Interpersonal, cognitive, and manual skills: How do they shape employment and wages?*

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Abstract

We study how interpersonal, cognitive, and manual skills affect employment and wages in a search and matching model through their impact on productivity, complementarity, job destruction, and the cost of unemployment. Combining several data sets on workers who acquired skills in vocational education and training (VET), we quantify each channel, allowing for unobserved heterogeneity in ability. All three skills increase productivity, yet they affect job destruction rates differentially. While manual skills are associated with lower job destruction, interpersonal and cognitive skills have the opposite effect. Focusing on low-ability workers, we then estimate the value of VET. Through VET, wages increase up to 10% and unemployment drops by over 50%. Low-ability workers thus have particularly large benefits from acquiring manual skills because they increase wages and shield from unemployment.

Keywords: Multidimensional skills, unemployment, wages, vocational education and training, labour market search.
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1 Introduction

Substantial changes in the demand for interpersonal, cognitive, and manual skills observed over recent decades (Beaudry et al., 2016; Deming, 2017; Lindenlaub, 2017; Roys and Taber, 2019) have had far-reaching consequences for workers' labour market outcomes such as wages and employment patterns. While the effect of multidimensional skills on wages, wage growth and job mobility has been extensively studied (Ingram and Neumann, 2006; Sanders and Taber, 2012; Roys and Taber, 2019; Guvenen et al., 2020; Lise and Postel-Vinay, 2020), far less is known about how different skills affect unemployment. Understanding the link between skills and unemployment as well as how it interacts with other labour market outcomes is key both for workers who decide which skills to acquire and for policy makers who design education curricula.

In this paper, we investigate how skills affect labour market outcomes through four channels: direct productivity effects (Beaudry et al., 2016; Deming, 2017), complementarity in firms' demand for different skills (Weinberger, 2014), differential risk of job destruction (Balsmeier and Woerter, 2019; Taber and Vejlin, 2020), and the cost of unemployment which can reflect different skill depreciation rates (Edin and Gustavsson, 2008; Nakajima, 2012). We distinguish between three different skill types - interpersonal, cognitive, and manual - and three different labour market outcomes - unemployment, wages, and labour market transitions.

We present a search and matching model to examine how, through these four channels, skills jointly shape workers' welfare in equilibrium. We focus on workers who acquired their skills in vocational education and training (VET). Since the VET skill content is regulated through education curricula and standardised exams, we can directly measure workers' acquired interpersonal, cognitive, and manual skills. In our set-up, workers differ in their unobserved ability and their acquired multidimensional skills. We then estimate the value of VET and the skills it confers for low-ability workers and discuss how this value arises.

We take our model to the data using the Swiss setting, where two thirds of a cohort enrol in VET. We have detailed information on labour market outcomes and skills of workers from 2004 to 2009. Our skills data comes from the Berufsinformationszentrum (BIZ), a career-counselling centre run by the Swiss government. The BIZ provides a detailed list of skills used in each of a total of 220 vocational occupations, grouping skills into three broad categories: interpersonal, cognitive, and manual. For labour market outcomes we use the SESAM survey which merges the Swiss Labour Force Survey, a representative panel, with administrative data on employment histories, unemployment benefits, and wages. We match the BIZ skills to the SESAM survey using the 5-digit occupational code of the learned occupation (i.e. the occupation in which a worker received his vocational education).

We take advantage of our rich data set to account for possible correlation between unobserved ability and occupational choice. First, we limit our analysis to workers who have obtained a VET degree as their highest education level. These workers tend to come from the intermediate and lower parts of the ability distribution, in contrast to workers who continue their education after completing VET. This restriction ensures that all workers in the sample differ primarily in their acquired skill bundles, while having limited heterogeneity in unobserved ability. Second, we control for the observed occupation-specific academic requirement index developed by Stalder (2011) which classifies occupations by high, intermediate, or low requirement. We show that this measure is a valid proxy for workers' average academic ability level on the occupational level. It enables us to disentangle the effects of *unobserved ability* by meeting academic requirements of the training occupation from the effects of *learned skills* on labour market outcomes. Variation within and across occupation clusters allows us to identify the model parameters using the Simulated Method of Moments.

Our estimation and simulation results offer the following insights. First, we find that all three skills have positive effects on productivity and wages, although to a different extent. Manual skills have the largest effect on productivity (at 1.24 Swiss francs per hour for an additional manual skill), followed by interpersonal and cognitive skills (at 1.15 and 0.59 Swiss francs per hour and skill, respectively).[1] We also estimate a substantial productivity premium in occupations with intermediate and high academic requirement levels (of 5.14 and 13.16 Swiss francs an hour, respectively). The selection role of the academic requirement helps explain the relative ranking of productivity effects of skills, which may appear surprising at first sight. Occupations with high interpersonal and cognitive skills tend to require a high academic level. Hence, large productivity (and wage) gains accrue from meeting the high academic level rather than from acquiring interpersonal and cognitive skills *per se*. Second, our simulation results reveal that skill-specific job destruction greatly affects workers' welfare through its impact on transitions into unemployment. Skill-specific job destruction also has an impact on wages, albeit a small one. This result highlights the importance of analysing different labour market outcomes jointly and using a combined measure of workers' welfare. Finally, we quantify the skill-specific cost of unemployment, which is largest for cognitive and interpersonal skills. This cost drives down reservation wages of workers with cognitive and interpersonal skills, which makes

[1]One Swiss franc corresponded to between 0.75-0.9 USD during our sample period.

them exit unemployment slightly faster.

The model set-up also allows us to shed light on the value of VET and the skills it confers. In a further analysis we focus on low-ability workers with and without a VET degree. We estimate wage returns to VET of around 4% to 10%. Workers' welfare, however, increases by 50% to 80% because of a second and far more important channel: VET benefits workers through higher job arrival and lower job destruction rates. By improving labour market transitions, VET thus decreases the unemployment rate faced by low-ability workers by one-half. In addition, VET leads to an increase in low-ability workers' reservation wages. This suggests that their low unemployment rate does not come at the cost of accepting low-paying jobs. This second analysis further pinpoints how labour market outcomes other than wages reveal crucial information about workers' welfare.

Our paper offers important insights into the multimensionality of skills. Our findings reveal that workers with low ability maximise their welfare when acquiring manual and - to a lesser extent - cognitive skills. Occupations which confer and use many manual skills pay higher wages and shield workers better from the risk of unemployment. Low-ability workers should thus select into manual-skill-intensive occupations. Workers with higher ability, however, should select into occupations which have a high academic requirement level and thus pay substantial wage premia. Only a small fraction of high-academic-requirement occupations use manual skills, while most of these occupations use cognitive and interpersonal skills. Workers with higher ability may therefore find acquiring cognitive and interpersonal skills more beneficial.

Our findings suggest that a general push towards acquiring more cognitive (or interpersonal) skills will not make all workers better off. Instead, our results speak to Roys and Taber (2019), who find that manual skills remain important for low-ability workers. When choosing which skills to acquire, workers should thus not simply focus on which skills afford highest wages, but take their own ability type into account. Similarly, policy makers who design education curricula should be well aware that firms exhibit strong heterogeneity in their demand for different types of skills and academic requirements. There remains scope for training in manual skills, in particular for workers with lower ability.

This paper ties into two strands of the literature. First, our paper relates to the growing body of research on the specificity of human capital and returns to heterogeneous skills. Recent contributions suggest that the number of years of education alone is not a sufficient measure of skill and propose alternative measures 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; Geel et al., 2011; Lise and Postel-Vinay, 2020; Rinawi and Backes-Gellner, 2021) or workers' observed initial abilities (Lindqvist and Vestman, 2011; Guvenen et al., 2020; Lise and Postel-Vinay, 2020). A general finding is that individuals move to occupations with similar skill requirements and wages are closely related to skills. Second, it contributes to our understanding of how vocational education affects 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; Dolado, 2015; 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; Adda et al., 2013; Kautz et al., 2014; Balestra and Backes-Gellner, 2017; Hanushek et al., 2017; Rinawi and Backes-Gellner, 2021).

Our paper differs from these studies in two important aspects. First, our empirical analysis of labour market outcomes uses a simple search and matching model, in which labour market outcomes are analysed as equilibrium outcomes of the demand and supply of multidimensional skills. This allows us to quantify through which channels skills impact labour market outcomes beyond wages and to provide novel evidence on how differences in unemployment rates across skills arise. Our simple model is inspired by the search and matching frameworks developed by Flinn and Mullins (2015) (FM) on workers with different schooling levels and the recent contribution by Lise and Postel-Vinay (2020) (LP) who study wage growth, skill accumulation and depreciation over the life-cycle of workers characterised by multidimensional skills. Our labour market model features almost the same transmission channels (productivity, unemployment cost and job destruction) as FM if the schooling level was replaced by our multidimensional skills vector. However, our focus and analyses are different from FM and more closely related to LP. Like LP, we focus on workers with interpersonal, cognitive, and manual skills. Our analysis also differs from LP in that we (i) abstract from life-cycle dynamics and (ii) investigate how multidimensional skills affect unemployment and labour market transitions. We include skill-specific costs of unemployment and differential job destruction as additional channels for skills to impact labour market outcomes. These additional two channels are key in explaining the large differences observed in unemployment rates and reservation wages across different occupation groups.[2]

[2] LP's multidimensional framework allows them to decompose wage growth over the life cycle and to quantify the cost of mismatch in skills, but they do not consider differences in unemployment rates and reservation wages across workers with different skills. A direct comparison - or combination - of LP's framework and our model is not possible as the data requirements to estimate each model are quite different. While LP's framework relies on a sample of long panel data to identify life-cycle dynamics, our model requires a large sample of workers with the same education level but different skills to identify skill-specific differ-

Second, we contribute to the study of labour market outcomes of VET workers.[3] We distinguish different occupations according to their level of interpersonal, cognitive, and manual skills as well as their academic requirement. This refined analysis provides new insights into the channels through which interpersonal, cognitive and manual skills affect labour market outcomes and their individual impact. We highlight that not all occupations confer the same returns in terms of wages and, more importantly, employment prospectives.

The paper proceeds as follows. Section 2 explains the institutional setting in Switzerland and describes the data. Section 3 presents empirical evidence on selection into occupations and on labour market outcomes. Section 4 introduces a simple search and matching model with heterogeneous workers. Section 5 outlines our structural estimation procedure and discusses identification. Section 6 presents the structural estimation results. Section 7 uses the estimated model and simulations to shed light on how skills affect labour market outcomes and quantifies the value of VET for low-ability workers. Section 8 concludes.

2 Institutional background and data

2.1 Institutional background

In Switzerland during the time period studied, students can follow two major pathways upon finishing compulsory education: They may either enrol in general or in vocational education. Appendix A presents a graphical illustration of the Swiss educational system. Around 25 to 30% of a cohort enrol in general education after passing an entrance exam. Students who successfully complete general education are awarded with a university entrance diploma. However, the large majority of a cohort, about 65%, enrol in vocational education and training (VET), a larger share than in any other country (Hanushek et al., 2017). VET offers great career opportunities, attracting students from all socioeconomic

ences in unemployment which only concerns a relatively small share of the overall labour force. Neither the NLSY79 nor our data set satisfy both requirements simultaneously.

[3] Adda et al. (2013) estimate a dynamic life-cycle model for skilled (i.e. workers with VET) and unskilled workers in Germany. Their focus is on differences in life-cycle dynamics (wage growth, labour mobility) between these two groups and how they differentially react to economic downturns. Saltiel (2021) develops a model of education pathways (general vs. vocational education, secondary vs. tertiary) and quantifies their returns in Switzerland. Neither paper differentiates between workers with different levels of interpersonal, cognitive, and manual skills.

and ability backgrounds, including high-ability students.

VET is a dual programme that combines formal education at a vocational school with on-the-job training at a host firm. VET programmes last three or four years. Around 20% of all VET graduates continue their formal education and complete a degree at a professional college or university. These graduates are however not the focus of our analysis.[4]

When pursuing a vocational education, a student must decide in which occupation to train and find a host firm. More than 200 occupations exist, ranging from care professionals, IT-technicians, insurance salesman to car mechanics. There are no formal academic restrictions to train in a certain occupation, but in practice not all occupations are equally demanding. Training firms thus select students based on prior academic performance and ability. Section 3.1 discusses the selection processes into occupations in more detail.

The content taught in vocational schools and firms is nationally regulated, and training quality is ensured by standardised examinations. The curricula are legally binding for all firms and schools. The apprenticeship contract has a fixed length and ends upon completion of the training period. Apprenticeship graduates have no obligation to stay with their host firms and neither have firms any responsibility for taking them on. The retention rate after graduation is only 35% (Schweri et al., 2003).

Skills acquired in VET are thus not firm-specific, but transferable across firms and occupations. The strong formalisation of the skills taught during VET ensures job and occupational mobility. Around 50% of workers in our sample still work in the same occupation as they had trained in, while among the remaining workers most had moved to an occupation which required similar skills as their training occupation.

2.2 Labour market data

Our main data source is the Swiss Social Protection and Labour Market (SESAM) survey, 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,

[4] Our data set does not contain information on which skills students acquire in tertiary education. Moreover, admission to tertiary education usually requires a special vocational diploma "Berufsmatura", which can be obtained in parallel to the VET degree, but which is more demanding. This means that VET workers with a tertiary degree usually have a high ability - which remains unobserved in our main data set - compared to workers whose highest education level is a VET degree and who mostly have a low or intermediate ability level. Appendix B provides more evidence on selection into different general and vocational educational pathways using the TREE data set.

educational, and labour market characteristics. The matched administrative data provides the duration of individual employment and unemployment spells, as well as monthly and yearly earnings, and unemployment benefits. One key variable of the survey is the learned occupation, i.e. the occupation in which an individual received vocational training.

