Working Paper No. 106

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UNIVERSITÄT BERN

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The Swiss Leading House on Economics of Education, Firm Behavior and Training Policies is a Research Program of the Swiss State Secretariat for Education, Research, and Innovation (SERI).

www.economics-of-education.ch

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Preliminary Version
(Please do not cite without contacting the authors)

February 2015

Abstract: In this paper we analyze the training curricula of VET (vocational education and training) occupations using detailed data on learned skills from official trainings regulations. We explore how differences in the skill bundles of occupational curricula can be measured and how such differences affect graduates' long-term labor market outcomes. Based on Lazear's skill weights approach, we develop novel measures for the skill distance between occupations and the specificity of occupations. We find that workers who change between occupations with very dissimilar skill weights are faced with lower wages after the change compared to workers who change to similar occupations. Additionally, workers who are trained in occupations with more specific skill bundles have a smaller probability of an occupational change. Our results shed light on the policy question of how the specificity of curricula affects the long-term flexibility outcomes of VET workers.

Keywords: vocational education and training, occupational mobility, human capital specificity

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† This study is partly funded by the Swiss Federal Office for Professional Education and Technology through its Leading House on the Economics of Education, Firm Behavior and Training Policies.

Introduction

Previous research has shown that early vocational specialization during VET-training facilitates the transition of youths into the labor market (Korpi, Graaf, Hendrickx, & Layte, 2003; Winkelmann, 2006) and supplies firms with skilled workers (Eymann, Müller, & Schweri, 2011). However, the question is whether the early specialization of VET-trained youths in a particular occupation later on develops into a disadvantage when they have to change jobs.[3] This, of course, depends on the skills[4] learned during the VET-training and thus on the curriculum of the respective occupation. Given the ever-increasing economic and technological change, the transferability of the skills taught during the VET-training and thus a well-balanced curriculum is more relevant than ever (Hanushek, Woessmann, & Zhang, 2011). Our aim is to contribute to the curriculum discussion by investigating from a personnel economics perspective how differences in the transferability of skills of an occupational curriculum can be measured and how such differences affect the long-term labor market outcomes of graduates. In particular, we focus on the determinants and consequences of occupational mobility. Our analysis is based on Lazear's (2009) skill weights approach that provides an ideal theoretical model to conceptualize the differences in the skill bundles of occupational curricula and to measure their specificity.

Some researchers and policymakers dealing with long-term labor market outcomes fear that too much specificity in vocational training might constrain the flexibility of workers. Therefore, they argue in favor of a "de-specialization" and consolidation of VET-occupations into fewer "core" occupations that are rather broad and unspecific (International Network on Innovative Apprenticeship, 2012; Rauner, 2012; Schellenbauer, Walser, Lepori, Hotz-Hart, & Gonon, 2010). Even though first steps in this direction have been implemented in the last decades, a striking example being the consolidation of seven industrial occupations into the occupation of polytechnics in the year 1997, this demand has not yet been implemented on a larger scale. And, as Wettstein (2012) points out, so far no scientific studies exist, which

[3] Data based on the Swiss census 2000 shows that among all VET graduates, an increasing number of workers (almost 60% in the year 2000) do not exercise the profession they learned during their initial training (Sheldon, 2005).

[4] Economic literature generally defines skills as "a worker's endowment of capabilities for performing various tasks" (c.f. Acemoglu & Autor, 2011).

would indicate that individuals from small and specialized occupations have a disadvantage regarding occupational mobility.

Previous research and policy makers defining the curricula of VET standards focused on so-called ‘key qualifications’ (“Schlüsselqualifikationen”) that can be flexibly adapted to changing skill requirements and are transferable across traditional occupational profiles. Early researchers proposed several concepts to increase the transferability of apprenticeship trainings (for an overview cf. Dörig, 1994). In an influential article, Mertens (1974) postulated that students should be enabled to transfer knowledge towards different contexts more easily by fostering their ability for analytical and critical thinking. These skills should be complemented with the ability to gather information independently and “learn how to learn” efficiently in order to quickly familiarize with new topics and technologies. Mertens (1974) referred to these skills as “basic or horizontal qualifications”. These research results were used in the development of training curricula to increase labor market flexibility, and today, this type of competencies constitutes an important part of modern apprenticeship training curricula (Goetze, 2002). For example, as our own investigations of Swiss apprenticeship curricula show, all modern training curricula contain a section dedicated to methodological and social competences. Mertens (1974) also proposed a second concept to increase transferability, the integration of “transversal knowledge elements” into vocational training curricula. These “transversal knowledge elements” are basically skill combinations which are used within a broad range of different work contexts and are thus not unique to single occupations. Examples of these transversal skills are customer service, work safety, or measurement technologies. These transversal skills can also facilitate labor market flexibility, but have received much less attention in curricula development so far.

In this paper we build on this research and further argue that long run labor market success is critically determined by the combination of such single skill components. As we will show, some occupations use combinations of skills, which are more general in the sense that the combinations are very similar across a wide range of occupations. Other occupations use combinations of skills that are very specific in the sense that they are required by very few other occupations. As argued by Lazear (2009) in his skill weights approach, workers with more general skill combinations have better external labor market options than workers with more specific skill combinations. Based on Lazear’s theory we develop a measure for the specificity of occupational curricula that allows predicting the labor market success of occupational graduates.

Lazear's (2009) skill weights approach provides an ideal theoretical model to conceptualize labor market relevant differences between occupations. His model studies firm-specificity of human capital and compares the weights of single skills in the skill bundle of the training company to the weights in the overall labor market as an indicator for firm-specificity. We adapt his model to measure the differences between occupations and develop two novel measures for the labor market potential of occupations. We measure the skill distance between two occupations and the degree of specificity of an occupation with respect to the overall labor market. We do this by comparing the bundle of skills in one occupation to the bundles of skills in one other or all other occupations in the overall labor market, respectively.

We create a new data set to identify the skill bundles of occupations by using official Swiss vocational training curricula of 80 VET-occupations. The curricula contain detailed information on skills that are taught in a VET-occupation. Based on these skill bundles, we first calculate a measure for the skill distance between all possible pairs of occupations. This skill distance captures the degree to which skills are transferable between occupations. Second, we calculate the degree of specificity of an occupation by combining the information on the skill distances between occupations with the frequencies of all these occupations in the overall labor market. To derive these frequencies, we use representative labor market data from the Social Protection and Labour Market (SESAM) panel. We then use these measures for the distances between different occupations and the specificity of a single occupation to study their effect on long-term labor market outcomes, i.e., on the probability of changing an occupation and on wage differences of occupational changers.

