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Labor market transitions after layoffs: the role of occupational skills*

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Abstract

In this paper, we study the role of occupational skills in individuals' labor market transitions. Using rich data on skills required in occupations, we introduce a concept of occupation-specific human capital and develop empirical measures for occupational specificity and occupation distance. We find a strong relationship between the degree of occupational specificity and individuals' mobility patterns and wages. In particular, after layoffs, individuals with more occupation-specific human capital are less likely to find reemployment in a different occupation and are more likely to suffer prolonged periods of unemployment. We also find that, upon reemployment, these individuals receive a wage premium. These results suggest a risk-return tradeoff to educational investments into more specific human capital. In addition, we develop a measure for the distance between occupations and find that individuals who move to occupations with similar skill requirements (i.e. lower distance) suffer smaller wage losses than individuals with more distant moves. Thus, we show that skills are transferable across occupations and that occupational specificity largely determines mobility patterns and wages after layoffs.

Keywords: occupational mobility, layoffs, unemployment, human capital, skills, occupational training

JEL classification codes: J620, J630, J640, J240

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1. Introduction

Continuing structural change is fundamentally altering the working environment in many sectors of the economy, leading to high rates of job mobility both in the United States and in Europe (Bachmann and Burda, 2009; Kambourov and Manovskii, 2008). Human capital theory provides a central framework for studying job mobility and the evolution of wages. (Becker, 1962) distinguishes between general skills that are useful in different jobs and specific skills that are not transferable across jobs. Worker reallocation and unemployment are more costly if skills are specific (Poletaev and Robinson, 2008). There is little consensus among scholars about how to measure human capital specificity empirically. More recently, scholars have justifiably argued that human capital specificity is linked with occupations (Autor et al., 2003; Gathmann and Schönberg, 2010; Kambourov and Manovskii, 2009; Poletaev and Robinson, 2008). The basic idea is that many occupations are similar in their basic skills and that specificity arises from differences in basic skill bundles. These bundles are specific in the sense that they are only productive in occupations where similar skills are required.

In this study, we apply this idea of occupation-specific human capital to analyze labor market transitions of laid-off workers. Most previous research has focused on job-to-job mobility, measuring the transferability of skills between jobs and relating it to the evolution of wages. A general finding is that individuals move to occupations with similar skill requirements (Gathmann and Schönberg, 2010) and that skill bundles are closely related to wages (Poletaev and Robinson, 2008). So far, only little research exists that takes into account other labor market outcomes. We try to fill this research gap by investigating whether occupation-specific human capital is associated with reemployment success. The rationale is straightforward: the more specific a worker's human capital, the fewer are the reemployment chances. However, to test this rationale we need a broader concept of occupation-specific human capital. Instead of merely relating the skill bundle of one job to the skill bundle of another job, we apply a novel theoretical approach and develop a continuous measure classifying a whole set of occupations in terms of their degree of specificity.

Conceptually, we draw on Lazear's skill-weights approach (2009) to develop such an encompassing measure. Lazear argues that one can view occupations as bundles of single skills. All skills are general, but each occupation uses a particular combination of these general skills. In Lazear's model, the specificity of a skill bundle is determined by the labor market demand for that particular skill bundle. More precisely, the weights assigned to the single skills in an occupation compared to the weights in the overall labor market make an occupation more or less specific. Skill bundles thus vary in their degree of specificity because demand on the labor market is higher for some skill weights than for others.

To measure the degree of specificity empirically, we need data on both the skills required in occupations and the labor market demand for occupation-specific skill bundles. This type of data is available in Switzerland. We use data from the *Berufsinformationszentrum* (BIZ); the state-led career-counseling center to construct occupation-specific skill bundles, The BIZ provides a detailed list of skills that are used in individual vocational occupations, covering a total of 220 occupations.[1] To infer the market demand for these skill bundles, we use the Social Protection and Labour Market (SESAM) survey. The SESAM is a representative survey that contains the distribution of occupations encompassing the entire workforce. Matching the skill bundles from the BIZ to the occupations in the SESAM allows constructing a continuous measure of occupational skill specificity. In addition, because the SESAM is a panel survey with individual employment histories, we can use it to investigate labor market transitions. It is linked with administrative data on wages, unemployment benefits, and the length of employment and unemployment spells. This administrative nature of our data minimizes the measurement error in wages and occupational coding.

In our econometric analyses, we estimate the probability of different post-layoff labor market outcomes (reemployment in the origin occupation, reemployment in a different occupation, continued unemployment, leaving the labor force) as a function of a worker's occupational specificity. Our analysis shows that the specificity of a skill bundle of an occupation, and not the occupation per se, crucially determines workers' labor market outcomes after layoffs. We then also examine the skill distance between occupations, which allows investigating how closely related wage losses are with differences in skill weights.[2] We find that the larger the distance between two occupations, the higher are the wage losses for workers who change between these occupations. Workers who move to occupations with a smaller distance are able to transfer a larger part of their skill bundle to the new job and, in turn, suffer smaller wage losses than workers who move to more distant occupations.

Our analyses show that it is not so much the occupation but rather the single skills and the bundling of these skills that determine how mobile workers are in the labor market. Some

[1] Since skill heterogeneity exists not only between but also within education classes (Backes-Gellner and Wolter, 2011; Christiansen et al., 2007; Geel and Backes-Gellner, 2011), we will focus on workers in the same education class to obtain unbiased effects.

[2] The literature on measuring the distance between occupations is relatively recent. Examples are Robinson (2011), who investigates the loss of human capital after an occupational change, and Firpo et al. (2011), who examine which skills are most vulnerable to offshoring.

of the skills that make up occupational skill bundles can always be applied in other occupations. But the degree to which this is possible varies across occupations. Policy makers are, therefore, well advised to address the specificity of the skill bundles that are offered in their VET system to ensure that workers not only have good short term but also sustainable long term employment opportunities.

2. Conceptual framework

2.1 The Skill-Based Approach

Building on Becker (1962), Lazear (2009) introduces a skill-weights model of human capital specificity. In his basic model only two skills (A and B) and two periods exist. Taken alone, no skill is specific. However, firms use the general skills A and B in different combinations, with firm-specific weights attached to them. The resulting skill bundles thus become firm-specific. An individual can acquire skills at cost $C(A,\ B)$ with $C_A, C_B \geq 0$ and $C_{AA}, C_{BB} < 0$. In the first period, individuals decide on a particular combination of A and B. In the second period, their payoff at firm i is determined by the simple earnings function $Y_i = \lambda_i A + (1-\lambda_i)B$, where $0 \leq \lambda \leq 1$ is the relative weight of skill A in firm i. The weight λ is particular to each firm and has density $F\ (\lambda)$.