Our observation period covers the years 2004 through 2009, for which SESAM offers consistent data.[5] Each individual remains in the SLFS panel for five years or less. During our sample period the survey was run on a yearly basis in the second quarter. We restrict our sample in the following way: First, we only keep individuals for whom we observe at least two consecutive years of data. Second, we focus on men who are between 20 and 62 years old. Third, we exclude individuals who are out of the labour force, but include part-time workers (who make up around 10% of the sample). We compute hourly wages by transforming monthly earnings into weekly earnings and dividing those by the weekly hours worked. We trim the wage distribution below the bottom 1% and above the top 1%.

In our main analysis we restrict the sample to workers with a VET degree as their highest education level. All workers have thus spent the same number of years in education. In total, our main sample consists of 5,103 workers and 13,474 person-year observations. For our analysis on the value of VET for low-ability workers, we additionally rely on a sample of 3,351 workers with compulsory education only (8,841 person-year observations).

2.3 Skills data

Our skill data comes from the career-counselling centre *Berufsinformationszentrum* (BIZ), which provides a detailed list of skills used in each VET occupation. VET students receive training in these skills and have to pass a standardised exam at the end of their training period to obtain their degree. We use the BIZ data to construct a measure of skills which are acquired during VET.[6]

The data set covers a total of 220 occupations that existed during the period we examine and identifies 24 main skills. Each skill is either classified as interpersonal (10 skills), cognitive (9 skills), or manual (5 skills). Examples include "ability to work in a team" (interpersonal), "spatial visualisation ability" (cognitive), and "fine motor skills" (manual).

[5] Switzerland was less affected by the global financial crisis than many other countries. Unemployment among VET workers dropped from 3.9% in 2004 to 2.8% in 2008, and increased to 4.1% in 2009.

[6] As informal on-the-job learning is not regulated, we do not observe the skills a worker acquires in a different occupation from the one he received training in. However, most of the occupational switching occurs within occupations which use similar skills as the ones learned during VET.

The 24 skills represent 24 dimensions of skill heterogeneity, resulting in 2^{24}, i.e., nearly 17 million potential skill combinations. 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. Depending on the occupation in which a worker is trained (i.e. his learned occupation in SESAM), the 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 painters acquire mostly manual skills (3 out of 5 skills). Appendix C provides more information on our skill measures and compares them with other measures.

Table 1 presents descriptive statistics on the acquired skills of the 5,103 male workers with a VET degree in our sample. We denominate this as the supply of skills.

Table 1: DESCRIPTIVE STATISTICS OF WORKERS' ACQUIRED SKILLS

Skill	Obs.	Mean	Std. Dev.	Correlation		
				interpersonal	cognitive	manual
interpersonal	5,103	1.81	1.71	1		
cognitive	5,103	2.14	1.27	0.330	1	
manual	5,103	1.23	0.82	-0.465	-0.262	1

Workers in our sample acquired on average 5.18 skills, of which 1.81 are interpersonal, 2.14 are cognitive and 1.23 are manual, respectively. While workers tend to acquire either many or few interpersonal skills (as indicated by the relatively large standard deviation), there is less variation in the number of cognitive and manual skills acquired. Moreover, workers specialise by either acquiring manual or non-manual (interpersonal/cognitive) skills as illustrated by the negative correlation coefficients in the right panel of Table 1. The supply of interpersonal and cognitive skills, instead, correlates positively. The two most common skill bundles - each with a share of almost 10% in the sample - are the 5 interpersonal - 3 cognitive - 0 manual skill bundle (incl. commercial clerks in retail and trade, administrative officers in travel agencies, administrative officers and commercial clerks in other service sectors), and the 1 interpersonal - 1 cognitive - 1 manual skill bundle (incl. electro-technicians, electro-technicians specialised in media, car mechanics and sanitation technicians).

3 Empirical evidence

3.1 Selection into training occupations

A priori, there are no formal academic restrictions on who can train in a certain occupation. In practice, however, not all occupations are equally demanding and training firms select students based on prior academic performance and ability. We rely on a discrete 6-level academic requirement index (ARI) developed by Stalder (2011) and based on an evaluation by career counselors to regroup all occupations into three broad groups: low requirement (ARI of 1 or 2, or unknown ARI), intermediate requirement (ARI of 3 or 4) and high requirement (ARI of 5 or 6).

We use the "Transitions from Education to Employment" longitudinal study (TREE) to present complementary evidence on selection into training occupations and acquiring skills - and how this relates to the ARI of an occupation - which is not available in our main data sets.[7] Table 2 presents the estimation results from Poisson regressions of the number of interpersonal, cognitive, and manual skills acquired by vocational students in the TREE data set on their pre-training PISA reading and math scores, and a range of self-assessed personality traits, both with (columns 2, 4 and 6) and without (columns 1, 3 and 5) controlling for the ARI.

While we do not find empirical evidence that personality traits such as persistence, ambition or locus of control predict the acquisition of interpersonal, cognitive, or manual skills in VET, academic ability does. Students with higher PISA reading scores tend to acquire significantly more cognitive (and to a lesser extent: interpersonal) skills, and significantly fewer manual skills (columns 1, 3 and 5, respectively). Students thus select into a training occupation based on their ability. However, once we control for the ARI of an occupation, neither personality traits nor PISA reading and math scores hold much additional explanatory power regarding the number of interpersonal, cognitive and manual skills a worker acquires in VET (columns 2, 4 and 6).[8] For interpersonal and manual skills, academic ability measures and personality traits are not jointly statistically significant at the 5% level after controlling for the ARI (columns 2 and 6). For cognitive skills, proxies of academic ability and personality traits are jointly statistically significant at the 1% level (column 4), but their quantitative impact on cognitive skill acquisition is only marginal. For example, a one standard deviation increase the PISA math score is predicted

[7] Appendix B describes the TREE data set in more detail.

[8] This does not preclude selection into occupations, and hence, acquiring skills, based on other factors such as preferences or local availability of apprenticeships. We expect the selection effect of these unobserved factors to be of a smaller magnitude than the effect of ability and personality traits. They are possibly even orthogonal to labour market outcomes.

Table 2: SELECTION INTO ACQUIRING SKILLS (TREE DATA)

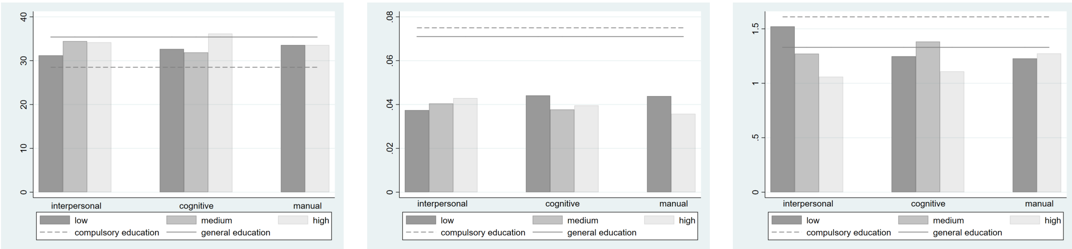
	Interpersonal		Cognitive		Manual	
	(1)	(2)	(3)	(4)	(5)	(6)
PISA math score	0.61	0.46	0.97	0.92*	-0.81	-0.65
	(0.92)	(0.87)	(0.68)	(0.52)	(0.62)	(0.52)
PISA reading score	2.01*	1.69	1.19*	0.37	-1.63**	-0.71
	(1.19)	(1.24)	(0.65)	(0.59)	(0.78)	(0.74)
Persistence	-0.29*	-0.26	0.02	0.09	0.11	0.01
	(0.17)	(0.18)	(0.11)	(0.09)	(0.10)	(0.10)
Locus of Control	-0.16	-0.19	-0.13	-0.17*	0.03	0.10
	(0.17)	(0.17)	(0.11)	(0.10)	(0.13)	(0.11)
Ambition	0.01	0.04	-0.04	-0.05	0.05	0.00
	(0.14)	(0.14)	(0.08)	(0.08)	(0.10)	(0.10)
Neuroticism	-0.04	-0.05	0.10**	0.10**	-0.04	-0.04
	(0.09)	(0.09)	(0.05)	(0.04)	(0.06)	(0.05)
Intrinsic Motivation	0.04	0.01	0.05	0.01	0.08	0.12
	(0.14)	(0.14)	(0.08)	(0.07)	(0.10)	(0.09)
Intermediate ARI		-0.10		0.54***		-0.10
		(0.23)		(0.09)		(0.09)
High ARI		0.25*		0.67***		-1.10***
		(0.15)		(0.10)		(0.18)
Constant	0.27	0.47	-0.15	-0.03	0.56	0.34
	(0.78)	(0.81)	(0.50)	(0.42)	(0.59)	(0.50)
Observations	215	215	215	215	215	215
Pseudo R-squared	0.03	0.04	0.02	0.08	0.02	0.07
Joint hyp. test	20.27***	13.46*	25.66***	19.59***	20.25***	11.45

Notes: This table shows the results of Poisson regressions on the number of interpersonal (columns (1) and (2)), cognitive (columns (3) and (4)), and manual skills (columns (5) and (6)) acquired in VET using the TREE data set. Each regression controls for PISA reading and math scores, a range of self-assessed personality traits, and a dummy variable for the academic requirement index of the training occupation (low, intermediate, high ARI). PISA scores are measured on a continuous scale from 0 to 1. Personality traits are measured on a continuous scale from 1 (very atypical) to 4 (very typical). Low ARI is the baseline. Robust standard errors in parentheses. The line "Joint hyp. test" shows the Chi-squared test statistic from a joint significance test on PISA math and reading scores, and all personality-related coefficients. *** p<0.01, ** p<0.05, * p<0.1

to increase the number of cognitive skills acquired by 0.08 skills, that is, less than a 4% increase compared to the average cognitive skill level.[9] Therefore, controlling for the ARI of the occupation in which a student trains allows us to disentangle reasonably well the effects of different *skills acquired* during VET on labour market outcomes from the effect of a worker's *ability*.

3.2 Labour market outcomes

Figure 1 depicts some descriptive statistics on labour market outcomes by the level of interpersonal, cognitive, and manual skills of VET workers (bars). The same statistics are presented for workers with completed compulsory education (i.e. nine years of schooling, dashed line) and workers with general education with 12 or 13 years of education (black line).



(a) Mean wages (b) Unemployment rate (c) Unemployment duration

Figure 1: Labour market outcomes by interpersonal, cognitive, and manual skills of VET workers

Notes: Compulsory education (9 years of education), VET (12 or 13 years) and general education (12 or 13 years). The different skill dimensions are not exclusive. For example, a worker with high interpersonal, high cognitive and low manual skills appears in each of the three skill dimensions. Wages and unemployment status are measured at a worker's first observed data point. Unemployment duration is measured at the last observed data point of every unemployment spell or when the worker exits the panel (whichever happens first).

With 33.6 Swiss francs per hour, VET workers earn on average higher wages than workers with only compulsory education (28.5 CHF), but lower wages than those with general education (35.4 CHF). Moreover, VET workers are unemployed at a rate of 4.1%. This is substantially lower than both the unemployment rate of workers with compulsory (7.5%) and with general education (7.1%).

Different VET workers acquired very different skill bundles. These skills are an important determinant of labour market outcomes. For example, higher interpersonal skills

[9] Whether the omission of academic ability and personality traits beyond the ARI leads to a potential upward- or downward bias in the estimated effect of cognitive skills on labour market outcomes is unclear and depends on the direct effect of these omitted variables on labour market outcomes. Given the small size of the effect on cognitive skill acquisition, the bias is likely to be very small.

are associated with higher wages, but also with a higher unemployment rate and shorter average unemployment duration. Having many manual skills, in contrast, is not associated with higher wages but lowers the unemployment rate while making the average unemployment spell slightly longer. One obvious concern is that workers may have selected into occupations for reasons correlated with subsequent labour market outcomes: For example, if occupations with many manual skills require lower levels of ability and offer lower wages, workers with lower (unobserved) ability select into these occupations. It is therefore not clear how much of the difference in labour market outcomes between occupations with different skill profiles can be attributed to the skills themselves and how much to selection based on unobserved ability. To alleviate these concerns we use the academic requirement index of occupations (ARI) to control for workers' average ability level on the occupational level. Table 3 presents reduced form regressions of (log) hourly wages and unemployment of VET workers on interpersonal, cognitive, and manual skills, a measure of the academic requirement level of the learned occupation (low, intermediate, and high ARI[10]), and a range of other control variables. Results in columns 1 to 3 relate to log hourly wages, results in columns 4 and 5 refer to a linear probability model of unemployment.

All three skills have positive returns to hourly wages across all specifications. Comparing specifications (1) with (2) and (3) reveals that controlling for selection into occupations based on ability (using the ARI measure as a control variable) is important for wages. In our preferred specification (3), occupations with an intermediate ARI pay on average 11.5% higher wages, and occupations with a high ARI pay 25.3% more compared to occupations with a low ARI (i.e. the baseline). Moreover, returns to cognitive skills decrease once we control for ARI. This suggests high returns to wage by *meeting* the intermediate or high *academic requirement level* and hence, being able to train in a high-cognitive-skill occupation rather than by *acquiring* cognitive skills. An additional interpersonal skill increases hourly wages by 4.8% (when abstracting from interaction effects), while the effect is 2.1% for a cognitive and 6.3% for a manual skill, respectively. The average skill bundle with 1.81 interpersonal, 2.14 cognitive and 1.23 manual skills thus increases wages by 9.2% compared to no skills. Overall, specification (3) explains 29.2% of the variation in log wages, while the same specification without controlling for skills would only explain 27.9% (not shown in table).

