Vocational Education and Underskilling: Lessons from European Skill Surveys*

Caroline Neuber-Pohl[1], Giovanni Russo[2], Giulia Santangelo[2], and Katarina Zigova[3]

[1]Federal Institute for Vocational Education and Training, Bonn, Germany
[2]European Centre for the Development of Vocational Training, Thessaloniki, Greece
[3]Institute of Business Administration, University of Zurich, Switzerland

April 15, 2025

Abstract

Vocational education shall equip students with a mix of general, occupational, and firm-specific skills—skills that are relevant for the world of work. In this paper we investigate whether workers with vocational background have an advantage to find jobs that match their skills. We do it by estimating the effect of vocational education on underskilling employing three different European skill surveys, each offering some unique perspective on skills. The surveys allow us to construct numerous self-reported measures of underskilling. In many cases we find that vocationally educated perceive on average smaller degree of underskilling as compared to workers with general education. Looking into mechanisms of this effect, we see that closeness of vocational education system to labour market is a relevant drivers of differences in underskilling between vocationally and generally educated workers. Using two different methods, we calculate actual degree of underskilling from actual skills data and find that actual underskilling proxies well the self-reported measures.

JEL-Code: I21, I26, J24
Keywords: underskilling, initial vocational education, collective skill formation system

*Preliminary draft prepared for AIEL 2025 in Milan. Please do not quote or circulate.
Corresponding author: katarina.zigova@business.uzh.ch

1 Introduction

Vocational education and training (VET) programmes prepare students for specific occupations providing them with skills that are relevant to the labour market (Eichhorst et al., 2015). Of the many labour market outcomes—e.g., employment, wages, job quality, career paths, job match—some are more closely linked to the VET system than others. Naturally, the outcomes that are closely linked to the VET system are those that could be regarded as the direct outcome of the role played by the VET system in an economy. The institutions and the governance mechanisms that control the supply of skills and their utilization in an economy is called a collective skills formation system (Thelen, 2004; Busemeyer and Trampusch, 2012). VET is part of this system and it plays a role alongside all other institutions; for example, the supply of skills may be collectively organized with the involvement of businesses, industry chambers, and unions supported by state in execution, finance, and monitoring (Busemeyer and Trampusch, 2012; Eichhorst et al., 2015; Ibsen and Thelen, 2024). The term collective skills system is used to denote a dual VET system. Here, we deviate from this convention and adopt a very broad definition of a collective skills system: all skills formation systems are characterized by a certain degree of collectivism. The measure of collectivism covary with the degree of closeness of the VET system with the world of work. Consequently, dual models of apprenticeship have the closest connection to the world of work and display the stronger degree of collectivism. The initial VET by providing education for youth not yet in the labour market plays a core role in such formation process. Its governance often foresees the participation of firms and employer associations in the VET curriculum (Thelen, 2004). While such participation can take on different forms in different countries (Mende et al., 2023), it is generally true that the initial VET programmes have a stronger connection to the world of work than general education programs (Bolli et al., 2018).[1]

The ability of the VET system to form skills that are valued by employers is central to the VET effectiveness. It is often assessed by measuring the advantages the VET confers to workers

[1] In addition to initial VET, most countries also have a continuous VET in place, alternatively called adult education, that provides training and learning while in the labour market. The skill consequences of continuous VET is beyond the scope of this study.

who have participated in such programmes compared to those who did not. For example, such effectiveness is reflected by shorter duration of the school-to-work transitions experienced by upper secondary VET graduates compared to graduates from general upper secondary schools (Middeldorp et al., 2019; Pastore et al., 2021). More often, however, the effects of VET on labour market outcomes are less clear-cut. The initial advantage is reversed later in their career, and this evidence has been used to question the effectiveness of initial VET. Compared to general education graduates, VET graduates tend to earn a higher wage in the first part of their career, but then the advantage evaporates and turn into a disadvantage later in their careers (Brunello and Rocco, 2017; Hanushek et al., 2017). Similarly, workers with a VET background are less likely to experience a spell of unemployment in the early part of their career (Vermeire et al., 2022). Yet, they also seem to be more likely to find fixed term contract and to be in jobs with lower skills requirements than workers with a general education background (Vermeire et al., 2022). The initial advantage of VET students in terms of the likelihood of being in employment evaporates over time (Forster et al., 2016; Forster and Bol, 2018; Hampf and Woessmann, 2017). These findings seem to suggest a policy trade-off between a short-term and long-term labour market outcomes (Hanushek et al., 2017), and signal inefficiencies of initial VET in the collective skills formation.

The reversal of the initial wage and employment advantage conferred by a VET background, however, has not been found when the analysis is performed within cohorts (Korber and Oesch, 2019; Hartog et al., 2021). In fact, the reversal of the initial VET advantage in wages and employment in analyses that do not take cohort effects in account may reflect the working of intervening variables (Hartog et al., 2021) and that the selected outcomes are only distally related to initial VET. Initial VET is tightly linked to the formation of skills that have currency on the labour market. Therefore, it is plausible that a VET background could lead to a good match between workers' skills and job skills requirements helping workers finding a fitting job. Workers with a VET background are less likely to experience educational mismatch and skills mismatch and this advantage tends to persist till retirement (Levels et al., 2014; Verhaest et al., 2018). The better match between workers' skills and job requirements is reflected in a lower incidence of training among students with a VET background compared to their colleagues with general education background (Forster and Bol, 2018; Tobback et al., 2024). Similarly, the gap in skills utilization between workers with a VET and a general background tends to remain stable over time (Schulz et al., 2023).

Analyses that use skills mismatch as a labour market outcome variable, find that a VET background gives an initial advantage in terms of match and job quality (Heijke et al., 2003; Tobback et al., 2024). This initial advantage decreases over time but never turns negative (Verhaest et al., 2018). This signals that initial VET is effectively contributing to the collective skills formation system. Mismatch conflates two types of misalignment between workers' skills and job requirements. Overskilling characterizes a situation in which workers' skills set is wider than what required by the job–the problem not directly linked to VET system–but how organizations use their workers' skills or are results of job search and recruitment frictions. On the contrary, underskilling is an issue that is directly connected to the VET system signalling that that the VET system is not delivering the skills required by employers. It is plausible that the relationship between a VET background and underskilling is stronger in VET systems that have a stronger linkage with the world of work (Levels et al., 2014). Conversely, when the VET system is weakly linked to the world of work, firms would experience difficulties in recruiting applicants with the skills required (Weaver and Osterman, 2017; Brunello and Wruuck, 2021), thus signalling that the VET system's contribution to the collective skills formation system is defective.

