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ABSTRACT

Wages and Employment: The Role of Occupational Skills*

How skills acquired in vocational education and training (VET) affect wages and employment is not clear. We develop and estimate a search and matching model for workers with a VET degree. Workers differ in interpersonal, cognitive and manual skills, while firms require and value different combinations of these skills. Assuming that match productivity exhibits worker-job complementarity, we estimate how interpersonal, cognitive and manual skills map into job offers, unemployment and wages. We find that firms value cognitive skills on average almost twice as much as interpersonal and manual skills, and they prize complementarity in cognitive and interpersonal skills. The average return to VET skills in hourly wages is 9%, similar to the returns to schooling. Furthermore, VET appears to improve labour market opportunities through higher job arrival rate and lower job destruction. Workers thus have large benefits from acquiring a VET degree.

JEL Classification: E24, J23, J24, J64

Keywords: occupational training, vocational education, labor market search, sorting, multidimensional skills

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1 Introduction

In the recent crisis of rising youth unemployment, some policy makers and researchers have suggested to strengthen vocational training to facilitate school-to-work transitions and to lower youth unemployment rates (Zimmermann et al., 2013). Conversely, others caution that specific vocational skills might become obsolete with technological progress compared to more general education (Hanushek et al., 2017; Krueger and Kumar, 2004b,a). The discussion on the merits and disadvantages of general versus vocational education largely ignores the heterogeneity of vocational education and training. It allows workers to train in many different occupations and hereby acquire different skill bundles. Different skill bundles are associated with very different labour market outcomes such as employment rates, wages and mobility (Ingram and Neumann, 2006; Lindqvist and Vestman, 2011).

In this paper, we aim to tackle the following three questions: How do different skills acquired in vocational education and training (VET) affect employment and wages? Which skills do firms demand most? What is the value of the skills acquired in VET for workers and firms? To answer these questions, we develop a simple search and matching model with workers and firms who differ in their multidimensional skill supply and demand. A worker's skill supply corresponds to the skills acquired during VET and remains constant over time. Firms use these skills in different combinations to produce an output. We adopt a production function that is linear in skills, with worker-job complementarity and correlated skill demands. Workers and firms match randomly, they engage in Nash bargaining over wages and jobs are destroyed exogenously.

Understanding the effect of VET skills on employment and wages is important. First, VET is a very common education programme in a number of European countries. Moreover, it has received increased attention by policy makers since the recent crisis. Second, it is not well understood whether VET affects employment, wages or both. Understanding the margin of adjustment is necessary when quantifying the benefits of VET.

We take our model to the data using survey and register data and information on skills acquired during VET for Switzerland. In Switzerland, around two thirds of a cohort enrol in VET and its vocational education system is considered to be among the best worldwide.[1] Our skill data comes from the *Berufsinformationszentrum* (BIZ), the state-led career-counselling centre. BIZ provides a detailed list of skills that are used in individ-

[1] Switzerland regularly ranks among the top three nations at the World Skills Championship (see https://api.worldskills.org/resources/download/8742/9562/10479?l=en and https://www.worldskills.org/about/members/switzerland/).

ual vocational occupations on the 5-digit level, covering a total of 220 occupations. We characterise each occupation by a multidimensional skill vector, distinguishing between interpersonal, cognitive and manual skills. For labour market outcomes we use the Social Protection and Labour Market (SESAM) survey. The SESAM consists of the Swiss Labour Force Survey, a representative panel survey, and register data on employment histories, unemployment benefits, and wages. Workers' skills are obtained from matching the skills of VET occupations in BIZ to the occupations in SESAM for which workers completed VET.

Our estimation results offer the following insights. Firms value interpersonal, cognitive and manual skills, though to a different extent. The average productivity of a cognitive skill is almost twice as high (at 2.25 Swiss francs per hour) as the one of an interpersonal (1.30 Swiss francs) or manual skill (1.35 Swiss francs). Moreover, firms have a high demand for complementarity in cognitive and interpersonal skills, and they tend to prefer either manual or non-manual specialists. The pattern of workers' skills supply matches the firms' demand for skills fairly well.

The returns to VET skills amount to 9% in hourly wages (and annual earnings) according to our simulation results. However, VET not only offers returns to skills in terms of wages, it also appears to improve labour market opportunities through higher job arrival rates and lower job destruction. This translates into longer employment and shorter unemployment spells for VET workers compared to workers without VET. VET benefits workers, while net benefits for firms could range from negative to positive, depending on the underlying assumptions of the counterfactual scenario.

This paper ties into two different strands of the literature. First of all, it contributes to the literature on vocational education and labour market outcomes. Vocational education is oftentimes thought of facilitating school to work transitions and keeping youth unemployment low (Ryan, 2001; Zimmermann et al., 2013). However, labour market outcomes beyond the initial transition phase have received little attention in the literature, so far. An exception presents the article by Hanushek et al. (2017), where the authors study employment rates over the life cycle and lifetime earnings by education type (general versus vocational) in 11 countries. Our paper differs from Hanushek et al. (2017) in two important aspects. First, our empirical analysis of labour market outcomes of VET workers makes use of a simple search and matching model.[2] In this framework labour market

[2]Two recent papers analyse on-the-job investment in general versus specific skills in a search and matching model, where specific skills are worthless outside the firm (Wasmer, 2006; Flinn et al., 2017). This paper instead focuses on transferable interpersonal, cognitive and manual skills acquired in VET prior to entering the labour market and how the affect labour market outcomes.

outcomes (i.e. employment and wages) are an equilibrium outcome of the demand and supply of VET labour. Focusing not only on VET labour supply, but also modelling the demand for VET labour allows us to obtain estimates of both workers' and firms' benefit from VET. This is important for evaluating the overall value of a vocational education system. Second, in our analysis, we distinguish different VET occupations according to their level of cognitive, interpersonal and manual skills. This refined analysis provides insights into how different skills affect labour market outcomes differently. It turns out that not all VET occupations confer the same returns in terms of wages and employment perspectives.

Our paper also relates to the growing literature on the specificity of human capital, occupations and returns to skills. Recent contributions suggest that the number of years of education alone is not a sufficient measure of skill and propose an alternative measure based on observed characteristics of jobs held by workers (Autor et al., 2003; Ingram and Neumann, 2006; Poletaev and Robinson, 2008; Lazear, 2009; Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010; Lise and Postel-Vinay, 2016). When analysing the returns to skills, most research focuses on the transferability of skills in job-to-job transitions and relates it to wage dynamics. A general finding is that individuals move to occupations with similar skill requirements (Gathmann and Schönberg, 2010) and that skills are closely related to wages (Poletaev and Robinson, 2008). While informative, a major shortcoming of this literature is that it considers job transitions and wages separately. Lise and Postel-Vinay (2016) are the first to develop and estimate an equilibrium search and matching model in which workers and firms (i.e. jobs) are heterogeneous in several skill dimensions (cognitive, manual, interpersonal).

Our paper builds on the framework developed by Lise and Postel-Vinay (2016), but modifies it in several aspects and applies it to a different context, that is, the Swiss labour market for VET workers. The main differences of our model are that workers' skills do not adjust over time, there is no on-the-job search, and we rely on a production function with worker-job complementarity as in Lazear (2009). Despite a different focus and modelling choices, we find similar qualitative results in terms of the relative productivity of the different skills and the complementarity-specialisation patterns in the demand for skills by firms as Lise and Postel-Vinay (2016) for the US.

The paper proceeds as follows. Section 2 provides information on VET in Switzerland, discusses the data sources and presents descriptive evidence on interpersonal, cognitive and manual skills and labour market outcomes of VET workers in Switzerland. In Section 3, we develop a simple model of search and matching in the labour market with a multidimensional skill vector. This model allows us to jointly study wages and employment outcomes of VET workers. Section 4 outlines our structural estimation procedure and discusses identification. Section 5 presents the estimation results, which form the basis of the simulations in Section 6 to estimate the value of VET. Section 7 concludes.

2 Institutional background and data

In this section we first describe the institutional background of Switzerland, a country with a long tradition of vocational education and training. We then go on to present and discuss the key features of the two main data sources used to analyse the impact of occupational skills on wages and employment dynamics of workers with completed VET.

2.1 Institutional background

About 65 percent of a Swiss youth cohort enrol in vocational education and training (VET), whereas only approximately 20% of a cohort choose general upper secondary school (i.e. college-bound high school) (CSRE, 2014). This share is larger than in any other country in which VET is available (Hanushek et al., 2017). In Switzerland, VET also attracts high ability students because of its excellent reputation and promising career opportunities. Generally, the quality of the VET system is considered to be very high (Hoeckel et al., 2009; Hoffman, 2011). This is highlighted by the fact that Switzerland's open and highly competitive economy relies on a skilled workforce that has to a large extent been trained in VET.

Training starts at around age 16 and lasts for three to four years. It is a dual programme that combines formal education and curriculum-based on-the-job training with an employer.[3] Skills acquired in VET are not firm-specific, but transferable. The curricula provide a mix of general and specialised occupational skills: Apprentices work for three to four days a week in their training firm and attend vocational school for one to two days a week. In the training firm, they acquire all occupational skills, learning about the firm's products and production technology, and general skills such as work values (accuracy, punctuality, etc.). In vocational schools, apprentices attend general education classes and occupation-specific lessons. The content taught in VET schools and in the firm is formally regulated and training quality is ensured by interim and final examinations based on regulated quality standards. The training content is regularly revised in

[3]There are different kinds of VET programmes in Switzerland. The most important and the most common one is the apprenticeship programme, which combines vocational school with on-the-job training at a host firm. Apprentices are paid a salary by the host firm. There exist also vocational schools (i.e. in business) which offer full-time vocational education in combination with an internship of several months.

a tripartite process, in which employer organizations, employee representatives, and the government participate (Rinawi and Backes-Gellner, 2014).

Upon successful completion of the programme, graduates receive a nationally recognised diploma. They are not bound to their training firm, but can now freely move around in the labour market. Indeed, the retention rate after graduation is only 35 percent (Schweri et al., 2003). Given that the Swiss educational system is characterised by a high degree of permeability, many workers with a VET diploma continue their educational pathway by earning a university degree or taking further classes at a professional college.[4]

2.2 Data

2.3 Main data sources

Our analysis builds on two main data sources: First, we use data on skills taught in VET from the career-counselling centre *Berufsinformationszentrum* (BIZ) to construct occupation-specific skill bundles. We describe this skill data source further below. Second, we use the Social Protection and Labour Market (SESAM) survey for labour market outcomes.