Our results show that workers who change between more distant occupations are faced with lower wages after the switch compared to workers who change to more similar occupations. Accordingly, workers who are trained in occupations with more specific skill bundles have a smaller probability of an occupational change, because their wage losses can expected to be larger when changing. The economic significance of the results is large, indicating that the specificity of an occupation as measured by our new indicator could be an important policy instrument for the development of VET curricula to increase the flexibility of VET-trained individuals.

The paper proceeds as follows. In the next section, we introduce Lazear's (2009) skill-weights model as a theoretical foundation to measure the distance between occupations and the specificity of occupations that can be expected to affect the long-term labor market outcomes

of graduates. The third section gives a brief overview over regulatory aspects of the Swiss VET system. Section four explains the empirical construction of our measures for distance and occupational specificity. We introduce our data and our dependent variables for measuring labor market outcomes, i.e. wage changes and probability of occupational changes in section five. In section six we explain our estimation strategy and in section seven we present our empirical results. The last section discusses the findings and concludes.

Theoretical Background: The Specificity of Occupations

So far, many studies have compared the labor market outcomes of VET-graduates and academic graduates.[5] For example, Eymann and Schweri (2011) find for Switzerland that individuals with tertiary academic education exhibit the highest probability of long-term occupational mobility. Upper secondary VET-graduates, on the other hand, are found to have only a marginally higher rate of mobility than individuals with compulsory schooling. However, these studies do not keep the level of education constant and even more so they do not distinguish between differences across occupations and VET-programs. Only little research exists on how various VET training programs differ in preparing graduates for long-term labor market outcomes and flexibility.

In this paper, we examine the differences between VET-occupations and their labor market consequences. A crucial aspect for labor mobility is human capital specificity. Economic theory has proposed different concepts of human capital specificity. While early research has focused on the role of firm-specific human capital (Becker, 1964), more recent empirical evidence suggests that occupation- or industry-specific human capital is an important determinant of earnings (Neal, 1995; Parent, 2000). Once occupational tenure is accounted for, firm tenure has only a very small effect on wages (Kambourov & Manovskii, 2009; Nawakitphaitoon, 2014).

We focus on the skill distances between occupations and the specificity of an occupation in comparison to the overall labor market as two important labor market indicators of occupational training curricula. Lazear (2009) presents a theoretical approach, which provides an ideal basis for our curriculum analysis. In his skill weights model, human capital specificity is determined at the level of single skills. Lazear's basic assumption is that all

[5] E.g. Eymann and Schweri (2011); Winkelmann (1996); Malamud and Pop-Eleches (2010); Hanushek, Woessmann, and Zhang (2011); Korpi and Mertens (2003).

skills are general and transferable across firms, but each firm requires different skills with different weights attached to them. This difference in skill weights across firms makes a worker's skill bundle more or less specific. The novelty of the model is that there is no a priori distinction between general and specific human capital. Instead, the key element of the model is the labor market demand for skills.

In Lazear's basic model, there are two completely general skills, A and B, and two periods. Firms use these skills in different combinations to produce output. The relative weight of skill *A* in firm *i* is denoted with λ_i, where $0<\lambda_i<1$. The productivity, or the potential earnings, of a worker with skills *A* and *B* in firm *i* is given by:

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

λ_i is a realization of the random variable λ, which has the probability density function f(λ). Investments in skills are made in the first period in firm *i* and payoffs are received in the second period in either the training firm *i* or an external firm *j*. Lazear mentions the idea that skill weights might also relate to occupations instead of firms. In this study, we translate Lazear's approach and use occupations instead of firms, i.e. workers are trained in an occupation *i* in the first period and receive payoffs in a second period either in the same occupations *i* or a different occupation *j*. From the modeling perspective, virtually nothing changes by expanding the skill weights view to occupations. An occupation is defined to be very specific if the skill weights of that occupation are very different from the mean of all occupations i.e. if $\lambda_i - \bar{\lambda}$ is high. The definition of the specificity of an occupation thus depends on labor market requirements. If the skill weights in an occupation are similar to many other occupations, then these skills can be easily marketed on the labor market. Such an occupation is therefore called highly general. On the other hand, if an occupation for example contains a dominant skill that is used in no other occupation, i.e. its skill weights are very unique, the skills can be less easily transferred to a different occupation. Such an occupation is therefore called highly specific.

In Lazear's model on firm-specific skills, the likelihood of changing the firm is lower if the firm's skill weights are more specific. Analogously, in our empirical analysis, we expect to find that the likelihood of changing occupations is lower if the skill weights of that occupation are more specific.

Lazear's model also helps to predict the wage changes that workers have to expect if they do change their job, or in our case their occupation. The productivity – and therefore the wage

changes – after a job change are given by the skill weights in the training firm *i* in comparison to the skill weights in the new firm *j* multiplied by the value of the respective skill:

$$W_{firm\,i} - W_{firm\,j} = \lambda_i A + (1-\lambda_i)B - \lambda_j A - \left(1-\lambda_j\right)B = (\lambda_i - \lambda_j)(A-B)$$

The more different the skill weights in the new firm in comparison to the old firm, the larger the wage change.

Accordingly, wage changes after an occupational change are given by the skill weights in the old occupation in comparison to the skill weights in the new occupation. Occupational changes most likely lead to wage losses only, because a new occupation can never perfectly match the skills in the old occupation, which makes a part of the worker's human capital obsolete.[6] Thus, in our empirical analysis, we expect to find that the more the weights in the new occupation differ from the old occupation, the larger is the wage loss.

To test our hypotheses we need precise data on the skills that people learn in well-defined training occupations. Second, we need data on the distribution of these occupations in the overall labor market as well as data on occupational changes of graduates from these occupations and their wages before and after changes. We use data for Switzerland, because VET-occupations and their skill requirements for the dual track training system are very precisely specified in comprehensive training ordinances. This enables us to construct a data set with all the needed specifications, i.e. we create a detailed data set on the skill bundles of a large number of occupations. Additionally, the Swiss SESAM data provides us with the necessary labor market information. Since the structure of the VET-system and the requirements it imposes on training in all VET-occupations is important to understand how we build our measures and how well they fit our data requirements, we provide a short description of the Swiss VET system in the next section.

[6] Lazear argues that it is unlikely to find another job that matches the worker's portfolio perfectly if the worker expected to remain with the initial firm for a long time and invested accordingly. Following this argument, it is certainly the case that workers intend to stay in their trained occupation forever (and the curricula are designed accordingly).