This paper focuses on the relationship between VET background and underskilling using multiple skill surveys performed in many European countries. While only few European countries have a VET pathway at the tertiary level, or its definition on this level is often fuzzy, all have a VET pathway at the upper secondary level.[2] Consequently, we restrict our analysis to comparison between VET and general education at the upper secondary level. Measurement of both variables of our core interest–VET and skills–are not easily measurable. First, is the ambiguity in defining skills mismatch (Felstead et al., 2016; McGuinness et al., 2018). There is a

[2]Ireland is the single exceptions, having only general education programs on the upper secondary level. The vocational training is almost fully provided by firms in form of entry training. But even Ireland has piloted a VET program in [Year] (add citation)

subjective and an objective assessment of underskilling. Subjective measures of underskilling are self-reported and thus imprecise, however, they are surely important for behaviour: workers behave according to their subjective perception of their situation. Objective measures compare workers' actual scores on selected skills with their underlying job requirements (Desjardins and Rubenson, 2011). Second, there are different ways of ascertaining a VET background. One way is a country expert assessment of VET or general education for each survey respondent. Another way is a direct self-reporting of vocational or general nature of educational qualifications, or self-reporting of typical-for-VET education features, like the period of time spent in a workplace or workplace instruction. Both information are useful because of different natures of vocational programs across countries (Hoidn and Šťastný, 2021).

There is no best way to address the potential imprecisions in measurement of underskilling and VET background. Therefore, our empirical strategy makes use of three survey data sets with multiple ways measuring underskilling and ascertaining VET background. The working hypothesis is that workers with an upper secondary VET background experience a smaller degree of underskilling compared to workers with a general upper secondary background. Our analysis has three defining characteristics. First, it is based on the segment of initial VET present in some form across all EU countries. Second, it focuses on an outcome, underskilling, which is closely linked to the role of initial VET in the collective skills formation system. Third, the robustness of the result to different ways of measuring underskilling and ascertain skills mismatch is the main contribution of the paper to the literature on skills mismatch. With our focus on European countries we leverage differences in the established VET systems across countries and pinpoint thereof relevance to labour market closeness.

In the next section, we describe our data sets and relevant variables. In section 3 we discuss our empirical strategy. We present our results, effect of VET in underskilling across multiple measures and surveys in section 4. Here we also discuss several mechanisms behind these effects. The last section offers concluding remarks.

2 Data

In our analysis we use both waves of the *European Skills and Job Survey* (ESJS1, 2014; ESJS2, 2021) and the OECD *Programme for the International Assessment of Adult Competencies* survey (PIAAC first cycle, 2012-17).[3] Currently, they are the most representative and the most exhaustive data source for European countries on self-reported skills (all three) and stock of skills (only PIAAC). From the perspective of our research the use of all of them in a single paper is due to variation in the way how underskilling is measured. Additionally, each survey has its specific component that enables us to expand on variety of underskilling measures.[4]

The ESJS1 (2014) surveys about 49'000 adult employees, aged 24 to 65, from all EU-27 member states and the United Kingdom (Cedefop, 2018). It collects detailed information on job-skill requirements, digitalization, skill mismatches, and workplace learning, with the aim to assess dimensions of skill shortages and skill underutilisation. The ESJS1 survey is the richest source of self-reported mismatch measures of general and of skill domain-specific nature. The ESJS2 (2021) surveys 46'213 adult employees, aged 24 to 65, in the EU-27 Member States, Norway, and Iceland (Cedefop, 2022). It examines drivers of skill development in relation to changing task complexity and skills requirements of jobs. The special focus of ESJS2 is in changing skill needs and job tasks of workers due to digitalization and underlying adaptability.

Both ESJS surveys contain only self-reported measures of skills and skill mismatch. We complement our analyses using the PIAAC dataset, which measures actual skills of prime age population via a standardized test in numeracy, literacy, and problem-solving skill domains, in addition we are able to create several underskilling measures based on self-reports, too (OECD, 2013, 2016).

[3] OECD (2013) reports first results based on PIAAC data. Both ESJS surveys are collected by the European Centre for the Development of Vocational Training (Cedefop). The first wave is available, after registration, free of charge via: https://www.cedefop.europa.eu/en/projects/european-skills-and-jobs-survey-esjs

[4] There are other surveys containing information on skills: The European Working Conditions Survey (EWCS) from Eurofound and the European Labour Force Survey (LFS) ad-hoc module on skills utilization. However, the EWCS does not include variables that could be used to identify a VET background, while the LFS ad-hoc module consits of a Job Requirement Module that allows inference on skills utilisation but does not contain a measure of underskilling. For these reasons the EWCS and the LFS ad-hoc module on skills utilization were not included in the analysis

In all three surveys, we focus on European Union countries, where the vocational education has a long tradition.[5] Moreover it allows us to leverage the differences in the nature of each country's VET system. We restrict the samples to 24-65 years-old individuals who hold an upper or post-secondary education as their highest educational attainment (levels 3 and 4 of ISCED 97), which is around 35-40% of the total samples. Excluding individuals holding other educational attainments is critical to the variable of our interest—vocational education. Namely, it generally does not exist on the lower secondary level. As for tertiary level, it exists in some countries, but its definition is not unified across countries. The VET share is 75% in ESJS1 where the VET secondary attainment is self-reported. It is less in ESJS2 and PIAAC (61%), where the VET degree is based on expert knowledge of the country's education systems and each respondent is aligned with an ISCED 35 or 45 attainment is a VET worker (cf. Table 1). The reduction in the VET share between the two rounds of ESJS surveys is also in line with the decrease in VET school enrolment experienced by most participating countries.

2.1 Measures of overall underskilling

In line with our earlier considerations upon relevance of VET education for individual skill formations, we focus on measures of job underskilling as collected by all three surveys. The ESJS1 survey is our richest source of self-reported underskilling. Survey participants are asked on three occasions upon their current mismatch on the job based on question *How would you best describe your skills in relation to what is required to do your job?*. We focus on those reporting *My skills are lower than what is required.* Their answers are recorded on three levels of precision. First as a plane dummy, where 1 is incidence of underskilling and zero is either perfect match or overskilling. The other two underskilling variables are measuring intensity of underskilling. One of them is a scale variable taking integer values from 0 to 5, where 0 is a perfect match or overskilling, and 1 to 5 are levels of underskilling from very low (=1) to very high (=5). The last variable measures respondents job-skill match on a percentage scale from 0 to 100 where 0 means perfect match and 100 is perfect mismatch. This last variable does not allow, by con-

[5] All EU 27 countries are included in both ESJS surveys. PIAAC data includes just 18 EU countries.

struction, statements of overskilling. ESJS1 also asks upon job-skill mismatch recollection at two earlier points in time: when starting the current job and in previous job. Currently only 5% of our sample report underskilling and the average intensity of underskilling is low at about 1 of 5 levels, or 17 from 100. The incidence of underskilling is higher at the earlier points in time, reflecting a learning job skills, and ultimately leading to lower underskilling (Table 1, Panel A).