In terms of unemployment, there are also some differences across skills. In particular,

[10]The academic requirement level is not observed for all occupations in our sample. Hence, we compute an aggregate measure at the occupation cluster level (16 clusters). This measure indicates the share of workers with low, intermediate and high ARI in each occupation cluster and thereby controls for the average unobserved ability.

Table 3: REDUCED-FORM LABOUR MARKET ESTIMATES FOR VET WORKERS.

	Log hourly wages			Unemployment	
VARIABLES	(1)	(2)	(3)	(4)	(5)
Interpersonal skills	0.053***	0.045***	0.048***	0.003***	0.003**
	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)
Cognitive skills	0.063***	0.027***	0.021***	-0.001	-0.003
	(0.006)	(0.008)	(0.008)	(0.001)	(0.002)
Manual skills	0.055***	0.082***	0.063***	-0.002	-0.001
	(0.009)	(0.010)	(0.009)	(0.002)	(0.002)
Interpersonal*cognitive	-0.012***	-0.010***	-0.012***		
	(0.001)	(0.001)	(0.001)		
Interpersonal*manual	-0.012***	-0.022***	-0.020***		
	(0.002)	(0.002)	(0.002)		
Cognitive*manual	-0.021***	-0.018***	-0.010**		
	(0.003)	(0.004)	(0.004)		
Age	0.051***	0.052***	0.044***	-0.004***	-0.004***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Age squared	-0.000***	-0.001***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intermediate ARI		0.147***	0.115***		-0.004
		(0.010)	(0.009)		(0.005)
High ARI		0.261***	0.253***		0.013
		(0.024)	(0.022)		(0.012)
Swiss			0.073***		
			(0.005)		
Married			0.075***		
			(0.006)		
Constant	2.149***	2.076***	2.181***	0.124***	0.125***
	(0.038)	(0.038)	(0.061)	(0.024)	(0.024)
Observations	12,059	12,059	11,845	13,474	13,474
R-squared	0.184	0.209	0.292	0.003	0.003
Dummies	No	No	Yes	No	No

Notes: Columns (1) to (3) have log hourly wages as the dependent variable and show least-squares estimates. Columns (4) and (5) have a dummy indicator for unemployment as the dependent variable and show estimates from a linear probability model. Skills are measured in absolute numbers: Interpersonal (0 to 10), cognitive (0 to 9) and manual (0 to 5). Intermediate ARI stands for the share of occupations within the same occupation cluster as the individual worker which have an intermediate academic requirement level. High ARI is the share with a high academic requirement level. Low ARI is the baseline. Dummies include year, region and firm size. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

workers trained in an occupation with many interpersonal skills tend to have significantly higher unemployment rates than those with fewer interpersonal skills. Workers in occupations with different ARIs all have a similar likelihood of unemployment, *ceteris paribus*. Our linear probability model in regression (5) explains 0.3% of variation in individual unemployment status, while the same specification without controlling for skills would only explain 0.2% (not shown in table). Skills thus explain some variation in log-wages and unemployment above and beyond what is captured by the ARI.

4 A simple matching model with multidimensional skills

To study the role of multidimensional skills and academic requirement levels in labour market outcomes, we present a simple general equilibrium search and matching model in the spirit of Pissarides-Mortensen-Diamond (Pissarides, 2000). Workers are heterogeneous. They are characterised by a set of observable multidimensional skills and an unobserved (one-dimensional) ability level. Firms use these skills in different combinations to produce an output. They also demand a certain academic requirement index (ARI). Jobs requiring a higher ARI, ceteris paribus, produce a higher 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 model are the multidimensional skill supply by workers and the multidimensional skill demand by firms. Workers are heterogeneous in their unobserved (to the econometrician, not the firm) ability type τ and have acquired different skills during VET $\tilde{x}$. Workers' acquired skills (observed) are allowed to be correlated with their unobserved ability type. Hence, each worker possesses a time-invariant and multidimensional skill-ability type bundle denoted by $x = (\tilde{x}, \tau)$. Each element of $\tilde{x}$ is non-negative and τ is composed of three discrete types (low, medium, high). Firms differ in their demand for skills, but they all value ability (that is, meeting a required academic level) in the same way. Their demand for a specific skill-ability bundle is denoted by skill weights α.

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

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

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 it is required to pay. Whenever a firm and a worker meet, the potential productivity of this match is assumed to be $p = \alpha' x$ (following Lazear, 2009; Flinn and Mullins, 2015). α is a skill weighting vector which is independently and identically distributed according to the multivariate distribution function $G(\alpha)$. The different components of α can be correlated (i.e. firms might be more likely to highly value some skill combinations compared to others), and each individual component of α is restricted to be non-negative. This implies that there are no (direct) costs for the firm when hiring a worker who has skills which are not needed by the firm. A filled job gets destroyed at rate $\eta(x)$. We assume that there is only exogenous vacancy creation.[11] The value of a filled job between a worker with skill-ability bundle x and a firm with skill weights α which pays wage w is given by:

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

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

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

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 weights $\alpha^*(x)$. It is the set of acceptable weighting vectors for which a worker with unobserved type and skills x is indifferent between employment and unemployment. It pins down the reservation wage $w^*(x)$:

[11] It is straightforward to extend the model to endogenous vacancy creation. Under the common free entry condition, the value of an unfilled vacancy is equal to 0 and the value of a filled job is the same as in our setting. However, in our data there are few unemployment-employment transitions observed. Our observed UE moments are imprecisely estimated and the model cannot match them well. We would not be able to identify differential job creation across skills.

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

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

$$h(x) = \lambda \int_{(\alpha(x)-\alpha^*(x))'x \geq 0} dG(\alpha). \quad (8)$$

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

$$[1-u(x)]\,\eta(x) = u(x)h(x) \quad (9)$$
$$u(x) = \frac{\eta(x)}{\eta(x)+h(x)}. \quad (10)$$

Differences in unemployment rates across skill-ability bundles x can thus be driven by differences in the rate of accepting job offers or by differences in job destruction rates. Using year-to-year transitions from unemployment to employment and vice versa across occupation clusters, we find that job separation rates (i.e. flows into unemployment) differ across occupation groups, while job finding rates are relatively similar (and not precisely measured).[12] This evidence points towards differential job destruction rates being key in explaining differences in unemployment rates.[13]

Despite its simplicity, the model has several appealing features. It allows us to jointly model (un-)employment and wages, which differ across acquired skills and also account for selection into acquiring certain skill bundles by ability types. The three key elements of the model are the demand for skills and value of ability types by firms $G(\alpha)$, the flow cost of unemployment for different skill bundles by the worker $b(x)$ and the differential destruction rates $\eta(x)$. The firm's skill demand $G(\alpha)$ and the worker's unemployment flow cost $b(x)$ together determine the set of reservation weights $\alpha^*(x)$ for which the worker and firm are indifferent between forming a match or not. The reservation weight impacts the arrival rate of acceptable job offers and hence, transition out of unemployment

[12]See the EU and UE rates from Table F.2 in the Appendix.

[13]Similar evidence is presented by Cairo and Cajner (2017) with regards to differences in unemployment rates by education levels in the US.

(see Equation (8)). They also affect wages through the reservation wage (see Equations (5) and (7)). The differential job destruction rates $\eta(x)$, on the other hand, affect transition into unemployment and wages through a change in the value of employment for the worker (see Equation (2)) and the value of a filled job for the firm (see Equation (3)).

5 Structural estimation

5.1 Parametric assumptions and functional forms

In this section we describe how we take the model to the data. First, we presume the labour market to be in steady state. Second, we make some parametric assumptions about the skill demand distribution $G(\alpha)$, the structure of the flow cost of unemployment $b(x)$ and job destruction $\eta(x)$. More specifically, we assume that the productivity of the match is given by the following equation:

$$\begin{aligned} p &= \alpha' x = \alpha_0 + \alpha_I x_I + \alpha_C x_C + \alpha_M x_M \\ &+ \alpha_{\tau_m} \mathbf{1}(\tau \geq ARI = m) + \alpha_{\tau_h} \mathbf{1}(\tau \geq ARI = h), \end{aligned} \tag{11}$$

where α_0 is a general productivity shock, α_I, α_C and α_M are the demand (or weights) for interpersonal, cognitive, and manual skills, respectively, and α_{τ_m} and α_{τ_h} are the productivity premiums of meeting the medium and high academic requirement level (compared to baseline requirement)[14], 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}. A positive correlation coefficient reflects a complementarity in the demand for two skills, a negative correlation coefficients reflects that firms prefer workers specialising either in one or the other skill. The ability type of a worker τ (i.e. low, medium or high) is known to the worker and firm, but not observed by the econometrician. A medium-ability worker increases productivity by a constant α_{τ_m}, a high-ability worker by a constant α_{τ_h}.

[14] This assumes that workers receive the premium for meeting the academic requirement level, not directly for their ability level. Workers with an ability below the required level are not hired. Workers with an ability level above the required level can be hired but only receive the premium for the required level.

This parametrisation of the productivity is parsimonious and flexible at the same time. It imposes worker-job complementarity, i.e. productivity is highest if the worker supplies the skills which are in high demand by the firm (see Lindenlaub (2017) for supporting empirical evidence of this assumption). This specific parametrisation allows for different means and variation in returns to each skill. Moreover, the Gaussian copula renders it possible for the demand of 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. To capture selection into skill acquisition, we allow for correlation between workers' ability τ and learned interpersonal, cognitive, and manual skills $\tilde{x}$ by using information on the observed correlation between the academic requirement level (ARI) of an occupation and its skills.

For 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, and b_j the marginal cost (or value) of unemployment of skill j. If b_j is negative, having more skills j makes being unemployed more costly (for example, because of skill depreciation which we do not model explicitly), while the opposite is true if b_j is positive.

Lastly, we impose the following linear structure on exogenous job destruction $\eta(x)$:

$$\eta(x) \quad = \quad \eta_0 + \eta_I x_I + \eta_C x_C + \eta_M x_M, \tag{13}$$

where η_0 is the baseline exogenous job destruction rate for someone without any skills, and η_j is the marginal effect of skill j on job destruction. If η_j is positive (negative), having more skills j increases (decreases) the rate of exogenous job destruction. This simple linear structure is motivated by the reduced form analysis presented in Table 3, which shows that some skills are associated with higher unemployment rates, while others are associated with slightly lower rates.

5.2 Estimation method and identification

We estimate the model using the Method of Simulated Moments (MSM) as in Flinn and Mullins (2015). We regroup workers into occupation clusters based on the skills they acquired in VET to increase the number of workers per cluster. To do this, we first divide each of the three skills 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. This leaves us with 16 occupation clusters, which are numbered from 3 to 18.

Our data set has two distinct key features which simplify identification substantially. First, we directly observe in which occupation a worker completed his education. Therefore, we know a worker's (learned) interpersonal, cognitive, and manual skills x_I, x_C and x_M, which we summarise as $\tilde{x}$. These skills are assumed to remain constant over time. Second, we use information on the academic requirement level (ARI) for each VET occupation. The observed shares of ARI in each occupation cluster (see Table D.1 in Appendix D) are used to calibrate the distribution of the (unobserved) ability types τ (low, medium, high).[15] Note that the ARI of an occupation is correlated with the skills it confers (i.e. occupations with many interpersonal/cognitive skills tend to have a higher average ARI than those with many manual skills).

Table E.1 in Appendix E gives an overview of all parameters of the model and the moments used for their identification. There are 24 parameters in total, but two parameters are calibrated outside the model. The remaining 22 parameters are identified through moments from the data using variation across and within occupation clusters.

We achieve identification of most model parameters by exploiting differences in mean hourly wages, the standard deviation of hourly wages, the first percentile of hourly wages, unemployment rates, and unemployment-employment (UE) and employment-unemployment (EU) transition rates across occupation clusters. Occupation clusters not only vary in terms of interpersonal, cognitive, and manual skills, but also by the shares of each ability type and the age composition. In spite of a relatively strong correlation between the share of intermediate/high ability types and the number of cognitive skills in an occupation, there is enough variation across the occupation clusters to identify these two sources separately. To account for differences in the age structure and differential returns to experience across occupation groups (which our model without on-the-job-search cannot generate), we produce age-adjusted wage distributions (normalised to age 40) and unemployment rates by regressing wages/unemployment on age and age squared and then keeping only the residual variation in the outcomes. Differences between age-adjusted and non-adjusted moments remain small, but we stick to the former.

We use the first percentile of hourly wages in each occupation cluster to identify the reservation wages $w^*(x)$. Together with the productivity-related parameters (see below),

[15] This assumes that workers with high (medium) ability select into occupations with a high (medium) ARI. We return to this assumption and its implication in Section 7.3.

they allow us to identify the common and skill-specific costs of unemployment. These are another 16 moments.

Given reservation wages $w^*(x)$, the calibrated value of the labour share β and using the parametric assumptions about the match productivity $p = \alpha' x$ in Equation (11), the productivity distribution matches one-to-one into the wage distribution given in Equation (5). Differences in mean and standard deviation of hourly wages across occupation clusters allow us to pin down the 13 parameters of the match productivity (i.e. the demand for each skill, the correlation of these skills, the general productivity and ARI-specific productivity premiums). Mean hourly wages and the standard deviation of hourly wages make up 32 moments.

