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'Wages and employment: The role of occupational skills'

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Wages and employment: The role of occupational skills*

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Abstract

We study how skills acquired in vocational education and training (VET) affect wages and employment dynamics in Switzerland. We present and estimate a search and matching model for workers with a VET degree who differ in their interpersonal, cognitive and manual skills. Assuming a match productivity which exhibits worker-job complementarity, we estimate how workers' skills map into job offers, wages and unemployment. Firms value cognitive skills on average almost twice as much as interpersonal and manual skills. Moreover, they prize complementarity in cognitive and interpersonal skills. We estimate average returns to VET skills in hourly wages of 9%. Furthermore, VET improves labour market opportunities through higher job arrival rate and lower job destruction. Workers thus have large benefits from getting a VET degree.

Keywords: Occupational training, labour market search, multidimensional skills.
JEL classification numbers: E23, J23, J24, J64.

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1 Introduction

When evaluating the effectiveness of education programmes in promoting labour market opportunities, a crucial question is whether the programmes should be vocationally or generally oriented. Vocational programmes are often associated with a more smooth school-to-work transition and with reduced levels of youth unemployment (Ryan, 2001; Scarpetta et al., 2010). Some scholars, however, caution that vocational education proves disadvantageous later in life (Hanushek et al., 2017) or for technology-adoption in the economy (Krueger and Kumar, 2004a,b; Rendall and Weiss, 2016). What this debate largely ignores is that vocational education allows workers to train in many different occupations and hereby acquire different skill bundles. These different skill bundles are associated with different labour market outcomes (Ingram and Neumann, 2006; Lindqvist and Vestman, 2011).

In this paper, we investigate how the skills acquired in vocational education and training (VET) affect wages and employment dynamics. Furthermore, we examine which skills are in high demand by firms. Finally, we attempt to quantify the value of the skills acquired in VET for workers and firms. To do so, we present 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 output. We assume a simple linear production function 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.

We take our model to the data combing labour force survey data with information on skills acquired during VET for Switzerland. VET is a very common education programme in a number of European countries. In Switzerland, around two thirds of a cohort enrol in VET and the 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 individual vocational occupations on the 5-digit level, covering a total of 220 occupations. We group the single skills in three broad categories, differentiating 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. To

[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/).

obtain VET workers' skill bundles, we match the BIZ skills to the SESAM survey using the 5-digit occupational code of the learned occupation.

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

To isolate and quantify the returns to skills, we compare the returns to VET with skills to VET without skills in our simulation. We find the returns to skills to amount to 9% in hourly wages. However, VET not only offers returns to skills in terms of wages, it also improves labour market opportunities through higher job arrival rates and lower job destruction. Taking into account selection into VET, we find that workers without VET and only compulsory education would have returns to a VET degree of 11% in hourly wages. Most importantly, however, they would see their unemployment drop (as a result of longer employment and shorter unemployment spells) and see their overall welfare increase by one third. Finally, a simple cost-benefit analysis reveals large benefits of VET for workers, while benefits for firms could range from negative to positive, depending on the underlying assumptions of the counterfactual scenario.

This paper ties into two strands of the literature. First, it contributes to the literature on vocational education and labour market outcomes. Vocational education is associated with facilitating school-to-work transitions and low youth unemployment (Plug and Groot, 1998; Ryan, 2001; Zimmermann et al., 2013; Eichhorst et al., 2015). However, evidence on longer-term labour market outcomes of vocational education is more scarce and more mixed (Dearden et al., 2002; Balestra and Backes-Gellner, 2017; Hanushek et al., 2017). Our paper also relates to the growing literature on the specificity of human capital 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; Eggenberger et al., 2018). A general finding is that individuals move to occupations with similar skill requirements and that skills are closely related to wages. While informative, a major shortcoming of this literature is that it considers job transitions and wages separately.

Our paper differs from these papers in two important aspects. First, our empirical analysis of labour market outcomes of VET workers makes use of a simple search and matching model, in which labour market outcomes (i.e. employment and wages) are an equilibrium outcome of the demand and supply of VET labour. We rely on the framework developed by Lise and Postel-Vinay (2016), but modify it in several aspects and apply it to a different context, the Swiss labour market for VET workers.[2] Focusing not only on VET labour supply, but also modelling the demand for VET labour allows us to study simultaneously the effect of skills on wages and employment. Moreover, it enables us to estimate both workers' and firms' benefit from VET. This is important for evaluating the overall value of a vocational education system. Second, we contribute to the study of long-term labour market outcomes of VET workers. We distinguish in our analysis different VET occupations according to their level of interpersonal, cognitive and manual skills. This refined analysis provides new 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 (to a lesser extent) employment perspectives.

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. Section 3 presents a simple model of search and matching in the labour market with a multi-dimensional 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

2.1 Institutional background

In Switzerland, compulsory school comprises nine years; six years of primary school and three years of lower secondary school. Different school-type models exist at the lower secondary level across and within cantons, though most models offer two or three tracks

[2] 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.

which differ in how intellectually demanding they are (i.e. upper-level, intermediate-level or basic courses). Upon finishing lower secondary school, pupils can follow different pathways.

For a general education, students attend the *Gymnasium*, for which they need to take an entry exam.[3] At the end of the *Gymnasium*, they have completed general upper secondary education (corresponding to 12 or 13 years of education) and are awarded with the university entrance diploma.

