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Occupational Specificity: A new Measurement Based on Training Curricula and its Effect on Labor Market Outcomes

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Occupational Specificity: A new Measurement Based on Training Curricula and its Effect on Labor Market Outcomes

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Abstract: This paper proposes a new measurement for the specificity of occupations based on a content analysis of training curricula that we link to labor market demands. We apply Lazear's (2009) skill weights approach and test predictions on labor market outcomes derived from his theory. We find clear evidence of a trade-off between earning higher returns with more specific training and higher occupational mobility with less specific training. Our measure improves the micro-foundation of human capital specificity and provides an evidence-based approach to evaluate the specificity of training curricula.

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

JEL Classification: I20, J24, J62

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1. Introduction

According to traditional human capital theory, investments in specific human capital are considered to be riskier than investments in general human capital, but specific investments are also considered to generate higher returns (Heijke & Borghans, 1998). On the one hand, they are considered riskier because they limit individuals' ability to adapt to technological change, a view based on the assumption that individuals with specific human capital will find adapting to and operating new technologies, machinery and services more difficult. This lower adaptability might cause wage losses or unemployment (Hanushek, Schwerdt, Woessmann, & Zhang, 2017; Krueger & Kumar, 2004). On the other hand, investments in specific human capital are viewed as generating higher returns, because they are more closely tied to actual job requirements, thereby leading to higher productivity (Gervais, Livshits, & Meh, 2008; Wasmer, 2006). Thus, workers who have to decide whether to invest into more or less specific human capital face a trade-off between a higher return in a given job and a higher risk if they are forced to (or want to) change their current job. Similarly, educational policy makers have to decide how to design educational curricula: more or less specific to provide workers with different choices. In this paper, we investigate the returns and risks of investments in human capital by providing a new specificity measure.

We develop a measure for the specificity of a worker's human capital investment based on the skill[1] bundles as specified in occupational training curricula. Previous research typically makes a simple dichotomy of definitions and assumes that academic (college and university) education provides general skills and that vocational education provides specific skills, and compares the labor market returns of academic and vocational education (Hanushek et al., 2017; Korpi & Mertens, 2003; Malamud & Pop-Eleches, 2010). Several more recent studies indirectly measure specificity based on the wage differentials of occupational changers (e.g., Coenen, Heijke, & Meng, 2014) or based on the relative distribution of workers across occupations (Shaw, 1987; Vogtenhubler, 2014). Few studies explicitly analyze the specificity of human capital investments based on subject choices within study programs (e.g. Silos & Smith, 2015; Tchuente, 2016), but no study so far has analyzed differences in the educational content on the level of single skills when measuring specificity.

[1] In line with the literature using a task-based approach, we define skills as "a worker's endowment of capabilities for performing various tasks" (cf. Acemoglu & Autor, 2011). This definition includes practical skills as well as theoretical and practical knowledge.

Our measure relies on the identification of the bundle of single skills learned during an education program. Theoretically, this approach draws on Lazear's (2009) "skill-weights approach," which assumes that all single skills are general but that the combinations and weighting of these single skills, i.e., their uses, in different jobs make skill bundles more or less specific. Comparing the bundle and weights of single skills given by the curriculum of a training program with the required skills and weights in the overall labor market provides us with a specificity measure for this training program.

Our approach is related to and extends the approach of Geel, Mure, and Backes-Gellner (2011) and Rinawi, Krapf, and Backes-Gellner (2014), who calculate occupational skill bundles and specificity measures using survey data, and data from occupational counseling services, respectively. While they use data on the occurrence of skills in occupations, our approach is to directly gather skills from occupational curricula and to additionally generate weights for these skills and incorporate these weights into our specificity measure. To test the validity of our specificity measure and its relevance for labor market outcomes and educational policy making, we draw on Lazear's skill weights approach to derive and test hypotheses on the expected labor market outcomes of graduates of more or less specific training programs. In particular, we investigate the longer-term labor market outcomes of these graduates, i.e., their probability of changing occupations, their unemployment durations and their expected incomes, both, in their original occupation and after occupational changes.

For our empirical analysis, we use Swiss vocational education and training (VET) curricula not only because they provide detailed data on the single skills and weights that individuals acquire during their training (as verified by state-mandated examinations), but also because these VET occupations cover more than two thirds of the Swiss labor market. This wide coverage allows us to calculate reliable specificity measures by comparing an occupation's skill weights with those on the overall labor market. If a particular occupation requires skills and weights that are used only in a small number of jobs in the overall labor market, the occupation is defined as specific. However, if a particular occupation requires skills and weights that are used in a large number of jobs, it is defined as general.

Our results show that graduates of occupations with specific skill bundles have a smaller probability of occupational changes and search longer for a new job when unemployed, so that they are less mobile than graduates of general occupations. Yet, our results also show that graduates of more specific occupations earn higher wages as long as they stay in the occupation for which they were trained (the “training occupation”). Thus, we find clear evidence for a trade-off between earning higher returns in more specific occupations and benefitting from a higher occupational mobility in less specific occupations. The economic significance of these results is large, indicating that the specificity of an occupation as measured by our new indicator could be informative for educational and labor market policy.

Our paper makes three scientific and one practical contribution. Our first and most important contribution is that we develop a new measure of occupational specificity that directly links the content of a training curriculum to the labor market specificity of that training. The measure is based on Lazear’s skill weights approach and links the bundles of single skills in a given curriculum with the bundles of skills existing in the labor market. Thus, we directly connect the content of training curricula with its specificity on the labor market. By applying Lazear’s framework and linking the content of training curricula to the demand in the respective labor market we provide a direct, curriculum-based measure of specificity and contribute to the empirical micro-foundation of the specificity of human capital. In contrast, previous literature has mainly used indirect measures of human capital specificity, such as measures based on worker mobility or tenure. These measures, while very helpful with respect to many empirical questions in labor economics, do not help to draw direct conclusions on the relation between the content of training curricula, their labor market specificity, and the respective labor market outcomes for graduates.

Second, we show that there is substantial variation in the occupational specificity of VET programs and that this makes a difference for the labor market outcomes of graduates. Using our measure, we find that training curricula for some occupations are rather general, whereas others are very specific, and that some types of occupations, which have been assumed to be very specific in the past (for example occupations with small numbers of graduates) can actually be quite general.

Third, our occupational specificity measure provides empirical support for Lazear’s skill weights approach because it shows a direct link between the specificity of skill bundles and the labor market outcomes of individuals that invested in this type of human capital. Thus, we provide first-hand evidence that supports Lazear’s theory by directly linking the bundles of single skills prescribed in training curricula to labor market outcomes of the respective graduates. We apply the measure to test three hypotheses derived from Lazear’s skill weights approach. The skill weights approach predicts that workers with specific training earn a specificity premium if they stay in their training occupation, change occupations less often, and have longer unemployment durations. All three predictions are borne out in the data.

Fourth, as a practical contribution, we provide a specificity measure based on curricula content that is shown to be closely related to real world labor market outcomes. Our specificity measure thus provides an evidence-based tool to evaluate the specificity of occupational training programs. It can help practitioners to develop or revise training curricula, and we briefly discuss under which conditions the measure might help curriculum developers to evaluate the potential outcomes of introducing new or of changing existing training curricula. In particular, our approach allows to measure the specificity of newly developed or revised training curricula before they are even implemented (which is not possible with specificity measures used in previous literature because they rely on historical labor market data). Thus, our measure provides an empirical method that contributes to the development of policy tools to evaluate expected outcomes of introducing new or revising existing training curricula. In this context, one important empirical insight of our analyses is that, when designing new training programs, policy makers have to be aware of a trade-off between higher returns of more specific trainings as long as graduates stay in their occupation versus higher risks of more specific trainings in case graduates need to or want to change their occupation.

The rest of the paper proceeds as follows. Section 2 introduces Lazear's (2009) skill weights approach. Section 3 gives a brief overview of the regulatory aspects of the Swiss VET system. Section 4 explains the empirical construction of our measure for occupational specificity. Section 5 presents our data and dependent variables for measuring labor market outcomes. Section 6 explains our estimation strategy and Section 7 shows our empirical results. Section 8 concludes.

2. Theoretical Background: The Specificity of Occupations

Lazear (2009) presents a theoretical approach that provides an ideal framework for our analysis. His skill weights approach determines human capital specificity at the level of single skills. Lazear's basic assumption is that all single skills are general and transferable across jobs, i.e., firms or occupations, but that each job requires different skills with different weights attached to them. This difference in skill weights across jobs makes a worker's skill bundle more or less specific. The approach assumes no a priori distinction between general and specific human capital. Instead, the key element of the approach is the labor market demand for single skills and specificity only result from differences in skills weights in one job compared to the skill weights that are required in the overall labor market.

To obtain a measure for the specificity of an occupation's skill bundle, we have to consider the skill bundle in an occupation in comparison to the skill bundles in the overall labor market, i.e. in all other available occupations. An occupation is defined as "specific" if the skill weights of that occupation are very different from the skills weights in all other occupations. If the skill weights in an occupation are similar to those in many other occupations, then we define such an occupation as less specific, or "more general." Occupational specificity thus depends on the distribution of occupations in the overall labor market.

Using Lazear's model of specificity allows us to derive three implications for workers' labor market flexibility and wages, implications that also provide us with a test for the validity and accuracy of our specificity measure. First, Lazear's model has implications for the level of wages in more or less specific occupations. While less specific skill bundles facilitate the transfer to occupations outside the individual's occupational domain, a higher degree of specificity implies a higher fit of the training to the required skills in an occupation. This higher fit increases productivity (and thus wages[2]) in the given occupation.[3] We therefore expect to find a positive correlation between occupational specificity and wages for occupational "stayers" (i.e., workers who never change occupations after their initial training) in our empirical analysis.

Second, as a skill bundle's specificity increases, its potential relevance in other occupations decreases. When an individual leaves his or her occupation, the expected return of less specific skill bundles in the overall labor market is higher than the return to specific skill bundles, because more skills can be transferred to the new occupation. We thus expect that the more specific the skill bundle of a training occupation, the smaller the likelihood of occupational mobility among workers trained in this occupation.

Third, we expect a higher specificity to be associated with a longer search period for workers who become unemployed. In terms of Lazear's model, more time allows an individual to

[2] Wages increase only if the additional surplus is shared between firms and workers. Assuming that the worker's bargaining position is largely determined by his options in his given occupation (options that do not depend on outside occupations), he or she should be able capture at least a part of the surplus.

[3] For a detailed discussion of the incentives for specialization of human capital investments in a model with two independent skills that are linear in utilization, see also Rosen (1983).

obtain more job draws on the external labor market, which increases the chance of finding better matching skill bundles. As the probability of finding a suitable outside option grows higher with more draws, workers from specific occupations can at least partly compensate for their initial disadvantage by searching for a longer period.[4]

Before we introduce the empirical implementation of the specificity measure in Section 4, we present a brief description of the Swiss VET system. To illustrate why VET curricula lend themselves to measuring occupational skills, we briefly discuss the importance of VET in the overall labor market, the structure and development process of VET curricula, and the relevant institutions that ensure the practical implementation of the training.