For PIAAC we can only construct a single overall underskilling measure, which is a dummy variable that takes the value 1 if the respondent does affirm to the question: *Do you feel that you need further training in order to cope well with your present duties?*, and simultaneously does not affirm the question: *Do you feel that you have the skills to cope with more demanding duties than those you are required to perform in your current job?*. This classification results in a similar share of underskilling (4.7%) as based on current underskilling using the ESJS1 data (4.9%) (c.f. Table 1, Panel A vs. B).

The overall underskilling in ESJS2 is based on a survey question regarding skills deficit: *To what extent do you need to further develop your overall level of knowledge and skills to do your main job even better?*. The underskilling measure is defined either as a dummy, where 0 indicates a skill match, and 1 underskilling, or on the scale 0 to 3 (0 not at all, 1 small extent, 2 moderate extent, 3 great extent), where larger value point to larger underskilling. Compared to ESJS1 and PIAAC, more than 80% of respondents are assigned as underskilled (Table 1, Panel C). The larger incidence of underskilling compared to ESJS1 is due to the prospective nature of the question: *Compare the skills that you have today to those you will need in the future to have a better performance*. With this formulation everybody that expect to increase its performance is underskilled. Those who are not underskilled according to this measure are those that cannot increase their performance or do not want to increase their performance.

2.2 Measures of underskilling in skill domains

Similarly to measures of overall underskilling, ESJS1 contains two follow up questions about incidence and intensity of underskilling in multiple skill domains. In this study we explicitly look at: specialized technical skills, numeracy skills, problem-solving skills, and information and communication technology (ICT) skills. Based on PIAAC survey we build three self-reported underskilling measures in numeracy, problem-solving and ICT domains. For this we standardized the first plausible value of each skill level and standardized job skill needs levels using questions about the frequency of relevant skill usage. We calculated a underskilling via difference between the respondents skill level with the job's skill needs. Finally, for each domain, we categorized the difference into 0-5 levels, where zero stands for overskilled and perfectly matched individuals and values 1 to 5 distinguish five levels of underskilling intensity.

Furthermore, we construct two actual underskilling measures with respect to numeracy skills and one actual measure of problem-solving skills. We utilize the first plausible value of the individual numeracy and problem-solving scores from PIAAC's standardized tests. For the first measure, we follow Pellizzari and Fichen (2017) who propose to evaluate the individual skill domain score to the lowest score of workers in the same ISCO 1-digit occupational group that claim to be well matched, i.e. who are neither underskilled nor overskilled according to their answer to the two above questions. Workers whose scores are below the lowest score of well matched workers, are classified as underskilled. It exists for both skill domains. For the second measure we follow Rodríguez et al. (2022) and assess underskilling based on their Job Analysis Method (JAM). For this, we use the expert rating provided in Rodríguez et al. (2022) and assess job requirements with regards to numeracy skills in an occupational group[6]. We classify a worker as underskilled according to this measure when she or he has a numeracy score that is lower than the JAM requirement levels. The JAM underskilling measure results in a higher share of workers who are classified as underskilled with regards to numeracy (22.8%) as compared to the PF measure (4.4%) (c.f. Table 1, Panel B). The expert ratings are not available for problem-solving skill domain.

In ESJS2, the ICT mismatch is based on need of skill development (*To what extent do you need to further develop your computer/IT skills to do your main job even better?*) and is defined on a scale 0 to 3, where 3 means the need to a 'great extent' to develop the skill. The measures of numeracy and technical mismatch are based on equivalent questions, but are quantified only

[6]We match on the ISCO 08 4-digit were possible, but go up to the 1-digit level as needed.

as dummies, where zero indicates a skill match, and 1 a mismatch. A correspondence overview of available underskilling measures across surveys used in our empirical analysis, we list in Table 2.

3 Empirical strategy

In our empirical specification we follow a similar path as Hanushek et al. (2017) who estimate the age profile of lifetime employment and earnings; and Verhaest et al. (2018) who estimate a graduation year profile of education and skill mismatches. In our case we explain underskilling by use of a following equation

$$y_i = \beta_0 + \beta_1 \mathrm{VET}_i + \boldsymbol{\gamma}\mathbf{X_i} + \theta_c + \lambda_t + \delta_c t + \varepsilon_{ict}, \tag{1}$$

where y_i is an underskilling measure of an individual i. The θ_c and λ_t stand for country and graduation year fixed effects. The country fixed effect control for time invariant specificities of countries' labour markets, while the graduation year fixed effects are dummies controlling for structural factors generally present at the time of an individual entering the labour market. To allow for country specific development related to labour market underskilling we include also country specific linear time trend $\delta_c t$ in graduation years. Furthermore, we cluster standard errors, ε_{ict}, on country$\times$ graduation year level. We justify our clustering level by the relevance of this grid for the VET variable.

The matrix $\mathbf{X}$ includes three sets of variables which further explain the individual skill mismatch, and control, albeit imperfectly, for selection into VET education due to observable characteristics. Accordingly, the vector $\boldsymbol{\gamma}$ stores the underlying coefficient estimates. The first set, contains five individual control dummies: female, post-secondary education, migration status, living with a partner and living with children. Next, job-specific controls include temporary contract and part time dummies, three tenure dummies, four occupation level dummies and, lastly, high job-autonomy, high-level of learning, and job-related technological change. Finally, in the third set are workplace-specific variables: three firm-size dummies and 15 industry dummies.

Our core interest lies in the distinction between the average underskilling of VET and generally educated individuals controlling for an extensive set of observables for selection into VET education track. Accordingly, in Equation 1 the coefficient of interest is β_1. If negative, secondary VET education leads to a smaller underskilling probability in the underlying skill as compared to generally educated. If positive, VET educated workers have higher levels of underskilling. Unlike the Verhaest et al. (2018) we refrain from using the interaction term between graduation year and VET education dummy in our baseline specification (Eq. 1). Verhaest et al. (2018) devote their analysis to the mismatch life-cycle analysis. Our descriptive statistics, however, show no differences in graduation year fixed effects between VET and generally educated.