SESAM is a matched panel data set linking the Swiss Labour Force Survey (SLFS) with data from different social insurance registers. The SLFS is a nationally representative, rotating household panel and offers a rich set of information on employment, sociodemographic, educational, and occupational characteristics. The matched social insurance information provides the duration of individual employment and unemployment spells, as well as monthly earnings and unemployment benefits.

Our observation period covers the years 2004 through 2009, for which SESAM offers consistent data. Each individual remains in the SESAM panel for five years or less. During our sample period, the survey was run on a yearly basis in the second quarter. It contains questions both about the current employment situation as well as about the past. We restrict our analysis to a sample of male individuals who are between 20 and 64 years old and who have obtained a VET degree as the highest education level.[5] We exclude individuals who are out of the labour force, but include part-time workers (who make up

[4]Admission at a university or a university of applied sciences usually requires a special vocational diploma 'Berufsmatura', which can be obtained in parallel to the nationally recognised VET degree. Based on the labour market data (SESAM), we estimate that around 20% of all VET graduates successfully complete a professional college/university of applied sciences (18.7%) or university (2.5%).

[5]To remove the bias from selection into education levels, we focus on workers with heterogeneous skills within the same education class (Backes-Gellner and Wolter, 2010; Geel and Backes-Gellner, 2011).

around 10% of the sample). For the analysis, we compute hourly wages and trim the wage distribution below the bottom 4% and above the top 0.5%. We only keep those individuals in the analysis for whom we observe at least two years of data. In total, our sample consists of 5,050 individuals and 13,734 person-year observations.

2.3.1 Occupational skills

We use data from the career-counselling centre *Berufsinformationszentrum* (BIZ) to construct a measure of skills that are acquired during VET. The BIZ provides a detailed list of skills that are used in different occupations, covering a total of 220 VET occupations that existed during the period we examine. The list comprises 26 different skills, of which we only use 24.[6] Each of these 24 skills is either classified as interpersonal (10 skills), cognitive (9 skills) or manual (5 skills). Examples include "ability to work in a team" (interpersonal), "visual thinking" (cognitive) and "fine motor skills" (manual).

These 24 skills represent 24 potential dimensions of skill heterogeneity across workers, resulting in $2^{24} = 16,777,216$ different skill bundles.[7] In order to reduce the dimensionality of the problem, we add up the number of acquired skills within each one of three skill dimensions: interpersonal, cognitive and manual.[8] Depending on the occupation in which VET students train, their acquired skill bundles differs substantially. For example, care professionals acquire only interpersonal skills (5 skills), and IT technicians acquire mostly cognitive skills (5 out of 7 skills acquired), and car mechanics acquire mostly manual skills (3 out of 5 skills acquired). There are many more VET occupations, some providing similar and others providing more balanced skill bundles than these three examples.

Table 1 presents descriptive statistics on the skills of the 5,050 workers with a VET degree in our sample.

The workers in our sample have acquired on average 1.81 interpersonal, 2.14 cognitive and 1.23 manual skills. Each skill dimension has a different distribution. The distribution of interpersonal skills is spread out. 60% of VET workers have acquired at most one interpersonal skill. Yet, a considerable fraction has acquired three or even five interpersonal skills (15% each). In comparison, the distributions of cognitive and manual skills are

[6] Based on the BIZ's own classification, we exclude "robust health" and "strong physique" because they describe physical attributes rather than skills that can be acquired.

[7] Note that each skill is either acquired or not (binary), we do not dispose of the intensity of use/acquisition of skills.

[8] This implies that each skill within a specific skill dimension is equally valuable. Appendix A shows how our skill measure compares with O*Net-based measures used in the related literature.

Table 1: DESCRIPTIVE STATISTICS FOR WORKERS' OCCUPATIONAL SKILLS.

	obs	mean	S.D.	distribution					
Skill dimension				0	1	2	3	4	5
interpersonal	5,050	1.805	1.711	1,239	1,854	267	779	163	748
cognitive	5,050	2.140	1.274	281	1,471	1,613	1,053	208	424
manual	5,050	1.228	0.820	1,075	1,925	1,872	178		

	correlation		
	interp	cogn	manual
interpersonal	1.000		
cognitive	0.328	1.000	
manual	-0.462	-0.261	1.000

smoother. Most workers have acquired one (29%), two (32%) or three (21%) cognitive skills. Only few workers have acquired fewer or more cognitive skills. Finally, more than 95% of all workers have acquired two or fewer manual skills, with a peak at two skills (38%).

Table 1 (panel below) also provides some insight into how the three skill dimensions are related. The two negative correlation coefficients with manual skills indicate that workers specialise by either acquiring manual or non-manual (interpersonal/cognitive) skills. The supply of interpersonal and cognitive skills, instead, correlates positively. Workers with high (low) interpersonal skills tend to have high (low) cognitive skills.

Figure 1 further visualizes the different skill bundles supplied by the workers in our sample. It displays the joint distribution of cognitive and interpersonal skills for each of the four different values of manual skills.

Each specific skill bundle has a different frequency. Some skill bundles make up 5% or more of the sample, for other skills bundles we do not have a single observation. Generally, skill bundles close to the horizontal 00-55 line (0 interpersonal-0 cognitive to 5 interpersonal-5 cognitive) are somewhat more frequent than those off this line, reflecting the positive correlation of these skills. Moreover, workers with relatively high manual skills have only few interpersonal and cognitive skills, and vice versa.

Given the range of each skill dimension, there are $6 \times 6 \times 4 = 144$ possible skill combinations. Effectively, we observe only 45 of them in our sample. To reduce the dimensionality further, we regroup workers into occupational clusters based on the set of skills they acquired during VET. To do this, we first divide each of the three skill dimen-

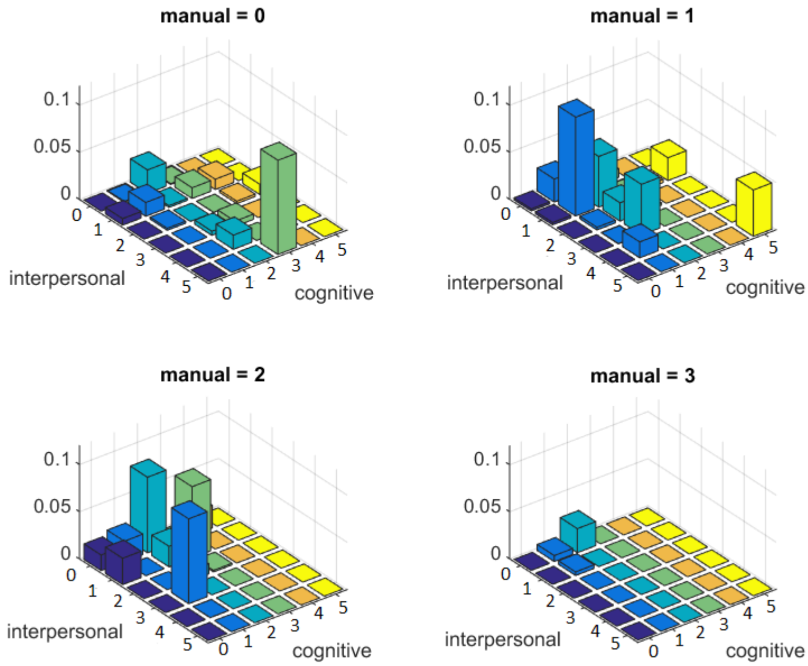

Figure 1: Skill bundles supplied by workers

sions into groups with the aim of creating groups of roughly equal size. We distinguish low (0), medium (1,2) and high (3 and above) interpersonal skills; low (0,1), medium (2) and high (3 and above) cognitive skills, and low (0,1) and high (2,3) manual skills. There are 18 ($3 \times 3 \times 2$) possible occupation clusters, but two remain empty without any observation.

2.3.2 Labour market outcomes

The specific skill bundle acquired in VET is a key determinant of labour market outcomes. Figure 2 illustrates this point by plotting hourly wages (left panel) and unemployment rates (right panel) of Swiss workers with a VET degree for different levels (black, grey and light-grey bars) of the three skill dimensions. For comparison purposes, the figure also depicts the respective hourly wages and unemployment rates of workers with only completed compulsory education (dashed line) and those with completed general upper secondary education, but without tertiary education (black line).

Occupations with high cognitive skills are characterised by higher hourly wages (by 4 Swiss francs) and slightly lower unemployment rates (by 0.5pp) than occupations with low cognitive skills. Having high interpersonal skills is associated with higher hourly wages (by 3 Swiss francs), but also with higher unemployment rates (by more than 1pp) than having low interpersonal skills. Finally, more manual skills are not associated with higher hourly wages (if anything, they are slightly lower). However, the unemployment

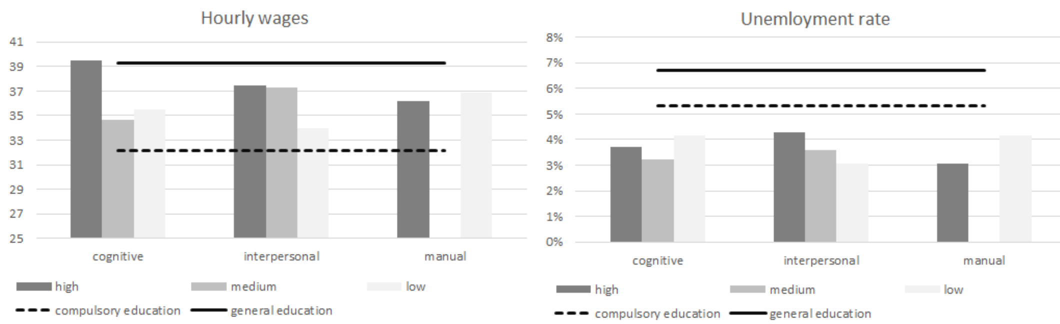

Figure 2: Hourly wages and unemployment rates by skill dimensions

rate is around 1pp lower for workers with high manual skills than for workers with low manual skills.

