Wage and employment dynamics: The role of occupational skills*

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May 18, 2017

Abstract

We develop and estimate a simple search and matching model of the Swiss labor market for workers who graduated from vocational education and training (VET) programs. While the skill bundle acquired in a VET program is occupation-specific, single skills that are part of the training can be transferred to other occupations. Combining detailed data on skills acquired in VET programs with the Swiss labor force survey, we examine how interpersonal, manual and cognitive skills map into job offers, unemployment and wages. Assuming that the match productivity exhibits worker-job complementarity, we estimate the demand for interpersonal, manual and cognitive skills and other parameters. Our findings suggest that the demand for interpersonal skills exceeds the demand for other skills, whereas workers acquire more cognitive than interpersonal and manual skills.

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

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*This study is partly funded by the Swiss Secretariat for Education, Research and Innovation through its Leading House on the Economics of Education, Firm Behavior and Training Policies. We wish to thank the Swiss Federal Statistical Office for data provision. The study also benefited from the support of the Swiss National Centre of Competence in Research LIVES – Overcoming vulnerability: Life course perspectives, which is financed by the Swiss National Science Foundation (grant number: 51NF40-160590), and from an SNSF Doc.Mobility Scholarship (project number: P1ZHP1_155498). Esther Mirjam Girsberger and Miriam Rinawi are grateful to the SNSF for financial support. In addition, we wish to thank Eric Bettinger, Tor Eriksson, Miriam Gensowski, Kalaivani Karunanethy, Rafael Lalive, Mark Lambiris, Edward Lazear, Ofer Malamud, Paul Ryan, Niels Westergaard-Nielsen, participants of the 17th Colloquium on Personnel Economics, participants of the Spring Meeting of Young Economists 2014, and participants of the 2014 Annual Congress of the European Economic Association for valuable comments on this as well as earlier versions of this study.

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1 Introduction

Continuing structural change is fundamentally altering the working environment in many sectors of the economy, leading to high rates of job mobility both in the United States and in Europe (Kambourov and Manovskii, 2008; Bachmann and Burda, 2010; Groes et al., 2015). Human capital theory (Becker, 1962) provides a central framework for studying job mobility and wage dynamics. A general finding of that literature is that individuals with more years of education fare better in the labor market (see e.g. Mincer, 1991). A more recent literature, however, argues that years of education are not an adequate measure of skills needed on a job and proposes alternative measures based on the observed skill characteristics (Autor et al., 2003; Ingram and Neumann, 2006; Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010). Thereby, this literature links human capital with occupations.

According to one prominent view (Lazear, 2009), all single skills are general in nature but combinations of single skills required in different jobs are firm-specific. Building on Mure (2007) and Geel et al. (2011), we extend Lazear's approach to the level of occupations, one can view occupations as skill bundles that combine single skills with particular weights and that thereby vary in specificity. This specificity in turn determines the degree to which skill bundles can be transferred from one occupation to another. The degree to which this skill transfer is possible varies across occupations. Analyzing job transitions in terms of skill transferability, a number of studies show empirically that worker reallocation and unemployment are more costly if skills are specific (Poletaev and Robinson, 2008).

In this study, we examine how skills acquired during vocational education and training (VET) programs affect employment and wages, and how these different labor market outcomes are determined simultaneously. VET is a very common education program in Austria, Denmark, Germany and Switzerland. Switzerland, in which more than two thirds of a cohort enroll in VET programs, has the most deregulated labor market among VET countries.[1] While a large number of studies has found VET to ease school-to-work transitions, some researchers caution that it may make employment transitions later in life more difficult (Krueger and Kumar, 2004a,b; Hanushek et al., 2017). In this study, we examine how these later-life outcomes, ultimately, depend on the skills acquired during VET programs.

A growing literature measures the returns to skills acquired early in life or in general

[1] Switzerland may thus be thought of as a counterexample to the theory laid out in Wasmer (2006) according to which investment in more specific skills may be related to labor-market protection.

education. Brunello and Schlotter (2011) provide an overview of the findings on cognitive and noncognitive skills and how these can be developed in education and training. Lindqvist and Vestman (2011), for example, show that noncognitive skills are important to avoid poor performance in the labor market, whereas cognitive skills help predict high wages. Fredriksson et al. (2015) show that the likelihood of finding a job that matches a worker's skills increases in their labor market experience. Inexperienced workers and workers who were hired from non-employment, on the other hand, match under greater uncertainty, and are more likely to separate within the first year on the job. Bagger et al. (2014) examine wage and employment dynamics in a discrete-time model with deterministic growth in general human capital in the number of years of labor market experience. Flinn et al. (2017) provide evidence for the importance of search frictions in Mincer wage regressions. We add to these studies by focusing on skills acquired in occupation-specific training in VET programs.

Most previous research has focused on job-to-job mobility, measuring the transferability of skills between jobs and relating it to wage dynamics. A general finding is that individuals move to occupations with similar skill requirements (Gathmann and Schönberg, 2010) and that skill bundles are closely related to wages (Poletaev and Robinson, 2008). This previous literature has considered labor-market transitions and wages separately, but there is a growing consensus that wage growth is closely related to labor-market transitions (see e.g. Jinkins and Morin, 2017; Lise and Postel-Vinay, 2017).

In this study, we develop a structural framework, in which employment status and wages are determined simultaneously. To do so, we build a simple search and matching model with heterogeneous workers and firms. Workers differ in skills and firms differ in their demand for skills. We estimate the model by combining individual data on labor market outcomes and data on skills trained in VET. Our analysis builds on Lise and Postel-Vinay (2017). They construct a model with a three-dimensional skill vector (cognitive, manual, interpersonal), where workers gradually adjust towards the skill requirements of their employers, and test their model empirically using skill requirements based on O*NET data combined with worker-level panel data from the NLSY79.

Our study differs from Lise and Postel-Vinay (2017) in that while they examine how workers adjust to employers' requirements that are assumed to be exogenous, we assume that workers' skills remain constant after completing their VET program. This assumption is reasonable for vocational occupations, where the content of the training curricula and the tasks performed on the job closely match. Unlike the U.S., the Swiss labor market has an institutionalized occupational structure, where occupations are structured according to the corresponding tracks of vocational qualifications and bound by vocational qualifications (Eyraud et al., 1990; Marsden, 1999). Major changes in employers' skill requirements are therefore directly translated into the training curricula. Given that the training curricula are constantly updated, our assumption of a one-to-one mapping also holds for technology shifts.