To identify the job arrival rate λ and the parameters of the job destruction rate, we rely on year-to-year unemployment-to-employment (UE) transitions, employment-to-unemployment (EU) transitions and unemployment rates by occupation clusters. In particular, differences in EU-transitions across occupation clusters provide identification for the general and skill-specific job destruction rates (i.e. η_0, η_I, η_C, η_M). Since we assume constant (i.e. skill-independent) job arrival and a parsimonious linear job destruction rate structure, it would suffice to use overall UE-transition and few EU-transition rates instead of all 32 moments. However, these additional moments also help us to pin down the reservation weights $\alpha^*(x)$ (and hence, reservation wages) and the parameters of the match productivity distribution $G(\alpha)$. In total, we have 48 moments related to unemployment and 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 the workers' bargaining power β to 0.67.[16] Finally, we fix the interest rate r at 5%.

Combining all this, we set up the following MSM estimator

$$\hat{\omega}_{N,W_N} = \arg\min_{\omega \in \Omega} \left(M_N - \tilde{M}(\omega) \right)' W_N \left(M_N - \tilde{M}(\omega) \right), \tag{14}$$

where ω is a parameter vector and Ω is the parameter space.

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

The parameter vector contains the general productivity location parameter μ_0 and scale parameter σ_0 (2 parameters), the skill-demand location μ_j and scale parameters σ_j (6 parameters), the correlation of skill-demands ρ_{ij} (3 parameters), the productivity premiums related to ARI α_{τ_m} and α_{τ_h} (2 parameters), the common and skill-specific flow costs of unemployment b_0, b_j (4 parameters), as well as the offer arrival rate λ (1 parameter), the common job destruction rate η_0 and skill-specific destruction rates η_j (4 parameters).[17]

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 deviation and the first percentile of hourly wages are bootstrapped using 1,000 replications.

5.3 Simulation procedure

To perform our estimation using MSM as in Equation (14), we need to compute the simulated counterpart of the observed moments described in Table E.1. Our target moments include the mean, standard deviation and first percentile of hourly wages by occupation cluster, the unemployment rate by occupation cluster, and the cluster-specific EU- and UE-transition rates. To do so, we assume the labour market to be in steady state. We then produce a simulated data set with 20 replicas of each worker in our observed data set (i.e. there are $20 * 5,103 = 102,060$ simulated workers). These simulated workers have approximately the same skill distribution $\tilde{x}$ as the observed sample. Moreover, we use the shares of ARI by occupation cluster as given in Appendix D to determine the conditional distribution of ability types by occupation cluster $F(\tau|\tilde{x})$. For each worker we simulate five consecutive labour market spells (i.e. employment and unemployment spells), the same (maximum) number of spells as in our observed data set. Our simulation protocol consists of the following steps:

1. For each worker in the simulated data set, we first determine his skill-ability bundle x. We keep the skill-ability bundle constant across all iterations and spells.
2. At the beginning of each new iteration, we first compute the reservation wage for each skill-ability bundle x. To do this, we find the fixed point of Equation (1) for each x.[18]

[17] We restrict the parameter space of the correlation coefficients to ensure symmetric positive semi-definite correlation matrix results. Moreover, skill-bundle-specific destruction rates $\eta(x)$ must be non-negative for all observed x.

[18] 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

3. Once the reservation wage $w^*(x)$ is known, we 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 with a resulting wage equal or above the reservation wage, there is a share $\kappa(x)$ who is unemployed in the first spell.[19] 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 $\eta(x)$. 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 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.

6 Results

6.1 Estimated parameters

Table 4 presents the point estimates and asymptotic standard errors of the model parameters. To facilitate the interpretation, we calculate the mean and standard deviation of the untruncated general productivity and skill demand distributions in the upper panel (in columns 4 and 5) in Swiss francs (CHF).

surplus and 0) by drawing 50 productivity shocks α and computing the average sample maximum of the employment surplus and 0.

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

Table 4: ESTIMATED PARAMETERS

	Estimation		Interpretation (in CHF)	
	Parameter	Std. Err.	Mean	Std. Dev
Productivity and premiums				
μ_0: General productivity (location)	3.58	0.02	37.61	12.34
σ_0: General productivity (scale)	0.32	0.01		
μ_I: Location of interpersonal skills	-0.33	0.34	1.15	1.45
σ_I: Scale of interpersonal skills	0.97	0.15		
μ_C: Location of cognitive skills	-0.94	1.43	0.59	0.67
σ_C: Scale of cognitive skills	0.91	0.62		
μ_M: Location of manual skills	-0.08	0.44	1.24	1.12
σ_M: Scale of manual skills	0.77	0.37		
ρ_{IC}: Interpersonal-cognitive correlation	0.95	0.14		
ρ_{IM}: Interpersonal-manual correlation	0.16	0.21		
ρ_{CM}: Cognitive-manual correlation	-0.02	0.06		
τ_{IM}: Premium of intermediate ARI	5.14	0.29		
τ_H: Premium of high ARI	13.16	0.74		
Offer and destruction rates				
λ: Offer arrival rate	0.99	0.03		
$\eta_0 * 100$: General destruction rate	2.43	0.10		
$\eta_I * 100$: Interpersonal-specific destruction rate	0.56	0.06		
$\eta_C * 100$: Cognitive-specific destruction rate	0.15	0.05		
$\eta_M * 100$: Manual-specific destruction rate	-0.17	0.05		
Unemployment cost				
b_0: General unemployment cost	-176.91	17.95		
b_I: Marginal cost of interpersonal skills	-11.05	5.83		
b_C: Marginal cost of cognitive skills	-15.06	13.68		
b_M: Marginal cost of manual skills	-0.77	3.77		
Loss function value at minimum	786.83			

Notes: The general productivity and skill demands follow a log-normal distribution. The mean of each distribution is given by $\exp(\mu + \sigma^2/2)$ and the variance by $\left[exp(\sigma^2) - 1\right] exp(2\mu + \sigma^2)$. Intermediate (high) ARI stands for occupations with an intermediate (high) academic requirement index. Low ARI is the baseline. The unemployment costs together with the productivity parameters and offer arrival rate determine the skill-ability-type-specific reservation wage. b_I corresponds to a -19% change in the average reservation wage with the mean value of interpersonal, cognitive, and manual skills. b_C and b_M correspond to -23% and -1% changes in the average reservation wage, respectively. Asymptotic standard errors are computed following French and Jones (2011).

The log-normal general productivity distribution has a mean of 37.61 CHF and a standard deviation of 12.34 CHF. The general productivity α_0 captures all variation in productivity which goes beyond differences in the academic requirement index (ARI), and differences in the demand and supply of skills. Jobs in occupations requiring an intermediate ARI have a productivity premium of 5.14 CHF. Occupations with a high ARI give rise to a premium of 13.16 CHF. These correspond to a 14% and 35% increase, respectively, over the mean baseline productivity.

The mean productivity for manual skills is highest at 1.24 CHF, followed by interpersonal (mean of 1.15 CHF) and cognitive skills (mean of 0.59 CHF). Despite a similar mean productivity, the demand for interpersonal skills is more dispersed than for manual skills.[20] Some firms demand high interpersonal skills and remunerate them accordingly, while others do not need and remunerate interpersonal skills. The relatively low estimated productivity associated with cognitive skills compared to the other two skills is in line with some preliminary evidence from Roys and Taber (2019)[21], while seemingly at odds with other estimates for the US (Lise and Postel-Vinay (2020)). One key explanatory factor behind our result is selection into occupations based on ARI (see Section 3.1). VET occupations which provide training in and use cognitive skills tend to require a high ARI. Therefore, VET workers reap high returns to meeting the intermediate or high ARI and hence, being able to train in an occupation with high cognitive skills, rather than from acquiring cognitive skills *directly*. Our estimates also reveal a strong complementarity in the demand for interpersonal and cognitive skills (correlation coefficient of 0.95). Firms with a high demand for interpersonal skills tend to also have a high demand for cognitive skills. This finding corroborates similar results reported for the US as in Lise and Postel-Vinay (2020) and Deming (2017).

In terms of job offer and destruction dynamics, we estimate that unemployed workers receive on average approximately one job offer within a year.[22] The baseline destruction

[20] For example, the productivity of an additional unit of skill at the top 5% of the distribution amounts to 3.56 CHF per hour for interpersonal, 1.75 CHF for cognitive and 3.28 CHF for manual skills, respectively. At the bottom 5% of the distribution, the marginal productivity is less than 0.30 CHF for each skill (i.e. 0.14 CHF for interpersonal, 0.09 CHF for cognitive, and 0.26 CHF for manual skills). The dispersion in skill-specific productivity generates considerable wage dispersion within each occupation cluster.

[21] Roys and Taber (2019) find preliminary evidence that manual skills offer the largest skill premium when compared with interpersonal and cognitive skills.

[22] The job arrival and job destruction rates could be underestimated compared to the data, possibly because we only have data on year-to-year labour market transitions and abstract from on-the-job search. In the data, around 1.6% of employed workers involuntarily change jobs within a year (due to layoff or a fixed-term contract ending), while the model only generates 1.2% of EUE transitions over a year. Hence, our model underpredicts worker reallocation by a quarter.

rate of jobs (i.e. without any skills) amounts to 2.4%, but it increases for each additional interpersonal and cognitive skill (by 0.56 pp and 0.15 pp, respectively), and it decreases for manual skills (by -0.17 pp per manual skill).[23] These skill-specific differences in job destruction are all statistically significant and consistent with our empirical evidence on differences in EU-transition rates (as an indicator for job separation) for workers differing in their interpersonal, cognitive, and manual skills.[24]

Finally, our estimates indicate that the cost of being unemployed increases with all three skills, possibly reflecting the cost of skill depreciation while unemployed. While the marginal cost of unemployment is small for manual skills (translating to a -1% change in the average reservation wage), it is large for interpersonal and cognitive skills (-19% and -23%, respectively). Hence, a worker with high interpersonal or cognitive skills finds being unemployed more costly and would therefore accept a lower wage to leave unemployment, *ceteris paribus*, than a worker with high manual skills. While the unemployment cost associated with interpersonal skills is statistically significant, the corresponding costs associated with cognitive, and manual skills are not.

6.2 Goodness of fit

Generally, our model replicates the main moments related to hourly wages well. It also reproduces the labour market status moments both overall (not directly targeted) and by occupation cluster (targeted). The model only slightly underpredicts the overall mean hourly wage at 36.23 CHF (36.52 CHF observed) and produces a marginally lower overall unemployment rate at 3.38% (3.49% in the data). This follows from the model slightly overpredicting the overall job-finding rate (63.4% simulated compared to 61% observed), while matching the overall job destruction rate (2.18% simulated, 2.21% observed). One dimension, in which the model fails to match the data, is the lowest percentile of hourly wages. The model generates a lowest percentile of hourly wages of 18.94 CHF, yet we observe 12.93 CHF in the data. Note that the first percentile and UE transition moments are imprecisely measured in the data, and therefore, they only receive a low weight in the estimation and are not always well matched by the model.

[23] Roys and Taber (2019) report similar preliminary evidence for the US where workers with many manual skills have higher employment rates than workers with many cognitive and interpersonal skills. Balsmeier and Woerter (2019) argue that a changing demand for skills - for example, as a result of digitalisation - can lead to differential destruction of jobs with heterogenous skills requirements.

[24] Reduced-form regressions of individual EU transitions among employed workers on interpersonal, cognitive, and manual skills reveal that more interpersonal skills are associated with significantly higher EU transitions, while more manual skills have lower (albeit not significantly) EU-transition rates. These regression results are available upon request.

The estimated model also fits the targeted moments by occupation cluster reasonably well, as displayed in Tables F.1 and F.2 in Appendix F. In particular, the model generates a similar ranking of occupation clusters for the moments on hourly wages, the unemployment rate, and the transition rate into unemployment.[25] This can be measured by the correlation coefficient between simulated and observed cluster-specific moments. It is 0.86 for mean wages, 0.72 for the standard deviations of wages, and 0.61 for the lowest wage percentiles. For example, our model reproduces reasonably well the *skill-specific pattern* in the lowest wage percentile (as indicated by the 0.61 correlation), even if the overall *level* of the first wage percentile is too high. The model also matches reasonably well the within-cluster variation of wages (i.e. standard deviation in hourly wages within occupation clusters) and the pattern across clusters, but somewhat overpredicts overall wage dispersion as given by the (non-targeted) standard deviation in the overall wage distribution. Unemployment and employment-unemployment (EU) rates present a similar case: While generating a similar *skill-specific pattern* as in the data (correlation of 0.64), our parsimonious model fails to produce the same range of unemployment and EU rates as observed in the data. Our estimated model (loss function of 786.83 computed from eq. 14) improves greatly over an estimated model allowing only for different ARI across occupation clusters but excluding any skill-specific parameters (loss function of 1,029.82, detailed results available upon request). While such a latter model could produce similar differences in mean wages across occupation clusters (due to different ARI) as indicated by the between cluster correlation of hourly mean wages, it fails to produce any differences in unemployment rates, and fits much worse the EU rate differences and within-occupation cluster wage variation as captured by the standard deviation.