In our estimation approach we first apply limited dependent variable models (probits, ordinal probits, and tobit), in agreement with the discrete nature of the dependent variables. Then we run linear probability models to estimate the marginal effect of having a VET background. We check whether the coefficients significant in the limited dependent specification remain significant in the linear specification. Consecutively, we apply linear probability model to obtain an estimate of the marginal effect of the variable of interest. The estimates from the linear probability model tend to be biased if predicted values lies beyond the unit (limited) interval (Horrace and Oaxaca, 2006). To account for this problem, we iteratively trim the estimation sample from the observations whose predicted value falls outside the admitted range (Chen et al., 2023) . We do this because our interest is in the interpretability of the Average Partial Effect (APE) of the VET background variable. Since all the data sets we use are cross-sectional, the linear probability specification, even if biased, tends to return conservative estimates of the APE (Chen et al., 2023). The linear specification, however, makes it possible to gauge the robustness of the estimates to omitted variable bias (Frank et al., 2023, 2013; Xu et al., 2019). An estimate is proclaimed as significant in the presence of unobserved heterogeneity if the percentage bias is at least 50%.

4 Results

4.1 Overall underskilling

Our measures of overall underskilling, would ideally reflect a general perception of the match between the individual vis-à-vis her current work. There are three measures of this type available in the ESJS1 and a single one in the PIAAC and two ESJS2. In Table 3 we report VET coefficients employing regression equation (eq. 1) without controls (column (1)), including fixed effects and linear time trends in graduation years (column (2)); adding individual (column (3)); and job and workplace-specific controls (column (4)).

Using any of the three measures of current underskilling in the ESJS1 survey we find that workers with a vocational education degree are both less underskilled (cf. Table 3, row (i)) and their underskilling is less intensive (cf. Table 3, rows (ii) and (iii)). Including fixed effects, country-specific linear trend and control variables does not change the coefficient of vocational education dummy much. Focusing on the full model (column (4)), the coefficients of the dummy and the 0-100 scale variables indicate a smaller mismatch by the same level of about 1.5 percentage point. For the 0-5 scale underskilling variable, the effect is somewhat smaller but qualitatively very similar. Using the mean of 17.2 (Table 1), the 1.5pp translates into a $\sim$9% smaller mismatch of vocationally educated workers. The smaller underskilling is also supported by high values of percentage bias. The inference thus is not likely to be reverted due to unobserved heterogeneity. The ESJS1 results are also in line with the findings of Verhaest et al. (2018) demonstrating a smaller rate of mismatch among those with a vocational background using measures of over- and underskilling. Using the contemporary PIAAC survey, where underskilling is measured as training needs we find no difference between vocational and generally educated workers (Table 3, Panel B).

The analyses carried out using th most recent ESJS2 survey does not support the results obtained analyzing the ESJS1, either. The ESJS2 the underskilling is measured as skill deficit, as incidence and intensity (Table 3, Panel C). VET workers self-report slightly larger underskilling as compared to generally educated workers. Economically this effect, however, remains small.

The mean overall underskilling in ESJS2 is 1.64. The effect size of 0.06 translates into a very small actual disadvantage for VET workers: their underskilling is only about 3.6% higher than for workers with general education. Moreover, the percentage bias is low at 18%-22%, when we include job and workplace characteristics into regression, thus it is likely the effect being overthrown when having a fuller account of unobserved heterogeneity (cf. Table 3, Panel C). The relationship between a vet background and underskilling is not supportive of the working hypothesis in the ESJS2 data set, independently from the way in which underskilling is measured, on a 0/1 scale or on a 0-3 scale. Notice that the measure of underskilling adopted in the ESJS2 is probably the measure with the weakest link with the underlying target. In fact, well functioning VET system, one that contributes to the collective skills formation may actually imply a poisitve relationship between a vet background and this measure of underskilling. For example, if the relationship between skills and perfromance is characterized by decreasing marginal perfromance, assuming that workers with a VET background are less underskilled than those with GE background, workers with VET background would need a larger increase in skills than that needed by workers with a GE background to attain the same level of productivity increase (Workers with a VET background are to the right of workers with a GE background in the skills distribution). A similar conclusion obtains when there are different expectations concerning perfromance increases between the two group of workers: those with a GE and a VET background. For example, having a VET background may give access to a community of practice and thus workers with a VET background may be used to larger performance improvements than workers with a GE background. Even with a constant marginal performance, workers with a vet background would need to report a larger expected increase in their skills to match their larger expected gain in performance with respect to workers with a GE background.

In the consecutive analysis we explore which specific skill domains drive the VET effects in overall underskilling.

4.2 Underskilling in skill domains

All three surveys collect explicit self-reports of underskilling in various skill domains, too. We focus on specialized-technical domain because it is by the nature of the survey question directly referring to vocational skills.[7] We also consider three further domains, numeracy, problem-solving and ICT skills, that are often referred as skills where VET workers likely have gaps when compared to generally educated workers. In Table 2 we overview which measures exists across the three surveys.

In both ESJS surveys the domain of specialized technical skills is the only domain that VET coefficient is significant in thereof underskilling (Table 4, Panels A and C). In all other domains the underskilling between VET and generally educated is generally not significantly different from each other even if the sign of vocational dummy often signalize lover underskilling. Apparently, it is the specialist skills domain due to which the VET workers differ from generally educated workers. Reflecting upon the percentage bias, this evidence is not strong, nevertheless it is the only skill domain which shows a systematic difference in underskilling. (cf. Table 3, both specialized technical rows). Moreover, for both surveys the VET effect size in underskilling of the specialized technical domain is exactly half of the effect of the VET effect size in the overall underskilling underscoring the importance of the domain.

In PIAAC survey vocational workers self-report more underskilling in numeracy and problem-solving domains. However these effects are not stable when adding more controls and the percentage bias is small. In ICT domain vocational workers self-report lower underskilling. This effect remains robust across specifications and the percentage bias is high (Table 4, Panel B).

4.3 Mechanisms of underskilling differences

One potential mechanism behind the overall effect could be a persistence of better job-skill match since earlier work experience. In addition to current overall skill mismatch, ESJS1, as the only survey of the three, also assesses retrospective mismatch: at the beginning of the current job and

[7] The underlying definition in both ESJS surveys is *"Technical skills (e.g. Specialist knowledge needed to perform job duties; Knowledge of particular products or services; Ability of operating specialized technical equipment)"*.

in the previous job. We thus repeat our analyses building underskilling measures for the two earlier career time points. For the situation at the beginning of the current job we could build both underskilling incidence and intensity, while the underskilling in the previous job exists only as a dummy variable. In Table 5 we report vocational dummy coefficients for all three measures. All three coefficients are negative, but only underskilling incidence is statistically significant. Even if the percentage bias reflect large uncertainty in the coefficient when having a full account of heterogeneity. Comparing the respective estimation coefficients, the extend of underskilling is larger for the current underskilling than for the earlier retrospection. Still the vocational dummy effects of the earlier job-skill matches suggest that workers with a vocational background start their jobs better matched with the underlying job requirements, and their perception is persistent and strengthen over time.