To measure skills empirically, we use data on the skills acquired in VET for each occupation. This type of data is available in Switzerland. Our skill data comes from the *Berufsinformationszentrum* (BIZ), the state-led career-counseling center. The BIZ provides a detailed list of skills that are used in individual vocational occupations, covering a total of 220 occupations.[2] To infer the wage distribution associated with these skill bundles, we use the Social Protection and Labor Market (SESAM) survey. The SESAM consists of the Swiss Labor Force Survey, a representative panel survey, and register data on employment histories, unemployment benefits, and wage dynamics. We match the skill bundles from the BIZ to the occupations in the SESAM to estimate the parameters of our structural model of wages and employment transitions. The administrative nature of our data minimizes the measurement error in wages and occupational coding.

Our model, which assumes worker-job complementarity, closely matches the observed moments in the data. The assumption of complementarity is in line with structural evidence presented in Lindenlaub (2017). Lindenlaub distinguishes between manual and cognitive skills and finds that worker-job complementarity has increased since the 1990s in cognitive inputs but decreased in manual inputs. We add a third dimension to the skill vector, interpersonal skills, and find that across the distribution of skill endowments in the labor market, firms' demand for these interpersonal skills is higher than for the former two skills. This result may reflect the recent rise in the importance of interpersonal skills in the labor market (Deming, 2015).

The paper proceeds as follows. In Section 2, we develop a simple model of matching in the labor market with a multi-dimensional skill vector. Section 3 presents the data and measures of skills in the labor market for VET workers in Switzerland. In Section 4 we take a descriptive look at the distributions of interpersonal, cognitive and manual skills, and examine how these are related to labor-market outcomes in the reduced form. Section 5 outlines our structural estimation procedure, Section 6 presents the results, and Section 7 concludes.

[2] Since skill heterogeneity exists not only between but also within education classes (Christiansen et al., 2007; Backes-Gellner and Wolter, 2010; Geel and Backes-Gellner, 2011), we will focus on workers in the same education class to obtain unbiased effects.

2 Matching with a multidimensional skill vector

In this section we develop a general equilibrium search and matching model in the spirit of Pissarides-Mortensen-Diamond (see Pissarides, 2000). The model features heterogeneous workers who are characterized by a multidimensional skill vector. Firms use skills in different combinations to produce an output.

Like most other papers in this literature, our model is in continuous time and features infinitely lived agents who discount time at rate r. We use a simple model of random search and exogenous job destruction. Our model differs from the existing ones on both the supply side and the demand side. Workers are heterogeneous in that they acquired different skills during their vocational education and training. Firms, on the other hand, differ in their demand for these skills.

Each worker is characterized by a multidimensional skill vector x. Under random search, an unemployed worker with skill vector x gets an unemployment flow of b and meets a firm at some constant rate λ. An employed worker gets a wage w and faces (exogenous) job destruction at rate η. The wage is a function of the worker's skill vector 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 Flinn and Mullins, 2015). α is a skill weighting vector which is independently and identically distributed according to the multivariate distribution function $G(\alpha)$. A filled job gets destroyed at rate η. We assume that there is no endogenous vacancy creation.[3] The value of a filled job between a worker with skills x and a skill weighting vector α is given by:

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

[3]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.

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 as:

$$\max_{w} \left[\frac{w + \eta V_U(x)}{r+\eta} - V_U(x)\right]^{\beta} \left[\frac{\alpha' x - w}{r+\eta}\right]^{1-\beta}. \tag{5}$$

This gives rise to the following wage equation:

$$w(\alpha, x) = \beta\alpha' x + (1-\beta) r V_U(x). \tag{6}$$

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 pin down the reservation wage $w^*(x)$:

$$\begin{aligned} w(\alpha^*(x), x) &= \beta\alpha^*(x)' x + (1-\beta) r V_U(x) = r V_U(x) && (7) \\ \longrightarrow w^*(x) &= \alpha^*(x)' x = r V_U(x). && (8) \end{aligned}$$

Let us now turn to the rate of a match being formed. It is the product of the offer rate λ and the probability of the skill vector α lying within or above the set of reservation skills. The rate of forming a match for worker x is given by:

$$h(x) = \lambda \int_{\alpha^*(x)} dG(\alpha). \tag{9}$$

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:

$$\begin{aligned} \left[1 - u(x)\right]\eta &= u(x) h(x) && (10) \\ \longrightarrow u(x) &= \frac{\eta}{\eta + h(x)}. && (11) \end{aligned}$$

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

3 Measurement and Data

In the empirical analysis, we rely on data from Switzerland, a country with a long tradition of vocational education and training (VET). We use two different sources of data for our empirical analysis: First, to construct occupation-specific skill bundles, we use data on skills taught in VET from the career-counseling center BIZ. Second, for labor market outcomes, we use the Social Protection and Labor Market (SESAM), a matched panel data set linking the Swiss Labor 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 behavior patterns, socio-demographic, 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 the SESAM offers consistent data. Each individual remains in the SESAM panel for five years in total and information from the survey is collected retrospectively. Our analysis is based on a sample of individuals with a VET degree who are between 18 and 65 years old. We exclude individuals who are out of the labor force, but include part-time workers. For the analysis, we compute hourly wages and trim the wage distribution below the bottom 5% and above the top 1%. Furthermore, we drop all observations with missing variables in the dependent or independent variables. Our sample excludes females because both skills and returns to skills differ substantially between male and female VET workers.

About 65 percent of a Swiss youth cohort enroll in VET, more than in other countries in which it is available. VET in Switzerland also attracts high ability students because of its excellent reputation and excellent career opportunities. Training starts at around age 16 and lasts three to four years. It is a dual program that combines formal education and curriculum-based on-the-job training with the employer. Skills can be classified as transferable and are not firm-specific. 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. Therefore, graduates are not bound to their training firm, but can freely move around in the labor market. Indeed, the retention rate after graduation is only 35 percent (Schweri et al., 2003). The training content is regularly revised in a tripartite process, in which employer organizations, employee representatives, and the government participate (Rinawi and Backes-Gellner, 2014).