Figure 2 also offers some insights into how VET workers fare compared to workers who have only completed compulsory education and to workers who have obtained general upper secondary education (rather than vocational). Indeed, average hourly wages of VET workers generally lie between those 'extremes'. Only VET workers with high cognitive skills earn hourly wages comparable to those of workers with general upper secondary education. However, VET workers do not primarily benefit from their training in terms of higher wages, but rather in terms of lower unemployment rates. Unemployment rates of VET workers are substantially lower than the unemployment rate of both workers with compulsory education (5.3%) or with general upper secondary education (6.7%).

Given the correlation of the three skill dimensions, we provide some further descriptive evidence on labour market outcomes. Table 2 shows descriptive statistics by occupational clusters, Table 3 presents reduced form regressions of (log) hourly wages and unemployment on interpersonal, cognitive and manual skills. The three panels in Table 2 relate to high, medium and low interpersonal skills, respectively. Within each panel, the upper part (3 lines) refers to high and the lower part (3 lines) to low manual skills. Finally, within each interpersonal-manual skill group cognitive skills go from high to medium to low.

Average hourly wages of VET workers differ substantially across occupational clusters, but they are generally above those of workers with only compulsory education. Most VET workers with high cognitive skills have average hourly wages of 39 Swiss francs and more, exceeding the average hourly wage of workers with general upper secondary education.

Table 2: DESCRIPTIVE STATISTICS BY OCCUPATIONAL CLUSTERS

		Obs	unemp	hourly wages mean	hourly wages std. dev.	age
H-interpersonal						
H-manual	H-cognitive	0	n.a.	n.a.	n.a.	n.a.
	M-cognitive	0	n.a.	n.a.	n.a.	n.a.
	L-cognitive	1,244	0.039	37.67	10.64	40.52
L-manual	H-cognitive	2,042	0.047	40.14	15.43	39.05
	M-cognitive	1,052	0.030	33.89	9.91	39.47
	L-cognitive	255	0.082	29.62	6.52	39.29
M-interpersonal						
H-manual	H-cognitive	1,094	0.018	40.09	10.74	44.46
	M-cognitive	456	0.024	38.06	12.87	41.49
	L-cognitive	446	0.027	33.73	9.77	41.78
L-manual	H-cognitive	940	0.040	39.13	11.88	42.20
	M-cognitive	1,028	0.040	35.89	9.07	41.82
	L-cognitive	1,801	0.048	36.09	11.22	39.36
L-interpersonal						
H-manual	H-cognitive	299	0.033	33.74	7.86	40.51
	M-cognitive	1,467	0.033	33.41	7.78	39.33
	L-cognitive	607	0.035	33.84	10.33	40.99
L-manual	H-cognitive	147	0.020	40.51	11.21	43.99
	M-cognitive	489	0.022	33.82	8.85	42.98
	L-cognitive	367	0.025	34.17	8.44	41.73
all clusters		13,734	0.037	36.55	11.39	40.70
Comparison with lower and next higher educational achievement						
Compulsory schooling		3,845	0.053	31.29	15.97	42.65
General upper secondary education		1,161	0.067	38.98	27.73	38.43

Table 3 shows that returns to all three skills appear positive, even after controlling for age. Returns to interpersonal and cognitive skills are in a similar range, while returns to manual skills are somewhat smaller. The negative interaction terms between skills could indicate a substitutability of these skills.

Table 3: REDUCED-FORM ESTIMATES.

	Log hourly wages		Unemployment	
Interpersonal skills	0.0497	***	0.0029	**
	(0.0041)		(0.0011)	
Cognitive skills	0.0511	***	-0.0017	
	(0.0053)		(0.0014)	
Manual skills	0.0337	***	-0.0020	
	(0.0075)		(0.0022)	
Interpersonal*cognitive	-0.0106	***		
	(0.0011)			
Interpersonal*manual	-0.0115	***		
	(0.0018)			
Cognitive*manual	-0.0169	***		
	(0.0032)			
Age	0.0430	***	-0.0057	***
	(0.0014)		(0.0011)	
Age squared	-0.0004	***	0.0001	***
	(1.76×10^{-5})		(1.35×10^{-5})	
Constant	2.3833	***	0.1503	***
	(0.0303)		(0.0237)	
R^2	0.2254		0.0034	
Observations	11,960		13,734	

Notes: The left-hand column, in which log hourly wages is the dependent variable shows least-squares estimates. The right-hand column, in which a dummy indicator for unemployment is the dependent variable, shows estimates from a linear probability model. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We also observe important differences in hourly wages within each cluster. A large part of the within-cluster variation reflects hourly wage differences stemming from differences in age, experience, region, industry and other factors. Having more interpersonal or cognitive skills is also associated with (slightly) higher standard deviation of hourly wages.

VET workers in all occupational clusters have lower unemployment rates than workers without VET (independent of their level of education).[9] Unemployment rates vary across occupational clusters, but these differences appear to be less systematic than for hourly wages. Table 3 indicates that having more interpersonal skills is associated with a slightly higher risk of unemployment, while cognitive and manual skills do not have a significant effect. Given that all VET workers were employed at a firm during their training, all observed differences in unemployment rates across occupational clusters must be the result of different labour market transitions after graduation. Appendix B presents further descriptive evidence on employment and unemployment transitions by occupational cluster.

We know from standard economic theory, however, that wages and unemployment are jointly determined. The previous analysis is thus purely descriptive. To understand the resulting wages and unemployment rates in different occupational clusters, we need to study how supply and demand for different skills interact and how they determine these equilibrium outcomes. To do so, we develop a simple search and matching model with occupational skills in the next section.

3 A simple matching model with occupational skills

To study the role of occupational skills in wages and (un-)employment dynamics, we develop a simple general equilibrium search and matching model in the spirit of Pissarides-Mortensen-Diamond (see Pissarides, 2000). Workers are heterogeneous. They are characterized by a set of skills which differ along several dimensions. Firms use these skills in different combinations to produce an output.

Our model is in continuous time and features infinitely lived agents who discount time at rate r. We assume that search is random and that jobs get exogenously destroyed. Key ingredients of our simple model are the multidimensional skill supply by workers and the multidimensional skill demand by firms. Workers are heterogeneous in that they acquired different skills during their vocational education and training. Each worker possesses an occupation-specific (time-invariant and multidimensional) skill bundle denoted by x. Each element of x is non-negative. Firms, on the other hand, differ in their demand for

[9] An exception presents the occupational cluster with high interpersonal, low manual and low cognitive skills for which the unemployment rate exceeds 8% and hourly wages are around 29 Swiss francs. This is the second smallest group in our sample and hence, the unemployment rate is less precisely measured than for the other occupational clusters.

these skills. Their demand for a specific skill combination is denoted by skill weights α.

Under random search, an unemployed worker with skill bundle x gets an unemployment flow of b and meets a firm at some constant rate λ. An employed worker receives wage w and faces (exogenous) job destruction at rate η. The wage is a function of the worker's skill bundle x, firms' skill weights α, and the resulting match productivity p. For simplicity, we assume that there is no on-the-job-search. The value functions of the worker's problem are given by:

$$rV_U(x) = b(x) + \lambda \mathbb{E}_w \max\left[V_E(w,x) - V_U(x), 0\right] \tag{1}$$
$$rV_E(w,x) = w + \eta\left[V_U(x) - V_E(w,x)\right], \tag{2}$$

where r is the instantaneous discount rate, V_U is the value of unemployment, and V_E is the value of employment. $\mathbb{E}_w$ denotes the expectation operator with respect to wages w.

A firm's value of a filled job depends on the productivity of the match p and the wage w which the firm needs to pay. Whenever a firm and a worker meet, the potential productivity of this match is assumed to be $p = \alpha' x$ (following Lazear, 2009; Flinn and Mullins, 2015). α is a skill weighting vector which is independently and identically distributed according to the multivariate distribution function $G(\alpha)$. Each component of α is restricted to be non-negative.[10] A filled job gets destroyed at rate η. We assume that there is no endogenous vacancy creation.[11] The value of a filled job between a worker with skill bundle x and a skill weighting vector α is given by:

$$rV_F(w,\alpha) = \alpha' x - w + \eta\left[V_F(w,\alpha)\right]. \tag{3}$$

The worker and the firm engage in Nash-bargaining over the wage w by solving the following bargaining problem:

$$\max_w \left[V_E(w,x) - V_U(x)\right]^{\beta}\left[V_F(w,\alpha)\right]^{1-\beta}, \tag{4}$$

where β is the worker's bargaining power. Using Equations (2) and (3), we can rewrite the Nash-bargaining problem and derive the following wage equation:

$$w(\alpha,x) = \beta\alpha' x + (1-\beta) rV_U(x). \tag{5}$$

Let us define the set of reservation skills $\alpha^*(x)$. It is the set of acceptable weighting vectors for which a worker with skills x is indifferent between employment and unemployment. Moreover, the reservation skills also pin down the reservation wage $w^*(x)$:

[10] This assumption implies that there are no (direct) costs for the firm when hiring a worker who has skills which are not needed by the firm.

[11] It is straightforward to extend the model to endogenous vacancy creation. Under the common free entry condition, the value of an unfilled vacancy is equal to 0 and the value of a filled job is the same as in our setting.

$$w(\alpha^*(x), x) = \beta\alpha^*(x)'x + (1-\beta)rV_U(x) = rV_U(x) \quad (6)$$

$$w^*(x) = \alpha^*(x)'x = rV_U(x). \quad (7)$$

We now turn to the rate of a match being formed. It is the product of the offer rate λ and the probability of the firm's skill weights α lying within or above the set of reservation skills. The rate of forming a match for a worker with skill bundle x is given by:

$$h(x) = \lambda \int_{\alpha^*(x)} dG(\alpha). \quad (8)$$

In a steady-state equilibrium, the inflow into and the outflow from unemployment need to be equal. This gives rise to the following equation, from which we can derive the likelihood of finding a worker with skills x in unemployment:

$$[1 - u(x)]\,\eta = u(x)h(x) \quad (9)$$

$$u(x) = \frac{\eta}{\eta + h(x)}. \quad (10)$$

Differences in unemployment rates across skill bundles x are thus driven by differences in the rate of accepting job offers (and not by differences in job destruction rates).