Another mechanism in underskilling differences between vocational workers can be caused by systematic difference between self-reported and actual underskilling. We can test this aspect using PIAAC survey which contains self-reported measures and allows to calculate actual underskilling measures. In Table 6 we report that vocational education effect is equivalent using self-reported and two variants of actual underskilling.

Europe has a large variety of vocational education systems. We are particularly interested in the tightness between labour market and initial vocational education. There is no unified view what such tightness might mean. Bolli et al. (2018) rely on expert interviews to gauge the closeness of VET education to labour market actors such as firms, trade chambers and professional associations. They develop a so-called education-employer-linkage (EEL) index for 18 countries. Some European countries have a well established system of apprenticeship contracts that are integral part of VET education allowing students to gather their skills via employee-like relationship with firms (e.g. Eichhorst et al., 2015). Lastly some countries, even those without apprenticeship, have a high share of workplace training as a part of their VET curriculum. All these features may signal closeness to labour market.

VET systems across the EU countries differ in their closeness to labour market and this may have an impact on underskilling of workers graduation from these systems. We distinguish three subset of countries with a demonstrably close connections between labour market and VET education: an above average EEL, apprenticeship countries, and countries with a high fraction (more than 50%) of workplace training (Table 7, bottom part). We re-estimate our full model of underskilling focusing on changes in coefficient of vocational education for the three subsets of countries. In Table 7 we report our results. For the ESJS1 survey the results for underskilling in the current job are most pronounced. For all country subsets the underskilling reduction for VET worker is stronger than in the whole sample. Compared to general education workers, VET workers are better job-skill matched in countries with VET systems that are close-knit to labour market needs. We evidence a stronger effect also in previous job match, albeit the effect ceased to be significant. There is no such pattern for the job-skill match at the beginning of the current job.

In contrast, our analysis of the PIAAC data (Table 7, Panel B) again fails to corroborate these findings. In none of the subsamples we observe a significant difference between vocationally and generally educated workers in terms of overall underskilling. However, in contrast to our analyses using the entire sample, we find no significantly higher likelihood of being underskilled with respect to numeracy in countries with a high prevalence of apprenticeship contracts (column (3)). Apprenticeships, which combine on-the-job training with classroom instruction, are designed to enhance the alignment between curricula and labor market demands (see for example Jansen et al., 2017). Consequently, our findings may suggest that in countries where vocational training is more frequently delivered through apprenticeships, the observed gap in numeracy skills between vocationally and generally educated workers may not materialize.

5 Conclusion

The aim of this paper is to investigate the contribution of the VET system to the collective skills system. We delimit our focus on the initial VET at upper- and post-secondary education levels, as at this level the initial VET is present in all EU countries. The VET system's role is to supply the occupational and professional skills at a scale. Underskilling is the labour market outcomes that is most closely related to the way in which the VET system discharges its function within the collective skills formation system. Consequently, the empirical analysis is built on the following working hypothesis: workers with a VET background would experience both a lower incidence and a lower degree of underskilling than workers with a general education background.

Three different data set with different definitions of underskilling and VET background to assess the robustness of the result to different measurement tools. Finally, since the data sets are cross-sectional in nature, the paper provides a measure of the robustness to the result against the influence of unobservable variables.

The results are not strong enough to support a clear conclusion on the VET ability to provide workers with the skills they need. In particular, a vet background is associated to a lower likelihood of overall underskilling when overall underskilling is measured by a subjective comparison between one's skills and the skills requirement of the job, as it is done in the ESJS1 data set. The coefficients thus obtained are also robust to the omitted variable bias, in the sense that the percentage of bias that would be needed to nullify the inference is implausibly high. However, this result has been found in the sample with the weakest statistical properties (it is a non-probability sample). This result was not replicated using the PIAAC data set using a concept of overall underskilling based on training needs. Since training needs may not represent a very good measure of underskilling, the paper analysed the relationship between a VET background and undeskilling in general skills, and on ICT, a technical skills (underskilling was assessed against an occupational norm; on the one hand this is a more objective measure, based on a assessed score on a given skill, on the other hand, the occupational norm might not be the right standard against which assess underskilling). No relationship between vet background is found for the general skills, while for ICT, a technical skill, a negative association between a vet background and underskilling is found. The estimate suggests that the relationship is robust to omitted variable bias.

The results found using the ESJS1 data set are not replicated on the ESJS2 data set. This is the data set with the most problematic definition of underskilling, one which is based on a measure of skills development that would support a foreseen improvement in work performance.

In a sense, it is a good thing that no relationship between a vet background and underskilling is found in the data set with the most problematic measure of overall underskilling.

All in all, the way underskilling is measured is important. The measure with the strongest linkage with the underlying concept (the difference between own skills and job skills requirement) suggests that VET is fulfilling its role in the collective skills formation system (providing workers with the right skills). However, this conclusion is only tentative, it must await further confirmation with the use of a sample with better statistical properties and of an analysis with appropriate design. With this in mind, it is hoped that a measure of overall underskilling based on the assessment of own skills against the skills required by the job, alongside with one or more variables to identify a VET background, will be included in a data set collected on a representative sample.

Based on self-reported underskilling, our results indeed show that having a VET background is associated with a lower incidence and a lower intensity of underskilling. Our results on actual underskilling measures, however, signal higher incidence of underskilling among VET workers. But even here, we find that for the subset of apprenticeship countries the VET workers are at least not less underskilled than their general education counterparts. Our results are based on cross-sectional evidence, but we could demonstrate a robustness of the VET effect estimate towards omitted variable bias in that we can in most cases invalidate the conclusions the bias should be implausible high. On this account our results are more robust when using underskilling intensity, rather than incidence.

Finally, the analysis based on the ESJS1 further suggests that workers with a VET background tend to experience a better quality match between their skills and the job skill requirements than workers with general education background already as they join the firm. That is, it appears that indeed the advantage from having a vocational background is linked to the better connection with the world of word. Altogether, our results suggest that the VET system discharges its role in the collective skills formation system egregiously, and they reinforce the recent literature on the non-inferiority of vocational path compared to general education path (e.g., Schweri et al., 2020; Silliman and Virtanen, 2022).

References

Bolli, T., Caves, K. M., Renold, U., and Buergi, J. (2018). Beyond employer engagement: measuring education-employment linkage in vocational education and training programmes. *Journal of Vocational Education Training*, 70(4):1–40.