3. Institutional Background: Prevalence and Regulation of VET Occupations in Switzerland

In Switzerland, VET is the predominant type of education at the secondary level. Two-thirds of a cohort of Swiss students attends VET after compulsory schooling. VET programs span between three to four years. They consist of two essential and well-defined parts that are combined according to official training regulations: on-the-job training while working at a firm and formal education at a vocational school. Each part, the firm as well as the school part, has detailed training curricula. Overall, VET regulations provide the training curricula for about 200 different occupations.[5] These curricula are legally binding for all firms and schools.[6] For each occupation, the training contents and goals are specified in detailed

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[4] If demand declines, workers also have the option of lowering their reservation wages to the market-clearing level instead of accepting unemployment. Workers with specific skill bundles face greater heterogeneity in valuation by potential employers than workers with general skill bundles. Lazear (2012) shows that, for these workers, the profit-maximizing strategy is to hold out for a better offer instead of accepting the market-clearing wage.
In Switzerland, most individuals are eligible for unemployment benefits. Unemployment insurance is mandatory for all employees and voluntary for the self-employed. The replacement rate is 70 percent of the insured wage and is paid for up to two years.

[5] This number does not include the less demanding two-year programs for the same occupations (Bundesamt für Statistik [BFS], 2009).

[6] Apprentices spend one to two days each week at school and three to four days at their training firm. In the firm, a certified trainer (*Berufsbildner*) teaches apprentices the practical foundations of their chosen occupation. Apprentices acquire a predefined set of skills through a structured learning-by-doing process while actively participating in the firm's production process. In the vocational schools, occupationally trained teachers give apprentices the necessary theoretical foundations for their occupation. In addition to these two training partners is often a third partner, the inter-firm learning center. These centers both teach and help apprentices practice occupational requirements that cannot be taught or practiced in the vocational school or training firm: These centers usually teach the latest occupational techniques and innovations, which some participating training firms might not have yet introduced (Rupietta & Backes-Gellner, 2012; Wettstein & Gonon, 2009).

occupational regulations approved by the federal government, i.e., the State Secretariat for Education, Research and Innovation (SERI).[7]

Each occupational training curriculum describes the educational learning outcomes on a three-hierarchical level of goals: first-level (competence areas), second-level (learning objectives), and third-level goals (operational goals) ("*Leitziel—Richtziel—Leistungsziel*").[8] A typical curriculum contains about 100 operational goals, specified within 30 pages of text.

The (third-level) operational goals describe specific, observable actions and behavior of the apprentices regarding precisely defined tasks. The operational goals are the basis for the daily trainings that apprentices receive in the companies and at school. From these goals, the trainers derive what they must teach their students and how they have to teach it, i.e. what activities or teaching materials they should use (Bundesamt für Berufsbildung und Technologie, 2007). These operational goals will later all be tested (practically and/or theoretically) in the final examination of an apprentice, and apprentices only pass the exam if they prove sufficient theoretical knowledge and practical skills in all the operational goals. It is therefore guaranteed that apprentices do acquire the skills that are listed in the operational goals and that therefore these operational goals provide a good indicator of the acquired skill bundles and thereby the specificity of the apprentices' human capital.

To construct our occupational specificity and distance measures, we use the training curricula for the 111 most common occupations. About 91 percent of all active workers with VET are trained in one of these 111 occupations, so we cover almost the entire relevant labor market of the workers in our sample.

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[7] These training regulations are the product of a negotiation between employer and employee representatives (the "professional organizations"), the Swiss federal state and the cantons. The development process is usually initiated by the professional organizations that recommend a new regulation or changes in existing regulations to the State Secretariat for Education, Research and Innovation (SERI). The SERI, after consultation with the appropriate professional organizations and the cantons, decides whether the regulation should be adopted. The cantons, in turn, issue training permits to firms and are responsible for supervising the vocational (State Secretariat for Education, Research and Innovation, 2014).

[8] This is called the "triplex" method of specifying occupational curricula. The SERI permits a second method, the "competencies-resources" method, which is applied in the health and metal-processing occupations. However, for our purposes, what is important is that these curricula also offer an inventory of all required skills similar to the hierarchical goals of the triplex method.

4. Measuring Occupational Specificity

4.1. Measuring the Bundle of Single Skills in Occupations

We gather the data on the skill bundles of occupations by performing a curriculum analysis. To construct our specificity measure, we need an *exhaustive* set of single skills in VET occupations. Moreover, we have to make sure that we recognize identical skills across occupations. In a first step, we identify single skills by using learning goals of the second hierarchical level. For example, a second-level learning goal for cooks is “nutrition”; it consists of the third level “operational” goals “nutrients,” “human metabolism,” and “human energy needs.”

Table 1: Examples for learning goal hierarchies for the occupations “Cook” (Koch EFZ) and “Baker-Confiseur” (Bäcker-Konditor-Confiseur EFZ), abridged version

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

Source: Authors’ compilation, based on Swiss VET regulations.

In the second step, we have to ensure that our list of skills is not only exhaustive but also *exclusive.* Thus, we compare all single skills across occupations and determine whether two skills are identical or different. In the example in Table 1, the skill “nutrition” appears in the curricula for both cooks and bakers (as well as some other occupations), and the third-level learning goals of "nutrition" are clearly identical in both curricula. Other cases are more complicated but we always single out a "lowest common multiple" for all single skills.[9]

With this procedure, we identify a set of 181 single skills. Although most skills find an equivalent in at least one, and very often multiple, other occupations, certain skills are unique to one occupation. In our data, such uniqueness appears in less than 20 percent of single skills. For example, only bakers learn how to bake, whereas (basic) cooking is also required by other occupations (e.g., caregivers).

Our approach also allows us to meet an essential part of Lazear's approach that has not been empirically operationalized so far: The weights of single skills in a particular occupation. As our single skills are derived from second-level learning goals, we approximate the weights of these single skills by counting the number of third-level operational learning goals and setting this number in relation to all operational goals in that occupation. This means that the skill weight of a single skill in a given occupation is defined by its share of operational goals compared to the overall number of operational goals in that occupation. Thus, we assume that the number of operational goals that is required for a single skill reflects the time and importance of that single skill in the respective occupation.[10]

We argue that this is a good approximation for two reasons. First, operational third level goals are structured according to Bloom's (1956) taxonomy. This structuring ensures that complex second level goals are divided in third-level sub-goals of similar complexity. Complex learning objectives are given more weight by more third-level operational goals, but the time required to achieve a third-level operational goal is relatively constant. Therefore, due to the curriculum development process of apprenticeship occupations in Switzerland, third-level

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[9] For example, cooks have two second-level goals for "raw materials": one for "vegetables" and one for "others," whereas bakers have only one goal that covers both. If there were a third occupation using only "vegetables," we would have to keep both skills separate. However, as no such third occupation exists, we can collapse the two second-level goals for cooks ("vegetables and others") into one single skill ("handling raw food materials").

[10] As the length of VET-programs is standardized, increasing the weight for one skill necessarily reduces the weight of all other skills in the bundle. For example, as cooks have 13 out of a total of 72 operational goals associated with "(food) raw materials," "raw materials" have a weight of 18 percent; and as bakers have 14 out of 64 goals associated with "raw materials," the weight is 22 percent. We determine the weights for both the practical and the schooling parts of the training, although for the schooling part our weights are the class schedule and the number of lessons assigned to a certain subject. The relative weights of the schooling skills, in comparison to the practical skills, are determined by the percentage of time spent at school and at work. As we know the exact proportion of time that 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, 40 percent of which they attend chemistry lessons. Thus chemistry makes up 12 percent of their skill bundle.

goals are ensured to take about the same amount of time to be mastered. Second, third-level training goals are tested in the final exams of the apprenticeship programs and thus have to be reliably and validly gradable. This implies that these goals have to be explained with a comparable degree of detailedness in order to be testable with comparable precision and quality across the training institutions.[11]

As a result, we have a full set of single skills with the respective weights for all occupations. In the next step, we use these weighted occupational skill bundles to construct our measure for the specificity of an occupation in relation to the overall labor market.

As examples for our single skills, Table 2 provides descriptive statistics for the 15 most prevalent skills across all occupations. The most widely used skill is “work safety,” followed by “operational planning”, “environmental protection” and “mathematics”.

[11] Of course, there will be occupations where single third-level goals need significantly more training time or effort than other third-level goals. These occupations introduce additional measurement errors and thus make the test of our hypotheses harder; if we still find statistically significant results, they provide an even stronger support for our hypotheses.

Table 2: Examples for Single Skills and Distribution of Skill weights (15 most prevalent skills across all occupations)

Skill	Required by # occupations	Min Skill weight	Mean Skill weight	Max Skill weight
Systematic analysis of work safety issues	104	0.002	0.066	0.183
Operational planning	97	0.005	0.043	0.204
Environmental protection	93	0.002	0.042	0.143
Mathematics	75	0.002	0.029	0.095
Quality assurance	70	0.002	0.032	0.176
Machinery maintenance and repair	68	0.001	0.028	0.094
Systematic documentation of products and processes	66	0.004	0.022	0.095
Sales techniques	63	0.002	0.071	0.325
Manual manufacturing	63	0.001	0.082	0.340
Data administration	61	0.000	0.038	0.374
Office/User software	55	0.003	0.030	0.174
Technical drawing	54	0.004	0.069	0.240
Logistics	54	0.002	0.034	0.446
Technical documentation	54	0.003	0.032	0.139
Physical principles	51	0.002	0.023	0.052

The table shows descriptive statistics for the most prevalent skills, based on their incidence. The mean values are weighted by the size of occupations.

On average, an occupation uses 21.4 single skills. The minimum number is of skills used by an occupation is 8 and the maximum is 38. The average skill weight over all occupations is 0.047.

4.2. Occupational Specificity

With this skill data at hand, we operationalize Lazear's skill weights approach and calculate our occupational specificity measure. Formally, a specific occupation is one that has skill weights that are far away from all other occupations and jobs and at the extreme, having no overlaps with other occupations at all. In line with previous literature (e.g. Nawakitphaitoon, 2014; Robinson, 2011), we call the degree of overlap between two skill bundles the "skill distance" between them. The *average distance* of an occupation's skill bundles to all other skill bundles thus measures the specificity of an occupation. To implement the measure empirically, we proceed in two steps. In the first step we calculate a measure for the skill distance between all occupational skill bundles. In the second step, we combine this information with labor market data to calculate an average distance measure for each occupation.

