are able to identify different clusters of occupations that are characterized by similar skill combinations within a given cluster and different skill combinations between clusters. We find that employees in very specific occupations have a comparatively higher probability of changing their occupation within than between skill clusters. Moreover, occupational mobility within a skill cluster is accompanied by wage gains, while mobility between skill clusters results in wage losses. Not surprisingly, the more specific the former occupation is, either the higher is the resulting wage loss or the smaller is the resulting wage gain depending on whether the move is between or within skill clusters, respectively. Therefore, the acquired skill combination rather than the occupation per se crucially determines the mobility of an employee.

Key Words: Skill-weights approach, mobility, skill clusters, apprenticeship training

JEL Classification: J62, M53

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1. Introduction

Due to technological progress, skill requirements not only increase rapidly but also change frequently (Autor et al. 2003, Autor/Dorn 2009). Thus, educational systems are increasingly faced with new challenges. They not only have to provide graduates with qualifications tailored to actual market needs, but with skills that are quickly adaptable to changing conditions and skill requirements (Borghans et al. 2005, Winkelmann 2006, Hotz-Hart 2008, Spitz-Oener 2008). Although this structural change challenges all established educational systems, vocational education and training (VET)[2] in particular is criticized as too inert and inflexible. In contrast to academic education, which is considered to be broad and general, VET is considered to be too much focused on narrow skill requirements within one particular occupation (Heckman 1994, Carnoy 1994 and 2004, Krueger/Kumar 2004, Aghion 2007). Nonetheless, empirical evidence casts doubt on these assumptions. In Europe, a very high proportion of young people pursue vocational training at the upper secondary level (OECD 2008), especially in German-speaking countries where about two-thirds of all young people acquire a vocational degree (see Table 1 in the Appendix).[3] At the same time, these countries belong to the strongest economies in the world, despite the fact that in Germany, for example, around 340 apprenticeship training occupations exist (BIBB 2009) and around 250 exist in Switzerland (BFS 2009). This high number of apprenticeship training occupations may suggest strong specialization and may lead to the conclusion that these VET graduates may be too inflexible and immobile, thereby hampering economic growth.

Thus, occurs the economic success of these countries despite a VET system that may cause inflexibility, or rather because of the particular strengths of a VET system that provides strong occupational skills without severely restricting mobility? To answer this question, we first must analyze how the level of flexibility of vocational education can actually be measured and how the degree of this flexibility is determined. In this paper, we argue that neither comparisons of academic education with vocational education nor the number

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[2] Vocational education and training (VET) is the most popular form of basic education in German speaking countries and a fundamental element of the education system. As a dual-track approach most VET programmes consist of part-time studies at a vocational school combined with a part-time apprenticeship at a host company. Vocational education and training takes place at upper-secondary level and is based on clearly defined curricula and national qualification procedures.

[3] In favour of VET, Winkelmann (1996) found that German apprenticeship training graduates transition more directly and faster into employment than university graduates.

of occupations, which are two common criterions, are relevant, but rather we must consider the specificity of the skill combination given the skill clusters in the overall economy. We show that the skill combination – and not the occupation per se – crucially determines the mobility and the wage consequences of an employee.

For example, an adolescent who wants to become a clockmaker should not necessarily be considered poorly equipped for future labor market requirements, even though his industry is small and shrinking. Rather, he is well equipped because his skill combination is very similar to skill combinations of other occupations in a large and growing skill cluster, which includes, for example, medical technicians or tool makers. Despite a seemingly very narrow and inflexible skill combination in his original occupation, he is nonetheless very flexible and well prepared for future labor market changes due to the sustainability of his acquired skills and his current skill cluster.

In the literature thus far, explanations of occupational mobility have been based on Becker's standard human capital theory (1964), which differentiates between general and specific human capital. This differentiation is based on the transferability of human capital, as specific human capital[4] is by definition a barrier to mobility. Investment in specific human capital reduces the mobility of workers and/or causes a wage loss in the case of a change (Casas-Arce 2004, Garloff/Kuckulenz 2006, Gathmann/Schönberg 2007)[5]. We focus on horizontal occupational mobility rather than on upward (or career) mobility and contribute to the existing literature. Kambourov/Manovskii (2009) found that occupational experience, which represents occupation-specific human capital, is a major determinant to earnings. Thus, as occupational experience rises with a worker's age or tenure occupational mobility declines (Shaw 1987, Kambourov/Manovskii 2008). Moreover, the more specific an occupation is, the more reduced are the later labor market chances of graduates (Borghans/Golsteyn 2007, Geel et al. 2009). Through occupational changes, employees attempt to realize better income possibilities or career chances (Fitzenberger/Spitz 2004). However, differentiating broad occupation subgroups based on their industry-affiliation, Goeggel/Zwick (2009) observe wage disadvantages after an occupational change out of

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[4] Specific human capital can be equivalent to firm-specific (e.g. Jovanovic 1979b), job-specific (e.g. Topel 1991), industry-specific (e.g. Neal 1995), occupation-specific (e.g. Shaw 1987) or task-specific (e.g. Gibbons/Waldman 2004) human capital.

[5] Search theories (e.g. Rogerson et al. 2005) and matching theories (e.g. Jovanovic 1979a, McCall 1990) suggest that with each further job change, the match between worker and firm or worker and occupation improves. As the success of these matches is not known in advance, changes are necessary to dissolve inefficient matches and increase wages.

former industrial occupations, whereas no wage effect is observed for former commerce and trading or crafts and construction occupations. Clark/Fahr (2001) found that an occupational change within a (1-digit) occupation category is wage–neutral, and training can thus be costlessly transferred, whereas a change into another occupation category leads to large wage losses. Thus, the transferability of acquired human capital across occupational boundaries is becoming more and more important in view of the increasing technological progress.

In our paper, we apply a new, skill-based point of view to analyze occupational mobility and focus on the labor market segment in which an occupation is classified rather than broad classification codes, since occupations with similar skill combinations can be clustered into labor market segments (or skill clusters, as we will also refer to them in the rest of this paper). This means that relevant and more important than the occupation per se is the skill combination acquired during apprenticeship training and required in that occupation. Within a given labor market segment, mobility should be easier due to similar required skills. Until now, labor market segmentation theory (Doeringer/Piore 1971, for an overview see Leontardi 1998) has considered classifications of occupations into segments. The resulting segments are based on different labor market characteristics, such as wages, job ladders, turnover or working habits, rather than the skills required in these occupations. Another strand of literature has analyzed occupational labour markets as opposed to external and internal labour markets (Marsden 1986, Eyraud et al. 1990); in this context, the importance of occupations with respect to mobility has already been stressed. The focus here is on the role of formal occupational degrees, but different degrees of occupational specificity are not distinguished.

However, to the best of our knowledge, all previous studies on occupational mobility have dealt with occupational codes and occupations per se, but they have not engaged in a detailed skill analysis, partly due to a lack of detailed skill data as well as to a lack of an analytical model that could guide a detailed empirical analysis of skills. Due to this lack of data and analytical foundation, empirical research on skill-based specificity is still at an early stage[6]. Nevertheless, in our paper, we are able to overcome both of these problems. First, we are able to work with a rich data set, which contains very detailed information on

[6] Ingram/Neumann (2006) suggest to measure the returns to skill based on the observed skill characteristics of a job instead of education per se (that is, years of education). In a recent paper, Poletaev/Robinson (2008) analyze mobility based on the skill portfolios of jobs and found that wage losses are more closely associated with switching skill portfolios than switching industry or occupation codes per se.

required skills. Second, we build on Lazear's skill-weights approach (2003), which is ideal for studying occupational specificity at the level of single skills as well as the resulting bundles of these skills. Our data are drawn from a recent German data set called the BIBB/BAuA-Survey 2005/06, which contains extensive individual information on the skills required and used at various workplaces as well as information on the educational and occupational career of individual employees. Thus, we are able to analyze occupational specificity and study the effects of occupation-specific skill combinations acquired during apprenticeship training on occupational mobility as well as on income prospects later on in a career.

