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Abstract

We study the role of occupational skills for labour market transitions after layoffs. Drawing on Lazear's skill-weights approach, we develop empirical measures for occupational specificity and the skill distance between occupations to investigate how skills map into job mobility and wages. Our analysis reveals several important insights. First, higher occupational specificity is associated with lower job mobility and longer unemployment duration. However, it is also associated with higher wages. Workers receive a wage premium of about 9% for reemployment in a one standard deviation more specific occupation. These results suggest a risk-return trade-off to educational investments into more specific skills. Second, the skill distance is negatively associated with wages. Workers moving between occupations with similar skill requirements suffer smaller wage losses than those with more distant moves. Thus, skills appear to be transferable across occupations and to play a pivotal role in the determination of wages.

JEL classification codes: J24, J62, J63, J64

1. Introduction

Structural change has, over the past decades, fundamentally altered the working environment in many sectors of the economy. The notion of a 'lifetime job' is hardly valid anymore; workers today need to be more mobile than earlier generations (Kambourov and Manovskii, 2008; Bachmann and Burda, 2010). Some economists are concerned that, in contrast to general education, vocational education provides students with skills that are too narrowly defined and deprive them of this much needed flexibility and mobility (Krueger and Kumar, 2004a, 2004b; Hanushek *et al*., 2017). However, this debate often overlooks that the simple dichotomy between general versus vocational education providing general versus specific skills does not hold. Skill heterogeneity exists not only between, but also within educational groups (Christiansen *et al*., 2007; Pfister *et al*., 2017). Indeed, several researchers have documented large differences in earnings across college majors (Arcidiacono, 2004; Altonji *et al*., 2014; Lemieux, 2014).

In this study, we turn our attention to vocational education and investigate differences in labour market outcomes for workers across vocational education and training (VET) occupations. We develop an empirical measure for the specificity of VET occupations and analyse whether, and if so, how specificity affects workers' mobility and wages after layoffs. Furthermore, we develop a measure for the skill distance between occupations to analyse whether wage trajectories are related to the proportion of skills transferred from the origin to the destination occupation.

To develop a measure for occupational specificity, we build on Lazear's skill-weights approach (Lazear, 2009).[1] In Lazear's model, specificity depends on the bundling and weighting of skills. The model's premise is that each occupation requires a variety of single skills. These single skills are general in that other occupations require them as well. However, different occupations require skills in different combinations and with different weights attached to them. For example, both bankers and electricians may need mathematical skills in their jobs, but with a different intensity. Additionally, bankers may need communication skills, while electricians may need fine-motor skills. The single skills are general per se, but the bundling and weighting

[1] While Lazear proposes a model of firm-specific human capital, he acknowledges that his model can easily be transferred to occupations. We assume that skill bundles vary not across firms, but across occupations. This assumption is plausible for the case of VET occupations, where the skill content is prescribed by standardized education curricula.

is specific to bankers and electricians. Lazear's model thus allows describing each occupation by its unique skill bundle.

How do these skill bundles differ in their specificity? In Lazear's model, specificity depends on observable market parameters. If the banker's skill bundle contains a large number of skills that are required in other occupations as well, then this skill bundle is labelled general. Contrarily, if the electrician's skill bundle contains only few skills that are also required in other occupations, then this skill bundle is labelled specific. Specificity is thus endogenously determined and subject to change, depending on external labour market parameters.[2]

In this study, we test theoretical predictions that directly follow from Lazear's model, namely that occupational specificity affects mobility and wages. In the analysis, we focus on layoffs, i.e. firm-initiated separations, where workers are forced to leave their firm. Conditioning on layoffs allows singling out the effects of occupational specificity for workers who face economic difficulties, when they lose their jobs due to reasons beyond their control. These effects are different for workers who quit voluntarily, as quits tend to improve labour market status. From a policy perspective, identifying which involuntary job switches can take place without major wage losses and without major interruptions is invaluable.

We use data from Switzerland, a country with an institutionalized VET system, where about two thirds of the workforce hold a VET degree. In Switzerland, the learning and training content of VET occupations is regulated in standardized education curricula. Within a VET occupation, job design and skill assignments are fairly homogenous across firms. We can thus construct skill bundles that vary not across firms or individuals, but across occupations.

Our skill data comes from the career choice book authored by Zihlmann *et al*. (2012). This book is the official career guide of the *Berufsinformationszentrum* (BIZ), the state-led career-counselling centre. The guide provides detailed descriptions of vocational occupations along with a list of their skill requirements. The list contains 26 skills in total, distinguishing between

[2] In this study, 'skill specificity' refers to occupation-specific skills and not to firm-specific skills as is the case in the traditional human capital theory (Becker, 1962). Becker distinguishes between general skills, useful in all workplaces, and specific skills, useful in the training firm only. Firms face a trade-off between acquiring skills from the external labour market by hiring, and developing workers' skills internally through training. Doeringer and Piore (1971) describe the functioning of Internal Labour Markets (ILMs) and provide support for the existence of an internal solution to this trade-off. Thanks to on-the-job training and the internalisation of organisational norms, employees in ILMs develop firm-specific skills and a firm-specific culture that support their progression along subsequent job ladders and internal hierarchies.

intellectual, personal, and physical skills. Some occupations require eleven different skills, while others require only three. To account for this heterogeneity in skill usage, we weight each skill with the total number of skills required in an occupation. Essentially, we describe each occupation by a weighted sum of skills.

We match our skill data to the Social Protection and Labour Market (SESAM) survey for the years 2004 through 2009. The SESAM consists of the Swiss Labor Force Survey matched with register data on employment histories, unemployment benefits, and wages. The SESAM thus allows investigating transition patterns of laid-off workers as well as quantifying their wage changes. It also allows constructing our occupational specificity measure. Recall that in Lazear's model, specificity is determined by labour market demand. Because the SESAM is a representative survey, it contains the frequency distribution of occupations for the entire Swiss workforce. We use this frequency distribution as a proxy for labour market demand.

Combining information on the frequency distribution and the skill bundle of each VET occupation in the labour market, we can infer the labour market demand for each skill bundle. If many workers use a particular skill bundle, demand for that skill bundle will be high. That skill bundle is thus general. Contrarily, if only few workers use a skill bundle, demand for that skill bundle will be low. That skill bundle is thus specific. Exploiting this variation, we construct a continuous measure of occupational specificity.