If a worker were certain to remain with his initial firm indefinitely, he would invest in the particular skill bundle that maximizes the payoff in the initial firm. But the model allows for separations. Because other firms might demand a different weighting of skills A and B, the worker's initial skill bundle might not be optimal in another firm, making part of his initial investment worthless. The expected loss of the initial investment is determined by the distance to the skill bundle on the labor market. If this distance is rather small, then the initial skill bundle is more general with respect to the external market demand. The smaller the distance, the smaller is the expected loss of the initial investment. The individual's maximization problem in this set-up is to choose the human capital investment strategy that maximizes net expected earnings while taking into account the outside job offer distribution and its implicit demand for combinations of skills.

Translating Lazear's idea of firm-specific human capital to the level of occupations, we argue that each occupation i requires a different combination of single skills with occupation-specific weights λ_i, thereby further developing an idea first applied by Geel et al. (2011).[3] We characterize occupations by skill bundles and determine their specificity by comparing them to the skill bundle in the labor market, which is defined as $\bar{\lambda}$. To compare the whole set of skills simultaneously, we construct skill vectors that allow ranking occupations.

Extending Lazear's model, we then compare occupations among themselves. In particular, we compare an individual's pre-layoff job with his post-layoff job to investigate the evolution of wages. The underlying hypothesis is that wage losses should be smaller if the two occupations are similar rather than dissimilar. With two very similar jobs, the worker is able to transfer most of his occupation-specific human capital from one job to the other and is paid accordingly. Following Poletaev and Robinson (2008), we use the Euclidean distance measure to quantify the difference in skill requirements between the occupations. We define the Euclidean distance between occupations X and Y as follows:

$$D_{XY} = \sqrt{\sum_{i=1}^{N}(X_i - Y_i)^2},$$

where the sub-index $i = 1 \ldots N$ indicates the number of skills forming the skill bundles. In the empirical analysis, we will regress post-layoff wages on this distance measure. Note that while layoffs may be considered exogenous; the skill distance is, in general, not. The regression results will thus not show the wage evolution of workers who are randomly assigned to new jobs. Rather, the results should be interpreted as quantifying the transferability of skills and relating skills to wages.

2.2 Estimation Strategy

Our analysis focuses on three central predictions: First, the more specific a worker's origin occupation is, the more difficult is finding reemployment. We expect that the relative specificity of workers' occupational skills lowers both their chances of finding reemployment in their origin occupation–because of the thin market–and of moving to a different occupation–because of the low demand for their skills–, thereby restricting the workers' sets of alternatives. Second, we expect occupational specificity to be associated with the wage losses the workers suffer. The direction of the effect is, however, ambiguous. While workers in more specific occupations might have to endure longer unemployment spells than workers in more general occupations, they may achieve a better match by the time they are reemployed. This may, at least partly, compensate for their longer unemployment spell. Third,

[3] The study by Geel et al. (2011) focuses on firm-financed apprenticeship training. Using data from the German BIBB/IAB Qualification and Employment Surveys, they construct an index of the skill specificity of different vocational occupations and find support for Lazear's theory.

focusing on occupational changes, we expect that the distance between pre- and post-layoff occupation will be associated with the extent of wage losses the workers suffer. The larger the skill distance, the fewer skills can be transferred to the new occupation and the higher the wage losses will be.

Search theory provides an appropriate framework to think about labor market transitions (Mortensen, 1986; Mortensen and Pissarides, 1999). In these models, individuals compare the present value of different labor market outcomes and choose the outcome with the highest utility. The multinomial logit is capable of capturing these ideas. Thus, in our analysis, we assume that a multinomial logit model (McFadden, 1974) describes the probability of transitions. While most previous research (Atkinson and Micklewright, 1991; Blanchard et al., 1990) distinguishes the outcomes employment, unemployment and leaving the labor force, we make the further distinction between employment in the origin occupation and employment in the new occupation. In our baseline model, our dependent variables are a set of four dummy variables indicating labor market status one year after the layoff: employed in the same occupation as before the layoff, employed in a different occupation, unemployed, and out of the labor force. For identification purposes we choose the most frequent outcome, "reemployed in the origin occupation," as the reference category.

The theoretical framework of multinomial logit models can be described as follows: Each individual *i* is faced with *J* different choices. The individual *i* assigns utility u_{ij} to choice *j* and selects the choice with the highest utility. The probability of making choice *j* conditional on observed characteristics *x* has the following form:

$$\pi_j(\mathrm{x}_i; \beta) = \frac{\exp\,(x_i{}'\beta_j)}{1 + \sum_{r=2}^{J} \exp\,(x_i{}'\beta_r)}$$

where

$$x_i{}'\beta = \beta_1 \cdot OS_i + c_i'\beta_2 + \beta_3 \cdot UR_i + \beta_4 \cdot LMT_i + \varphi + \delta.$$

The individual's choice is explained by our variable of interest, occupational specificity (*OS*), a comprehensive set of individual (age, tenure, gender etc.) and firm characteristics (sector and firm size of the previous firm), c_i, and the state of the labor market (*UR* and *LMT*). *UR* is the local unemployment rate, which describes the number of searchers. *LMT* is the labor market thickness on the occupation level, used a proxy for the outside job offer distribution. Finally, φ are time dummies, and δ are region dummies.

In the first specification (Table 8), we include wages earned before layoff and unemployment benefits received during the unemployment spell alongside the other individual characteristics to control for the worker's reservation wage and his value of non-participation. However, wages and benefits are, to some extent, outcomes of skills. Controlling for wages may therefore bias our estimates. In the second specification (Table 9) we report results without controlling for wages and benefits. Our results remain largely unaffected.

We then use monthly gross wages as dependent variable to explore how occupational specificity affects wages conditional on being reemployed. We use Poisson pseudo-maximum estimation (Balestra and Backes-Gellner, 2013; Santos Silva and Tenreyro, 2006) where the parameters of interest solve the condition

$$\sum_{i=1}^{n} [y_i - \exp(x_i'\beta)] \cdot x_i = 0,$$

with

$$x_i'\beta = \beta_1 + \beta_2 \cdot OS_i + \beta_3' c_i,$$

where y_i is monthly wages, OS_i is the specificity in the origin occupation, and c_i is the vector of controls that we have included previously, i.e., individual and firm characteristics, *UR* and *LMT*, and year and region dummies. Finally, we analyze whether the distance of moves is associated with the evolution of wages. Again, using Poisson regression, we estimate parameters that solve the equation

$$\sum_{i=1}^{n} [y_i - \exp(x_i'\beta)] \cdot x_i = 0,$$

where

$$x_i'\beta = \beta_1 + \beta_2 \cdot Lwage_i + \beta_3 \cdot distance_i + \beta_4 \cdot interaction_i + \beta_5' w_i.$$

3. Data

In the empirical analysis, we use data from Switzerland, a country with a long tradition of vocational education and training, where more than half of the workforce holds a VET degree.[4] We use three different types of data for our empirical analysis: First, to construct occupation-specific skill bundles, we use data on skills used in an occupation from the career-counseling center BIZ. Second, to measure transition outcomes, we use the Social Protection and Labour Market (SESAM), a survey data set that is linked with administrative data on employment and unemployment spells. Third, to control for regional and time-specific

[4] We have included a section with detailed information on the Swiss Vocational Education and Training System in the Appendix.

employment opportunities, we use data on the monthly unemployment rates from the Swiss Federal Statistical Office.