Taken together, our study is innovative in at least three ways. First, we analyze occupational mobility at the level of single skills as well as the resulting combinations of these skills. Second, we use Lazear's skill-weights approach (2003) as a theoretical framework that provides us with a new empirical approach to operationalize occupational specificity as well as examine occupational mobility. The application of Lazear's skill-weights approach allows for a micro-founded analysis of specific and general human capital. Third, we determine labor market segments, i.e., skill clusters containing a variety of occupations with similar skill combinations. We analyze the effects of the specificity of skills acquired during occupational training on occupational mobility within and between skill clusters and investigate the impact of such occupational changes on income.

Our results show that the definition of skill specificity based on Lazear's skill-weights approach provides a good measure to study the labor market flexibility of various occupations. In doing so, we also provide a micro-foundation for occupational labor market theory that allows us to study the effect of occupational specificity on occupational mobility and wages. We find that the more specific the skill combination of an occupation is, the smaller is the probability that employees change the occupation not only within the labor market as a whole but even within the relevant skill cluster. Nonetheless, employees in very specific occupations have a comparatively higher probability of changing their occupation within a skill cluster than between skill clusters. Therefore, within skill clusters, flexibility is facilitated, whereas between skill clusters, flexibility is constrained. Further findings indicate that occupational mobility within a skill cluster is honored with a wage gain, whereas occupational changes between skill clusters are accompanied by wage losses. The latter represents in part the losses of returns to the formerly-acquired skill portfolio of the apprenticeship training occupation. Not surprisingly, the higher the specificity degree of the former occupation is, either the higher is the resulting wage loss or the smaller is the resulting wage gain, depending on whether the move is between skill clusters or within a skill cluster, respectively.

The remainder of this paper is structured as follows. In Section 2, we use Lazear's skill-weights model (2003) to construct a measure for occupational specificity and derive testable implications regarding occupational mobility and wages after the completion of apprenticeship training. In Section 3, we introduce the data set and explain the specifications of variables, particularly occupational specificity, which is our main explanatory variable. In Section 4, we explain our estimation methods and present empirical results in Section 5. We conclude with a short summary and implications in Section 6.

2. Theoretical Framework: The Skill-Weights Approach

Lazear's main assumption is that all skills are naturally general. All firms can use general skills, but the required combination of skills varies from firm to firm. Specificity therefore occurs as firms demand different combinations and different weights of skills. These varying demands result in firm-specific skills. In the basic skill-weights model, there are only two skills and two periods. The two skills are general and can thus be used at other firms as well. A worker invests in either skill in the first period and receives a payoff in the second period. In the first period, the worker decides to acquire particular amounts of skills A and B at cost $C(A,B)$, which determines his payoff in the second period. His payoff at firm i is determined according to the following earnings function:

$$y_i = \lambda_i A + (1-\lambda_i)B$$

λ_i is the relative weight of skill A in firm i. Since λ_i may be different from the relative weight of skill A in any other firm j, the worker must determine the extent to which he wants to acquire skills A and B, given that he stays at the initial firm or moves on to another firm with skill-weights λ_j. If the employee is certain that he will remain at the initial firm indefinitely, then he would focus on λ_i and invest in the skill bundle that maximizes his income at the initial firm. However, if the employee cannot be certain that he will stay at his original firm, he must consider looking for a new job in another firm. Other firms may demand a different weighting of skills, and the employee's skill bundle may not be optimal in an outside firm, rendering part of the employee's investment worthless. Therefore, in this case, the worker may be faced with a wage loss. The outside market determines how much his investment will depreciate, which is given in the model by the difference between the weight of the initial firm and the expected market weight, λ_i - $\bar{\lambda}$. Thus, skill combinations can be rather general or rather specific. If a combination is rather general, then the difference between the weight of the initial firm and the market weight λ_i - $\bar{\lambda}$ is small, as is the expected wage loss. However, if a skill combination is rather specific, the difference λ_i - $\bar{\lambda}$ is large, and the wage loss is large as well. Thus, starting in an occupation with a specific bundle of skills strongly determines mobility and income for the rest of a worker's career.

Application to apprenticeship training

We use the basic idea behind Lazear's skill-weights approach to apply it to apprenticeship training in which the combination of acquired skills is given by the apprenticeship training occupation. This idea was even mentioned by Lazear (2003: 23) himself, who suggests that skill-weights are not only specific to firms, but rather all individuals in an occupation have identical skill-weights. Therefore, occupations empirically matter. However, he has not further developed this argument, and there has yet to be any empirical investigation on this topic thus far. In our application, we use *occupation-specific* rather than firm-specific skill-weights for the first time, and we enlarge the number of skills under study because in reality, there are not only two distinct skills as in Lazear's model. Instead, a greater number of different skills must be considered.

Although skills are naturally general, the combination of these skills used in a specific occupation is unlikely to be replicated in many, if any, other occupation. Intuitively, employees in occupations with more specific skill combinations are faced with higher losses if they change their occupation, as they cannot make use of all skills acquired at the first occupation. However, a worker must decide early in his career on his human capital investment strategy. He must choose an occupation with a specific skill combination, which he acquires during vocational education and training during an investment period. A worker's investment problem involves choosing an occupation and investing accordingly in skills A and B, knowing that he may most likely remain in the original occupation even if he has a probability of moving to another occupation either voluntarily or involuntarily. Therefore, the expected lifetime net earnings are not only dependent on the skill-weights of the first occupation for which the individual is trained but also on the distribution of skill-weights outside the original occupation in the general labor market. Once workers have chosen a particular occupation, they invest in the occupation-specific skill combination in the first period, which will not only affect their wage in the next period but also for the rest of their career. The intuition is as follows. If an individual knows for sure that he will stay in the original occupation, only the skill-weights of the initial occupation matter. On the contrary, if a worker is certain to change the occupation after graduation, only the skill-weights in the outside labor market matter. However, ex ante, the individual may not know if he must change occupations, so he must consider the expected outside skill-weight $\bar{\lambda}$ while making the investment decision.

Moreover, while Lazear's model considers the outside market as a whole as a relevant factor in occupational changes, we believe that in line with labor market segmentation theory (Doeringer/Piore 1971)[7] and occupational labor market theory (Marsden 1986), the labor market is not a single competitive market but is composed of a variety of segments, which may not all be equally relevant in the case of an occupational change. In our paper, we define occupational segments based on skill combinations, and we expect the labor market to be segmented into different *skill clusters* that share similar skill combinations within clusters but have different skill combinations across clusters. We use cluster analysis to divide the labor market into such labor market segments containing all occupations with comparable or similar skill-weights. The intuition should be clear; that is, even after an occupational change, an investment in a skill combination can still be valuable and productively used if the former and the new occupations are classified into the same skill cluster and require very similar skill combinations. Thus, the skill cluster with its average skill-weight $\bar{\lambda}_k$ represents the segment of the labor market that is relevant for potential occupational changes without a major loss in human capital investments. Therefore, the difference between the skill-weights of an individual occupation in comparison to the skill-weights of the respective skill segment $\lambda_i - \bar{\lambda}_k$ defines the cluster specificity of an occupation. These differences may vary, but compared to the differences in skill-weights on the overall labor market $\lambda_i - \bar{\lambda}$, the differences in skill-weights within a cluster $\lambda_i - \bar{\lambda}_k$ are limited. Thus, for a particular occupation, the skill-weights of its particular skill cluster and the size of this cluster are the factors that are important in occupational investment decisions because these two factors determine mobility and wages later on. To test this

[7] Labor market segmentation means the division of the labor market into separate submarkets or segments, as distinguished by different labor market characteristics, that reflect within-market barriers that constrain mobility (Reich et al. 1973, Osberg et al. 1987, Flatau/Lewis 1993). Virtually all labor market studies have shown that the labor force is segmented in some sense. Using the terminology of dual labor market theory, the labor market is segmented into primary and secondary markets.

implication, we differentiate two types of occupational specificity, namely, "general specificity", which compares the skill-weights of an occupation with the distribution of skill-weights across the entire labor market, and "cluster specificity", which compares the skill-weights of an occupation with the skill-weights across the respective skill cluster. Furthermore, we define three types of occupational mobility: first, occupational mobility in general; second, occupational mobility *within* a skill cluster; and third, occupational mobility *between* skill clusters.