Despite its simplicity, the model has several appealing features. It allows us to jointly model (un-)employment and wages, which differ across skill bundles. Two key elements of the model are the demand for skills by firms $G(\alpha)$ and the flow cost of unemployment for different skill bundles by the worker $b(x)$. Together they determine the set of reservation productivities $\alpha^*(x)$ for which the worker and firm are indifferent between forming a match or not. The reservation productivity impacts the arrival rate of acceptable job offers and hence, unemployment dynamics (see Equation (8)), and wages (see Equation (5)).

4 Structural estimation

4.1 Parametric assumptions and functional forms

In this section we describe how we take the previously developed model to the data. To do so, we make some parametric assumptions about the skill demand distribution $G(\alpha)$ and the flow cost of unemployment $b(x)$. More specifically, we assume that the productivity of the match is given by the following equation,

$$p = \alpha' x = \alpha_0 + \alpha_I x_I + \alpha_C x_C + \alpha_M x_M, \quad (11)$$

where α_0 is a general productivity shock, and α_I, α_C and α_M are the demand for interpersonal, cognitive and manual skills, respectively. We assume that α_0 is independently and identically distributed according to a log-normal distribution with location μ_0 and scale σ_0. Whenever a worker and a firm meet, they draw a new general productivity shock α_0. Moreover, the general productivity shock is assumed to be independent of the skill-specific demands (and the skill supply). The skill-specific demands α_j with $j = I, C, M$ are assumed to be distributed according to a Gaussian copula with log-normal marginals with location μ_j and scale σ_j. The correlation between two skill-specific demands i and j is given by ρ_{ij}.

This parametrisation of the productivity is at the same time parsimonious and flexible. It imposes worker-job complementarity, for which evidence presented in Lindenlaub (2017) provides support. This specific parametrisation allows for different mean and variation in returns to each skill dimension. Moreover, the Gaussian copula renders it possible for the different skills to be positively or negatively correlated. A positive correlation indicates complementarity in the demand for skills, a negative correlation between two skills indicates that firms prefer specialists.

We also impose some structure on the flow cost of unemployment $b(x)$. We opt for the following parsimonious structure:

$$b(x) \quad = \quad b_0 + b_I x_I + b_C x_C + b_M x_M, \tag{12}$$

where b_0 is the general flow cost of unemployment common to all workers (i.e. we expect b_0 to be negative), and b_j the marginal cost (or value) of unemployment of skill j. If b_j is positive, having more skills j makes being in unemployment less costly, while the converse is true if b_j is positive.

4.2 Estimation method and identification

We estimate the model by using the Method of Simulated Moments (MSM) as in Flinn and Mullins (2015). Table 4 gives an overview over all parameters of the model and which moments are used for their identification. There are 19 parameters in total, but two parameters are calibrated outside the model. The remaining 17 parameters are identified by moments from the data. Notice that we directly observe the workers' skill bundle x, which simplifies the identification of the model substantially. We regroup workers with different skill bundles x into the same 16 occupational clusters as outlined in Section 2.3.1.

Identification of many parameters of the model is achieved by exploiting differences in mean hourly wages, unemployment rates, etc. between occupational groups. Let us

Table 4: Model parameters and corresponding moments

Parameter	Moment	#
Productivity and skill-specific demands (log-normal marginals)		
General productivity: μ_0, σ_0	Mean & standard deviation of hourly wages	
	by occupation cluster	32
Interpersonal skills: μ_I, σ_I	same as above	
Cognitive skills: μ_C, σ_C	same as above	
Manual skills: μ_M, σ_M	same as above	
Correlations: ρ_{IC}, ρ_{IM}, ρ_{CM}	same as above	
Flow cost of unemployment		
Common flow cost: b_0	First percentile of hourly wages	
	by occupation cluster	16
Interpersonal skills cost: b_I	same as above	
Cognitive skills cost: b_C	same as above	
Manual skills cost: b_M	same as above	
Offer arrival and destruction rates		
Offer arrival rate: λ	Yearly UE-transition rates by occupation cluster	16
Destruction rate: η	Yearly EU-transition rates by occupation cluster	16
	Unemployment rates by occupation cluster	16
Calibrated parameters		
Bargaining power worker: $\beta = 0.67$	Siegenthaler and Stucki (2015)	
Interest rate: $r = 0.05$		
	Total moments	96

suppose we knew reservation wages $w^*(x)$ and take the parametric assumptions about the match productivity $p = \alpha' x$ in Equation (11) and the calibrated value of the labour share β as given. Hence, we know that the productivity distribution matches one-to-one into the wage distribution given in Equation (5). Differences in mean hourly wages and in standard deviation of hourly wages across occupational groups allow us to pin down the eleven parameters of the match productivity (i.e. the demand for each specific skill, the correlation of these skills, and the general productivity). Mean hourly wages and the standard deviation of hourly wages are 32 moments.

We use the first percentile of hourly wages in each occupational cluster to identify the reservation wages $w^*(x)$. Together with the productivity-related parameters (identified above), they allow us to identify the common and skill-specific costs of unemployment. These are another 16 moments.

To identify the job arrival rate λ and the job destruction rate η, we rely on year-to-year unemployment-to-employment (UE) transitions, employment-to-unemployment (EU) transitions and unemployment rates by occupational clusters. In fact, given that we assume constant (i.e. skill-independent) job arrival and job destruction rates, it would suffice to use overall UE- and EU-transitions rather than by occupational cluster. However, these additional moments also help us to pin down the reservation productivities $\alpha^*(x)$ (and hence, reservation wages) and the parameters of the match productivity distribution $G(\alpha)$. In total, we have 48 moments related to labour market transitions.

Following Flinn (2006), we use information from outside the sample on firms' capital share to identify the firm's surplus. We set β to 0.67.[12] Finally, we fix the interest rate r at 5%.

Combining all this, we set up the following MSM estimator

$$\hat{\omega}_{N,W_N} = \arg\min_{\omega\in\Omega} \left(M_N - \tilde{M}(\omega)\right)' W_N \left(M_N - \tilde{M}(\omega)\right), \tag{13}$$

where ω is a parameter vector and Ω is the parameter space. The parameter vector contains the general productivity location parameter μ_0 and scale parameter σ_0, the skill-demand location μ_j and scale parameters σ_j (in total, 6 parameters), the correlation of

[12]The labour share, which is often used as a proxy for workers' bargaining power, has traditionally been thought to be constant at around two thirds (see Kaldor, 1957). While Karabarbounis and Neiman (2014) observe that the labour share has been declining to around 60 percent in the United States and many other countries since around 1980, Switzerland appears to be an exception, where it has actually remained at around 67 percent (see Siegenthaler and Stucki, 2015).

skill-demands ρ_{ij} (3 parameters), the common and skill-specific flow costs of unemployment b_0, b_j, as well as the offer arrival rate λ and the job destruction rate η. The parameter space corresponds to the real numbers for the location parameters μ_0, μ_j and the flow costs of unemployment b_0, β_j, to positive real numbers for the scale parameters σ_0, σ_j, the offer arrival rate λ and the destruction rate η, and to real numbers between -1 and 1 for the correlation coefficients. Furthermore, we restrict the parameter space of the correlation coefficients to ensure that the resulting symmetric correlation matrix is positive semi-definite. W_N is a diagonal matrix with elements equal to the inverse of the (squared) standard error of the corresponding observed moment M_N. The standard errors for the observed mean hourly wages, unemployment rates, UE- and EU-transition rates are estimated from the sample moments, the standard error of the standard deviations and the first percentile of hourly wages was bootstrapped using 1,000 replications.

4.3 Simulation procedure

To perform our estimation using MSM, we need to compute the simulated counterpart of the observed moments described in Table 4 used to evaluate Equation (13). Our target moments include the mean, standard deviation and first percentile of hourly wages by occupational cluster, unemployment rates by occupational cluster, as well as the occupation cluster-specific EU- and UE-transition rates. To do so, we produce a simulated data set with 20 replica of each worker in our observed data set (i.e. there are $20*5,050 = 101,000$ simulated workers). These simulated workers have (approximately) the same skill distribution x as the observed sample. For each worker we simulate five consecutive labour market spells (i.e. employment and unemployment spells). Our simulation protocol consists of the following steps:

1. For each individual in the simulated data set, we first determine their skill bundle x. We keep the skill bundle constant across all iterations.

2. At the beginning of each new iteration, we first compute the reservation wage for each skill bundle x. To do this, we need to find the fixed point of Equation (1) for each x.[13]

3. Once the reservation wage $w^*(x)$ is known, we can simulate the labour market state and wage (if any) in the first spell. For this purpose we draw a productivity shock

[13] To find the fixed point, we first rearrange Equation 2 and substitute it into Equation (1). We then (numerically) evaluate the right-hand-side of Equation (1) (i.e. the expected maximum of the employment surplus and 0) by drawing 50 productivity shocks α and computing the average sample maximum of the employment surplus and 0.

α, which results in a potential wage $w(x, \alpha)$. If the resulting wage is below the reservation wage, the worker is unemployed in the first spell. Among those workers with a resulting wage equal or above the reservation wage, there is a share κ who is unemployed in the first spell.[14] The remaining workers are employed in the first spell and get wage $w(x, \alpha)$.

4. We then simulate the duration of the first spell of each worker. For those who are employed, we draw the duration of their employment spell from an exponential distribution with destruction rate η. Unemployed workers receive a wage offer (determined by the draw of a productivity shock α) after a duration, which is drawn from an exponential distribution with offer arrival rate λ. If the wage offer is above the reservation wage, the worker accepts and becomes employed. Otherwise he continues his search and receives a next wage offer according to the same rules as described for the first offer. If he declines five consecutive offers, his first unemployment spell ends and he starts his second unemployment spell.

5. We repeat steps 2) to 4) to simulate also the data for the second to the fifth labour market spell (with $\kappa = 0$). Using the information on the employment status at the beginning of the first spell, the wage and the employment status after one year (using the data on the duration of each spell), we can compute the simulated moments.