For our analysis, we define a three-dimensional skill vector x, where each dimension captures a different type of skill set that is acquired during VET education. We operationalize the skills using data from the career-counseling center *Berufsinformationszentrum* (BIZ). The BIZ provides a detailed list of skills that are used in individual occupations, covering a total of 220 VET occupations that existed during the period that we examine. The list comprises 26 different skills, 24 of which were classified as manual (5 skills), cognitive (9 skills), or interpersonal skills (10).[4] Examples include "fine motor skills" (manual), "visual thinking" (cognitive), and "ability to work in a team" (interpersonal). Some occupations such as sales persons use 12 different skills, while others such as road builders use only four skills. On average, an occupation uses seven skills. In essence, the 24 skills represent 24 potential dimensions of skill heterogeneity across workers, which we aggregate into three dimensions by adding up skills in the three categories.

4 Descriptive Statistics and Reduced-Form Analysis

The sample of analysis consists of 12,083 observations. We start by discussing descriptive statistics on workers' skills as shown in Table 1. On average, workers in the sample have acquired 1.61 interpersonal skills, 1.24 manual skills and 1.97 cognitive skills. Despite similar mean values, the distribution of each skill type looks fairly different. Workers' interpersonal skills follow a bimodal distribution with a peak at 0/1 skills and another (smaller) peak at 3/4 skills. The supply of manual skills is right-skewed, with a peak at 1/2 skills. Finally, the supply of cognitive skills is lightly skewed to the right, with a peak at 2 cognitive skills. The two negative correlation coefficients with manual skills indicate that workers specialize by either acquiring manual or non-manual (interpersonal/cognitive) skills. Workers with high (low) interpersonal skills tend also to have high (low) cognitive skills as suggested by the positive correlation between these two skills.

Figure 1 further visualizes which combinations of skills are supplied by workers of our sample. It displays the distributions of cognitive and interpersonal skills for each of the four different values of manual skills. We observe that the biggest mass is at small values for all three different skills. Also, for most of the possible combinations of the three different skills that are possible, there are no observations in our data. Given the range of each skill dimension, we have in total $6 \times 6 \times 4 = 144$ possible skill combinations. Effectively, we observe only 45 of them in our sample.

In order to reduce the dimensionality of the problem, we regroup the workers in our

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

Table 1: DESCRIPTIVE STATISTICS FOR SKILLS BY TYPE.

Skill type	obs	mean	S.D.	distribution						correlation		
				0	1	2	3	4	5	interp	manual	cogn
interpersonal	12,083	1.609	1.493	3,109	4,576	650	1,970	1,239	539	1.000		
manual	12,083	1.240	0.805	2,441	4,684	4,581	377			-0.342	1.000	
cognitive	12,083	1.972	1.251	896	3,615	4,884	1,252	492	944	0.207	-0.110	1.000

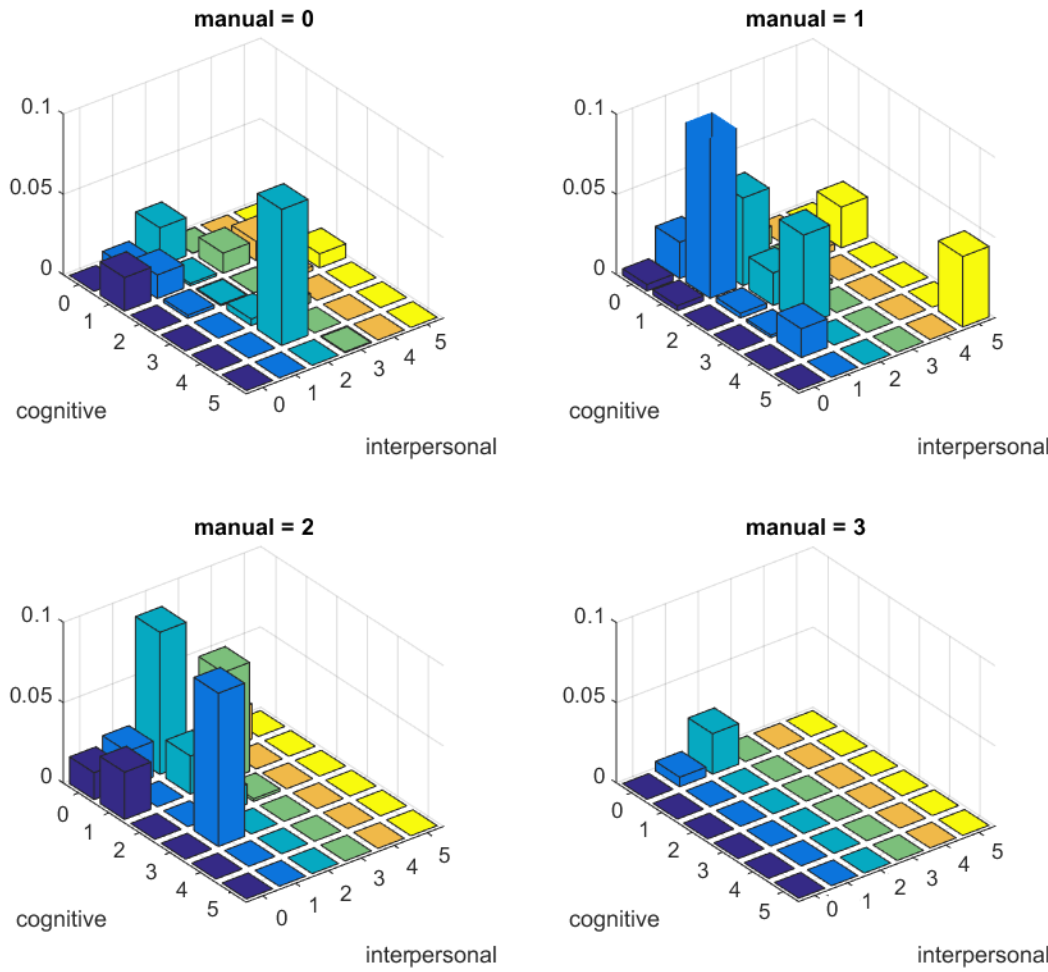

Figure 1: Skill combinations supplied by workers

sample into occupational clusters based on the set of skills they acquired during VET. To do this, we first divide each of the three skill classes into groups. The implementation of this classification takes into account the specific distribution of each skill type and aims at creating groups of roughly equal sizes. Therefore, we distinguish low (0,1), medium (2) and high (3 and above) interpersonal skills; low (0), medium (1,2) and high (3 and above) cognitive skills, and low (0,1) and high (2,3) manual skills. Of a maximum of 18 ($3 \times 2 \times 3$) possible clusters, 2 remain empty with no observations.