Institutional Background: Regulations of Dual Track VET Occupations

In Switzerland dual track VET programs consist of two essential parts that are each well-defined and combined according to official training ordinances, i.e. training while working at a firm is combined with formal education at a vocational school. Both have their own detailed curricula that span over a period of three to four years. Overall, there are official training ordinances for about 250 different occupations (State Secretariat for Education, Research and Innovation, 2014). The curricula are legally binding for all firms that train apprentices in these occupations.[7] Apprentices spend one to two days a week at school and three to four days at their training firm. In the firm, apprentices are taught practical foundations of their occupation by a certified trainer (Berufsbildner). They acquire a predefined set of skills through a structured learning by doing process while actively participating in the firm's production. In the vocational schools, on the other hand, apprentices are taught the theoretical foundations by occupationally trained teachers. In addition to these two training partners there is often a third training partner, the inter-firm learning centers. They teach and practice occupational requirements that cannot be taught or practiced in the vocational school or training firm, i.e. their focus usually is on teaching the most modern occupational techniques and innovations that often have not yet arrived in all the participating training firms (Wettstein & Gonon, 2009).

At the end of their apprenticeship, the students have to pass a practical and a theoretical exam, which are both state-monitored. Apprentices who show a satisfactory level in all the skill requirements that are laid out in the official training curricula of their occupation receive their federal VET diploma (Eidgenössisches Fähigkeitszeignis EFZ). The training curricula describe the educational objectives in great detail and contain three hierarchical levels of goals: first level goals (competence areas), second level goals (learning objectives), and third level (operational) goals ("Leitziel – Richtziel – Leistungsziel"). For each goal, the occupational curriculum specifies the location (firm, school or inter-firm learning centers)

[7] For each occupation, the training contents and goals are specified in detailed training regulations, which are approved by the State Secretariat for Education, Research and Innovation (SERI). These training regulations are not developed by federal authorities, but by trade-, employer and employee organizations (hereafter called professional organizations), which can submit a new regulation or changes in existing regulations to the SERI. The SERI then, after consultation with the involved professional organizations and the cantons, decides if the regulation should be adopted (Wettstein & Gonon, 2009, pp. 100–104). The cantons in turn issue training permits to firms and are responsible for the supervision of the vocational schools (State Secretariat for Education, Research and Innovation, 2014).

where students are introduced to a task and where they practice it. A typical curriculum contains about 100 operational goals and 30 pages of text. We use these detailed training curricula for the 80 most common occupations that cover about 73 percent of the active workforce (with VET training) to construct our occupational specificity and distance measures.

Measuring Occupational Distance and Specificity

Skill Bundles of Occupations

To construct our empirical measures we use the information provided by official, legally binding training ordinances. Previous research has used other methods to measure the skill content of occupations, for example standardized job descriptors (e.g. the U.S. Dictionary of Occupational Titles DOT, cf. Ingram & Neumann, 2006; Poletaev & Robinson, 2008; Robinson, 2011) or survey information on the skills that are required in individual worker's jobs (e.g. the German BIBB/IAB Qualification survey, cf. Bublitz, 2013; Fedorets, 2011; Gathmann & Schönberg, 2010; Mure, 2007; Wiederhold, Nedelkoska, & Neffke, 2013). However, for our purpose, these methods are not adequate, because they do not measure curriculum content.

Before we construct our specificity and distance measures we need a full set of all single skills that is exhaustive (i.e. it encompass the entire range of all occurring skills) and exclusive across all occupations (i.e. identical skills must be identified). We identify the single skills by using the second level goals. In the first step, we list all second level goals of all occupations and thereby gather the full (exhaustive) set of all occurring skills. For example, a second level goal for cooks is "nutrition" (under the first level goal of "preparing food"). It includes the operational goals "nutrients", "human metabolism", "human energy needs" and more.

Table 1: Extract of the goal hierarchies for cooks (Koch EFZ) and bakers-confiseurs (Bäcker-Konditor-Confiseur EFZ), simplified

Cook	**Baker**
1. Preparing Food 1.1. Raw Materials (vegetables) 1.1.1. Flour 1.1.2. Fruits 1.1.3. … 1.2. Raw Materials [2] (others) 1.2.1. Meat 1.2.2. Oils 1.2.3. … 1.3. Nutrition 1.3.1. Nutrients 1.3.2. Metabolism 1.3.3. … 1.4. Cooking 1.5.… 2. Hygiene 3. ...	1. Craft and technology 1.1. Raw Materials 1.1.1. Flour 1.1.2. Meat 1.1.3. … 1.2. Nutrition 1.2.1. Nutrients 1.2.2. Metabolism 1.2.3. … 1.3. Baking 1.4. … 2. Business Administration 3. Hygiene and safety 4. …

Source: Own compilation based on Swiss VET regulations.

In the second step, we compare the second level skill sets of two occupations and determine if two skills are actually identical, i.e. we make sure that all skills are exclusively defined. Consider the example in table 1. The skill “nutrition” appears in the curricula of cooks and bakers (and some other occupations as well). When we compare the descriptions and third level goals of “nutrition” in both curricula, it is obvious that they are identical, given that both curricula use the exact same words. However, some cases are more complicated. Cooks have two second level goals for “raw materials”, one for vegetables and one for others. Bakers only have one goal, but it covers both, vegetables and “other raw materials”. Imagine there would be a third occupation that uses only vegetables. In this case, we would have to keep both skills separately. However, since there is no such occupation, we can collapse the two second level goals for cooks (vegetables and others) into one single skill (food raw materials). We continue this comparison process until we have basically compared the skill sets of every occupation with all the others. With this procedure, we find a set of about 150 single skills. Although most skills find an equivalent in at least some other occupation, it may occur that a skill is unique to one single occupation (less than 20% of the single skills). For example, bakers are

the only ones who learn how to bake, while (basic) cooking is also required by other occupations (e.g. caretakers).

In contrast to previous studies using skill data, we also need detailed information about the weights of the single skills in a particular occupation. We approximate these weights by simply counting the number of third level (operational) goals that are specified for that single skill in a curriculum. This can be explained by coming back to the example of cooks and bakers: if cooks have 13 operational goals for "(food) raw materials" (out of total 72 goals), "raw materials" have a weight of 18 percent; if on the other hand bakers have 14 of a total of 64 goals associated with "raw materials", their weight is 22 percent. We do so because we assume that the importance of a skill in an occupation is reflected in the extent of the specifications that are given to it. We do this not only for the practical training but also for the schooling parts of the training for which we use the class schedule and the exact number of lessons assigned to a certain subject as our weights.[8]

As a result we now have a full set of single skills and the respective weights for all occupations. In the next step we use these weighted skill bundles to construct our measures for the distance between any two occupations and for the specificity of an occupation in comparison to the overall labor market.