Testable Implications

According to Lazear, mobility is more likely if the skill-weights in one's actual employment are very similar to the skill-weights on the external labor market. Thus, we expect the following patterns to occur with respect to occupational mobility within and between skill clusters:

H1a *The more specific are the skill requirements of an occupation as compared to the overall labor market, the smaller is the likelihood that a worker will change the occupation after completion of apprenticeship training.*

H1b *The more specific are the skill requirements of an occupation as compared to the overall labor market, the greater is the likelihood that a worker who changes the occupation will change it within a skill cluster rather than between skill clusters.*

H1c *The more specific are the skill requirements of an occupation as compared to its respective skill cluster, the smaller is the likelihood that a worker will change the occupation even within this skill cluster.*

Furthermore, according to the skill-weights view, wage losses as well as wage gains may occur after occupational changes[8]. If someone who changes an occupation finds a job in an occupation in which the required skill combination is very similar to the former occupation, he does not lose much in terms of initial human capital investment and can use formerly acquired skills as productively as before. He may even gain by switching, for example, into an occupation with labor shortages and accordingly higher wages. Thus, for mo-

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[8] The wage effects of occupational changes reveal information about the skills of an individual that are transferable across occupations. Human capital theory predicts a wage loss in case of mobility after training if this training provided the individual with specific skills. The empirical effect of training on wages can be seen as an indicator of the degree of specificity of the training obtained (Loewenstein/Spletzer 1999, Garloff/Kuckulenz 2006).

bile individuals within clusters, wages may either remain constant or even increase. However, for changes between clusters, the skill combination will be very different from the original occupation. Thus, cluster changers severely lose in terms of their initial human capital investment as skills may no longer be used as productively as before, which may not be offset by wage gains due to a higher demand for the new occupation. This leads us to the following hypotheses:

H2 *a) Occupational changes between skill clusters are most likely to cause wage losses.*

b) The size of the respective wage loss is expected to be larger the more specific are the skill requirements of the training occupation as compared to the overall labor market.

H3 *a) Occupational changes within skill clusters are most likely to cause wage gains.*

b) The size of a respective wage gain is expected to be smaller the more specific are the skill requirements of the training occupation within its respective skill cluster.

3. Data and Variable Construction

Our empirical estimation is based on the BIBB/BAuA Working-Population-Survey 2005/06[9], a cross-sectional sample of the working population in Germany of about 20,000 respondents, with data obtained using computer-based and oral interviews. The dataset contains retrospective information on educational and occupational careers as well as the current income of the interviewees and – most importantly – the required skills at the workplace in detail. The inclusion of information on skills required in an occupation is a crucial and unique feature of this dataset. In our study, we focus on skilled workers with apprenticeship training and are thus able to generate occupation-specific skill portfolios, i.e., the skill bundles that are typically acquired in an occupation during apprenticeship training. Occupations are grouped according to the (2-digit) classification of occupational titles by Germany's Federal Employment Bureau in 1992, resulting in 71 occupations[10]. We can then cluster these occupation-specific skill portfolios and thus distinguish between occupations that are similar and those that are different in their required skills. This allows

[9] BIBB/BAuA-Erwerbstätigenbefragung is a survey jointly conducted by the German Federal Institute for Vocational Training (Bundesinstitut für Berufsbildung, BIBB) and the Federal Institute for Occupational Safety and Health (Bundesanstalt für Arbeitsschutz und Arbeitsmedizin, BAuA).

[10] We lose some occupations that have too few observations per occupation to adequately represent the corresponding skill portfolio.

us to distinguish all occupational changes in within and between skill cluster changes. Furthermore, we calculate the general specificity of an occupation as well as its cluster specificity in order to empirically test our hypotheses about occupational mobility and its effect on income.

We restrict our analysis to individuals between 18 and 65 years of age (the mandatory age of retirement for paid employees). Furthermore, we exclude all civil servants and all self-employed people (because they have no layoff risk). After eliminating observations with missing data, a sample of 4,217 male[11] employees is included in the analysis. Descriptive statistics of all variables used in our analysis are given in Table 2 in the Appendix.

Required Skills and Occupation-Specific Skill Portfolios

Based on the large set of questions about a worker's required skills, we are able to generate skill portfolios; see Table 3 in the Appendix for a complete list of skills. The respondents were asked to report on skills that are required to perform their current job. If the respective skill is required at the workplace, the dummy variable takes the value of 1; if the skill is not required, it is 0. The left panel of Figure 1, for example, shows the skill portfolio of an individual office clerk.

Figure 1 about here

To determine the skill portfolio in an occupation, we use information on individual skill profiles of those respondents who completed apprenticeship training in a particular occupation[12]. The aggregation of this individual information by occupation leads to a weighted occupation-specific skill portfolio (see Figure 1, right panel) showing the relative frequency of different skills required in a particular occupation. Thus, we know the relative frequency of all individual skills in each occupation and are able to compare different distributions of skills.

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[11] We restrict our analysis to male employees to avoid difficulties related to the interrupted labor market histories of women.

[12] To determine the skill portfolio of an occupation, we only look at workers who are still in the same occupation as during their apprenticeship to ensure that we actually are measuring the skills required for one particular occupation.

Skill Clusters

To determine how similar or dissimilar the skill combinations of the 71 occupations are, we perform a cluster analysis (a more detailed description of our cluster analysis can be found in Appendix A). A cluster analysis maximizes the homogeneity of skill combinations within clusters and maximizes heterogeneity between clusters, and thus, it is an ideal statistical method to identify the similarity or dissimilarity of occupational skill clusters (Mardia et al. 1979, Aldenderfer/Blashfield 1984, Bortz 1989). We perform a cluster analysis using the 71 occupations as the units of analysis and the thirteen skills as the variables used to define the clusters. We apply a two-stage procedure in which a hierarchical algorithm (i.e., Ward's minimum variance method) is first used to define the number of clusters. This result serves as the starting point for the second stage of subsequent non-hierarchical clustering (i.e., the K-means procedure). Research has shown that the two-stage procedure increases the validity of solutions (Punj/Stewart 1983, Ketchen/Shook 1996).

As a result, we find six distinct skill clusters[13], each of which contains occupations with similar skill combinations. In order to summarize the characteristics of these clusters, in Table 4 in the Appendix, the relative importance of the single skills per skill cluster are presented.

Explanatory Variables: Cluster Specificity and General Specificity

We use an index to measure the degree of specificity of occupations according to the skill-weights approach; for more information, see Geel, Mure and Backes-Gellner (2008) in which we described the operationalization of the specificity index in more detail. The skill portfolios of occupations in the same skill cluster show very similar frequencies of required skills as expected. To determine the skill-weights within a skill cluster, we aggregate the skill-weights of all occupations in the cluster. In doing so, we receive six cluster-specific skill combinations, which represent the average skill-weights of this respective labor market segment. Comparing the importance of single skills in an occupation with the

[13] The cluster analysis fulfils the robustness check according to Wagschal's F-Test (1999: 272); 80% of the calculated F-values do not exceed the value of 1, which means that the variance within the clusters is smaller than the total variance.

relevant skill cluster (see Figure 2, left panel)[14], we are able to derive the cluster specificity of a particular occupation.