Table 2 provides descriptive statistics on unemployment, hourly wages and age by occupational cluster. The upper panel relates to high, the intermediate panel to medium and the lowest panel to low interpersonal skills, respectively. Within each panel the upper part (3 lines) refer to high and the lower part (3 lines) to low manual skills. Finally, we vary cognitive skills from high to medium to low.

First of all, we notice that despite an attempt to form clusters of relatively equal size, the cluster size varies substantially. Some clusters like 5 (H-L-M, high interpersonal - low manual - medium cognitive), 12 (M-L-L) and 14 (L-H-M) are very large while other clusters like 6 (H-L-L) and 16 (L-H-H) are very small.

Overall, we observe small positive correlations between having been trained in occupations that use more interpersonal skills with both hourly wages and the chances of being unemployed. Occupations with high manual skills are characterized by low unemployment rates and low wages. In both of these cases, unemployment and wages are positively correlated. The only skill type, for which we do not observe such a trade-off, is cognitive skills. We observe a positive correlation between hourly wages and cognitive skill endowments, whereas unemployment is virtually unrelated to cognitive skill endowments. These results are confirmed in the reduced-form regression shown in Table 3.

Moreover, Table 2 displays evidence that mean hourly wages not only vary across clusters, but there are also important differences in hourly wages within each cluster. A large part of the within-cluster variation captures hourly wage differences stemming from differences in age, experience, region, industry and other factors. Having more interpersonal or cognitive skills is associated with (slightly) higher standard deviation of hourly wages. However, even the L-L-L cluster has a fairly large variation in hourly wages.

Table 4 provides an overview of year-to-year labor market transitions by skill clusters. In total, about 89% of the labor force remain in the same job as indicated by the 'EE stay' rate. Another 6.8% has switched jobs (possibly, by going through a short spell

Table 2: DESCRIPTIVE STATISTICS BY CLUSTERS.

		Obs	unemp	hourly wages mean	hourly wages std. dev.	age
H-interpersonal						
H-manual	H-cognitive	n.a.	n.a.	n.a.	n.a.	n.a.
H-manual	M-cognitive	n.a.	n.a.	n.a.	n.a.	n.a.
H-manual	L-cognitive	1,152	0.042	37.55	10.02	40.52
L-manual	H-cognitive	609	0.066	32.88	9.88	36.70
L-manual	M-cognitive	1,750	0.050	38.20	12.78	38.84
L-manual	L-cognitive	237	0.084	31.30	9.71	39.13
M-interpersonal						
H-manual	H-cognitive	840	0.020	31.30	9.71	39.14
H-manual	M-cognitive	435	0.028	37.59	11.18	41.78
H-manual	L-cognitive	355	0.028	34.08	8.61	41.38
L-manual	H-cognitive	844	0.045	39.13	11.16	42.41
L-manual	M-cognitive	933	0.045	35.99	9.03	41.58
L-manual	L-cognitive	1,819	0.053	36.42	10.44	39.74
L-interpersonal						
H-manual	H-cognitive	264	0.038	33.98	7.95	39.89
H-manual	M-cognitive	1,372	0.039	33.47	7.54	38.90
H-manual	L-cognitive	540	0.043	33.66	9.11	41.17
L-manual	H-cognitive	131	0.031	39.57	9.70	44.11
L-manual	M-cognitive	394	0.030	33.40	7.40	42.08
L-manual	L-cognitive	408	0.017	36.11	9.24	41.43
all clusters		12,083	0.043	36.29	10.37	40.43

of unemployment) as given by the 'EE change' rate. Transitions from unemployment to employment make up 1.5%, whereas transitions from employment to unemployment are 1.9% over our period of observations. Overall, these numbers indicate rather low job mobility. The rates of 'EE same' and 'EE change' are strongly negatively correlated and sum up to almost 95%, while job destruction and job finding rates are positively correlated. These factors contribute to having relatively small differences in unemployment rates across clusters[5]. Workers trained in occupations with low interpersonal, high manual and high cognitive skills are most likely to switch at a rate of 9.5%. At the other end of the spectrum, workers trained in occupations that provide them with medium interpersonal, high manual and medium cognitive skills are the least likely to switch. Their job switching rate is 3.3%

[5]Notice that all workers were employed at their training firm during VET. Differences in unemployment must arise from different labor market transitions after graduating from VET.

Table 3: REDUCED-FORM ESTIMATES.

	Log hourly wages		Unemployment	
Total interpersonal skills	0.0091	***	0.0046	***
	(0.0017)		(0.0014)	
Total manual skills	-0.0263	***	-0.0027	
	(0.0029)		(0.0023)	
Total cognitive skills	0.0031	*	-0.0009	
	(0.0018)		(0.0016)	
Age	0.0431	***	-0.0093	***
	(0.0013)		(0.0014)	
Age squared	-0.0004	***	0.0001	***
	(1.64×10^{-5})		(1.66×10^{-5})	
Constant	2.5333	***	0.2244	***
	(0.0261)		(0.0292)	
R^2	0.2219		0.0074	
Observations	11,564		12,083	

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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: 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	708	0.897	0.056	0.014	0.017	0.016
L-manual	H-cognitive	364	0.843	0.080	0.016	0.030	0.030
	M-cognitive	1059	0.864	0.076	0.020	0.025	0.014
	L-cognitive	149	0.826	0.074	0.027	0.040	0.034
M-interpersonal							
H-manual	H-cognitive	523	0.939	0.044	0.006	0.008	0.004
	M-cognitive	276	0.935	0.033	0.004	0.022	0.007
	L-cognitive	221	0.887	0.086	0.014	0.009	0.005
L-manual	H-cognitive	530	0.894	0.053	0.015	0.021	0.009
	M-cognitive	565	0.883	0.065	0.014	0.028	0.009
	L-cognitive	1,110	0.900	0.082	0.018	0.015	0.021
L-interpersonal							
H-manual	H-cognitive	148	0.858	0.095	0.007	0.034	0.007
	M-cognitive	851	0.880	0.082	0.012	0.015	0.011
	L-cognitive	328	0.921	0.037	0.012	0.012	0.018
L-manual	H-cognitive	83	0.904	0.048	0.000	0.024	0.024
	M-cognitive	246	0.919	0.057	0.008	0.004	0.012
	L-cognitive	252	0.901	0.075	0.012	0.008	0.004
all clusters		7,413	0.885	0.068	0.015	0.019	0.014

5 Structural Analysis

5.1 Estimation method and identification

The main interest of this paper is to shed light unto how occupational skills acquired in VET programs determine labor market outcomes such as employment status and wages. The search and matching model that we have developed in Section 2 offers us a simple framework to study these outcomes. It allows us to derive a wage offer distribution conditional on skills x of the worker (Equation 6), the reservation wage for which the worker is indifferent between working and staying in unemployment (Equation 8) and, finally, the probability of getting an acceptable wage offer and a match being formed (Equation 9).