Skill Distance

The idea of our distance measure is that it captures the overlap of the skill bundles of two occupations and that it indicates the extent to which skills can or cannot be used after an occupational change between these two occupations. In Lazear's model with only two skills it is straightforward to calculate the distance between two skill bundles: it is the difference in the relative skill weights ($\lambda_i - \lambda_j$). Since in our empirical application we have up to 150 single skills instead of two, we have to extend his idea to a multidimensional case. We do this by using the angular separation as introduced by Gathmann and Schönberg (2010).[9] We

[8] The relative weights of the schooling skills in comparison to the practical skills are determined by the share of time spend at school and at work. Since we know the exact proportion of time apprentices spend at the vocational school, we can weigh the skills learned at school and in practice accordingly. For example, lab assistants spend 30 percent of their time at school, and 40 percent of this time they attend chemistry lessons, so chemistry makes up 12 percent of their skill bundle.

[9] The angular distance is used in a similar context by Fedorets (2011) and Bublitz (2013). Alternative approaches to measure the transferability of human capital include measures based on the Euclidian distance (e.g. Robinson (2011)), factor score changes (e.g. Poletaev and Robinson (2008)) and differences and the frequency of occupational changes (e.g. Shaw (1987)), among other concepts.

calculate the distance between all the 3160 possible pairs[10] of occupational skill vectors according to following formula that also shows the conceptual overlap to Lazear's skill weights model.

$$AngularSep_{AB} = \frac{\sum_{i=1}^{n} x_{Oi} * x_{Pi}}{\sqrt{\sum_{i=1}^{n} {x_{Oi}}^2 * \sum_{i=1}^{n} {x_{Pi}}^2}}$$

O and *P* denote two occupations and x_{Oi} is the skill weight of skill *i* in occupation *O*. We assume that VET-workers hold a skill portfolio according to the skill weights of their training occupation, i.e. $\lambda = A$ and $(1 - \lambda) = B$. The numerator thus corresponds to the potential earnings of a worker in another occupation as specified in formula (1) of the skill-weights model. Each skill weight is multiplied with the corresponding weight of the succeeding occupation and then summed up. If a skill is used extensively in both skill bundles, the product and thus the degree of transferability of the skill to the new occupation is high. If a skill has a high weight in the worker's original occupation but not in the new one, the degree of transferability is low from the old to the new occupation. The denominator normalizes the results such that the sum always lies between zero and one. Since the angular separation captures similarity rather than distance, we reverse the measure such that a higher number corresponds to a larger distance and less skill overlap: distance = 1 – angular separation.[11]

We calculate this distance for all possible pairs of occupations so that we have an empirical distance measures for all possible occupational changes in our data set. The closest occupational change that we observe in our data takes place between a car mechanic and a motorcycle mechanic with a very small distance of 0.013; so these two occupations have almost the same skill bundle and weights. The most distant move that we ever observe in our data is from a production mechanic (Produktionsmechaniker EFZ) to a commercial employee (merchant; Kaufmann EFZ) with an almost maximum possible distance of 0.998. The most frequent change observed in the data is from a commercial employee to a retailer with a fairly

[10] $(n = \frac{80*(80-1)}{2} = 3160)$.

[11] Compared to alternatives distance measures e.g. the Euclidian distance, the angular separation method has several advantages for our application. Since we have more than 150 skill dimensions, many of our skill vectors are highly diversified. If two occupations are highly diversified, the vector endpoints will lie close to the origin of the coordinate system. The vectors will be "close" by the Euclidian measure, even if they are in fact completely orthogonal and use no identical skills at all. The angular separation is purely directional and thus insensitive to the length of a vector.

small distance of 0.188. The closest and most distant changes of selected occupations are shown in table 2.[12]

Table 2: Distance between selected occupations

Change from	Distance to (closest and most distant)	Distance measure	No. of obs.
Kaufmann EFZ	Detailhändler EFZ	0.188	174
	Produktionsmechaniker	0.998	4
Sanitärinstallateur EFZ	Heizungsinstallateur EFZ	0.163	3
	Kaufmann EFZ	0.971	3
Grafiker EFZ	Polygraf EFZ	0.116	5
	Schreiner EFZ	0.893	1
Fachmann Gesundheit EFZ	Fachmann Betreuung EFZ	0.039	38
	Gärtner EFZ	0.985	3
Elektroniker EFZ	Informatiker EFZ	0.181	4
	Kaufmann EFZ	0.962	2
Florist EFZ	Gärtner EFZ	0.273	2
	Polymechaniker EFZ	0.977	1
Lebensmitteltechnologe	Milchtechnologe EFZ	0.215	1
	Kaufmann EFZ	0.982	1
Metallbauer EFZ	Carrossier Spenglerei	0.095	3
	Landwirt	0.908	2
Laborant (Chemie) EFZ	Med. Praxisassistent EFZ	0.540	3
	Fachmann Betreuung EFZ	0.917	1

Source: own calculations, based on SESAM 1999-2009 and skill-data from Swiss trainings regulations; Number of observations includes changes in both directions; Occupations are selected to give an impression for various sectors and branches.

Occupational Specificity

The idea of our specificity measure is that, in analogy to Lazear's model, it captures how specific the skill bundle of an occupation is in comparison to the skill bundles of all occupations used in the overall labor market. Therefore, to measure the specificity of an occupation, we have to combine the information on the distance between any two occupations with representative labor market data for all workers with VET education. We use the number of jobs in all of our occupations to represent the distribution of the skill bundles in the overall

[12] All full list of all occupational distances is available upon request from the authors.

labor market. In detail, we construct the specificity measure by calculating a weighted average distance of any one occupation to all other occupations in the labor market. The weights are the relative frequencies of the jobs in one occupation in comparison to jobs in all other occupations in the labor market. By doing so we incorporate the potential demand for a particular occupational skill bundle in our occupational specificity measure. The specificity measure is thus mathematically equivalent to the expected average distance that workers have to bridge if they are forced to leave their occupation and randomly take the next vacant job. This also means that our degree of specificity is dependent on the labor market and cannot be derived by only comparing the skill bundles across occupational curricula. A rather general skill bundle includes many transversal skill elements and exhibits a small difference between its own skill weights and the outside market weights.