The distance measure we calculate in the first step captures the overlap of the skill bundles of two occupations, thus indicating the extent to which skills can be used after an occupational change between these two occupations. We use the angular distance measure as introduced to the skill literature by Gathmann and Schönberg (2010).[12] We calculate the distance between all 6,105 possible pairs[13] of occupational skill vectors according to the following formula:

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

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 bundle according to the skill weights of their training occupation. Each skill weight in the original occupation is multiplied by the corresponding weight in the new occupation and then added up. If a skill is used extensively in both occupations, the product—and thus the overlap in the skill use in 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 from the old to the new occupation is low.[14] The denominator normalizes the results such that the sum always lies between zero and one.[15]

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[12] The angular distance is used in a similar context by Fedorets (2011) and Bublitz (2013). Alternative approaches to measuring the transferability of human capital include measures based on the Euclidian distance (e.g., Robinson, 2011) or factor score changes (e.g., Poletaev and Robinson, 2008).
Compared to alternative distance measures, the angular distance has several advantages for our application. As we have more than 180 skill dimensions, many of our skill vectors are highly diversified. If two occupations are highly diversified, the vector endpoints would lie close to the origin of the coordinate system. Thus the vectors will be "close" by the Euclidian measure, even if they are completely orthogonal and use no identical skills at all. The angular distance is purely directional and thus insensitive to the length of a vector.

[13] $(n = \frac{111*(111-1)}{2} = 6105)$.

[14] There is a growing body of literature examining the transferability of skills between occupations and showing that differences in tasks between occupations can explain the wage changes of individuals switching occupations (e.g. Fedorets, 2011; Gathmann & Schönberg, 2010; Nawakitphaitoon & Ormiston, 2016; Nedelkoska, 2010; Poletaev & Robinson, 2008; Robinson, 2011). Our approach is closely related to and builds on this literature. The literature on skill transferability examines how the similarity in skills between jobs affects wage changes in a particular employment relationship; in Appendix A, we examine whether our skill data can replicate some of the main results of the transferability literature. However, the transferability literature does not measure the specificity of skill bundles with regard to the entire labor market, i.e., if a particular skill bundle offers more or fewer employment opportunities.

[15] As the angular distance captures similarity rather than distance, we reverse the measure such that a higher number corresponds to a larger distance and less skill overlap, i.e., we define: Skill distance = 1 – angular distance.

The closest occupational change we observe in our data is from a vegetable grower to a fruit grower, with a very small distance of 0.033. These two occupations have almost the same skill bundles and weights. The most distant change we observe is from a mechanical technician (Produktionsmechaniker) to a commercial employee (Kaufmann), with a distance of 0.999. The most frequent change we observe in the data is from a commercial employee to a retailer with a distance of 0.447. The closest and most distant changes of selected occupations appear in Table 3.[16]

Table 3: Distance between selected occupations

Change from …	Change to … closest and most distant occupation	Distance measure
Commercial employee	Retail employee	0.447
	Mechanical technician	0.999
Plumber	Tinsmith	0.184
	Commercial employee	0.985
Graphic designer	Multimedia designer	0.149
	Cabinetmaker	0.945
Health care worker	Social care worker	0.136
	Gardener	0.986
Electronics technician	Automatician	0.409
	Commercial employee	0.964
Florist	Gardener	0.559
	Mechanical engineer	0.993
Food technologist	Miller	0.177
	Commercial employee	0.972
Metal worker	Panel beater	0.347
	Farmer	0.800
Laboratory assistant	Chemical and pharmaceutical tech.	0.485
	Social care worker	0.966

We report only changes that occurred at least once. Occupations are selected to give an impression of various sectors and branches. Source: Authors' calculations, based on skill data from Swiss training regulations and the Social Protection and Labour Market Survey (SESAM), 1999-2009.

In a second step, we combine the information on the distance between any two occupations with representative labor market data for all workers with a VET education. To represent the

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

distribution of the skill bundles in the overall labor market, we use the number of jobs in all 111 occupations.

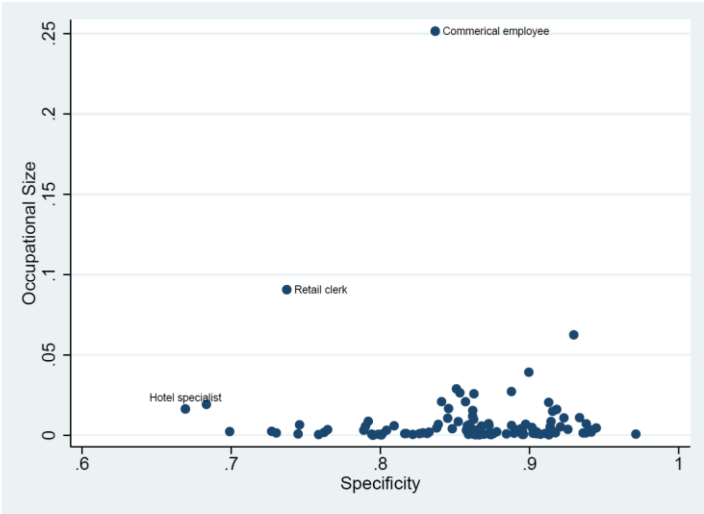
In detail, we construct the specificity measure by calculating a weighted average distance from any one occupation to all other occupations in the labor market. The weights are the relative employment shares of occupations. We thus incorporate the potential demand for a particular occupational skill bundle in our occupational specificity measure. The specificity measure is mathematically equivalent to the expected average distance that workers have to bridge if they are forced to leave their occupation and randomly accept the next available job. A rather general skill bundle exhibits a small difference between its own skill weights and the outside market weights. To account for changes in the labor market demand for skills during the period, we calculate the specificity measure for each year (1999 - 2009) separately.

The most specific training occupation is paper technologist (Papiertechnologe); the least specific training occupation is hotel management clerk (Hotelfachmann). We show the specificity measure of all occupations in Table B1 in the Appendix.

The distribution of jobs in the labor market is a key factor in the skill weights approach. Importantly, the specificity of an occupation does not depend on its own size, i.e. the number of jobs in this occupation. Rather, it depends on the relative size of occupations in the outside labor market. Thus, the specificity of occupations is relatively stable over the observation period, although some occupations experienced quite a dramatic decline or increase in the employment shares. Figure 1 shows the relationship of average occupational size and specificity for our sample occupations. Small occupations can be very unspecific, e.g., if they are positioned in a sizable skill cluster with many similar occupations. Empirically we observe that the correlation between the size of an occupation and our specificity measure is only 0.02.

In the next step, we apply our specificity measure to test the hypotheses derived from Lazear on the expected labor market outcomes of different occupations.

Figure 1: Occupational Specificity and Occupational Size



The figure shows a scatterplot of occupational specificity and size (employment share of all VET workers in percent) for each occupation.

5. Data

We test our hypotheses using the Social Protection and Labour Market (SESAM) survey provided by the Swiss Federal Statistical Office.

5.1. The SESAM Labor Market Data

The SESAM combines the Swiss Labour Force Survey (SLFS) with several social insurance registers. The survey, conducted yearly by the Statistical Office, comprises a representative sample of the Swiss population over the age of 15 with about 50,000 randomly selected interviews per year. The SESAM provides rich information on employment status, education histories, and socio-demographics. It has a rolling panel structure, following individuals for up to five years. We use data from 1999 to 2009. The panel structure allows us to identify an individual’s occupational change by comparing his or her occupation codes in two consecutive years. We can check whether an individual has completed (upper secondary) VET and whether he or she is still working in the original training occupation. Additionally, we have information on firm tenure and administrative wage data for each job.

To identify occupational changes, we use the Swiss Standard Classification of Occupations (SBN2000) provided in the SESAM. We consider changes at the most disaggregate level of occupations (the 5-digit level), because at this level we can precisely match the occupations with our VET programs.[17] For each individual, we compare the 5-digit occupation for each pair of consecutive years t_0 and t_1.[18] We assume that workers who have graduated before our observation period hold a skill bundle that roughly corresponds to the skill bundle as specified in the latest legal training curriculum, i.e., we assume that workers will have updated their skill bundle according to the most recent requirements while working on the job. Nevertheless, in Section 7.4 we perform robustness checks restricting the sample to workers who have graduated no earlier than 1999.[19]

5.2. 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. We include all individuals who have completed a training program in one of the 111 certified VET occupations for which we have skill data.[20] We exclude individuals who have acquired additional formal qualifications (i.e., higher professional qualifications, vocational baccalaureate, and university degree). This restriction ensures that we have a homogeneous sample of individuals with a uniform level of education.

After eliminating observations with missing data, we have a sample of 16,175 individuals (or 62,977 single observations) trained in one of the 111 training occupations for which we have skill data. As mentioned earlier, these 111 occupations cover about 91 percent of all VET-trained individuals in the data. In total, we observe 2,209 individuals who performed an occupational change during the sample period.

For the wage analysis, we use the register-based wage data from the SESAM. As part-time employment is very common in Switzerland (33.6 percent of all workers work less than 90 percent), we include part-time workers and calculate full-time equivalent wages for their

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

[18] We also perform our estimations with occupational changes defined on the 3-digit level; more information is presented in the robustness checks in section 7.4.

[19] VET occupations are regularly revised. In this process, occupations are sometimes assigned a new name and SBN code. In such cases, using a SERI-provided database on the evolution of VET occupations (Grebasch, 2013), we merge the two codes. We do not consider an individual’s changing from an old to a new code as an occupational change. In other words, we assume that the individual updated his or her knowledge with on-the-job practice. In case of revisions, we always analyze the most up-to-date training regulation that came into force before 2009.

[20] As the share of self-employed workers varies greatly between occupations, we include self-employed workers. However, we include a dummy variable for self-employment in our estimations.

primary job.[21] We adjust the wages for inflation (base year 2004). Table 4 presents descriptive statistics for the full sample of individuals.

Table 4: Descriptive statistics - Full sample

Variable	N	Mean	St. Dev.	Min	Max
Individual characteristics					
Age	16,175	40.476	11.372	18	64
Firm tenure	16,175	9.599	9.298	0	47.4
Male	16,175	0.523	0.499	0	1
Married	16,175	0.552	0.497	0	1
Swiss	16,175	0.692	0.462	0	1
Labor market status					
Fulltime	16,175	0.705	0.456	0	1
Wage	16,175	5,590.953	2,281.793	450	19,850
Size of occupation (in % of total VET labor market)	16,175	0.087	0.103	0.001	0.277
Self-employed	16,175	0.1339	0.3405	0	1
Top management position	16,175	0.1247	0.3304	0	1
Management position	16,175	0.1969	0.3977	0	1
Explanatory variable					
Occupational specificity measure	16,175	0.847	0.062	0.669	0.971

Note: We report all variables when an individual first enters the sample.