Our approach is related to Geel *et al.* (2011) and Eggenberger *et al.* (2018), who calculate specificity measures using survey data and data from training curricula, respectively. Geel *et al.* (2011) develop a measure for the German labour market, which we cannot apply to the Swiss case. Eggenberger *et al.* (2018) develop a measure for Switzerland. While rich and detailed, their measure covers the most common occupations only. For our study, a full coverage is crucial, because layoffs may occur more often in less common occupations. Therefore, we decide to use less detailed skill data, which have the great advantage of covering the full set of VET occupations.

We run three types of analyses. First, we estimate the probability of different post-layoff labour market outcomes as a function of a worker's occupational specificity. Second, we investigate the relation between occupational specificity and wages. Third, we analyse whether the skill distance matters for wage trajectories. Our results indicate that skill bundles crucially determine labour market outcomes. First, we find that workers with more specific skill bundles are less likely to switch occupations and more likely to remain unemployed one year after the layoff. Second, we find a positive association between occupational specificity and wages. Workers receive a wage premium of about 9% for reemployment in a one standard deviation more specific occupation. These results suggest a risk-return trade-off in the sense that investments into more specific human capital are associated with higher wages but also with higher risk of unemployment and lower job mobility. Third, we find that the change in wages is directly associated with how similar the origin and the destination occupation are in terms of their skill bundles. This result is consistent with the idea that human capital is partially transferable across occupations.

Our contributions to the literature are twofold: First, we introduce a continuous measure of occupational specificity that allows examining how occupational specificity is related to mobility and wages. We also develop a skill distance measure that allows analysing the wage consequences of occupational mobility. Second, we provide novel empirical results that reveal that it is not so much the occupation, but instead single skills and the bundling of these skills that determine how mobile workers are and how their wages evolve.

Understanding the relationship between skill bundles and labour market outcomes is crucial for estimating the costs associated with worker turnover in the form of loss of specific human capital. Measuring human capital not by years of education or firm tenure but by skill bundles reveals which reallocations can take place without any major destruction of human capital. Our analysis also shows that the simple dichotomy between general and vocational education providing general and specific skills is less straightforward than previous studies assumed. Policy discussions should thus focus less on the perceived differences between general and vocational education, but instead on how the bundling and weighting of single skills affect labour market outcomes.

2. Conceptual framework

2.1. Occupational specificity

Traditionally, economists measure labour market skills by years of education (Card, 1999). According to our skill concept, however, a year spent in VET programme *X* is not equivalent to a year spent in VET programme *Y*, because these programmes teach different skill bundles.

Following Lazear's skill-weights approach (2009), we expect this difference in skill bundles to matter for workers' mobility and wages.

Lazear (2009) introduces a skill-weights view of human capital and models skill bundles to vary by firm. His main assumption is that all skills are general, but that firms require different types of skills with different weights attached to them. The combination and weighting of individual skills makes a skill bundle firm-specific. If workers were certain to remain with their initial firm indefinitely, they would invest in the particular skill bundle that maximizes their payoff in that initial firm. But, because other firms demand a different combination and weighting of skills, the initial skill bundles may not be optimal in other firms, making part of their initial investment worthless. The difference in skill weights across firms makes a skill bundle more or less specific.

We translate Lazear's idea of firm-specific human capital to the level of occupations. We define an occupation as requiring a different combination of single skills with occupation-specific weights, thereby further developing an idea first applied by Geel *et al*. (2011). We then calculate the skill specificity of each occupation (i.e. *occupational* specificity) by comparing an occupation's skill weight to the skill weight in the labour market. The market skill weight is the weighted sum of all occupational skill bundles in the labour market.

The difference in skill weights makes a skill bundle more or less specific. An occupation is specific, if its skill weight is very different from the skill weights of the other occupations in the labour market. Conversely, an occupation is general, if its skill weight is very similar to the skill weights in many other occupations. Occupational specificity thus depends on the frequency distribution of skill bundles in the labour market. However, this does not necessarily imply that small occupations are all specific, while large occupations are all general. While the size of the occupation certainly plays a role, the focus lies on the underlying skill bundles and on their frequency distribution.

Lazear's model allows deriving a number of empirically testable implications for laid-off workers' transition patterns and their wage trajectories. First, a more specific skill bundle implies a smaller skill overlap with other occupations. This smaller overlap makes switching occupations more costly. Therefore, we expect to find a negative association between occupational specificity and the likelihood of occupational change. Moreover, because of the smaller skill overlap, the number of job offers and the quality of prospective matches is likely lower for workers laid off from more specific occupations than for those from more general occupations. Therefore, we expect to find a positive association between occupational specificity and the likelihood of prolonged periods of unemployment.

Second, a more specific skill bundle also implies a better fit of the training with the skills required in an occupation. The reason lies in workers' allocation of time[3]: if workers dedicate their time to acquiring a skill bundle that perfectly fits the skill requirements of one occupation, they can maximize their wages in that occupation. The more specific the skill bundle, the more time workers will spend on acquiring skills that are only useful in one occupation and the less time they will spend on skills that are useful elsewhere. The corner solution of this maximization problem is a skill bundle that is solely useful in one and not in any other occupation. The better fit implies a higher productivity and thus higher wages. Therefore, we expect to find a positive association between occupational specificity and wages.

Third, Lazear's model also allows predicting wage trajectories after an occupational change. Because a more specific skill bundle implies a smaller skill overlap with other occupations, an occupational change out of a specific occupation will likely result in lower wages, because of a poorer match. Therefore, we expect to find a positive association between occupational specificity and the wage loss suffered from a layoff.

2.2. Labour market thickness

From the skill-weights view it follows that, as in traditional job search theory, the thickness of the labour market crucially affects labour market outcomes. Lazear models an increase in market thickness as allowing for more offers. In thicker markets, workers get multiple draws and can select the offer that best suits their skill bundle. As markets become thicker, workers are thus more likely to find a job where skill demand closely matches their skill bundles. The likelihood of receiving a job offer that requires skills in the same combination and weighting as the origin occupation increases. Conversely, in thin markets, workers may have to settle for a job that makes little use of their skill bundles.

[3] Rosen (1983) first developed this argument in a model with two independent skills that are linear to utilisation. He postulated that the return to investment in a particular skill is increasing in its subsequent rate of utilisation because investment costs are independent of how the acquired skills are employed. This element of fixed investment costs makes it advantageous to specialize investment resources to a narrow band of skills and employ them as intensively as possible. In his model, by moving to a corner and investing in only one of the two skills, workers do not lose any value and save costs by eliminating investment in one activity.