3.1 Skill Bundles, Specificity, and Distance

The career-counseling center BIZ provides a detailed list of skills that are used in individual occupations, covering a total of 220 VET occupations.[5] The list comprises 26 different skills and distinguishes between physical, intellectual, and personal skills. Examples include "fine motor skills," "visual thinking," and "ability to work in a team."[6] Each occupation has an average of seven skills. In essence, the 26 skills represent 26 potential dimensions of skill heterogeneity across workers. We can thus generate unique skill bundles for each of the VET occupation in our data. To account for the varying intensity with which skills are used, we weight each skill with the number of skills in an occupation. For example, if an occupation uses four different skills, we attach a weight of 0.25 to each skill, while in an occupation with eight different skills; each skill receives a weight of 0.125.

We then use the SESAM to construct the skill bundle on the Swiss labor market, $\bar{\lambda}$.[7] Since SESAM is representative it contains the distribution of occupations of the entire Swiss workforce. For each wave in our dataset, we know the distribution of the workforce across occupations, and, for each occupation, we know the respective skill bundle. Using both types of information, we rank each of the 26 single skills in the labor market according to their frequency. In essence, this constitutes the market skill bundle, $\bar{\lambda}$.[8] We then determine the degree of specificity of an occupation by comparing the rank of each of the single skills with their rank on the external labor market. By doing so, we adapt the approach of Geel et al. (2011).

To better understand our approach, take the occupations banker and electrician as an example. For simplicity, assume that only these two occupations exist in the labor market. In addition, we limit our example to a four-dimensional skill vector, i.e., the two occupations are characterized by the presence or absence of only four skills.[9] Assume further that a banker has

[5] The list comprises 220 VET occupations, with training lasting from two to four years. However, the two-year training does not lead to a certified VET degree. Because we take into account only workers with a certified VET degree, we exclude all two-year long trainings. This procedure leaves us with a total of 156 VET occupations.

[6] Note that these data are a snapshot, i.e. we assume that skill requirements do not change over the considered time period, i.e. 2004 to 2009.

[7] As SESAM uses the same occupational categories as the BIZ, we can easily match the information from our occupation-specific skill bundles. The occupational code available in both data is the *Schweizer Berufsnomenklatur 2000* (SBN2000), a five-digit code.

[8] To account for changes in skill demand over time, we calculate the market bundles separately for each wave.

[9] In the actual data we have 26-dimensional skill vectors for the occupations.

the skills "abstract-logical thinking" and "mathematical skills," and an electrician has the skills "mathematical skills," "fine motor skills," and "spatial thinking." Thus, the skill bundle of the labor market $\bar{\lambda}$ contains four skills. Considering these four skills, the skill bundles of the occupations are:

banker's skill bundle

$$\lambda_B = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \end{pmatrix} \begin{array}{l} \text{abstract-logical thinking} \\ \text{mathematical skills} \\ \text{fine motor skills} \\ \text{spatial thinking} \end{array}$$

electrician's skill bundle

$$\lambda_E = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 1 \end{pmatrix} \begin{array}{l} \text{abstract-logical thinking} \\ \text{mathematical skills} \\ \text{fine motor skills} \\ \text{spatial thinking} \end{array}$$

In the next step, we compare these skill bundles to the market skill bundle. The market bundle in this example is a four-dimensional skill vector and contains a ranked order of skills. The rank order is determined by the frequency of skills in the market. Suppose that the labor market comprises 500 bankers and 300 electricians. Looking at the underlying skill bundles, we see that 500 workers use the skill "abstract-logical thinking," 800 workers use the skill "mathematical skills," and 300 workers use the skills "fine motor skills" and "spatial thinking." Thus, in our example labor market with only bankers and electricians, the market skill bundle $\bar{\lambda}$ is composed of:

market skill bundle

$$\bar{\lambda} = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \cdot \begin{pmatrix} 500 \\ 800 \\ 300 \\ 300 \end{pmatrix} \begin{array}{l} \text{abstract-logical thinking} \\ \text{mathematical skills} \\ \text{fine motor skills} \\ \text{spatial thinking} \end{array}$$

which leads to the following ranked order of skills:

ranked order of skills

$$R = \begin{pmatrix} 2 \\ 1 \\ 3 \\ 3 \end{pmatrix} \begin{array}{l} \text{abstract-logical thinking} \\ \text{mathematical skills} \\ \text{fine motor skills} \\ \text{spatial thinking} \end{array}$$

Finally, we derive the specificity measure for the occupation-specific skill bundle by dividing the ranked order of skills by the number of skills used in an occupation. This procedure allows taking into account the intensity with which a skill is used in an occupation. Coming back to our previous example, the bank clerk uses two skills and therefore we assign the value 0.5 to each skill. He uses the skills with an intensity of 50 percent. The electrician uses three skills and therefore we assign the value $0.\overline{3}$ to each of his skills. He uses each skill with an intensity of $33.\overline{3}$ percent.

Formally, the specificity measure is defined as:

specificity measure of an occupation j $$S_j = \frac{\sum_{i=1}^{2} m_i}{\sum_{i=1}^{2} n_i} = \frac{sum\ of\ ranks}{sum\ of\ skills}$$

Turning to our example, the banker's specificity is:

specificity measure of a banker $$S_b = \frac{sum\ of\ ranks}{sum\ of\ skills} = \frac{2+1+0+0}{2} = 1.5$$

and the electrician's specificity is:

specificity measure electrician $$S_e = \frac{sum\ of\ ranks}{sum\ of\ skills} = \frac{0+1+3+3}{3} = 2.\overline{3}$$

According to our specificity measure we see that electrician is a more specific occupation than banker. Applying this procedure to the whole set of occupations in the labor market, we develop a continuous measure of occupational specificity.

Next, we compute the skill distance between occupations applying the Euclidean distance formula. As pointed out before, in our empirical analysis, we use 156 different occupations. Thus, we obtain $156 \times 157/2 = 12{,}246$ pairwise measures of Euclidean distance between the occupations in our sample. Thereby, we quantify the proportion of transferable skills for each possible occupational change in our data.

