Technequality

Understanding the relation between technological innovations and social inequality

Preparing Today's Youths for Tomorrow's labour Market. Analyses of the relationship between initial education and skills acquisition across countries and over time

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We assess the extent to which education systems in European countries effectively support the acquisition of skills that will maximize employability of school leavers on a labour market affected by automation. We provide various empirical analyses of cross-national skills and education surveys (international students and adult competencies assessment surveys and national skills and education surveys). We focus on digital literacy, computer skills, and problem solving. We also assess whether VET systems should teach general skills and scrutinize the relationship between educational expansion and technological change.

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Management Summary

Technological innovations continuously alter skills needs on the labour market. This is true not only for employees engaged in routine tasks but, to an increasing extent, will also apply to employees in professions and with complex non-routine tasks. As a consequence, technological innovations will lead to a shift in skills needs on the labour market. In this report we assess the extent to which education systems in European countries are effectively support the acquisition of skills that will maximize employability of school leavers. We provide various empirical analyses of cross-national skills and education surveys (international students and adult competencies assessment surveys and national skills and education surveys).

In Chapter 1, we study the extent to which children's acquisition of relevant skills (e.g. computer skills problem solving skills) relates to characteristics of schools and education systems, using PISA data and data from the International Computer and Information Literacy Study (ICILS). We examine cross-national inequality in the acquisition of computing and problem solving skills by parents' socioeconomic status and gender. We further assess how social background and gender inequalities in relevant skills vary by the characteristics of the educational systems. We conclude that although there are sizeable differences between countries, most of the variation in test scores is observed within countries, between schools. As our exploratory cross-country analysis shows, most differences between countries are not related to system characteristics. This implies that individual and school differences matter the most. With regard to the school characteristics, most of the observable variation in computer literacy and computational thinking across schools is explained by the composition of the students in the school. In larger schools, with more favourable ratios between teachers and students, and sufficient ICT resources at a school, computer literacy tends to be higher. Compared to computer information literacy (CIL), the analysis of computational thinking (CT) shows that most of the individual-level variance is explained by the composition of the school too. Furthermore, the composition variables at the school level also explained most of the school-level variance. Our results also imply that substantial gains in both CIL and in CT skills come from the usage outside of the school environment. Using computers in school helps, but using computers outside schools for other than school purposes is what promotes these skills the most. In line with these findings, we find that the variation in problem-solving skills between countries is considerable, but that the variation within countries between schools is even larger. The composition of student populations (gender, migration, SES, age) accounts for almost one sixth of the between-country variation and between-school variation in test scores. Once we take school characteristics into account as well, such as private/public school, autonomy, extra-curricular creative activities and the student-teacher-ratio, we account for some additional five percent of the between-school variation. Private schools have a higher average performance than public schools, and extra-curricular activities are associated with a higher problem-solving proficiency. A better student-teacher ratio also helps. Characteristics of the educational systems and other country characteristics we considered explain differences in average proficiency levels across countries only to a minor extent.

In Chapter 2, we study determinants of the working populations' ICT skills in 18 European countries, with a special focus on the contextual level. To explain gaps in adults' ICT skills across countries, we use existing micro-level theories and extend them by five explanatory factors at the contextual level: ICT infrastructure, ICT usage, technical skills demand, adult education infrastructure, and level of gender equality. We apply our framework to data from the first cycle of the OECD's Programme of the International Assessment of Adult Competencies (PIAAC) that offers objective measures of adults' ICT skills. To analyse these data, we use multilevel regression models to decompose variance, identify and model possible gaps, and test hypotheses about the connection between skill gaps and national educational systems. Regarding micro-level determinants of ICT skills, our findings support previous research. On the contextual level, we found a country's ICT infrastructure to be a relevant determinant of the working population's ICT skills. Moreover, we found some support for a country's ICT usage and its adult education infrastructure as relevant explanatory factors for country-differences in the working populations' ICT skills. We could not find support for a meaningful relationship of a country's technical skills demand and level of gender inequality with their working populations' ICT skills.

The introduction of technology has been said to require a substantial increase in the educational attainment of the citizens of industrial nations. However, education is also sometimes seen as the driver of workplace transformations, with employers responding to the increasing supply of highly educated workers by introducing changes in the organization of work. In Chapter 3, we delve into this matter. We examine whether educational expansion is a response to exogenous changes in the structure of employment, or a factor that in itself can change the structure of production. Previous studies have mainly linked educational reforms to wages, not the production process more directly. This paper examines the relationship between educational expansion and technological change using evidence on changes in educational attainment and job complexity in 14 European countries between 1995 and 2015. We explore the link between educational expansion and job complexity at the societal level. We conclude that although much has been made of the importance of education as a vehicle for social change, we basically find no support for the view that education is the transformative force it has been made out to be. This implies that it is technological change, rather than educational expansion.

In Chapter 4 we examine the effect of general skills on wages for vocationally educated workers with a qualification at upper secondary level. While general skills are considered crucial for labour market success of workers in general, it is not clear whether this also holds for the vocationally educated workers. We use the recently developed concept of effective skills to identify the relation between general skills and wages for this group. The results indicate that general skills strongly affect wages of vocationally educated workers and are not less important than for generally educated workers from upper secondary education. For vocationally educated males these effects are specifically salient for prime age and older workers (36 and above). For vocationally educated females, general skills are most important in the beginning of their career. Since general skills are so important for vocationally educated, the next question is which characteristics of vocational education systems are associated with cross-national differences in the proficiency levels. We show that a strong vocational orientation of the educational system is not associated with the skills of vocationally educated, but they are systematically related to the skills of those educated in general tracks. A strong vocational orientation of the educational system leads to a more selective group of students who follow the general tracks. This characteristic is thus associated with an increasing gap between the vocational and those educated in general tracks. Skill proficiency levels of vocationally educated are not systematically related to whether vocational programs in a country are primarily school-based or workplace-based.

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Chapter 1

Educating Today for Tomorrow’s labour Market: The Role of Schools and School Systems in Teaching Children Computer and Problem-Solving Skills

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1.1 Introduction

European labour markets are currently undergoing a technological transformation of historical significance. An increasing number of job tasks can be entrusted to machines because of startling innovations in robotics, artificial intelligence, computer capacity, and data storage. Machines have long been proficient in routine tasks but are now also increasingly proficient in complex non-routine tasks (Brynjolfsson and McAfee, 2014; Susskind and Susskind, 2015). Consequently, tasks of existing jobs change (Arntz et al., 2017; Acemoglu and Restrepo, 2019), and so do the skills required to be productive in these jobs. And yet it is not clear which skills are required in an automated labour market. Most scholars agree that on automated labour markets, workers' employability and productivity will likely strongly be determined by the extent to which workers can compete with machines, work with machines, build machines, or complement machines (Brynjolfsson and McAfee, 2014; Frey and Osborne, 2017). This chapter provides data analyses that examine to what extent and how European education systems and schools contribute to teaching pupils the skills that are necessary to achieve these ends.

We focus on two skills domains that are commonly thought to be amongst the most important skills in the 21st century (see e.g.: Brynjolfsson and McAfee, 2014; World Economic Forum, 2020a): ICT skills – or more specifically, computer and information literacy (CIL) and computational thinking (CT) – and creative problem-solving skills. During the first two decades of the 21st century, computer skills and digital literacy have become increasingly important for workers' employability and productivity (Acemoglu and Autor 2011; Lane and Conlon, 2016; OECD, 2013; 2020). Two trends suggest that computer skills will become even more relevant in the next two decades. First, increasing digitization of developed economies, accelerated by the Covid-19 pandemic, further exacerbates the relevance of digital skills for a larger share of the workforce (OECD, 2020). Second, the ongoing work automation will likely increase the need for digital skills in many jobs (Brynjolfsson and McAfee, 2014; Frey and Osborne, 2017). However important, the empirical literature on digital skills acquisition of children is still relatively modest. The literature mostly focuses on a single country or a selected group of countries (DeBortoli et al., 2014; Siddiq and Scherer, 2016; Throndsen and Hatlevik, 2016; Senkbeil, 2018; Aydin, 2021), hampering our understanding of cross-national differences and the relevance of national education systems. Cross-national analyses focus mostly on explaining gender differences, and disregard other important social cleavages, such as the importance of children's socioeconomic background (Punter, Meelissen and Glas, 2017; Gebhardt et al., 2019).

The second and related set of skills often deemed important are higher-order cognitive skills (World Economic Forum, 2020b). The task-based literature on automation argues that routine tasks are most strongly automatable, but cognitive tasks are less likely to be substituted by computers (cf. Acemoglu and Autor, 2011). Therefore, cognitive skills remain essential for human employability (Brynjolfsson and McAfee, 2014; Arntz, Gregory and Zierhan, 2017). In this paper, we focus on a specific set of cognitive skills, i.e. creative problem-solving skills. Toghether with digital skills, creativity and analytic thinking are among the most important skills for tomorrow's labour markets (World Economic Forum, 2020a), and it is crucial to understand how they are best learned. Large cross-national analyses suggest that education systems and schools may impact the acquisition of problem-solving skills, but existing analyses are limited in scope and focus on a limited set of characteristics of schools and education systems (cf. Scherer and Beckman, 2014; Dronkers, Levels and De Heus, 2014).

To fully reap the economic and societal benefits from digitization and automation and optimally realize their potential for economic growth, it is essential to create a future labour force with the necessary skills (World Economic Forum, 2020b). To do so effectively, it is crucial to understand how to create the circumstances that allow us to teach children relevant skills effectively and efficiently. In this chapter, we present analyses that aid this understanding. We answer the following research questions: a) to what extent are there cross-national differences in the extent to which pupils are proficient in computer and information literacy (CIL), computational thinking (CT), and complex problem-solving (PS), b) to what extent are there cross-national differences in gender and SES inequalities in CIL, CT and PS, and c) to what extent and how do characteristics of teachers, schools, and education systems contribute to explaining these differences?

To answer our research questions, we analyse two data sets. First, we study CIL and CT using cross-national data on 9,449 children from Germany, Finland, France, Luxembourg, and Portugal from the International Computer and Information Literacy Survey (ICILS) 2018 (Fraillon et al., 2019). These data contain information about a wealth of characteristics of pupils, their families, their teachers, and their schools and are well-suited for understanding the role of education systems (Gebhardt et al., 2019). Crucially, they also contain measurements of children's computer use, and direct psychometric measurements of computer and information literacy and computational thinking skills. This allows us to analyse the relevance of children's behaviour and direct school contexts for acquiring the relevant skills. We merge the ICILS data with macro-level data on education systems and analyse these data in two ways. In a first step, we run by-country regression analyses to explore the relevance of individual and school characteristics for individuals' CIL and CT. In a second step, we use the outcomes of these by-country analyses as input for exploratory cross-national analyses that help us assess the potential role of education systems and country characteristics.

The second set of analyses focusses on problem-solving skills using data on 91,152 15-year old pupils from 19 countries, from the 2012 wave of the tri-annual Programme for International Student Assessment (PISA) (OECD, 2014a). These data contain direct psychometric measures of problem-solving skills, using computer-based assessments to measure individuals' capacity and willingness "to engage in cognitive processing to understand and resolve problem situations where a method of solution is not immediately obvious" (OECD, 2013; p.122). We model variation in these skills and the related gender and socioeconomic gradients between countries, and within countries between schools. To explain this variation, we run three-level hierarchical random intercept models.

This chapter is arranged as follows. Section 1.2 focusses on analysing ICT skills. (more specifically: CIL and CT). Section 1.3 focusses on analysing creative problem solving. Section 1.4 draws some general conclusions and Section 1.5 offers policy implications from the findings of our analyses.

1.2 Analyses of Computer and Information Literacy and Computational Thinking Skills

1.2.1 Theory & Hypotheses

In this chapter we draw our attention to the ability to use information communication technology – ICT skills – as the ability set most directly related to the demand of technologized workplaces and their potential determinants. In order explain differences in students' ICT skills, we draw on three major theories of skill acquisition – practice engagement theory (Reeder, 1994), constructivist learning theories (Bandura, 1971; Piaget, 1969), and social cognitive theory (Bandura, 1986; Compeau & Higgins, 1995). All three theories argue that the acquisition of a certain skill is strongly determined by its regular use both inside and outside of formal learning contexts. Practice engagement theory argues that to acquire a certain skill, this skill must be involved in daily life. Constructivist learning theories especially highlight the relevance of out-of-school learning (non-formal and informal learning) for skill acquisition and improvement. Social cognitive theory understands human functioning, including ICT skills, as a result of personal, behavioural, and environmental determinants. The theory stresses the role of ICT use as a behavioural determinant for adults' ICT skills. Personal determinants include personal factors such as ICT self-efficacy, ICT attitudes, or privacy concerns. Environmental determinants include factors such as ICT and training access (cf. Bandura, 1986; Hoffmann et al., 2015). Based on these theoretical considerations, we derive a set of hypotheses for computer and information literacy and computational thinking. For both measures of ICT related skills, we expect to find the variation of these skills to be larger within countries between schools compared to the variation between countries (see OECD 2014b for other domains).

Practice engagement theory, constructivist learning theories, and social cognitive theory argue for a positive effect of practice and exposure within and outside of schools on ICT-related skills. We expect practice to have a positive effect on both skill measures (hypothesis 1). Constructivist learning theories emphasize the role of out-of-school learning. Thus, we expect the ICT use outside of school for out-of-school purposes to have a stronger positive effect on computer and information literacy (CIL) and computational thinking (CT) compared to within-school ICT practice (hypothesis 2). Accordingly, better ICT infrastructure at the student's household is related to higher ICT skills (hypothesis 3).

We take advantage of the fact that ICILS data highlight different aspects of ICT skills. While CIL measures information literacy in receptive and productive communicative contexts, CT encompasses problem specification and solution creation that can be implemented by computers (Fraillon et al., 2020). In line with the findings of Fraillon et al. (2020), we expect girls to show an advantage over boys in CIL, while we expect boys to outperform girls in CT. For the socio-economic background (SES) of students, we expect to find lower CIL and CT scores of students with low SES (hypothesis 4).

Different levels of practice and exposure may play out differently for girls and boys and for children with high/low SES. We know from previous research that boys do better in ICT skills in less favourable learning environments, e.g. in settings with low teacher-student ratios. Thus, we expect girls to profit more from enabling learning environments than boys (hypothesis 5), i.e. girls profit more from their ICT use outside of school for out-of-school purposes and from the existing household's infrastructure than boys do. For students from low SES backgrounds, we also expect to find a stronger positive effect of exposure on CIL and CT skills than for students with high SES backgrounds (hypothesis 6). We expect a compensating effect, and assume that exposure does more to low SES children with respect to their CIL and CT skills than to high SES children.

Next to the home environment, schools are young students' most relevant learning context. We do expect to find a large variation of ICT skills between schools. Based on the findings of previous research we will consider schools' ICT infrastructure and teachers' ICT characteristics as relevant determinants of students' ICT skills. Previous literature (Gerick, 2018) has identified three groups of relevant school-level variables to affect the acquisition of ICT skills: (1) ICT infrastructure, (2) teacher's ICT characteristics and (3) school visions or strategies.

A school's ICT infrastructure, determined by ICT equipment and by the available technical and pedagogical support, can be considered one of the most relevant prerequisites for successfully implementing digital technologies into teaching and learning. We, therefore, expect a better ICT infrastructure at school to be related to higher ICT skills among students (hypothesis 7).

A good ICT infrastructure at school can be brought into action only through the teachers' capability and willingness to use and integrate ICT in their teaching. We thus expect teachers' own ICT experience and teachers' actual use of ICT in class to be positively related to students' ICT skills (hypothesis 8).