For a vocational education and training (VET), students have to apply for an apprenticeship position with a host firm. The apprenticeship is a dual programme that combines formal education at a vocational school with on-the-job training at the host firm.[4] Training starts after completion of compulsory education and, depending on the occupation, lasts for three to four years. Skills acquired in vocational education are not firm-specific, but transferable across firms and occupations. The content taught in vocational schools and firms is formally regulated. Training quality is ensured by interim and final examinations based on common quality standards. The training content is regularly revised in a tripartite process, in which employer organisations, employee representatives, and the government participate (Eggenberger et al., 2018).

Upon completion of the VET programme, successful students receive a nationally recognised diploma. They are not bound to their host 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.[5]

About 65 percent of a Swiss youth cohort enroll in VET. 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.

[3] In many cantons, only pupils who attended an upper-level school track have access to the Gymnasium. Those with an intermediate-level track may repeat a completed school year in an upper-level track to get into the Gymnasium.

[4] There exist also vocational schools (i.e. in business) which offer full-time vocational education in combination with an internship of several months. This type of vocational education is relatively rare in Switzerland.

[5] Admission to 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%) later on.

2.2 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 that 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 and yearly 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 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 their highest education level.[6] We exclude individuals who are out of the labour force, but include part-time workers (who make up 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 Descriptive statistics and reduced-form evidence

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. BIZ provides a detailed list of

[6]By focusing on workers who have acquired different skill bundles within the same education level, we limit the bias from selection into different education levels (Backes-Gellner and Wolter, 2010; Geel and Backes-Gellner, 2011). Appendix A provides some descriptive evidence from the Swiss TREE data on selection into vocational and general education tracks by cognitive abilities and personality traits of students. It shows that students in vocational education are heterogeneous (as in other education pathways). Moreover, students in the vocational track who subsequently enroll in tertiary education are similar in their characteristics to those with in the general education track, while those with only compulsory education resemble students in the vocational track who do not enroll in further studies at a later stage.

skills which are acquired and used in each VET occupation. Apprentices studying for a VET occupation receive training in these skills and have to pass a standardised exam at the end of their training period. The BIZ data covers a total of 220 VET occupations that existed during the period we examine. The list comprises 26 different skills, of which we use 24.[7] 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 dimensions of skill heterogeneity across workers, resulting in $2^{24} = 16,777,216$ different potential skill bundles. In order to reduce the dimensionality of the problem, we add up the number of acquired skills within each of the three skill dimensions: interpersonal, cognitive and manual.[8] Depending on the occupation in which VET students train, their acquired skill bundle differs substantially. For example, care professionals acquire only interpersonal skills (5 skills), IT-technicians acquire mostly cognitive skills (5 out of 7 skills), and car mechanics acquire mostly manual skills (3 out of 5 skills). There are many more VET occupations, some providing similar and others providing more balanced skills bundles than these three examples.

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

Table 1: DESCRIPTIVE STATISTICS FOR WORKERS' OCCUPATIONAL SKILLS.

	obs	mean	S.D.	distribution of number of skills					
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

The workers in our sample have acquired on average 1.81 interpersonal skills, 2.14 cognitive skills and 1.23 manual skills. Each skill dimension has a different distribution.

[7]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.

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

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 smoother. Most workers have acquired one (29%), two (32%) or three (21%) 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 (right panel) 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 visualises the different skill bundles (or combinations) 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.