We do not attempt to estimate the full search and matching model, but instead focus on estimating the wage offer distribution, the reservation wage and unemployment for different skill groups. To this end, we use the Method of Simulated Moments as in Flinn and Mullins (2015). In order to achieve identification, we make certain parametric assumptions about the skill demand distribution $G(\alpha)$. More specifically, as outlined in Section 2, we assume that the productivity of the match is given by the following equation:

$$p \;=\; \alpha' x = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3, \tag{12}$$

where α_0 is a general productivity shock, and α_1, α_2 and α_3 are the demand for interpersonal, manual and cognitive 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. Moreover, the general productivity shock is assumed to be independent of the skill-specific demands. The skill-specific demands α_j with $j = 1, 2, 3$ 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}.

The match productivity distribution $p = \alpha' x$ is obtained from these parametric assumptions, and the parameters on the productivity shock distribution and the demand for skills. For given values of the labor share β and reservation wages $w^*(x)$, the match productivity distribution matches one-to-one into the wage distribution given in equation 6.

Following Flinn (2006), we use information from outside the sample on firms' surplus β. We set it to 0.67.[6] Moreover, we use the previously defined 16 occupational clusters for a discrete approximation of x. To calibrate reservation wages $w^*(x)$, we use the observed minimum hourly wage in each occupation cluster x. Based on the calibrated reservation wages and the parametric assumptions on the productivity and skill-demand distributions, we can use the observed wage distributions for each occupation cluster to identify the distributional parameters (i.e. location, scale and correlation parameters of the general productivity and skill-specific demands). More specifically, we target the mean hourly wage and the standard deviation of hourly wages for each occupation cluster. This gives us 32 moments that are related to wages.

In order to identify the offer arrival rate, we match the unemployment rate of each occupation cluster (16 moments). In total, we thus have 48 moments. From Equation (11)

[6] The labor 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 labor 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).

we see that unemployment rates do not allow us to separately identify the offer arrival rate and the job destruction rate. We can only estimate how many job offers are made per job destroyed.

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), as well as the offer arrival rate λ. The parameter space corresponds to the real numbers for the location parameters and λ, to positive real numbers for the scale parameters and to real numbers between -1 and 1 for the correlation coefficients. Furthermore, we restrict the parameter space of the correlation coefficients in such a way as 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 mean hourly wages and unemployment rates are estimated from the sample moments, the standard error of the standard deviations was bootstrapped using 1,000 replications.

5.2 Simulation procedure

In order to perform our estimation using simulated method of moments, we need to construct the simulated moments as given in Equation (13). The moments we target are the cluster-specific mean hourly wages and standard deviations of hourly wages, as well as the cluster-specific unemployment rates. To do so, we produce a simulated data set with 20,000 individuals that have (approximately) the same skill distribution x as the observed sample.

For each individual in the simulated data set, we determine their skill level x, which we keep constant across all iterations. At each simulation iteration we draw a general productivity shock α_0 (which follows a log-normal distribution with location μ_0 and scale σ_0) and skill-specific demands α_1, α_2 and α_3 (which follow a Gaussian copula with log-normal marginals with parameters μ_j, σ_j and ρ_{ij}). If the resulting productivity of the drawn match is above the calibrated reservation wage, the individual accepts the job and a match is formed. Otherwise, they reject the offer. Using the wage equation (see Equation 6), we can compute the wage of each match that was formed. Using the simulated wage data and the simulated probability of a match being formed, we can compute the simulated cluster-specific mean of hourly wages, the standard deviation of hourly wages and the unemployment rate.[7]

We iterate this process for different values of ω using a Nelder-Mead simplex algorithm until the minimum of the loss function is found.

6 Results

6.1 Estimated parameters

Table 5: ESTIMATED PARAMETERS.

General productivity				
	Location		Scale	
	Estimate	Std. Err.	Estimate	Std. Err.
μ_0, σ_0: General productivity	3.66	0.009	0.32	0.003
Skill-specific demands				
	Location		Scale	
	Estimate	Std. Err.	Estimate	Std. Err.
μ_1, σ_1: Interpersonal skills	-0.55	0.05	1.53	0.08
μ_2, σ_2: Manual skills	-1.31	1.39	0.09	6.63
μ_3, σ_3: Cognitive skills	-0.89	0.47	0.12	3.63
	Correlation			
	Estimate	Std. Err.		
ρ_{12}: Interpers-manual correlation	-0.31	50.31		
ρ_{13}: Interpers-cognitive correlation	0.21	8.28		
ρ_{23}: Manual-cognitive correlation	-0.11	137.17		
Offer and destruction rates				
	Rate			
	Estimate	Std. Err.		
λ: Offer arrival rate	1.26	4.23		
η: Destruction rate (calibrated)	0.05	n.a.		

The estimation results on the productivity distributions and on the offer arrival rate are given in Table 5. We estimate the location and scale of the log-normal general productivity distribution at 3.66 and 0.32, respectively. Therefore, the mean of the general

[7]The simulated unemployment rate is computed from the simulated probability of a match being formed and the job arrival rate λ, assuming that the job destruction rate η is fixed at 0.05.

productivity is around 41.07 Swiss francs Or about 42 USD per hour.[8] We find that the demand for interpersonal skills has the largest location and scale parameters at -0.55 and 1.5, respectively. The location parameter of the demand for manual skills is estimated at -1.31, and the one for cognitive skills at -0.89. Moreover, we find that the demand for cognitive skills is slightly more dispersed than the one for manual skills as indicated by the scale parameters of 0.12 and 0.09, respectively. However, these two scale parameters are estimated very imprecisely. Most of the other parameters, with the exception of the location parameter of the demand for manual skills, are estimated with high precision as indicated by the low standard errors.