Moreover, the estimated model not only explains well the cluster-specific means and standard deviations of hourly wages, but it also does a decent job at matching cluster-specific wage distributions (not targeted) as shown in Figure F.1 in the Appendix. The good fit in 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 occupation cluster for which our model does not perform well. The occupation cluster with high interpersonal, low manual and cognitive skills (i.e. line 4 in Tables F.1 and F.2) counts relatively few observations (and hence, receives less weight for matching the observed moments) 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

[25] Regarding UE transition rates our model generates a different pattern from the observed data. Given the small number of observations per cluster and hence, the low weight attributed to these moments, this cannot come as a surprise.

to replicate these numbers. It overpredicts the mean and the standard deviation of hourly wages (by 4 and almost 3 CHF, respectively), and underpredicts the unemployment and job destruction rate (each by approximately 3 pp).

7 The value of VET and skills

7.1 Channels of how skills affect labour market outcomes

Skills impact workers' labour market outcomes through different channels. They directly affect productivity and indirectly work through complementarity, the (flow) cost of unemployment, and differential risk of job destruction. Each of these four channels modifies the worker's value of being employed and unemployed through its effects on wages, reservation wages, and unemployment rates. Similar to Flinn and Mullins (2015), we define workers' overall welfare as a weighted sum of worker welfare for a given distribution of skills and ability types x:

$$W = \sum_{x} Prob(x) \left[rV_u(x)u(x) + (1 - u(x)) \int_{w^*(x)}^{\infty} rV_E(w, x)\, dF(w|E, x) \right], \qquad (15)$$

where the expression W equals the population expectation of unemployed and employed workers' welfare, $rV_u(x)$ is the value of being unemployed, and $rV_E(w, x)$ is the value of employment at wage w, $u(x)$ is the probability of being unemployed given characteristics x, and $Prob(x)$ is the share of workers with characteristics x observed in the sample. We investigate the contribution of each channel by simulating how workers' overall welfare W, the average value of unemployment and employment, as well as moments on wages and labour market status change as a result of eliminating a particular transmission channel.[26] We present the results of these simulations in Table 5. Column 2 corresponds to the estimated model as given in Section 6, denoted as baseline scenario. The four channels studied are the role of complementarity in the demand for skills (1), the productivity of skills (2), the skill-specific unemployment cost (3), and the skill-specific job destruction rate (4). The "uncorrected" column presents the quantitative impact of skills through each channel on workers' welfare, and its different components. The "at

[26]Moments on hourly wages and labour market status are computed from the estimated/simulated model. The value of unemployment and employment is calculated for each worker in the model sample using the estimated/simulated parameters and re-arranged equations 1 and 2. Overall welfare is calculated as the average welfare across all employed and unemployed workers in the model sample as shown in equation 15.

mean" column simulation provides an estimate on the distributional effect of each channel with the mean productivity/unemployment cost or job destruction being kept constant.

Table 5 shows that overall workers' welfare strongly depends upon skill-specific job destruction (4) and productivity of skills (2), and - to a slightly lesser extent - through skill-specific unemployment costs (3) (with a 19%, -12.9% and 6.7% impact shown in the "uncorrected" column, respectively). While all three channels are important, they work through different mechanisms. First, skills substantially increase productivity and, as such, increase the surplus of worker-job matches, resulting in higher wages. As reservation wages also react to this channel, skill-specific productivity changes leave labour market status and transitions largely unaffected. Second, skill-specific job destruction, in contrast, directly affects transitions into unemployment. Overall unemployment is lower when skill-specific job destruction is absent, increasing the value of employment and unemployment as both wages and reservation wages increase. Third, the skill-specific unemployment costs are important determinants for the reservation wages, particularly so for cognitive and interpersonal skills. Once these costs are eliminated, being unemployed becomes less costly for workers. This translates into substantially increased reservation wages and somewhat higher wages, while again leaving labour market transitions mostly unaffected. Finally, we also find that complementarity in the demand for skills plays a marginal role for wages and labour market transitions.

The "at mean" columns inform about the effect of each channel on overall wage dispersion beyond shifting the mean as described before. Our results show that in absence of any of the three channels the resulting wage dispersion (as measured by the standard deviation in hourly wages) would be higher, not lower. The specific correlation between the skills and the ARI of occupations partially explains this finding. Occupation clusters with a large share of medium and high ARI tend to provide skills which provide lower returns to wages, and vice versa. This leads to a dampening of overall wage dispersion. We return to this point in Section 7.3.

7.2 The complex effects of interpersonal, cognitive, and manual skills

We now turn to quantifying the value of interpersonal, cognitive and manual skills acquired in VET. We do so by eliminating each one of the four channels first separately and then jointly for each of the three skills. We thus run $(4 + 1) * 3 = 15$ simulation scenarios in total. For each scenario, we compute simulated welfare and its three components: the unemployment rate, the value of employment and unemployment.

Figure 2 shows the percentage changes in welfare (Subfigure a)) and its components

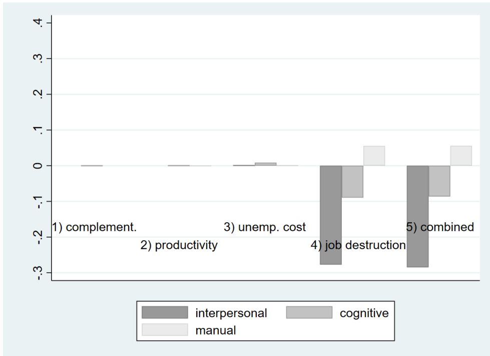
Table 5: CHANNELS OF HOW SKILLS AFFECT WAGES, UNEMPLOYMENT AND WELFARE

	Estimation	Simulations								
	baseline	(1) Complementarity	(2) Productivity		(3) Unemployment cost		(4) Job destruction		(1) to (4) combined	
		Uncorrected	Uncorrected	At mean	Uncorrected	At mean	Uncorrected	At mean	Uncorrected	At mean
Mean hourly wage	36.2	36.2	31.6	36.3	38.4	36.3	37.6	36.3	34.8	36.4
Std dev hourly wage	11.9	11.8	10.8	12.1	12.4	12.2	11.7	12.2	10.8	12.4
1% lowest wage	18.9	19.2	15.3	18.4	20.9	18.6	19.9	18.6	18.4	18.0
Avg. unempl. rate	3.4%	3.4%	3.4%	3.4%	3.4%	3.4%	2.3%	3.4%	2.4%	3.4%
EU rate	2.2%	2.2%	2.2%	2.2%	2.2%	2.2%	1.6%	2.2%	1.6%	2.2%
UE rate	63.4%	63.4%	63.2%	63.8%	63.4%	63.2%	64.0%	63.0%	63.8%	63.1%
Avg. value of unemployment	13.8	13.8	9.1	13.5	21.4	15.1	18.9	15.2	19.7	15.1
Avg. value of employment	21.4	21.4	18.7	21.5	22.6	21.4	25.3	21.2	23.4	21.2
W: Overall welfare	21.1	21.1	18.4	21.3	22.6	21.2	25.2	21.0	23.3	21.0
Change in overall welfare (compared to baseline)		0.0%	-12.9%	0.6%	6.7%	0.1%	19.0%	-0.6%	10.2%	-0.6%

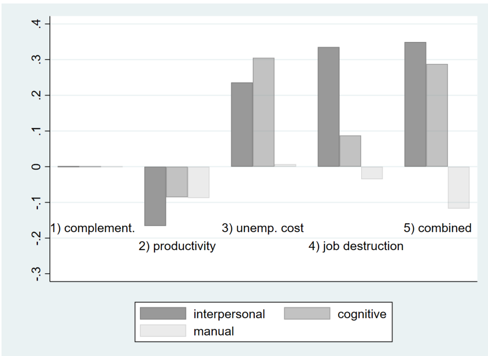
Notes: The four simulation scenarios evaluate the labour market and welfare effects of eliminating each of the following four channels: (1) complementarity in the demand for skills: $\rho_{IC} = \rho_{IM} = \rho_{CM} = 0$. (2) productivity of skills: $\mu_I = \mu_C = \mu_M = -\infty$, $\sigma_I = \sigma_C = \sigma_M = 0$. (3) skill-specific cost of unemployment: $b_I = b_C = b_M = 0$. (4) skill-specific job destruction: $\eta_I = \eta_C = \eta_M = 0$. The last two columns combine restrictions (1) to (4). They do not equal to the mean of columns (1) to (4) because of non-linearities and correlations in the parameters. Each scenario is simulated with the restricted skill-specific parameters as named above without correcting the overall mean parameter ("uncorrected") and with correcting the overall mean parameter ("at mean"). These two scenarios are equivalent for the complementarity channel (1). The "uncorrected" simulation provides an estimate of the quantitative overall (mean) effect of each channel, the "at mean" simulation provides an estimate on the distributional effect of each channel.

(Subfigures b) unemployment rate, c) value of unemployment, and d) value of employment) for each simulation scenario compared to the baseline scenario (i.e. when each channel is operational for each skill as in the estimated model).

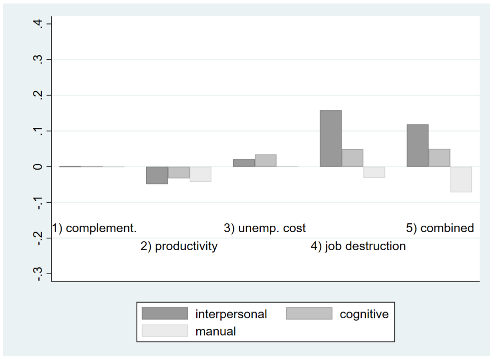
(a) Welfare



(b) Unemployment rate



(c) Value Unemployment



(d) Value Employment

Figure 2: The effects of interpersonal, cognitive, and manual skills on welfare and its components

Notes: The four simulation scenarios evaluate the welfare effects (and its components) of eliminating each of the following four channels for every skill j: (1) complementarity in the demand for skills: $\rho_{j,j-1} = 0$. (2) productivity of skills: $\mu_j = -\infty$, $\sigma_j = 0$. (3) skill-specific cost of unemployment: $b_j = 0$. (4) skill-specific job destruction: $\eta_j = 0$. The last set of bars (5) in every subfigure combines channels (1) to (4). The combined effect of (1) to (4) in (5) does not equal the sum of every individual scenario because of non-linearities and correlations in the parameters. Each scenario is simulated with the restricted skill-specific parameters without correcting the overall mean parameter. This simulation provides an estimate of the quantitative overall (mean) effect of each channel. A negative change represents an increase in welfare (or one of the components) due to skill j, whereas a positive change represents a decrease in welfare (or one of the components).

For scenario 1, we find that for all welfare components (Panels a) through d)), the complementarity channel is negligibly small for all three skills. In contrast, for scenario 2, the productivity channel is very important. If we shut down this channel, workers' welfare (Panel a)) is lower. The quantitative impact is largest for interpersonal skills (-5.2%), followed by manual and cognitive skills (-4.4% and -3.4%, respectively). Further, the productivity of skills increases both the value of employment through its effect of wages (Panel c)), but also the value of unemployment (i.e. reservation wages) (Panel d)). However, the unemployment rate (Panel b)) is unaffected.

For scenario 3, we find that the cost of unemployment is relatively large for interpersonal and cognitive skills (their absence increases welfare by 2.5% and 4%, respectively), but not for manual skills (-0.1%). Given these costs, workers with interpersonal and cognitive skills want to exit unemployment more quickly. These skill-specific unemployment costs put pressure on their reservation wages as shown in Panel d), which in turn negatively affect their wages and hence, the value of employment. However, the impact on the unemployment rate is small like for the productivity channel in scenario 2.

For scenario 4, we find that unemployment is greatly affected by skill-specific destruction rates. While manual skills shield against job destruction, more interpersonal and cognitive skills are associated with higher job destruction. When skill-specific job destruction is absent, the value of employment, the value of unemployment and finally, welfare would be higher (+16.5% for interpersonal and +5.2% for cognitive, -3.2% for manual skills).

Finally, the last columns in each subfigure show the total impact of shutting down all skill channels, again separately for each skill. Overall, we show that workers' welfare would increase when interpersonal and cognitive skills are absent (by 12.6% and 5.6%, respectively), but decrease without any manual skills (-7.4%). This result is puzzling at first sight and begs the question of why any worker would receive training in an occupation with high cognitive or interpersonal skills. We answer this question in the next section where we examine the role of the ARI and its link with the skills occupations confer.

7.3 The role of the academic requirement index

In the previous simulations, we shut the different channels of how skills affect welfare but kept the ARI fixed. However, there is a strong correlation between the ARI and skills of VET occupations. Most occupations with a high ARI also confer and use relatively many interpersonal and cognitive skills. In contrast, occupations with many manual skills tend to have a low ARI. Occupations with high manual skills *and* a high ARI are scarce. In fact, there are only two high manual-high ARI occupations - namely, laboratory technicians and automation technicians - among more than 200 VET occupations. In our sample, a mere 2.2% of all workers hold a VET degree in one of these two occupations. Most students with high ability thus face a trade-off between either training in occupations which confer high manual skills but have a low ARI or occupations with many interpersonal/cognitive skills and a high ARI.

To illustrate this trade-off, Table 6 presents welfare, wages, and unemployment of highly able workers (using the estimated parameters reported in Table 4) for different occupation clusters with a given ARI. Note that the productivity premium arises for workers who meet the ARI, but it is not larger for those workers who exceed it.[27] Column (1) refers to occupations with high manual skills (and low interpersonal and cognitive skills) with a low ARI. Occupations included in this cluster are gardener, butcher, roofer and plasterer. Columns (2) and (3) present the results for automation and laboratory technicians, respectively. These are the only two occupations with high manual skills and high ARI. Finally, columns (4) to (7) refer to a selection of different occupations with low manual skills, intermediate/high interpersonal or cognitive skills, and a high ARI.