We show the empirical results for our specificity measures in table 8 in the appendix. As can be seen, the most specific occupation is watchmaker (Uhrmacher Rhabillage EFZ). The most general (unspecific) occupation is merchant (Kaufmann EFZ).

Table 3: Skill weights (examples)

Skill	Required by x occupations	Min weight	Mean weight	Max weight	Polytechnics	Commercial employees	Watchmakers	Logistics expert
Top 12								
Work safety	77	0.008	0.070	0.286	0.044	0.000	0.013	0.128
Operational planning	73	0.002	0.025	0.203	0.008	0.023	0.040	0.008
Mathematics (School)	51	0.002	0.018	0.091	0.029	0.010	0.025	0.010
Quality assurance	43	0.008	0.009	0.176	0.000	0.000	0.060	0.006
Documentation	43	0.004	0.010	0.106	0.000	0.000	0.004	0.008
Manual manufacturing	41	0.000	0.015	0.340	0.091	0.000	0.000	0.000
Customer service	41	0.002	0.044	0.450	0.000	0.100	0.010	0.060
Office/User software	41	0.004	0.021	0.126	0.016	0.037	0.000	0.048
Machinery care	38	0.004	0.012	0.089	0.008	0.000	0.000	0.000
Data administration	36	0.000	0.013	0.107	0.000	0.028	0.000	0.008
Stock keeping/logistics	36	0.002	0.044	0.446	0.000	0.047	0.002	**0.446**
Physics	35	0.002	0.005	0.061	0.033	0.000	0.017	0.000
					…	…	…	…
Automated manufacturing	9	0.004	0.011	0.038	**0.225**	0.000	0.000	0.000
Business administration	24	0.002	0.076	0.224	0.000	**0.224**	0.000	0.008
Precision assembly	14	0.004	0.006	0.557	0.070	0.000	**0.557**	0.000

Table shows descriptive statistics for the most prevalent skills, based on incidence. Occupations are chosen to represent each quarter of the specificity distribution. The mean values are weighted by the size of occupations. Skills printed in bold are the most important skill of the respective occupation.

Table 3 gives an impression of the skill bundles of watchmakers, merchants, polytechnics and logistic experts. We show descriptive statistics for the twelve most prevalent skills across all occupations (and three other skills). The table shows that watchmakers have very specific skill weights, because they have a strong focus on precision manufacturing. However, a high weight on one skill necessarily means a lower weight on all other skills. If an occupation scores exceptionally high on a single skill, this occupation becomes specific, even if the skill category per se is widely distributed.

Consider for example the skill “logistics”. In most curricula, “logistics” does not account for more than ten percent of all specified goals. An exception is logistic specialists (Logistiker EFZ). For them, almost 45 percent of all goals fall into this category. Many workers in sales and even in production learn basic skills in logistics, such as stock-keeping and simple storage techniques. Logistics specialists master all these simple tasks, but in addition are also familiar with complex allocation techniques and warehouse management systems. This specialized knowledge may not be of much use if the logistic specialist switches occupations. Thus, even though logistic experts are skilled in some of the most widely used skills, their overall skill bundle is rather specific.

Data

Labor Market Data

Our data source for the labor market histories of individuals is the Social Protection and Labour Market (SESAM) survey provided by the Swiss Federal Statistical Office. It is a combination of the Swiss Labour Force Survey (SLFS) and additional matched information from several social insurance registers. The SLFS is conducted annually via telephone interviews. It comprises a representative sample of the Swiss population over the age of fifteen with about 50,000 interviews per year (15,000 until 2001) selected at random from the telephone book (Bundesamt für Statistik, 2011). It provides rich information on employment status, education histories and socio-demographics. The SESAM has a rolling panel structure; individuals are followed for up to five years and we use data from the years 1999 to 2009. This allows us to identify occupational changes by comparing occupation codes in two consecutive years. We have information on the firm tenure and administrative wage data for each job. Additionally, we can check if individuals have completed a dual track VET training and if they are still working in their original training occupation.

To identify occupational changes, we rely on the Swiss Standard Classification of Occupations (SBN2000) provided in the SESAM. We compare the occupation of an individual for each pair of consecutive years t_0 and t_1 during the sample period. We consider changes at the most disaggregate level possible (the five-digit level). On this very detailed level, we can precisely match the SBN codes to the corresponding VET training programs.[13] We assume the skills required in an occupation to be identical during our whole observation period (1999-2009). Additionally, we merge the codes of revised training occupations with the codes of their predecessor occupations using a database on the evolution of VET occupations provided by the SERI (Grebasch, 2013).[14]

Sample and Descriptive Statistics

Our sample includes individuals with a VET diploma between the ages of 18 and the mandatory retirement age (64 for women and 65 for men). Individuals must have worked at least once during the observation period in order to be included. We include all individuals who are working in one of the 80 (certified) VET-training occupations (for which we have skill data) when we observe them for the first time. We exclude individuals who have acquired additional formal qualifications (e.g. higher professional qualifications, vocational baccalaureate, university degree). This restriction ensures that we have a very homogeneous sample of individuals with a uniform level of education. Occupational changes are quite common; overall, 40 percent of all workers in our data are not employed in their training occupation anymore when we observe them for the first time. In this study, we focus on career changes. Workers who change to managerial positions within the same occupational field (occupational advancement e.g. from merchant to chief accountant) are coded as occupation stayers. After eliminating observations with missing data, the sample counts 15,260 individuals (or 62,107 single observations) trained in one of the 80 training occupations for which we have skill data. As mentioned earlier, these 80 occupations cover 73

[13] In some rare cases, corresponding three and four-year apprenticeships are pooled in the same 5-digit occupation, e.g. we cannot distinguish Automobil-Fachmann EFZ/Automobil-Mechatroniker EFZ. However, the skill portfolios of these occupations are identical with the exception that the four-year programs include some additional topics.

[14] VET occupations are regularly revised. In this process, occupations are sometimes assigned with a new name and SBN code. For example the occupation “Mechapraktiker” was revised in 2008 and is now known as “Produktionsmechaniker EFZ”. If an individual changes between old and new codes, we do not consider this to be an occupational change. The individual merely followed the technological progress. In other words we assume that he or she updated his knowledge with on-the-job practice.

percent of all VET-trained individuals in the data.[15] In total, we observe 1,232 individuals, who performed an occupational change during the sample period (and between two of our 80 occupations).