In order to evaluate the effect of skills on productivity, we take a worker with mean general productivity and add mean skill endowments from Table 2, i.e. we add $\bar{x}_1 = 1.609$ interpersonal skills, $\bar{x}_2 = 1.240$ manual skills and $\bar{x}_3 = 1.972$ cognitive skills to the mean general productivity measured by $\bar{x}_0 = 1$, their productivity will go up from 41.07 Swiss francs to

$$\sum_{i=0}^{3} \bar{x}_i \cdot \exp\left(\mu_i + \frac{\sigma_i^2}{2}\right) = 45.21 \text{ Swiss francs.}$$

Having mean interpersonal, manual and cognitive skills compared to not having any of these skills results in a productivity increase of 4 Swiss francs per hour. Using the values from Table 5, we can also compute the marginal value of having an additional unit of a specific skill. At the mean demand of each of these skills, productivity would increase to 47.19 Swiss francs if a worker had one additional interpersonal skill, i.e. the marginal value equals 1.85 Swiss francs per hour for interpersonal skills. For the other two skills, we find lower marginal returns of 0.41 Swiss francs for cognitive skills, and 0.27 Swiss francs for manual skills. These marginal returns vary substantially with skill demand α. Let us suppose that the worker meets a firm with a high demand for a specific-skill, e.g. at the top 5% of the distribution. The marginal value of an additional skill unit is now 7.12 Swiss francs per hour for interpersonal, 0.50 for cognitive and 0.31 for manual skills, respectively. The large dispersion in the demand for interpersonal skills makes waiting for a better offer more attractive for someone with high interpersonal skills. In contrast, the demand for cognitive and manual skills is relatively compressed.

Notice that the estimated parameters of the general productivity distribution are relatively large compared to the skill-specific demands. Analogous to a random effect in a regression model, the general productivity parameter α_0 captures all variation in individual productivity that is not related to differences in skill demand and skill supply. Variation

[8]Notice that the mean of a log-normally distributed random variable is equal to $\exp(\mu + \sigma^2/2)$.

in α_0 may therefore arise from variables which we do not model explicitly. These include observed variables such as age, experience, tenure, industry, and region, as well as unobserved idiosyncratic factors.[9]

We find some (weak) evidence that the demands for interpersonal and cognitive skills are complementary. Furthermore, we uncover that firms tend to have a demand either for manual or non-manual skills as suggested by the negative correlation coefficient between manual and the other skills. However, the large standard errors indicate that these parameters are very imprecisely estimated. One possible reason for this imprecision could be the skewed skill supply distributions, which limits the models capacity to identify the 'true' correlation coefficient of firms' demand for different skills.

Finally, we estimate that an unemployment worker receives on average around 1.25 job offers per year. This result obtains under the assumption that 5% of jobs get destroyed per period.[10] Again, the offer rate is not precisely estimated. One reason is that unemployment rates (which are the moments we target to identify this parameter) do not vary systematically across different occupation clusters and thus, it is difficult to identify the offer arrival rate well.

6.2 Skills supplied by the workers and the demand for skills

Productivity in our model is determined by skill supply, i.e. the vector x a worker is endowed with, and by firms' demand for these skills α. The functional form $p = \alpha' x$ implies worker-job complementarity. Evidence presented in Lindenlaub (2017) provides support for this assumption, but also suggests changing patterns in the degree of complementarity over time. This does, however, not pose a problem in our setting because we only use the relatively short time period 2004-2009 of the SESAM data.

[9] An alternative procedure would have been to regress productivity p on the observables in our data and to examine how VET skills are related to the resulting residuals rather than to p itself. We have opted against this alternative for two reasons. First, as shown in Table 2, the heterogeneity in observable characteristics across VET workers is rather low. While there is some variation e.g. in mean age across occupational clusters with a maximum difference of about 7.4 years between clusters 4 and 16, it is generally pretty close to 40 years. Second, there are countless possibilities to specify these regressions, which would make the interpretation of the residuals very difficult.

[10] This assumption appears reasonable given that around 1.9% of the work force move from employment to unemployment within one year, and 6.8% of the work force move from employment to a new employment situation within one year (see Table 4). This second number also includes employment-unemployment-employment transitions.

The assumption of complementarity entails that productivity is highest if the worker supplies the skills which are in high demand by the firm. Figure 2 depicts histograms of the demand of 20,000 firms for interpersonal, manual and cognitive skills. Beware that the demand for interpersonal skills has a different scale on the x-axis from the other skills.

As already discussed previously, demand for interpersonal skills is highest, intermediate for cognitive and lowest for manual skills. As shown by the large dispersion, some firms have a very high demand for interpersonal skills, while other firms value these skills very little. The demand for cognitive skills is less dispersed, and the one for manual skills even less so. Given that the marginal returns are highest for interpersonal skills, one would expect individuals in the labor market to invest into the acquisition of interpersonal skills. It may, therefore, come as a surprise that, as shown in Table 1, the mean number of cognitive skills a worker is endowed with is higher than the mean number of interpersonal skills. Our findings suggest that productivity could be increased if workers received training in VET occupations that provide them with more interpersonal skills, and fewer manual and cognitive skills - assuming that the acquisition of these different skills is equally costly.

One explanation for this apparent mismatch between supply and demand for skills may be that the importance of interpersonal skills is a very recent phenomenon. Deming (2015) shows that between 1980 and 2012, employment has grown disproportionately in occupations with training programs that provide workers with many interpersonal skills. Keep in mind that the average worker in our sample is about 40 years old and has, thus, obtained his training 20 years ago. It may simply take a while for the tripartite organization consisting of government as well as employer and employee representatives outlined in Section 3 to adapt training schedules to this new situation and, even more importantly, for the workers graduating from these new programs to enter the labor market. In fact, the descriptive statistics on workers' skill endowments (see Table 2) suggest that workers are gradually adapting to these new demands: Those workers who have received training in occupations with high interpersonal skills are on average slightly younger than those who trained in occupations with medium or low interpersonal skills.