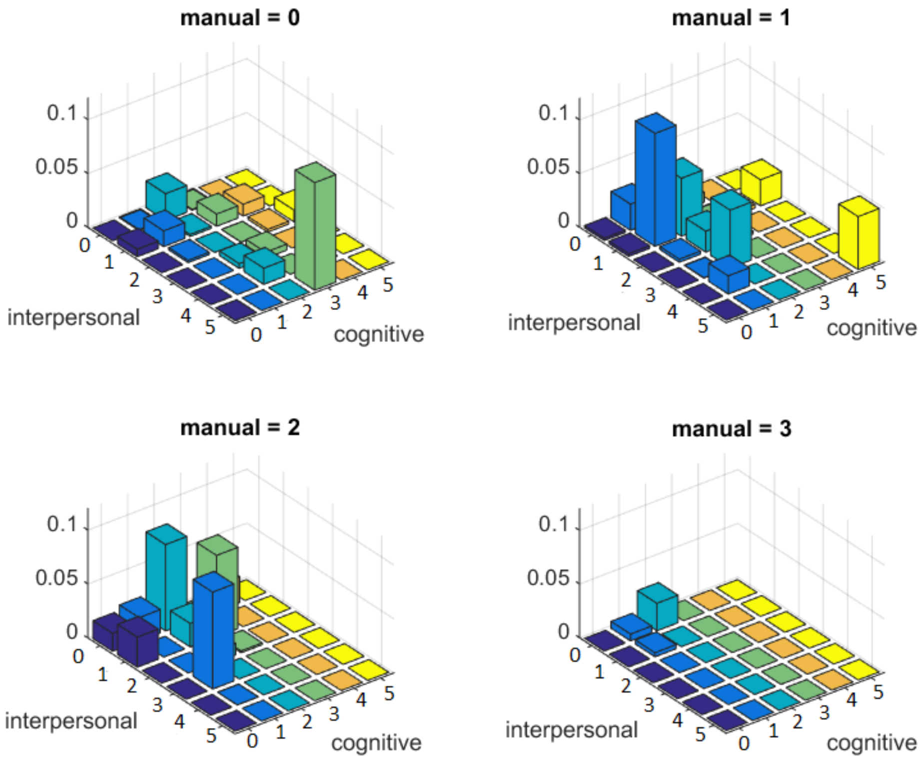

Figure 1: Skill bundles supplied by workers

Skill bundles differ greatly by frequency. Some skill bundles make up 5% or more of the sample, for other skill 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. For the subsequent descriptive analysis and estimation of the model in Section 4.2, we regroup workers into occupational clusters based on the skills they acquired during VET. To do this, we first divide each of the three skill dimensions into 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 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 completed compulsory education (dashed line) and those with general upper secondary education (black line) as their highest education level.

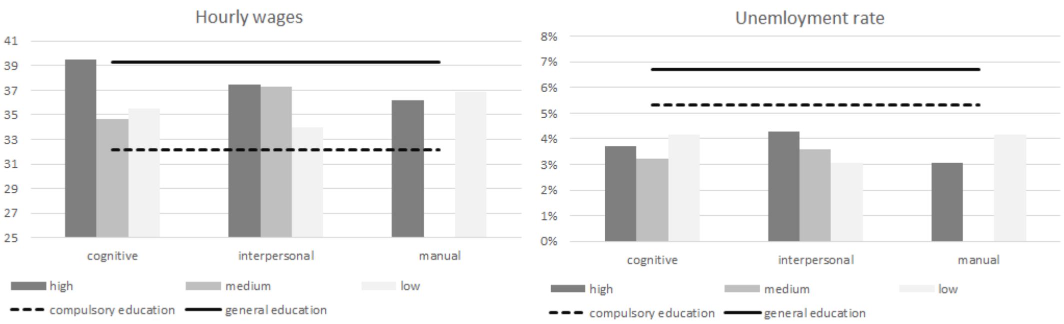

Figure 2: Hourly wages and unemployment rates by skill dimensions

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. Occupations with high interpersonal skills are characterised by higher hourly wages (by 3 Swiss francs), but also higher unemployment rates (by more than 1pp) than those with low interpersonal skills. Finally, more manual skills are not associated with higher hourly wages (if anything, they are slightly lower). However, the unemployment rate is around 1pp lower for workers with high manual skills than for workers with low manual skills.

Figure 2 also offers some insight into how VET workers fare compared to workers who have only completed compulsory education (9 years) and to workers who have completed general upper secondary education (12 to 13 years). Average hourly wages of VET workers generally lie between these two comparison groups. Only VET workers with high cognitive skills earn hourly wages comparable to those of workers with general upper secondary education. VET workers seem not to 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 rates of both workers with compulsory education (5.3%) and 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 (H), medium (M) and low (L) 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 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.

We also observe important differences in hourly wages within each cluster. Part of the within-cluster variation reflects differences in the exact number of skills, part of it stems from differences in age, experience, region, industry and other factors within clusters (not shown). Having more interpersonal or cognitive skills is also associated with a (slightly)

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

Notes: H-interpersonal stands for high (3 and more), M-interpersonal for medium (1 or 2), and L-interpersonal for low (none) interpersonal skills. H-cognitive stands for high (3 and more), M-cognitive for medium (2) and L-cognitive for low (none or one) cognitive skills. H-manual stands for high (2 or 3) and L-manual for low (none or one) manual 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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.[10] Table 3 indicates that having more interpersonal skills is associated with

[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.

[10] Note that all observed differences in unemployment rates of VET workers across occupational clusters must be the result of differences in labour market transitions after graduation, as all VET workers were employed

a slightly higher risk of unemployment, while cognitive and manual skills do not have a significant effect. Appendix C 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 present 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 employment dynamics, we present a simple general equilibrium search and matching model in the spirit of Pissarides-Mortensen-Diamond (see Pissarides, 2000). Workers are heterogeneous. They are characterised 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 demand for skills 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 these skills. Their demand for a specific skill bundle 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

during their training.

worker's problem are given by:

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

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 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.[11] A filled job gets destroyed at rate η. We assume that there is no endogenous vacancy creation.[12] The value of a filled job between a worker with skill bundle x and a firm with a skill weighting vector α is given by:

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

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

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

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:

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

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 $w^*(x)$:

$$w(\alpha^*(x), x) = \beta\alpha^*(x)' x + (1-\beta) rV_U(x) = rV_U(x) \quad (6)$$
$$w^*(x) = \alpha^*(x)' x = rV_U(x). \quad (7)$$

[11] 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.

[12] 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.

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:

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

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:

$$[1 - u(x)]\,\eta = u(x)h(x) \tag{9}$$

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

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 described model to the data. First, we presume the labour market to be in the steady state. Second, 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,

$$p = \alpha' x = \alpha_0 + \alpha_I x_I + \alpha_C x_C + \alpha_M x_M, \tag{11}$$

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 negative, having more skills j makes being in unemployment more costly (for example, because of skill depreciation), 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. To reduce the number of moments and increase the number of observations for each moment, we regroup workers with different skill bundles x into the 16 occupational clusters outlined in Section 2.3.1.