To clarify, specificity and distance capture different information. Two occupations can be similar in terms of specificity, and yet they can be quite different in terms of Euclidean distance and vice versa. While the specificity is determined by comparing an occupational skill bundle (in our example λ_B or λ_E) with the market skill bundle ($\bar{\lambda}$), the Euclidean distance is determined by comparing the skill bundles across two occupations (D_{BE}). While the specificity measure allows determining the probability of occupational change and the probability of finding reemployment, the distance measure allows quantifying the proportion of transferable skills and the associated evolution of wages.

Table 1 gives an example to illustrate this difference. In our data, the Euclidean distance ranges from 0 to 1.4142. At the lower end, there is, for instance, the combination of farmer and forest manager. These two occupations have the exact same skill vectors. Hence, the specificity measure is the same for the two occupations, and their distance is 0. The Euclidean distance is also low between a food technician and a fruit farmer. These two occupations differ in one skill requirement only. This one skill is technical understanding, which is required for food engineers but not for fruit experts. However, technical understanding is a very specific skill causing the two occupations to differ substantially in terms of occupational specificity. At the higher end of the distribution of occupational distances in our example, we find the combination of recyclists (who work in waste management) and pre-school teachers. These two occupations differ substantially in terms of their skill bundles, which is why their Euclidean distance is high. Thus, if a recyclist starts working as a pre-school teacher he can transfer hardly any skills.

{Table 1 here}

3.2 The Social Protection and Labour Market Survey

To construct our outcome variable we use the SESAM data, which is a matched panel data set linking the Swiss Labour Force Survey (SLFS) with data from different social insurance registers. The social insurance registers provide the exact daily duration of all individual employment and unemployment spells, as well as monthly earnings and the exact amount of unemployment benefits received. Thus, the SESAM provides a rich set of information on individual education histories, employment behavior patterns, and socio-demographics. The panel structure allows following individuals over time so that we can analyze their labor market transitions following layoffs.

The SESAM has at least three advantages over regular household surveys commonly used in the literature studying labor market transitions. First, their administrative nature ensures that we observe the wage associated with each job and the exact date of a job change. Second, measurement error in wages and occupational titles is much less of a problem than in typical survey data. We are thus able to reduce the bias in our estimates. Third, while most data sets use occupational codes on the 2-digit or 3-digit level, the SESAM uses 5-digit codes. This very detailed coding prevents us from aggregating occupations that are in fact rather dissimilar in terms of their skill bundles.[10] We should thus be able to trace labor market transitions very precisely.

[10] For example, in our data we can distinguish between a fruit farmer and a vintner. These are different VET occupations with different VET curricula, but their occupational codes are almost the same, namely, 11201 and 11202.

3.3 Sample and Descriptive Statistics

Our sample contains workers who have been laid off and who fulfill the following conditions: (1) workers holding a VET degree, (2) workers between 18 and 65 years of age, and (3) workers who have been laid off at least once during the observation period and whom we can observe for at least one year after the layoff. Our sample includes both male and female workers. We also include part-time workers since the share of part-time workers in Switzerland is very large.

We know from previous studies that self-reported data on layoffs might contain response bias (Bertrand and Mullainathan, 2001). However, in our data this does not seem to be the case. Table 2 shows the distribution of possible answers to the survey question "Why are you unemployed?" Since the reason layoff is the highest reported incidence, we assume that the social desirability bias is minimal. Moreover, the table shows that the reason "layoff" is the only involuntary job loss, whereas all the other reported reasons seem to be initiated directly by the worker.

{Table 2 here}

Further, we assume that non laid-off workers and laid-off workers do not differ systematically in the sense that our results are representative for the entire workforce. In the following we show descriptively that this assumption is reasonable. Table 3 reports summary statistics for the main variables of the entire SESAM sample while Table 4 reports summary statistics for a sample that is restricted to laid-off workers.

Table 3 shows that 46 percent of the sample is male; 56 percent of the individuals are married, and 48 percent are Swiss nationals. Individuals are on average 41 years old and the average tenure is 6.6 years. About 69 percent of the sample is working or has worked fulltime. In Switzerland, working between 70 to 90 percent of the time, instead of 100 percent, is very common. The fulltime working hours are 42 hours per week. On average, individuals earn 4,090 CHF per month and receive 139 CHF of unemployment benefits. [11]Wages are zero for the unemployed and, respectively, benefits are zero for the employed. The sector is coded according to the 2-digit NOGA08, and the firm size is a categorical variable with five categories. The region captures the 26 cantons in Switzerland and the unemployment rat is measured at the cantonal level.

In the laid-off sample, about 50 percent of the sample is male. Fifty two percent of the

[11] We have included a section on the Swiss UI-system in the Appendix.

individuals are married and about 51 percent are Swiss nationals. Individuals are on average 42 years old and have three years of tenure. Since all these individuals are laid-off at some point average tenure is of course lower than in the full sample. Sixty two percent of the sample is working or has worked fulltime. The average wage is 3,631 CHF and the average monthly unemployment benefits are 915 CHF. Because labor market thickness and occupational specificity are measured only for the laid-off sample of VET workers, we only report them in Table 4. Both variables have been standardized to have a mean of zero and a standard deviation of one. Thickness varies between -0.841 and 1.801, while the specificity measures varies from -1.945 to 2.049. Overall, the observable characteristics do not differ greatly between the two samples, which is why we assume that our figures are still representative.

{Tables 3 and 4 here}

Next, we want to see whether workers in a certain occupation at a certain point in time were disproportionally hit by layoffs. If this were the case, our estimates might be distorted. Table 5 reports the layoff rate at the 2-digit NOGA08 level over the observation period in the SESAM data. The incidence remains stable over the years, indicating that the recent recession appears to have had no great impact on layoffs in Switzerland—at least not until 2009.

{Table 5 here}

Finally, our observation period covers 2004 through 2009, a period that might bias our estimation results due to the recent economic crisis that started in late 2008. During the crisis, the number of layoffs may have been disproportionally high, and workers searching for employment may have faced adverse conditions. Figure 1 plots the rate of laid-off workers over time comparing them to the unemployment rate. The figures move in parallel downwards from 2004 to 2008, and the increase from 2008 to 2009 is quite moderate. The overall unemployment rate increased from 3.4 percent in 2008 to 4.3 percent in 2009, while the layoff rate increased less sharply, from 2.2 percent to 2.6 percent. In line with previous findings (Lazear and Spletzer, 2012) our descriptive evidence contradicts the naive intuition that layoffs increase disproportionally during times of crisis.