A third condition for successfully developing students' ICT skills are appropriate school visions and strategies for teaching ICT implemented by the school administrators. We argue that the higher the experience with ICT skills by the school principal, the ICT coordinator or the teachers, the more sophisticated the vision and strategy, and the higher the students' ICT skills (hypothesis 9).

For ICT skills, we expect to find differences between countries, even though they may be smaller than differences within countries between schools. The ICILS data only gathered data on a restricted set of European countries: France, Portugal, Finland, Germany, and Luxembourg, we are restricted to Western European. Portugal and Finland are best examples of Southern and Nordic European settings, and France, Germany, and Luxembourg are examples of Continental settings. Due to the limited number of countries, we focus on country-specific analyses. Nevertheless, we use descriptive analyses to investigate the correlations between country-level characteristics on the one hand and CIL and CT measures on the other hand. We consider economic, technological, and institutional factors on the country level and test their correlation with CIL and CT scores.

Research & development investments in a country should directly increase ICT skills. Hence, the higher the expenditures in the percentage of GDP in research & development, the higher the average CIL and CT scores. Economic inequality is by and large expected to lower the average ICT skill development, as fewer students from less privileged backgrounds have access to ICT hardware and appropriate learning practice. Thus, we expect the GINI-coefficient, a well-known measure of income inequality, to be negatively related to ICT skills (hypothesis 10).

In general, we expect students to perform better in CIL and CT tests in technologically-advanced countries because of everyday practice with digital processes, like online shopping, gaming, communication, or business. The indicator for the use of digital technologies is the average percentage of people in a country that submitted completed forms to public authorities over the internet in the last 12 months. This measure gives us an idea about the permeation of and practice with digital devices in day-to-day life among adults, which should work as a blueprint for the digital behaviour of adolescence as well. Hence, we expect the use of digital technologies in a country to positively correlate with students' ICT skills (hypothesis 11).

Also, the educational systems are expected to have a decisive impact on the ICT skill levels. Countries differ in the degree of standardization of teaching content (input standardization) and the existence of centralized tests (output standardization). In countries with high input and output standardization, the educational systems are arguably less flexible to adapt quickly to new skill demands, like in the case of ICT skills. Thus, countries with high input and output standardization should lag behind and have on average lower ICT skills (hypothesis 12). And yet the penalty for highly standardized countries should be moderate if the emphasis on the importance of out-of-school experiences placed by constructivist theories is on the target.

Last, we argue that private schools are probably better equipped to foster ICT skills. Private schools are more flexible in their curriculum, they can autonomously select educators based on their (ICT) skill set, and they are free to invest more resources in ICT hardware. Hence, students from private schools should perform better in CIL and CT skills compared to students in public schools (hypothesis 13). However, private schools are often an indicator of existing economic and social disparities in a given country. As we expect inequality to lower a country's average ICT skills among students, a high level of income inequality might reduce the positive effect of private schools.

1.2.2 Data

To assess the influence of education systems on Computer and Information Literacy (CIL) and Computational Thinking (CT), we make use of the IEA's International Computer and Information Literacy Study (ICILS) from 2018 (Fraillon et al., 2019). We analyse data from Germany (DEU), Finland (FIN), France (FRA), Luxembourg (LUX) and Portugal (PRT).

1.2.2.1 Dependent variables

The ICILS data includes two different dimensions of ICT skills: computer and information literacy (CIL) is defined as "an individual's ability to use computers to investigate, create, and communicate in order to participate effectively at home, at school, in the workplace, and in society" (Fraillon et al. 2013, p. 17). The second dimension, computational thinking (CT), is defined as "an individual's ability to recognize aspects of real-world problems which are appropriate for computational formulation and to evaluate and develop algorithmic solutions to those problems so that the solutions could be operationalized with a computer" (Fraillon et al. 2019, p. 27). While CIL measures information literacy in receptive and productive communicative contexts and thus refers stronger to information and communication digital skills, CT encompasses problem specification and solution creation that can be implemented by computers and thus refers stronger to problem-solving digital skills.

Our dependent variables are measured through computer-based assessments based on tangible problems. As the real proficiency of students in CIL or CT can only be inferred from their assessment responses, in the surveys, plausible values are used to make a correct inference. A plausible value is a likely score of proficiency drawn from the marginal posterior of the latent distribution. Five plausible values are used (OECD, 2014a; Fraillon et al., 2019). To handle the plausible values, we make use of the Stata's repest package (Avvisati & Keslair, 2014). We ran our analyses with a normalized final student weight on all plausible values with replicate weights (Avvisati & Keslair, 2014; OECD, 2009, chapter 5). The computer and information literacy scale and the computational thinking scale are calibrated to have a mean of 500 and a standard deviation of 100 (Fraillon et al., 2019. p. 55).

1.2.2.2 Independent variables

Our individual level covariates are *age* in years, *sex* (1 = girls), an variable distinguishing on being *born abroad* with the following categories (0) students and/or at least one parent born in country of test; (1) student born in country of test but both/only parent(s) born abroad; and (2) student and both/only parent(s) born abroad. We also distinguish whether the student speaks the *language of the test at home*. Furthermore, we include the national index of socioeconomic background (NISB), an index of highest parental education, highest parental occupation, and the number of books at home with a mean of 0 and a standard deviation of 1 across equally weighted countries.

We also consider whether students have *internet access at home* (0/1) and the time they have been *using a laptop, smartphone and tablet* (0-4 Likert scales). We also use the indicator on whether the student *takes courses* on computing, computer science, information technology or informatics in the current school year (0/1) and what they then study: general *ICT tasks* or *coding tasks* (0-3 Likert scales). Lastly, we assess the effect of *using ICT at school or at home for school or other purposes*.

At the school level, we include the *ratio between school size and teacher*. Moreover, we include the categorical variable on *school size*, with 1-300; 301-600; 601-900 and 901 and more as the four categories. We include both variables. Furthermore, we incorporate the *school composition* that signals either that a school has more affluent than disadvantaged (0), an equal amount (1) or more disadvantaged than affluent in their school (2).

Furthermore, we use an indicator of the teacher's opinion on the *availability of ICT resources* at school with a mean of 50 and a standard deviation of 10 for equally weighted countries. We also include the *ratio of school size and number of ICT devices* at school as well as the constructed scale on *availability of a variety of ICT resources at school according to the ICT coordinator* (mean of 50; standard deviation of 10; equally weighted countries).

We also consider the *ICT experience of teachers during lessons* indicated with (0) never, (1) less than two years, (2) two to five years, and (3) more than five years is included as well as the *ICT experience in years in the school,* which is a dummy variable indicating whether (1) or not (0) there is more than 10 years of ICT experience within the school according to the ICT coordinator. We also include the *use of ICT for teaching practices,* which is a scale with a mean of 50 and a standard deviation of 10 across equally weighted countries[1]. For all teacher's indicators we consider the average of the teachers at the school level.

On the country-level we include the *standardisation of input and output* (Bol & Van de Werfhorst, 2013), the expenditures in percentage of GDP in *research & development* in a country (OECD, 2021a), the GINI-coefficient to measure *income inequality* (OECD, 2021b) and the average percentage of people in a country that *submitted completed forms to public authorities, over the internet*, last 12 months (Digital Agenda Data EU, 2021). Moreover, we include the ICILS indicator on the *percentage of students going to a public school, autonomy of governance and autonomy of assessment*. The first of these ICILS-based items is a percentage. The item on autonomy of governance is obtained by taking the answers to the question on autonomy of governance (How much autonomy do schools with students in the target grade have regarding how they operate in order to meet their statutory obligations?) for each type of school (public/private) and multiplying that by the percentage of students in that type of school in that country. The three numbers for each type of school are averaged and expressed on a scale from 0 to 1. The third items question was on autonomy of assessment (How much autonomy do schools with students in the target grade have regarding the assessment of student achievement in computer and information literacy (or its equivalent)?) and was handled the same as the autonomy of governance item.

Descriptive statistics for the individual, school and country levels are in Appendix A. The eventual analytical sample is established by a list-wise deletion on the individual and school-level characteristics.

1.2.3 Analytical strategy

1.2.3.1 Cross-country differences in skill acquisition

To study the extent to which acquisition of CIL and CT relates to education systems, we first show descriptive statistics of average proficiency levels across countries and across schools. In a second step, we explain these average proficiency levels with individual and school-level characteristics in a multi-level regression framework. For all models, we estimate separate country regressions as our number of countries is too low to make meaningfully and statistically sound estimations of the effects of national-level characteristics. In a third step, we relate the CIL and CT acquisition to country-level characteristics in a descriptive comparative and highlight the correlation between country-level characteristics and CIL and CT skills.

[1] The are also scales on emphasis on ICT learning and ICT efficacy of teachers, but those indices cause multicollinearity in regression models.

Within our multilevel structure, we first assess the variance at the individual and school level by only estimating the grand mean (α_c), the error term at the school-level (ω_{jc}) and the error term at the individual level (υ_{ijc}). With the variance parameters estimated by the model we can calculate the intra-class correlation. Second, we estimate proficiency in CIL and CT skills using multilevel mixed-effects models. Model 1 consists of the general background variables; in Model 2 we enter a structural indicator on internet at home. In Model 3 we include experience with devices. In Model 4 studying ICT in school and use of ICT in school are added. In Model 5 we enter where one uses ICT (school/outside school) and for what purpose (school/outside school). Model 6 is an all-included model. At the school level, we enter structural indicators on the school in Model 7 and include availability in school in Model 8. In Model 9, we include the experience of teachers with ICT. In Model 10, we include information on the teachers' use of ICT and, in Model 11, we include all variables. Third, we correlate different country-level contexts on CIL and CT skill acquisition. We will first relate the uncontrolled proficiency levels of CIL and CT to the country-level indicators. We will then relate the individual-level controlled proficiency levels of CIL and CT to the country-level indicators. To not conflate school-system characteristics with country-system characteristics, we do not show school-level controlled plots.

1.2.3.2 Examining inequality in the acquisition of CIL and CT skills

From the above-mentioned individual-level models we can already grasp some inequalities in parent's socioeconomic status (NISB) and gender. Here, we show these inequalities in a descriptive way across schools. Furthermore, we show the cross-level interaction effects to assess the association between the characteristics of the schools and socioeconomic status and gender inequalities. Within our cross-level interaction models we first assess whether the effect of school characteristics vary between boys and girls and between those from different socio-economic statuses. Secondly, we relate the individual level and school level coefficients of the estimated models to country-level characteristics to assess whether those coefficients vary over country characteristics. This approach is descriptive and exploratory by nature.

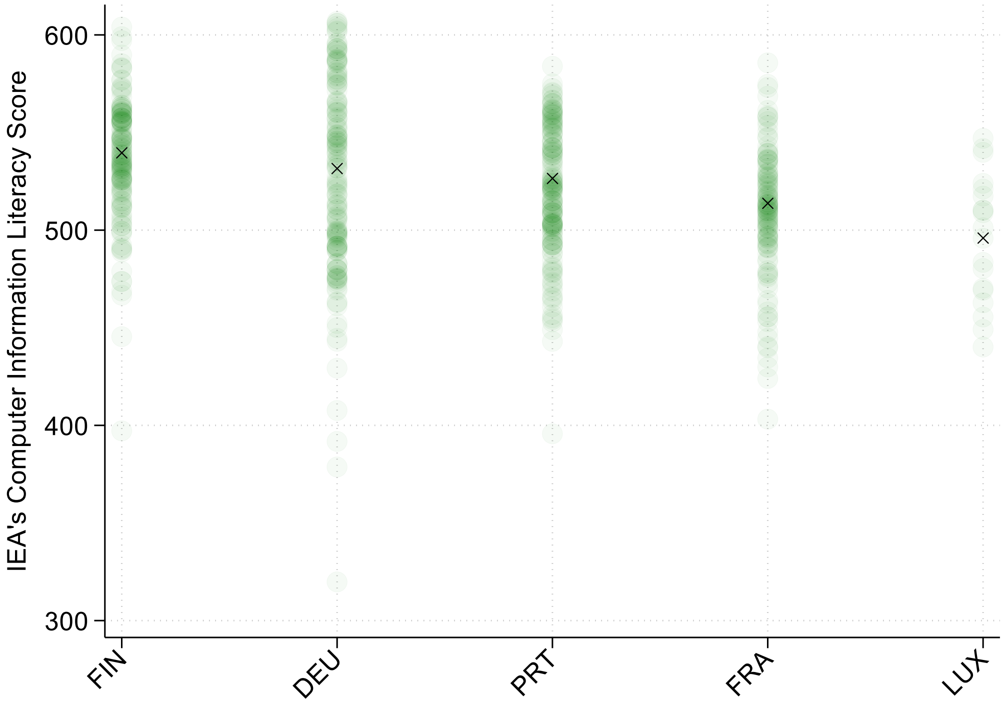
1.2.4 Empirical Results on Computer and Information Literacy

1.2.4.1 Variation across countries and schools

In Figure 1, we show descriptively the difference in Computer and Information Literacy for the different European countries. The X's shows the country mean, whereas the green dots show the school averages. The difference between the highest average score of Finland and the lowest of

Luxembourg, are about 45 points, what amounts to about one standard deviation. However, the variance between schools within a country is considerably larger.

Figure 1. Between and within-country CIL



Notes: estimates obtained by using multiple imputation techniques for the five sample plausible values. Raw scores. ICILS average = 500; standard deviation = 100.

1.2.4.2 Explaining variations across schools and countries

As can be seen in Table 1, we ran our regression models for each country separately. The first model estimates all individual-level factors simultaneously. In Table B1 in the Appendix B, we show the models in which we add the different individual level indicators separately. In Table B2 in Appendix B, we look at the variance components. For all five countries, the intra class correlation lies between .4 and .5, meaning that there is quite some variation at the school level and that it justifies the multi-level structure of the regression estimates. Furthermore, comparing the variance components in panel B with those in panel A shows that the reduction in variance by entering composition indicators of the student population is about 5 to 10%.

Before we relate the results to our hypotheses, a striking result from our individual level control variables is that experience with devices is positively related to CIL, but that this holds only for computers, not for smartphone and tablets. Then, relating the results in model 1 to our hypotheses shows that we cannot reject hypothesis 1 as using ICT has a positive effect on CIL. After adding up all four coefficients of the ICT use and purpose, the effect is still positive. Comparing those effects in model 1 also leads to the failure of rejecting hypothesis 2. Outside school ICT is stronger related than within school ICT use on CIL score across all countries in the analysis. The internet connection indicator result leads to partly not rejecting hypothesis 3; only in Finland, Luxembourg and Germany the hypothesis should be rejected. We fail to reject hypothesis 4 as the results show that girls have an advantage over boys (but for Portugal) and the socioeconomic status effect is positive.

Models 2 through 5 estimates school-level variables separately and in model 6 we estimate them all simultaneously[2]. Model 2 shows that the ratio between school size and teachers is negatively related to CIL for Germany and France, positively related in Finland and unrelated in Luxembourg and Portugal. The size of the school is positively related to CIL except for Luxembourg; in the latter, the signs is negative. The relationship also seems not to be uniform across the countries. In some countries, the increase appears incremental, whereas in others there is only an effect for the largest schools, while in other countries we see a reversed u-shape. Schools with a more or less equal composition of students according to their socio-economic background show negative correlations, while it appears that the more schools comprise of disadvantaged pupils, the lower the CIL score is. The exception is Finland, where we see a positive effect for schools with more disadvantaged students.