Individuals are on average 40 years old and have been working for the same firm for 9.6 years. The average observation period per individual is 3.3 years. About 52 percent of the sample is male, and 55 percent are married. A two-sided t-test shows that males work in more specific occupations than females. About 70 percent are Swiss nationals.[22] The average gross wage (earned income) is 5,587 Swiss Francs (approx. US$ 6,942) per month.

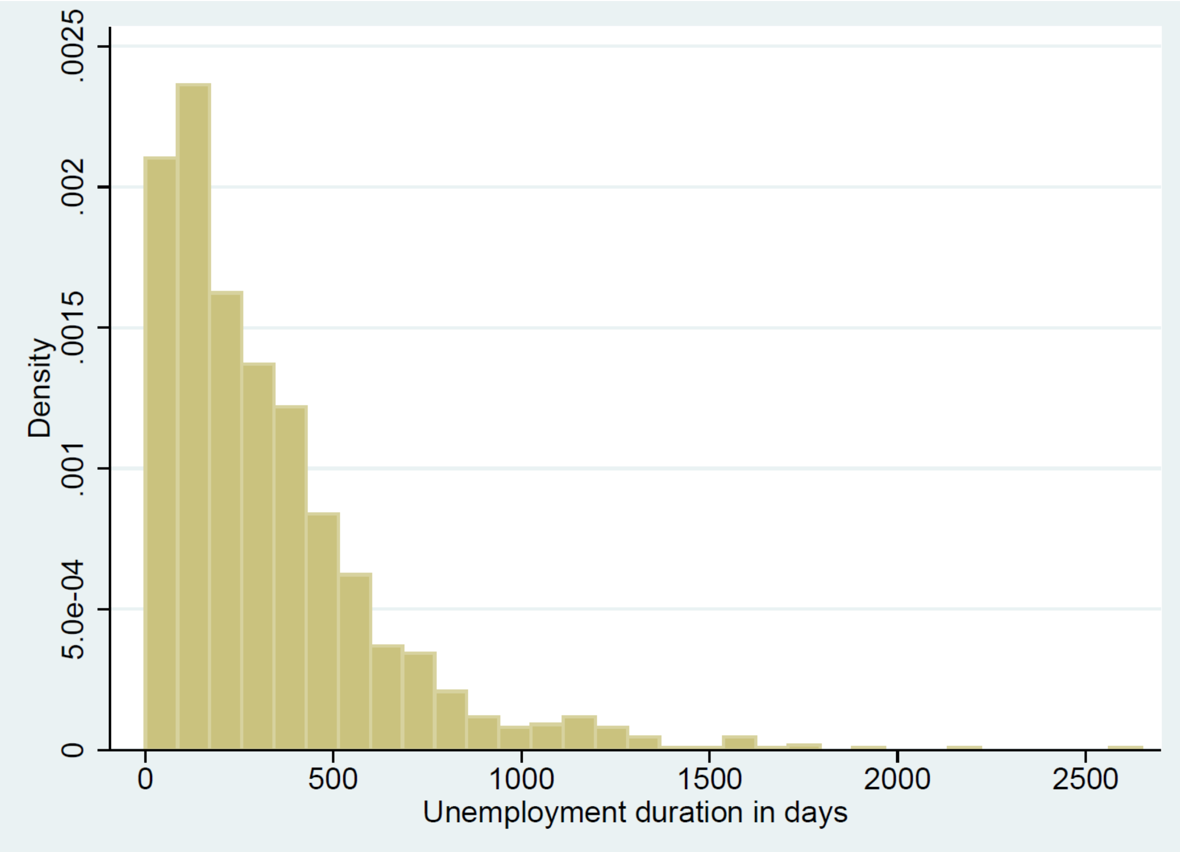
Our data also allows us to observe self-reported data on unemployment spells and their duration in days. For the unemployment duration analysis, we include all VET workers who report being unemployed during our observation period (or in the year preceding the first

[21] To increase the plausibility of our analysis, we drop observations with wages belonging to the highest or lowest 0.5 percent. If the individual was not working in the same firm for the entire month before the annual survey, we set the wage to missing (n=74), because the wage in this month will most likely be too low.

[22] Of the non-Swiss nationals, a large proportion (nearly 60%) has completed their secondary education in Switzerland. Of the remaining workers, approximately 50% are immigrants from Germany and Austria, which are countries that have VET systems and training curricula that are very similar to the Swiss. We performed our main estimations for both sub-samples and find very similar results for both populations.

survey interview).[23] In total we observe 1,201 valid unemployment spells that fulfill this criterion. Figure 2 shows the distribution of these spells.

Figure 2: Unemployment Duration



The figure plots the distribution of the unemployment spell durations of workers who got unemployed during the observation period (1999-2009).

6. Empirical Estimation

Corresponding to our three hypotheses, we examine the correlation of our specificity measure and the labor market outcomes of graduates in three separate estimations: In the first estimation, we test the effect of specificity on wage levels of occupational stayers and changers, in the second on occupational mobility, and in the third on unemployment durations.

[23] Give a certain degree of measurement error we delete spells that are inconsistent over consecutive years. Additionally, as longer spells have a higher probability of being reported, short spells are likely to be underrepresented. We expect that both issues can induce only a downwards bias in our estimates.

6.1. Occupational Specificity and Wages

Lazear's model predicts higher wages for workers who have invested in specific occupational skill bundles, at least as long as they stay in the occupation and use these specialized skills. We estimate an OLS Mincer-type earnings function to test for a correlation between occupational specificity and wages. We include a dummy variable for observations of workers who are still working in their original training occupation, and interact this dummy variable with the specificity of the worker's training occupation (model 1).

$$\begin{aligned}\log(wage) = \; & \alpha + \beta_1 specificity_{iO} + \beta_2 Stay_i + \beta_3 Stay_i X specificity_{iO} + \beta_4 SO_{iO} \\ & + \beta_5 male_i + \beta_6 swiss_i + \beta_7 married_i + \beta_8 age_i + \beta_9 age_i^2 + \beta_{10} UR_i \\ & + \beta_{11} tenure_i + \beta_{12} tenure_i^2 + \beta_{13} \text{self-employed}_i + managerial\,position_i \\ & + firmsize_i + \varphi_t + \omega_i + \varepsilon\end{aligned}$$

The variable "$specificity_{iO}$" denotes the specificity of individual *i* who was originally trained in occupation *O*.[24] We control for the size of an occupation in our regression analysis. The variable "size of occupation" (SO) measures how many people are working in a given occupation in a year, i.e. its employment share. Large occupations offer more job opportunities, which could influence a worker's outside offers and bargaining power.

We include a comprehensive set of individual characteristics (gender, age, nationality, marital status, and self-employment), all of which influence individual's wage levels and the probability of occupational changes (Bleakley & Lin, 2012; Eymann & Schweri, 2011; Fitzenberger & Kunze, 2005; Shaw, 1987).

Additionally, we control for several job-related characteristics. We include tenure with the current firm as a proxy for additional firm-specific human capital.[25] We also include dummies for firm size because employees from large firms earn a firm-size wage premium (e.g. Lallemand, Plasman, & Rycx, 2007) and change occupations less often, at least shortly after

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[24] We also estimated all our models with a squared term for the specificity measure and do not find any significant non-linear effects.

[25] The recent literature explores the importance of industry-specific tenure for wage determination (Kambourov & Manovskii, 2009; Sullivan, 2010). Unfortunately, we cannot contribute to this discussion because we lack information about the industry in which workers have completed their training. It is also not feasible to reconstruct this information from the training occupation as such, because a large proportion of individuals is trained in occupations that may be acquired in a variety of different industries (e.g., commercial employees, the largest occupational group in Switzerland, may receive training in a variety of different industries such as banking, retail, transportation, chemistry, and many more). Thus, we cannot measure or reconstruct original industries or industry changes.

the completion of the training (e.g., Bougheas & Georgellis, 2004; Winkelmann, 1996). If small firms are active mainly in specialized occupations, our results could be biased.

A potential concern might be that occupational codes could change with the hierarchical position within a firm. In addition to tenure, we include a dummy for top managers and one for middle managers (workers with personnel responsibilities). Furthermore, ω_i and φ_t denote region (cantons) and year fixed effects, respectively, and the regional (cantonal) unemployment rate (*UR*) controls for local labor market conditions.

6.2. Occupational Specificity and Occupational Mobility

For graduates of occupations with a highly specific skill bundle, we expect a lower rate of occupational mobility. To test our hypothesis, we use a probit model and maximum likelihood estimation (Wooldridge, 2002). Our explanatory variables are (model 2):

$$\begin{aligned}\Pr(change = 1|\boldsymbol{x}) \\ &= \Phi(\beta_0 + \beta_1 specificity_{iO} + \beta_2 SO_{iO} + \beta_3 male_i + \beta_4 swiss_i + \beta_5 married_i \\ &+ \beta_6 age_i + \beta_7 age_i^2 + \beta_8 UR_{it} \ + \beta_9 tenure_i + \beta_{10} tenure_i^2 \\ &+ \beta_{11}\text{self-employed}_i + \beta_{12}\log(wage)_i + managerial\ position_i \\ &+ firmsize_i + \varphi_t + \omega_i)\end{aligned}$$

The dependent variable is one if the worker changed occupations during the observation period and zero otherwise. We expect a negative association of our main variable of interest, skill specificity, and the occupational mobility of workers. We estimate two specifications.

In the base specification, we include the control variables from model 1, namely occupational size, age, age squared, gender, nationality, marital status, tenure, tenure squared, self-employed, hierarchical position, firm size, local (cantonal) unemployment rates, as well as year and region dummies.

In a second specification, we add a control for the worker's wage before the change. Higher wages are generally associated with lower occupational mobility (e.g. Parrado, Caner, & Wolff, 2007). As the specificity of occupations might affect the occupational changing behavior of workers through an effect on their earnings, this second specification should be considered only as robustness test (reduced form effect). If job characteristics, particularly wages, are determined by differences in the specificity of occupations, these characteristics could capture a part of the specificity effect.

6.3. Occupational Specificity and Unemployment Duration

As an alternative indicator for workers' labor market flexibility, we investigate the effect of occupational specificity on unemployment durations. Given our theoretical model, we hypothesize that workers from specific occupations, after becoming unemployed, need more time to find new employment. To test this hypothesis, we estimate a Cox proportional hazard model of the following type, taking into account the right censoring of our data (model 3):

$$hi(\tau) = h_0(\tau) \cdot \exp(\beta_1 Specificity_{iO} + \beta_2 SO_{iO} + X'\beta)$$

This model describes exit to work after τ days of unemployment for an individual who entered unemployment at time $\tau=0$ and who has received training in an occupation with a given specificity. The control variables include age, age squared, gender, nationality, marital status, region, year, and the local unemployment rate. All control variables are evaluated in the year the workers first enter unemployment. A negative value of β_1 implies a decrease of the hazard rate and thus a longer unemployment duration for individuals with more specific training.