Identification of many parameters of the model is achieved by exploiting differences in mean hourly wages, the standard deviation of hourly wages, the first percentile of hourly wages, unemployment rates, and UE- and EU-labour market transition rates between occupational groups. Let us suppose we knew reservation wages $w^*(x)$ and take

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

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 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.[13] 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 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

[13]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).

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 errors of the standard deviations and the first percentile of hourly wages were 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 cluster-specific EU- and UE-transition rates. To do so, we assume the labour market to be in steady state and produce a simulated data set with 20 replicas 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 worker in the simulated data set, we first determine his 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.[14]

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 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

[14] 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.

with a resulting wage equal or above the reservation wage, there is a share $\kappa(x)$ who is unemployed in the first spell.[15] 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. He searches until he receives an acceptable wage offer.

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 (in columns 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.[16]

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

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

[16] 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		

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 a 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 a correlation coefficient of 0.94. The correlation of the demand for 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 unemployment 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.[17] However, these costs are not very precisely estimated.[18]

[17] 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).

[18] 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.

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).

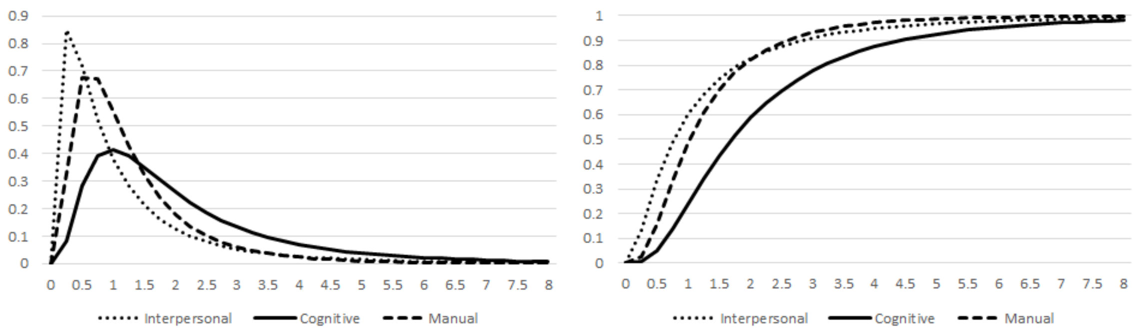

Figure 3: Marginal probability density function and cumulative distribution function for the demand of interpersonal, cognitive and manual skills

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 certain 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.[19]

[19]Notice that the demands in thes histogrammes are truncated at a productivity of 6 CHF. All higher productivity realisations are regrouped in the highest category of the histogrammes.

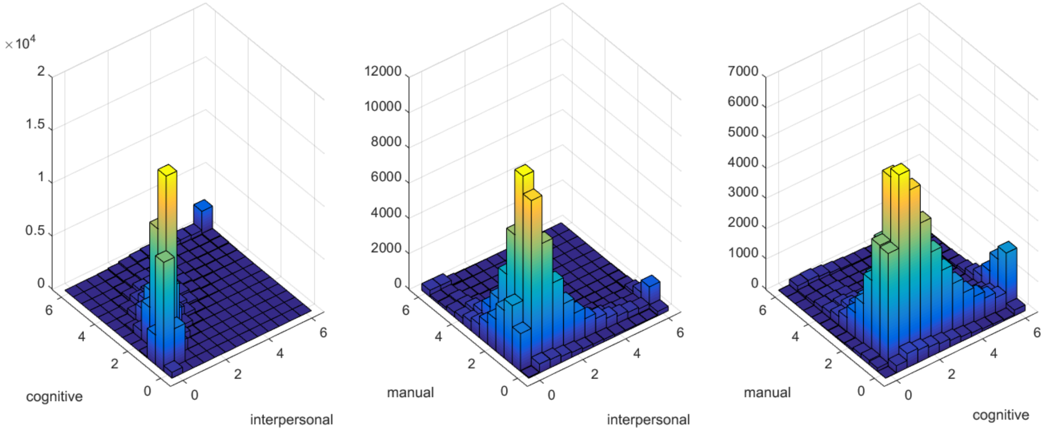

Figure 4: Joint sampling density for the demand of interpersonal, cognitive and manual skills

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. As shown in Table 1, workers have acquired on average more cognitive skills (2.14) than interpersonal and manual skills (1.81 and 1.23, respectively). The alignment also holds true for skill bundles. Firms demand a high 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). At the same time, 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 complementarity in the demand for skills 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 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 different skill bundles with the same number of skills, but one is highly demanded (i.e. interpersonal-cognitive) while the other 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 combinations but prefer manual or non-manual specialists.

5.3 Goodness of fit

Tables D.1 and D.2 in Appendix D display how well our model is able to match the cluster-specific moments observed in the data.