{Figure 1 here}

Now we turn to analyzing our outcome variable descriptively. We distinguish four possible outcomes: (1) being reemployed in the same occupation, (2) being reemployed in a different occupation, (3) being unemployed, or (4) being out of the labor force. Table 6 gives a brief overview of the observed labor market transitions. In our sample, one year after the layoff, about 61 percent of all laid-off workers are reemployed, about 18 percent remain unemployed, and 20 percent have left the labor force. Among the reemployed workers, about 20 percent have changed their occupation.

{Table 6 here}

The distribution of outcomes differs strongly across different occupational groups. Table 7 reports some examples of how occupational groups and their labor market transitions. Reemployment is more likely, for example, for advertising, marketing, and tourism professionals as well as hygienists, health and personal care professionals. More than 70 percent of workers in these occupations are reemployed within one year after the layoff. In contrast, post and telecommunications professionals were the least likely to be reemployed in our period of time. Occupational changes after layoffs also vary substantially. Only one third of the workers in advertising, marketing, and tourism change their occupation, while more than half of the laid-off hygienists, health and personal care professionals are reemployed in a different occupation. In addition, 80 percent of workers in post and telecommunications change their occupation, whereas only 23 percent of graphic industry professionals do so. These descriptive patterns are indicative that the occupation does indeed matter for labor market outcomes.

{Table 7 here}

4. Results

4.1 Labor Market Transitions and Occupational Specificity

Tables 8 through 10 report estimation results of the effect of occupational specificity on labor market transitions. We first show how occupational specificity affects the log-odds ratios of the different alternatives compared to the baseline outcome "being reemployed in the same occupation." Then, in Table 10, we show how occupational specificity affects all four outcome probabilities. For the sake of interpretation, we standardized the independent variable of interest, occupational specificity, before running our regressions.

In Table 8 column (1), the coefficient of interest, "occupational specificity," is negative and statistically significant at the one percent level. This implies that the log-odds ratio of finding reemployment in a different occupation compared to reemployment in the initial occupation is decreasing in occupational specificity. The higher the degree of specificity of a worker's initial occupation, the less demand there will be for his skills in other occupations, and the less likely he will be able to switch to a different occupation.

Column (2) shows estimates for how occupational specificity affects the probability of remaining unemployed. Occupational specificity increases the log odds ratio of still being unemployed versus having found reemployment in the same occupation. The effect is statistically significant at the ten percent level.

Column (3) shows how occupational specificity affects the log odds ratios of dropping out of the labor force versus having found reemployment in the same occupation. The coefficient is again negative and statistically significant. The higher the occupational specificity, the less likely the worker will leave the labor force. This finding may be due to high-specificity jobs paying high wages and consequently also high UI benefits.

Among the control variables, labor market thickness as expected decreases the likelihood of still being unemployed versus finding employment in the same occupation. The intuition is straightforward: The more jobs a laid-off worker can choose from, i.e., the higher the labor market thickness, the more likely that the worker will find a job in the occupation for which he is trained. Surprisingly, labor market thickness increases the likelihood of leaving the labor force versus finding employment in the same occupation.

The unemployment rate increases the likelihood of switching occupation. With a high unemployment rate, workers might prefer switching occupation and realizing a poorer match to remaining unemployed since the threat of prolonged unemployment spells is more immanent. Unemployment benefits increase the probability of remaining unemployed and they decrease the likelihood of switching occupation and of leaving the labor force. Wages earned in the origin occupation decrease the likelihood of choosing any other outcome than being reemployed in the origin occupation. Given that these variables are proxies for reservation wages and ability, the signs of these coefficients are in line with expectations.

However, as lagged wages and benefits may be endogenous, these coefficients should be interpreted with caution (Abowd and Kang, 2002). Wages are an outcome of skills and of skill specificity. This suggests that the regression equation underlying the outputs in Table 8 may be misspecified, which would bias the coefficient on occupational specificity. In Table 9, we, therefore, repeat the multinomial logit regression without controlling for wages and unemployment benefits. We find the coefficients of interest are unaffected by whether we control for incomes or not. They change neither in direction nor in levels of statistical significance. To test for the critical IIA (Independence of Irrelevant Alternatives) assumption, we perform the Hausman-McFadden test (Hausman and McFadden, 1984). The test results show that we cannot reject the null hypothesis that the outcomes are independent of other alternatives. Thus, our model does not seem to violate the IIA assumption. In an alternative, unreported specification, we clustered our standard errors at the sector level. Clustering does not change the results qualitatively.

{Tables 8 and 9 here}

Table 10 reports marginal effects of a one standard deviation change in occupational specificity on all four outcomes considered in our analysis based on the estimates from Table 9. Our results indicate that an increase in occupational specificity by one standard deviation increases the probability of reemployment in the next year in the origin occupation by 3.2 percentage points and of remaining unemployed in the next year by 4 percentage points. The chances of having found reemployment in a different occupation and of having left the labor force during the year after the job loss, however, decrease by 4.5 percentage points and by 2.7 percentage points, respectively, if occupational specificity increases by one standard deviation. A comparison of these changes to the average probabilities of the four outcomes across all individuals in our sample who lost their job shows that a one standard deviation increase in occupational specificity raises the chances of continued unemployment by one fifth. Overall, our results suggest that workers in more specific occupation are most likely to find reemployment in their original occupation and to keep collecting UI benefits for longer while they are searching for a job in their original occupation.

{Table 10 here}

4.2 The Relationship Between Wages and Specificity

Table 11 reports estimates from a wage regression that uses the Poisson method, where the dependent variable is monthly wages and the sample comprises individuals who are reemployed one year after the layoff. In the first specification we regress wages on occupational specificity without controls. We find a positive correlation between the degree of specificity and wages. It appears that workers receive a wage premium of about 5 percent for employment in a one standard deviation more specific occupations.

Upon including all control variables, the positive association increases slightly and remains statistically significant. Thus, among those who have found reemployment, higher specificity is associated with higher wages. These results suggest an efficient risk-return trade-off in the sense that investments into more specific human capital are associated with higher returns but also with higher risk of unemployment after layoffs (Christiansen et al., 2007; Tuor and Backes-Gellner, 2010). Our results suggest that the wage losses incurred from layoffs are smaller for workers in highly specific occupations if they find reemployment.

{Table 11 here}

4.3 The Relationship Between Wages and Occupational Distance

We investigate the relationship between wages and the occupation distance, again using Poisson estimation. We standardize the independent variable "Euclidean Distance" before running our regressions. Table 12 shows how pre-layoff wages are correlated with post-layoff wages among those who have found reemployment in our sample, and how this relationship is driven by the distance between pre- and post-layoff job. Our approach follows Gathmann and Schönberg (2010), who find a positive correlation of wages in the old and new job, indicating that more able workers always earn more. However, in their sample of voluntary transitions, workers move into distant occupations only if these occupations pay high wages. Gathmann and Schönberg (2010), therefore, observe a positive correlation between occupational distance and new wages.