Finally, we iterate this process (steps 2) to 5)) for different values of ω using a Nelder-Mead simplex algorithm until the minimum of the loss function is found.

5 Results

5.1 Estimated parameters

Table 5 presents point estimates and asymptotic standard errors of the model parameters. In the upper panel of column 4 and 5 we also show the (untruncated) mean and standard deviation of the general productivity and skill demand distributions. These numbers are more readily interpretable than the location and scale parameters of the log-normal distribution.[15]

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[14] This ensures that the unemployment rate at the beginning of the first spell equals the expression in Equation (10). κ equals $\frac{\eta-(1-p)(\eta+\lambda p)}{p(\eta+\lambda p)}$, where p is the fraction of those who have a potential wage equal or above the reservation wage.

[15] Notice that the mean of a log-normally distributed random variable is equal to $\exp(\mu + \sigma^2/2)$, and the variance is given by $\left[exp(\sigma^2) - 1\right] exp(2\mu + \sigma^2)$.

Table 5: ESTIMATED PARAMETERS

Productivity				
	Estimate	Std. Err.	Mean	Std dev.
μ_0: General productivity (location)	3.647	0.099	40.335	13.142
σ_0: General productivity (scale)	0.318	0.030		
μ_I: Interpersonal skills (location)	-0.261	0.761	1.288	1.727
σ_I: Interpersonal skills (scale)	1.014	0.342		
μ_C: Cognitive skills (location)	0.527	0.373	2.245	1.954
σ_C: Cognitive skills (scale)	0.750	0.164		
μ_M: Manual skills (location)	0.025	1.960	1.329	1.096
σ_M: Manual skills (scale)	0.720	1.122		
ρ_{IC}: Interpersonal-cognitive correlation	0.937	0.071		
ρ_{IM}: Interpersonal-manual correlation	-0.319	0.542		
ρ_{CM}: Cognitive-manual correlation	-0.088	0.553		
Offer and destruction rates				
λ: Offer arrival rate	1.065	0.007		
η: Destruction rate	0.034	0.003		
Unemployment cost				
b_0: General unemployment cost	-174.995	96.799		
b_I: Marginal cost interpersonal skills	-23.104	14.075		
b_C: Marginal cost cognitive skills	-30.765	15.530		
b_M: Marginal cost manual skills	-34.864	43.592		

The log-normal general productivity distribution has a mean of 40.36 CHF and a standard deviation of 13.14 CHF. The general productivity α_0 captures all variation in productivity which is not related to the demand and supply of interpersonal, cognitive and manual skills. It includes the effect of age, experience, tenure, industry, and region, as well as the impact of unobserved idiosyncratic factors.

The demand for (and returns to) cognitive skills is highest, followed by manual and interpersonal skills. The mean productivity of cognitive skills is estimated at 2.25 CHF with a standard deviation of 1.95 CHF. Although the mean productivity for manual and interpersonal skills is very similar at 1.33 CHF and 1.29 CHF, respectively, the demand for interpersonal skills is more dispersed (with an estimated standard deviation of 1.73 CHF). Some firms demand high interpersonal skills (and remunerate them accordingly), while other firms do not need and remunerate interpersonal skills. In contrast, the demand for manual skills is more compressed with a standard deviation of 1.10 CHF.

We find evidence of strong complementarity in the demand for interpersonal and cognitive skills, with an estimated correlation coefficient of 0.94. The correlation of the demand of these two skills with manual skills is negative, albeit not significant, indicating that firms require workers specialised either in manual or non-manual skills.

Despite a different context, model and sample, our estimates on the productivity distributions compare well with the production function estimates reported by Lise and Postel-Vinay (2016) for the US. In particular, our estimates suggest the same order (and relative magnitude) in productivity, that is, cognitive skills clearly dominate manual and interpersonal skills. Moreover, we also find complementarity between interpersonal and cognitive skills (our correlation coefficient is somewhat higher), and a negative correlation between interpersonal and manual skills.

In terms of job creation and destruction dynamics, we estimate that unemployed workers get on average 1.07 job offers over a year, while 3.4% of filled jobs get destroyed over the same time.

Finally, our estimates indicate that the cost of being in unemployed increases with all three skills, possibly reflecting the cost of skill depreciation while unemployed. The marginal cost of unemployment is lowest for interpersonal skills and highest for manual skills.[16] However, these costs are not very precisely estimated.[17]

5.2 The supply and demand for skills

The productivity of a match is determined by the skills supplied, i.e. the skill bundle x a worker is endowed with, and by a firm's demand for these skills α. Our parametric specification of the productivity as $p = \alpha' x$ implies worker-job complementarity. This entails that productivity is highest if the worker supplies the skills which are in high demand by the firm.

Figure 3 depicts the marginal probability density function (left panel) and the cumulative distribution function (right panel) for the estimated demand of interpersonal (dotted lines), cognitive (black lines) and manual skills (dashed lines).

[16] If the marginal cost of unemployment by skill is interpreted as the cost of skill depreciation, our results reflect the same pattern as the speed (and cost) of skill accumulation and depreciation found by Lise and Postel-Vinay (2016).

[17] Note that none of the parameters related to manual skills are precisely estimated. Given that the skill supply of workers is very skewed towards few manual skills, it appears that these parameters are not well identified and therefore, not precisely estimated.

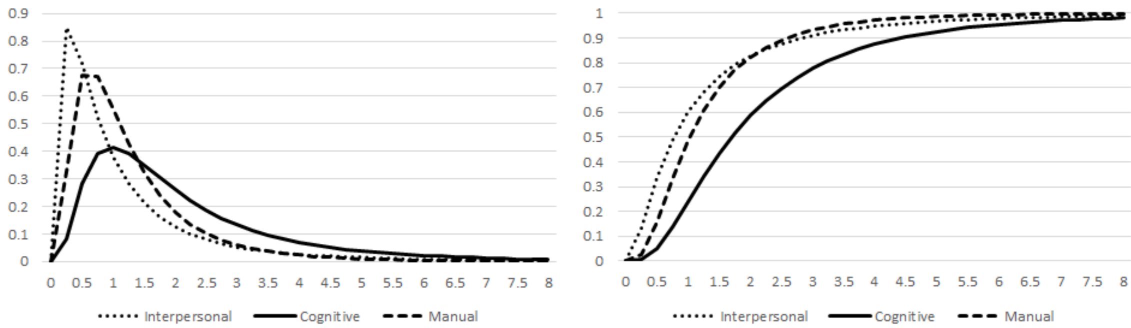

Figure 3: Marginal probability density function and cumulative distribution function for the demand of interpersonal, cognitive and manual skills

Table 5 showed that the mean productivity is equal to 1.29 CHF for interpersonal, 2.25 CHF for cognitive and 1.33 CHF per hour for manual skills, respectively. However, these returns vary substantially with the relative position of the firm in the demand for these skills. Let us suppose that the worker meets a firm with a high demand for a specific skill, i.e. at the top 5% of the distribution. As shown in Figure 3 (right panel), the productivity of an additional unit of skill at the upper end amounts to 4.08 CHF per hour for interpersonal, 5.82 for cognitive and 3.35 for manual skills, respectively. The large dispersion in the demand for interpersonal and cognitive skills might make waiting for a better offer more attractive (ceteris paribus) for workers with high levels of these skills.

This simple analysis ignores that the demand for different skills is correlated. Figure 4 thus plots the joint distribution of the demand for cognitive-interpersonal (left panel), manual-interpersonal (middle panel) and cognitive-manual (right panel) skills.[18]

Figure 4 (left panel) illustrates well the strong positive correlation between the demand for interpersonal and cognitive skills, with a high density along the 00-66 diagonal. The middle and right panel show the (weaker) negative correlation between the demand for manual skills and interpersonal/cognitive skills. In this case, we observe a somewhat higher frequency along the 06-60 line.

Generally, our results suggest that the skill supply is well aligned (though not perfectly) with the demand for skills. The demand for cognitive skills is highest, with an average productivity of 2.25 CHF. At the same time workers have acquired on average more cognitive skills (2.14, see Table 1) than interpersonal and manual skills (1.81 and 1.23, respectively). The alignment also holds true for skill bundles. Firms demand a high

[18]Notice that the demands in this histogram are truncated at a productivity of 6 CHF. All higher productivity realisations are regrouped in the highest category of the histogram.

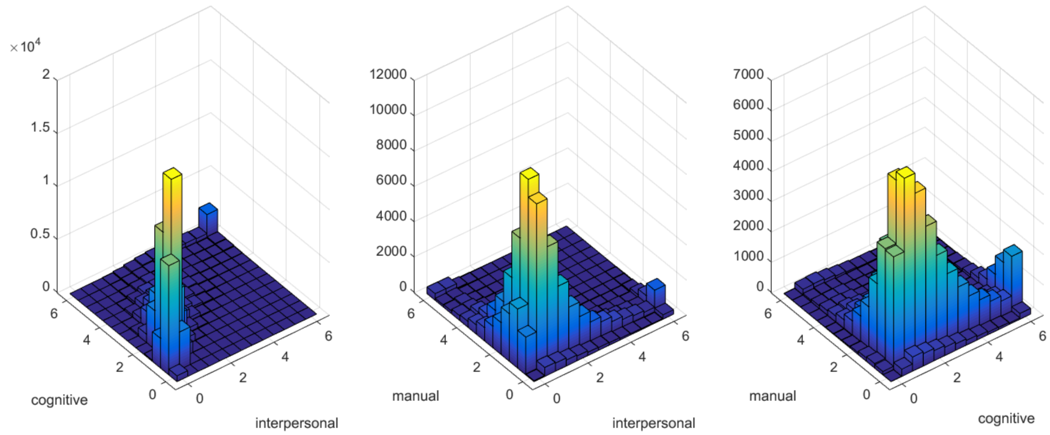

Figure 4: Joint sampling density for the demand of interpersonal, cognitive and manual skills

complementarity of cognitive and interpersonal skills (correlation of 0.94), and workers with high cognitive skills also tend to have high interpersonal skills (correlation of 0.33). Moreover, firms have a slight preference for either manual or non-manual specialists (i.e. with a manual-interpersonal skill demand correlation of -0.32 and manual-cognitive correlation of -0.09). Workers also show a tendency to either specialise in manual or non-manual skills (with a manual-interpersonal correlation of -0.46 and a manual-cognitive correlation of -0.26).