Looking at the scales on availability of ICT resources according to teachers, it shows a positive correlation with CIL, though not statistically significant in Germany and France. The availability according to the ICT coordinator of the school shows a more mixed picture, as it is positively related to CIL in Germany, but negatively in Luxembourg. The ratio between ICT devices and students is only positively related with CIL in Germany and Portugal. We thus cannot unequivocally reject the seventh hypothesis.

In model 4 we include experience with ICT of both the teacher and ICT coordinator of the school. The experience of the coordinator is significantly positively correlated with CIL skills in Germany and Finland, while it is negatively correlated in France and non-related in Luxembourg and Portugal. Teacher's experience only positively related to CIL skills of the students in Finland and Luxembourg. In model 5, bringing the ICT in practice in the lessons by teachers is negatively related to CIL skills in Germany, France and Luxembourg, while unrelated in Finland and Portugal. The eighth hypothesis we thus cannot reject in Luxembourg and Finland, though we can do so in Germany, Portugal and France. With regard to hypothesis 9, for Germany and Finland general ICT experience in school is positively related to students' CIL skills, thus failing to reject that hypothesis in those countries.

Lastly, the complete school level model, number 6, seems to show that the school size effect for the smallest categories is more often explained by the composition effect of the other variables in the

[2] Given the low number of school in the Luxembourg sample, results regarding school level factors in Luxembourg should be interpreted with caution in model 6.

model. The same holds for the composition category in which there are more or less equal affluent and disadvantaged students in a school; that category turns insignificant in most countries. The ratio between devices and students turns statistically significantly positive in the final model in Luxembourg. For the experience of the ICT coordinator, the coefficients in Germany and France turn statistically insignificant.

Turning again to the variance components in Table B2 in Appendix B, the included variables explain about 8% (Portugal) to 22% (France) of the country variance, and 1% (Germany) to 3% (France) of the individual level variance. If we relate the information from the regression models in a correlational way to country characteristics, we obtain Figure 2. It shows the relationship between eight country-level characteristics and the individual-level controlled model estimate country mean for CIL skills. We also obtained those figures with the predicted score of the empty model, but differences are nihil. Figure 2 shows that only the country characteristics about the percentage of public schools relate clearly with the CIL score: the higher the public school percentage the higher the CIL score. The rest of the correlates do show much leeway within the 95% confidence interval and thus lack precision to discern meaningful relationships between variables. With that in mind, one could observe a negative effect of the standardisation of input for CIL scores. Relating this information back to our hypotheses, we have to reject hypothesis 10, 11 and are inclined to also reject the 12th hypothesis, as both standardisation indicators do not show a clear relationship with CIL. Nonetheless, the direction of the standardisation of input is in line with the hypothesis. Lastly, we have to reject hypothesis 13, as the correlation between public school attendance and CIL is positive, not negative.

Table 1. CIL Regression analysis for each country

Model 1	DEU		FIN		FRA		LUX		PRT	
Age (in years)	-7.675	***	-12.792	***	-21.053	***	-10.026	***	-5.410	***
	1.824		1.935		1.944		1.336		1.221	
Sex (1=girl)	11.493	***	21.808	***	15.709	***	17.175	***	4.225	
	1.646		1.960		1.511		1.984		2.321	
(At least) one parent born abroad	3.188		-18.709	*	-6.714	*	-8.141	***	-7.530	*
	3.882		8.501		3.192		2.433		3.653	
Born abroad	8.108	*	-11.841		5.418		1.565		-15.797	**
	3.814		7.757		4.656		1.393		6.059	
Language spoken at home same as test language	25.447	***	28.236	***	19.597	***	4.579		-3.963	
	4.046		3.877		2.150		2.528		4.094	
Socioeconomic background	6.735	***	14.370	***	17.687	***	11.693	***	10.639	***
	1.535		0.660		1.083		1.308		0.902	
Internet access at home	-0.888		18.137		27.025	**	11.356		25.803	***
	12.337		9.984		9.213		7.746		4.254	
Computer experience	10.937	***	13.003	***	9.936	***	9.262	***	9.782	***
	0.757		0.705		0.683		0.539		0.603	
Smartphone experience	-5.266	***	-6.884	***	-10.240	***	-8.960	***	-7.074	***
	1.343		0.673		0.977		0.597		1.044	
Tablet experience	-6.282	***	-4.304	***	-3.359	***	-1.343		-2.770	***
	0.918		0.819		0.421		0.797		0.828	
Studies ICT in current school year	8.130	***	15.467	***	-7.492	**	-22.126	***	22.056	***
	2.233		1.858		2.496		1.743		3.033	
Learning coding tasks	-0.213		-1.092	***	-0.881	***	-0.737	***	-0.978	***
	0.140		0.105		0.114		0.095		0.144	
Learning ICT tasks	0.019		1.250	***	0.928	***	0.162		-0.208	
	0.108		0.105		0.072		0.083		0.189	
Use ICT at school for school purposes	-0.175		2.564	**	1.436	*	-0.235		-2.040	
	0.918		0.889		0.672		0.678		1.142	
Use ICT at school for other purposes	0.337		2.154	**	-2.323	***	2.648	***	-0.426	
	0.551		0.805		0.521		0.583		0.303	
Use ICT outside school for school purposes	-1.217		0.140		0.023		-0.914		0.499	
	0.760		0.694		0.594		0.528		0.780	
Use ICT outside school for other purposes	16.454	***	12.860	***	12.971	***	9.818	***	9.900	***
	1.093		0.872		0.717		0.792		0.851	
Constant	543.874	***	572.327	***	699.969	***	613.834	***	570.261	***
	35.881		33.492		31.347		19.279		18.102	
School variance	3.631	***	2.879	***	2.784	***	2.877	***	3.069	***
	0.043		0.054		0.070		0.079		0.052	
Individual variance	3.990	***	4.098	***	4.072	***	4.149	***	3.980	***
	0.014		0.018		0.012		0.009		0.010	

Source: ICILS 2018. Repetitive weights are applied.

Table 1. CIL Regression analysis for each country (continued)

Model 2	DEU		FIN		FRA		LUX		PRT	
Ratio of school size and teachers	-476.762	***	130.984	***	-404.523	***	35.334		3.021	
	75.776		21.798		45.012		44.615		4.194	
School size: 201-600 students	22.280	**	10.389	***	2.110			***	23.163	***
	7.700		1.511		2.452				2.368	
School size: 601-900 students	40.387	**	5.658	**	-1.971		-11.143	***	27.620	
	7.714		1.777		1.884		3.501		1.961	
School size: 901 or more students	39.913	***	35.967	***	17.420	***	-11.042	***	22.749	***
	7.926		4.633		5.223		3.328		1.581	
Schools with equal amount of affluent and disadvantaged students	-7.891	***	4.700	***	-2.084	***	-19.337	***	-2.245	***
	2.428		1.419		1.741		2.856		2.396	
Schools with more disadvantaged students than affluent students	-43.963	***	5.625	***	-12.660	***	-33.506	***	-8.563	***
	2.459		1.157		1.881		1.828		2.036	
Constant	552.649	***	554.455	***	729.383	***	624.301	***	551.670	***
	38.624		34.252		32.307		21.157		17.851	
School variance	3.274	***	2.780	***	2.601	***	2.442	***	3.017	***
	0.042		0.056		0.061		0.153		0.039	
Individual variance	3.988	***	4.098	***	4.071	***	4.149	***	3.978	***
	0.014		0.018		0.012		0.009		0.010	
Model 3	**DEU**		**FIN**		**FRA**		**LUX**		**PRT**	
Availability of ICT resources at school (ICT Coordinator)	1.753	***	0.105		-0.082		-1.362	***	-0.018	
	0.164		0.114		0.070	***	0.109		0.095	
Ratio of school size and number of ICT devices	0.854	**	0.237		-0.679		0.951		0.207	*
	0.328		0.670		0.499		0.958		0.104	
Availability of computer resources at school (Teachers)	0.244		1.319	***	0.197		2.568	***	0.466	*
	0.361		0.372		0.300		0.457		0.229	
Constant	452.146	***	499.011	***	698.375	***	549.815	***	546.669	***
	45.814		35.081		31.986		24.235		23.383	
School variance	3.569	***	2.870	***	2.776	***	2.739	***	3.064	***
	0.040		0.046		0.070		0.069		0.052	
Individual variance	3.990	***	4.098	***	4.072	***	4.149	***	3.980	***
	0.014		0.018		0.012		0.009		0.010	
Model 4	**DEU**		**FIN**		**FRA**		**LUX**		**PRT**	
10 or more years ICT experience in the school	15.923	***	1.891	*	-5.045	***	4.477		-2.034	
	1.840		0.897		1.483		2.463		1.463	
ICT experience with ICT use during lessons	-2.784		13.908	*	14.904		63.276	***	-0.661	
	9.446		6.672		11.618		6.899		4.078	
Constant	542.158	***	537.373	***	666.913	***	456.685	***	572.655	***
	50.436		38.193		36.308		28.484		23.529	
School variance	3.608	***	2.876	***	2.772	***	2.813	***	3.068	***
	0.042		0.054		0.069		0.081		0.051	
Individual variance	3.990	***	4.098	***	4.072	***	4.149	***	3.980	***
	0.014		0.018		0.012		0.009		0.010	
Model 5	**DEU**		**FIN**		**FRA**		**LUX**		**PRT**	
Use of ICT for teaching practices in class	-2.552	***	0.585		-0.209		2.187	*	0.977	**
	0.562		0.364		0.623		0.866		0.364	
Constant	667.795	***	543.241	***	710.435	***	506.621	***	522.707	***
	48.388		34.242		36.045		48.557		28.617	
School variance	3.620	***	2.878	***	2.782	***	2.874	***	3.063	***
	0.041		0.053		0.072		0.076		0.055	
Individual variance	3.990	***	4.098	***	4.072	***	4.149	***	3.980	***
	0.014		0.018		0.013		0.009		0.010	

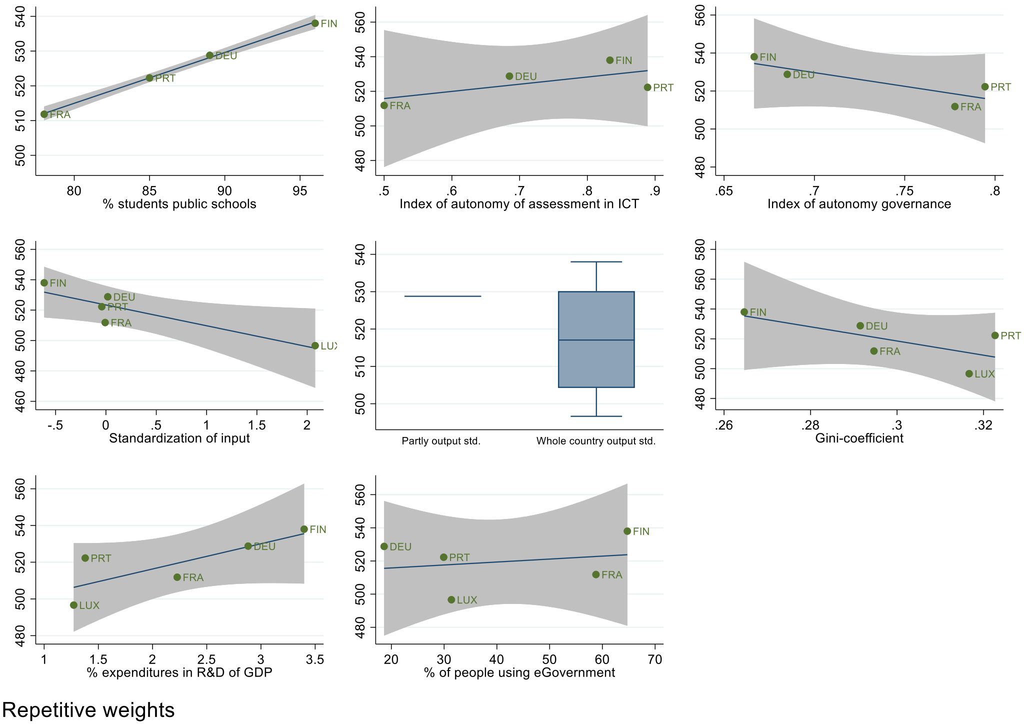
Source: ICILS 2018. Repetitive weights are applied. Models 2 through 5 include also individual level characteristics.

Table 1. CIL Regression analysis for each country (continued)

Model 6	DEU		FIN		FRA		LUX		PRT	
Age (in years)	-7.065	***	-12.881	***	-20.885	***	-9.842	***	-5.471	***
	1.757		1.950		1.945		1.329		1.226	
Sex (1=girl)	10.693	***	21.607	***	16.264	***	17.218	***	4.303	
	1.612		1.981		1.507		2.050		2.324	
(At least) one parent born abroad	3.618		-19.703	*	-6.767	*	-6.795	**	-7.876	*
	3.783		8.393		3.200		2.533		3.643	
Born abroad	8.926	*	-13.678		8.865		3.461	*	-16.785	**
	3.772		7.674		4.928		1.584		6.093	
Language spoken at home same as test language	24.268	***	28.272	***	19.173	***	5.626	*	-4.147	
	4.035		3.964		2.246		2.443		4.151	
Socioeconomic background	5.737	***	14.014	***	16.593	***	10.811	***	9.871	***
	1.514		0.696		1.079		1.308		0.908	
Internet access at home	-1.249		17.807		22.317	**	15.118		26.311	***
	12.364		10.017		8.622		8.798		4.223	
Computer experience	10.816	***	12.964	***	10.070	***	9.174	***	9.792	***
	0.767		0.702		0.716		0.532		0.600	
Smartphone experience	-5.056	***	-6.990	***	-10.238	***	-8.719	***	-7.108	***
	1.292		0.658		0.977		0.597		1.051	
Tablet experience	-6.116	***	-4.499	***	-3.509	***	-1.349		-2.900	***
	0.909		0.811		0.425		0.783		0.839	
Studies ICT in current school year	7.854	***	15.119	***	-7.269	**	-20.027	***	22.222	***
	2.125		1.830		2.411		2.135		2.967	
Learning coding tasks	-0.216		-1.118	***	-0.849	***	-0.710	***	-0.969	***
	0.137		0.104		0.112		0.091		0.145	
Learning ICT tasks	0.015		1.257	***	0.911	***	0.193	*	-0.200	
	0.109		0.107		0.068		0.090		0.189	
Use ICT at school for school purposes	-0.170		2.576	**	1.307		-0.213		-2.054	
	0.938		0.879		0.670		0.577		1.124	
Use ICT at school for other purposes	0.318		2.097	*	-2.048	***	2.471	***	-0.422	
	0.508		0.814		0.541		0.623		0.302	
Use ICT outside school for school purposes	-1.111		0.167		-0.320		-0.927		0.537	
	0.767		0.697		0.602		0.539		0.770	
Use ICT outside school for other purposes	16.570	***	12.927	***	12.964	***	9.658	***	9.747	***
	1.077		0.887		0.709		0.776		0.857	
Ratio of school size and teachers	-491.563	***	75.675	***	-426.444	***	311.230	***	22.985	***
	71.161		21.744		36.514		54.172		3.442	
School size: 201-600 students	6.554		10.928	***	4.698			***	24.893	***
	7.236		1.842		2.694				2.023	
School size: 601-900 students	21.145	**	4.867	*	1.619		7.168		29.068	***
	7.109		1.919		2.319		3.969		1.854	
School size: 901 or more students	27.245	***	37.468	***	25.502	***	0.841		24.612	***
	7.125		4.388		6.747		3.575		1.396	
Schools with equal amount of affluent and disadvantaged students	2.898		4.150	**	-2.885		3.699		-3.445	
	2.681		1.463		1.725		3.328		2.672	
Schools with more disadvantaged students than affluent students	-39.523	***	5.344	***	-13.407	***	-26.652	***	-9.336	***
	2.351		1.125		1.693		1.747		2.146	
Availability of ICT resources at school (ICT Coordinator)	1.293	***	-0.043		-0.227	*	-0.636	***	0.010	
	0.126		0.113		0.091		0.145		0.099	
Ratio of school size and number of ICT devices	-0.669	**	-1.337		-1.243	*	4.018	***	0.007	
	0.217		0.706		0.515		0.887		0.112	
Availability of computer resources at school (Teachers)	0.522		0.799		0.824		1.700	**	-0.013	
	0.353		0.473		0.534		0.581		0.211	
10 or more years ICT experience in the school	-1.493		2.498	*	-0.230		16.831	***	-0.904	
	1.731		1.181		1.649		2.675		1.552	
ICT experience with ICT use during lessons	7.659		14.544		-14.318		80.594	***	-12.467	**
	11.937		7.595		10.222		9.689		4.283	
Use of ICT for teaching practices in class	-2.184	***	-0.511		-3.101	**	-6.811	***	1.836	***
	0.505		0.390		1.074		1.306		0.389	
Constant	588.050	***	510.999	***	898.197	***	638.393	***	491.989	***
	60.457		43.126		48.009		73.651		30.360	
School variance	3.196	***	2.774	***	2.531	***	-0.928		2.998	***
	0.042		0.047		0.082		7.448		0.043	
Individual variance	3.987	***	4.097	***	4.071	***	4.150	***	3.979	***
	0.014		0.018		0.012		0.009		0.010	

Source: ICILS 2018. Repetitive weights are applied.