Figure 2 about here

We therefore rank the skills of each occupation and each skill cluster according to their relative frequencies. For each occupation, we calculate the distances between the ranks of single skills in the occupation portfolio and the respective labor market segment. An example of how these distances look is given in the right panel of Figure 2. Next, we weight these absolute rank-differences of all single skills with the corresponding relative frequency of the respective skill cluster and summed them. The larger this number is, the more atypical are the skills needed for a particular occupation even within its labor market segment. Thus, an increase in this number indicates that the skill-weights in the occupation are quite different from the skill-weights in its respective labor market segment. Therefore, this variable provides us a degree of specificity as indicated by the skill-weights approach. Cluster specificity ranges from 1.2 to 10.8 units, with a mean of 3.7 units. According to our hypotheses, we therefore expect a higher cluster specificity to correspond with a lower rate of occupational change within a skill cluster as well as with a higher loss in income associated with an occupational change.

The general specificity is generated in the same way, but the occupation-specific skill combination is compared to the overall labor market; that is, to the average skill combination of all occupations rather than to its respective skill cluster. The resulting general specificity ranges from 4.5 to 15.1 units, with a mean of 8.5 units. As expected, general specificity has a higher mean and range than cluster specificity, since the latter involves a comparison of more similar occupations. However, we accordingly expect a higher degree of general specificity to correspond with a lower rate of occupational change both in general and between skill clusters as well as with a higher loss in income associated with an occupational change.

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[14] Because of the clustering method, the most important skill in each occupation is most likely to also be the most important skill in its relevant skill cluster; therefore, a large part of the occupation-specific skill portfolio is likely to be usable in its labor market segment. Across skill clusters, if the most important skill in the occupation is not equally important in other labor market segments, a large part of the occupation-specific skill portfolio is likely to become useless if an individual changes occupations between these segments.

Dependent Variables: Occupational Mobility and Income

As already noted, occupational mobility is measured using three different variables. We generate a variable representing an occupational change during an individual's working life, which stands for general occupational mobility. With this variable, we compare the current occupations of workers with the occupations of their apprenticeship training. If workers no longer work in their original occupation, we consider this an occupational change, and the dependent variable takes the value of 1; it takes the value of 0 if the occupation remains unchanged. Overall, about 58% of employees in our sample changed their occupation, while about 42% did not. Second, we generate a mobility variable covering only occupational changes occurring within a skill cluster or labor market segment, which represents mobility to an occupation with similar skill-weights. To do this, we compare the cluster of the current occupation with the cluster of the apprenticeship training occupation. If an individual changed the occupation and remained in the same skill cluster, the dummy variable takes the value 1; if the individual did not change the occupation or changed the occupation but did not remain in the same skill cluster, it takes the value 0. About 21% of all employees changed their occupation within their respective skill cluster. Third, we generate a mobility variable covering only occupational changes occurring between skill clusters, representing mobility into an occupation with relatively different skill-weights. Here, we compare once more the cluster of the current occupation with the cluster of the apprenticeship training occupation. If the individual changed the occupation and the skill cluster, the dummy variable takes the value 1; if the individual did not change the occupation or changed the occupation but remained in the same skill cluster, it takes the value 0. About 37% of employees changed their occupation between skill clusters. Thus, if occupation-specific human capital is important, the wage loss for those who change occupations between skill clusters will be higher than for those who change occupations within skill clusters or for those who stay in their occupations.

Furthermore, the survey contains self-reported information on monthly earnings and the average hours of work per week, and thus, we were able to calculate individual hourly wages[15]. In our estimates, the logarithm of wages is used as the dependent variable. On average, male employees in Germany earned about EUR 15.5 per hour in 2005.

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[15] We dropped observations with earnings above the 99th percentile or below the 1st percentile so that the results are not determined by outliers.

4. Estimation Methods

Probability of Occupational Mobility

First, we study the impact of occupational specificity on the occupational mobility of employees. According to our hypotheses, we not only differentiate between so-called occupational stayers and occupational changers, but we also differentiate occupational changers into changers within a skill cluster and changers between skill clusters. We apply simple probit models with the probability of changing occupations as the dependent variable and the two different types of specificity as explanatory variables (Wooldridge 2009: 575-578). In addition, we use a standard set of control variables in our regression models[16]. We include socio-economic characteristics such as age as well as dummies for having children and for participation in further vocational training. We also include a dummy indicating if an individual lives in East Germany, because earnings as well as the costs of living are expected to still differ between East and West Germany. Other control variables include the size of the firm (four dummies), the industry sector (five dummies), and the highest educational degree (four dummies).

Income Effects of Occupational Mobility

Second, we test the wage effects of different types of occupational mobility. We study the impact of occupational specificity and mobility on income by estimating a log-linear ordinary least square (OLS) regression. We control for a variety of demographic variables and interpret the coefficients of the occupational change dummies and the specificity degree. The basic equation we estimate can be written as:

$$\ln y = \alpha + \beta_1 M + \beta_2 Z + \beta_3 (Z * M) + \beta_4 X + \varepsilon$$

Note that $\ln y$ is log hourly earnings. M contains the dummies for the two different types of occupational change (i.e., either within or between skill clusters); therefore, β_1 is the influence of an occupational change on earnings. Z contains the main explanatory variable

[16] As a robustness check, we computed the regressions with occupational clusters to consistently estimate the standard errors and also obtained significant results; models 1 and 3 were significant at the 10% level, and model 2 was significant at the 1% level.

for specificity; therefore, β_2 is the influence of the specificity degree on earnings. Z*M is an interaction term[17] we include to analyze the combined effect of specificity and mobility, β_3. X contains the control variables, while β_4 is the coefficient vector. ε represents an unobservable error.

5. Empirical Results

Probability of Occupational Mobility

We now discuss the key results concerning occupational specificity and mobility. In the following table, the marginal effect of each variable is shown, which is the derivative of each outcome probability with respect to the explanatory variable evaluated at the sample means of the independent variables. In model 1 (Table 5), we analyze occupational mobility in general across the entire labor market and find a negative impact of general specificity as expected according to hypothesis H1a. An increase of the specificity degree of a training occupation per unit relative to those occupations with average specificity in the whole labor market results in a decrease in the probability of an occupational change of 2.4%. This means the more specific the apprenticeship training occupation is as compared to the whole labor market, the smaller is occupational mobility after graduation.

Table 5 about here

In the next step, we are interested in differences in mobility patterns. To test hypothesis H1b, we apply our labor market segmentation and only look at occupational changers to compare occupational mobility within and between skill clusters. In line with our hypothesis, we expect that the higher the general specificity is, the more likely are occupational changes into occupations with relatively similar skill requirements (i.e., within a skill cluster) than changes into occupations with relatively dissimilar skill requirements (i.e., between skill clusters). Indeed, general specificity enhances occupational changes within a skill cluster as compared to occupational changes between skill clusters; see model 2 in

[17] To reduce potential problems with multicollinearity due to interaction effects between a quantitative variable and a dummy variable in multiple regression analysis, we center the quantitative variable prior to the formation of the product term (Jaccard et al. 1990, Aiken/West 1991) so that a specificity degree of 0 corresponds to the mean specificity.

Table 5. An increase in specificity per unit results in an increase in the probability of an occupational change within a skill cluster of 8.9% as compared to an occupational change between skill clusters. Therefore, although an occupation is very specific, a graduate is nonetheless able to change the occupation after graduation into an occupation with similar skills within a labor market segment.

According to hypothesis H1c, we finally analyze individual mobility behavior within a skill cluster (model 3, Table 5). Although occupations grouped in a skill cluster have similar skill requirements, they nonetheless differ in specificity, as we have shown in the operationalization of the specificity degree. As expected, we find that even within a skill cluster, individuals with more cluster-specific occupations are less likely to change their occupations within their labor market segment. An increase in cluster specificity per unit results in a decrease in the probability of an occupational change within a skill cluster of 3.2%.