7. Results and Robustness Checks

7.1. Occupational Specificity and Wages

We present the estimation results for the effect of specificity on workers' average wage level (model 1) in Table 5. The coefficient of the interaction term between "in training occupation" and "specificity" is positive and significant at the one percent level. This significant interaction is in line with our hypothesis that trained individuals who stay in a specific occupation receive a wage premium. The baseline coefficient of the specificity measure for the changers is positive and marginally significant. This finding indicates that changers with highly specific training are generally not punished for completing training in a high-specificity occupation after changing their occupation. It does, however, appear that these changers lose the specificity premium they had in their original occupations. Note that this result holds for the sample of all observed occupational changes (be they voluntary or involuntary) and thus, β_1 and β_3 do not necessarily identify a causal wage effect of specificity. As workers usually switch to "close" occupations (Gathmann & Schönberg, 2010; Geel & Backes-Gellner, 2011), part of this effect is also likely due to workers from highly specific occupations switching to occupations still requiring relatively specific skill bundles.

Table 5: Occupational Specificity and Wages, OLS (model 1)

	Coefficient	*SE*
Specificity (std.)	0.0191*	(0.0099)
In training occupation (1=yes)	0.0193	(0.0223)
In training occ. X Specificity	0.0333***	(0.0116)
Size of occupation (std.)	0.0717***	(0.0067)
Age	0.0389***	(0.0033)
Age squared	-0.0004***	(0.0000)
Male	0.1861***	(0.0173)
Swiss	0.0666***	(0.0088)
Married	0.0160	(0.0115)
Self-employed	-0.2908***	(0.0350)
Fulltime work	-0.0021	(0.0136)
Firm tenure	0.0094***	(0.0007)
Firm tenure squared	-0.0001***	(0.0000)
Local unemployment rate	-0.0096	(0.0071)
Constant	7.2898***	(0.0877)
Year and region dummies	included	
Firm size dummies	included	
Managerial position dummies	included	
F-statistics	702.3	
R^2	0.2588	
N	62,977	

*Table reports coefficients of an OLS regression; dependent variable: (log) wages; robust standard errors in parentheses (clustered by training occupation), * (**,***) denotes statistical significance at the 10% (5%,1%) level.*

Staying in the original training occupation is rewarded only in specific occupations; at the mean level of specificity, staying is not positively associated with higher wages. While this finding may appear surprising, it is in line with the literature reporting very heterogeneous effects for changing out of the learned VET occupation, depending on the sample used and the definition of occupational changes (see Göggel & Zwick, 2012; Müller & Schweri, 2015).

As for the control variables, occupational size has a highly significant and positive coefficient. Larger training occupations pay higher wages. However, this effect might be driven by a few large occupations and disappears when we control for the intellectual demand level of occupations in Section 7.4 (Robustness checks).

7.2. Occupational Specificity and Occupational Mobility

We show the results for our hypothesis on the effect of occupational specificity on occupational mobility (model 2) in Table 6. The estimated coefficient for the occupational specificity measure has the expected negative sign and is statistically significant at the one percent level. Individuals from occupations with more specific skill bundles exhibit significantly less occupational mobility.[26] Learning a specific occupation thus seems to tie workers more strongly to their occupation.

[26] This in line with empirical results of Rinawi et al. (2014), who also use SESAM wage data but use ratings of career centers to construct a specificity measure.

Table 6: Occupational mobility, probit regressions (model 2)

	Coef.	*dy/dx*	*Coef.*	*dy/dx*
Specificity (standardized)	-0.0861***	-0.0174***	-0.0799***	-0.0161***
	(0.0242)		(0.0232)	
Size of occupation	-0.0962***	-0.0194***	-0.0812***	-0.0163***
	(0.0220)		(0.0240)	
Age	-0.0097	-0.0020	-0.0029	-0.0006
	(0.0095)		(0.0100)	
Age squared	0.0001	0.0000	-0.0000	-0.0000
	(0.0001)		(0.0001)	
Male	0.1365*	0.0275*	0.1664**	0.0334**
	(0.0757)		(0.0769)	
Swiss	0.0065	0.0013	0.0170	0.0034
	(0.0460)		(0.0463)	
Married	-0.0608**	-0.0123**	-0.0578**	-0.0116**
	(0.0259)		(0.0258)	
Self-employed	-0.1105	-0.0223	-0.1581**	-0.0317**
	(0.0692)		(0.0696)	
Local unemployment rate	-0.0300	-0.0060	-0.0324	-0.0065
	(0.0405)		(0.0404)	
Firm tenure	-0.0391***	-0.0079***	-0.0375***	-0.0075***
	(0.0057)		(0.0058)	
Firm tenure squared	0.0008***	0.0002***	0.0007***	0.0001***
	(0.0001)		(0.0001)	
Fulltime employment	-0.0141	-0.0028	-0.0108	-0.0022
	(0.0347)		(0.0342)	
Ln (wage before change)			-0.1803***	-0.0362***
			(0.0422)	
Firm size dummies	included		included	
Managerial position dummies	included		included	
Year and region dummies	included		included	
Pseudo R^2	0.063		0.066	
N	16,175		16,175	

*Table reports marginal effects at the means; robust standard errors in parentheses (clustered by training occupation), * (**,***) denotes statistical significance at the 10% (5%,1%) level.*

An increase in the specificity index of one standard deviation decreases the probability of belonging to the group of occupational changers during the observation period by about 1.7 percentage point. While the effect may appear relatively small, it should be put in perspective to the average changing rate during the observation period, which is about 13.6 percent.

The control variables are in line with our expectations. The size of an occupation has a highly significant negative influence on the probability of changing. Workers in small occupations switch occupations more often. Small occupations that cover a niche in the labor market are obviously not an obstacle to labor mobility. This finding is in line with Lazear's model, as workers in occupations with a large number of jobs are expected to have more appropriate job options within the same occupation.

When introducing the job-specific controls in specification 2, the estimated specificity coefficient is only slightly smaller. Tenure with the last firm has a highly significant and decreasing negative effect, suggesting that the loss of firm-specific human capital might also be an important factor for changing occupations. In contrast, when we control for tenure, age has no significant effect on the probability of belonging to the group of changers, likely due to the high multicollinearity of both variables. Finally, the results show that workers with higher wages are significantly more likely to stay in the same occupation than those with lower wages.

7.3. Occupational Specificity and Unemployment Duration

Table 7 presents the estimated effects of occupational specificity on unemployment durations.[27] Specification 2 additionally includes time and region fixed effects. According to Lazear's model, individuals with specific training need more draws from the distribution of skill combinations if they are to find suitable new options. Since more draws require more time, we expect workers with more specific training to take more time to find new employment.

[27] An analysis of the Schönfeld residuals (Grambsch & Therneau, 1994) shows no evidence that the proportional hazard assumption might be violated (not reported).

Table 7: Unemployment duration (model 3)

	Hazard Ratios	
	Spec. (1)	*Spec. (2)*
Specificity (standardized)	0.9416***	0.9221***
	(0.0193)	(0.0203)
Size of occupation (standardized)	0.9886	0.9924
	(0.0214)	(0.0265)
Age	0.9873	0.9787
	(0.0187)	(0.0196)
Age squared	0.9999	1.0001
	(0.0002)	(0.0003)
Male	0.9382	0.9078
	(0.0876)	(0.0808)
Swiss	1.1298*	0.9877
	(0.0821)	(0.0810)
Married	0.9746	1.0133
	(0.0876)	(0.0881)
Local unemployment rate	0.8581***	1.0375
	(0.0241)	(0.1298)
Year and region dummies	Not included	Included
Log-likelihood	-3813	-3753
Number of spells	1,201	1,201

*Table presents the results of the unemployment duration regression model as hazard ratios based on the Cox estimator. Total number of spells = 1,201, total number of failures =649. Robust standard errors in parentheses (clustered by training occupation)[28]; * (**, ***) denotes statistical significance at the 10% (5%, 1%) level.*

Corroborating our previous results, a one standard deviation higher occupational specificity reduces the hazard of finding a job (in a worker's original occupation or any other occupation) by about 6 to 8 percent, compared to an individual with otherwise identical covariates.

7.4. Robustness Checks

To test the robustness of our results, this section addresses three potential issues of our estimation approach. First, we narrow down the sample to young workers only, because one could argue that their skill bundle most closely corresponds to the skill bundle specified in the latest training curricula. Second, we consider a broader definition of occupational changes,

[28] We include workers with more than one unemployment spell. As clustering the standard errors on the individual level decreases the standard errors, we report the more conservative estimates and cluster on the occupational level.

namely on the 3-digit instead of the 5-digit level. Third, we address the issue of unobserved heterogeneity with two additional tests.

Our first robustness check concerns our assumption that workers who earned their degree long before our observation period may not have the same skill bundles as recent graduates. In the previous estimations, we assumed that these workers have upgraded their skill bundle while working on the job, and thus hold a skill bundle that corresponds to the skill bundle specified in the most recent legal training curricula. However, to address the concern of outdated skill bundles we repeat our analysis and restrict the sample only to workers who graduated during our observation period (1999-2009) because they are most likely to have graduated under the most recent generation of curricula.

We report the results for our main estimations in Tables B2 - B4. Although the sample size is greatly reduced, the size of the effect is in general robust, and the significance of the results does not drop substantially. The estimated effects of specificity are higher for occupational changes (model 2) and unemployment durations (model 3) and slightly less pronounced for the wage estimation (model 1). But overall, the results are very stable and all hypotheses are born out in the data.

In our second robustness check, we consider an alternative definition of occupational changes. One could argue that changes in occupational codes at the 5-digit level might involve career advancements within the same group of occupation (e.g. from "commercial employee" to "accountant"), which may lead to different results than a change from one group of occupation to another group of occupation (e.g. from "commercial employee" to "IT specialist"). Since we talk about career changes, we therefore perform the estimations using only changes on the 3-digit occupational classification to see whether our results are robust. However, as can be seen in Tables B5 and B6 in the Appendix, the results do not change much when using this alternative specification.[29]

A third concern is that some of the variation measured across training programs could be due to workers' selection into programs based on ability, risk preferences or other unobservables. Although we focus on a relatively homogenous group of workers and it seems likely that the heterogeneity in that sample is already small, there could still be sorting according to ability

[29] Please note that we still match the specificity on the 5-digit level. The results of model 3 do not change, as the model does not look at occupational changes.

or risk preferences within that group. Although we cannot fully rule this out, we argue that there are at least four reasons to believe that these problems are not the only drivers of our results.