The effect of this demand-complementarity can also be illustrated as follows: Let us suppose a worker has to decide whether to train in an occupation specialising in manual or interpersonal skills. If the worker acquires five skills, he would get on average a post-VET wage of 34.37 CHF per hour if he specialises in manual, and 34.76 CHF per hour if he specialises in interpersonal skills, respectively. What would happen if the worker did not fully specialise, but if he rather acquired three manual or interpersonal skills in combination with two cognitive skills? His average hourly wage would be 34.46 CHF for the manual-cognitive skill bundle, and 35.89 CHF for the interpersonal-cognitive skill bundle. There is a wage difference of 4% between two equally equipped skill bundles, but one which is highly demanded (i.e. interpersonal-cognitive) and one which is not (i.e. manual-cognitive). Note that replacing two (relatively lowly remunerated) manual skills against two (highly remunerated) cognitive skills results in almost no wage increase, because firms do not value manual-cognitive skill complementarities but prefer manual or non-manual specialists.

This demand-complementarity may be particularly pronounced in the context of VET because of its particular institutional setup. As pointed out previously, training curricula are regularly revised and updated in a tripartite process. The close collaboration between educators and firms is likely to ensure that the skills taught during the VET programmes and the skills needed on the job have large overlaps.

5.3 Goodness of fit

Tables C.1 and C.1 in Appendix C display how well our model is able to match the cluster-specific moments observed in the data. In general, the model is reasonably well fitted.

A comparison of observed and simulated moments shows that the model generally performs well at replicating both the moments related to hourly wages (mean, standard deviation and first percentile), as well as the unemployment rates, and the moments related to transitions into and out of unemployment by cluster. The model slightly underpredicts the overall mean hourly wage at 35.84 CHF (36.55 CHF observed), but it closely fits the overall standard deviation of hourly wages at 10.23 CHF (10.82 CHF observed) and the overall first percentile of hourly wages at 18.91 CHF (18.94 CHF observed). In terms of unemployment, our model produces a slightly lower overall unemployment rate (3.25%) than the one observed in the data (3.7%), the main reason being that the model overpredicts the overall job-finding rates (65% simulated compared to 59% observed) while the job destruction rates are on average precisely matched (2.1% simulated, 2.2% observed).

While the fit of the model in the overall mean of the targeted moments is reasonably good, it does not generate the same degree of variation across occupational clusters in the mean hourly wages that we observe in the data. In particular, the model generally produces too low hourly wages for occupation clusters with high cognitive skills. In terms of unemployment, the observed cluster-specific unemployment rates do not follow a systematic linear pattern and they are imprecisely measured in the observed data (i.e. relatively large standard errors). Hence, it cannot come as a surprise that the model does not match them particularly well. The feature of increasing unemployment rates with interpersonal skills (see the reduced form results in Table 3) is only weakly reproduced by our model: The weighted unemployment rate is 3.28% for those with high interpersonal skills (4.29% observed) and 3.17% for those with low interpersonal skills (3.05% observed).

In fact, the model does not only explain the cluster-specific means and standard deviations of hourly wages, but it does also a good job at matching almost all cluster-specific wage distributions as shown in Figure 5. In addition, the good fit of the wage distributions validate our parametric assumption of log-normality of the general productivity as well as of the skill-specific demands.

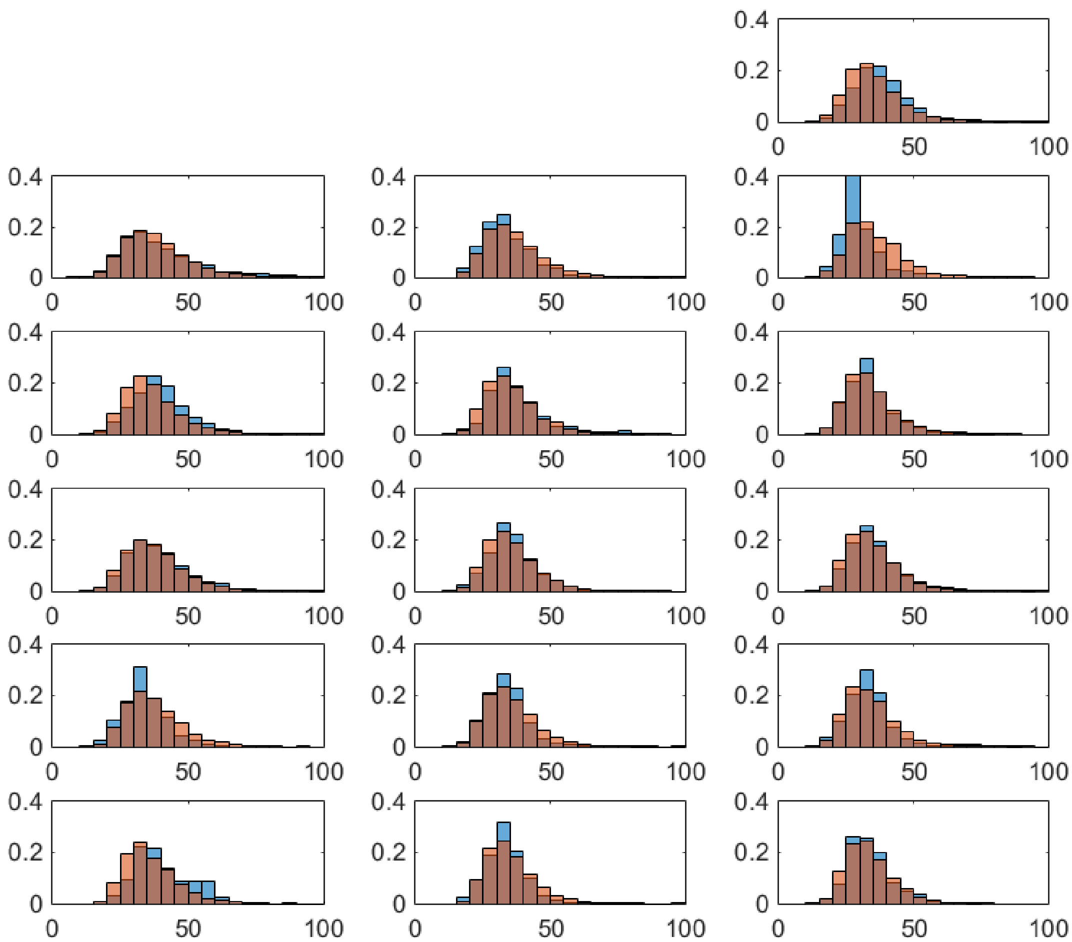

Figure 5: Goodness of fit: Wage distributions of observed (blue) and simulated (orange) wages by occupation cluster

There is, however, one cluster, for which our model performs badly in most respects. This concerns the high-interpersonal-low-manual-low-cognitive cluster in line 6 in Table C.1. This occupation cluster counts relatively few observations and appears to be an outlier. It has by far the lowest mean hourly wage (almost 4 CHF lower than all other clusters), the lowest standard deviation in hourly wages and the highest unemployment rate at 8.2%. Our model fails to replicate these patterns and overpredicts the mean and the standard deviation of hourly wages (see also Figure 5). Moreover, the model clearly underpredicts the unemployment rate.

6 The value of VET

6.1 The value of skills and VET for workers

To quantify the value of the skills acquired in VET and the VET degree in itself, we compare average wages, unemployment rates, unemployment duration, and annual earnings in three different scenarios in Table 6: a baseline scenario, one assuming that only the VET degree is remunerated but not the acquired skills, and one with compulsory education.[19]

The baseline scenario (VET with skills) presents labour market outcomes for workers who have completed a VET degree and who have acquired interpersonal, cognitive and/or manual skills. It corresponds to our estimated specification from Section 5. In the second scenario (VET without skills), we simulate the outcomes of these workers assuming that the skills acquired in VET are worthless. That is, we assume that skills neither impact productivity nor the flow value of unemployment. Nevertheless, the comparison of the baseline and second scenario does not allow us to capture the overall effect of VET which goes beyond the effect of occupational skills. To get an (upper bound) estimate of the order of magnitude of the importance of the VET degree itself, we present in the third scenario the outcomes of workers who have completed compulsory education, but have not obtained a VET degree or further education in an estimated simplified model.[20] Under the assumption of positive selection into VET, we can interpret the outcomes of these workers as a lower bound estimate for the counterfactual of VET workers without a VET degree.

[19] Average hourly wages, the first percentile of hourly wages and unemployment rates are computed from the simulated model. Unemployment duration is calculated as $\frac{1}{h}$, where h is the average estimated rate of accepted offers. Annual earnings are obtained as the product of annual earnings when employed (assuming 2,040 working hours a year) and the employment share.

[20] Table D.1 in Appendix D reports the estimated parameters of this simple search model for workers with only completed compulsory education. In this simplified model all parameters related to skills are dropped.

Table 6: VALUE OF VET: WAGES, UNEMPLOYMENT AND EARNINGS

	VET with skills (estimation)	VET without skills (simulation)	no VET (estimation)
Avg. productivity (in CHF)	49.1	40.5	47.2
Avg. hourly wage (in CHF)	35.9	32.8	31.5
First percentile of hourly wages (in CHF)	18.8	18.9	14.8
Unemployment rate	3.25%	3.26%	6.49%
Avg. unemployment duration (in years)	0.94	0.94	1.18
Avg. annual earnings	70,794	64,806	60,011

Comparing the first two scenarios, we find that the skills acquired in VET translate on average into an hourly wage increase of 3.60 Swiss francs. Hence, the returns to the skills of a 3-year or 4-year VET degree amount to around 9.2%.[21] These returns are of a similar magnitude as the returns to a year of schooling on wages of around 10% reported in the literature (Card, 1999).

Workers without VET earn somewhat lower hourly wages than those with VET but without skills (31.5 versus 32.8 Swiss francs). This results in an (upper bound) estimate of the returns to a VET degree (without skills) of 4%.