Figure 2. Graphs of country characteristics correlates with CIL scores.



Notes: estimates obtained by using multiple imputation techniques for the five sample plausible values. X-axis are country level indicators, Y-axis is predicted country level score of the full individual level model.

1.2.4.3 Gender and SES inequality and the role of education systems

In Table 2, we show the interaction effects of gender and socioeconomic status with the indicators on use of ICT and the purpose of using ICT. In general, there is no predominant interaction effect present across all countries that we analyse. In Luxembourg, girls' effect on CIL of use of ICT at school for other purposes is lower than for boys. The effect of use of ICT outside school for other purposes is smaller for girls in Germany and Finland. The moderation effects of socioeconomic status are mixed for use of ICT at school for other purposes: the higher the socioeconomic status the larger the effect is in Finland and Portugal, but smaller in Luxembourg. The effect of using ICT outside school for school purposes is larger for girls in Germany and France. Thus, hypothesis 5 is refuted, as well as hypothesis 6.

In Appendix B, Table B3, the interaction effects of gender are shown for the school level variables with Computer and Information Literacy. All the effects are estimated while controlling for the individual level indicators. Noteworthy results are that in France, Luxembourg, and Portugal the more ICT coordinator indicated that there are resources available at the school the smaller the gender gap is (a negative main effect combined with the positive interaction effect). For other interaction effects with sex, it holds that it is only significant in one or two countries that are analysed.

Table 2. Differential effects of ICT use and use purpose by Gender and SES for CIL scores

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT	
Sex (1=girl)	13.305	*	13.798	*	16.136	***	10.816	***	-3.016		11.183	***	21.808	***	14.602	***	31.668	***	2.619	
	6.420		5.542		3.634		3.241		6.084		2.377		3.292		2.577		4.970		3.626	
Use ICT at school for school purposes	0.132		1.522		1.505	*	-1.178		-3.037		-0.168		2.564	**	1.436	*	-0.340		-2.055	
	1.430		1.355		0.701		0.862		1.634		0.927		0.885		0.672		0.660		1.144	
Use ICT at school for other purposes	0.321		2.190	**	-2.323	***	2.664	***	-0.459		0.276		2.154	*	-2.540	***	4.871	***	-0.678	
	0.533		0.817		0.521		0.583		0.315		0.618		0.889		0.594		0.984		0.628	
Use ICT outside school for school purposes	-1.227		0.142		0.021		-0.850		0.570		-1.218		0.140		0.013		-0.898		0.535	
	0.755		0.694		0.606		0.528		0.822		0.760		0.695		0.596		0.531		0.795	
Use ICT outside school for other purposes	16.443	***	12.787	***	12.973	***	9.739	***	9.937	***	16.450	***	12.860	***	12.961	***	9.772	***	9.893	***
	1.087		0.876		0.723		0.777		0.830		1.092		0.893		0.719		0.798		0.861	
Sex (1=girl) # Use ICT at school for school purposes	-0.690		2.216		-0.148		2.017		2.286											
	2.117		1.690		1.360		1.113		1.941											
Sex (1=girl) # Use ICT at school for other purposes											0.123		0.000		0.464		-4.296	***	0.492	
											0.536		0.885		0.684		1.190		0.867	
Constant	542.603	***	576.898	***	699.684	***	615.252	***	573.664	***	544.071	***	572.328	***	700.857	***	612.222	***	570.919	***
	35.782		33.153		32.757		19.906		18.942		35.994		33.754		30.810		19.297		18.553	
School variance	3.632	***	2.881	***	2.783	***	2.875	***	3.066	***	3.631	***	2.879	***	2.784	***	2.870	***	3.070	***
	0.043		0.053		0.070		0.079		0.053		0.043		0.053		0.070		0.079		0.052	
Individual variance	3.990	***	4.098	***	4.072	***	4.148	***	3.980	***	3.990	***	4.098	***	4.072	***	4.147	***	3.980	***
	0.014		0.018		0.012		0.009		0.010		0.014		0.018		0.013		0.009		0.010	
	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT	
Sex (1=girl)	13.951	***	25.932	***	10.471	*	16.759	***	4.655		56.658	***	47.502	***	5.126		34.491	***	-4.478	
	4.098		5.446		4.436		4.078		4.591		13.184		6.796		9.613		9.615		6.074	
Use ICT at school for school purposes	-0.187		2.596	**	1.484	*	-0.232		-2.043		-0.319		2.635	**	1.456	*	-0.219		-2.006	
	0.912		0.888		0.699		0.672		1.149		0.913		0.888		0.683		0.679		1.136	
Use ICT at school for other purposes	0.342		2.175	**	-2.360	***	2.648	***	-0.427		0.444		2.277	**	-2.343	***	2.533	***	-0.437	
	0.554		0.815		0.532		0.582		0.302		0.546		0.802		0.532		0.550		0.304	
Use ICT outside school for school purposes	-0.880		0.649		-0.643		-0.969		0.556		-1.128		0.139		-0.003		-0.823		0.500	
	0.870		0.868		0.628		0.507		0.977		0.765		0.694		0.584		0.507		0.784	
Use ICT outside school for other purposes	16.441	***	12.915	***	12.924	***	9.811	***	9.903	***	20.155	***	15.737	***	11.778	***	11.989	***	8.890	***
	1.085		0.853		0.730		0.817		0.861		1.506		1.256		1.288		1.516		1.097	
Sex (1=girl) # Use ICT outside school for school purposes	-0.787		-1.224		1.460		0.121		-0.133											
	1.256		1.222		1.151		1.053		1.223											
Sex (1=girl) # Use ICT outside school for other purposes											-9.586	***	-5.573	***	2.309		-4.011		1.931	
											2.785		1.302		2.045		2.086		1.564	
Constant	542.597	***	569.458	***	703.136	***	613.921	***	570.064	***	528.714	***	559.255	***	704.515	***	605.789	***	576.033	***
	35.908		33.433		31.943		19.287		18.150		35.651		34.150		30.483		20.807		18.558	
School variance	3.632	***	2.878	***	2.781	***	2.877	***	3.069	***	3.625	***	2.880	***	2.785	***	2.874	***	3.072	***
	0.042		0.054		0.071		0.079		0.052		0.041		0.053		0.069		0.079		0.052	
Individual variance	3.990	***	4.098	***	4.072	***	4.149	***	3.980	***	3.988	***	4.097	***	4.072	***	4.148	***	3.980	***
	0.014		0.018		0.012		0.009		0.010		0.013		0.018		0.012		0.009		0.010	

Source: ICILS 2018. Repetitive weights are applied. Models include also individual level characteristics.

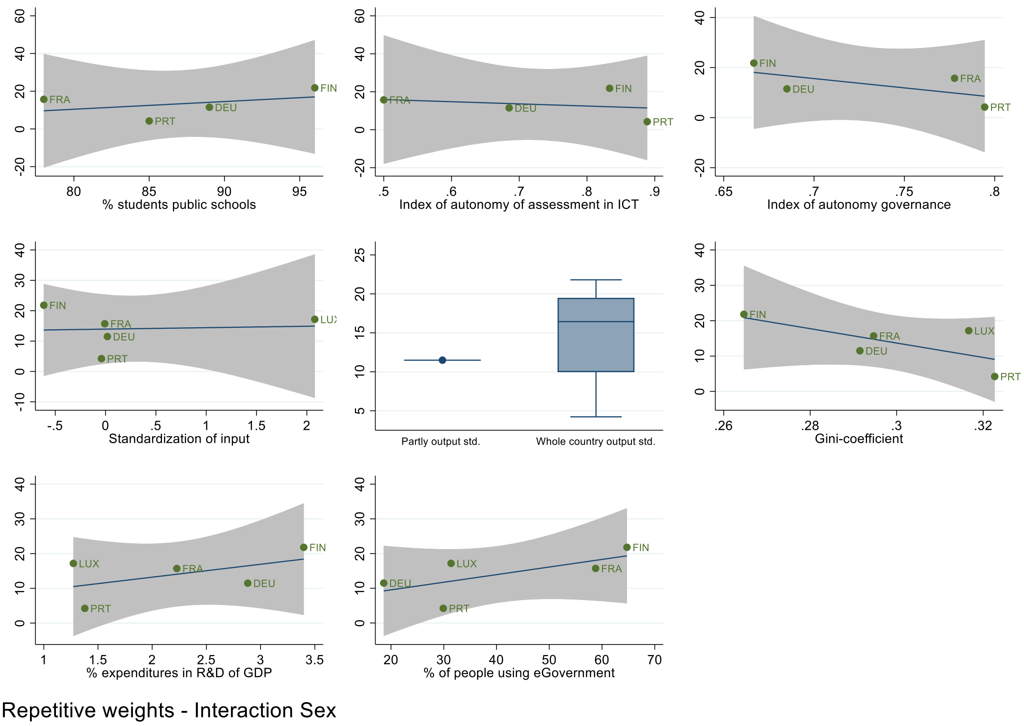
Table 2. Differential effects of ICT use and use purpose by Gender and SES for CIL scores (continued)

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT
Socioeconomic background	11.127	***	11.598	***	14.773	***	11.319	***	14.677	***	8.200	***	8.407	***	17.026	***	15.315	***	7.013
	2.849		2.994		1.791		2.844		2.653		2.229		2.076		1.334		1.818		2.214
Use ICT at school for school purposes	-0.258		2.584	**	1.437	*	-0.240		-2.062		-0.155		2.556	**	1.464	*	-0.360		-2.050
	0.884		0.912		0.675		0.682		1.141		0.930		0.894		0.684		0.678		1.141
Use ICT at school for other purposes	0.354		2.157	**	-2.276	***	2.654	***	-0.396		0.351		2.117	**	-2.341	***	2.746	***	-0.472
	0.548		0.794		0.516		0.600		0.304		0.552		0.775		0.534		0.567		0.310
Use ICT outside school for school purposes	-1.227		0.134		0.036		-0.915		0.454		-1.199		0.156		0.010		-0.840		0.495
	0.755		0.692		0.594		0.528		0.780		0.752		0.694		0.599		0.523		0.783
Use ICT outside school for other purposes	16.262	***	12.868	***	12.993	***	9.829	***	9.860	***	16.389	***	13.053	***	12.980	***	9.645	***	9.952
	1.015		0.871		0.722		0.799		0.860		1.069		0.871		0.733		0.796		0.854
Socioeconomic background # Use ICT at school for school purposes	-1.716		0.777		1.009		0.119		-1.306										
	1.091		0.792		0.684		0.629		0.720										
Socioeconomic background # Use ICT at school for other purposes											-0.579		1.468	**	0.275		-1.094	*	1.130
											0.512		0.500		0.645		0.546		0.474
Constant	542.923	***	572.157	***	699.952	***	613.650	***	569.825	***	544.173	***	571.101	***	700.072	***	615.510	***	572.128
	36.209		33.273		31.393		19.326		18.118		35.790		33.515		31.266		18.910		18.616
School variance	3.631	***	2.879	***	2.785	***	2.878	***	3.067	***	3.631	***	2.878	***	2.785	***	2.881	***	3.071
	0.042		0.054		0.069		0.078		0.053		0.042		0.054		0.068		0.080		0.052
Individual variance	3.989	***	4.098	***	4.072	***	4.149	***	3.980	***	3.990	***	4.098	***	4.072	***	4.148	***	3.979
	0.014		0.018		0.012		0.009		0.010		0.014		0.018		0.012		0.009		0.010

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT
Socioeconomic background	0.866		14.278	***	12.801	***	7.550	*	11.096	**	12.564		7.882		16.851	***	10.939	**	9.374
	2.674		1.965		1.900		3.469		4.108		7.305		4.653		2.888		4.064		5.004
Use ICT at school for school purposes	-0.071		2.563	**	1.490	*	-0.214		-2.044		-0.216		2.537	**	1.441	*	-0.233		-2.033
	0.915		0.894		0.668		0.679		1.158		0.882		0.890		0.669		0.679		1.135
Use ICT at school for other purposes	0.320		2.154	**	-2.342	***	2.554	***	-0.422		0.367		2.066	**	-2.323	***	2.640	***	-0.432
	0.551		0.807		0.519		0.558		0.313		0.552		0.767		0.521		0.568		0.314
Use ICT outside school for school purposes	-1.079		0.143		0.046		-0.881		0.489		-1.223		0.169		0.023		-0.903		0.500
	0.739		0.687		0.604		0.530		0.776		0.761		0.694		0.595		0.534		0.780
Use ICT outside school for other purposes	16.725	***	12.863	***	13.042	***	10.107	***	9.895	***	15.879	***	13.321	***	12.992	***	9.871	***	9.955
	1.057		0.883		0.732		0.743		0.844		0.771		0.896		0.754		0.713		0.824
Socioeconomic background # Use ICT outside school for school purposes	1.928	*	0.027		1.378	**	1.180		-0.142										
	0.909		0.544		0.508		0.835		1.140										
Socioeconomic background # Use ICT outside school for other purposes											-1.229		1.403		0.185		0.175		0.280
											1.536		0.990		0.634		0.777		1.015
Constant	542.554	***	572.294	***	700.905	***	611.369	***	570.193	***	545.965	***	570.269	***	700.280	***	613.581	***	570.466
	35.627		33.593		31.177		19.606		18.448		33.969		34.271		30.949		19.664		18.712
School variance	3.635	***	2.879	***	2.786	***	2.880	***	3.069	***	3.630	***	2.875	***	2.784	***	2.877	***	3.069
	0.045		0.053		0.069		0.078		0.053		0.042		0.056		0.068		0.079		0.052
Individual variance	3.989	***	4.098	***	4.072	***	4.148	***	3.980	***	3.990	***	4.098	***	4.072	***	4.149	***	3.980
	0.014		0.018		0.013		0.009		0.010		0.014		0.018		0.013		0.009		0.010