First, regarding problems due to ability sorting, we can empirically look into how intellectually demanding the different occupational training programs, into which the individuals would sort themselves, are. To address the problem, we use an existing measure on how "intellectually demanding" different occupational programs in Switzerland are. It is a 6-point scale measure that was developed by Stalder (2011) and is based on an evaluation by career counselors of the intellectual requirements of all occupations. Unfortunately, the measure is available only for 89 of our 111 occupations, thus reducing our sample, but for the remaining, i.e., all quantitatively important occupations, the correlation between the "ability requirements measure" and our specificity measure is very low (0.069). Therefore, we conclude that it seems rather implausible that high ability individuals systematically self-select or are sorted into occupations with high specificity because these occupations are particularly demanding. When we control for "intellectual demand requirements" in our empirical estimations, it does not weaken the relationship between our specificity measure and the outcome variable in any of our models (Tables B7-B9). This finding is inconsistent with an assumption that our results are mainly driven by differences in intellectual demand. Therefore, it seems unlikely that ability sorting is the sole driver of our main results; instead it seems reasonable to assume that the differences in the specificity of the occupational training programs can explain at least a part of the different labor market outcomes.

Second, regarding the problem that risk-oriented individuals sort into different occupations, we argue that such an assumption is not fully consistent with our empirical results. If we would assume that risk-oriented individuals often choose specific occupations (and that this willingness to take risks is compensated with higher wages), this could explain our wage results. However, it could still not explain why more risk-oriented workers would change occupations less often and particularly why they would have longer unemployment durations. But we do observe that workers with specific occupations change less often and have longer unemployment durations. Thus, we argue that risk preferences alone cannot explain our results.

Third, regarding the problem of selection into occupations in principal, previous empirical studies have shown that teenagers who choose an apprenticeship at the age of fifteen have a strong preference for those occupations that are regionally available (Oswald & Backes-Gellner, 2014), which substantially restricts their spectrum for self-selection.

Fourth, a potential means to control for at least time-invariant unobserved labor market characteristics (e.g. time-invariant selection of students into occupations) is to exploit the time variation of the occupational specificity within occupations only. Unfortunately, our data is not well suited for such an analysis because our observation period is relatively short and the variation of the specificity of occupations over the observation period is very small compared to the variation between occupations, which makes identifying significant effects unlikely. Nevertheless, we repeat all the main estimations with training occupations fixed effects. As expected, the overall significance of the coefficients on the main variables of interest are somewhat reduced, but we still find significant effects in all three models and they are in accordance with our previous interpretations. We show the results of these estimations in Tables B10 - B12 in the Appendix.

Thus, although we cannot completely rule out that there is endogenous sorting, it seems plausible that this is not the only explanation for the empirical patterns that we observe. In any case, even if the effects are not purely causal, we still believe that the pattern we observe are interesting and deserve the attention of educational policy makers, because they show how specificity is distributed, and to what extent and with what consequences workers are able to change their occupations.

8. Conclusions

We analyze the curricula of VET and, drawing on Lazear’s (2009) “skill weights” approach, calculate specificity measures for training occupations. By comparing the skill bundles of VET occupations to the average skill distribution in the labor market, we examine the extent to which VET occupations include skills that are required across a wide range of occupations, and thus capture the specificity of an occupation.

We provide three main findings. First, we show that small occupations with a limited supply of jobs are not necessarily specific and that large occupations with many jobs are not necessarily more general. We thus argue that the number of jobs in an occupation or the number of different occupations in a VET system per se is not what is relevant for the flexibility of workers. Instead, what matters are the overlap and weights of skill bundles across occupations.

Second, we find that workers who stay in their training occupation benefit from training that is more specifically tailored to one occupation and receive higher wages on average. Additionally, we do not find evidence that, of all changers (be they voluntary or involuntary), those with more specific skill bundles have significantly lower wages after changing their occupation. Instead, our results indicate that, on average, workers who change from highly specific occupations do not have lower wages than other changers, but they do lose their specificity premium. However, we cannot distinguish between voluntary and involuntary changers and do not know to what extent this result is driven by, for example, self-selection.

Third, we find that specificity has implications for a worker's labor market flexibility. The higher the specificity of an occupation, the smaller the probability that workers change their occupation. If individuals from highly specific occupations change their occupation, they lose the wage premium of that highly specific occupation and have thus higher wage losses than workers from general occupations who never had such premium. Additionally, workers with more specific training need more time to find employment again after becoming unemployed.

Our approach to evaluate the specificity of training curricula is not limited to Switzerland and does not exclusively apply to countries with vocational education and training systems; instead, it is rather generalizable. This approach could be used to evaluate curricula of all educational programs that strive to prepare students with labor market-oriented skills. Conversely, it is unlikely to be important for kindergarten and may be less important for primary and lower secondary education because a direct connection to labor market skills is less important for these programs.

Our approach can thus guide decision makers whenever the specificity of a training program is to be evaluated, even if that program is new. The implementation requires two steps. First, sufficiently detailed information on the skills supplied by the training program need to be collected (which, as we have shown, can be elicited directly from the training curricula themselves). Second, information on skill requirements in the relevant labor market needs to be collected. As we show, this information may be gathered by aggregating and weighting the information on the skills of all training curricula in a given market. This information could also be relevant for prospective students choosing among vocational degrees or designing their own curriculum.

For large-scale curriculum changes, one would need to consider general equilibrium effects. If the same skill is changed (added or dropped) in many curricula at the same time, the distribution of skill bundles in the overall labor market changes as well, and the net effect of these changes may be different from the one that is expected from small and isolated changes, and based on a partial equilibrium analysis. However, as our empirical approach cannot model general equilibrium effects, our findings are restricted to incremental changes in curricula (which are, in reality, the most frequent changes). Further research could thus examine this issue by investigating historical large-scale changes and by using longer time spans.

A lot of research still has to be done, before one can draw final conclusions for educational policy making from our empirical results. However, we provide novel results that lay important foundations for new policy conclusions on the design of training curricula. So far, there was only very limited empirical knowledge on occupational specificity that could be directly related to the content of training curricula. This feature is however very important for policy makers, who have to decide on new or revising old occupational curricula and, who, by taking these decisions induce important and long-term labor market outcomes. Our study is a first piece of empirical evidence to close this gap and to indicate which types of curricula changes will more likely result in higher or lower mobility and higher or lower wages for stayers or movers.

To better address the problem of unobserved heterogeneity, future research could try to exploit time variation with longer panel data sets. By constructing a panel of occupational skill content over a much longer time, future research could examine what happens if occupations become more or less specific over time (e.g. due to curricula changes) and could use this variation to identify the effects controlling for unobserved occupational and individual heterogeneity. Future research could also try to model student’s occupational choice, for example by using pre-training measures and employing a selection model to control for potential endogenous sorting.

9. Appendix

9.1. Appendix A: Occupational Distance

According to Lazear's idea of skill-bundle-specific human capital, a worker's wage after an occupational change should depend on the distance between the worker's skill weights (the skill weights of the training occupation) and the required skill weights in the target occupation. To test the theoretical predictions of Lazear's model 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 4):

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

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 firm but not their occupation. The main explanatory variable is the skill distance measure between the worker's origin occupation O_1 and the target occupation O_2 ($distance_{O1-O2}$).

If a worker is equipped with the optimal skill bundle for the new occupation, he or she should earn a wage close to the average first-year wage of workers who change firms, but not occupations. If the worker performs a distant switch and can thus use only a small part of his or her skill-specific human capital, he or she should earn a significantly lower starting salary. We use a standard set of control variables ($X_{i,t}$) including age, age squared, tenure (in the previous job), tenure squared, nationality and marital status, as well as region (ω_i) and year (φ_t) dummies.

Here, we focus on the subsample of changers. Because we expect the immediate wage change to be the best indicator for the skill-mismatch, we focus on monthly wages in the first year after the change. For inclusion in analysis, workers must thus be employed in the year before and immediately after the change.[30] After applying our sample restrictions, the subsample for which we have wage data reduces to 1,316 individual cases.[31]

[30] If an individual changes his or her occupation two 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.
[31] This number is lower than the number of changers reported in section 5.2, because we now additionally require valid wage data in the year after the change (not only before the change).

Table A1: Occupational Distance and Post-Switching Wages, OLS (model 4)

	Coefficient	*SE*
Distance (standardized)	-0.0227*	(0.0131)
Age	0.0225**	(0.0098)
Age squared	-0.0003**	(0.0001)
Male	0.1964***	(0.0277)
Swiss	0.0452	(0.0292)
Married	-0.0224	(0.0290)
Firm tenure	0.0206***	(0.0048)
Firm tenure squared	-0.0004**	(0.0002)
Constant	-0.5544***	(0.1805)
Year and region dummies	included	
F-statistics	4.458	
R^2	0.1042	
N	1,316	

*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.*

Table A1 reports the results for model 4. Our distance measure has predictive power in explaining human capital loss for workers changing occupations. The estimated coefficient of the distance measure is significantly negative at the ten percent level. A high distance leads to a skill-specific human capital mismatch and a lower starting wage at the new job after the change. This result is in line with Lazear's skill weights approach of human capital and confirms that our distance measure is a valid input for the construction of our specificity measure.[32] A one standard deviation larger distance between occupation of origin and target occupation reduces the proportion of the individual's wage to the average entry wage by about two percent.

[32] Our result is also in line with previous research on occupational mobility using a task-based approach. Recent empirical studies examining the dissimilarity between occupations and the consequences for wage changes include for example: Geel and Backes-Gellner (2011); Nedelkoska (2010); Poletaev and Robinson (2008); Rinawi et al. (2014); Wiederhold, Nedelkoska, and Neffke (2013); Nawakitphaitoon (2014); Gathmann and Schönberg (2010).