Table 4 presents descriptive statistics for the full sample of individuals (including those who changed their occupation). Please note that all control variables are evaluated when the individual first enters the sample. For comparison, table 5 shows the same statistics for those individuals only who changed their occupation during the observation period.

Table 4: Descriptive statistics - Full sample

Variable	N	Mean	St. Dev.	Min	Max
Individual characteristics					
Age	15,260	40.52	11.39	18	64
Firm tenure	15,260	9.54	9.34	0	46.40
Male	15,260	0.498	0.500	0	1
Married	15,260	0.555	0.497	0	1
Swiss	15,260	0.699	0.459	0	1
Labour market status					
Fulltime	15,260	0.684	0.465	0	1
Wage	15,260	5,680.1	2,754.6	98.8	41,687.1
Firm size	15,260	9.945	4.387	1	14
Size of occupation	15,260	2,566.16	2,892.09	7	7,138
Explanatory variable					
Occupational Specificity Measure	15,260	0.798	0.086	0.601	0.928

Source: own calculations, based on SESAM 1999-2009.

Individuals are on average 40 years old and have been working for the same firm for 9.5 years. The average observation period per individual is 3.2 years. About 50 percent of the sample is male and 55 percent are married. 70 percent are Swiss nationals. The average gross wage (earned income) is 5,650 Swiss Francs. All individuals in this sample are employed before changing their occupation.[16]

[15] In Switzerland individuals with VET training make up an important part of the labor market, with almost two thirds of all youths enrolling each year (State Secretariat for Education, Research and Innovation, 2014).
[16] Please note that they still might have unemployment spells during the observation period. We additionally performed a robustness test (not reported) where we also included initially unemployed individuals, which did not qualitatively change our results. Note that we cannot include controls for tenure, wage and firm size in this robustness check.

Table 5: Descriptive statistics - Occupation switchers only

Variable	N	Mean	St. Dev.	Min	Max
Individual characteristics					
Age	1’232	38.16	11.20	18	64
Firm tenure	1,232	6.54	7.85	0.008	46.40
Male	1,232	0.496	0.500	0	1
Married	1,232	0.519	0.500	0	1
Swiss	1,232	0.696	0.460	0	1
Labour market status					
Fulltime	1,232	0.652	0.477	0	1
Wage	1,232	5,353.4	5,246.3	152.1	40,983
Firm size	1,232	9.884	4.270	1	14
Workers in occupation	1,232	1,754.83	2,379.91	7	7,138
Explanatory variable					
Specificity Measure	1,232	0.789	0.094	0.601	0.928

Source: own calculations, based on SESAM 1999-2009.

The subsample of the occupational changers is almost two years younger and has significantly lower wages. Additionally, changers are more often working part-time. There are no significant differences in gender for occupational changers and non-changers. Concerning the size of an occupation, workers in thinly populated occupations change their occupation more often. The specificity measure as our explanatory variable is on average slightly lower for the subsample of occupational changers.

To study the wage effects of occupational changes, we focus on the subsample who changed their occupation during the observation period. Workers must be employed in the year before and immediately after the change to be included in the wage analysis.[17] We use the register based wage data from the SESAM. We include part-time workers since part-time employment is quite common in Switzerland (33.6 percent work less than 90 percent, see Bundesamt für Statistik, 2014), but we calculate the workers full-time equivalent wages per month for their main job.[18] The wages are adjusted for inflation (base year 2004). After applying our sample

[17] If an individual changed his occupation twice or more times during the five-year observation period, we analyze only the wage effect of the first change to avoid cases where individuals hold jobs only temporarily.
[18] To increase the plausibility of our analysis, we drop observations with wages belonging to the highest or lowest per mille (n=64). If the individual was not working in the same firm for the entire month before the interview, we set the wage to missing (n=74), because the wage in this month will most likely be too low.

restrictions, the subsample for which we have wage data reduces to 1,142 individual cases.[19] Most interestingly, 78 percent of all occupational changers achieved a wage gain already in the first year after the change.

Empirical Estimation

Occupational Distance and Post-Switching Wages

We estimate the effect of our occupational distance measure on the post-switching wages of workers. According to Lazear's concept of specific human capital, this difference should depend on the distance of the worker's skill weights (the skill weights of the training occupation) and the required skill weights in the target occupation. Recent empirical studies indeed find evidence that wages after an occupational change depend negatively on the dissimilarity or the skill distance between occupations (Gathmann & Schönberg, 2010; Geel & Backes-Gellner, 2011; Nedelkoska, 2010; Poletaev & Robinson, 2008; Rinawi, Krapf, & Backes-Gellner, 2014; Wiederhold et al., 2013). To confirm the theoretical predictions and to show that our skill bundles have predictive power for post-switching wages, we estimate the following model (similar to the specification of Nedelkoska, 2010) using OLS estimations (model 1):

$$w_{i,O2,t+1} - \overline{w}_{O2} = \beta * distance_{i,O1-O2} + \gamma * X_{i,t} + \delta * unempl.rate_t + \varphi_t + \omega_i + \varepsilon_{i,O,t}$$

The dependent variable is the deviation of the individual's wage after the change ($w_{O2,t+1}$) from the average starting wage in the target occupation ($\overline{w}_{O2}$). We calculate the starting wage in an occupation by taking the average first-year-wage of individuals who change their workplace (firm) but not their occupation. The main explanatory variable is the skill distance measure between the worker's origin occupation and the target occupation ($distance_{O1-O2}$). If a worker is equipped with the optimal skill-portfolio for the new occupation, he should earn a wage close to the average first-year wage of workers who change the firm, but not the occupation. If the candidate performs a distant switch and can thus use a small part of his skill-specific human capital only, he should earn a lower starting salary. We include a standard set of control variables ($X_{i,t}$) including age, age squared, nationality and marital

[19] This number is lower than the number of changers reported in table 5, because we now additionally require valid wage data in the year after the change (and not only before the change).

status, as well as region (ω_i) and year (φ_t) dummies. In a second specification, we add tenure in the previous job and tenure squared as controls.