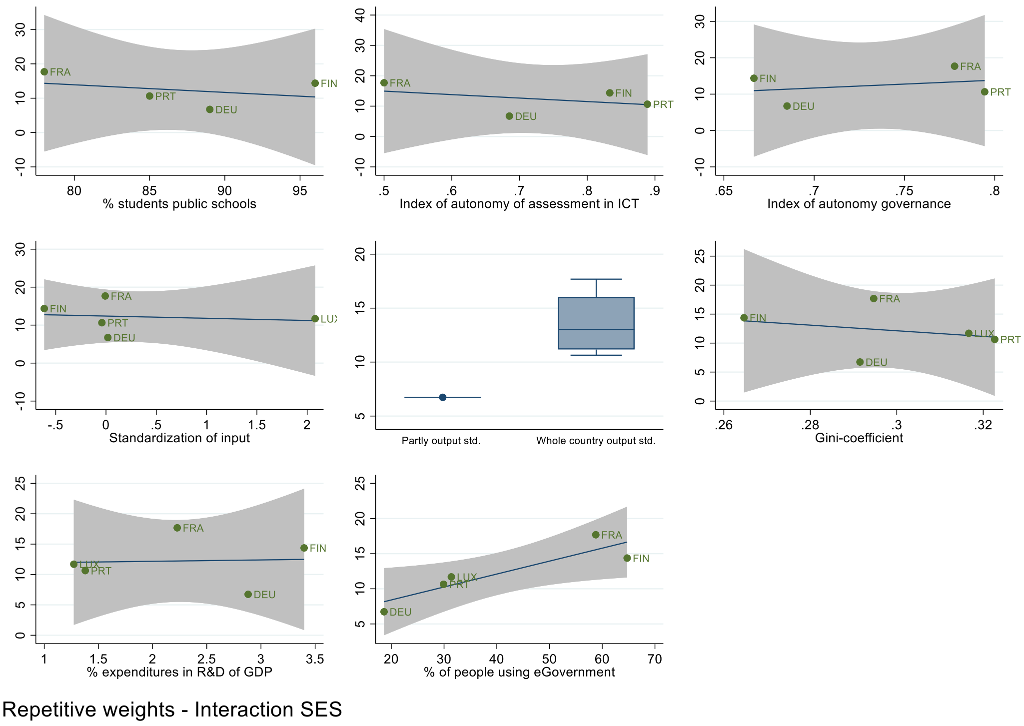
With regard to the moderation effect of the school characteristics with the socioeconomic background, as shown fully in Table B4 in Appendix B, it holds that only the teachers ICT experience during the lessons has a structural interaction effect over multiple countries. For Germany and Finland, it holds that the socioeconomic effect on CIL is lower when the teacher has a lot of ICT experience during classes. For France, the opposite holds: there students with a high socioeconomic background seem to profit more from an experienced teacher than those with a low socioeconomic background. As the number of countries prevent us from estimating a multi-level model with country as the second level, we correlate the coefficients of the within-country model to country-level characteristics. We estimate the individual-level controlled model, as we want to refrain from conflating possible school characteristics that are part of an education system and thus could be a country-level variable in itself.

Figure 3. Graphs of correlates between the sex coefficient on CIL scores and country characteristics



Notes: estimates obtained by using multiple imputation techniques for the five sample plausible values. X-axis are country level indicators, Y-axis are coefficients of the sex indicator from Model 1 of Table 1.

Figure 4. Graphs of correlates between the socioeconomic status coefficient on CIL scores and country characteristics



Notes: estimates obtained by using multiple imputation techniques for the five sample plausible values. X-axis are country level indicators, Y-axis are coefficients of the socioeconomic status indicator from Model 1 of Table 1.

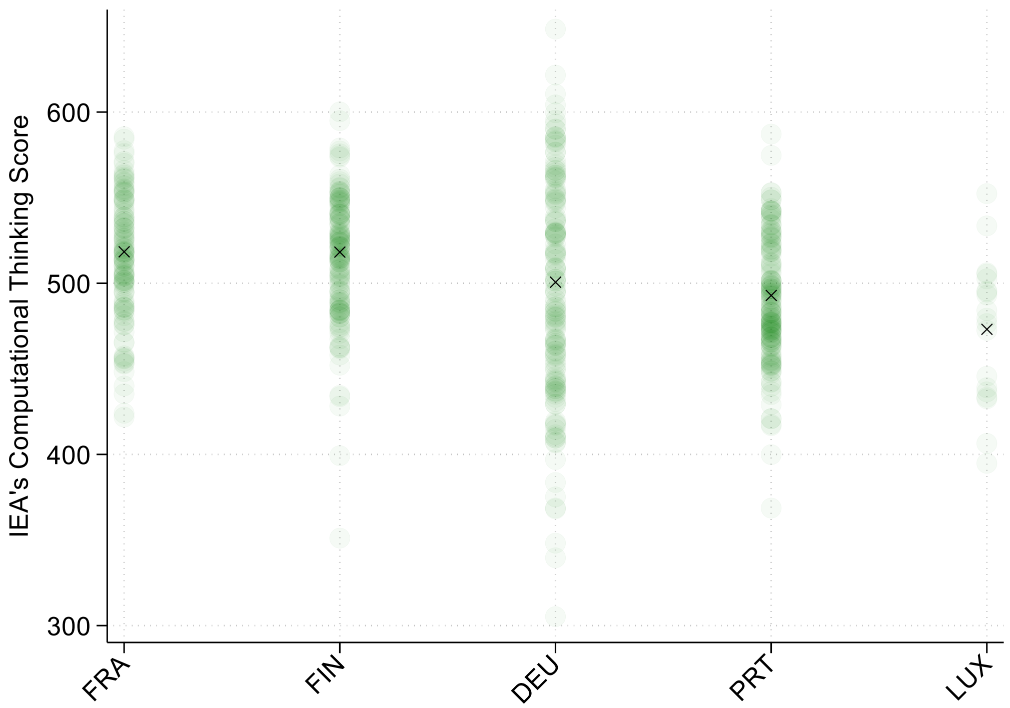
First, we look at the effect of a diverse set of country level variables on the coefficient that the multi-level model estimated for girls, of course compared to boys. As can be seen in Figure 3, it is quite difficult to see any correlational relationship between country characteristics and the girl's coefficient. If we would see the grey 95% confidence interval area see as a space through which we have to draw line, one can see that there are a variation of different lines and thus slope possible. This making an interaction effect with sex most unlikely. As the variation in the standardisation of output is minimal, we have used a boxplot to show that only partly having legislation for standardisation of output does not meaningfully deviate from those countries in which there is output standardisation everywhere. Turning to the interaction with SES we see, again little traction. The exception is making use of eGovernment: the higher the SES the more using eGovernment correlates with Computer Information Literacy.

1.2.5 Empirical results on the acquisition of Computational Thinking

1.2.5.1 Variation across countries and schools

In Figure 5, the across-country differences in Computer and Information Literacy for the different European countries are depicted. The X's shows the country mean, whereas the green dots show the school averages. The difference between the highest average of France and the lowest of Luxembourg is about 45 points, which is close to a standard deviation of the test score scale. As with CIL, here the between school variation is bigger than the between country variation.

Figure 5. Between and within-country CT



Notes: estimates obtained by using multiple imputation techniques for the five sample plausible values. Raw scores. ICILS average = 500; standard deviation = 100.

1.2.5.2 Explaining variation across schools and countries

As can be seen in Table 3, we ran our regression models for each country separately. Model 1 estimates all those effects simultaneously. In Table C1 in Appendix C, we show in Panel A to F the different individual level effects separately. In Table C2 in Appendix C, we look at the variance components. The null model in panel A shows that for all countries the intra class correlation lies between .4 and .5 (as it did in the CIL model), again justifying the multi-level structure of the regression estimates. Furthermore, the reduction in variance by entering composition indicators in panel B is about 5 to 10%. The results of the individual level control variables reveal, quite interestingly, that only experience with computers is positively related with CT, not so much the experience with smartphone or tablet. Looking at the results in model 1 and relate them to our hypotheses, we fail to reject the first hypothesis because after adding up all four coefficients of the ICT use the effect is still positive. The same effects in model 1 also fails to reject hypothesis 2. Outside school ICT use is stronger related than within school ICT use with the CT score, which holds for all countries. The internet connection indicator result leads to partly rejecting hypothesis 3; only in France the hypothesis should not be rejected.

Table 3. CT Regression analysis for each country (continued)

Model 1	DEU		FIN		FRA		LUX		PRT	
Age (in years)	-9.535	***	-13.791	***	-21.842	***	-15.827	***	-13.292	***
	2.591		2.264		2.231		1.784		1.532	
Sex (1=girl)	-12.906	***	5.861	**	-17.394	***	-14.831	***	-26.781	***
	3.461		2.071		1.417		2.559		2.640	
(At least) one parent born abroad	6.169		-34.605	**	-20.970	***	2.318		-7.465	*
	4.961		11.042		4.202		1.546		2.972	
Born abroad	-1.325		-14.775		16.448	*	11.586	***	-14.809	**
	7.195		9.230		7.748		2.716		4.607	
Language spoken at home same as test language	28.160	***	18.254	***	24.295	***	7.246	*	-21.784	***
	5.165		3.590		3.802		3.232		5.350	
Socioeconomic background	12.031	***	20.488	***	23.307	***	13.189	***	14.629	***
	2.103		0.927		1.518		1.083		0.957	
Internet access at home	-12.547		-21.935	*	30.000	**	15.502		4.279	
	15.032		11.190		9.454		8.594		5.476	
Computer experience	7.837	***	14.385	***	9.723	***	9.184	***	9.648	***
	0.857		0.757		0.714		0.997		0.716	
Smartphone experience	-7.359	***	-4.959	***	-10.425	***	-12.849	***	-8.506	***
	1.183		0.941		1.176		1.332		1.420	
Tablet experience	-5.963	***	-8.600	***	-4.019	***	-0.655		-0.920	
	1.173		1.123		0.504		0.657		1.247	
Studies ICT in current school year	19.890	***	18.877	***	-3.160		-19.880	***	17.208	***
	4.743		1.974		2.708		2.432		3.478	
Learning coding tasks	-0.594	**	-1.127	***	-1.056	***	-0.922	***	-0.938	***
	0.181		0.140		0.114		0.141		0.176	
Learning ICT tasks	-0.189		0.917	***	0.597	***	0.266		-0.124	
	0.178		0.124		0.079		0.173		0.177	
Use ICT at school for school purposes	-3.128	***	3.927	***	3.944	***	-1.530		-6.413	***
	0.836		1.026		0.736		1.177		1.296	
Use ICT at school for other purposes	-0.558		5.698	***	-4.834	***	2.792	***	-1.192	*
	1.139		1.376		0.635		0.497		0.608	
Use ICT outside school for school purposes	-4.213	*	-1.508		-2.017	***	-1.787	*	-0.121	
	1.777		0.794		0.494		0.839		0.747	
Use ICT outside school for other purposes	16.444	***	13.080	***	14.259	***	11.872	***	14.443	***
	1.591		1.346		0.708		1.049		0.978	
Constant	615.077	***	624.607	***	748.207	***	688.344	***	697.920	***
	47.674		34.392		33.298		27.373		24.547	
School variance	3.878	***	3.119	***	2.899	***	3.173	***	3.060	***
	0.035		0.066		0.049		0.077		0.038	
Individual variance	4.304	***	4.333	***	4.235	***	4.426	***	4.086	***
	0.015		0.013		0.010		0.016		0.012	

Source: ICILS 2018. Repetitive weights are applied

Table 3. CT Regression analysis for each country (continued)

Model 2	DEU		FIN		FRA		LUX		PRT	
Ratio of school size and teachers	-403.523	***	57.783	*	-246.273	***	-60.165		9.136	*
	50.465		23.518		66.113		84.017		4.460	
School size: 201-600 students	5.844		14.588	***	3.368			***	19.650	***
	6.886		2.156		3.264				2.628	
School size: 601-900 students	34.650	**	7.060	**	-0.253		-15.672	***	21.111	
	6.459		2.049		2.501		5.243		3.494	
School size: 901 or more students	31.426	***	43.459	***	20.511	***	-15.167	***	16.354	
	7.210		4.428		5.228		5.902		2.439	
Schools with equal amount of affluent and disadvantaged students	-8.214	***	5.126	***	4.365	***	-26.374	***	2.501	***
	2.789		1.869		3.037		1.873		1.719	
Schools with more disadvantaged students than affluent students	-60.024	***	6.871	***	-8.348	***	-41.570	***	-4.989	***
	3.221		1.400		2.071		2.983		2.821	
Constant	640.650	***	608.154	***	762.067	***	719.299	***	683.094	***
	44.870		34.760		31.894		22.701		25.038	
School variance	3.536	***	3.028	***	2.801	***	2.818	***	3.038	***
	0.029		0.068		0.054		0.119		0.056	
Individual variance	4.301	***	4.333	***	4.234	***	4.426	***	4.084	***

	0.015		0.013		0.010		0.016		0.013	
Model 3	DEU		FIN		FRA		LUX		PRT	
Availability of ICT resources at school (ICT Coordinator)	1.932	***	0.240	*	0.070		-1.024	***	-0.075	
	0.227		0.118		0.078		0.156		0.093	
Ratio of school size and number of ICT devices	0.909	**	-0.346		-0.777		5.290	***	0.372	***
	0.349		0.729		0.496		1.106		0.088	
Availability of computer resources at school (Teachers)	0.777		0.798	*	-0.384		1.370	**	0.127	
	0.480		0.391		0.477		0.462		0.174	
Constant	489.123	***	571.253	***	768.748	***	653.923	***	693.202	***
	57.936		29.349		37.688		38.919		29.758	
School variance	3.833	***	3.115	***	2.893	***	3.061	***	3.053	***
	0.037		0.061		0.049		0.066		0.037	
Individual variance	4.304	***	4.333	***	4.234	***	4.426	***	4.086	***
	0.015		0.013		0.010		0.015		0.012	
Model 4	DEU		FIN		FRA		LUX		PRT	
10 or more years ICT experience in the school	16.807	***	-1.057		-0.273		4.857	**	-2.211	
	2.646		1.047		1.724		1.809		1.657	
ICT experience with ICT use during lessons	-1.164		27.663	***	51.475	***	90.241	***	-21.418	***
	10.911		7.595		12.007		9.549		5.108	
Constant	608.746	***	558.373	***	625.123	***	465.476	***	750.967	***
	48.302		37.979		48.463		42.389		22.287	
School variance	3.865	***	3.112	***	2.866	***	3.099	***	3.047	***
	0.036		0.068		0.053		0.086		0.044	
Individual variance	4.304	***	4.333	***	4.235	***	4.426	***	4.086	***
	0.015		0.013		0.010		0.016		0.012	
Model 5	DEU		FIN		FRA		LUX		PRT	
Use of ICT for teaching practices in class	-2.956	***	-0.205		-1.943	*	4.163	***	0.895	***
	0.793		0.466		0.875		0.542		0.271	
Constant	758.553	***	634.826	***	845.293	***	484.423	***	654.371	***
	52.105		33.977		33.445		30.268		25.225	
School variance	3.868	***	3.118	***	2.880	***	3.162	***	3.056	***
	0.033		0.066		0.061		0.077		0.039	
Individual variance	4.305	***	4.333	***	4.235	***	4.426	***	4.086	***
	0.015		0.013		0.010		0.016		0.012	

Source: ICILS 2018. Repetitive weights are applied. Models 2 through 5 include also individual level characteristics.