Moreover, skills are closely related to each other. The correlations between the endowments in Table 1 show that workers who have many interpersonal skills tend to also have many cognitive skills but few manual skills. In line with this observation, Deming (2015) finds that the importance of interpersonal skills has increased most strongly in occupations with training programs that also provide workers with high levels of cognitive skills, thus providing evidence for complementarity between cognitive and interpersonal

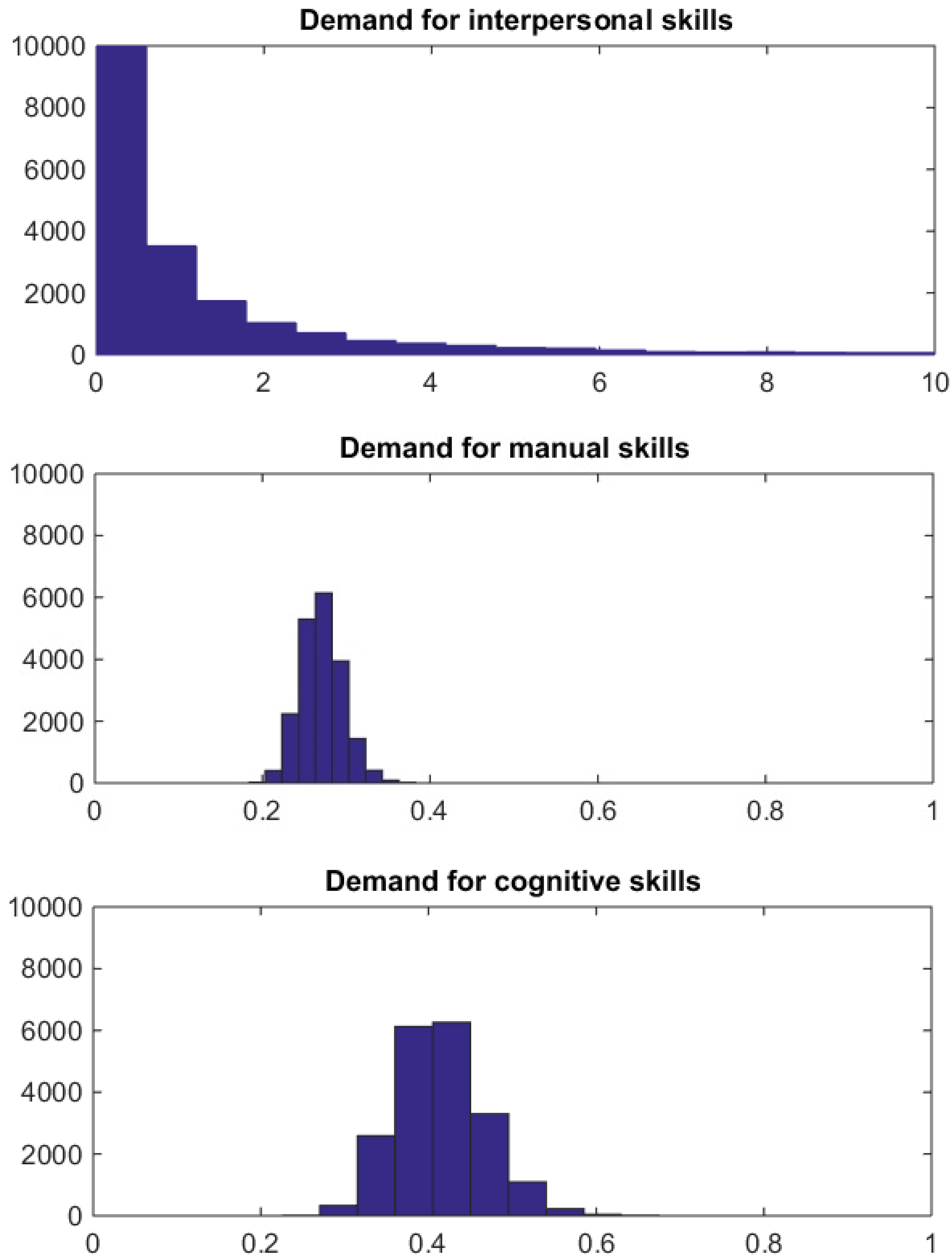

Figure 2: Marginal densities of demand for skills (different scales)

skills. This complementarity in interpersonal-cognitive skill supply is also reflected in the estimated positive correlation between the demand for these two skills (see Table 5).

However note that our estimates of this complementarity are not precise.

Overall, we find that having a skill bundle (e.g. high manual, but low interpersonal and cognitive skills) which is very different from what is highly demanded by firms (workers with high interpersonal skills) does neither results in higher unemployment nor in (much) lower hourly wages. Why is such a mismatch not (more) costly? It turns out that having graduated from VET is very valuable in itself as indicated by the relatively high general productivity. The specific bundle of skills acquired is much less important than having a VET degree.

6.3 Goodness of fit

Table 6 displays how well our model is able to match the moments observed in the data. A comparison of observed and simulated moments shows that the model performs well at replicating mean hourly wages and the standard deviation of hourly wages. There are, however, two clusters, for which our model performs less well than for the others. These are the high-cognitive and low-cognitive clusters in the high-interpersonal, low-manual panel in lines 4 and 6 in Table 6. These two clusters are characterized by relatively few observations and high standard errors, so the model's failure to match the observed moments in these clusters as well as in others should not be surprising. In fact, clusters 4 and 6 have among the lowest mean hourly wages despite relatively high interpersonal skills.

With respect to unemployment rates, our model produces a similar (slightly lower) overall unemployment rate (3.9%) to the one observed in the data (4.3%). However, it is not able to generate the variation across occupational clusters that we observe in the data. Given that observed cluster-specific unemployment rates do not follow a systemic (linear) pattern, it cannot come as a surprise that the model does not match them well. The feature of increasing unemployment rates with interpersonal skills (see the reduced form results in Table 3) is reproduced to some extent by our model: The weighted unemployment rate is around 3.88% for those with high interpersonal skills versus 3.85% for those with low interpersonal skills.

In fact, the model does not only explain cluster-specific mean and standard deviation of hourly wages, but it does a really good job at matching almost all cluster-specific wage distributions as shown in Figure 3. Again, the negative outliers are clusters 4 and 6, for which the model generates simulated wages that have higher means and that are more dispersed than in the data.

Table 6: GOODNESS OF FIT.