A number of empirically testable implications follow. First, for workers who suffered a layoff, an increase in market thickness should be related to a decrease in unemployment duration. Second, workers in thicker markets should be less likely to change occupations. They are more likely to find a job opportunity within their occupational field. Third, perhaps counterintuitively, wages upon reemployment may be smaller in thick markets. As the number of offers increases, workers may be less inclined to continue waiting for the best quality match and instead opt for an offer that does not perfectly correspond to their skill bundles. However, because we are estimating mobility patterns and wages separately, we cannot assess which choice ultimately dominates.

2.3. Skill distance

Recent studies on the transferability of skills have introduced the concept of 'skill distance' to measure the proportion of skills that is transferred during an occupational change (Poletaev and Robinson, 2008; Gathmann and Schönberg, 2010; Robinson, 2018). This distance measure captures the skill overlap of two occupations. A large distance indicates that the overlap is small, while a small distance indicates that the occupations have very similar skill bundles.

For example, Poletaev and Robinson (2008) use a skill distance measure to investigate the source of human capital specificity. They find wage losses of displaced workers to be more closely associated with switching skills than with switching industry or occupation. Robinson (2018) measures the skill distance to contrast involuntary and total mobility. He shows that while involuntary mobility involves a high incidence of loss of specific human capital, voluntary occupational mobility appears to involve limited specific human capital loss. Gathmann and Schönberg (2010) study the transferability of skills in the German labour market. They introduce the concept of task tenure, reflecting the time a worker spends on a specific task. They find that task tenure is an important source of wage growth. Moreover, they show that wage losses after displacement are lower if workers find employment in an occupation with similar skill requirements.

The crucial difference between these studies and Lazear (2009) is that the former do not account for the demand side. They investigate realized transitions, compare the underlying skills, and estimate the resulting wage losses. They do not account for the demand for any given skill or skill combination, which allows predicting transition patterns and wages. Job offers are explicitly modelled in Lazear (2009), while they are absent in the skill distance literature.

The disadvantage of our continuous measure of occupational specificity is, however, that it does not allow a pair-wise comparison of jobs. By construction, it always compares one occupation with all other occupations in the labour market. Therefore, we draw on the skill distance literature to relate changes in wages to the skill bundles of two occupations. We expect to find a direct relationship between the proportion of transferred skills and the extent of the wage change. If two jobs have very similar skill bundles, workers should be able to transfer most of their human capital from one job to the other. Conversely, the more dissimilar the new job is to the old one, the fewer skills can be transferred. Therefore, we expect to find a negative association between the skill distance and wage trajectories. In principle, workers who switch jobs may improve their match, thereby realizing a wage gain. Empirically, this is primarily observed for quits (Altonji and Williams, 1992).

Finally, our approach differs in two more aspects from the skill distance studies. First, they aggregate their single skills to broad skill categories. While this aggregation eases computation and exposition, it may overlook finer differences in skill requirements that may be important in explaining mobility and wages. Therefore, we account for each skill separately. Second, they use three-digit and two-digit occupational codes, while we use the five-digit level. Our skill data clearly reveal that skill requirements differ greatly at this disaggregated occupational level. Using a more coarse level would likely overlook relevant differences in skill requirements across occupations.

3. Operationalization

3.1. Measuring occupational specificity

To better understand how we construct our continuous measure of occupational specificity, let us walk through an example. Take the occupations of banker and electrician and assume that only those two occupations exist in the labour market. In addition, assume that a four-dimensional skill vector describes all skills, i.e. our occupations are characterized by the presence or absence of only four skills. Assume further that bankers use the skills ‘abstract-logical thinking' and 'mathematical skills', while electricians use 'mathematical skills', 'fine motor skills', and 'spatial thinking'.

In the first step, we describe the occupational skill bundles as follows:

$$\textit{banker's skill bundle} \qquad \lambda_B = \begin{pmatrix} 1 \\ 0 \\ 1 \\ 0 \end{pmatrix} \begin{array}{l} \textit{abstract-logical thinking} \\ \textit{fine motor skills} \\ \textit{mathematical skills} \\ \textit{spatial thinking} \end{array}$$

$$\textit{electrician's skill bundle} \qquad \lambda_E = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 1 \end{pmatrix} \begin{array}{l} \textit{abstract-logical thinking} \\ \textit{fine motor skills} \\ \textit{mathematical skills} \\ \textit{spatial thinking} \end{array}$$

In the second step, we construct the market skill weight. Our market skill weight is a four-dimensional skill vector that contains a ranked order of skills. The rank order is given by the frequency distribution of skills in the labour market. Suppose that the market comprises 500 bankers and 300 electricians. Looking at the underlying skill bundles, 500 workers use the skill 'abstract-logical thinking', 800 use 'mathematical skills', and 300 use 'fine motor skills' and 'spatial thinking'.

Thus, in our labour market with only bankers and electricians, the market skill weight is defined as:

$$\textit{market skill weight} \qquad \bar{\lambda}_M = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} * \begin{pmatrix} 500 \\ 300 \\ 800 \\ 300 \end{pmatrix} \begin{array}{l} \textit{abstract-logical thinking} \\ \textit{fine motor skills} \\ \textit{mathematical skills} \\ \textit{spatial thinking} \end{array}$$

This leads to the following ranked order of skills: 'mathematical skills' is the most general and 'abstract-logical thinking' the second most general skill, whereas 'fine motor skills' and 'spatial thinking' are the most specific skills, because only 300 workers use them.

In the third step, we derive the specificity measures for the occupational skill bundles by dividing the sum of ranks by the sum of skills used in an occupation. Formally, occupational specificity is defined as:

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

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

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

The electrician's specificity is:

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

According to this hypothetical specificity measure, electrician is thus a more specific occupation than banker. Applying this procedure to the whole set of occupations, we can develop a continuous measure of occupational specificity. Specificity is thus endogenously determined, depending both on the occupation's underlying skill bundle and the frequency distribution of skills in the labour market.

3.2. Measuring labour market thickness

To construct a measure of labour market thickness (LMT), we use the frequency distribution of occupations. We divide the sum of workers in one occupation by the total size of the labour market. In our example, LMT assumes a value of 0.625 (500/800) for bankers and 0.375 (300/800) for electricians. This measure implies that bankers have more draws than electricians do.