Table 3. CT Regression analysis for each country (continued)

Model 6	DEU		FIN		FRA		LUX		PRT	
Age (in years)	-8.794	***	-13.972	***	-21.812	***	-16.009	***	-13.381	***
	2.518		2.274		2.233		1.864		1.557	
Sex (1=girl)	-14.099	***	5.748	**	-16.987	***	-15.314	***	-26.639	***
	3.403		2.100		1.423		2.469		2.662	
(At least) one parent born abroad	7.204		-36.170	***	-21.532	***	3.579	*	-7.846	**
	4.891		10.953		4.326		1.506		2.969	
Born abroad	0.562		-17.039		18.800	*	14.227	***	-15.695	***
	7.261		9.161		7.677		2.920		4.518	
Language spoken at home same as test language	26.508	***	18.107	***	23.574	***	8.755	*	-21.888	***
	5.185		3.642		3.821		3.572		5.343	
Socioeconomic background	10.433	***	19.973	***	22.720	***	12.049	***	14.000	***
	2.095		0.927		1.543		1.093		1.045	
Internet access at home	-12.367		-23.019	*	26.537	**	20.286	*	4.935	
	15.093		11.215		9.224		9.424		5.744	
Computer experience	7.555	***	14.346	***	9.791	***	9.062	***	9.653	***
	0.845		0.760		0.763		0.984		0.724	
Smartphone experience	-6.840	***	-5.159	***	-10.285	***	-12.401	***	-8.540	***
	1.154		0.955		1.189		1.339		1.419	
Tablet experience	-5.803	***	-8.868	***	-4.112	***	-0.708		-1.044	
	1.175		1.126		0.549		0.639		1.281	
Studies ICT in current school year	19.891	***	18.647	***	-3.327		-17.746	***	17.126	***
	4.577		1.963		2.692		3.191		3.546	
Learning coding tasks	-0.611	***	-1.150	***	-1.025	***	-0.872	***	-0.930	***
	0.180		0.140		0.115		0.132		0.178	
Learning ICT tasks	-0.201		0.917	***	0.575	***	0.294		-0.120	

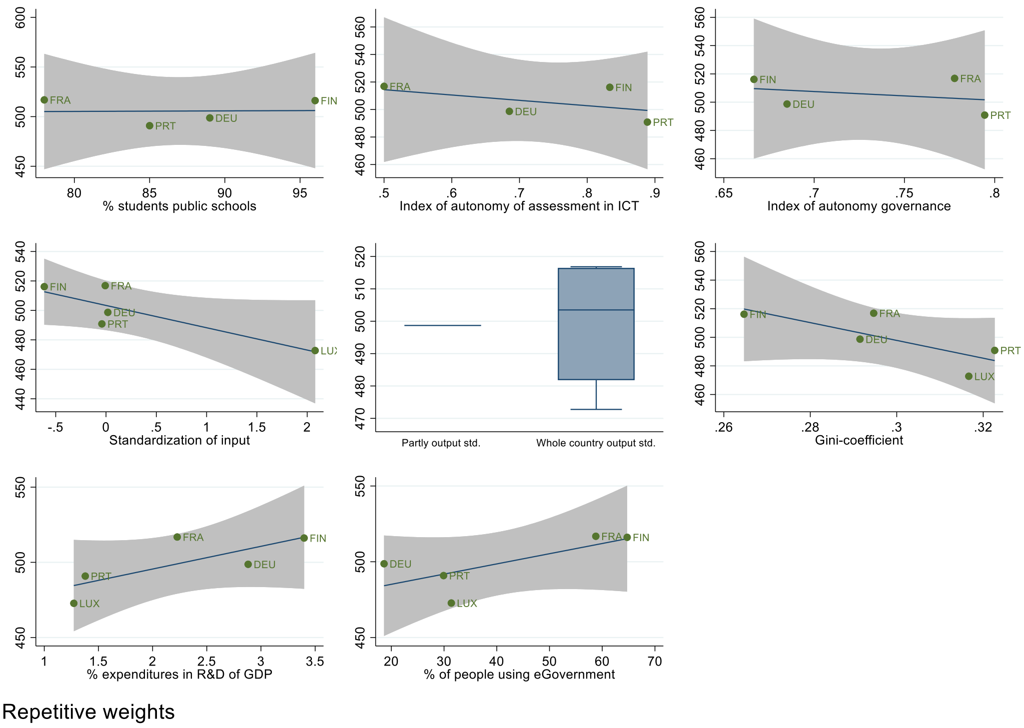
	0.174		0.126		0.077		0.178	***	0.178	***
Use ICT at school for school purposes	-3.151	***	4.023	***	3.811	***	-1.328		-6.413	
	0.805		0.991		0.731		1.230		1.274	
Use ICT at school for other purposes	-0.436		5.603	***	-4.473	***	2.334	***	-1.194	*
	1.085		1.396		0.643		0.594		0.604	
Use ICT outside school for school purposes	-4.111	*	-1.425		-2.413	***	-1.831	*	-0.135	
	1.757		0.805		0.499		0.855		0.741	
Use ICT outside school for other purposes	16.555	***	13.181	***	14.265	***	11.839	***	14.268	***
	1.524		1.377		0.715		1.059		0.980	
Ratio of school size and teachers	-556.368	***	17.543		-277.294	***	327.615	***	13.014	**
	54.805		26.342		56.936		67.371		4.286	
School size: 201-600 students	-14.273	*	13.846	***	5.866			***	21.108	***
	6.937		2.493		3.640				2.254	
School size: 601-900 students	11.145		3.817		2.432		23.925	***	21.607	***
	6.416		2.440		2.994		3.340		3.111	
School size: 901 or more students	16.455	*	47.503	***	29.890	***	6.560		16.851	***
	6.853		4.236		7.185		4.512		1.712	
Schools with equal amount of affluent and disadvantaged students	5.412		3.967	*	1.962		16.369	**	2.245	
	2.948		1.878		2.985		5.391		1.527	
Schools with more disadvantaged students than affluent students	-54.343	***	6.491	***	-9.393	***	-29.825	***	-6.017	*
	3.233		1.349		1.620		3.210		2.860	
Availability of ICT resources at school (ICT Coordinator)	1.538	***	0.074		-0.056		0.227		-0.088	
	0.212		0.121		0.096		0.142		0.125	
Ratio of school size and number of ICT devices	-1.036	***	-2.839	***	-0.990	*	11.195	***	0.309	**
	0.273		0.852		0.501		1.396		0.095	
Availability of computer resources at school (Teachers)	0.819		0.404		0.963		-0.261		-0.484	*
	0.608		0.493		0.758		0.574		0.218	
10 or more years ICT experience in the school	-5.312	*	-0.596		3.126		29.100	***	-2.238	
	2.604		1.496		1.861		3.941		1.679	
ICT experience with ICT use during lessons	7.309		28.194	**	27.175	*	146.683	***	-31.865	***
	10.613		9.259		12.413		19.803		5.517	
Use of ICT for teaching practices in class	-3.192	***	-1.032	*	-4.599	***	-11.680	***	2.440	***
	0.734		0.491		1.357		1.476		0.417	
Constant	712.498	***	579.975	***	887.563	***	811.677	***	668.723	***
	59.297		41.778		53.571		79.225		22.524	
School variance	3.467	***	3.008	***	2.697	***	0.041		3.001	***
	0.035		0.065		0.089		6.061		0.058	
Individual variance	4.300	***	4.332	***	4.235	***	4.428	***	4.084	***
	0.015		0.013		0.010		0.016		0.013	

Source: ICILS 2018. Repetitive weights are applied

We fail to reject hypothesis 4 as the results show that boys have an advantage over girls, apart from Finland where the reverse is true. Moreover, the socioeconomic status effect is positive thus also not rejecting that part of the fourth hypothesis.

Models 1 through 5 estimate school level variables separately and in model 6 we estimate them all simultaneously. Model 2 shows that the ratio between school size and teachers is, as it was with CIL, negatively related to CT for Germany and France, positively related Finland and are unrelated in Luxembourg and Portugal. The size of the school is positively related to CT, except for Luxembourg where it is negative. For schools with a more or less equal amount of affluent and disadvantaged students reveals a mixed picture across countries: in Finland, France and Portugal there seems to be a positive relationship whereas in Germany and Luxembourg it is negative. The more schools comprise of disadvantaged pupils, the lower the CT score is, except for Finland. With regard to the availability of ICT resources according to teachers, the correlates with CT were positive for Finland and Luxembourg. The availability according to the ICT coordinator of the school shows a more mixed picture, as it is positive related to CT in Germany and Finland, but negatively in Luxembourg. The ratio between ICT devices and students is only positively related with CIL in Germany, Luxembourg and Portugal. In all, this makes that the support for hypothesis 7 is mixed. In model 4 we include experience with ICT of both the teacher and ICT coordinator of the school. The experience of the coordinator is positively related in Germany and Luxembourg, while unrelated in the other countries under analysis. For the experience of the teacher, all but Germany appears to yield positive coefficients. In model 5, bringing the ICT in practice in the lessons by teachers is negatively related to CT in Germany and France, while positively related in Luxembourg and Portugal. We thus cannot reject the eight hypotheses in all countries but Germany, while hypothesis 9 (on experience) is not rejected in Germany and Luxembourg. Lastly, in the complete school level model, in model 6, the school size indicator is somewhat less stark as it is probably explained by the other school variables. Furthermore, the classroom ICT practice turns significant for all countries compared to model 5.

Figure 6. County-level correlates of Computational Thinking



Notes: estimates obtained by using multiple imputation techniques for the five sample plausible values. X-axis are country level indicators, Y-axis is predicted country level score of the full individual level model.

Turning to the variance components in Table C3 in Appendix C, the explained variance at the country level in model 6 lies between 9% (Finland) and 19% (France) and at the individual level the explained variance lies between 1% (Germany) and 3% (France and Portugal). In Figure 6, we show the relationship between 8 country level characteristics and the predicted country level means of the individual level model of computational thinking. We also obtained the predicted score of the empty model, though difference are negligible. Figure 6 shows the correlates do show a lot of room to deviate within the 95% confidence interval and thus lack precision to discern meaningful relationships between variables. In all, we have to reject hypotheses 10 to 13.

1.2.5.3 Gender and SES inequality and the role of education systems

The moderation effects of sex and socioeconomic status with the indicators on use of ICT and the purpose of using ICT for the CT score are depicted in Table 4. As with the CIL analysis, moderation effects are not really robust. For girls in Luxembourg the effect of use of ICT at school for other purposes is about zero, while positive for boys (combining the main effect with the interaction effect). The effect of use of ICT outside school for other purposes is smaller for girls in Germany and Finland, as it was with the CIL skills, but for CT this holds also in Luxembourg. The moderation effects of socioeconomic status somewhat more prevalent across countries. For use of ICT at school for school purposes: the higher the socioeconomic status the larger the effect is in Finland. The effect of using ICT at school for other purposes is larger for higher socioeconomic status students in Finland, while the opposite is observed in Luxembourg. The effect of using ICT outside school for school purposes is less negative and even turns positive the higher the socioeconomic status is in Germany and France. The effect of using ICT outside school for other purposes is smaller for higher socioeconomic status students in France, while larger in Portugal. Hypotheses 5 is refuted, as well as hypothesis 6 (but for France).

In Appendix C, Table C3, the interaction effects of sex are shown for the school level variables with Computational Thinking. All the effects are estimated while controlling for the individual level indicators. Noteworthy results are that in France, Luxembourg and Portugal the effect of ICT coordinator indicating that degree of resources available at the school is less negative or positive for girls and non-existent or negative for boys. For Finland, the positive availability effect is almost zero for girls. Second, the interaction of student-teacher ratio with sex appears to be negative in France, Luxembourg and Portugal though to a varying degree of significance, meaning that girls have a less positive or even negative ratio-effect. Third, in Finland and Luxembourg the effect of the teacher indicating availability of computer resources at school makes the advantage for girls in those countries smaller. In Germany the disadvantage of girls becomes smaller the more ICT resources there are available. For the moderation with the socioeconomic status (Table C4, in Appendix C), it holds that the effects are different in the countries in analysis, or quite imprecisely estimated, as some effects are only significant at the 5%-level.

With regard to the country characteristics moderations, we correlate the coefficients of the within-country model to country-level characteristics. We remain estimating the individual level controlled model, as to not obfuscate possible school characteristics that are part of an education system.

Table 4. Differential effects of ICT use and use purpose by Gender and SES for CT scores

	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT
Sex (1=girl)	-17.031	-10.062	-23.927 ***	-16.146 **	-25.985 ***	-9.694	6.152	-14.817 ***	6.363	-27.337 ***
	9.137	7.725	4.759	5.469	4.368	5.666	3.587	2.772	9.451	3.398
Use ICT at school for school purposes	-3.828 ***	1.856	2.898 ***	-1.725	-6.304 ***	-3.205 ***	3.924 ***	3.945 ***	-1.684	-6.418 ***
	1.025	1.690	0.753	1.318	1.575	0.857	1.033	0.737	1.199	1.297
Use ICT at school for other purposes	-0.522	5.769 ***	-4.848 ***	2.795 ***	-1.188	0.072	5.734 ***	-4.330 ***	6.042 ***	-1.279 *
	1.111	1.405	0.636	0.497	0.616	1.435	1.499	0.569	1.270	0.590
Use ICT outside school for school purposes	-4.192 *	-1.504	-1.972 ***	-1.774 *	-0.129	-4.210 *	-1.507	-1.992 ***	-1.764 *	-0.109
	1.786	0.797	0.513	0.829	0.742	1.777	0.794	0.497	0.844	0.757
Use ICT outside school for other purposes	16.468 ***	12.935 ***	14.224 ***	11.856 ***	14.439 ***	16.486 ***	13.084 ***	14.281 ***	11.804 ***	14.440 ***
	1.590	1.370	0.711	1.052	0.984	1.588	1.376	0.710	1.046	0.980
Sex (1=girl) # Use ICT at school for school purposes	1.570	4.406	2.256	0.417	-0.251					
	2.631	2.326	1.676	1.174	1.303					
Sex (1=girl) # Use ICT at school for other purposes						-1.273	-0.072	-1.080	-6.283 **	0.171
						1.113	0.998	0.915	2.148	0.614
Constant	617.940 ***	633.715 ***	752.580 ***	688.636 ***	697.541 ***	613.038 ***	624.468 ***	746.127 ***	686.007 ***	698.146 ***
	47.910	33.038	33.704	27.226	24.504	48.209	34.924	33.774	27.189	24.443
School variance	3.877 ***	3.122 ***	2.899 ***	3.173 ***	3.060 ***	3.878 ***	3.119 ***	2.897 ***	3.166 ***	3.060 ***
	0.035	0.065	0.049	0.077	0.039	0.035	0.066	0.049	0.080	0.039
Individual variance	4.304 ***	4.332 ***	4.234 ***	4.426 ***	4.086 ***	4.304 ***	4.333 ***	4.234 ***	4.424 ***	4.086 ***
	0.015	0.013	0.010	0.016	0.012	0.015	0.013	0.010	0.015	0.012
	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT
Sex (1=girl)	-9.506	7.649	-21.661 ***	-6.635	-16.732 *	82.329 ***	48.217 ***	-27.710 **	3.023	-19.071 *
	8.147	5.332	5.115	7.541	7.289	21.284	10.201	9.674	9.309	7.760
Use ICT at school for school purposes	-3.144 ***	3.941 ***	3.982 ***	-1.587	-6.478 ***	-3.429 ***	4.044 ***	3.962 ***	-1.513	-6.443 ***
	0.839	1.015	0.765	1.209	1.312	0.865	1.012	0.746	1.173	1.299
Use ICT at school for other purposes	-0.551	5.707 ***	-4.864 ***	2.787 ***	-1.223 *	-0.329	5.899 ***	-4.853 ***	2.673 ***	-1.183
	1.139	1.387	0.651	0.496	0.622	1.167	1.387	0.645	0.508	0.606
Use ICT outside school for school purposes	-3.746	-1.288	-2.560 ***	-0.707	1.203	-4.034 *	-1.510	-2.042 ***	-1.692 *	-0.122
	2.552	0.975	0.643	1.394	1.590	1.783	0.797	0.491	0.850	0.744
Use ICT outside school for other purposes	16.426 ***	13.103 ***	14.220 ***	12.023 ***	14.508 ***	24.237 ***	17.822 ***	13.096 ***	14.110 ***	15.337 ***
	1.590	1.331	0.711	1.126	0.995	2.288	1.697	1.266	1.565	0.916
Sex (1=girl) # Use ICT outside school for school purposes	-1.088	-0.531	1.189	-2.381	-3.102					
	2.476	1.348	1.330	1.933	2.578					
Sex (1=girl) # Use ICT outside school for other purposes						-20.213 ***	-9.187 ***	2.251	-4.135 *	-1.712
						3.974	2.065	2.100	1.714	1.955
Constant	613.306 ***	623.364 ***	750.765 ***	686.609 ***	693.313 ***	582.958 ***	603.078 ***	752.642 ***	680.052 ***	692.798 ***
	49.663	34.616	32.440	27.645	22.488	49.449	35.600	31.878	26.788	21.346
School variance	3.878 ***	3.119 ***	2.897 ***	3.173 ***	3.061 ***	3.871 ***	3.120 ***	2.901 ***	3.171 ***	3.058 ***
	0.036	0.066	0.050	0.077	0.039	0.034	0.065	0.048	0.078	0.037
Individual variance	4.304 ***	4.333 ***	4.234 ***	4.426 ***	4.085 ***	4.299 ***	4.331 ***	4.234 ***	4.426 ***	4.086 ***
	0.015	0.013	0.010	0.015	0.013	0.014	0.013	0.010	0.015	0.012

Source: ICILS 2018. Repetitive weights are applied. Models include also individual level characteristics.