Brunello, G. and Rocco, L. (2017). The effects of vocational education on adult skills, employment and wages: What can we learn from PIAAC? *SERIEs*, 8(4):315–343.

Brunello, G. and Wruuck, P. (2021). Skill shortages and skill mismatch: A review of the literature. *Journal of Economic Surveys*, 35(4):1145–1167.

Busemeyer, M. R. and Trampusch, C. (2012). *The Comparative Political Economy of Collective Skill Formation*. Oxford University Press, Oxford.

Cedefop (2018). *Insights into skill shortages and skill mismatch: Learning from Cedefop's European skills and jobs survey*. Publications Office of the European Union, Luxembourg.

Cedefop (2022). *Setting Europe on course for a human digital transition: new evidence from Cedefop's second European skills and jobs survey*. Publications Office of the European Union, Luxembourg.

Chen, K., Martin, R. S., and Wooldridge, J. M. (2023). Another look at the linear probability model and nonlinear index models.

Desjardins, R. and Rubenson, K. (2011). An analysis of skill mismatch using direct measures of skills.

Eichhorst, W., Rodríguez-Planas, N., Schmidl, R., and Zimmermann, K. F. (2015). A road map to vocational education and training in industrialized countries. *ILR Review*, 68(2):314–337.

Felstead, A., Gallie, D., and Green, F. (2016). *Measuring skills stock, job skills, and skills mismatch*. Oxford University Press, Oxford.

Forster, A., Bol, T., and van de Werfhorst, H. (2016). Vocational education and employment over the life cycle. *Sociological Science*, 3:473–494.

Forster, A. G. and Bol, T. (2018). Vocational education and employment over the life course using a new measure of occupational specificity. *Social Science Research*, 70:176–197.

Frank, K. A., Lin, Q., Xu, R., Maroulis, S., and Mueller, A. (2023). Quantifying the robustness of causal inferences: Sensitivity analysis for pragmatic social science. *Social Science Research*, 110:102815.

Frank, K. A., Maroulis, S. J., Duong, M. Q., and Kelcey, B. M. (2013). What would it take to change an inference? using rubin's causal model to interpret the robustness of causal inferences. *Educational Evaluation and Policy Analysis*, 35(4):437–460.

Hampf, F. and Woessmann, L. (2017). Vocational vs. general education and employment over the life cycle: New evidence from PIAAC. *CESifo Economic Studies*, 63(3):255–269.

Hanushek, E. A., Schwerdt, G., Woessmann, L., and Zhang, L. (2017). General education, vocational education, and labor-market outcomes over the lifecycle. *Journal of Human Resources*, 52(1):48–87.

Hartog, J., Raposo, P., and Reis, H. (2021). Fluctuations in the wage gap between vocational and general secondary education: lessons from portugal. *Journal of Population Economics*, 35(2):643–675.

Heijke, H., Meng, C., and Ris, C. (2003). Fitting to the job: the role of generic and vocational competencies in adjustment and performance. *Labour Economics*, 10(2):215–229.

Hoidn, S. and Šťastný, V. (2021). Labour market success of initial vocational education and training graduates: A comparative study of three education systems in central europe. *Journal of Vocational Education Training*, 75(4):629–653.

Horrace, W. C. and Oaxaca, R. L. (2006). Results on the bias and inconsistency of ordinary least squares for the linear probability model. *Economics Letters*, 90(3):321–327.

Ibsen, C. L. and Thelen, K. (2024). Arrangers and orchestrators: the diverging role of the state in danish and german vocational education and training. *Socio-Economic Review*, page mwae022.

Jansen, A., de Grip, A., and Kriechel, B. (2017). The effect of choice options in training curricula on the demand for and supply of apprentices. *Economics of Education Review*, 57:52–65.

Korber, M. and Oesch, D. (2019). Vocational versus general education: Employment and earnings over the life course in switzerland. *Adv Life Course Res*, 40:1–13.

Levels, M., Van der Velden, R., and Di Stasio, V. (2014). From school to fitting work: How education-to-job matching of European school leavers is related to educational system characteristics. *Acta Sociologica*, 57(4):341–361.

McGuinness, S., Pouliakas, K., and Redmond, P. (2018). Skills mismatch: concepts, measurement and policy approaches. *Journal of Economic Surveys*, 32(4):985–1015.

Mende, C., Oswald-Egg, M. E., and Caves, K. M. (2023). *VET System Governance: A systematic literature review*, volume 14. ETH Zurich, Chair of Education Systems, Zurich.

Middeldorp, M. M., Edzes, A. J. E., and van Dijk, J. (2019). Smoothness of the school-to-work transition: General versus vocational upper-secondary education. *European Sociological Review*, 35(1):81–97.

OECD (2013). OECD skills outlook 2013: First results from the survey of adult skills. OECD Publishing. http://dx.doi.org/10.1787/9789264204256-en.

OECD (2016). OECD skills matter: Further results from the survey of adult skills. OECD Publishing. http://dx.doi.org/10.1787/9789264258051-en.

Pastore, F., Quintano, C., and Rocca, A. (2021). Some young people have all the luck! the duration dependence of the school-to-work transition in Europe. *Labour Economics*, 70.

Pellizzari, M. and Fichen, A. (2017). A new measure of skill mismatch: theory and evidence from piaac. *IZA Journal of Labor Economics*, 6:1–30.

Pérez Rodríguez, S., Van der Velden, R., Huijts, T., and Jacobs, B. (2024). Identifying literacy and numeracy skill mismatch in oecd countries using the job analysis method. *Oxford Economic Papers*, 76(3):859–876.

Rodríguez, S. P., van der Velden, R., Huijts, T., and Jacobs, B. (2022). Identifying literacy and numeracy skill mismatch in oecd countries using the job analysis method. Roa-rm-2021/11.

Schulz, W., Solga, H., and Pollak, R. (2023). Vocational education, tertiary education, and skill use across career stages. *European Sociological Review*, 39(5):741–758.

Schweri, J., Eymann, A., and Aepli, M. (2020). Horizontal mismatch and vocational education. *Applied Economics*, 52(32):3464–3478.

Silliman, M. and Virtanen, H. (2022). Labor market returns to vocational secondary education. *American Economic Journal: Applied Economics*, 14(1):197–224.

Thelen, K. (2004). *How Institutions Evolve: The Political Economy of Skills in Germany, Britain, the United States and Japan*. Cambridge University Press., Cambridge, New York:.