We use a country-year aggregation when constructing LMT. We acknowledge that this is a somewhat coarse measure, as we do not account for regional labour markets. However, for our empirical application, this definition is reasonable. Switzerland is overall quite small and has an excellent public transportation system. Therefore, it is plausible to assume that individuals would take into account offers not only from their immediate surroundings, but also from a larger region. This is likely to be more pronounced for workers who lost their jobs involuntarily.

3.3. Measuring skill distance

To calculate the skill distance between two occupations, we follow previous research and use the Euclidean distance. The Euclidean distance between two points in Euclidean space with the coordinates *(x, y)* and *(a, b)* is simply the length of the line segment connecting them. It is given by $dist\big((x,y)(a,b)\big) = \sqrt{(x-a)^2 + (y-b)^2}$.

In our application, we describe two occupations X and Y by their skill bundles λ_x and λ_y. Their respective weighting factors, which reflect how intensively skills are used, depend on the number of skills used in the occupation. Letting $i = 1 \dots N$ indicate the number of skills used, we define the Euclidean distance between occupations X and Y as follows:

$$D_{XY} = \sqrt{\sum_{i=1}^{N} \left(\frac{1}{N_X}\lambda_{x,i} - \frac{1}{N_Y}\lambda_{y,i}\right)^2} \qquad (1)$$

The Euclidean distance varies between zero and one. It is zero for occupations that use identical skill bundles and one if two occupations use completely different skills bundles.

Coming back to our example of bankers and electricians, the Euclidean distance between those two occupations is:

$$D_{BE} = \sqrt{\begin{pmatrix} 0.5 & & 0 \\ 0 & & 0.3 \\ 0.5 & - & 0.3 \\ 0 & & 0.3 \end{pmatrix}^2} = \sqrt{0.5^2 + (-0.3)^2 + 0.2^2 + (-0.3)^2} = 0.685.$$

Judging whether this skill distance of 0.685 is large or not, is only possible by comparing this value to the distances between other occupations.

4. Data and descriptive statistics

4.1. Data

Our core data is the Social Protection and Labour Market (SESAM) survey, a matched panel linking the Swiss Labour Force Survey (SLFS) with data from various social insurance registers. The SLFS is a nationally representative, rotating household panel based on a sample of about 100,000 interviews. It provides information on employment, socio-demographic, educational, and occupational characteristics. The social insurance registers provide the daily duration of employment and unemployment spells, as well as monthly wages and unemployment benefits. The panel structure allows observing individuals before, during, and after the layoff.

Our skill data comes from the career choice book authored by Zihlmann *et al*. (2012). This book is the official career guide of the *Berufsinformationszentrum* (BIZ), the state-led career-counselling centre. Therefore, we refer to our skill data as 'BIZ data'. Besides containing very comprehensive job and training descriptions, the career guide also provides a detailed list of skills that are required in different VET occupations. This list comprises 26 single skills, distinguishing between intellectual, personal, and physical skills. Table 1 gives an overview of the occupational skill requirements.

{Table 1 here}

The BIZ data show the presence and absence of required skills in an occupation. However, they do not account for the intensity of skill usage. Arguably, this is a simplified description of an occupation's skill requirements. Bearing in mind the institutional context of Switzerland, however, this description is reasonable. As previously explained, standardized education curricula regulate the training content of VET occupations. Therefore, the presence of a skill in the BIZ data indicates at least a minimum level of knowledge and usage of that skill. For any one skill listed in an occupation's skill requirements, a minimum level is guaranteed through the curricula.

Furthermore, occupations vary in the total number of required skills in the BIZ data. We construct an approximate intensity weight by taking into account this variation. For example, workers who require four skills receive a weighting of 0.25 for each single skill, while those requiring eight skills receive a weighting of 0.125. While not a perfect measure, this procedure does account to some extent for the intensity in skill usage.

4.2. Variable construction

For our measure of occupational specificity, we use both the BIZ data and the SESAM. The BIZ data allows constructing a unique skill bundle for each occupation, and the SESAM allows classifying the specificity of that skill bundle.

First, we describe each occupation by its skill bundle. Second, we construct the market skill weight by ranking each skill according to how frequently it is used in the labour market. Because the SESAM provides the frequency distribution of workers across occupations, for each skill, we know how many workers in the labour market are using it. Third, we determine the occupational specificity by comparing individual occupational skill bundles with the market skill weight. To account for changes in skill demand over time, we calculate the market skill weight separately for each survey wave. The degree of occupational specificity thus varies over time.

Table 2 shows the average specificity ranking of skills, ordered by increasing specificity. The most general skills are ‘organisational skills’, followed by ‘service mindedness’, and ‘sense of responsibility’. The most specific skills are ‘empathy’, followed by ‘creativity’, and ‘reliability’. In the empirical analysis, we exclude the skills ‘robust health’ and ‘strong constitution’, because they describe physical attributes rather than skills that can be acquired.

{Table 2 here}

For our measure of LMT, we also use the SESAM. Specifically, we again use the frequency distribution of workers across occupations. For each year and occupation, we divide the sum of workers in one VET occupation by the total sum of workers in VET occupations in the data set, i.e. we compute the relative employment shares. Finally, for our measure of skill distance, we apply equation (1) to our occupational skill bundles and calculate the Euclidean distance for each possible occupational pair.

4.3. Sample

Our sample comprises individuals in VET occupations, aged between 18 and 65. To be included in the sample, these individuals have to be laid off at least once during the observation period, and we have to observe them 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 large. After creating the panel, we are left with a sample of 4,698 observations. The drop in observations is this large, because the average unemployment rate is only 3.28%. In addition, only about 13% of the unemployed report having been laid off, whereas the rest are unemployed for other reasons.

Table 3 provides descriptive statistics for the sample, consisting of individuals who are either employed, unemployed or have left the labour force. About 50% of the sample is male, 57% are married, and about 44% are Swiss nationals. Individuals are on average 41 years old and have about three years of tenure. Since all these workers are laid off at some point, average tenure is rather low. About 55% of the sample is working or has worked full-time. The average monthly wage is about 3,800 Swiss francs. This sample average is below the national average (about 5,000 CHF for VET workers), because all individuals experience a layoff during the observation period with zero wages and positive unemployment benefits. Similarly, average monthly unemployment benefits are about 950 Swiss francs. This sample average is below the national average, because all individuals are employed at some point during the observation period with positive wages and zero benefits.[4]

To simplify the interpretation, we standardize occupational specificity and LMT to have a mean of zero and a standard deviation of one. Their values indicate the difference from the mean of the original variable in number of standard deviations. For example, a value of 0.5 indicates that the value for that case is half a standard deviation above the mean, while a value of -2 indicates that a case has a value two standard deviations lower than the mean. We also scale the skill distance to ease interpretation. We simply divide each value by the variable's maximum value to ensure that the skill distance varies between 0 and 1, while not distorting the distributional features of the variable.