Occupational Specificity and Occupational Mobility

To test our main hypothesis, we estimate the effect of occupational specificity on the probability of changing occupations using a probit model. Individuals change their occupation if they expect to gain more utility from changing than from not changing. Let $U_{switch,i} - U_{stay,i} = y_i^*$ denote an individual's net benefit of changing his occupation versus the alternative, which is staying. The utility difference, denoted $y_i^* = x_i'\beta + \varepsilon_i$ depends on the expected skill weights mismatch when changing, but it is not directly observable. However, we do observe whether an individual changed his occupation or not. Therefore, $y_i^* > 0$ if and only if $y_i = 1$ (occupational change) and $y_i = 0$ (no change) if otherwise. Thus, we can rewrite the probability of changing $P\{y_i = 1\} = P\{x_i'\beta + \varepsilon_i > 0\} = P\{-\varepsilon_i \leq x_i'\beta\} = F(x_i'\beta)$, where F denotes the distribution function of ε_i which is assumed to have a standard normal distribution. To estimate the model, we use maximum likelihood estimation (Wooldridge, 2002). Our explanatory variables are:

$$x_i'\beta = \beta_1 specificity + \beta_2 OS + \beta_3 male + \beta_4 swiss + \beta_5 married + \beta_6 age + \beta_7 age^2 + \beta_8 UR + \beta_9 tenure + \beta_{10} tenure^2 + \beta_{11}\log(wage) + fimsize + \varphi_t + \omega_i$$

We expect a negative influence of our main variable of interest, the skill specificity of training curricula, on the occupational mobility of workers in VET occupations. We introduce the following control variables, which are related to occupational mobility.

The variable "size of occupation" (OS) measures how many people are currently working in the same occupation. We control for the size of an occupation in our regression analysis, because large occupations offer a larger range of specializations and workers in large occupations might have more suitable job options in their current occupation.[20] We expect that the more people work in the same occupation as a given worker, the more options he has to find a suitable job without changing his occupation.

[20] It is important to note that the size of an occupation does not determine its specificity. Small occupations might be very unspecific, for example if they are positioned in the center of a sizable local skill cluster, close to many similar occupations. The correlation between the specificity measure and the size of an occupation is 0.02.

We include a comprehensive set of individual characteristics (gender, age, nationality and marital status) which have been shown to influence the probability of occupational changes (Bleakley & Lin, 2012; Eymann & Schweri, 2011; Fitzenberger & Kunze, 2005; Shaw, 1987). Furthermore, ω_i and φ_t denote region and year fixed effects, respectively, and the regional (cantonal) unemployment rate (*UR*) controls for local labor market conditions. We include tenure with the current firm as control variable, which has been established as a proxy for firm-specific human capital by a vast number of empirical papers (e.g. Kambourov & Manovskii, 2009; Sullivan, 2010). Employees from large firms have been found to change occupations less often, at least shortly after the completion of the training (e.g. Bougheas & Georgellis, 2004; Winkelmann, 1996). If small firms are mainly active in specialized occupations, this could bias the results of the specificity measure, which is why we include dummies for firm size (14 categories). We additionally add a control for the worker's wage before the change. Higher wages are associated with less occupational mobility (Parrado, Caner, & Wolff, 2007). If high specificity occupations pay higher wages, this might induce a downward bias the estimation of the specificity coefficient.

Results

Post-Switching Wages

First, we test if the relationship between our distance measure and the post-switching wages is significantly negative. Table 6 reports the results for model 1, which explains workers' deviation from the mean starting wage in the new occupation depending on the skill distance to her or his previous occupation.

Table 6: Wages after change - Results

	Specification (1)	*Specification (2)*
Distance	-0.1468***	-0.1413***
	(0.0533)	(0.0529)
Age	0.0073	0.0048
	(0.0102)	(0.0103)
Age squared	0.0000	0.0000
	(0.0001)	(0.0001)
Male	0.1884***	0.1592***
	(0.0310)	(0.0325)
Swiss	0.0718**	0.0545
	(0.0357)	(0.0360)
Married	0.0126	0.0017
	(0.0345)	(0.0336)
Firm tenure		0.0222***
		(0.0064)
Firm tenure squared		-0.0004***
		(0.0002)
Constant	-0.2641	-0.2145
	(0.2029)	(0.1990)
Year and region dummies	included	included
F-statistics	3.802	4.516
R^2	0.070	0.096
N	1,142	1,142

*Table reports coefficients of an OLS regression; dependent variable: deviation from mean (log) entry wage after change; (robust) standard errors in parentheses, * (**,***) denotes statistical significance at the 10% (5%,1%) level.*

Our distance measure has predictive power in explaining human capital loss when changing occupations. The estimated coefficient of the distance measure is significantly negative on the 1 percent level. A high distance leads to a skill-specific human capital mismatch and a lower starting wage at the job after the switch. This result is in line with the skill weights model of human capital and previous research on occupational mobility.

Males have significantly higher (full-time) wages compared to females in the same occupation, even though all workers have the same level of education and we control for (pre-change) tenure in specification 2. Tenure in the last firm before the change also has a positive effect, which is consistent if skills are transferable between occupations.

Occupational Mobility

The results for our main hypothesis (model 2) are shown in table 7. The occupational specificity measure has the expected negative effect and is statistically significant on the 1 percent level. Individuals from occupations with specific training skill bundles exhibit significantly less occupational mobility (in line with Rinawi et al., 2014). Learning a specific occupation ties a worker to this occupation.

Table 7: Occupational mobility, probit regressions - Results

	Coef.	*dy/dx*
Specificity (standardized)	-0.1032***	-0.0132
	(0.0269)	
Size of Occupation	-0.0001**	-0.0000
	(0.0000)	
Age	-0.0015	-0.0002
	(0.0113)	
Age squared	-0.0000	-0.0000
	(0.0001)	
Male	0.1347	0.0172
	(0.0853)	
Swiss	0.0317	0.0041
	(0.0433)	
Married	-0.0458	-0.0059
	(0.0468)	
Local unemployment rate	0.0013	0.0002
	(0.0501)	
Firm tenure	-0.0456***	-0.0058
	(0.0066)	
Firm tenure squared	0.0009***	0.0001
	(0.0001)	
Fulltime employment	-0.1560***	-0.0200
	(0.0294)	
Ln (wage before change)	-0.2012***	-0.0258
	(0.0484)	
Year and region dummies	included	
Firmsize dummies	included	
Pseudo R^2	0.074	
N	15,260	

*Table reports marginal effects at the means; robust standard errors in parentheses (clustered by specificity), * (**,***) denotes statistical significance at the 10% (5%,1%) level. Source: own calculations, based on SESAM 1999-2009.*

An increase in the specificity index of one standard deviation decreases the probability to belong to the group of occupational changers during the observation period by about 1.3

percentage points. The predicted probability difference between the most specific (watchmaker) and the most unspecific occupation (merchant) is -8.0 percentage points (0.123-0.043), evaluated at the mean of all other variables.