In our sample of laid-off workers, in contrast, workers might face a different set of options.[12] Their fallback position is unemployment instead of staying at the old job. We regress log post-layoff wages on pre-layoff wages, on our measure of occupational distance, and on an interaction term between the two. The coefficient on pre-layoff wages indicates how post-layoff wages change in percent if pre-layoff wages, ceteris paribus, increase by 1,000 CHF. The distance coefficient shows how post-layoff wages change with occupation distance. Finally, the coefficient on the interaction term shows how this effect of occupation distance varies across individuals who were in different income groups before losing their jobs.

Specification (1) does not account for the distance of occupational changes. The correlation is positive and statistically significant. One thousand Swiss Francs higher monthly wages before the layoff translate into about 5 percent higher monthly wages in the new job. In specification (2) we include distance between the pre-layoff and the post-layoff occupations into our regression. The estimate of the correlation between pre-layoff and post-layoff wages is hardly affected, and distance is negatively correlated with post-layoff monthly wages.

[12] Indeed, Gathmann and Schönberg (2010) also provide evidence that displaced workers incur higher wage cuts if they have to accept employment in more distant occupations.

Specification (3) includes the full model with occupation distance and its interaction term with pre-layoff wages. The correlation between distance itself and post-layoff wages becomes more negative and highly statistically significant after including the interaction term between pre-layoff wages and distance. For a (hypothetical) worker with zero pre-layoff wages before the job loss, a one-standard-deviation increase in occupation distance results in an eight percent drop in wages in the new job. With each increase in pre-layoff earnings by 1,000 CHF, this effect decreases by a bit less than one percent. For a worker with pre-layoff earnings of about 9,000 CHF, the occupation distance between the origin and the new occupation is unrelated to wages in the new job. We interpret this finding as confirmation that the laid-off workers in our sample could, indeed, not afford to be as selective as the voluntary movers in Gathmann and Schönberg (2010).

Workers with low pre-layoff wages only move to distant occupations if they have a very limited set of alternatives. If employment in the same or in related occupations is not available, they have to accept job offers in distant occupations even though this implies significantly lower wages. Distant occupational transitions thus entail significant wage cuts for these low-wage workers. This relationship becomes weaker with increasing pre-layoff wages. Individuals with higher earnings seem to be more similar to the voluntary movers in Gathmann and Schönberg (2010).

{Table 12 here}

5. Conclusion

This paper analyzes job mobility and the evolution of wages of laid-off workers. We use Lazear's theoretical skill-weights approach (2009) to introduce a new concept of occupation-specific human capital. Using rich data on skills required in different occupations, we construct an empirical measure for occupation-specific skill bundles and provide a detailed empirical analysis of the effect of occupational specificity on labor market transitions after layoffs. Using multinomial logit regressions, we provide evidence that occupational specificity reduces occupational mobility and increases the length of unemployment spells. A one standard deviation increase in our occupational specificity measure raises the chances of continued unemployment one year after a job loss by four percentage points. However, we also find that individuals in more specific occupations have higher expected wages after layoffs, suggesting a risk-return tradeoff to educational investments into more specific occupations.

Our approach provides distinct advantages over the use of industry or occupation codes. Associating a skill vector with single occupations allows ranking and comparing occupations according to basic skill combinations. Industry or occupation codes only allow for the classification of different occupations instead of general or specific skill vectors within a given occupation.

Our analysis shows that some not very common occupations that may be considered as providing very narrow labor market options contain a bundle of general skills that allows workers to change occupations rather easily. Thus, breaking down occupations into skill bundles and classifying occupations by our specificity measure helps to better understand labor market transition patterns and employment outcomes.

Further, we construct a measure for the distance between occupations that shows the extent to which a skill bundle can be used when switching occupations. We show that the larger the distance between two occupations the higher is the wage loss of laid-off workers when switching between those occupations. This result also confirms Gathmann and Schönberg (2010), who find that wage losses due to displacement depend on labor market thickness.

From a policy point of view, our study contributes to the ongoing discussion on whether vocational occupations are too narrowly defined and whether vocational education and training, thus, makes it difficult for workers to adapt to technological and structural change (Zhang et al., 2011). We show that it is not the occupation per se but rather the compatibility of the skill bundle of an occupation in comparison to the labor market demand and in comparison to the skill bundle of other occupations that matter for future labor market success. Thus, policy discussions should not focus on whether or not too many VET occupations exist but rather on the skill bundles taught in these occupations. Again, applying the naive definition of a specific (in the sense of rare) occupation is misleading. Rare occupations might contain a large share of general skills, in which case workers in these occupations will be highly flexible. Thus, policy makers are well advised to ensure that vocational occupations contain skill bundles that meet the overall market demand of skill bundles so that workers have outside options and are flexible enough to change occupations and/or employers.

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TABLES

Table 1: Example pairwise occupational distances and specificities				
Occupation X	Specificity X	Occupation Y	Specificity Y	Euclidean Distance
Farmer	0.22	Forester	0.22	0.000
Food technician	0.21	Fruit farmer	0.09	0.707
Recyclist	0.45	Pre-school teacher	0.17	1.414
Note: Measures of occupational specificity relate to the year 2004.				

Table 2: Reported reasons for unemployment		
	Freq.	Percent
Layoff	6,196	13.22
Retirement	5,962	12.72
Sickness/accident	5,831	12.44
End of fixed-term contract	4,884	10.42
Bad working conditions	4,241	9.05
Early retirement	3,832	8.18
First job	2,913	6.22
Fed up with job	2,829	6.04
Personal reasons	2,086	4.45
Other reason	1,885	4.02
Care service	1,867	3.98
Starting education	1,403	2.99
Military service	1,189	2.54
Wish to change occupation	1,069	2.28
Ceding own business	397	0.85
Mandatory retirement	285	0.61
Total	45,440	100

Table 3: Descriptive statistics – entire SESAM sample					
	Obs.	Mean	St. Dev.	Min	Max
Male	212,632	0.459	0.498	0	1
Married	212,632	0.564	0.496	0	1
Swiss	212,632	0.478	0.500	0	1
Age	212,632	40.861	13.586	15	65
Tenure	212,632	6.624	8.749	0	51
Fulltime	212,632	0.691	0.462	0	1
Monthly wage	212,632	4,090	4,385	0	35,550
UI benefits	212,632	139	816	0	20,383
Sector	212,632	57	29	0	97
Firm size	212,632	11	4	1	14
Region	212,632	13	9	1	26
Local unemployment rate	212,632	3.363	1.377	0.70	7.60