Summing up our initial empirical findings, occupational specificity has a negative and significant effect on occupational mobility. As expected based on Lazear's theory, graduates in very specific occupations relative to the overall labor market are stuck in their occupation because only small parts of their skills can still be used if they change their occupation, while large parts of their human capital investments are lost. Therefore, the value of their particular skill combinations will be dramatically reduced, and occupational mobility becomes heavily restricted. But moreover, we showed that the labor market can be segmented into skill clusters. Mobility into occupations with similar skill requirements (i.e., within a skill cluster) is easier as compared to moving into another labor market segment (i.e., between skill clusters). Thus, although an apprenticeship training occupation is very specific, a graduate can indeed still be mobile within a labor market segment. Therefore, an employee with a specific skill combination is not completely stuck in his occupation, but he is insofar bound to the original occupation as he can lose the productive value of formerly acquired skills in the case of an occupational change.

Income Effects of Occupational Mobility

We now discuss the key results concerning the income effects of occupational specificity and mobility. Estimation results with robust standard errors are provided in Table 6. In model 4, we test our second hypothesis and analyze occupational changes *between* skill clusters. In accordance with hypothesis H2a, we find a negative impact of an occupational change between skill clusters on income. An occupational change between skill clusters is associated with a 5% reduction in hourly wages as compared to the wages of those who stay in their occupations. The coefficient of general specificity is statistically insignificant, but the interaction term between general specificity and an occupational change between skill clusters is statistically significant and negative, as expected according to hypothesis H2b. So in case of an occupational change between skill clusters, the more specific the skill portfolio in an occupation is relative to the overall labor market, the higher is the wage loss that a cluster changer has to bear. A per-unit increase of general specificity results in a decrease of 1.2% in hourly wages of a cluster changer as compared to an occupational stayer with average specificity. Therefore, employees who change their skill clusters suffer a wage loss that increases with the specificity of the skill requirements of the former occupation.

Table 6 around here

In the last step, we test our third hypothesis focusing on labor market segments, and we analyze occupational changes within a skill cluster; see model 5 in Table 6. As expected according to our hypothesis H3a, occupational changes within skill clusters have a positive and significant effect on income. An occupational change within a skill cluster is associated with a 6.8% increase in income relative to occupational stayers. In line with hypothesis H3b, cluster specificity has a negative and significant effect on income, while the coefficient of the interaction term is statistically insignificant. This means that a per-unit increase in cluster specificity is associated with a 1.0 percentage point decrease in income relative to those occupations with average specificity. Therefore, an occupational change within a skill cluster is honored with a wage gain. However, the more specific the skill portfolio of the former occupation is relative to the respective skill cluster, the smaller is the wage gain.

In summary, we found that employees changing to occupations with similar skill-weights (i.e., within skill clusters) can obtain a wage gain; however, employees changing to completely different occupations (i.e., between skill clusters) suffer a wage loss. The highest wage losses are for those who change occupations between skill clusters and who have initially chosen a very specific training occupation. The highest wage gains are for those who change occupations within a skill cluster and have initially chosen a non-specific apprenticeship training occupation. These findings suggest that (some) skills acquired during apprenticeship training can still be productively used after changing into an occupation with similar skill-weights within a labor market segment, but when workers change occupations between skill clusters, they lose part of the return of their formerly-acquired productive skills in the new occupation. Therefore, as Marsden (1986: 234) has already stated, having made their initial investment in apprenticeship training, skilled workers have an incentive to move into occupations that enable them to maintain their skills. Occupational mobility can benefit a worker if he loses neither the skills acquired nor their return. As our results show, in the case of an occupational change within skill clusters, occupation-specific skills remain relevant across occupational boundaries, while occupation-specific human capital is not completely lost.

6. Conclusions

Our analysis of occupational mobility shows that although vocational education and training (VET) is criticized as too inert and inflexible and too focused on narrow skill requirements, VET does not severely restrict mobility but rather still grants graduates flexibility. Several conclusions can be drawn about the specificity of occupational skill combinations and their implications on occupational mobility and income. The first is that there is evidence of distinct segments within the labor market; skill clusters exist that contain occupations with similar skill-weights. In line with labor market segmentation theory (Doeringer/Piore 1971), occupations can be classified into skill clusters based on their required skill combinations. Second, the required skill combination is a good measure for the flexibility of occupations and determines the specificity degree of an occupation. The more specific an occupation is, the smaller is the probability that employees change their occupation not only across the entire labor market but even within their skill cluster. Nonetheless, even employees in specific occupations can be mobile, as they have a comparatively higher probability of changing occupations *within* a skill cluster rather than *between* skill clusters. Therefore, within skill clusters, flexibility is facilitated, whereas between skill clusters, flexibility is constrained. Third, an occupational change within skill clusters is possible without losing formerly acquired skills and is, moreover, honored with a wage gain. Since the required skill combination is quite similar, the return on the formerly acquired skills is not lost. However, occupational mobility into occupations with very different skill combinations, e.g., occupational mobility between skill clusters, is associated with a wage loss because the returns on formerly acquired skills are lost in part. Not surprisingly, the higher the specificity degree of the former occupation is, either the higher is the resulting wage loss or the smaller is the resulting wage gain depending on whether the change is between or within skill clusters, respectively. Obviously, occupational mobility is not only motivated by increased pay. Empirically, many employees change occupations between clusters, even though these changes are associated with a wage loss. Thus, it is unclear why such changes are observed at all. We assume that these changes are, for example, related to health, family or general changes in one's personal situation. Overall, we find clear evidence supporting our theoretical predictions, and thus, occupational specificity can be analyzed according to Lazear's skill-weights approach (2003). Therefore, the acquired skill combination – and not the occupation per se – crucially determines the mobility of an employee.

Our findings lead to several implications for research and educational politics. In a comparison of vocational education and training versus academic training, appropriate measures have to be used to determine relative competitiveness of programs. Therefore, previous conclusions have to be reviewed. First, regarding educational politics, it is important to look not only at a single occupation while thinking about future competitiveness and mobility issues but also at the occupational cluster within which a particular occupation is located, since the cluster is as important (or even more important) for mobility and earnings as the occupation itself. Thus, choosing a seemingly outdated and very specific occupation could be a better decision, if it is in a prosperous cluster, than choosing a seemingly general occupation that lies is in a very small and less prosperous cluster. Second, we find that the relevant parameter to evaluate the flexibility of an occupational system and the employability of its graduates is neither the number of apprenticeship training occupations nor the narrowness of skill requirements in a particular occupation but rather the specificity of skill combinations in comparison to similar occupations within the skill cluster and in comparison to the rest of the labor market. Based on Lazear's skill-weights approach, we argue that the specificity of the skill combination in an occupation is the relevant issue to be analyzed, and these skill combinations can be quite similar, even though there is a multitude of occupations. Of course, the question then arises as to why so many different apprenticeship training programs are needed when skill combinations are similar. We assume that a larger variety of single occupations is necessary for the viability of apprenticeship training because on the one hand, it guarantees better incentives for firms to invest in training since occupations that are more tailored toward actual firm needs are more cost-efficient than occupations that are very broad and general. On the other hand, a larger variety of single occupations makes the overall system more manageable for educational policy makers as well as for firms because it allows the system to develop gradually without excessive frictions or risks, which would be the case if there were only very few consolidated occupations about which all firms had to reach a consensus. Thus, having a variety of single training occupations avoids the problem of "putting all of one's eggs in one basket", as articulated by Lazear (2002).

References

Aghion, P. (2007): "Growth and the Financing and Governance of Education." Keynote lecture for the 2007 Meeting of the German Economic Association.

Aiken, L.S.; S.G. West (1991): *Multiple Regression: Testing and Interpreting Interactions*. Newbury Park: SAGE.