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 devi-

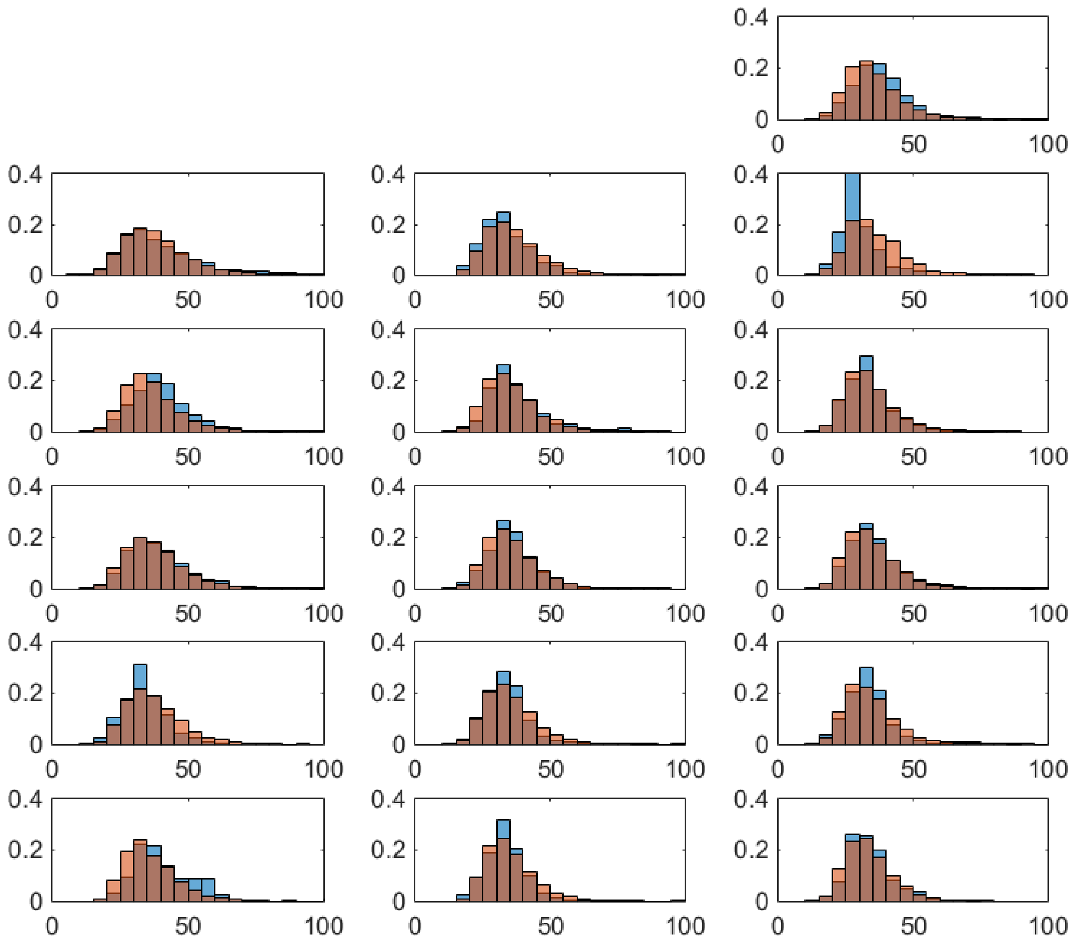

Figure 5: Goodness of fit: Wage distributions of observed (blue) and simulated (orange) wages by occupation cluster

ations 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 validates our parametric assumption of log-normality of the general productivity as well as of the skill-specific demands.

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 D.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 returns to VET skills

To quantify the value of the skills acquired in VET, we compare average wages, unemployment rates, unemployment duration, and annual earnings in two different scenarios in Table 6.[20]

The baseline scenario (VET with skills) presents these outcomes for workers who have obtained 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 the same workers with a VET degree, but assuming that the skills acquired in VET are worthless. That is, we assume that skills neither impact productivity nor the cost of unemployment. Moreover, we assume that VET workers without skills would still face the same job offer and destruction rates.

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

	VET with skills (estimation)	VET without skills (simulation)
Avg. productivity (in CHF)	49.1	40.5
Avg. hourly wage (in CHF)	35.8	32.8
1st percentile hourly wage (in CHF)	18.8	18.9
Unemployment rate	3.3%	3.3%
Avg. annual earnings (in CHF)	70,794	64,806

Comparing these two scenarios, we find that the skills acquired in VET translate on average into an hourly wage increase of 3 Swiss Francs. This wage increase is solely derived from the skills acquired during VET and not from obtaining the VET degree. Hence, the returns to the skills of a 3-year or 4-year VET degree amount to around 9.1%.[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). Notice that we calculate returns to VET only

[20] 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.

[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.

for those who obtain a VET degree but do not continue their training further. Overall returns to VET might be larger given that some workers with a VET degree (who are not in our sample) go on to study for a tertiary degree and earn even higher wages.

However, occupational skills not only affect productivity (and hence, hourly wages), but they also have an impact on the probability of unemployment. We find that VET workers without skills would not see their unemployment rate rise compared to VET workers with skills. This result is due to occupational skills impacting reservation wages (and hence, unemployment rates) through two opposed channels. First, skills 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 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%.

6.2 The value of VET for those with low abilities

Returns to VET skills differ across workers in different occupational skill groups. Moreoever, workers who only completed compulsory education might benefit substantially from obtaining a VET degree and the skills it confers. To evaluate the value of a VET degree for these workers, we estimate a simple search model for workers with compulsory education (but nothing more). Table E.1 in Appendix E reports the estimated parameters of this simple search model for workers with only compulsory education. In this simplified model all parameters related to skills are dropped.