Table 4: Descriptive statistics – laid-off sample					
	Obs.	Mean	St. Dev.	Min	Max
Male	3,706	0.494	0.500	0	1
Married	3,706	0.516	0.500	0	1
Swiss	3,706	0.512	0.500	0	1
Age	3,706	42.093	12.172	18	65
Tenure	3,706	2.987	5.604	0	44
Fulltime	3,706	0.615	0.487	0	1
Monthly wage	3,706	3,631	3,438	0	33,150
UI benefits	3,706	915	2,039	0	20,350
Sector	3,706	57	28	0	96
Firm size	3,706	3	2	1	5
Region	3,706	13	9	1	26
Local unemployment rate	3,706	3.253	1.290	0.70	7.60
Labor market thickness	3,706	0	1	-0.841	1.801
Occupational specificity	3,706	0	1	-1.945	2.049

Table 5: Layoff rate X 100 by industry over time						
Sector	2004	2005	2006	2007	2008	2009
Agriculture and Forestry	1.97	0.66	1.14	1.10	0.80	1.44
Art	1.41	1.15	1.33	1.16	0.77	0.67
Banking and Insurance	0.91	0.87	0.91	0.48	0.60	0.94
Commerce and Trade	1.86	1.72	1.70	1.67	1.27	1.34
Construction	2.47	2.41	2.26	1.87	1.05	1.07
Education	0.82	0.48	0.61	0.48	0.52	0.60
Freelance Service Industry	2.73	1.94	1.79	1.58	0.74	0.71
Health and Social Services	0.92	1.07	0.84	0.98	0.58	0.53
Hospitality Industry	3.88	2.83	3.04	2.76	2.44	3.18
Information and Comm.	2.02	2.05	1.65	0.70	0.54	1.01
Manufacturing	1.77	1.71	1.57	1.61	1.13	0.81
Public Administration	0.75	0.43	0.71	0.48	0.33	0.64
Real Estate	2.81	1.70	2.88	1.83	1.99	2.90
Transport	1.45	1.31	1.65	0.97	0.74	0.94

Figure 1: Unemployment rate vs. rate of laid-off workers

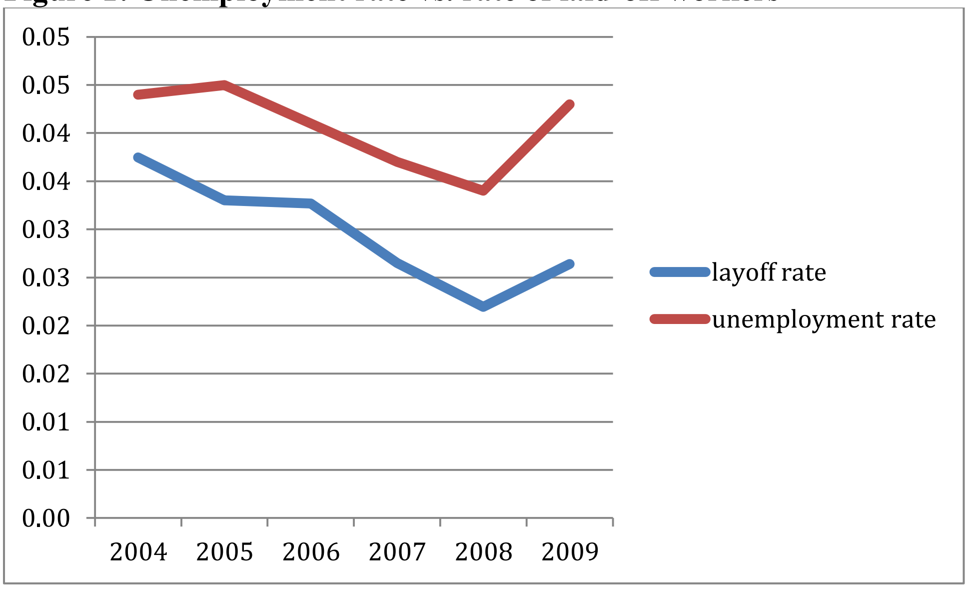

Table 6: Decomposition of separations on destination states

	% of all separations
Total	100
unemployment-to-employment	61.24
of which	
same occupation	80.05
different occupation	19.95
unemployment-to-unemployment	18.32
unemployment-to-out of the labor force	20.44

Table 7: Examples of labor market transitions by occupational group

	Obs.	(1)	(2)	(3)	(4)	(5)
Advertising, marketing, and tourism professionals	30	0.77	0.1	0.13	0.7	0.3
Hygienists, health and personal care professionals	85	0.73	0.08	0.19	0.47	0.53
Trade and commerce professionals	202	0.62	0.15	0.23	0.68	0.32
Wood processing and paper production professionals	21	0.52	0.14	0.33	0.72	0.28
Graphic industry professionals	25	0.52	0.32	0.16	0.77	0.23
Post and telecommunications professionals	21	0.48	0.24	0.29	0.2	0.8
Overall	0.62	0.62	0.15	0.23	0.32	0.3

Note: (1) denotes reemployment one year after the layoff, (2) denotes continued unemployment one year after the layoff, (3) denotes having left the labor force. (4) denotes reemployment in the same occupation and (5) denotes reemployment in a different occupation.

Table 8: Multinomial Logit Regression: Occupational specificity

and employment status controlling for income			
	occupational change	unemployed	out of the labor force
Constant	-0.955	-4.470*	-11.64
	(2.352)	(2.632)	(1,299)
Occupational Specificity	-0.454***	0.282*	-0.561**
	(0.152)	(0.160)	(0.242)
LM thickness	-2.634	-3.590*	8.879***
	(2.117)	(2.007)	(3.014)
Unemployment rate	0.889*	0.767	-0.996
	(0.490)	(0.496)	(0.804)
UI benefits/ 1000	0.0194***	0.0390***	-0.0548**
	(0.0061)	(0.0059)	(0.0219)
L.wage/1000	-0.0105***	-0.0242***	-0.0646***
	(0.0032)	(0.0043)	(0.0069)
Age	-0.0383	0.0461	-0.181**
	(0.0654)	(0.0719)	(0.0886)
Age squared	0.0003	-0.0002	0.0033***
	(0.0008)	(0.0008)	(0.001)
Tenure	-0.0890	0.177*	-0.654***
	(0.107)	(0.101)	(0.131)
Tenure squared	0.0174*	0.0104	0.0347***
	(0.0091)	(0.009)	(0.0092)
Swiss	0.0735	-0.707***	-0.0255
	(0.218)	(0.230)	(0.316)
Male	0.0879	-0.683***	0.792**
	(0.216)	(0.224)	(0.324)
Full-time	0.201	-1.558***	4.609***
	(0.231)	(0.242)	(0.607)
Firm size	Yes	Yes	Yes
Sector	Yes	Yes	Yes
Region	Yes	Yes	Yes
Year	Yes	Yes	Yes
Pseudo R^2	0.4596	0.4596	0.4596
Observations	1,248	1,248	1,248
Note: the base outcome is being reemployed in the same occupation. MNL regression (standard errors in parentheses) Significance levels: * < 0.1; ** < 0.05; *** < 0.01			