Tobback, I., Verhaest, D., Baert, S., and De Witte, K. (2024). Vocational education, general education, and on-the-job learning over the life cycle. *European Sociological Review*, 40(2):189–207.

Verhaest, D., Lavrijsen, J., Van Trier, W., Nicaise, I., and Omey, E. (2018). General education, vocational education and skill mismatches: Short-run versus long-run effects. *Oxford Economic Papers*, 70(4):974–993.

Vermeire, E., De Cuyper, N., and Kyndt, E. (2022). *Preparing Students for the School-to-Work Transition: A Systematic Review of Research on Secondary School-Based Vocational Education*, pages 367–398. Springer International Publishing, Cham.

Weaver, A. and Osterman, P. (2017). Skill demands and mismatch in u.s. manufacturing. *ILR Review*, 70(2):275 – 307.

Xu, R., Frank, K. A., Maroulis, S. J., and Rosenberg, J. M. (2019). konfound: Command to quantify robustness of causal inferences. *The Stata Journal*, 19(3):523–550.

Table 1: Descriptive statistics of vocational dummies and underskilling measures in all surveys

	Mean	(Std. dev.)	N
	Panel A: *ESJS1*		
vocational educ.: 0/1	0.756	(0.430)	15,889
Overall underskilling measures:			
current: 0/1	0.048	(0.214)	15,818
current: 0-5	0.097	(0.493)	15,806
current: 0-100	17.244	(15.051)	15,889
when starting the current job: 0/1	0.225	(0.418)	15,778
when starting the current job: 0-5	0.543	(1.145)	15,740
in previous job: 0/1	0.112	(0.316)	14,545
Underskilling measures in domains:			
specialized tech.: 0-5	0.097	(0.511)	15,617
numeracy: 0-5	0.052	(0.356)	15,672
problem-solving: 0-5	0.042	(0.321)	15,568
ICT: 0-5	0.053	(0.349)	15,621
	Panel B: PIAAC		
vocational educ.: 0/1	0.609	(0.488)	19,777
Overall underskilling measures:			
current: training needs: 0/1	0.047	(0.212)	19,777
Underskilling measures in domains:			
numeracy: 0-5	0.697	(0.909)	19,777
problem-solving: 0-5	0.533	(0.863)	19,777
ICT: 0-5	0.490	(0.968)	19,777
Underskilling measures in domains: actual			
numeracy PF: 0/1	0.044	(0.205)	19,326
numeracy JAM: 0-5	0.685	(0.890)	19,777
problem-solving PF: 0/1	0.036	(0.187)	16,698
	Panel C: ESJS2		
vocational education: 0/1	0.615	(0.486)	11,361
Overall underskilling measures:			
current: skill deficit: 0/1	0.888	(0.315)	11,360
current: skill deficit: 0-3	1.640	(0.853)	11,360
Underskilling measures in domains			
specialized tech.: 0/1	0.387	(0.487)	11,356
numeracy: 0/1	0.283	(0.451)	11,363
ICT: 0-3	1.409	(0.935)	11,358

Notes: ESJS1 (2014), PIAAC (2012-2015), and ESJS2 (2021) subsamples of ISCED 3-4 educational attainment. The samples within all three surveys slightly differ due to varying non-response for different mismatch questions. PIAAC data are further limited to 18 EU countries to align with the both ESJS surveys. For PIAAC Panel, underskilling indicated as (JAM) is derived using *Job Analysis Method* (Pérez Rodríguez et al., 2024); underskilling indicated as (PF) uses the methodology of Pellizzari and Fichen (2017). For ESJS2 (2021) the Computer Assisted Web Interview (CAWI) sample is considered. All means are weighted by the corresponding sampling weights.

Table 2: Underskilling measures across the surveys

ESJS1	ESJS2	PIAAC
	Panel A: *Overall underskilling*	
current job: 0/1		current job: 0/1
current job: 0-5	current job: 0-3	
current job: 0-100		
start. current job: 0-5		
	Panel B: *Skill domains underskilling*	
specialized tech.: 0-5	specialized tech.: 0/1	
numeracy: 0-5	numeracy: 0/1	numeracy: 0-5
		numeracy-actual PF: 0/1
		numeracy-actual JAM: 0-5
problem-solving: 0-5		problem-solving : 0-5
		problem solving-actual PF: 0/1
ICT: 0-5	ICT: 0-3	ICT: 0-5

Notes: Table overviews all underskilling measures we use in our regression analysis by survey.

Table 3: Effect of vocational education on self-reported underskilling

	Without controls		With controls	
Underskilling measure:	(1)	(2)	(3)	(4)
Panel A: *ESJS1*				
(i) current: 0/1	-0.021***	-0.020***	-0.019***	-0.024***
	(0.005)	(0.006)	(0.006)	(0.006)
% bias to invalidate inference	49.15	43.78	41.96	48.65
(ii) current: 0-5	-0.055***	-0.052***	-0.051***	-0.076***
	(0.013)	(0.014)	(0.014)	(0.016)
% bias to invalidate inference	54.14	48.72	48.08	58.22
(iii) current: 0-100	-1.538***	-1.596***	-1.599***	-1.516***
	(0.357)	(0.354)	(0.359)	(0.355)
% bias to invalidate inference	54.52	56.48	56.04	54.03
Panel B: *PIAAC*				
(iv) current: training need 0/1	0.005	-0.002	-0.003	0.006
	(0.003)	(0.004)	(0.005)	(0.005)
Panel C: *ESJS2*				
(v) current: skill deficit 0/1	0.024**	0.027***	0.025**	0.032**
	(0.010)	(0.010)	(0.010)	(0.013)
% bias to invalidate inference	21.36	25.27	19.02	21.92
(vi) current: skill deficit 0-3	0.070***	0.067***	0.059**	0.059**
	(0.025)	(0.025)	(0.024)	(0.025)
% bias to invalidate inference	31.26	27.55	19.12	17.61
country & graduation year FE		yes	yes	yes
country-specific linear trend		yes	yes	yes
individual controls			yes	yes
job/workplace-specific controls				yes

Notes: ESJS1, PIAAC, and ESJS2 subsamples of ISCED 3-4 educational attainment. Reported is only the coefficient of the vocational education dummy. Each coefficient stems from a separate linear regression with an underskilling measure as dependent variable (see row headings) optionally including fixed effects and control variables (see bottom part of the table). Observations are weighted by sampling weights. Percentage bias to invalidate inference we report only for significant vocational education coefficients. Robust standard errors clustered by country × graduation year are in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 4: Effect of vocational education on self-reported underskilling in skill domains