9.2. Appendix B: Additional Tables

Table B1: Specificity measures (all occupations)

Occupation (German)	Occupation (English)	Specificity
Papiertechnologe EFZ	Paper Technologist	0.971
Uhrmacher Rhabillage	Watchmaker	0.945
Zahntechniker EFZ	Dental Technician	0.941
Innendekorateur Polster	Interior Decorator	0.940
Bekleidungsgestalter EFZ	Clothes Designer	0.938
Milchtechnologe EFZ	Dairy Technician	0.938
Podologe EFZ	Podiatrist	0.936
Maler EFZ	Painter	0.934
Fachmann Gesundheit EFZ	Healthcare Worker	0.930
Strassenbauer EFZ	Road Builder	0.926
Gärtner EFZ	Gardener	0.923
Elektroniker EFZ	Electronics Engineer	0.921
Fachmann Betreuung EFZ	Social Care Worker	0.918
Textilpfleger EFZ	Textile Worker	0.917
Oberflächenbeschichter EFZ	Electroplater	0.916
Automobil-Mechatroniker EFZ	Automotive technician	0.915
Produktionsmechaniker EFZ	Mechanical Technician	0.914
Landmaschinenmechaniker EFZ	Agricultural Machinery Mechanic	0.914
Feinwerkoptiker EFZ	Precision Optician	0.913
Informatiker EFZ	IT Specialist	0.913
Motorradmechaniker EFZ	Motorcycle Mechanic	0.911
Ofenbauer EFZ	Stove Builder	0.907
Graveur EFZ	Engraver	0.905
Gleisbauer EFZ	Track Worker	0.905
Fotograf EFZ	Photography Expert	0.904
Konstrukteur EFZ	Design Engineer	0.903
Isolierspengler EFZ	Insulation Installer	0.902
Automatiker EFZ	Automation Engineer	0.902
Gebäudereiniger EFZ	Building Cleaner	0.900
Zeichner EFZ (Hochbau)	Draughtsman (Architecture)	0.897
Kaminfeger EFZ	Chimney Sweeper	0.896
Gusstechnologe EFZ	Casting Technologist	0.895
Grafiker EFZ	Graphic Designer	0.895
Gipser	Plasterer	0.894
Forstwart EFZ	Forester	0.893
Kosmetiker EFZ	Beautician	0.891
Tierpfleger EFZ	Animal Caretaker	0.890
Polygraf EFZ	Desktop Publisher	0.888
Polymechaniker EFZ	Mechanical Engineer	0.888
Printmedienverarbeiter EFZ	Print Media Processor	0.884

Table B1: continued

Occupation (German, continued)	Occupation (English, continued)	Specificity
Orthopädist EFZ	Orthopedic Technician	0.878
Netzelektriker EFZ	Powerline Technician	0.876
Geomatiker EFZ	Surveyor	0.874
Müller EFZ (LM)	Miller	0.873
Multimediagestalter	Multimedia Designer	0.873
Kunststofftechnologe EFZ	Plastics technologist	0.873
Zimmermann EFZ	Carpenter	0.873
Heizungsinstallateur EFZ	Installer for Heating Systems	0.873
Elektroplaner EFZ	Electrical Designer	0.869
Schmied-Hufschmied	Blacksmith	0.869
Sanitärinstallateur EFZ	Plumber	0.868
Weintechnologe EFZ	Wine Technologist	0.867
Florist EFZ	Florist	0.866
Glasmaler EFZ	Glass Painter	0.866
Formenbauer	Florist	0.866
Anlagenführer EFZ	Plant Operator	0.866
Tiermedizinischer Praxisassistent EFZ	Veterinary Nurse	0.866
Betonwerker EFZ	Concrete Craftsman	0.864
Info- und Dokumentationsassistent	Information and Documentation Expert	0.863
Strassentransportfachmann EFZ	Road Builder	0.863
Medizinischer Praxisassistent EFZ	Medical Assistant	0.863
Gebäudetechnikplaner	Building Services Planner	0.862
Coiffeur EFZ	Hairdresser	0.862
Anlagen- und Apparatebauer EFZ	Plant and Equipment Manufacturer	0.862
Maurer EFZ	Bricklayer	0.862
Polybauer EFZ (Dachdecken)	Building Constructor	0.861
Goldschmied EFZ	Goldsmith	0.861
Fachmann Hauswirtschaft EFZ	Domestic Worker	0.859
Musikinstrumentenbauer EFZ	Musical Instrument Maker	0.859
Boden-Parkettleger EFZ	Floor Layer	0.858
Lebensmitteltechnologe EFZ	Food Technologist	0.858
Elektroinstallateur EFZ	Electrician	0.857
Logistiker EFZ	Logistician	0.853
Bäcker-Konditor-Confiseur EFZ	Baker-Confectioner	0.852
Landwirt EFZ	Farmer	0.851
Spengler EFZ	Tinsmith	0.848
Schreiner EFZ	Cabinetmaker	0.846
Laborant EFZ	Laboratory Assistant	0.845
Koch EFZ	Specialist in Professional Kitchen	0.841
Drucktechnologe EFZ	Printing Technologist	0.839
Dentalassistent EFZ	Dental Assistant	0.838
Kaufmann EFZ	Commercial Employee	0.837
Chemie- und Pharmatechnologe EFZ	Chemical and Pharmaceutical Technologist	0.833
Multimediaelektroniker EFZ	Multimedia Electronics Technician	0.831
Winzer EFZ	Grape Grower	0.829
Glaser EFZ	Glazier	0.826
Gemüsegärtner EFZ	Vegetable Grower	0.822
Schuhmacher EFZ	Shoemaker	0.817
Mikrozeichner EFZ	Micro Designer	0.816
Fleischfachmann EFZ	Butcher	0.809
Bahnbetriebsdisponent	Railway Operations Manager	0.804
Steinbildhauer EFZ	Stonesculptor	0.801

Table B1: continued

Occupation (German, continued)	Occupation (English, continued)	Specificity
Obstfachmann EFZ	Fruit Farmer	0.801
Steinmetz EFZ	Stonemason	0.799
Metallbaukonstrukteur EFZ	Metal Construction Engineer	0.795
Holzhandwerker EFZ	Woodworker	0.795
Fotofachmann EFZ (Finish/Verkauf)	Photography Expert	0.794
Metallbauer EFZ	Metal Worker	0.792
Fachmann Kundendialog EFZ	Customer Dialogue Specialist	0.790
Carrossier Lackiererei EFZ	Body Painter	0.789
Carrossier Spenglerei EFZ	Panel Beater	0.765
Drogist EFZ	Druggist	0.762
Keramiker EFZ	Ceramist	0.759
Pharma-Assistent EFZ	Pharmaceutical Assistant	0.746
Textiltechnologe EFZ (Design)	Textile Technologist	0.745
Detailhandelsfachmann EFZ	Retail Clerk	0.737
Augenoptiker EFZ	Optician	0.730
Polydesigner EFZ (Realisation)	Polydesigner	0.727
Buchhändler EFZ	Bookseller	0.699
Restaurationsfachmann EFZ	Specialist in Restaurant Service	0.683
Hotelfachmann EFZ	Hotel Management Clerk	0.669

The reports the specificity measure for each training occupation, averaged over the years 1999-2009. Source: Authors' calculations, based on the SESAM 1999-2009 and skill data from Swiss trainings regulations.

Table B2: Occupational Specificity and Wages, OLS (model 1), young workers only (graduation year ≥ 1999)

	Coef.
Specificity (std.)	0.0108
	(0.0075)
In training occupation (1=yes)	0.0053
	(0.0138)
In training occ. X Specificity	0.0204*
	(0.0104)
Size of occupation (std.)	0.0205
	(0.0221)
Local unemployment rate	-0.0250
	(0.0167)
Constant	6.8593***
	(0.1290)
Individual and job controls (age, age^2, gender, nationality, marital status, tenure, $tenure^2$, fulltime work, self-employment)	included
Year and region dummies	included
Firm size dummies	included
Managerial position dummies	included
F-statistics	441.4
R^2	0.2890
N	9,375

*Table reports coefficients of an OLS regression; dependent variable: (log) wage; robust standard errors in parentheses (clustered by training occupation), * (**,***) denotes statistical significance at the 10% (5%,1%) level.*

Table B3: Occupational mobility, probit regressions (model 2), young workers only (graduation year ≥ 1999)

	Coef.	*dy/dx*	*Coef.*	*dy/dx*
Specificity (standardized)	-0.0865**	-0.0206**	-0.0841**	-0.0201**
	(0.0359)		(0.0352)	
Size of occupation	-0.1157***	-0.0276***	-0.1094***	-0.0261***
	(0.0262)		(0.0256)	
Age	-0.0382*	-0.0091*	-0.0311	-0.0074
	(0.0231)		(0.0244)	
Age squared	0.0004	0.0001	0.0003	0.0001
	(0.0003)		(0.0003)	
Male	0.1974***	0.0471***	0.2095***	0.0499***
	(0.0724)		(0.0733)	
Swiss	-0.0416	-0.0099	-0.0426	-0.0102
	(0.0706)		(0.0706)	
Married	-0.1011	-0.0241	-0.1038	-0.0247
	(0.0995)		(0.0997)	
Self-employed	-0.0027	-0.0006	-0.0169	-0.0040
	(0.1510)		(0.1553)	
Local unemployment rate	0.0898	0.0214	0.0874	0.0209
	(0.1589)		(0.1590)	
Firm tenure	-0.0308*	-0.0073*	-0.0293*	-0.0070*
	(0.0166)		(0.0168)	
Firm tenure squared	0.0008*	0.0002*	0.0007	0.0002
	(0.0005)		(0.0004)	
Fulltime employment	-0.1565	-0.0373	-0.1531	-0.0365
	(0.1207)		(0.1195)	
Ln (wage before change)			-0.1144	-0.0273
			(0.1022)	
Firm size dummies	included		included	
Managerial position dummies	included		included	
Year and region dummies	included		included	
Pseudo R^2	0.088		0.088	
N	1,832		1,832	

*Table reports marginal effects at the means; robust standard errors in parentheses (clustered by training occupation), * (**,***) denotes statistical significance at the 10% (5%,1%) level.*

Table B4: Unemployment duration, proportional hazards model (model 3), young workers only (graduation year ≥ 1999)

	Hazard Ratios	
	Spec. (1)	*Spec. (2)*
Specificity (standardized)	0.8622*	0.7601***
	(0.0737)	(0.0801)
Size of occupation (standardized)	0.7746***	0.7403*
	(0.0645)	(0.1162)
Age	0.9726	0.9862
	(0.0702)	(0.1213)
Age squared	0.9997	0.9996
	(0.0011)	(0.0018)
Male	1.0711	1.2565
	(0.2104)	(0.2829)
Swiss	1.6439**	1.5088
	(0.3244)	(0.3787)
Married	1.1027	1.3638
	(0.3125)	(0.4245)
Local unemployment rate	0.8818*	0.8556
	(0.0665)	(0.3406)
Year and region dummies	Not included	Included
Log-likelihood	-695.3	-660.9
Number of spells	286	286

*Table presents the results of the unemployment duration regression model as hazard ratios based on the Cox estimator. Total number of spells = 286, total number of failures = 160. Robust standard errors in parentheses (clustered by training occupation); * (**,***) denotes statistical significance at the 10% (5%,1%) level.*

Table B5: Occupational Specificity and Wages, OLS (model 1), 3-digit level

	Coefficient	*SE*
Specificity (std.)	0.0187*	(0.0102)
In training occupation (1=yes)	0.0234	(0.0217)
In training occ. X Specificity	0.0311***	(0.0109)
Size of occupation (std.)	0.0711***	(0.0066)
Age	0.0391***	(0.0032)
Age squared	-0.0004***	(0.0000)
Male	0.1857***	(0.0172)
Swiss	0.0666***	(0.0088)
Married	0.0160	(0.0114)
Self-employed	-0.1436***	(0.0316)
Fulltime work	-0.0022	(0.0136)
Firm tenure	0.0093***	(0.0007)
Firm tenure squared	-0.0001***	(0.0000)
Local unemployment rate	-0.0096	(0.0072)
Constant	7.1370***	(0.0967)
Year and region dummies	included	
Firm size dummies	included	
Managerial position dummies	included	
F-statistics	719.9	
R^2	0.2589	
N	62,977	