In Table 7 we compare labour market outcomes such as hourly wages, annual earnings, unemployment rates and welfare of these workers with the respective outcomes of workers with VET. In order to account for selection into different occupational skill groups in VET, we limit our comparison to two occupational skill groups in which workers have on average similarly low cognitive abilities and comparable personality traits.[22] These are the occupational cluster with intermediate interpersonal, intermediate cognitive and low manual skills (i.e. cluster 11) and the cluster with high manual, intermediate cognitive and low interpersonal skills (i.e. cluster 14). Outcomes of workers with compulsory education are shown in column 2, while the corresponding outcomes of workers in clusters 11 and 14 are given in columns 3 to 6, respectively. Columns 3 and 5 present the estimated

[22] See Table A.1 in Appendix A for details on cognitive abilities (PISA math and reading scores) and self-assessed personality traits (persistence, locus of control, ambition) of workers in different educational tracks and occupational skill clusters.

results for VET workers with a VET degree and VET skills, while columns 4 and 6 relate to the simulations results for VET workers without skills. The difference between these two scenarios allows us to disentangle the effect of the VET degree versus VET skills.

Table 7: VALUE OF VET FOR LOW-ABILITY WORKERS: WAGES, UNEMPLOYMENT, EARNINGS AND WELFARE

	no VET	VET cluster 11		VET cluster 14	
		with skills	without	with skills	without
	(estimation)	(estimation)	(simulation)	(estimation)	(simulation)
Avg. productivity (in CHF)	47.0	47.6	40.4	47.7	40.4
Avg. hourly wage (in CHF)	31.5	35.5	32.9	35.1	32.8
1st percentile wage (in CHF)	14.8	19.3	18.8	19.2	18.8
Unemployment rate	6.5%	3.3%	3.3%	3.4%	3.4%
Avg. annual earnings (in CHF)	60,011	70,048	64,831	69,139	64,726
Job destruction rate (per year)	0.058	0.034		0.034	
Job offer rate (per year)	0.84	1.06		1.06	
Value of unemployment	0	10.91		9.39	
Value of employment	14.51	21.79		20.75	
Avg. welfare	13.57	21.44		20.33	

We find that returns to VET (degree and skills) in hourly wages would amount to 11.5% (in cluster 14) and 12.8% (in cluster 11) for those with compulsory education. 4.4pp of this effect can be attributed to the return to the VET degree without skills (comparing columns 4 and 6 with column 2), while the remaining returns can be attributed to VET skills. In addition to lower hourly wages, workers with only compulsory education also have a risk of unemployment which is almost twice as high as their similarly able peers with a VET degree in clusters 11 and 14 (6.5% versus 3.4%). Altogether, this results in 13% to 14% lower annual earnings for workers without a VET degree and skills.

The lower part of Table 7 offers valuable insights into how these large differences emerge. The unemployment rate differential is driven by the fact that workers without VET face harsher labour market conditions, both in terms of higher job destruction (0.058 versus 0.034 for those with VET) and lower job offer arrival rates (0.84 offers per year versus 1.06 offers per year for those with VET). Moreover, when considering workers' welfare, we find that the average welfare of those without VET is around one third lower than the one of their similarly able peers with VET. Not only are workers with compulsory education more likely to find themselves in unemployment, but their welfare both in unemployment and when employed is much lower.

6.3 A simple cost-benefit analysis

Table 8 presents the estimated yearly costs and benefits of VET for workers, firms, and the Swiss state in 2009. Our framework allows us to compute the net benefits for workers and firms. The benefits of workers are calculated as the difference in annual earnings between VET workers with skills and VET workers without skills (lower bound estimate) or workers without VET (upper bound estimate) shown in Tables 6 and 7. The 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). Given that our data does not contain any information about the costs of VET, we draw on VET cost estimates from the Federal Office of Statistics of Switzerland for the State and firms (lower bound cost estimate for firms)[23] and a survey among firms on VET training costs in 2009 by Strupler and Wolter (2012) (upper bound cost estimate for firms).[24]

Table 8: Cost-benefit analysis of VET in 2009 (in mio CHF)

	Costs	Benefits
Workers		10,196 to 18,360
Firms	2,754 to 5,350	-11,165 to 75,829
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 benefits for firms ranges from -11 billion to 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), all 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

[23] These numbers are published by the Federal Office of Statistics 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).

[24] Notice that these costs overestimate the net costs of VET for firms, as they do not factor in the productivity of VET workers during their training (but includes their wages as costs). For two out of three firms, these productivity gains outweigh the costs of VET for firms over the duration of the apprenticeship as shown in Wolter et al. (2006).

workers is lower ($49.1 - 35.9 = 13.2$ CHF) than for non-VET workers ($47.2 - 31.5 = 15.7$ CHF).[25] 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.[26] However, workers stand to benefit massively from VET and 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 and studies how their wages and employment are determined simultaneously. We distinguish workers who have acquired different bundles of interpersonal, cognitive and manual skills in VET programmes. We analyse empirically how their skills affect job offers, wages and unemployment 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, cognitive and manual 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 (though to a weaker extent) by the supply of skill bundles by workers, indicating that the supply of VET skills matches the demand for these skills.

For workers with a VET degree, the average returns to VET skills amount to 9% in hourly wages according to our simulation results. Furthermore, obtaining a VET de-

[25]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.

[26]This finding is similar to Wolter et al. (2006) who find a large heterogeneity in benefits (and costs) for firms to provide vocational training for apprentices. While Wolter et al. (2006) provide a cost-benefit analysis for the duration of the apprenticeship, our analysis attempts to measure the benefits of the VET system for the whole economy beyond the training period.

gree improves 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 analysis also reveals that workers who only get compulsory education could expect returns to a VET degree of around 11% in hourly wages and their welfare would increase by one third through better labour market opportunities. In this exercise we take into account that workers with only compulsory education have lower cognitive abilities, but we show that they are nonetheless comparable to workers with a VET degree in certain occupational skill groups. This warrants further attention from policy makers.