	Without controls		With controls	
Underskilling in domain:	(1)	(2)	(3)	(4)
	Panel A: *ESJS1*			
specialized technical: 0-5	-0.014	-0.030**	-0.027*	-0.034*
	(0.013)	(0.015)	(0.016)	(0.020)
% bias to invalidate inference		2.52	14.06	13.62
numeracy: 0-5	-0.006	-0.012	-0.012	-0.012
	(0.008)	(0.010)	(0.010)	(0.012)
problem-solving: 0-5	-0.009	-0.009	-0.009	-0.012
	(0.007)	(0.008)	(0.009)	(0.011)
ICT: 0-5	-0.009	-0.015	-0.017*	-0.015
	(0.009)	(0.010)	(0.010)	(0.014)
% bias to invalidate inference			10.63	
	Panel B: *PIAAC*			
numeracy 0-5	-0.002	0.012	0.025	0.059***
	(0.017)	(0.017)	(0.017)	(0.017)
% bias to invalidate inference				43.30
problem-solving 0-5	0.124***	0.046**	0.028	0.049***
	(0.020)	(0.019)	(0.019)	(0.019)
% bias to invalidate inference	69.21	17.51		25.45
ICT 0-5	-0.139***	-0.147***	-0.200***	-0.102***
	(0.016)	(0.019)	(0.018)	(0.019)
% bias to invalidate inference	77.21	74.70	82.10	63.36
	Panel C: *ESJS2*			
specialized technical 0/1	0.032**	0.035**	0.035**	0.034**
	(0.014)	(0.014)	(0.014)	(0.014)
% bias to invalidate inference	15.18	22.14	23.73	17.14
numeracy 0/1	-0.005	-0.007	-0.009	-0.001
	(0.012)	(0.012)	(0.012)	(0.012)
% bias to invalidate inference				
ICT 0-3	-0.034	-0.019	-0.026	0.008
	(0.024)	(0.025)	(0.025)	(0.025)
% bias to invalidate inference				
country & graduation year FE		yes	yes	yes
country-specific linear trend		yes	yes	yes
individual controls			yes	yes
job/workplace-specific controls				yes

Notes: ESJS1, PIAAC, and ESJS2 subsamples of ISCED 3-4 educational attainment. Reported is only the coefficient of the vocational education dummy. Each coefficient stems from a separate linear regression with an underskilling measure as dependent variable (see row headings) optionally including fixed effects and control variables (see bottom part of the table). Observations are weighted by sampling weights. Percentage bias to invalidate inference we report only for significant vocational education coefficients. Robust standard errors clustered by country × graduation year are in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 5: Effect of vocational education on self-reported underskilling in the earlier career stages

	when starting the current job		in the previous job
	0/1	0-5	0/1
	(1)	(2)	(3)
vocational education	-0.016	-0.059**	-0.012
	(0.010)	(0.029)	(0.008)
% Bias to invalidate inference		4.92	

Notes: ESJS1 (2014), subsample of ISCED 3-4 educational attainment. Reported is only the coefficient of the vocational education dummy. Each coefficient stems from a separate linear regression with a self-reported underskilling measure as dependent variable (see column headings) including full set of fixed effects and control variables equivalently as in Table 3 column (4). Robust standard errors clustered by country × graduation year are in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 6: Effect of vocational education on self-reported vs. actual underskilling

	self-reported 0-5	actual PF 0/1	actual JAM 0-5
numeracy	0.059***	0.022***	0.159***
	(0.017)	(0.004)	(.016)
% bias to invalidate inference	43.30	63.00	80.40
problem solving	0.043***	0.012***	n.a.
	(0.015)	(0.004)	
% bias to invalidate inference	28.47	36.38	

Notes: PIAAC (2012-2015) subsamples of ISCED 3-4 educational attainment. Reported is only the coefficient of the vocational education dummy. Each coefficient stems from a separate linear regression an underskilling measure as dependent variable (see row headings) including full set of fixed effects and control variables equivalently as in Table 3 column (4). Robust standard errors clustered by country $\times$ graduation year are in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 7: Effect of vocational education on underskilling by closeness to labour market of the VET systems

countries *Dependent variable:*	All (1)	Apprenticeship (2)	High EEL (3)	High WPT (4)
specialized technical: 0-5	-0.034*	-0.090	-0.051	-0.101
	(0.020)	(0.093)	(0.057)	(0.071)
numeracy: 0-5	-0.012	-0.166**	-0.059	-0.148**
	(0.012)	(0.072)	(0.038)	(0.057)
problem-solving: 0-5	-0.018	-0.043	-0.038*	-0.040
	(0.016)	(0.036)	(0.022)	(0.028)
ICT: 0-5	-0.015	0.084*	0.044	0.044
	(0.014)	(0.050)	(0.031)	(0.036)
		Panel B: *PIAAC*		
numeracy 0-5	0.059***	-0.011	0.058*	0.118***
	(0.017)	(0.048)	(0.032)	(0.032)
problem-solving 0-5	0.049***	0.050	0.062**	0.118***
	(0.019)	(0.054)	(0.029)	(0.031)
ICT 0-5	-0.102***	-0.100	-0.081**	-0.088**
	(0.019)	(0.064)	(0.038)	(0.041)
		Panel C: *ESJS2*		
specialized technical 0/1	0.034**	-0.009	0.004	-0.006
	(0.014)	(0.033)	(0.025)	(0.026)
numeracy 0/1	-0.001	-0.047*	-0.031	-0.035*
	(0.012)	(0.025)	(0.019)	(0.021)
ICT 0-3	0.008	-0.087*	-0.066*	-0.067
	(0.025)	(0.048)	(0.039)	(0.041)
		Austria	Austria	Austria
		Denmark	Denmark	Denmark
		Germany	Germany	Germany
		Luxembourg		Luxembourg
			Finland	Finland
			Estonia	Belgium
			Poland	Croatia
			Slovenia	Latvia
				Netherlands

Notes: ESJS1 (2014), PIAAC (2012-2015), and ESJS2 (2021) subsamples of ISCED 3-4 educational attainment. Reported is only the coefficient of the vocational education dummy. Each coefficient stems from a separate linear/probit regression an underskilling measure as dependent variable (see row headings) including full set of fixed effects and control variables equivalently as in Table 3 column (4). For the ease of comparison, the first column repeats results including all countries shown in previous tables. Observations are weighted by sampling weights. PIAAC rows do not include Croatia, Denmark, Estonia, Latvia and Luxembourg, as these countries did not participate in the PIAAC survey. The public use file of Austria contains only categorical age variable, thus we do not consider it in our analysis. Robust standard errors clustered by country $\times$ graduation year are in parentheses. *p<0.10, **p<0.05, ***p<0.01