The control variables are in line with our expectations. The size of an occupation has a negative influence on the switching probability. Workers in populated occupations seem to have more appropriate job options within the same occupation. Tenure with the last firm has a highly significant and decreasing negative effect, which suggests that the loss of firm-specific human capital might be an important factor when changing occupations. On the other hand, age has no significant effect on the probability to belong to the group of switchers. Finally, the results show that workers with higher wages are significantly more likely to stay in the same occupation than workers with lower wages. However, separate regressions show the specificity measure is robust to the inclusion of the wage control.

Discussion and Conclusions

We analyze the curricula of apprenticeship trainings regulations and use them to extract basic skill bundles of the corresponding occupations. Following the model of Lazear (2009), we present evidence that human capital can be broken down to a bundle of basic skills, which can be used in a wide variety of jobs. Skills acquired in the previous occupation are not lost if workers change into occupations with similar skill requirements. The overlaps of skill bundles between two occupations have explanatory power for the wages after an individual switches from one occupation to another. VET is not a “closed” system that sentences students to a lifetime bet on a potentially disappearing occupation but an opportunity to collect a bundle of skills that can be leveraged in other occupations as well. However, these basic skill bundles can be ranked in terms of how specific they are, compared to the average skill distribution in the labor market.

The degree to which human capital acquired during VET is specific to occupations is an important policy issue for the curricula development of apprenticeship occupations. Pupils must decide for an apprenticeship occupation at a young age. Choosing a highly specific occupation can limit their options later, when personal or economic changes call for flexibility. In this regard, apprentices might profit from more widely applicable skills to increase their flexibility.

Our specificity measure captures the extent to which training occupations include skills that are required or utilized as a shared knowledge base across a wide range of applications.

Consequently, we argue that the measure we develop helps to shed light on the intensely debated educational policy question of how an occupation could and should be shaped to include more “transversal knowledge elements” and to offer flexibility and favorable long-term labor market outcomes for apprentices. We show that occupations are sets of general single skills that become specific only by the weights that they have in different occupational curricula. We also show that the higher the specificity of an occupation, the smaller is the probability that workers will change their occupation. If individuals from highly specific occupations do switch their occupation, they have to expect a wage penalty after the change.

At the same time, we show that, unlike the policy discussions suggests, small occupations with only a limited supply of jobs are not necessarily specific and larger occupations with more jobs are not necessarily general. We thus argue that the number of jobs in an occupation or the number of different occupations in a VET-system is not per se what is relevant for the flexibility of workers. What does however matter is the overlap and weights of skill bundles across occupations. Policymakers developing or modifying occupational training standards should therefore always evaluate the applicability of the skill bundle in reference to the labor market and particularly in comparison to neighboring occupations from different industries to reduce the risk of creating occupations that are likely to become obsolete. Our method provides a first conceptual basis for such an analysis and might help to identify which skill bundles and weights constitute “transversal knowledge elements” in occupational curricula. For example, skills in sales techniques, workplace safety, business processes or mathematics generate access to a great number of occupations. However, the advantage of creating occupations that are more general has to be counterbalanced by the disadvantage of a smaller fit of skills in the actual occupation and job.

Appendix

Table 8: Specificity measures (all occupations)

Occupation	Specificity	Occupation (continued)	Specificity
Uhrmacher Rhabillage	0.962	Grafiker EFZ	0.869
Innendekorateur (Polster)	0.952	Kaufmann EFZ	0.868
Milchtechnologe EFZ	0.945	Schmied-Hufschmied	0.868
Polybauer EFZ (Dachdecken)	0.935	Forstwart EFZ	0.866
Automobil-Mechatroniker	0.934	Schreiner EFZ (Bau)	0.866
Zahntechniker EFZ	0.931	Spengler EFZ	0.865
Informatiker EFZ	0.931	Gebäudereiniger	0.860
Motorradmechaniker EFZ	0.930	Drucktechnologe EFZ	0.860
Maler	0.930	Elektroinstallateur	0.859
Gärtner EFZ (GL)	0.929	Koch	0.857
Fachmann Gesundheit EFZ	0.922	Metallbauer	0.856
Strassenbauer EFZ	0.922	Florist	0.855
Coiffeur	0.919	Goldschmied EFZ	0.851
Konstrukteur EFZ	0.918	Lebensmitteltechnologe EFZ	0.848
Produktionsmechaniker EFZ	0.917	Netzelektriker EFZ	0.848
Landwirt EFZ	0.916	Multimediaelektroniker EFZ	0.846
Fotograf EFZ	0.916	Carrossier Lackiererei	0.845
Fachmann Betreuung EFZ	0.915	Fachmann Hauswirtschaft EFZ	0.842
Dentalassistent EFZ	0.915	Strassentransportfachmann EFZ	0.841
Zeichner EFZ	0.914	Carrossier Spenglerei	0.837
Landmaschinenmechaniker EFZ	0.910	Logistiker EFZ	0.835
Automatiker EFZ	0.908	Boden-Parkettleger EFZ (Textil)	0.833
Elektroniker EFZ	0.908	Müller EFZ (LM)	0.832
Gipser	0.907	Glaser EFZ	0.822
Polymechaniker EFZ	0.907	Fotofachmann EFZ	0.819
Bekleidungsgestalter	0.905	Medizinischer Praxisassistent	0.815
Kaminfeger	0.904	Laborant EFZ (Chemie)	0.799
Polygraf EFZ	0.898	Fleischfachmann	0.794
Feinwerkoptiker EFZ	0.890	Schuhmacher EFZ	0.794
Printmedienverarbeiter	0.889	Fachmann Kundendialog	0.790
Gebäudetechnikplaner (Heizung)	0.889	Hotelfachmann	0.788
Elektroplaner EFZ	0.888	Bahnbetriebsdisponent	0.788
Heizungsinstallateur EFZ	0.888	Augenoptiker EFZ	0.782
Zimmermann EFZ	0.886	Detailhandelsfachmann EFZ	0.779
Kosmetiker EFZ	0.886	Drogist EFZ	0.777
Anlagen- und Apparatebauer EFZ	0.882	Restaurationsfachmann	0.757
Bäcker-Konditor-Confiseur EFZ	0.879	Pharma-Assistent EFZ	0.740
Sanitärinstallateur EFZ	0.875	Polydesigner EFZ	0.737
Maurer EFZ	0.875	Buchhändler EFZ	0.696
Formenbauer	0.874		

Source: own calculations, based on SESAM 1999-2009 and skill-data from Swiss trainings regulations.

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