{Table 3 here}

Table 4 gives an overview of the most specific and most general occupations in the sample. The most specific occupation is recyclist, followed by textile carer, and hospitality specialist. The most general occupation is jeweller, followed by technical surgical assistant, and housekeeper. This ranking shows how Lazear's model proves the conventional understanding

[4] In Switzerland, applicants eligible for unemployment benefits receive 70% of their last wage during an unemployment spell for up to two years. For the average VET worker, unemployment benefits thus amount to 3,500 Swiss francs per month.

of specific and general occupations wrong. The jeweller's skill bundle contains skills that are useful in many other occupations. Therefore, albeit being small, it is a general occupation. Conversely, textile carers appear to require skills useful in only few other occupations. Albeit being quite common, textile carer is thus a specific occupation.

{Table 4 here}

Table 5 shows distant and close occupation pairs. Close pairs are commercial employees and office assistants, as well as computer scientists with a general specialization and those with a specialization in application development. Examples of distant pairs are cleaners and healthcare professionals, as well as early childhood educators and office assistants.

{Table 5 here}

5. Estimation strategy

5.1. Identification

Because we analyse individuals who report having been laid off, two main identification concerns arise. First, the self-reported measure may be biased. Second, our sample may not properly represent the overall working population. Addressing the first concern, a recent study by Balestra and Backes-Gellner (2017) investigates earnings losses for different types of separations using the SESAM. They find that no unemployment reason other than layoff causes a permanent wage loss, which is indicative that the self-reported measure in the SESAM is not biased.

Addressing the second concern, a common strategy in the literature is to focus on displaced workers, i.e. those suffering an involuntary job loss due to firm closure or downsizing that is unrelated to the performance of the particular employee (Gibbons and Katz, 1991; Neal, 1995; Dustmann and Meghir, 2005). Unfortunately, the SESAM does not distinguish between different reasons for the layoff.[5] Therefore, we cannot exclude that our estimated effects are arising from specific groups of the population, as layoffs may not be conditionally exogenous.

[5] The only Swiss data on displaced workers is a cross-sectional survey of 1,200 workers in the manufacturing sector.

However, our sample clearly eliminates the upward bias in returns to human capital from improved firm matches. Similar to the exogenously displaced, laid-off workers lose their current match and start searching for a new one. They accept a job offer if its value exceeds their value of unemployment. In contrast, voluntary job switchers are likely to be observed only when the value of the new job exceeds that of the old one. We can thus single out the effects of occupational specificity for workers who face economic difficulties.

Finally, while the displacement literature generally focuses on long-term wage dynamics (Burda and Mertens, 2001; Farber, 2005; Couch and Placzek, 2010), we focus on the short term due to data limitations. Because our BIZ skill list is a cross-section, we have to assume that skill requirements do not significantly change over the observation period. While this assumption is plausible for our time span of six years, it becomes unrealistic if we were to investigate a worker's full career. Any analysis investigating long-term labour market outcomes should account for changes in skill requirements. In Switzerland, unfortunately, such longitudinal skill data is not available. Therefore, our analysis is limited to the short-term effects of layoffs.

5.2. Estimation equations

To investigate the relationship between occupational specificity and labour market transitions, we assume that a multinomial logit model (MNL) describes the transition probabilities of laid-off workers. The theoretical framework of McFadden's (1974) discrete choice model can be described as follows: individual i assigns a utility to alternative j and chooses the alternative with the highest utility. The probability of transition type j depends on a vector of observed characteristics, X_i. Mathematically, the probability that worker i chooses alternative j is expressed as follows:

$$\pi_j(x_i;\beta) = \frac{exp\left(x_i'\beta_j\right)}{1+\sum_{r=2}^{J} exp\left(x_i'\beta_r\right)} \qquad (2)$$

$$with \;\; x_i'\beta = \beta_0 + \beta_1 OS_i + c_i'\beta_2 + \beta_3\, LMT_i + \beta_4\, UR_r + \varphi_t + \delta_r$$

In the baseline model, our dependent variables are four dummy variables indicating labour market status one year after the layoff: reemployed in the origin occupation (i.e. the same occupation as before the layoff), reemployed in a different occupation, unemployed, and out of the labour force. For identification purposes, we choose the most frequent outcome—reemployed in the origin occupation—as the reference category.

The observed characteristics x_i' include our main variable of interest, OS_i, occupational specificity in the origin occupation. Furthermore, the vector c_i' comprises a set of controls used in conventional job search models (Mortensen, 1986; Mortensen and Pissarides, 1999). They include age and age squared (in years), tenure and tenure squared (in years), a part-time dummy, gender and nationality dummies, as well as firm size categories and industry dummies. To control for labour market conditions, we also include LMT_i, labour market thickness and UR_r, the regional unemployment rate. Finally, φ_t and δ_r are time and region dummies.

By construction, our specificity measure depends on the frequency distribution of skill bundles in the labour market. An occupation's degree of specificity is thus partly driven by that occupation's size. This could bias the results in that small occupations would tend to be more specific, while large occupations would tend to be more general. To isolate the 'specificity effect' from the 'occupation size effect', we include LMT as a crucial control variable. By doing so, we factor out the 'occupation size effect', i.e. the part of occupational specificity that arises from the frequency distribution of occupations. As a result, the coefficient for occupational specificity measures only the specificity of the occupational skill bundle, unaffected by the size of the occupation.

To investigate the association between occupational specificity and wages, we run OLS regressions on our sample of reemployed workers. Further, to investigate whether the relationship between wages and specificity holds beyond our restricted sample, in a second specification, we repeat the analysis without conditioning on laid-off workers. The estimation equation is defined as follows:

$$ln\, w_{it} = \beta_0 + \beta_1 OS_{it} + \beta_2 \ln w_{i,t-1} + c_{it}'\beta_3 + \beta_4 LMT_{it} + \beta_5\, UR_{rt} + \varphi_t + \delta_r + \varepsilon_{it} \quad (3)$$

where $ln\, w_{it}$ is the monthly log wage of individual i at time t, OS_{it} is the specificity in the current occupation, $ln\, w_{i,t-1}$ is the lagged log wage, while all other variables are the same as in Equation (2). The error term ε_{it} is assumed to have a mean of zero and to be independent and identically distributed.