Occupational skills not only affect productivity (and hence, hourly wages), but they also have an impact on the probability of unemployment. Table 6 shows that VET workers without skills would not see their unemployment rate rise compared to the baseline of VET and skills. This is due to occupational skills impacting reservation wages (and hence, unemployment rates) in two opposing ways. First, they increase the expected value of matches and as such, translate into higher reservation wages. Second, we estimate that being in unemployment is more costly with more skills - possibly because of skill depreciation - and hence, having more skills lowers reservation wages. In our current setting, these two forces almost cancel each other out and leave unemployment rates unaffected. As a consequence, the difference in annual earnings between VET workers with and without skills also amounts to 9.2%.

The main difference in outcomes, however, occurs in unemployment rates. Workers without VET have a risk of unemployment which is almost twice as high (6.5% versus

[21] Note that apprentices studying for a VET degree spend around one third of their time in school and two thirds working in their training firm.

3.3%). These workers face lower job arrival rates and higher job destruction rates (see Tables D.1 and 5). Altogether, this results in 5.2% lower annual earnings of workers without a VET degree.

Overall, our findings show that occupational skills of VET pay off in terms of higher hourly wages. Moreover, the VET degree itself appears to provide better access to jobs and more job stability. Returns to a VET degree (and the skills it confers) measured in annual earnings thus range on average from 9.2% (lower bound) to 18% (upper bound).

6.2 A simple cost-benefit analysis

Table 7 presents the estimated yearly costs and benefits of VET for firms, workers and the Swiss state in year 2009. Our framework allows us to compute the estimated net benefit for firms and workers. The estimated net benefits of firms are computed from the annual profit on VET workers (upper bound estimate) - as productivity minus wage - or the difference in annual profits between VET workers and non-VET workers (lower bound estimate). The benefits of workers are calculated as the difference in annual earnings between VET workers and VET workers without skills (lower bound estimate) or workers without VET (upper bound estimate) shown in Table 6. Given that our data does not contain any information about the costs of VET, we draw on VET cost estimates from the Swiss Federal Statistical Office for the State and firms (lower bound cost estimate for firms)[22] and a survey among firms on VET training costs in 2009 by Strupler and Wolter (2012) (upper bound cost estimate for firms).

Table 7: Cost-benefit analysis of VET in 2009 (in mio CHF)

	Costs	Benefits
Firms	2,754 to 5,350	-11,165 to 75,829
Workers		10,196 to 18,360
State (incl. cantons)	3,560	
Total	6,314 to 8,910	-969 to 94,189

Our results show that the benefit of all workers with VET amounts to 10 to 18 billion Swiss francs a year. The estimated net benefit for firms ranges from -11 billion to

[22]These numbers are published by the Swiss Federal Statistical Office as part of the statistics on public education expenditures (only in German and French) on https://www.bfs.admin.ch/bfs/de/home/statistiken/bildung-wissenschaft/bildungsindikatoren/indikatoren/ausgaben-berufsbildung.assetdetail.4182700.html (accessed online on June 1, 2018).

more than 75 billion, the result of two different counterfactual scenarios. In the first scenario (upper bound estimate), we assume that the jobs, which are filled with VET workers would not exist otherwise and hence, the annual profit on VET jobs are the net benefit. In the alternative scenario (lower bound estimate), the jobs of the firm could be filled with non-VET workers, though with the productivity and wages of non-VET workers. The net benefit in this second scenario is negative (-11 billion), as the hourly net profit on VET workers is lower ($49.1-35.9 = 13.2$ CHF) than for non-VET workers ($47.2-31.5 = 15.7$ CHF).[23] Whether the overall benefit of VET outweighs its cost or not (and by how much) depends crucially on the alternative production options of firms without the VET system. However, the overall benefit of a VET system can potentially be very large.

7 Conclusion

This paper provides a structural examination of the Swiss labour market for workers who graduated from vocational education and training (VET) in Switzerland. We distinguish workers who have acquired different bundles of interpersonal, manual and cognitive skills in VET programmes. We analyse empirically how their skills affect job offers, unemployment and wages using a simple search and matching framework. Under the assumption that match productivity exhibits worker-job complementarity for each of these skills, we identify and estimate the demand of firms for interpersonal, manual and cognitive skills and their interactions.

We find that the demand for (and hence, returns to) cognitive skills dominates the demand for interpersonal and manual skills. The average productivity of cognitive skills is almost twice as high as the one of interpersonal and manual skills. The finding of larger returns in wages to cognitive skills than non-cognitive skills is in line with the results by Lise and Postel-Vinay (2016) and Lindqvist and Vestman (2011) reported for the US and Sweden, respectively. Moreover, we also find evidence of complementarity between cognitive and interpersonal skills, and evidence of firms specialising either in manual or non-manual jobs. The high demand for complementarity in cognitive and interpersonal skills is also mirrored by the supply of skill bundles by workers, indicating that the supply of VET skills matches well the demand for these skills.

For workers, the average returns to VET skills amount to about 9% in hourly wages

[23]To obtain firms' net benefit, we multiply the hourly net profit with the respective employment shares of 96.8% and 93.5%, respectively, and with annual working hours of 2,040. The average productivities and wages are shown in Table 6.

according to our simulation results. Furthermore, a VET degree also appears to improve labour market opportunities of workers through higher job arrival rates and lower job destruction. Overall, workers reap large benefits from VET, while the benefits for firms cannot be as easily narrowed down and depend on the assumptions in the counterfactual scenario.

Our model and estimation come with a number of limitations. We make some parametric assumptions on the match productivity to identify and estimate the demand for each skill from observed wage distributions. In spite of these limitations, our model achieves a fairly good fit of the wage moments observed in the data, while unemployment rates are slightly less well matched (though they are also less precisely measured in the data).

References

Autor, David H., Frank Levy, and Richard J. Murnane, "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 2003, *118* (4), 1279–1333.

Backes-Gellner, Uschi and Stefan C. Wolter, "Guest editorial: The economics of vocational education and training policies," *International Journal of Manpower*, 2010, *31*, 492–494.

Card, David, "Chapter 30 - The Causal Effect of Education on Earnings," in Orley C. Ashenfelter and David Card, eds., *Handbook of Labor Economics*, Vol. 3, Elsevier, 1999, pp. 1801 – 1863.

CSRE, *Swiss Education Report 2014*, Swiss Coordination Centre for Research in Education, Aarau, 2014.

Flinn, Christopher, "Minimum wage effects on labor market outcomes under search, matching, and endogenous contact rates," *Econometrica*, 2006, *74* (4), 1013–1062.

_ **, Ahu Gemici, and Steven Laufer**, "Search, matching and training," *Review of Economic Dynamics*, 2017, *25*, 260–297.

_ **and Joseph Mullins**, "Labor market search and schooling investment," *International Economic Review*, 2015, *56* (2), 359–398.

Gathmann, Christina and Uta Schönberg, "How General Is Human Capital? A Task-Based Approach," *Journal of Labor Economics*, 01 2010, *28* (1), 1–49.

Geel, Regula and Uschi Backes-Gellner, "Occupational mobility within and between skill clusters: an empirical analysis based on the skill-weights approach," *Empirical Research in Vocational Education and Training*, 2011, *3* (1), 21–38.

Hanushek, Eric A., Guido Schwerdt, Ludger Woessmann, and Lei Zhang, "General Education, Vocational Education, and Labor-Market Outcomes over the Lifecycle," *Journal of Human Resources*, 2017, *52* (1), 48–87.

Hoeckel, Kathrin, Simon Field, and W. Norton Grubb, *OECD Reviews of Vocational Education and Training: A Learning for Jobs Review of Switzerland 2009* 2009.

Hoffman, Nancy, *Schooling in the Workplace: How Six of the World's Best Vocational Education Systems Prepare Young People for Jobs and Life*, Harvard Education Press, 2011.

Ingram, Beth F. and George R. Neumann, "The returns to skill," *Labour Economics*, February 2006, *13* (1), 35–59.

Kaldor, Nicholas, "A model of economic growth," *The economic journal*, 1957, *67* (268), 591–624.

Kambourov, Gueorgui and Iourii Manovskii, "Occupational Specificity Of Human Capital," *International Economic Review*, 02 2009, *50* (1), 63–115.

Karabarbounis, Loukas and Brent Neiman, "The Global Decline of the Labor Share," *The Quarterly Journal of Economics*, 2014, *129* (1), 61–103.

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

_ **and** _ , "US-Europe differences in technology-driven growth: quantifying the role of education," *Journal of Monetary Economics*, January 2004, *51* (1), 161–190.

Lazear, Edward P., "Firm-Specific Human Capital: A Skill-Weights Approach," *Journal of Political Economy*, October 2009, *117* (5), 914–940.

Lindenlaub, Ilse, "Sorting Multidimensional Types: Theory and Application," *Review of Economic Studies*, 2017, *84* (2), 718–789.

Lindqvist, Erik and Roine Vestman, "The Labor Market Returns to Cognitive and Noncognitive Ability: Evidence from the Swedish Enlistment," *American Economic Journal: Applied Economics*, 2011, *3* (1), 101–128.

Lise, Jeremy and Fabien Postel-Vinay, "Multidimensional Skills, Sorting, and Human Capital Accumulation," Technical Report, University College London 2016.

Pissarides, Christopher A., *Equilibrium unemployment theory*, MIT press, 2000.

Poletaev, Maxim and Chris Robinson, "Human capital specificity: evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000," *Journal of Labor Economics*, 2008, *26* (3), 387–420.

Rinawi, Miriam and Uschi Backes-Gellner, "The Effect of Performance Pay on the Retention of Apprenticeship Graduates: A Panel Data Analysis," Economics of Education Working Paper 0104, University of Zurich 2014.

Ryan, Paul, "The school-to-work transition: a cross-national perspective," *Journal of economic literature*, 2001, *39* (1), 34–92.

Schweri, Jürg, Samuel Mühlemann, Yasmina Pescio, Belinda Walther, Stefan C. Wolter, and Lukas Zürcher, *Kosten und Nutzen der Lehrlingsausbildung aus der Sicht Schweizer Betriebe*, Rüegger Verlag, Chur Zürich, 2003.

Siegenthaler, Michael and Tobias Stucki, "Dividing the Pie: Firm-Level Determinants of the Labor Share," *Industrial and Labor Relations Review*, 2015, *68* (5), 1157–1194.