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).

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A Selection into vocational and general education

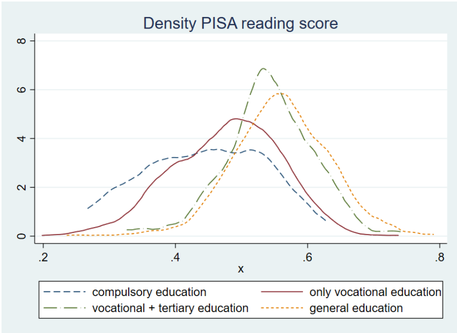
In this Appendix we present some evidence on selection into vocational and general upper secondary education in Switzerland in the early 2000s. To do so, we rely on the TREE longitudinal study, which followed the careers of Swiss participants of the PISA assessment in 2000. The interest in this data set lies in its information about the standardised PISA test scores, (self-assessed) personality traits and education choices of students at the end of their compulsory schooling (after 9 school years at age 16 approximately) and in subsequent waves. The TREE data set only covers workers of one cohort and hence, the sample size of this data set is much smaller than the SESAM data set used in our main analysis.[27] However, it is well suited to document pattern of initial selection into different education tracks.

Figure A.1 presents the distribution of cognitive abilities (as measured by PISA scores in reading and math in 2000) and self-assessed personality traits (persistence, locus of control and ambition in 2001) for male students who either selected into a 3- or 4-year VET track, into general upper secondary education (general education) or who were not enrolled in any further education programme (compulsory education) one year after graduating from compulsory lower secondary education (9 years of education). Those selecting a VET track are split into those who only complete vocational education (denoted by 'only vocational education'), and those who will complete vocational education and eventually enroll into tertiary education within 10 years after graduating from lower secondary education (denoted by 'vocational + tertiary education').

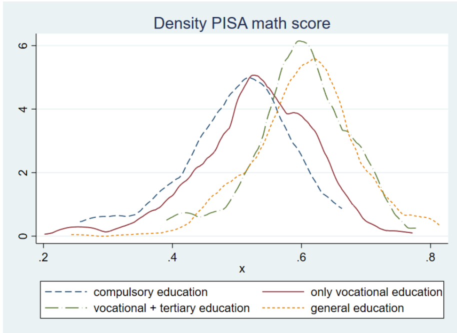
Students in the vocational education track have on average lower cognitive abilities than those in the general education track, but higher than those with only compulsory education. It is important to note that students with vocational education are heterogeneous: Students who only complete vocational education are more comparable to those with compulsory education than to their peers in vocational education who will eventually enroll in tertiary education. In terms of personality traits, differences across education tracks are less stark. For locus of control and ambition, the respective distributions differ only marginally. For persistence, we find that students in the vocational and general education track are on average more persistent than those who do not go beyond compulsory education.

[27]There is also non-negligeable sample attrition from one wave to the next.

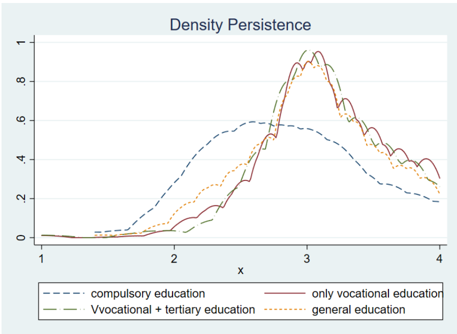
Figure A.1: Selection into compulsory, vocational and general education



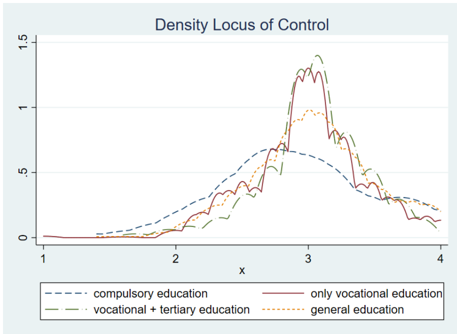
(a) PISA reading score



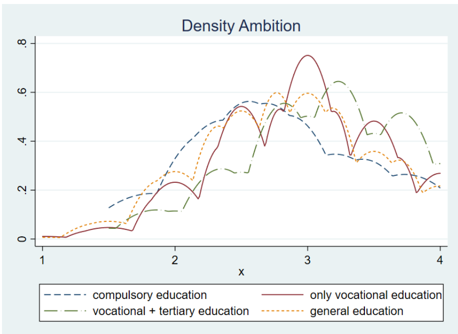
(b) PISA math score



(c) Persistence (self-assessed)



(d) Locus of Control (self-assessed)



(e) Ambition (self-assessed)

Notes: Standardised PISA reading and math scores lie between 0 and 1. Personality traits ’Persistence’, ’Locus of control’ and ’Ambition’ are the average over a number of ordinal survey questions relative to each trait which can take on value 1 ’not at all true’, 2 ’hardly true’, 3 ’moderately true’, and 4 ’exactly true’.