To investigate how skills are related to the change in wages between pre- and post-layoff jobs, we again run OLS estimations on our sample of reemployed workers. Equation (3) then modifies to:

$$\Delta\, ln\, w = \beta_0 + \beta_1 \Delta\, OS \;+ \beta_2\, ln\, w_{i,t-1} + c'_{it}\beta_3 + \beta_4 LMT_{it} + \beta_5 UR_{rt} + \varphi_t + \delta_r + \varepsilon_{it} \quad (4)$$

where the dependent variable is the log wage change between pre- and post-layoff jobs. Our main variable of interest, $\Delta\, OS$, is the change in occupational specificity between pre- and post-layoff jobs. All other variables are the same as before.

In a final regression, we study whether the skill distance is associated with changes in wages. Again, we use OLS to estimate the parameters that solve the equation:

$$\Delta\, ln\, w = \beta_0 + \beta_1 distance \;+ \beta_2 \ln w_{i,t-1} + c'_{it}\beta_3 + \beta_4 LMT_{it} + \beta_5 UR_{rt} + \varphi_t + \delta_r + \varepsilon_{it} \quad (5)$$

where the dependent variable is again the log wage change and our main variable of interest is now $distance_{it}$, the skill distance measure. Again, we include all controls from the previous equations.

6. Results

6.1. Occupational specificity and labour market transitions

Table 6 shows how specificity affects the log-odds ratios of the alternative outcomes compared to the baseline outcome 'reemployed in the origin occupation'. The parameters of the MNL model are not straightforward to interpret. Looking at the log-odds ratios, a positive parameter means that the probability of choosing j increases relative to the probability of the base outcome. However, the magnitude of the parameter has no direct intuitive meaning.

In Table 6 column (1), the coefficient of interest, 'occupational specificity', is negative and statistically significant at the 5%-level. This implies that the log-odds ratio of finding reemployment in a different occupation compared to reemployment in the origin occupation is decreasing in occupational specificity. We thus confirm our hypothesis: the higher the degree of specificity, the less likely workers will switch occupations.

Column (2) shows the estimates for the probability of remaining unemployed one year after the layoff versus the baseline outcome. Occupational specificity increases the log-odds ratios of still being unemployed versus having found reemployment in the origin occupation. The effect is statistically significant at the 1%-level. Thus, again we confirm our hypothesis: the higher the degree of specificity, the more likely workers will remain unemployed in the period following the layoff, potentially waiting to find reemployment in their origin occupation.

Column (3) shows that occupational specificity does not affect the log-odds ratios of dropping out of the labour force versus the baseline outcome. The decision to leave the labour force appears to be driven by age and tenure effects rather than by the specificity of a worker's occupation.

Among the control variables, labour market thickness (LMT) significantly decreases the likelihood of remaining unemployed versus finding employment in the same occupation. This finding is straightforward: the more job offers laid-off individuals have, i.e. the higher the LMT, the more likely they will find employment. Similarly, LMT marginally decreases the likelihood of leaving the labour force versus finding employment in the same occupation. Perhaps surprisingly, males are significantly more likely to still being unemployed one year after the layoff. This finding may be explained by men's higher reservation wage. Furthermore, males are less likely to have left the labour force versus being reemployed in the same occupation. This result may be related to the relatively low female labour force participation in Switzerland, implying that women tend to leave the labour market after being laid off.

To interpret the effects of occupational specificity on the probability scale, we compute marginal effects. Table 7 reports marginal effects of a one standard deviation increase in occupational specificity on all four outcomes. Our results indicate that for worker i with mean characteristics $\bar{x}_i$, an increase in occupational specificity by one standard deviation decreases the probability of being reemployed in a different occupation by about four percentage points. The more specific the skill bundle, the less likely thus is an occupational change. Furthermore, the probability of remaining unemployed increases by about four percentage points if occupational specificity increases by one standard deviation. Finally, the average probabilities, i.e. the probability of choosing one of the j alternatives for all individuals in the sample, suggest the following: workers laid off from more specific occupation are most likely to find reemployment in their origin occupation, second most likely to remain unemployed for a longer time span, and the least likely to leave the labour force.

{Tables 6 and 7 here}

6.2. Occupational specificity and wages

Table 8 reports estimates from the log-linear wage regressions. Column 1 shows the results for the restricted sample of workers who are reemployed one year after the layoff. We find a highly significant positive correlation between the degree of specificity and wages: workers receive a wage premium of about 9% for reemployment in a one standard deviation more specific occupation. Column 2 shows the results for the full sample. The relationship continues to be positive, but the effect size decreases. In the full sample, the wage premium of a one standard deviation more specific occupation amounts to 2.5%. This drop in effect size may be due to several reasons. First, it is an empirical regularity that workers experience wage decreases already in the periods prior to the layoff. Research for Switzerland quantifies these losses to around 4-6% (Balestra and Backes-Gellner, 2017). Second, workers who are reemployed one year after the layoff are likely to represent a positive selection with a high match quality. Overall, we can confirm our hypothesis that higher specificity is associated with higher wages.

Among the control variables, the coefficients are in line with expectations. LMT has a statistically significant negative effect on wages. For the reemployed, wages are smaller in labour markets with a higher concentration of workers in the relevant occupations. Age and tenure have the expected U-shaped and inverse U-shaped effects.

Table 9 shows OLS estimates with the change in log wages before and after the layoff as dependent variable. Column (1) shows the relationship between changes in log wages and changes in occupational specificity. The coefficient is positive and marginally statistically significant. This positive association indicates that an increase in specificity is associated with a wage gain, whereas a decrease in specificity is associated with a wage loss. Therefore, we cannot confirm our hypothesis that higher specificity is related to higher wage loss after the layoff.