Strupler, Miriam and Stefan C. Wolter, *Die duale Lehre: eine Erfolgsgeschichte - auch für die Betriebe*, Ruegger Verlag, 2012.

Wasmer, Etienne, "General versus specific skills in labor markets with search frictions and firing costs," *The American Economic Review*, 2006, *96* (3), 811–831.

Zihlmann, René, Anna Voigt Lutz, Claudia Butz, and Manfred Fasel, *Berufswahlbuch 2012/13 mit Berufswahl-Kompass*, Cornelsen Schweiz Schulverlage, 2012.

Zimmermann, Klaus F, Costanza Biavaschi, Werner Eichhorst, Corrado Giulietti, Michael J Kendzia, Alexander Muravyev, Janneke Pieters, Núria Rodríguez-Planas, Ricarda Schmidl et al., "Youth unemployment and vocational training," *Foundations and Trends® in Microeconomics*, 2013, *9* (1–2), 1–157.

A Comparison of skill measures for Swiss VET occupations with O*Net-based measures

Table A.1: CORRELATIONS BETWEEN SKILL MEASURES.

	interp. (VET)	manual (VET)	cogn. (VET)	interp. (O*Net)	manual (O*Net)	cogn. (O*Net)
interpersonal (VET)	1.0000					
manual (VET)	-0.9098	1.0000				
	(0.0000)					
cognitive (VET)	0.2826	-0.5007	1.0000			
	(0.0044)	(0.0000)				
interpersonal (O*Net)	0.4860	-0.4957	0.1801	1.0000		
	(0.0000)	(0.0000)	(0.0729)			
manual (O*Net)	-0.2467	0.2564	-0.1434	-0.2456	1.0000	
	(0.0134)	(0.0100)	(0.1546)	(0.0138)		
cognitive (O*Net)	0.0889	-0.2708	0.3556	0.2096	-0.0099	1.0000
	(0.3793)	(0.0064)	(0.0003)	(0.0363)	(0.9222)	

Notes: Correlation coefficients between skill measures based on BIZ list of skills required in training for VET occupations and skills resulting from principal components analysis of skills, abilities, knowledge, work activity and work context in O*Net data. P-values in parentheses.

We validate our skill measures by comparing them to corresponding measures constructed from the O*Net database. For 100 out of 220 VET occupations we observe the corresponding occupation in the O*Net data set, for which we retrieve the O*Net measures for more than 200 skills, abilities, knowledge, work activities and work context. Similar to Lise and Postel-Vinay (2016), we perform Principal Component Analysis on these 200 variables and retain the three principal components. We combine these three principal components and impose three exclusion restrictions to interpret the measures as cognitive, manual and interpersonal skills: 1) the mathematics score only reflects cognitive skills, 2) the manual dexterity score only reflects manual skills, 3) the social perceptiveness score only reflects interpersonal skills. We then correlate these O*net skill measures with our corresponding skill measure derived from the BIZ list compiled by Zihlmann et al. (2012). The correlation coefficients thus obtained are: 0.25 (manual), 0.34 (cognitive), and 0.48 (interpersonal), respectively. All correlations are statistically different from 0 at the 99% significance level.

This procedure confirms that the skills conferred in VET training in Switzerland correlate significantly with the skills used in corresponding occupations in the United States. There may, however, still be large differences between the skills of a Swiss carpenter and the skills of a US carpenter. We retain our skill measures as they cover a larger set of VET occupations in our sample and reflect more precisely the specific skills acquired in VET in Switzerland.

B Labour market transitions by occupational cluster

Table B.1: DESCRIPTIVE STATISTICS: TRANSITION RATES.

		Obs	EE stay	EE change	UE	EU	UU
H-interpersonal							
H-manual	H-cognitive	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
	M-cognitive	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
	L-cognitive	774	0.882	0.063	0.016	0.023	0.016
L-manual	H-cognitive	1,235	0.867	0.065	0.023	0.024	0.022
	M-cognitive	670	0.828	0.121	0.021	0.027	0.004
	L-cognitive	164	0.793	0.091	0.030	0.055	0.030
M-interpersonal							
H-manual	H-cognitive	690	0.935	0.049	0.004	0.007	0.004
	M-cognitive	288	0.924	0.038	0.014	0.017	0.007
	L-cognitive	279	0.889	0.075	0.014	0.018	0.004
L-manual	H-cognitive	589	0.894	0.053	0.015	0.021	0.009
	M-cognitive	634	0.877	0.068	0.019	0.028	0.008
	L-cognitive	1,098	0.859	0.080	0.025	0.020	0.018
L-interpersonal							
H-manual	H-cognitive	173	0.850	0.104	0.006	0.035	0.006
	M-cognitive	914	0.877	0.085	0.014	0.016	0.008
	L-cognitive	374	0.912	0.043	0.016	0.013	0.016
L-manual	H-cognitive	94	0.926	0.043	0.000	0.011	0.022
	M-cognitive	310	0.913	0.065	0.010	0.006	0.006
	L-cognitive	223	0.906	0.058	0.013	0.018	0.004
all clusters		8,509	0.879	0.071	0.018	0.021	0.012
Compulsory schooling		2,225	0.887	0.051	0.027	0.022	0.015
General upper secondary education		685	0.806	0.093	0.036	0.036	0.028

C Goodness of fit

Table C.1: Goodness of fit I: Wages

		Mean hourly wage			Std. dev. hourly wage			Lowest 1% hourly wage		
		Observed	Std.Error	Simulated	Observed	Std.Error	Simulated	Observed	Std.Error	Simulated
H-interpersonal										
H-manual	H-cognitive	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
	M-cognitive	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
	L-cognitive	37.67	0.323	35.19	10.64	0.411	10.14	19.20	0.427	18.52
L-manual	H-cognitive	40.14	0.369	38.59	15.43	0.380	12.98	18.42	0.304	18.47
	M-cognitive	33.89	0.328	36.38	9.91	0.372	10.77	17.97	0.274	18.76
	L-cognitive	29.62	0.452	35.73	6.52	0.424	10.55	18.13	0.630	18.15
M-interpersonal										
H-manual	H-cognitive	40.09	0.339	36.50	10.74	0.346	10.15	20.99	0.596	19.58
	M-cognitive	38.06	0.630	35.42	12.87	0.898	9.69	19.27	0.653	19.02
	L-cognitive	33.73	0.494	33.53	9.77	0.702	8.98	18.05	0.429	18.01
L-manual	H-cognitive	39.13	0.417	37.75	11.88	0.450	11.18	19.27	0.726	19.32
	M-cognitive	35.89	0.303	35.49	9.07	0.299	9.61	18.23	0.458	19.31
	L-cognitive	36.09	0.284	34.14	11.22	0.403	9.08	19.12	0.314	18.66
L-interpersonal										
H-manual	H-cognitive	33.74	0.485	37.37	7.86	0.400	10.52	18.91	0.706	20.34
	M-cognitive	33.41	0.216	35.08	7.78	0.330	9.20	19.06	0.403	19.20
	L-cognitive	33.84	0.452	33.75	10.33	0.854	8.98	18.44	0.487	18.74
L-manual	H-cognitive	40.51	0.983	36.25	11.21	1.271	10.00	21.86	2.263	19.06
	M-cognitive	33.82	0.444	34.93	8.85	0.879	8.94	18.03	0.611	19.78
	L-cognitive	34.18	0.483	33.56	8.44	0.513	8.65	18.83	0.922	18.42

Table C.2: GOODNESS OF FIT II: UNEMPLOYMENT AND LABOUR MARKET TRANSITIONS

		Unemployment rate			EU rate			UE rate		
		Observed	Std.Error	Simulated	Observed	Std.Error	Simulated	Observed	Std.Error	Simulated
H-interpersonal										
H-manual	H-cognitive	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
	M-cognitive	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
	L-cognitive	0.039	0.005	0.037	0.024	0.006	0.023	0.500	0.104	0.643
L-manual	H-cognitive	0.047	0.005	0.032	0.025	0.005	0.022	0.509	0.068	0.655
	M-cognitive	0.030	0.005	0.029	0.027	0.006	0.018	0.813	0.101	0.650
	L-cognitive	0.082	0.017	0.032	0.058	0.019	0.021	0.500	0.167	0.638
M-interpersonal										
H-manual	H-cognitive	0.018	0.004	0.034	0.009	0.004	0.021	0.500	0.224	0.651
	M-cognitive	0.024	0.007	0.028	0.018	0.008	0.021	0.667	0.211	0.565
	L-cognitive	0.027	0.008	0.037	0.018	0.008	0.019	0.800	0.200	0.669
L-manual	H-cognitive	0.040	0.006	0.034	0.028	0.007	0.021	0.778	0.101	0.647
	M-cognitive	0.040	0.006	0.033	0.029	0.007	0.020	0.722	0.109	0.723
	L-cognitive	0.048	0.005	0.031	0.023	0.005	0.022	0.542	0.073	0.663
L-interpersonal										
H-manual	H-cognitive	0.033	0.010	0.030	0.035	0.014	0.024	0.500	0.500	0.684
	M-cognitive	0.033	0.005	0.034	0.017	0.004	0.022	0.650	0.109	0.627
	L-cognitive	0.035	0.007	0.030	0.014	0.006	0.018	0.500	0.151	0.606
L-manual	H-cognitive	0.020	0.012	0.032	0.011	0.011	0.022	0.000	0.100	0.618
	M-cognitive	0.022	0.007	0.029	0.007	0.005	0.020	0.500	0.224	0.567
	L-cognitive	0.025	0.008	0.030	0.023	0.010	0.015	0.750	0.250	0.643

D Estimation results: Compulsory education

Table D.1: ESTIMATED PARAMETERS (COMPULSORY EDUCATION)

General productivity			
	Estimate	Std. Err.	
μ_0: Location	3.81	n.a.	Mean: 47.25
σ_0: Scale	0.31	n.a.	Variance: 219.44
Offer and destruction rates			
λ: Offer arrival rate	0.844	n.a.	
η: Destruction rate	0.058	n.a.	
Flow value of unemployment			
b_0: Unemployment flow	-254.35	n.a.	