*Table reports coefficients of an OLS regression; dependent variable: (log) wages; robust standard errors in parentheses (clustered by training occupation), * (**,***) denotes statistical significance at the 10% (5%,1%) level.*

Table B6: Occupational mobility, probit regressions (model 2), 3-digit level

	Coef.	*dy/dx*	*Coef.*	*dy/dx*
Specificity (standardized)	-0.0571**	-0.0108**	-0.0501**	-0.0094**
	(0.0258)		(0.0248)	
Size of occupation	-0.0824***	-0.0156***	-0.0660***	-0.0124**
	(0.0231)		(0.0252)	
Age	-0.0154	-0.0029	-0.0078	-0.0015
	(0.0106)		(0.0112)	
Age squared	0.0001	0.0000	0.0001	0.0000
	(0.0001)		(0.0001)	
Male	0.1333	0.0252	0.1657**	0.0312**
	(0.0834)		(0.0841)	
Swiss	0.0096	0.0018	0.0207	0.0039
	(0.0459)		(0.0461)	
Married	-0.0720***	-0.0136***	-0.0691**	-0.0130**
	(0.0273)		(0.0272)	
Self-employed	-0.1352*	-0.0256**	-0.1890***	-0.0355***
	(0.0701)		(0.0709)	
Local unemployment rate	-0.0121	-0.0023	-0.0148	-0.0028
	(0.0445)		(0.0447)	
Firm tenure	-0.0376***	-0.0071***	-0.0358***	-0.0067***
	(0.0052)		(0.0053)	
Firm tenure squared	0.0007***	0.0001***	0.0007***	0.0001***
	(0.0001)		(0.0001)	
Fulltime employment	-0.0452	-0.0085	-0.0415	-0.0078
	(0.0373)		(0.0367)	
Ln (wage before change)			-0.1984***	-0.0373***
			(0.0433)	
Firm size dummies	included		included	
Managerial position dummies	included		included	
Year and region dummies	included		included	
Pseudo R^2	0.063		0.065	
N	16,175		16,175	

*Table reports marginal effects at the means; robust standard errors in parentheses (clustered by training occupation), * (**,***) denotes statistical significance at the 10% (5%,1%) level.*

Table B7: Occupational Specificity and Wages, OLS (model 1), Intellectual demand

	Coefficient	*SE*
Specificity (std.)	0.0094	(0.0072)
In training occupation (1=yes)	0.0203	(0.0220)
In training occ. X Specificity	0.0377***	(0.0117)
Size of Occupation (std.)	0.0115	(0.0178)
Age	0.0386***	(0.0034)
Age squared	-0.0004***	(0.0000)
Male	0.1833***	(0.0160)
Swiss	0.0586***	(0.0074)
Fulltime work	0.0203	(0.0123)
Married	-0.0010	(0.0143)
Firm tenure	0.0095***	(0.0007)
Firm tenure squared	-0.0001***	(0.0000)
Local unemployment rate	-0.0098	(0.0072)
Constant	6.9258***	(0.0901)
Year and region dummies	included	
Firm size dummies	included	
Hierarchical position dummies	included	
Intellectual demand level (Stalder, 2011)	included	
F-statistics	1792.0	
R^2	0.2669	
N	61,867	

*Table reports coefficients of an OLS regression; dependent variable: (log) wage; robust standard errors in parentheses (clustered by training occupation), * (**,***) denotes statistical significance at the 10% (5%,1%) level.*

Table B8: Occupational mobility, probit regressions (model 2), Intellectual demand

	Coef.	*dy/dx*	*Coef.*	*dy/dx*
Specificity (standardized)	-0.0848***	-0.0168***	-0.0808***	-0.0160***
	(0.0200)		(0.0189)	
Size of Occupation	-0.1780***	-0.0354***	-0.1798***	-0.0356***
	(0.0544)		(0.0503)	
Age	-0.0107	-0.0021	-0.0033	-0.0006
	(0.0097)		(0.0101)	
Age squared	0.0001	0.0000	0.0000	0.0000
	(0.0001)		(0.0001)	
Male	0.1275*	0.0253*	0.1595**	0.0315**
	(0.0690)		(0.0693)	
Swiss	0.0036	0.0007	0.0127	0.0025
	(0.0469)		(0.0471)	
Married	-0.0503*	-0.0100*	-0.0460*	-0.0091
	(0.0279)		(0.0279)	
Self-employed	-0.1049*	-0.0208*	-0.1536**	-0.0304**
	(0.0626)		(0.0639)	
Local unemployment rate	-0.0201	-0.0040	-0.0221	-0.0044
	(0.0406)		(0.0407)	
Firm tenure	-0.0388***	-0.0077***	-0.0373***	-0.0074***
	(0.0058)		(0.0059)	
Firm tenure squared	0.0008***	0.0001***	0.0007***	0.0001***
	(0.0001)		(0.0001)	
Fulltime employment	-0.0320	-0.0064	-0.0301	-0.0060
	(0.0340)		(0.0342)	
Ln (wage before change)			-0.1968***	-0.0389***
			(0.0399)	
Firm size dummies	included		included	
Hierarchical position dummies	included		included	
Year and region dummies	included		included	
Intellectual demand level (Stalder, 2011)	included		included	
Pseudo R^2	0.065		0.068	
N	15,747		15,747	

*Table reports marginal effects at the means; robust standard errors in parentheses (clustered by training occupation), * (**,***) denotes statistical significance at the 10% (5%,1%) level.*

Table B9: Unemployment duration, proportional hazards model (model 3), Intellectual demand

	Hazard Ratios	
	Spec. (1)	*Spec. (2)*
Specificity (standardized)	0.9500	0.9291**
	(0.0308)	(0.0296)
Size of occupation (standardized)	1.2459*	1.1841*
	(0.1457)	(0.1108)
Age	0.9826	0.9766
	(0.0189)	(0.0202)
Age squared	1.0000	1.0001
	(0.0002)	(0.0003)
Male	0.9626	0.9181
	(0.0929)	(0.0851)
Swiss	1.1116	0.9733
	(0.0814)	(0.0825)
Married	1.0050	1.0459
	(0.0891)	(0.0891)
Local unemployment rate	0.8552***	1.0423
	(0.0237)	(0.1337)
Year and region dummies	Not included	Included
Intellectual demand level (Stalder, 2011)	Included	Included
Log-likelihood	-3729	-3670
Number of spells	1180	1180

*Table presents the results of the unemployment duration regression model as hazard ratios based on the Cox estimator. Total number of spells = 1’180, total number of failures = 637. Robust standard errors in parentheses (clustered by training occupation); * (**,***) denotes statistical significance at the 10% (5%,1%) level.*

Table B10: Occupational Specificity and Wages, OLS (model 1 with occupation FE)

	Coefficient	*SE*
Specificity (std.)	0.0753**	(0.0350)
Stayer (1=yes)	0.0146	(0.0242)
Stayer X Specificity	0.0307***	(0.0115)
Size of occupation (std.)	-0.0218	(0.0152)
Age	0.0380***	(0.0036)
Age squared	-0.0004***	(0.0000)
Male	0.1843***	(0.0069)
Swiss	0.0601***	(0.0068)
Married	0.0199	(0.0123)
Self-employed	-0.1275***	(0.0233)
Fulltime work	0.0052	(0.0122)
Firm tenure	0.0095***	(0.0006)
Firm tenure squared	-0.0001***	(0.0000)
Local unemployment rate	-0.0090	(0.0075)
Constant	6.8936***	(0.1052)
Occupation dummies	**included**	
Year and region dummies	included	
Firm size dummies	included	
Managerial position dummies	included	
R^2	0.2826	
N	62,977	

*Table reports coefficients of an OLS regression; dependent variable: (log) wages; robust standard errors in parentheses (clustered by training occupation), * (**,***) denotes statistical significance at the 10% (5%,1%) level.*

Table B11: Occupational mobility, linear probability model (equivalent to model 2 with occupation FE)

	Coef.	*Coef.*
Specificity (standardized)	-0.0650* (0.0344)	-0.0622* (0.0344)
Size of occupation	-0.0561*** (0.0215)	-0.0564*** (0.0215)
Age	0.0022** (0.0011)	0.0032*** (0.0011)
Age squared	-0.0000* (0.0000)	-0.0000** (0.0000)
Male	0.0234*** (0.0051)	0.0282*** (0.0052)
Swiss	-0.0046 (0.0036)	-0.0031 (0.0036)
Married	-0.0074** (0.0032)	-0.0068** (0.0032)
Self-employed	0.0096* (0.0058)	0.0060 (0.0059)
Local unemployment rate	-0.0191*** (0.0042)	-0.0190*** (0.0042)
Firm tenure	-0.0169*** (0.0005)	-0.0166*** (0.0005)
Firm tenure squared	0.0004*** (0.0000)	0.0004*** (0.0000)
Fulltime employment	-0.0002 (0.0052)	-0.0004 (0.0052)
Ln (wage before change)		-0.0258*** (0.0040)
Occupation dummies	**included**	**included**
Firm size dummies	included	included
Managerial position dummies	included	included
Year and region dummies	included	included
R^2	0.051	0.052
N	43,795	43,795

*Table reports the coefficients of a linear probability model; robust standard errors in parentheses (clustered by training occupation), * (**,***) denotes statistical significance at the 10% (5%,1%) level. In contrast to the main estimations, we have used each annual observation of an individual as an independent observation to use as much of the year-to-year variation as possible. The number of observations is lower than in model 1, because we focus on occupational changes during the observation period and thus cannot use an individual's first observation. Due to the well-known incidental parameter problem in non-linear models with fixed effects (Wooldridge, 2002), we present the coefficients of a linear probability model.*

Table B12: Unemployment duration (model 3 with occupation FE)

	Hazard Ratios	
	Spec. (1)	*Spec. (2)*
Specificity (standardized)	0.1146***	0.2306
	(0.0682)	(0.2362)
Size of occupation (standardized)	8.2679***	2.8276**
	(1.9295)	(1.4712)
Age	0.9958	0.9926
	(0.0235)	(0.0259)
Age squared	0.9998	0.9998
	(0.0003)	(0.0003)
Male	0.8891	0.8052*
	(0.1349)	(0.1028)
Swiss	1.1371	0.9732
	(0.0967)	(0.1029)
Married	0.9858	0.9983
	(0.1176)	(0.1103)
Local unemployment rate	0.8491***	0.8804
	(0.0255)	(0.1066)
Occupation dummies	**Included**	**Included**
Year and region dummies	Not included	Included
Log-likelihood	-3762	-3703
Number of spells	1,201	1,201

*Table presents the results of the unemployment duration regression model as hazard ratios based on the Cox estimator. Total number of spells = 1,201, total number of failures = 649. Robust standard errors in parentheses (clustered by training occupation); * (**,***) denotes statistical significance at the 10% (5%,1%) level.*

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