Column (2) shows how the skill distance between pre- and post-layoff occupations is driving changes in wages. For a one-unit increase in skill distance, post-layoff wages decrease by about 23%. Thus, in the extreme case of workers moving to a completely dissimilar occupation, they suffer a wage loss of about 23%. For less distant moves, wage losses are more moderate. For example, for a one standard deviation increase in skill distance, post-layoff wages decrease by about 6%. Note that while layoffs may be considered exogenous, the skill distance is, in general, not. Our results do not show wage trajectories of workers who are randomly assigned to new jobs. Instead, the results should be interpreted as quantifying the transferability of skills and relating skills to wages.

The results in Table 9 thus partly confirm our hypotheses. First, we do not find a wage penalty related to higher specificity. Among workers who are reemployed one year after the layoff, those who were laid off from more specific occupations do not seem to have suffered larger wage losses than those laid off from more general occupations. Second, we find that the larger the skill distance, the greater the associated wage loss. Therefore, it appears that staying close to the skill bundle of the origin occupation is beneficial, as workers can transfer large parts of their skill bundle from the origin to the destination occupation. Taken together, our results suggest a risk-return trade-off in the sense that investments into more specific human capital are associated with higher wages, but also with lower mobility and higher risk of unemployment.

{Tables 8 and 9 here}

7. Conclusion

This study investigates labour market transitions of laid-off workers in vocational occupations. Some economists argue that vocational education provides students with specific skills that prepare them to work in one particular occupation only, locking them into that occupation. They are concerned that vocational skills are too narrowly defined and deprive workers of any mobility (Krueger and Kumar, 2004a, 2004b; Hanushek *et al.,* 2017).

However, already a simple examination of skill requirements of vocational occupations reveals that the dichotomy between general and vocational education providing general and specific skills is not straightforward. Many vocational occupations require, for example, language skills, organisational skills, and communication skills. Arguably, these are general skills, which are transferable across occupations.

Rather than comparing educational degrees, we analyse the heterogeneity of skills within the same type of education. Drawing on Lazear's skill-weights approach, we describe vocational occupations in terms of their skill bundles and build occupation-specific skill weights to measure their degree of specificity. We then test several hypotheses on how skills map into job mobility and wages.

We find that workers who were laid off from more specific occupations are less likely to find reemployment in a different occupation than workers laid off from more general occupations. Moreover, the more specific their origin occupation, the more likely workers stay unemployed one year after the layoff, possibly waiting for a job opportunity in their origin occupation. Relating occupational specificity to wages, we find higher specificity to be associated with higher wages.

We also investigate the transferability of skills in more detail. We calculate the skill distance between occupations, which indicates how similar the origin and the destination occupation are in terms of their skill bundles. Confirming earlier results for the US and Germany (Poletaev and Robinson, 2008; Gathmann and Schönberg, 2010; Robinson, 2018), we find wage trajectories after layoffs to be strongly related to the skill distance. The larger the skill distance between two occupations, the higher the wage loss for workers who switch between these occupations.

Our study derives several important and novel insights. We show that single skills and the bundling and weighting of these skills crucially affect mobility and wages. Because of the ongoing structural transformation of the economy, this result is of particular interest. Educational policy makers should focus on the actual skill content of different education curricula, rather than on the labels 'general education' and 'vocational education'. Our result is also in line with earlier studies such as, for example, Ingram and Neumann (2006), who explore the difference between the return to years of education and the return to skills and show that, after accounting for skills, the return to years of education has remained constant in the US since 1970.

Furthermore, our findings suggest a risk-return trade-off for educational investments in more specific skills. While workers in more specific occupations appear less mobile than workers in more general occupations, they are compensated for their lower mobility with higher wages. Accounting for the specificity of an occupation is thus crucial for occupational sorting. Within the same type of education, more risk-loving individuals can maximize earnings if they sort into more specific occupations. However, they should be aware of their more limited reemployment options if laid off.

Finally, we find that the amount of skills that are transferred between occupations crucially determines wage trajectories. Some job reallocations could thus take place without any major destruction of human capital. To minimize wage losses, workers are well advised to be aware of the skill similarity between any two occupations and to search for reemployment in skill-neighbouring occupations.

Supplementary material

Supplementary material is available on the OUP website. These are the replication files along with the non-confidential data used for the analysis. The Social Protection and Labour Market survey is confidential, but can be accessed upon request from the Swiss Federal Statistical Office. The BIZ skill data are available from the book by Zihlmann *et al.* (2012).

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Tables

Table 1. Skill categories in Zihlmann *et al.* (2012)

Category	Skills
Intellectual skills	abstract-logical thinking, creativity, language skills, mental flexibility, organisational skills, practical understanding, sense of aesthetics, spatial perception, technical understanding.
Personal skills	ability to work in a team, communication skills, empathy, hygiene awareness, openness, patience and perseverance, psychological stability, reliability, sense of responsibility, service mindedness.
Physical skills	fine motor skills, manual dexterity, no fear of heights, physical mobility, robust health, sense of taste, strong constitution.

Source: Zihlmann *et al.* (2012), translated by the authors.

Table 2. Specificity ranking of skills

Skill	Ranking	Skill	Ranking
Organisational skills	1	Patience and perseverance	13
Service mindedness	2	Fine motor skills	14
Sense of responsibility	3	No fear of heights	15
Ability to work in a team	4	Mental flexibility	16
Language skills	5	Practical understanding	17
Communication skills	6	Psychological stability	18
Technical understanding	7	Hygiene awareness	19
Manual dexterity	8	Sense of taste	20
Abstract-logical thinking	9	Physical mobility	21
Sense of aesthetics	10	Reliability	22
Spatial perception	11	Creativity	23
Openness	12	Empathy	24

Source: Authors' calculations, based on SESAM linked with BIZ data.

Table 3. Descriptive statistics

Variables	Mean	St. Dev.	Min	Max
Occupational specificity	0	1	-3.534	2.542
Labour market thickness	0	1	-0.918	2.688
Skill distance	0.170	0.267	0	1
Male	0.507	0.500	0	1
Married	0.567	0.496	0	1
Swiss	0.435	0.496	0	1
Age	40.81	11.38	18	65
Tenure	3.433	5.787	0.005	43.95
Full-time	0.543	0.498	0	1
Wage	3,813	3,293	0	17,612
Unemployment benefits	946	1,865	0	9,272
Firm size	9.653	4.540	0	14
Industry	7.719	3.862	0	17
Region	13.05	8.948	1	26
Local unemployment rate (%)	3.282	1.323	0.7	7.6

Notes: The number of observations is 4,698.
Source: Authors' calculations, based on SESAM linked with BIZ data.