Table 9: Multinomial Logit Regression: Occupational specificity and employment status			
	occupational change	unemployed	out of the labor force
Constant	-1.244	-6.047**	-13.153
	(2.322)	(2.516)	(1,743.921)
Occupational Specificity	-0.461***	0.307*	-0.464**
	(0.150)	(0.157)	(0.214)
LM thickness	-2.378	-3.573*	7.471***
	(2.091)	(1.917)	(2.534)
Unemployment rate	1.056**	1.077**	-0.560
	(0.486)	(0.477)	(0.654)
Age	-0.0543	0.0467	-0.279***
	(0.0641)	(0.0686)	(0.0748)
Age squared	0.000543	-0.000178	0.00438***
	(0.000761)	(0.000787)	(0.000849)
Tenure	-0.283**	-0.0422	-1.113***
	(0.126)	(0.120)	(0.151)
Tenure squared	0.0408***	0.0353**	0.0664***
	(0.0144)	(0.0143)	(0.0140)
Swiss	0.0160	-0.746***	-0.0630
	(0.213)	(0.218)	(0.258)
Male	0.0804	-0.663***	0.914***
	(0.213)	(0.211)	(0.256)
Full-time	-0.0351	-1.986***	4.086***
	(0.221)	(0.227)	(0.607)
Firm size	Yes	Yes	Yes
Sector	Yes	Yes	Yes
Region	Yes	Yes	Yes
Year	Yes	Yes	Yes
Pseudo R^2	0.3826	0.3826	0.3826
Observations	1,248	1,248	1,248
Note: The base outcome is being reemployed in the same occupation. MNL regression (standard errors in parentheses) Significance levels: * < 0.1; ** < 0.05; *** < 0.01			

Table 10: Marginal effects of a change in occupational specificity				
	same occupation	occupational change	unemployed	out of the labor force
Occupational specificity	0.032**	-0.045***	0.040***	-0.027*
	(0.020)	(0.014)	(0.014)	(0.014)
Average probability	0.497	0.136	0.219	0.148
Note: Marginal effects of a one standard deviation change in occupational specificity on the four outcome probabilities.				

Table 11: Occupational specificity and log monthly wages		
	monthly wage post	monthly wage post
Specificity	**0.044***	**0.056***
	(0.024)	**(0.032)**
Controls	No	Yes
Observations	764	764
Method	Poisson	Poisson
Sample	Reemployed	Reemployed
Note: Robust standard errors in parentheses		
Significance levels: * < 0.1; ** < 0.05; *** < 0.01		

Table 12: Move distance and the correlation of wages across jobs			
	(1)	(2)	(3)
	Log wage post layoff	Log wage post layoff	Log wage post layoff
Pre-layoff wage	0.047***	0.045***	0.042***
	(0.006)	(0.006)	(0.006)
Distance		-0.034*	-0.077***
		(0.015)	(0.024)
Pre-layoff wage x Distance			0.008**
			(0.004)
Controls	Yes	Yes	Yes
Method	Poisson	Poisson	Poisson
Observations	750	750	750
Note: Standard errors in parentheses; Significance levels: * < 0.1; ** < 0.05; *** < 0.01			

Appendix A. The Swiss Vocational Education and Training System

Vocational education and training (VET) constitutes the main pathway for young people into the Swiss labor market. It is the most common form of post-compulsory education and training in Switzerland; each year about 70 percent of a youth cohort enrolls in apprenticeship training programs. On average, apprentices are 17 years old when they enter VET programs. The most common form of apprenticeship training is the dual program, which combines formal education at a vocational school with training in and working for a training firm. This on-the-job training provides apprentices with the practical know-how, knowledge, and skills they need for their chosen occupation.

More than 200 VET programs exist and they generally take three or four years to complete. In our study, we were able to use information on 156 of these VET occupations. Apprentices spend one or two days per week in vocational schools, and three or four days with their training firms. In the vocational schools, the apprentices typically learn the more theoretical material that is part of their training. Some of the training within companies takes place in group training centers rather than on the job. If they pass both theoretical and practical examinations at the end of their program, the participants receive "Federal VET Diplomas."

VET programs follow a rigid structure. The VET system is centrally managed at the federal level and characterized by strong institutional involvement of professional organizations. A body composed of three different parties ("three-partite" organization) regulates the course content: employer organizations, employee representatives and the government. In practice, however, employer organizations have the greatest influence. The strong involvement of employer organizations is meant to make sure that the course content of dual-track VET programs closely matches the needs of the labor market. This three-partite organization imposes legal requirements for the content, which must be covered in the VET programs. The Berufsinformationszentrum (BIZ) collected information on 26 skills that are required in 220 different VET programs. We use this information in our paper.

Unlike other sectors of the Swiss educational system, apprenticeship training is market-driven, i.e., young people have no guarantee of receiving an apprenticeship place, nor are firms obligated to provide training.

B. Unemployment Insurance in Switzerland

The State Secretariat for Economic Affairs (SECO) administers unemployment insurance in Switzerland. Contributions to unemployment insurance are equal to 2.2 percent of monthly gross wages up to 10,500 CHF (126,000 CHF per year). Employers and employees pay equal shares of this insurance premium, i.e. each contributes 1.1 percent. Additionally, 1 percent of monthly gross wages beyond 10,500 CHF has to be paid as a "solidarity supplement." These contributions are mandatory for all employees in Switzerland. Self-employed workers can join unemployment insurance on a voluntary basis.

To be eligible for unemployment benefits, an applicant must fulfill a number of conditions. Spells of less than two days are too short to be considered as unemployment. An unemployed person must live in Switzerland and has to apply for benefits at the local registration office. There they will be assigned a caseworker, who can impose benefit sanctions if the job seekers fail to apply for jobs (Arni et al., 2013). The applicant must have contributed during at least 12 months over the preceding two years. If they are eligible, an unemployed person receives 70 percent of their insured wages (maximum 70 percent of 10,500 CHF) during an unemployment spell of up to two years. Under certain circumstances (obligation to provide for children; disability), the replacement rate can increase from 70 to 80 percent.