Table A.1 provides summary statistics for PISA scores (reading, math) and personality traits by education tracks (upper panel), as well as by occupation cluster for those within the vocational education track. It also gives the share of each occupation cluster who will enroll in tertiary education within 10 years.

Breaking up the vocational education track into VET occupation clusters which differ in their skill mix reveals a large heterogeneity across clusters. Students in some VET occupations (like occupation cluster 11 with intermediate interpersonal, low manual and intermediate cognitive skills, or cluster 14 with low interpersonal, high manual and intermediate cognitive skills) have on average the same cognitive abilities as those with only compulsory education. In contrast, students in other VET occupations (like cluster 10 with intermediate interpersonal, low manual and high cognitive skills) resemble on average quite closely students in general education in terms of their cognitive abilities and personality traits. Their rate of enrolling in tertiary education within 10 years is also much higher than the one of the former groups.

Overall, we find that the distributions of personality traits and cognitive abilities of students in different education tracks overlap to a large extent. This suggests that students in the vocational education track at the lower ability end resemble those who only get compulsory education, while those at the higher end are as good as those who pursue a general education track. By focussing our analysis only on students who complete vocational education but do not eventually enroll in tertiary education, we limit the issue of selection on ability to a considerable degree.

Table A.1: PISA scores and personality traits

		PISA read			PISA math			Persistence			Locus of control		Ambition		Enroll in
		Obs	Mean	Std.	Obs	Mean	Std.	Obs	Mean	Std.	Mean	Std.	Mean	Std.	tertiary
Compulsory education		77	0.44	0.09	39	0.50	0.09	48	2.88	0.62	2.94	0.59	2.81	0.69	
Vocational education (all)		1,311	0.49	0.08	697	0.54	0.09	1,080	3.15	0.48	3.01	0.42	2.99	0.63	16.6%
of which: only vocational		1,093	0.48	0.08	580	0.53	0.09	890	3.15	0.49	3.00	0.43	2.96	0.62	
of which: vocational + tertiary		218	0.54	0.07	117	0.60	0.07	190	3.14	0.48	3.04	0.39	3.12	0.64	
General education		689	0.56	0.07	373	0.61	0.08	585	3.05	0.51	3.05	0.46	2.87	0.65	
Vocational education by occupation cluster															
		H-interpersonal													
H-manual	H-cognitive	0			0			0							
	M-cognitive	0			0			0							
	L-cognitive	3	0.50	0.07	1	0.53	0	3	3.53	0.31	3.33	0.58	3.17	0.29	n.a.
L-manual	H-cognitive	39	0.50	0.09	20	0.55	0.06	29	2.99	0.57	2.88	0.43	2.87	0.67	8.1%
	M-cognitive	50	0.48	0.08	28	0.52	0.08	44	3.10	0.59	2.96	0.56	2.95	0.66	4.0%
	L-cognitive	0			0			0							
		M-interpersonal													
H-manual	H-cognitive	1	0.55	n.a.	0			1	3.2	n.a.	2.4	n.a.	2.5	n.a.	n.a.
	M-cognitive	21	0.45	0.06	14	0.55	0.05	18	3	0.38	3.11	0.33	3.06	0.66	0%
	L-cognitive	26	0.48	0.08	13	0.49	0.09	20	3.13	0.52	2.94	0.46	3.13	0.67	11.5%
L-manual	H-cognitive	144	0.54	0.07	76	0.59	0.09	115	3.05	0.51	2.99	0.49	2.93	0.65	31.3%
	M-cognitive	38	0.44	0.07	23	0.50	0.08	31	3.27	0.49	3.01	0.44	2.97	0.60	5.3%
	L-cognitive	99	0.49	0.08	47	0.56	0.09	83	3.14	0.53	3.07	0.40	2.94	0.68	23.2%
		L-interpersonal													
H-manual	H-cognitive	57	0.47	0.09	35	0.51	0.11	45	3.21	0.44	3.06	0.38	3.06	0.65	7.0%
	M-cognitive	50	0.42	0.10	20	0.48	0.09	38	3.25	0.57	3.01	0.55	2.93	0.72	4.0%
	L-cognitive	38	0.47	0.08	22	0.50	0.09	31	3.19	0.45	3.08	0.49	2.95	0.61	10.5%
L-manual	H-cognitive	5	0.52	0.07	1	0.57	n.a.	3	3.33	0.31	3.07	0.31	3.33	0.76	20.0%
	M-cognitive	32	0.45	0.08	21	0.54	0.08	23	3.30	0.42	3.07	0.31	3.23	0.61	6.3%
	L-cognitive	18	0.49	0.07	10	0.54	0.07	18	3.29	0.41	3.06	0.43	3.06	0.66	11.1%
Vocational education (matched)		619	0.49	0.09	329	0.54	0.09	501	3.15	0.51	3.02	0.45	2.98	0.65	

Notes: Standardised PISA reading and math scores lie between 0 and 1. Personality traits 'Persistence', 'Locus of control' and 'Ambition' are the average over a number of ordinal survey questions relative to each trait which can take on value 1 'not at all true', 2 'hardly true', 3 'moderately true', and 4 'exactly true'. 'Tertiary' denotes the share who enroll in tertiary education within 10 years of graduating from compulsory education.

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

Table B.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.

C Labour market transitions by occupational cluster

Table C.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

D Goodness of fit

Table D.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 D.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

E Estimation results: Compulsory education

Table E.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.	