Aldenderfer, M.S.; R.K. Blashfield (1984): *Cluster Analysis.* SAGE University Papers on Quantitative Applications in the Social Sciences, No. 07-044. Beverly Hills: SAGE.

Autor, D.H.; F. Levy; R.J. Murnane (2003): "The skill content of recent technological change: An empirical exploration." *Quarterly Journal of Economics*, 118(4): 1279-1333.

Autor, D.; Dorn, D. (2009): "This Job is "Getting Old": Measuring Changes in Job Opportunities using Occupational Age Structure". *American Economic Review*, *99*(2), 45-51.

Becker, G.S. (1964): *Human capital: A theoretical and empirical analysis, with special reference to education*. New York: National Bureau of Economic Research.

BFS (2009): "Statistik der beruflichen Grundbildung 2008." Neuchâtel: BFS.

BIBB (2009): "Neue und modernisierte Ausbildungsberufe 2009." Bonn: BIBB.

Borghans, L.; B. ter Weel; B.A. Weinberg (2005): "People People: Social Capital and the Labor-Market Outcomes of Underrepresented Groups." *IZA Discussion Paper No. 1494*.

Borghans, L.; B.H.H. Goldsteyn (2007): "Skill transferability, regret and mobility." *Applied Economics*, 39(13): 1663-1677.

Bortz, J. (1989): *Statistik für Sozialwissenschaftler*. Berlin/Heidelberg/New York: Springer.

Carnoy, M. (1994): "Efficiency and equity in vocational education and training policies." *International Labour Review*, 133(2): 221-240.

Carnoy, M. (2004): "Education for All and the quality of education: a reanalysis." Background paper prepared for the Education for All Global Monitoring Report 2005, The Quality Imperative.

Casas-Arce, P. (2004): "Firm Provision of General Training and Specific Human Capital Acquisition." University of Oxford, Department of Economics Discussion Paper No. 198.

Clark, D.; R. Fahr (2001): "The Promise of Workplace Training for Non-College-Bound Youth: Theory and Evidence from German Apprenticeship." IZA Discussion Paper No. 378.

Doeringer, P.B.; M.J. Piore (1971): *Internal labor markets and manpower analysis*. Lexington, Mass.: Heath.

Eyraud, F.; Marsden, D.; & Silvestre, J. (1990): Occupational and internal labour markets in Britain and France. *International Labour Review*, *129*(4), 501.

Fitzenberger, B.; Spitz, A. (2004): "Die Anatomie des Berufswechsels : eine empirische Bestandsaufnahme auf Basis der BIBB/IAB-Daten 1998/1999" Zentrum für Europäische Wirtschaftsforschung. Discussion Paper No. 04-05. Mannheim

Flatau, P.R.; P.E.T. Lewis (1993): "Segmented labor markets in Australia." *Applied Economics*, 25(3): 285-294.

Garloff, A.; A. Kuckulenz (2006): "Training, Mobility, and Wages: Specific Versus General Human Capital." *Jahrbücher für Nationalökonomie und Statistik*. Stuttgart: Lucius&Lucius, 226/1: 55-81.

Gathmann, C.; U. Schönberg (2007): "How General is Human Capital? A Task-Based Approach." *IZA Discussion Paper No. 3067*.

Geel, R; J. Mure; U. Backes-Gellner (2008): "Specificity of Occupational Training and Occupational Mobility: An Empirical Study Based on Lazear's Skill-Weights Approach" *Swiss Leading House Working Paper* No. 38.

Geel, R; J. Mure; U. Backes-Gellner (2009 forthcoming): "Bildung und Mobilität - Erklärungen mit Hilfe des Skill-Weights Approach" *Empirische Pädagogik*.

Gibbons, R.; M. Waldman (2004): "Task-Specific Human Capital." *American Economic Review*, 94(2): 203-207.

Goeggel, K.; T. Zwick (2009): "Good Occupation - Bad Occupation? The Quality of Apprenticeship Training." ZEW Discussion Paper No. 09-024.

Heckman, J.J. (1994): "Is job training oversold?" *The Public Interest*, 115: 91-115.

Hotz-Hart, B. (2008): "Erfolgskonzept 'duale Berufsbildung' im Wandel." *75 Jahre eidgenössisches Berufsbildungsgesetz. Politische, pädagogische, ökonomische Perspektiven*, ed. by T. Bauder, F. Osterwalder. Bern: hep Verlag, 93-127.

Ingram, B.; Neumann, G. (2006): „The returns to skill" *Labour Economics*, *13*(1), 35-59.

Jaccard, J.; C.K. Wan; R. Turrisi (1990): "The Detection and Interpretation of Interaction Effects Between Continuous Variables in Multiple Regression." *Multivariate Behavioral Research*, 25(4): 467-478.

Jovanovic, B. (1979a): "Job Matching and the Theory of Turnover." *Journal of Political Economy*, 87(5): 972-990.

Jovanovic, B. (1979b): "Firm-Specific Capital and Turnover." *Journal of Political Economy*, 87(6): 1246-1260.

Kambourov, G.; I. Manovskii (2008): "Rising Occupational and Industry Mobility in the United States: 1968-97" *International Economic Review*, 49(1): 41-79.

Kambourov, G.; I. Manovskii (2009): "Occupational Specificity of Human Capital." *International Economic Review*, 50(1): 63-115.

Ketchen, D.J.; C.L. Shook (1996): "The Application of Cluster Analysis in Strategic Management Research: An Analysis and Critique." *Strategic Management Journal*, 17(6): 441-458.

Krueger, D; K.B. Kumar (2004): "Skill-Specific rather than General Education: A Reason for US-Europe Growth Differences?" *Journal of Economic Growth*, 9(2): 167-207.

Lazear, E.P. (2002): "Education in the Twenty-First Century" Hover Institution Press. Stanford

Lazear, E.P. (2003): "Firm-Specific Human Capital: A Skill-Weights Approach." NBER Working Paper No. 9679. New Draft, Stanford University, 2009.

Leontardi, M.R. (1998): "Segmented Labour Markets: Theory and Evidence." *Journal of Economic Surveys*, 12(1): 63-101.

Loewenstein, M.A.; J.R. Spletzer (1999): "General and Specific Training: Evidence and Implications." *Journal of Human Resources*, 34(4): 710-733.

Mardia, K.V.; J.T. Kent; J.M. Bibby (1979): *Multivariate Analysis*. London: Academic Press.

Marsden, D. (1986): *The End of Economic Man? Custom and Competition in Labour Markets*. Brighton: Wheatsheaf Books.

McCall, B.P. (1990): "Occupational Matching: A Test of Sorts." *Journal of Political Economy*, 98(1): 45-69.

Neal, D. (1995): "Industry-Specific Human Capital: Evidence from Displaced Workers." *Journal of Labor Economics*, 13(4): 653-677.

OECD (2008): *Education at a Glance 2008*. OECD.

Osberg, L.; R. Apostle; D. Clairmont (1987): "Segmented labour markets and the estimation of wage functions." *Applied Economics*, 19(12): 1603-1624.

Poletaev, M.; C. Robinson (2008): "Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984-2000." *Journal of Labor Economics*, 26(3): 387-420.

Punj, G.; D.W. Stewart (1983): "Cluster Analysis in Marketing Research: Review and Suggestions for Application." *Journal of Marketing Research*, 20(2): 134-148.

Reich, M.; D.M. Gordon; R.C. Edwards (1973): "A Theory of Labor Market Segmentation." *American Economic Review*, 63(2): 359-365.

Rogerson, R.; R. Shimer; R. Wright (2005): "Search-Theoretic Models of the Labor Market: A Survey." *Journal of Economic Literature*, 43(4): 959-988.

Shaw, K. L. (1987): “Occupational Change, Employer Change, and the Transferability of Skills” *Southern Economic Journal*, 53(3): 702-719.

Spitz-Oener, A. (2008): "The returns to pencil use revisited." *Industrial and Labor Relations Review*, 61(4): 502-517.