Table 4. Differential effects of ICT use and use purpose by Gender and SES for CT scores (continued)

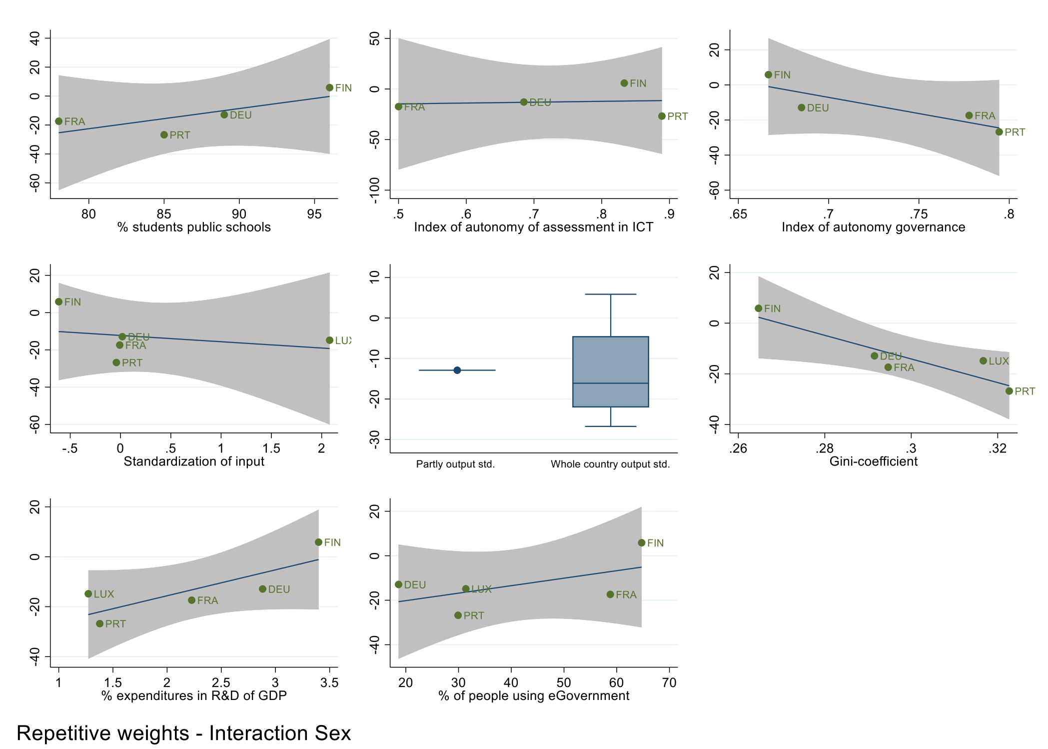
	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT
Socioeconomic background	11.018 ***	10.550 ***	19.887 ***	13.893 ***	11.649 ***	10.075 *	10.311 ***	20.291 ***	19.420 ***	11.438 ***
	3.108	2.875	2.051	3.164	3.430	4.234	2.278	1.544	2.631	2.763
Use ICT at school for school purposes	-3.108 ***	3.997 ***	3.945 ***	-1.520	-6.399 ***	-3.154 ***	3.913 ***	4.068 ***	-1.744	-6.423 ***
	0.833	1.105	0.740	1.186	1.293	0.834	1.041	0.744	1.211	1.300
Use ICT at school for other purposes	-0.562	5.710 ***	-4.781 ***	2.781 ***	-1.214 *	-0.577	5.634 ***	-4.918 ***	2.960 ***	-1.232
	1.138	1.353	0.616	0.517	0.613	1.130	1.319	0.665	0.474	0.629
Use ICT outside school for school purposes	-4.211 *	-1.533	-2.001 ***	-1.785 *	-0.087	-4.238 *	-1.481	-2.078 ***	-1.659	-0.125
	1.776	0.791	0.493	0.838	0.769	1.759	0.796	0.508	0.853	0.744
Use ICT outside school for other purposes	16.488 ***	13.108 ***	14.285 ***	11.853 ***	14.473 ***	16.530 ***	13.409 ***	14.301 ***	11.574 ***	14.486 ***
	1.549	1.336	0.720	1.046	0.994	1.571	1.322	0.723	0.981	0.996
Socioeconomic background # Use ICT at school for school purposes	0.395	2.782 ***	1.186	-0.223	0.965					
	0.934	0.723	0.875	0.878	0.951					
Socioeconomic background # Use ICT at school for other purposes						0.771	2.506 ***	1.259	-1.884 *	0.993
						1.142	0.663	0.706	0.778	0.810
Constant	615.290 ***	624.032 ***	748.189 ***	688.692 ***	698.260 ***	614.644 ***	622.477 ***	748.707 ***	691.196 ***	699.508 ***
	47.899	34.052	33.331	27.147	24.579	47.945	34.189	33.160	26.968	25.150
School variance	3.878 ***	3.120 ***	2.897 ***	3.173 ***	3.060 ***	3.878 ***	3.114 ***	2.899 ***	3.179 ***	3.066 ***
	0.035	0.066	0.049	0.077	0.039	0.035	0.067	0.048	0.079	0.039
Individual variance	4.304 ***	4.332 ***	4.234 ***	4.426 ***	4.086 ***	4.304 ***	4.332 ***	4.234 ***	4.425 ***	4.085 ***
	0.015	0.013	0.010	0.016	0.012	0.015	0.013	0.010	0.016	0.013

	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT
Socioeconomic background	-0.734	22.179 ***	17.734 ***	10.416 **	12.565 *	22.929 **	10.658 *	32.057 ***	12.477 ***	7.579 *
	6.965	2.115	2.096	3.540	5.162	7.436	4.656	3.295	2.835	3.098
Use ICT at school for school purposes	-2.904 ***	3.948 ***	4.006 ***	-1.516	-6.397 ***	-3.202 ***	3.887 ***	3.893 ***	-1.528	-6.375 ***
	0.759	1.043	0.743	1.174	1.313	0.861	1.039	0.733	1.177	1.280
Use ICT at school for other purposes	-0.597	5.702 ***	-4.858 ***	2.729 ***	-1.207 *	-0.500	5.564 ***	-4.840 ***	2.785 ***	-1.227 *
	1.131	1.384	0.639	0.464	0.615	1.166	1.321	0.635	0.491	0.616
Use ICT outside school for school purposes	-3.908 *	-1.554 *	-1.989 ***	-1.765 *	-0.077	-4.225 *	-1.464	-2.014 ***	-1.776 *	-0.116
	1.739	0.738	0.513	0.836	0.777	1.775	0.789	0.494	0.838	0.747
Use ICT outside school for other purposes	17.040 ***	13.027 ***	14.341 ***	12.065 ***	14.468 ***	15.366 ***	13.779 ***	14.036 ***	11.922 ***	14.746 ***
	1.487	1.349	0.731	1.071	0.981	1.849	1.266	0.755	0.975	1.010
Socioeconomic background # Use ICT outside school for school purposes	4.195 *	-0.509	1.573 *	0.790	0.640					
	1.793	0.776	0.673	0.923	1.382					
Socioeconomic background # Use ICT outside school for other purposes						-2.299	2.125	-1.934 **	0.165	1.563 **
						1.748	1.128	0.742	0.528	0.571
Constant	612.214 ***	625.228 ***	749.308 ***	686.684 ***	698.209 ***	618.956 ***	621.452 ***	744.920 ***	688.109 ***	699.048 ***
	47.250	34.450	33.082	27.559	24.910	46.888	34.769	33.262	27.298	24.765
School variance	3.883 ***	3.119 ***	2.899 ***	3.175 ***	3.060 ***	3.877 ***	3.113 ***	2.893 ***	3.173 ***	3.059 ***
	0.036	0.066	0.048	0.076	0.039	0.035	0.068	0.050	0.078	0.038
Individual variance	4.302 ***	4.333 ***	4.234 ***	4.426 ***	4.086 ***	4.304 ***	4.333 ***	4.234 ***	4.426 ***	4.085 ***
	0.014	0.013	0.010	0.015	0.012	0.015	0.013	0.010	0.016	0.012

Source: ICILS 2018. Repetitive weights are applied. Models include also individual level characteristics.

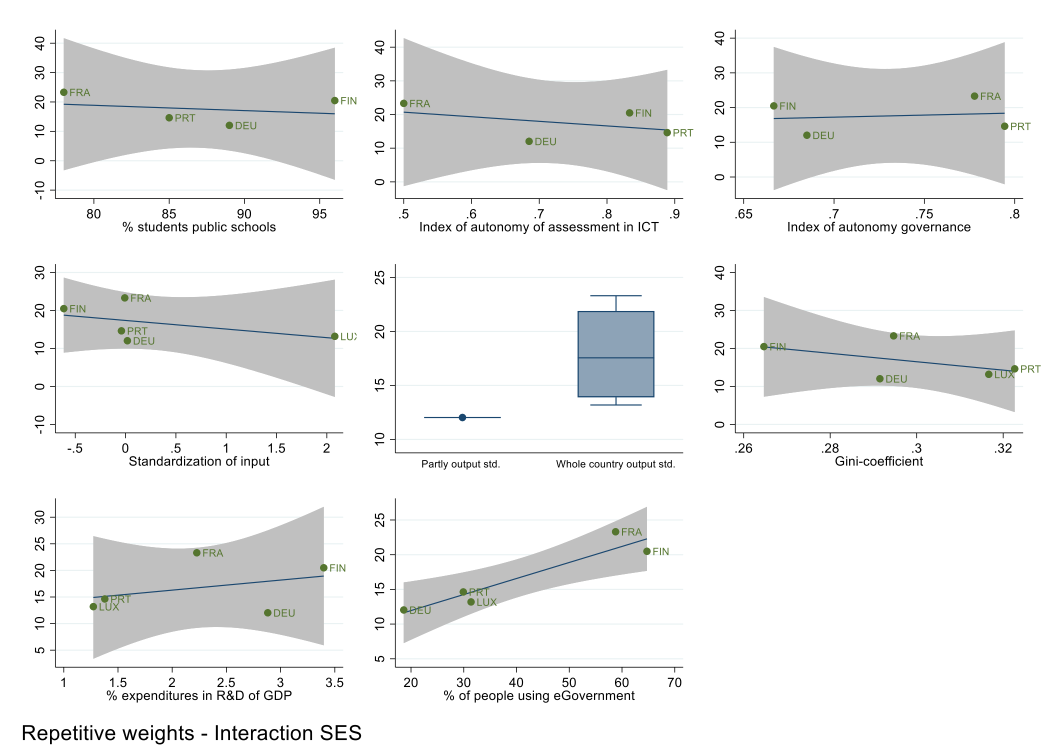
First, we look at the effect of a diverse set of country level variables on girls, compared to boys. In Figure 7, it is rather hard to see correlations between country characteristics and the girl's coefficient. Again, treating the grey 95% confidence interval area see as a space through which we have to draw line, a variation of different slopes are possible. We tentatively conclude that there is no sex interaction effect for CT, except for a negative correlation with the Gini-coefficient. For the standardisation of output the results show no substantial deviation from those countries in which there is output standardisation everywhere. For the interaction with SES it holds that the CT figures look very similar to the CIL figures. The exception might be again eGovernment: the higher the SES the more using eGovernment correlates with Computational Thinking.

Figure 7. Graphs of correlates between the sex coefficient on CT scores and country characteristics



Notes: estimates obtained by using multiple imputation techniques for the five sample plausible values. X-axis are country level indicators, Y-axis are coefficients of the sex indicator from Model 1 of Table 3.

Figure 8. Graphs of correlates between the socioeconomic status coefficient on CT scores and country characteristics



Notes: estimates obtained by using multiple imputation techniques for the five sample plausible values. X-axis are country level indicators, Y-axis are coefficients of the sex indicator from Model 1 of Table 3.

1.3 Analyses of Problem Solving Skills

1.3.1 Theory & Hypotheses

While in the previous section we were looking at ICT skills as a direct measure of digital skills, we now turn our focus to a second set of skills often deemed important and needed for education and the workplace in current and future economies, namely problem-solving skills. Problem solving-skills are one crucial example of higher order cognitive skills (others include critical thinking, creativity col labouration, communication, information or technical skills). In the 21st century, individuals increasingly face challenging, nonrecurring problems and situations that are uncertain and without precedent (Autor, Levy and Murnane, 2003; Van Laar, Van Deursen, Van Dijk & De Haan, 2020). Problem-solving skills allow workers to deal effectively with these complex nonroutine situations (Van Laar, Van Deursen, Van Dijk & De Haan, 2020).

We draw on resources and appropriation theory to explain individual-level differences in students' problem-solving skills (De Haan, 2004; Van Dijk, 2005). This theoretical approach relates differences in individuals' (digital) skills to differences in their available resources, including temporal (time for skill usage), material (infrastructure to use skills), mental and motivational (e.g., learning style), social (social network to assist skill usage), and cultural (e.g., religion, language) resources. The differences in individuals' available resources relate to personal categories and positions in a society. Van Laar et al. (2020) distinguish the personal and positional categories into demographic (e.g., age, gender, and race or ethnicity), socioeconomic (e.g., education, income, and labour position), and personality or psychological determinants (e.g., personal traits and intelligence). Based on resources and appropriation theory (De Haan, 2004; Van Dijk, 2005), we expect older students, male students, students from higher SES backgrounds and students without migration background to score higher in problem-solving skills, although the advantage of older students and male students should be moderate (for a systematic literature review, see Van Laar et al. 2020).