Table 4. Most general and most specific occupations

Occupation	Occupational specificity, standardized
Most general	
Jeweller	- 3.534
Technical surgical assistant	- 2.306
Housekeeper	- 2.215
Baker/confectioner	- 1.198
Textile designer (weaving)	- 1.963
Most specific	
Recyclist	2.542
Textile carer	2.267
Hospitality specialist	2.092
Office assistant	2.090
Textile care assistant	1.993

Source: Authors' calculations, based on SESAM linked with BIZ data.

Table 5. Skill distance across occupation pairs

Occupation pairs	Skill distance
Close occupations	
Computer scientist (general) – computer scientist (application development)	0.126
Commercial employee – office assistant	0.167
Commercial employee – logistician	0.192
Retail assistant – commercial employee	0.195
Draughtsman – design engineer	0.218
Distant occupations	
Cleaner – healthcare professional	1
Early childhood educator – office assistant	1
Electrical practitioner – healthcare professional	0.943
Catering professional – foundation engineer	0.913
Polygraph – building cleaner	0.894

Source: Authors' calculations, based on SESAM linked with BIZ data.

Table 6. Multinomial Logit Regression: Occupational specificity and employment status

	occupational change	*unemployed*	*out of the labour force*
Occupational specificity	-0.2514**	0.2904***	0.1703
	(0.1074)	(0.1112)	(0.2637)
Labour market thickness	-0.0545	-0.2507**	-0.4709*
	(0.1198)	(0.1139)	(0.2827)
Unemployment rate	0.3643	0.3818	0.1472
	(0.3530)	(0.3581)	(0.9879)
Age	-0.0984**	0.0285	-0.3827***
	(0.0480)	(0.0519)	(0.1176)
Age squared	0.0011*	-0.0002	0.0047***
	(0.0006)	(0.0006)	(0.0014)
Tenure	-0.1316*	0.4774***	0.3231***
	(0.0706)	(0.0451)	(0.0843)
Tenure squared	0.0038*	-0.0110***	-0.0061**
	(0.0021)	(0.0015)	(0.0025)
Swiss	-0.0728	-0.7560***	-0.5280
	(0.1570)	(0.1678)	(0.4296)
Male	0.0757	0.4213**	-1.1697**
	(0.1718)	(0.1743)	(0.4867)
Married	0.3188**	-0.2634	0.0481
	(0.1582)	(0.1606)	(0.4264)
Full-time	0.0703	-1.9475***	-0.1559
	(0.1625)	(0.1691)	(0.4119)
Firm size	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Region	Yes	Yes	Yes
Year	Yes	Yes	Yes
Pseudo R^2	0.235	0.235	0.235
Observations	1,705	1,705	1,705

Notes: The base outcome is 'reemployed in the origin occupation'. Standard errors in parentheses. *** p < 0.01, ** p< 0.05, * p< 0.1.
Source: Authors' calculations, based on SESAM linked with BIZ data.

Table 7. Marginal effects of a one standard deviation change in occupational specificity

	same occupation	*occupational change*	*unemployed*	*out of the labour force*
Occupational specificity	-0.0018 (0.0160)	-0.0378*** (0.0128)	0.0373*** (0.0121)	0.0023 (0.0048)
Average probability	0.552	0.154	0.267	0.027

Notes: Marginal effects of a one standard deviation change in occupational specificity on the four outcome probabilities. Standard errors in parentheses. *** p < 0.01, ** p< 0.05, * p< 0.1.
Source: Authors' calculations, based on SESAM linked with BIZ data.

Table 8. Occupational specificity and wages

	Log wage	*Log wage*
Lagged log wage	0.3170***	0.7242***
	(0.0311)	(0.0075)
Occupational specificity	0.0933***	0.0247***
	(0.0300)	(0.0032)
Labour market thickness	-0.0567*	-0.0073**
	(0.0308)	(0.0032)
Unemployment rate	-0.1075	0.0016
	(0.1035)	(0.0092)
Age	0.0236**	0.0180***
	(0.0117)	(0.0018)
Age squared	-0.0002*	-0.0002***
	(0.0001)	(0.0000)
Tenure	-0.1255***	-0.0012
	(0.0246)	(0.0007)
Tenure squared	0.0052***	0.0001**
	(0.0012)	(0.0000)
Swiss	0.0510	0.0101**
	(0.0376)	(0.0043)
Male	0.1725***	0.0905***
	(0.0448)	(0.0063)
Married	0.0116	-0.0338***
	(0.0374)	(0.0044)
Full-time	0.4397***	0.1752***
	(0.0508)	(0.0073)
Firm size	Yes	Yes
Industry	Yes	Yes
Region	Yes	Yes
Year	Yes	Yes
R^2	0.522	0.710
Observations	1,104	47,807

Notes: Robust standard errors in parentheses. *** p < 0.01, ** p< 0.05, * p< 0.1.
Source: Authors' calculations, based on SESAM linked with BIZ data.

Table 9. Occupational specificity, skill distance, and change in wages

	Change in log wages	*Change in log wages*
Change in specificity	0.0332*	
	(0.0172)	
Skill distance		-0.2371***
		(0.0821)
Lagged log wage	-0.6817***	-0.6907***
	(0.0313)	(0.0312)
Labour market thickness	0.0057	0.0037
	(0.0216)	(0.0219)
Unemployment rate	-0.1304	-0.1170
	(0.1044)	(0.1041)
Age	0.0240**	0.0234**
	(0.0117)	(0.0117)
Age squared	-0.0003*	-0.0002*
	(0.0001)	(0.0001)
Tenure	-0.1288***	-0.1335***
	(0.0247)	(0.0258)
Tenure squared	0.0053***	0.0056***
	(0.0012)	(0.0013)
Swiss	0.0560	0.0516
	(0.0382)	(0.0379)
Male	0.1669***	0.1708***
	(0.0452)	(0.0451)
Married	0.0012	0.0088
	(0.0374)	(0.0373)
Full-time	0.4477***	0.4535***
	(0.0513)	(0.0509)
Firm size	Yes	Yes
Industry	Yes	Yes
Region	Yes	Yes
Year	Yes	Yes
R^2	0.552	0.554
Observations	1,104	1,104

Notes: Robust standard errors in parentheses. *** p < 0.01, ** p< 0.05, * p< 0.1.
Source: Authors' calculations, based on SESAM linked with BIZ data.