VET occupations with a high ARI pay considerably higher wages (columns 2 to 7) than occupations with high manual skills and low ARI (first column). However, these former occupations are also characterised by (slightly) higher unemployment rates due to higher job destruction rates. Overall, the positive wage effect dominates, so that welfare is higher among occupations with a high ARI. Given the substantial premium paid in occupations with a high ARI, highly able workers thus want to train in these occupations even if they often provide only low manual skills.

7.4 The value of VET for workers with low ability

Completing VET provides workers with valuable skills which affect a worker's labour market outcomes through multiple channels. However, a VET degree provides a value which goes beyond the direct effect of the acquired skills. In particular, it opens up labour market opportunities, which would otherwise not be available.[28]

As shown in Figure B.1 in the Appendix, most VET students who do not eventually enrol in tertiary education have lower academic scores than the median student who enrols in general education. If VET was not available to these former students, only few would complete a higher secondary education (12 years of schooling) at all. Instead, most would only complete the nine years of compulsory education. Thus, these low-ability workers are arguable the ones who substantially benefit from having a VET degree and the skills it confers.

[27] We assume that those who fall short of the ARI of an occupation cannot train in it (see Stalder (2011)). This seems reasonable as VET students need to find a host firm for their training.

[28] Adda et al. (2013) estimate a dynamic life-cycle model for skilled (i.e. VET workers) and unskilled workers in Germany. They show that returns to VET go beyond the direct wage effects as they offer different labour market opportunities (i.e. lower job destruction and higher job arrival rates during economic downturns for skilled workers).

Table 6: HIGH MANUAL SKILLS OR GETTING HIGH ACADEMIC PREMIUM?

	Estimation (selected clusters and ARI)						
	High manual low ARI	High manual high ARI		Low manual high ARI			
	low I - low C cluster 15 (1)	med I - med C cluster 7 (2)	med I - low C cluster 8 (3)	high I - med C cluster 5 (4)	med I - high C cluster 10 (5)	med I - low C cluster 12 (6)	low I - med C cluster 16 (7)
Mean hourly wage	33.1	45.4	45.8	43.9	43.2	44.3	44.3
Std dev hourly wage	8.3	8.5	9.1	9.8	8.7	8.5	8.8
1% lowest wage	19.7	31.0	30.8	29.4	28.1	30.0	30.1
Unempl. Rate	2.3%	2.8%	3.6%	3.5%	3.1%	2.9%	3.2%
EU rate	1.2%	1.5%	2.0%	3.8%	2.3%	1.8%	0.3%
UE rate	62.1%	70.6%	70.0%	50.0%	61.3%	62.2%	75.0%
Value of unemployment	18.2	24.4	25.4	19.5	19.2	25.9	24.7
Value of employment	23.1	27.9	28.1	23.4	24.8	27.7	28.6
Overall welfare	22.9	27.8	28.0	23.2	24.7	27.6	28.5
Share in sample	4.4%	1.2%	1.1%	0.5%	4.9%	1.5%	0.4%

Notes: These moments and welfare values are obtained for the model sample using the estimated parameters reported in Table 4 and under the assumption of high ability. A high-ability worker can train in any occupation regardless of the occupation's ARI (academic requirement index). Cluster 15 (low interpersonal, low cognitive, high manual) for low ARI includes the following occupations: gardener, butcher, roofer and plasterer. Clusters 7 and 8 with high manual skills and with high ARI include automation and laboratory technicians. Occupations in clusters 5, 10, 12 and 16 have intermediate or high interpersonal or cognitive skills, low manual skills and a high ARI. They include occupations such as multimedia technician, electronic technician, draughtsman. All moments (in particular, unemployment moments) can be affected by some degree of simulation noise.

To evaluate the overall value of a VET degree, we now compare the labour market outcomes of VET workers with a low ARI with those of workers who have only completed compulsory education.[29] For this purpose, we estimate a simple search model for workers with only compulsory education as a benchmark. Table G.1 in Appendix G reports the estimated parameters. We estimate the productivity distribution, the general cost of unemployment, as well as the job arrival and destruction rates. All parameters related to skills are dropped.

Table 7 presents labour market outcomes from our main estimation for all VET workers with a low ARI (column (1)), and for VET workers with a low ARI in clusters 11 (column (2)) and 14 (column (3)), respectively. The next three columns show the simulation results for the same outcomes of VET workers with a low ARI who train in fictitious occupations which confer four interpersonal (4), cognitive (5) or manual skills (6), respectively. Finally, column (7) shows the estimated labour market outcomes for workers with only compulsory education using the simplified model presented in Appendix G. In VET clusters 11 and 14 workers have equally low academic scores as those with only compulsory education. Cluster 11 confers medium interpersonal and cognitive skills, and low manual skills. It includes occupations such as florist, car varnisher, ceramic painter, and housekeeper. Cluster 14 is characterised by high manual, medium cognitive, and low interpersonal skills. This cluster includes occupations such as painter, tiler, plumber, and metal worker.

Returns to hourly wages of a VET degree for workers with low ability vary between 4% (in cluster 11) and 10% (in cluster 14) compared to workers with only compulsory education. These average returns to wages for workers with low ability are neither negligible nor substantial. Given that apprentices studying for a VET degree spend around one third of their time in school and two thirds working in their host firm, these returns appear to be of a similar magnitude than the returns to an additional year of education estimated at around 10% in the literature (Card, 1999; Adda et al., 2013).

However, our estimated model points towards a second channel of how a VET degree affects workers' welfare, which is far more consequential. In fact, low-ability workers

[29] One could also use this method to estimate the value of VET for workers with a high ARI. However, the assumption that high-ARI students would not have completed a higher secondary education degree if VET had not been available to them, is harder to justify than for low-ARI students. A non-negligeable share of high-ARI students might have earned a general education degree in the absence of VET. Therefore, the counterfactual scenario is unclear and the value of VET for high-ARI workers cannot be reliably calculated within our framework.

Table 7: VALUE OF VET FOR WORKERS WITH LOW ABILITY

	Estimation - VET - low ARI						**Simulation - VET - low ARI**						**Estimation - no VET**
	all		cluster 11 med I med C low M		cluster 14 low I med C high M		4 interpersonal		4 cognitive		4 manual		all
	(1)		(2)		(3)		(4)		(5)		(6)		(7)
Mean hourly wage	32.4	6%	31.6	4%	33.5	10%	30.9	2%	30.9	2%	34.5	13%	30.4
Std dev hourly wage	8.7		8.6		8.6		9.1		8.5		8.7		9.0
1% lowest wage	17.7		17.3		18.9		15.9		16.7		20.0		14.9
Unempl. Rate	2.9%	-54%	3.2%	-50%	2.3%	-64%	4.5%	-29%	3.3%	-48%	2.0%	-68%	6.3%
EU rate	1.8%		2.0%		1.4%		3.0%		1.9%		1.1%		3.7%
UE rate	61.4%		66.2%		63.6%		60.7%		64.7%		62.9%		57.0%
Value of unemployment	12.9		12.2		16.5		8.3		13.0		18.2		0.0
Value of employment	20.4		19.1		22.8		16.0		19.2		25.5		13.5
Overall welfare	20.2	60%	18.9	50%	22.6	80%	15.7	24%	19.0	51%	25.4	102%	12.6
Share among all low-ARI	100%		15%		25%		n.a.		n.a.		n.a.		

Notes: Scenarios (1) to (3) show the estimation results on labour markets for low-ability workers (who train in an occupation which requires only a baseline ARI) overall (1), and for occupation clusters 11 and 14. Scenarios (4) to (6) show simulation results on labour market outcomes for low-ability workers in three fictitious occupations, which confer either only four interpersonal (4), four cognitive (5), or four manual skills (6). The second column in each scenario (1) to (6) gives the percentage change with respect to no VET- scenario, shown in (7) for selected moments. Workers in clusters 11 and 14 have equally low academic scores as those with only compulsory education (see Appendix Table B.1). Cluster 11 has medium interpersonal and cognitive skills, and low manual skills. Cluster 14 is characterised by high manual, medium cognitive, and low interpersonal skills.

with a VET degree find themselves in a very different labour market. This labour market offers jobs at a higher rate and is characterised by substantially lower job destruction. Combining these two effects leads to low-ability VET workers having unemployment rates of 2.3% to 3.2%, which are less than half of the unemployment rate of their peers with only compulsory education (6.3%). Not only is unemployment less likely for these VET workers, they also have a higher value when unemployed, as captured by the reservation wage. This result indicates that the lower unemployment rates of VET workers do not come at the cost of accepting any job but - on the contrary - in spite of being pickier about accepting jobs. Thus, when comparing workers' welfare, we find that low-ability VET workers have a welfare level which is between 50% and 80% higher than their peers' with compulsory education. This difference is substantially larger than the one suggested by the returns to hourly wages only. One explanation for these large welfare gains could be that workers also acquire non-cognitive skills such as being punctual, cooperation with others, and perseverance in their vocational education - competences which are highly valued in the labour market (Kautz et al., 2014).

The simulation results of the three fictitious occupations provide further insights into which skills are most valuable for a low-ability worker, who enrolled in VET. Both only-interpersonal and only-cognitive skills occupations attract positive returns to wages of around 2% and reduce unemployment by 29% and 48%, respectively, compared to not having a VET degree. Yet, manual skills are clearly the most valuable: The wage returns to four manual skills amount to 13% and unemployment drops by 68% compared to no-VET degree. This translates into doubling the welfare of a low-ability worker. Workers with low ability thus should train in occupations which confer many manual skills and some cognitive skills.

8 Conclusion

This paper provides a structural examination of the Swiss labour market for workers who graduated from vocational education and training (VET). We distinguish between workers who have acquired different bundles of interpersonal, cognitive, and manual skills in VET programmes and differ in their unobserved ability. We study how this affects their labour market outcomes. For this purpose, we make use of a simple search and matching model where workers' skills impact labour market outcomes through four channels: productivity, skill-complementarity, job destruction and cost of unemployment.

We find that skill-specific job destruction rates and productivity have the largest effects on workers' labour market outcomes, followed by skill-specific costs of unemployment. While the first one mainly impacts (transitions into) unemployment, the latter two affect wages. We also use our model framework to quantify the value of a VET degree and its skills for low-ability workers. Returns are sizeable both in terms of wages and unemployment. Returns to wages amount to 4% to 10% for these workers, while unemployment drops by more than 50% compared to their peers with compulsory education only. This second finding results from improved labour market opportunities through more job offers and lower job destruction. Low-ability workers thus have large overall benefits from getting a VET degree, in particular from manual skills which increase wages and shield from unemployment.

Our estimation and simulation results highlight the importance of analysing different labour market outcomes jointly rather than focusing solely on wages which do not always mirror employment outcomes. Skills work through different channels on these outcomes. It is crucial to quantify each channel for every skill to account for the overall value of VET and understand how worker's welfare arises.

Finally, the findings of our paper reveal the need for a nuanced skills policy. Workers with low ability are best off when mainly acquiring manual skills. Occupations which confer and use many manual skills pay higher wages and shield workers better from the risk of unemployment. Workers with higher ability, however, should train in occupations which require a higher ability level but also pay a substantial wage premium. Only a small fraction of high-requirement occupations use manual skills, while most of these occupations use cognitive and interpersonal skills. Higher ability workers may therefore find acquiring cognitive and interpersonal skills more beneficial. Not all workers should thus acquire the same skills. Instead there is an important interaction between acquiring skills, the required ability to do so and the demand for different skills. This should be taken into account when shaping education and training programmes.

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A The Swiss Education System

Figure A.1 presents a simplified overview of the educational system in Switzerland. The education system is geographically diverse as the authority over education lies with the cantons rather than with the federal government. This figure shows some of these cantonal differences such as the different timing of when tracking starts (i.e. in most cantons primary school lasts six years and tracking starts in year 7, however, in some cantons tracking starts as early as year 5). Moreover, in some cantons VET is primarily available through training at host firms, while other cantons (mostly in the French-speaking parts) also offer it through vocational schools.

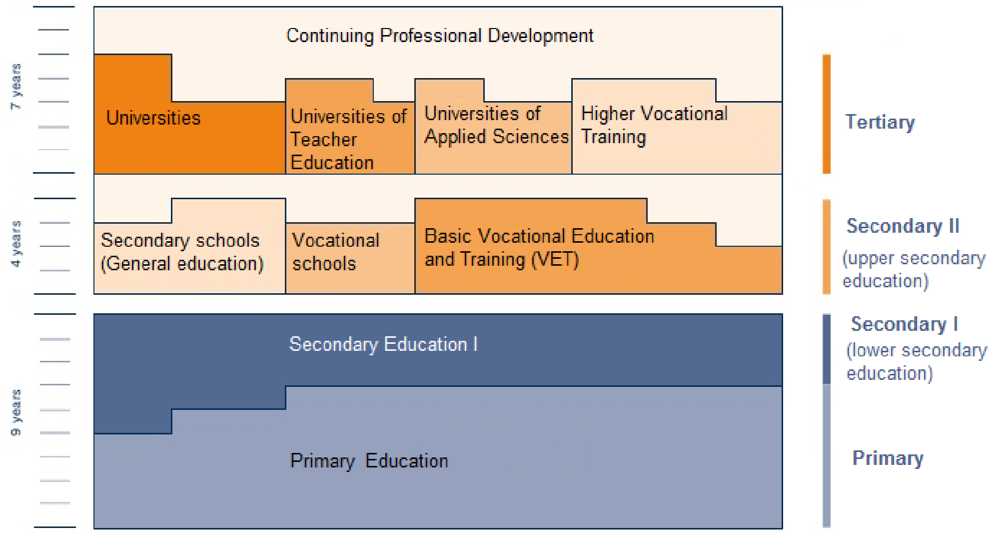


Figure A.1: Educational system in Switzerland
Source: PH Zürich. Modified by Authors.