		Mean hwage			Std. dev. hwage			Unemployment rate			Min. wage
		Observed	Std.Error	Simulated	Observed	Std.Error	Simulated	Observed	Std.Error	Simulated	Observed
H-interpersonal											
H-manual	H-cognitive	n.a.	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.	n.a.
	L-cognitive	37.55	0.302	36.98	10.018	0.273	10.603	0.0417	0.006	0.0386	18.45
L-manual	H-cognitive	32.88	0.414	38.89	9.883	0.455	10.733	0.0657	0.010	0.0389	18.56
	M-cognitive	38.20	0.313	37.76	12.776	0.273	10.844	0.0497	0.005	0.0388	18.50
	L-cognitive	31.30	0.659	38.15	9.714	0.924	10.836	0.0844	0.018	0.0387	18.55
M-interpersonal											
H-manual	H-cognitive	39.76	0.358	35.71	10.273	0.292	9.440	0.0202	0.005	0.0385	18.59
	M-cognitive	37.60	0.543	35.88	11.175	0.564	9.231	0.0276	0.008	0.0387	18.52
	L-cognitive	34.08	0.464	34.95	8.612	0.494	8.938	0.0282	0.009	0.0384	18.94
L-manual	H-cognitive	39.13	0.393	36.56	11.155	0.344	9.488	0.0450	0.007	0.0384	18.70
	M-cognitive	35.99	0.302	35.87	9.029	0.290	9.438	0.0450	0.007	0.0385	18.50
	L-cognitive	36.42	0.252	35.25	10.440	0.271	9.266	0.0528	0.005	0.0386	18.45
L-interpersonal											
H-manual	H-cognitive	33.98	0.499	34.74	7.946	0.401	8.750	0.0379	0.012	0.0383	18.89
	M-cognitive	33.47	0.208	34.47	7.537	0.240	9.071	0.0386	0.005	0.0385	18.45
	L-cognitive	33.66	0.401	34.78	9.110	0.561	9.495	0.0426	0.009	0.0385	18.52
L-manual	H-cognitive	39.57	0.861	34.10	9.702	0.571	8.227	0.0305	0.015	0.0385	18.73
	M-cognitive	33.40	0.378	33.73	7.396	0.353	8.529	0.0305	0.009	0.0387	18.82
	L-cognitive	36.11	0.461	34.81	9.240	0.445	9.622	0.0172	0.006	0.0386	18.63

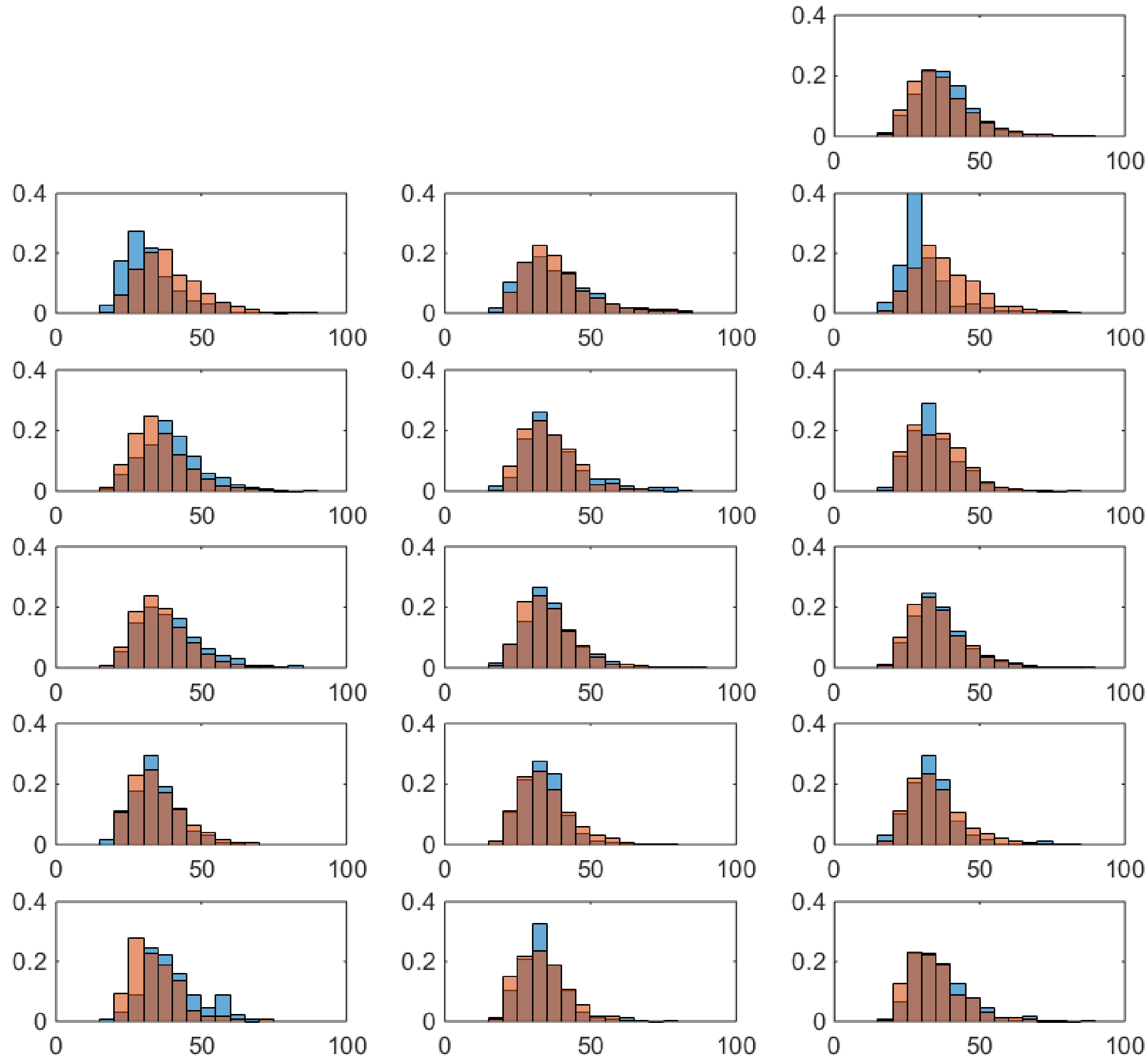

Figure 3: Goodness of fit: Wage distributions of observed (blue) and simulated (orange) wages by occupation cluster

7 Conclusion

This paper provides a structural examination of the Swiss labor market for workers who graduated from vocational education and training (VET) programs in Switzerland. We distinguish workers who have acquired different bundles of interpersonal, manual and cognitive skills in VET programs. We analyze 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.

We find that the demand for (and hence, returns to) interpersonal skills dominates the demand for cognitive and manual skills. At the mean skill endowment and mean general productivity, an additional unit of interpersonal skills increases productivity by 4 percent or 1.85 Swiss francs per hour, compared to 0.41 for cognitive and 0.27 for manual skills. Interestingly, the average worker with a VET degree has acquired slightly more cognitive (1.9) than interpersonal skills (1.6). Our results thus suggest that productivity could be increased if workers received more training in VET occupations that provide them with interpersonal skills, rather than with cognitive skills. This holds only if acquisition of interpersonal skills is similarly (or less) costly.

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 very good fit of the moments observed in the data.

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