Topel, R. (1991): "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority." *Journal of Political Economy*, 99(1): 145-176.

Wagschal, U. (1999): *Statistik für Politikwissenschaftler*. München/Wien: Oldenbourg.

Ward, J.H. (1963): "Hierarchical Grouping to Optimize an Objective Function." *Journal of the American Statistical Association*, 58(301): 236-244.

Winkelmann, R. (1996): "Employment Prospects and Skill Acquisition of Apprenticeship-Trained Workers in Germany." *Industrial and Labor Relations Review*, 49(4): 658-672.

Winkelmann, R. (2006). Qualifikationsspezifische Beschäftigungsperspektiven und berufliche Flexibilität. Berufsbildungsökonomie: Stand und offene Fragen, ed. by A. Frick and A. Wirz. Bern, h.e.p. Verlag: 75-106.

Wooldrige, J. (2009). “Introductory Econometrics: A Modern Approach” South-Western Cengage Learning.

Appendix

A. Cluster Analysis

The statistical problem of classifying occupations into groups that are as homogeneous as possible when compared with others can be solved by applying cluster analysis (Aldenderfer/Blashfield 1984). Cluster analysis is concerned with the problem of whether observations on several subjects (in this case, occupations) along various variables (i.e., the skill combinations required by the occupations) can be clustered into groups according to these characteristics and whether these groups can be regarded as distinct from one another[18]. Several algorithms are available for choosing clusters, which can be categorized as hierarchical or partitioning. We apply a two-stage procedure as a solution recommended by various authors (Punj/Stewart 1983, Ketchen/Shook 1996) in which a hierarchical algorithm is first used to define the number of clusters. Second, this result then serves as the starting point for subsequent non-hierarchical clustering.

In the first stage, we use Ward's (1963) minimum variance method to determine the number of clusters in the dataset. This hierarchical method generates clusters in order to minimize the within-cluster variance, and as such, it is best suited for studies in which no outliers exist and in which the number of observations in each cluster is expected to be approximately equal (Ketchen/Shook 1996, Punj/Stewart 1983). By examining the results of this preliminary analysis[19], we determine a candidate number of six clusters for the following iterative partitioning analysis. Note that our research follows Osberg et al. (1987), who applied six labor market segments and is along the line of the six broad occupational groups according to the 1-digit classification codes of occupational titles by Germany's Federal Employment Bureau in 1992.

The second stage consists of an iterative partitioning analysis for the refinement of the clusters (Punj/Stewart 1983). Non-hierarchical methods have two potential advantages over hierarchical methods (Ketchen/Shook 1996) if the number of clusters is specified a

[18] Cluster analysis has become a common tool for academic researchers in marketing who rely on this technique to segment the market and develop empirical groupings that may serve as the basis for further analysis.

[19] We visually inspected the dendrogram that gives the distances between observations within clusters and distances between clusters (Wagschal 1999, Ketchen/Shook 1996) and used Mardia et al.'s (1979: 365) rule of thumb, $g \sim (n/2)^{1/2}$ for determining the number of groups.

priori. First, as non-hierarchical methods allow observations to switch between clusters, they are less impacted by outliers. Second, because of these multiple passes through the data, the final solution optimizes within-cluster homogeneity and between-cluster heterogeneity. The most popular partitioning, non-hierarchical clustering method is the K-means procedure (Bortz 1989). Since this method aims to minimize the sum of squared distances from all points to their cluster centers, this should result in compact clusters. We use the K-means procedure, as it appears to outperform other iterative and hierarchical clustering methods if a non-random starting point is specified (Punj/Stewart 1983). To test the efficiency of the cluster analysis, we applied the F-value test according to Wagschal (1999: 272); 80% of the computed F-values do not exceed the value of 1, which means the variance within the skill clusters is smaller than the total variance.

B. Tables

Table 1: Enrollment in Upper Secondary Programs (2006, in %)

	Vocational
Austria	71.8
Canada	5.4
Denmark	47.8
France	43.1
Germany	59.4
Italy	24.9
Japan	23.7
Netherlands	67.5
Spain	42.5
Sweden	54.2
Switzerland	64.2
United Kingdom	41.7
OECD average	**44.0**

Source: OECD 2008

Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Occupational Specificity in General	8.5	2.3	4.5	15.1
Occupational Cluster Specificity	3.7	2.3	1.2	10.8
Occupational Change	0.58	0.49	0	1
Occupational Change ***within*** Skill Cluster	0.21	0.41	0	1
Occupational Change ***between*** Skill Clusters	0.37	0.48	0	1
Hourly wage (ln)	2.5	0.47	0.8	3.8
Male	0.54	0.50	0	1
Age	40.2	9.8	18	65
Married	0.52	0.50	0	1
Children	0.45	0.50	0	1
Blue collar	0.35	0.48	0	1
German Nationality	0.97	0.16	0	1
East Germany	0.15	0.35	0	1
Tenure	10.8	9.1	0	49
Further training	0.57	0.50	0	1
Lower secondary school (Hauptschule)	0.29	0.46	0	1
Intermediate secondary school (Realschule)	0.54	0.50	0	1
High school diploma (Abitur)	0.16	0.36	0	1
No graduation	0.01	0.08	0	1
Firm size under 10 employees	0.20	0.40	0	1
Firm size between 10 and 49 employees	0.28	0.45	0	1
Firm size between 50 and 249 employees	0.23	0.42	0	1
Firm size over 250 employees	0.28	0.45	0	1
Industry	0.32	0.47	0	1
Handcraft	0.15	0.36	0	1
Trade	0.18	0.39	0	1
Service	0.34	0.47	0	1
Other sector	0.01	0.09	0	1

Source: BIBB/BAuA 2005/2006, own calculations.

Table 3: Required Skills

List of skills	
1	Natural Science
2	Craft
3	Technical
4	Pedagogic
5	Law
6	Medical
7	Project management
8	Design/Layout
9	Maths/Statistics
10	German/Orthography
11	Computer
12	Commercial
13	Foreign Languages

Source: BIBB/BAuA 2005/2006

Table 4: The Relative Importance of Single Skills per Skill Cluster

Relative Importance		Clusters					
		1	2	3	4	5	6
Skills	Natural Science	0.35	0.22	0.15	0.29	0.06	0.18
	Craft	0.41	0.83	0.75	0.40	0.04	0.14
	Technical	0.58	0.72	0.33	0.63	0.16	0.14
	Pedagogic	0.04	0.10	0.07	0.12	0.16	0.35
	Law	0.11	0.11	0.07	0.15	0.37	0.19
	Medical	0.00	0.05	0.03	0.03	0.05	0.34
	Project management	0.03	0.08	0.05	0.16	0.18	0.10
	Design/Layout	0.03	0.06	0.08	0.31	0.15	0.08
	Maths/Statistics	0.24	0.50	0.22	0.52	0.27	0.14
	German/Orthography	0.16	0.20	0.10	0.29	0.62	0.39
	Computer	0.06	0.17	0.04	0.48	0.55	0.09
	Commercial	0.17	0.06	0.09	0.03	0.39	0.19
	Foreign Languages	0.03	0.06	0.07	0.22	0.28	0.09

Source: BIBB/BAuA 2005/2006, own calculations.