B Selection into vocational and general education

We present further evidence on selection into vocational and general education in Switzerland. We use the "Transitions from Education to Employment" longitudinal study (TREE). The TREE study is a panel survey which follows students through their post-compulsory education and training into employment. The data collects information about the standardised PISA test scores and self-assessed personality traits prior to completing compulsory education. It also records education, training and employment outcomes of study participants in subsequent waves. The data used in this paper covers one cohort of approximately 2,000 students in their last year of compulsory education in year 2000 (wave 1).[30]

Figure B.1 presents the distribution of standardised PISA test scores in reading and maths (as a measure of ability) and the distribution of self-assessed personality traits (persistence, locus of control and ambition) of male pupils in their last year of compulsory education. We split the pupils according to their future education pathway: compulsory education, vocational education (3- or 4-year VET) only, vocational + tertiary education, and general education.

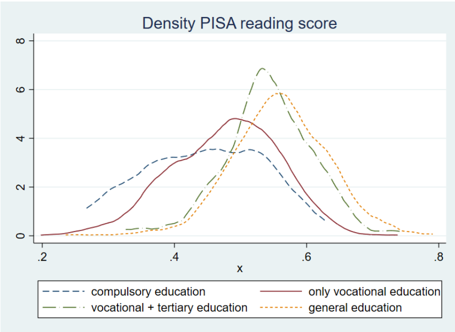
We find a fair amount of heterogeneity in PISA test scores both within and across education groups. Pupils in the vocational education track have on average lower reading and maths test scores than those in the general education track, but higher scores than those with compulsory education only. Distinguishing vocational pupils by their future education level is crucial. The PISA test scores distributions of vocational pupils who later enrol in tertiary education dominate the ones of "only vocational" pupils, but they are similar to those of general education pupils. This suggests that "vocational + tertiary" pupils have comparable academic abilities to their peers in general education. In contrast, reading and maths scores of most pupils with only vocational education fall short of the median pupil in general education. Instead, their score distributions resemble those of pupils with only compulsory 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 pupils in the vocational and general education track are on average more persistent than those who do not go beyond compulsory education.

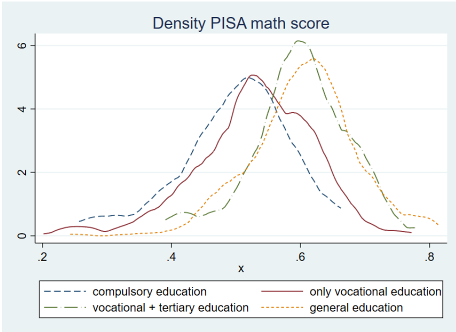
Table B.1 provides summary statistics for PISA test scores (reading, maths) and personality traits by education tracks (upper panel), as well as by occupation cluster (as defined in the beginning of Section 5.2) for those within the vocational education track. It also gives the share of each occupation cluster who enrol in tertiary education within 10 years.

Breaking up the vocational education track into occupation clusters which differ in their skill

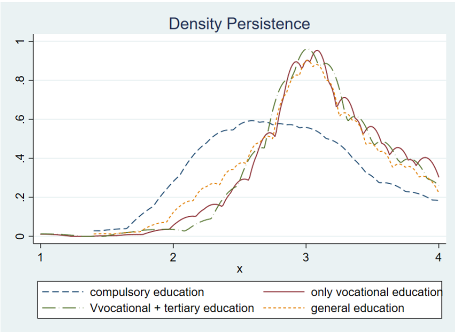
[30] Due to sample size issues, non-negligible attrition in subsequent waves and missing information, this data cannot be used to estimate the labour market model in our paper.



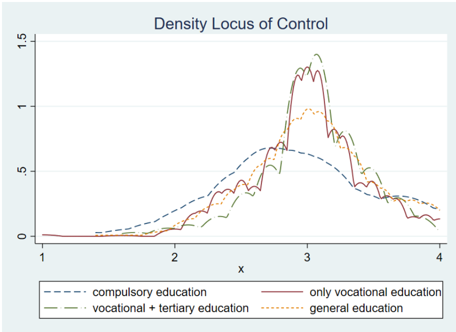
(a) PISA reading test score



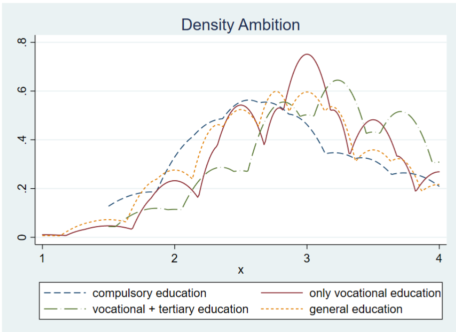
(b) PISA math test score



(c) Persistence (self-assessed)



(d) Locus of Control (self-assessed)



(e) Ambition (self-assessed)

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

Notes: Standardised PISA reading and maths test 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’. We distinguish: compulsory education (those who do not enrol in any further education programme), only vocational education (those who complete vocational education, but do not enrol in tertiary education within 10 years of graduation), vocational + tertiary education (those who complete vocational education and eventually enrol into tertiary education within 10 years after graduating from VET), and general education (those who complete 12 or 13 years of general education such as Gymnasium).

Table B.1: PISA SCORES AND PERSONALITY TRAITS

Interpers.	Manual	Cognitive	PISA read Obs	PISA read Mean	PISA read SD	PISA maths Obs	PISA maths Mean	PISA maths SD	Persistence Obs	Persistence Mean	Persistence SD	LoC Mean	LoC SD	Ambition Mean	Ambition SD	Enrol in 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: enrol in 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																
Interpers.	Manual	Cognitive														
High	High	Low	3	0.50	0.07	1	0.53	0	3	3.53	0.31	3.33	0.58	3.17	0.29	n.a.
	Low	High	39	0.50	0.09	20	0.55	0.06	29	2.99	0.57	2.88	0.43	2.87	0.67	12.8%
		Medium	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%
		Low	0			0			0							
Medium	High	High	1	0.55	n.a.	0			1	3.20	n.a.	2.40	n.a.	2.50	n.a.	n.a.
		Medium	21	0.45	0.06	14	0.55	0.05	18	3.00	0.38	3.11	0.33	3.06	0.66	0%
		Low	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%
	Low	High	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%
		Medium	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%
		Low	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%
Low	High	High	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%
		Medium	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%
		Low	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%
	Low	High	5	0.52	0.07	1	0.57	0	3	3.33	0.31	3.07	0.31	3.33	0.76	20.0%
		Medium	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%
		Low	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 (only 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 maths test scores lie between 0 and 1. Personality traits “Persistence”, “LoC” (Locus of control) and “Ambition” are the average over a number of ordinal survey questions relative to each trait. They can take on value 1 “not at all true”, 2 “hardly true”, 3 “moderately true”, and 4 “exactly true”. “Enrol in tertiary” denotes the share who enrol in tertiary education within 10 years of graduating from compulsory education.

mix reveals a large heterogeneity across clusters. Pupils 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 abilities as those with only compulsory education. In contrast, pupils in other VET occupations (like cluster 10 with intermediate interpersonal, low manual, and high cognitive skills) resemble quite closely pupils 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 abilities of pupils in different education tracks overlap to a large extent. Pupils in the vocational education track at the lower ability end resemble those who only get compulsory education, while pupils at the higher end resemble those who pursue a general education track. By focussing our analysis on workers who complete vocational education, but do not eventually enrol in tertiary education, we limit the heterogeneity in unobserved ability to a considerable degree.

C BIZ skill measures and their robustness

All BIZ skills are classified either as interpersonal, cognitive or manual according to Zihlmann et al. (2012). We use 24 out of 26 skills. Interpersonal skills include high sense of responsibility, high ability to work in a team, high sociability, communication talent, service orientation, hygiene awareness, high reliability, high mental stability, patience, and high empathy. Cognitive skills include mental flexibility, abstract-logical thinking skills, practical understanding, spatial visualisation ability, technical understanding, talent for languages (oral and written), creativity, sense of aesthetics, and organisational talent. The manual skills include physical agility, manual dexterity, good fine motor skills, good sense of taste and smell, and head for heights. The two excluded "skills" are robust health and strong physique because they describe physical attributes rather than skills that can be acquired.

We add up the number of acquired skills within each of the three skills. Each worker has acquired 0 to 5 interpersonal skills, 0 to 5 cognitive skills, and 0 to 3 manual skills. Figure C.1 visualises the different skill bundles supplied by the workers in our sample. It displays the joint distribution of cognitive and interpersonal skills for each of the four different values of manual skills.

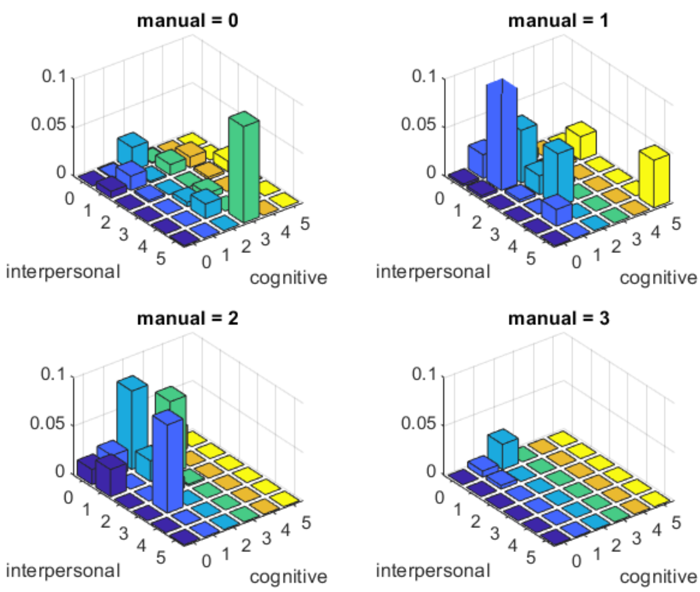


Figure C.1: Skill bundles supplied by workers

Given the range of each skill, there are $6 \times 6 \times 4 = 144$ possible skill bundles. Effectively, we observe only 45 of them in our sample. Not all skill bundles are equally frequent. 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. The two most common skill bundles are the 5 interpersonal - 3 cognitive - 0 manual skills bundle (which includes administrative assistants), and the 1 interpersonal - 1 cognitive - 1 manual skills bundle (which includes car mechanics). Each of these two skill bundles makes up almost 10% of the sample.

We validate our skill measures by comparing them to two alternative measures such as 1) a *relative* skill measure where interpersonal, cognitive and manual skills in each occupation are measured as a percentage of total skills and 2) a PCA-based measure where we perform Principal Component Analysis on the 24 skills of our 200 VET occupations and retain the three principal components. We then combine these three principal components and impose three exclusion restrictions to interpret the measures as interpersonal, cognitive, and manual skills.

We replicate the empirical analysis of Table 3 using these two alternative measures. The results are available upon request. Our main empirical results from the paper still stand when using the relative skill measures: Interpersonal and manual skills have significantly higher returns to wages than cognitive skills once we control for the academic requirement index (ARI) of an occupation, the effects of intermediate and high ARI on wages and unemployment are quantitatively very similar, and having acquired more interpersonal skills is associated with a significantly higher likelihoood of being unemployed. The results for the PCA-based skill measures align only partially with our main results in the paper. Higher interpersonal PCA-measured skills are still associated with significantly higher unemployment. However, the relative ranking of wage returns to PCA-measured skills now places cognitive skills before manual and interpersonal skills, while the wage premia of intermediate ARI becomes 0 and the wage premia of high ARI shrinks by one half compared to the main results. The cognitive PCA-skill measure confounds cognitive skills acquired in VET and higher ability, while interpersonal and manual PCA-based skills are highly negatively correlated (-.80 correlation coefficient). Given that the three principal components in the PCA only explain 33% of the variation in the 24 underlying binary variables, the PCA-based skill measures are not appropriate for our setting where we are interested in understanding the effect of *learned skills* on various labour market outcomes.

D Academic requirement index and skills of occupations

This appendix presents the skills and the respective shares of the low, intermediate and high academic requirement index (ARI) for each occupation cluster. The ARI is an index ranging from 1 to 6 based on Stalder (2011). We regroup Stalder's index into a baseline level (ARI of 1 or 2 or unknown), an intermediate level (ARI of 3 or 4) and a high level (ARI of 5 or 6). This information is used to ensure that our simulated model sample has approximately the same observed and unobserved characteristics as the data sample.

Table D.1: ACADEMIC REQUIREMENT INDEX AND SKILLS OF VET OCCUPATIONS

Skills			Share in	ARI		
Interpersonal	Manual	Cognitive	sample	Baseline	Intermediate	High
High	High	Low	9.1%	5.0%	95.0%	0%
	Low	High	14.9%	1.8%	44.9%	53.4%
		Medium	7.7%	74.1%	19.8%	6.1%
		Low	1.9%	96.7%	3.3%	0%
Medium	High	High	7.9%	5.4%	79.4%	15.2%
		Medium	3.3%	66.5%	0%	33.5%
		Low	3.2%	88.3%	11.7%	0%
	Low	High	6.8%	17.3%	10.0%	72.7%
		Medium	7.5%	79.0%	18.7%	2.3%
		Low	13.2%	21.3%	67.0%	11.7%
Low	High	High	2.1%	0%	100%	0%
		Medium	10.8%	97.8%	2.2%	0%
		Low	4.4%	99.1%	0.9%	0%
	Low	High	1.1%	1.9%	64.2%	34.0%
		Medium	3.5%	42.9%	57.1%	0%
		Low	2.7%	70.2%	29.8%	0%

E Identification: Parameters and moments

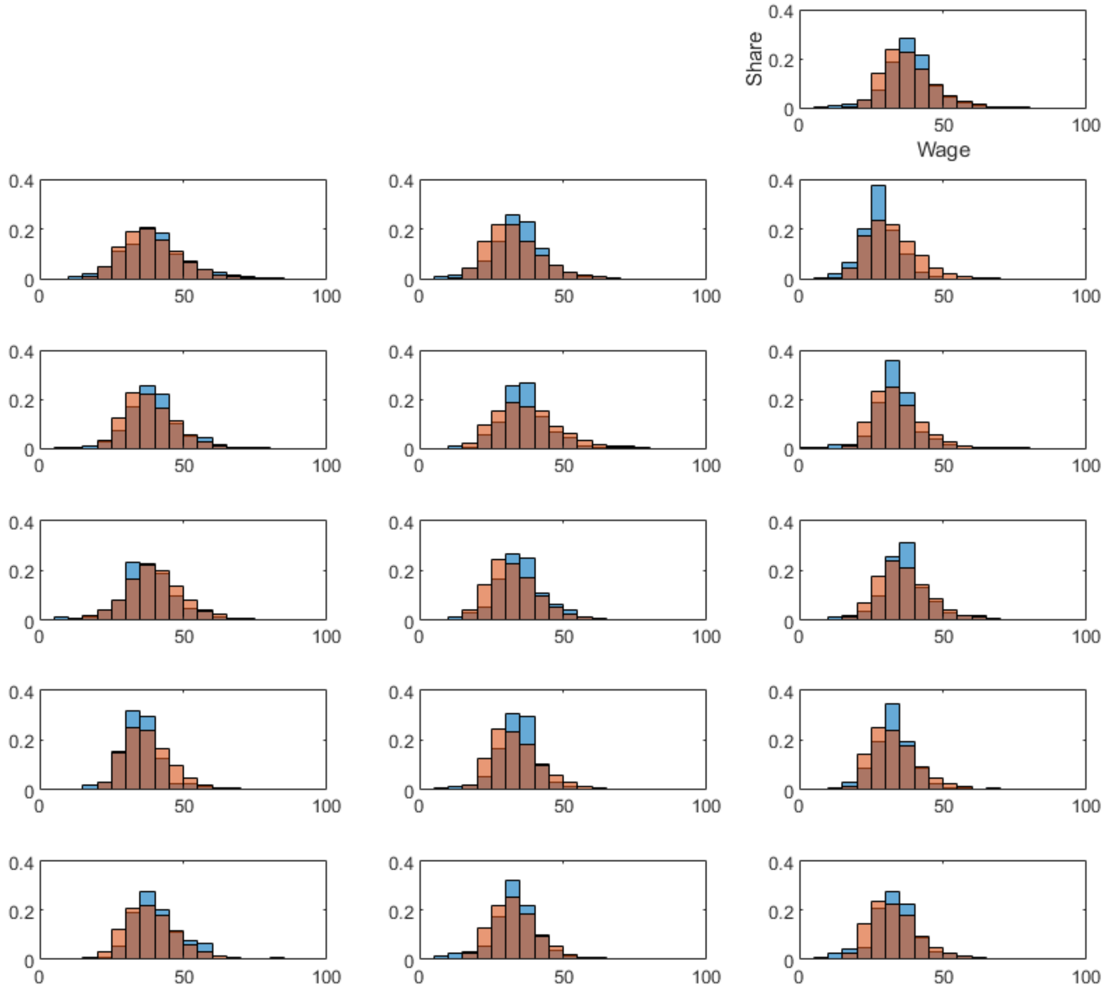
This appendix presents a table summarising which moments are used to identify all parameters in the model.

Table E.1: MODEL PARAMETERS AND CORRESPONDING MOMENTS

Parameter	Moment	#
Productivity and skill-specific demands (log-normal marginals)		
General productivity: μ_0, σ_0		
Interpersonal skills: μ_I, σ_I		
Cognitive skills: μ_C, σ_C	Mean & standard deviation of age-adjusted hourly wages by occupation cluster	32
Manual skills: μ_M, σ_M		
Correlations: ρ_{IC}, ρ_{IM}, ρ_{CM}		
Type-specific productivity gain: α_{τ_m}, α_{τ_h}	same as above, it relies on the distribution of τ being known for each occupation cluster	
Flow cost of unemployment		
Common flow cost: b_0		
Interpersonal skills cost: b_I		
Cognitive skills cost: b_C	First percentile of age-adjusted hourly wages by occupation cluster	16
Manual skills cost: b_M		
Offer arrival and destruction rates		
Offer arrival rate: λ	Yearly UE-transition rates by occupation cluster	16
General destruction rate: η_0		
Interpersonal skills marginal destruction: η_I	Yearly EU-transition rates by occupation cluster	16
Cognitive skills marginal destruction: η_C	Age-adjusted unemployment rates by occupation cluster	16
Manual skills marginal destruction: η_M		
Calibrated parameters		
Bargaining power worker: $\beta = 0.67$	Siegenthaler and Stucki (2015)	
Interest rate: $r = 0.05$		
	Total moments	96

F Goodness of fit

This appendix shows how well our model fits the observed moments. Tables F.1 and F.2 present the goodness of fit of the targeted moments. Figure F.1 displays the complete observed and simulated wage distributions (i.e. histograms) of all 16 occupation clusters. This figure goes beyond the directly targeted moments on hourly wages which only include the mean, standard deviation and lowest 1% of hourly wages for each occupation cluster.



Notes: The first two lines of figures relate to the occupation clusters with high interpersonal skills (the first for high manual, the second for low manual), the two middle lines are intermediate interpersonal skills (high, low manual) and the last two lines for low interpersonal skills (high, low manual). Cognitive skills vary from high (first column), to intermediate (second column) and low (third column).

Figure F.1: Goodness of fit: Wage distributions of observed (blue) and simulated (orange) wages by occupation cluster

Table F.1: GOODNESS OF FIT I: WAGES

Skills			Mean hourly wage			Std. dev. hourly wage			Lowest 1% hourly wage		
Interpersonal	Manual	Cognitive	Observed	Std. Err.	Simulated	Observed	Std. Err.	Simulated	Observed	Std. Err.	Simulated
High	High	Low	38.49	0.28	38.10	9.27	0.29	9.06	12.58	1.46	22.34
	Low	High	39.86	0.29	39.32	11.92	0.25	11.14	14.89	0.82	19.84
		Medium	34.34	0.31	33.15	9.42	0.29	9.70	12.48	1.38	17.07
		Low	28.03	0.43	32.42	6.37	0.34	9.11	12.70	1.77	16.96
Medium	High	High	39.66	0.31	38.75	9.59	0.29	9.28	16.78	2.09	22.71
		Medium	37.29	0.49	37.33	9.96	0.52	10.71	14.81	2.50	19.07
		Low	33.57	0.43	34.12	8.47	0.58	8.69	10.59	2.73	19.52
	Low	High	38.25	0.36	40.18	10.13	0.33	10.01	9.74	2.20	18.71
		Medium	35.12	0.29	32.83	8.81	0.28	8.79	12.92	1.28	17.59
		Low	37.15	0.23	36.39	9.15	0.27	9.18	13.74	1.24	19.83
Low	High	High	34.94	0.44	37.70	7.07	0.49	8.48	15.78	1.76	22.85
		Medium	34.04	0.20	33.62	7.38	0.27	8.63	11.63	1.64	18.97
		Low	33.02	0.38	33.12	8.79	0.53	8.36	12.63	1.98	19.75
	Low	High	40.83	0.80	38.94	9.06	0.87	9.41	23.15	3.95	22.09
		Medium	33.03	0.42	33.38	8.47	0.40	8.64	9.65	1.68	17.89
		Low	33.33	0.52	33.04	9.51	0.59	8.56	10.23	1.53	18.17
All (not directly targeted)			36.52		36.23	9.81		11.95	12.93		18.94
Contribution to loss function					286.0			112.0			273.3
Correlation obs. & sim. moments					0.86			0.72			0.61
Correlation obs. & sim. moments in model without skills					0.83			0.50			0.61

Notes: The table displays the observed moments, their standard errors and simulated counterparts from the model for the mean hourly wage, the standard deviation in hourly wages and the 1% of hourly wages. The first 16 rows relate to the targeted moments for each occupation cluster in the sample. Row 17 relates to the overall moments which are not directly targeted. Line 18 shows the correlation between the observed and simulated moments (as a measure of fit for between occupation cluster variation), while row 19 shows the same correlation between the observed and simulated moments for a model without skills (but allowing for different ARI across occupation clusters).

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

Skills			Unemployment rate			EU rate			UE rate		
Interpersonal	Manual	Cognitive	Observed	Std. Err.	Simulated	Observed	Std. Err.	Simulated	Observed	Std. Err.	Simulated
High	High	Low	0.038	0.006	0.038	0.023	0.006	0.027	0.500	0.104	0.658
	Low	High	0.046	0.005	0.052	0.026	0.005	0.036	0.519	0.069	0.657
		Medium	0.029	0.005	0.039	0.026	0.006	0.025	0.875	0.085	0.570
		Low	0.080	0.017	0.052	0.059	0.019	0.026	0.556	0.176	0.606
Medium	High	High	0.017	0.004	0.031	0.006	0.003	0.018	0.500	0.224	0.649
		Medium	0.023	0.007	0.029	0.018	0.008	0.021	0.750	0.250	0.677
		Low	0.024	0.007	0.028	0.019	0.008	0.017	0.800	0.200	0.625
	Low	High	0.040	0.007	0.030	0.029	0.007	0.025	0.765	0.106	0.625
		Medium	0.038	0.006	0.030	0.030	0.007	0.020	0.706	0.114	0.682
		Low	0.044	0.005	0.029	0.021	0.004	0.019	0.587	0.073	0.595
Low	High	High	0.027	0.010	0.025	0.037	0.015	0.018	1.000	0.250	0.639
		Medium	0.033	0.005	0.023	0.017	0.004	0.014	0.650	0.109	0.639
		Low	0.036	0.008	0.023	0.014	0.006	0.012	0.500	0.151	0.621
	Low	High	0.020	0.012	0.033	0.011	0.011	0.014	0.000	0.250	0.657
		Medium	0.021	0.007	0.032	0.007	0.005	0.019	0.750	0.250	0.579
		Low	0.026	0.008	0.022	0.023	0.010	0.014	0.750	0.250	0.574
All (not directly targeted)			3.49%		3.38%	2.18%		2.21%	61.0%		63.4%
Contribution to loss function					46.4			36.2			32.9
Correlation obs. & sim. moments					0.64			0.44			-0.31
Correlation obs. & sim. moments in model without skills					-0.01			0.08			0.21

Notes: The table displays the observed moments, their standard errors and simulated counterparts from the model for the unemployment rate, the employment-unemployment (EU) and the unemployment-employment (UE) yearly transition rate, respectively. The first 16 rows relate to the targeted moments for each occupation cluster in the sample. Row 17 relates to the overall moments which are not directly targeted. Row 18 shows the correlation between the observed and simulated moments (as a measure of fit for between occupation cluster variation), while line 19 shows the same correlation between the observed and simulated moments for a model without skills (but allowing for different ARIs across occupation clusters).

G Estimation results: Compulsory education

This appendix presents the estimation results of a simple search model for a sample of workers who only have completed compulsory education. In this simplified model all parameters related to skills (i.e. skill-specific productivity, destruction rates, unemployment costs) are dropped. We use the same estimation algorithm as for the full model. Table G.1 presents the estimated parameters and standard errors, table G.2 reports the fit of the targeted moments.

Table G.1: ESTIMATED PARAMETERS: COMPULSORY EDUCATION

	Estimate	Std. Err.	Mean	Std. Dev
μ_{00}: General productivity (location)	3.78	0.07	45.72	13.47
σ_{00}: General productivity (scale)	0.29	0.02		
λ_{00}: Offer arrival rate	0.87	0.05		
$\eta_{00} * 100$: Destruction rate	5.77	0.33		
b_{00}: General unemployment cost	-246.35	55.05		

Notes: The general productivity follows a log-normal distribution. The mean is given by $\exp(\mu + \sigma^2/2)$ and the variance by $\left[exp(\sigma^2) - 1\right] exp(2\mu + \sigma^2)$. Asymptotic standard errors are computed following French and Jones (2011).

Table G.2: GOODNESS OF FIT: COMPULSORY EDUCATION

	Observed	Std. Err.	Simulated
Mean hourly wage	30.76	0.10	30.44
Std. dev. hourly wage	8.49	0.10	8.97
Lowest 1% hourly wage	7.13	0.45	14.90
Unemployment rate	0.066	0.003	0.063
EU rate	0.032	0.002	0.037
UE rate	0.619	0.027	0.570