Table 5: Probability of Occupational Mobility (Probit Model)

	Model 1:		Model 2:		Model 3:	
Dependent Variable	**Occupational Change in general**		**Occupational Change *within* Skill Clusters**		**Occupational Change *within* Skill Clusters**	
Reference Category	*Occ. Stayers*		*Occ. Changers between Clusters*		*Occ. Stayers*	
Focus	Overall Labor Market		Overall Labor Market		Labor Market Segment	
	dF/dx	Std. Err.	dF/dx	Std. Err.	dF/dx	Std. Err.
Occupational specificity in general	-0.024	0.004 ***	0.086	0.006 ***		
Occupational cluster specificity					-0.032	0.006 ***
Age	0.033	0.006 ***	-0.015	0.008 **	0.017	0.008 **
Age squared	0.000	0.000 ***	0.000	0.000 *	0.000	0.000
Married	-0.001	0.020	-0.018	0.024	-0.030	0.025
Children	0.002	0.020	0.021	0.024	0.013	0.025
Further training	-0.036	0.020 *	-0.029	0.020	-0.029	0.020
East Germany	0.006	0.028	-0.006	0.030	-0.006	0.030
Ref.Cat: Firm size ≥ 250 employees						
Firm size ≤ 9 employees	-0.072	0.028 **	0.031	0.034	-0.043	0.033
Firm size between 10 and 49 employees	-0.081	0.023 ***	-0.054	0.025 **	-0.105	0.026 ***
Firm size between 50 and 249 employees	-0.054	0.022 **	-0.003	0.024	-0.053	0.025 **
Ref.Cat: Services						
Industry	0.003	0.022	0.096	0.024 ***	0.019	0.028
Handcraft	-0.277	0.026 ***	0.166	0.039 ***	-0.194	0.027 ***
Trade	0.064	0.026 **	-0.050	0.029	0.036	0.037
Other Sector	-0.221	0.072 ***	-0.104	0.095	-0.246	0.044 ***
Ref.Cat: Intermediate secondary school						
No school	0.262	0.123 **	0.056	0.119	0.056	0.119
Lower secondary school	0.060	0.022 ***	-0.025	0.023	-0.025	0.023
High school diploma	0.022	0.026	0.164	0.033 ***	0.164	0.033 ***
Number of observations	4'217		2'590		2'417	
Wald chi2 (17)	443.22		280.88		239.37	
Prob > chi2	0.00		0.00		0.00	
Pseudo R2	0.08		0.10		0.08	

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%; robust standard errors; all coefficients represent marginal effects.

Source: BIBB/BAuA 2005/2006, own calculations.

Table 6: Income Effects of Occupational Mobility (OLS Regression)

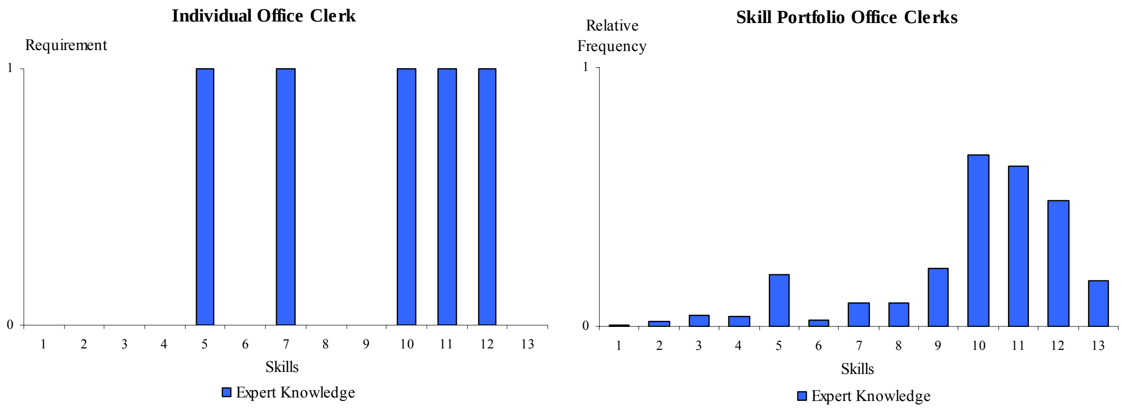
	Model 4:			Model 5:		
Dependent Variable: Hourly Wage (ln)	**Occupational Change *between* Skill Clusters**			**Occupational Change *within* Skill Clusters**		
Reference Category	*Occ. Stayers*			*Occ. Stayers*		
Focus	Overall Labor Market			Labor Market Segment		
	Coef.	Std. Err.		Coef.	Std. Err.	
Occ. Change *between* Skill Clusters	-0.050	0.015	***			
Occ. Specificity in General	0.005	0.005				
Interaction Term	-0.012	0.007	*			
Occ. Change *within* Skill Cluster				0.068	0.017	***
Occ. Cluster Specificity				-0.010	0.004	**
Interaction Term				0.002	0.009	
Age	0.035	0.005	***	0.030	0.006	***
Squared Age	0.000	0.000	***	0.000	0.000	***
Married	0.054	0.015	***	0.036	0.017	**
Children	0.012	0.015		0.025	0.017	
Tenure	0.021	0.002	***	0.018	0.002	***
Tenure Squared	0.000	0.000	***	0.000	0.000	***
German Nationality	0.059	0.036		0.015	0.034	
Blue Collar	-0.173	0.014	***	-0.132	0.016	***
East Germany	-0.285	0.019	***	-0.297	0.021	***
Further training	0.101	0.012	***	0.059	0.013	***
Ref.Cat: Firm size ≥ 250 employees						
Firm size ≤ 9 employees	-0.225	0.024	***	-0.201	0.024	***
Firm size between 10 and 49 employees	-0.159	0.016	***	-0.142	0.018	***
Firm size between 50 and 249 employees	-0.091	0.015	***	-0.082	0.018	***
Ref.Cat: Services						
Industry	0.181	0.018	***	0.052	0.021	**
Handcraft	0.077	0.021	***	-0.049	0.023	**
Trade	-0.024	0.022		-0.098	0.025	***
Other Sector	0.009	0.057		-0.122	0.057	**
Ref.Cat: Intermediate secondary school						
No school	0.011	0.068		-0.064	0.064	
Lower secondary school	-0.052	0.013	***	-0.056	0.015	***
High school diploma	0.097	0.020	***	0.088	0.022	***
Constant	1.701	0.104	***	1.911	0.110	***
n		3427			2417	
F-Statistics		108.11			73.31	
Prob > F		0.00			0.00	
R-Squared		0.40			0.38	

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%; robust standard errors.

Source: BIBB/BAuA 2005/2006, own calculations.

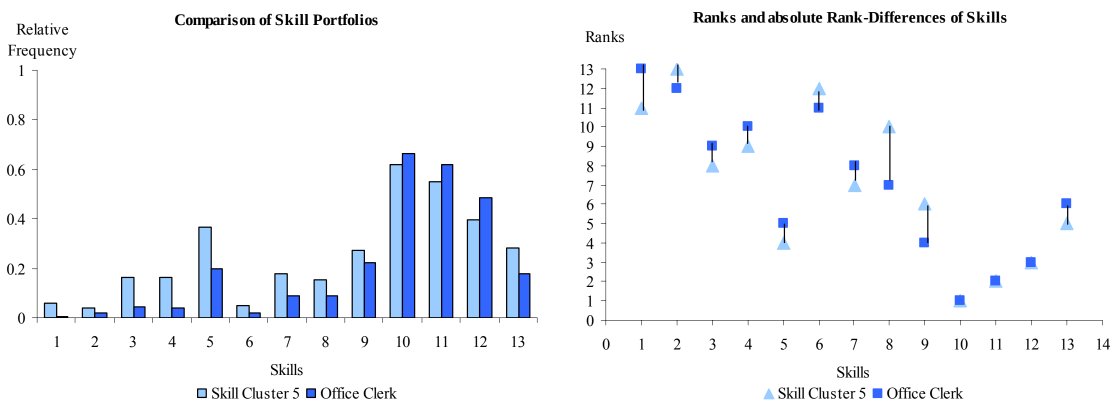
C. Figures

Figure 1: Skill Portfolio of Office Clerks: Individual and Occupational Level



Source: BIBB/BAuA 2005/2006, own calculations.

Figure 2: Comparison of an Occupation-Specific Skill Portfolio with the Skill Portfolio of the Relevant Skill Cluster



Source: BIBB/BAuA 2005/2006, own calculations.