Just as for ICT skills, next to the home environment, schools are young students' most relevant learning context with regard to problem-solving skills. As with ICT skills and other domain-specific competences, we expect to find a large variation in problem-solving skills between schools rather than between countries. Based on findings from previous research, we consider four school-level characteristics which we expect to affect students problem-solving skills. First, we consider the school type (private/public). Private schools should be better equipped, more autonomous in selecting their students and teachers, and more flexible in their curriculum, which altogether should positively affect students problem-solving skills. Second, we consider the level of school autonomy directly, referring to a school's capacity to hire and fire teachers, to determine teachers' salaries, define budget allocation, and determine students' admission and disciplinary and assessment policies, as well as manoeuvring over the supply and content of courses. We expect a larger autonomy to result in a better capacity of schools and their teachers to adapt the content of teaching toward an increasingly important set of skills, i.e., problem-solving skills, which is usually not yet embedded in national curricula. Third, we will consider the student-teacher ratio. The fewer students a teacher has to teach, the better s/he can respond to each students' individual needs and support them in their individual skill development, thus resulting in higher problem-solving skills. Fourth, we consider the extent of extracurricular activities. Previous research found that extracurricular activities positively affect students' confidence in their ability, which in turn positively affects their learning strategies and academic outcomes (e.g., Chan 2016, Eccles et al. 2003, Stuart et al. 2011). We expect extracurricular activities to enhance students problem-solving skills through co-operative activities and hands-on experiences.

Also for problem-solving skills we expect to find differences between countries, even though they may be smaller than differences within countries between schools. The PISA data allows us to study the country-level as a second, contextual level in our analyses. Based on findings from previous research, we consider six country-level characteristics of the education systems and the economic and cultural environments in

European societies which we expect to affect students problem-solving skills. Countries differ in the degree of standardization of teaching content (*input standardization*) and in the existence of central examination (*output standardization*). In countries with high input and output standardization, the educational systems are arguably less flexible to adapt quickly to new demands, like the rising demand for problem-solving skills and other higher-order cognitive skills. Thus, we expect countries with high input and output standardization to lag behind countries with lower standardization levels in terms of students' proficiency in problem-solving. If the constructivist learning theories with their emphasis on out-of-school experience holds, this malus for highly standardized countries should be moderate. As a further characteristic of the educational system, we analyse the type of *study program*. Previous research has shown that in most countries (Germany and Russia being exceptions), students in vocational study programs score higher in problem-solving as compared to students in general study programs with similar skills in mathematics, reading and science skills (OECD, 2014b: 96ff; Levy, 2010). Vocational study programs are considered to stronger promote hand-on learning. This means that they are believe to equip students for tackling complex, real-life problems in contexts usually not encountered at school (Levy, 2010; OECD, 2014b: 98f.). We therefore expect a higher share of upper secondary students in vocational study programs to be positively related to ther average level of students' problem-solving skills in a country.

We further consider two economic determinants: research & development and the level of income inequality. We expect *research & development* investments to have a rather direct impact on problem-solving skills. We expect higher expenditures in the percentage of GDP in research & development to coincide with better average students' performance in problem-solving skills. *Economic inequality*, however, is expected to lower the average problem-solving skill development because fewer students from less privileged backgrounds have access to appropriate learning environments. Thus, we expect a higher level of income inequality to negatively relate with problem-solving skills.

Finally, we analyse a country's level of digitalization and adult's willingness to learn. Previous research has found that digital and problem-solving skills are positively related (OECD, 2014b). In more *digitalized countries,* it can be assumed that students are more often faced with new situations and challenges and that students are forced to apply problem-solving and digital skills to address these new situations. We therefore expect students in more digitalized countries to score higher in problem-solving. We also expect that students in countries where adults show a higher *willingness to learn* to score higher in problem-solving skills. Parents usually act as role models for their children. In countries where the adult population is more prone to learning children are also likely socialized into a stronger willingness to learn, which in turn can be expected to increase their skill set in problem-solving.

1.3.2 Data and Methods

This section uses data from the 2012-round of the OECD's Programme for International Student Assessment (PISA) (OECD, 2014a). PISA collected background information and test-score data on adolescents aged approximately 15 years old in all OECD countries. Testing tool place in school and with respect to a variety of competence domains. Side to literacy and numeracy, the 2012-round also included test-score data on problem solving skills.

The overall sample in PISA 2012 includes 271,323 respondents. The restriction to European countries left us with 143,660 respondents. Among this restricted sample we selected only respondents from those countries for which we had comparable information on country-level characteristics, which resulted in a sample of 108,141 respondents. After list-wise deletion on the analytical variables at the individual level, we obtained a final sample of 91,152 respondents spanned across 19 European countries: Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, Great-Britain, Hungary, Ireland, Italy, the Netherlands, Norway, Poland, Slovakia, Slovenia, and Sweden. All analyses use design weights to ensure the representativity of the findings. Design weights provided in PISA are adjusted according to our sample selection (weights are normalised to that the sum of the weights is equal to the number of respondents in the analytical sample).

1.3.2.1 Test scores

Problem-solving skills in PISA are measured using computer-based assessments based on near real-life problems. The PISA testing framework involves five plausible values of a child's performance as to make inference on the actual child's proficiency level. A plausible value is a likely score of proficiency drawn from the marginal posterior of the latent distribution. Taken together, the five plausible values yield an unbiased estimates of real proficiency score (OECD, 2019a, 2019b). The raw scores (each plausible value) are normalized to have an average of 500 and a standard deviation of 100 across OECD countries. Some of the previous studies use multiple imputation techniques to average out estimates from the five sample (plausible values) and adjust the standard errors accordingly (see, for example, Bol, Witschge, Van de Werfhorst, and Dronkers (2014) and Jacobs and Wolbers (2018). For the sake of simplicity and parsimony, we only use imputation techniques in the bivariate analyses (descriptive step) and run the analyses on the first plausible value only in the multivariate analyses (explanatory step).

1.3.2.2
Independent variables

The two main stratification dimensions of interest at the individual level are gender and socioeconomic background. *Gender* refers to students' biological sex at birth. The *socioeconomic background* (SES) of the family of origin is proxied by the PISA's index of economic, social, and cultural status (ESCS). The other covariates at the individual level used in the analyses are students' *migration background* (at least one parent born abroad) and *exact age at testing*.

We focus on a series of characteristics of the educational systems at the school level. *School type* distinguishes public, private, and private but government-dependent schools. *School autonomy* is an index reflecting the autonomy a school has in hiring and firing teachers, determining teachers' salaries, defining budget allocation, determining students' admission and disciplinary and assessment policies, as well as manoeuvring over the supply and content of courses. One could indicate whether the principal, teacher, school governing board, regional authority or national education authority was responsible. If principal, teachers or school governing board was selected the item was scored 1, otherwise 0. Weighted Likelihood Estimation are applied so that countries were equally weighted is constructing the individual score on the scale. Subsequently, they were transformed to an OECD-country mean of 0 and a standard deviation of 1. The indicator was available in the PISA data set. The *student-teacher ratio* measures the average number of students per teacher. Finally, the index of *extracurricular creative activities* measures the number of cultural and creative activities taking place in school as indicated by the principal, such as, band, orchestra or choir, school play or musical, and art clubs (OECD, 2014b). The indicator was available in the PISA data set. All school-level variables are directly available in PISA 2012 from the school questionnaires filled out by the principal.

At the country level, we focus on a series of characteristics of the education systems and the economic and cultural environments in European societies. First, we focus on input and output standardisation in the education systems. *Input standardisation* refers to the extent to which schools can decide how and what to teach. This concept recall school autonomy (at the school level) but refers to the country level and is restricted to the content and modes of teaching only. *Output standardisation*, instead, is a dummy variable indicating the existence of central examination in a country. The third characteristic of education systems is the index of *vocational enrolment*. This index is based on the share of students in vocational programs in upper secondary education calculated with both OECD and UNESCO data. *Input* and *output standardisation* and the index of *vocational enrolment* are taken directly from Bol and van de Werfhorst (2013). *Input standardisation* and *vocational enrolment* were standardised to have a mean of 0 and a unit standard deviation in Bol and van de Werfhorst's sample; we kept the same metric for our analyses. The economic indicators used in the analyses are the percentage of GDP spent on *research & developm*ent (OECD, 2021a) and the GINI-coefficient to measure the level of *income inequality* (OECD, 2021b). Finally, we also measure the level of digitalization and the willingness to learn of the adult population in a country. The level of digitalization refers to the average percentage of individuals that submitted forms to public authorities via web in the last 12 months (Digital Agenda Data EU, 2021). We refer to this variable as the extent of the *digital contacts with the government*. The willingness to learn, instead, is measured by averaging the *index of learning strategies* available at the individual level in PIAAC. This index is obtained by merging information on six items indicating how much one uses the following learning strategies (5 points Likert scale): “Relate new ideas into real life”; “Like learning new things”; “Attribute something new”; “Get to the bottom of difficult things”; “Figure out how different ideas fit together” and “Looking for additional info”. A higher value indicates that those learning strategies are more often employed in a country. Table D1 in Appendix D shows descriptive statistics for all variables used in the analyses.

1.3.3 Analytical strategy

The analyses are structured around two research questions: (1) How the acquisition of problem-solving skills relates to characteristics of education systems; and (2) How gender and social inequalities in the acquisition of problem-solving skills relate to characteristics of education systems. Research question 1 (RQ1) implies a comparison in the *levels* of problem-solving skills across countries and schools to gauge insights on the role of contextual characteristics (varying both across countries and across different schools in the same country). Research question 2 (RQ2) implies a comparison in the amount of (gender and SES) *inequality* across countries and schools to gauge insights on the role of contextual characteristics (again, varying both at the country and the school level).

The empirical analyses related to each of the two research questions are divided in two steps. In the first step, we *describe* contextual variations in the levels or the amount of (gender and SES) inequality in problem-solving skills across countries and schools. In the second step, we try to *explain* variations across countries and schools via institutional characteristics at both the country and the school level. Notwithstanding these similarities, the two research questions required somewhat tailored strategies of analyses, which briefly describe below.

RQ 1: Study variations in the levels of problem-solving skills

We relied on raw test-score data to study variations in the levels of proficiency across countries and schools. Raw scores represent *absolute measures* of achievement and are directly comparable across students in different schools and countries by design. As mentioned in the previous section, the raw data are normalised to have a mean of 500 and a standard deviation of 100 across OECD countries (in our selected sample the average is 500 while the standard deviation slightly lower than 100, see Table D1 in Appendix D).

The first, *descriptive* step relies on the comparison of point averages of raw proficiency scores across countries and schools. This description explores the overall contextual variations in proficiency levels by ranking countries and visualizing the heterogeneity across schools in the same country. The second, *explanatory* step relies on hierarchical models with a three-level structure (individuals, schools, countries) where only the intercept (the average proficiency) is allowed to vary across levels. These models partition the total variation in raw proficiency scores and allow us to explore 1) the amount of variation occurring at individual, school, and country level; and 2) the role of selected school- and country-level characteristics in explaining such variations. To this end, we adopt a stepwise approach by enriching a null model (partitioning the variance in the three levels) with individual characteristics (jointly), school characteristics (jointly), and country-level characteristics (included once a time for the sake of parsimony).

RQ 2: Study variations in (gender and SES) inequality in problem-solving skills

We relied on z-standardised scores within countries to study gender and SES inequality in proficiency across countries and schools. The z-standardised scores represent *relative measures* of achievement and describe the relative position of students in a country's achievement distribution. The use of a relative measure seems justified by our focus on *inequality* rather than proficiency *levels* in RQ 2. The within-country standardisation imposes a mean of 0 and a unit standard deviation in each country. Hence, we study gender and SES inequality from a distributional perspective concerned with the amount of group-based inequality occurring within each national context rather than across national contexts.[3]

The *descriptive* step of the analyses relies on the comparison of the raw gender gaps and SES gradients in z-standardised problem-solving scores across countries and schools. Raw gender gaps are computed as differences in the average z-score of boys and girls in each country and school. Hence, positive gaps reflect boys' advantages. SES gradients are obtained from bivariate OLSs regressing standardised scores on the SES index (ESCS) in each country and school. Hence, positive gradients reflect an advantage of higher compared to lower SES students. The second, *explanatory* step of the analyses relies on three-level hierarchical models with random intercept, similar to RQ 1.[4] In this setting, we first estimate the average gender gaps and SES gradients in all countries (as a benchmark) when conditioning out other individual- and school-level characteristics. We then examined variations in gender and SES inequality across contexts via cross-level interactions with country and school-level characteristics (we included interactions one at a time for the sake of parsimony).

[3] A corollary of this decision is that the same amount of relative inequality in two national contexts (say among boys and girls) may hide a different amount of inequality in absolute terms across the contexts.

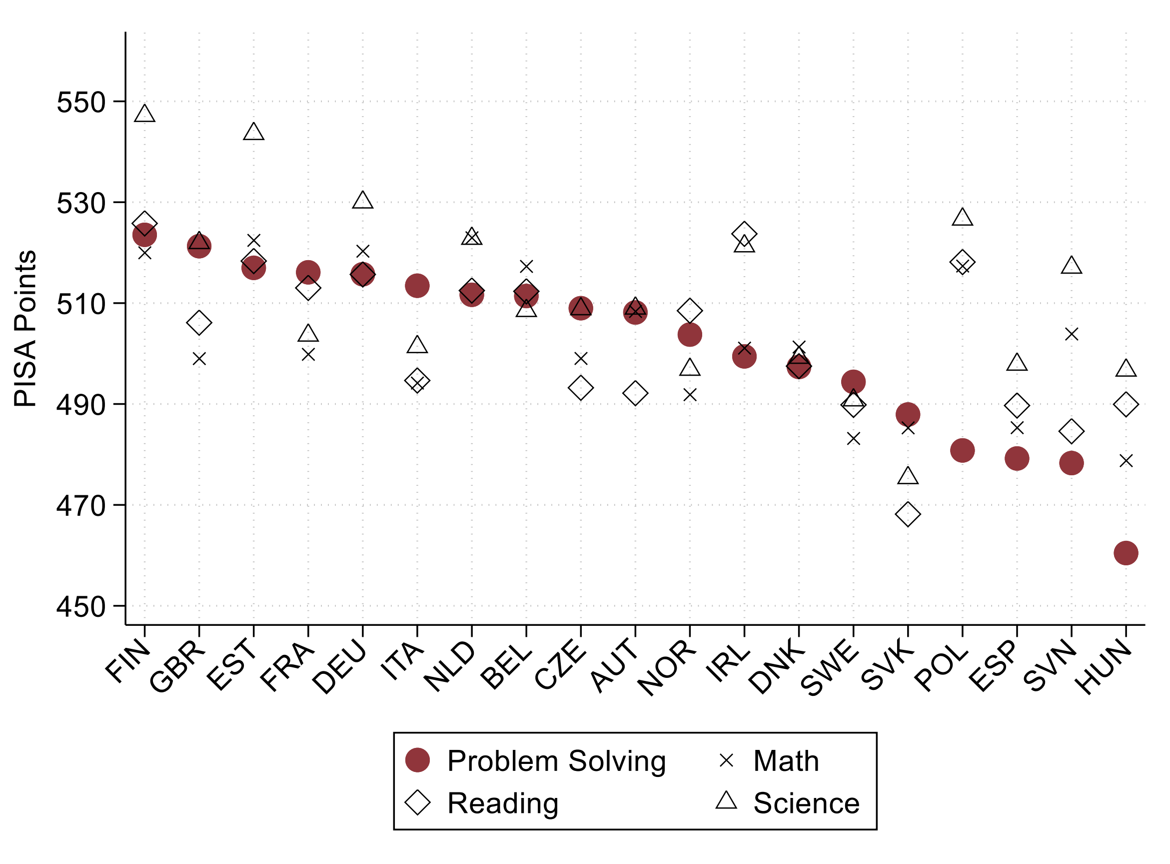
[4] In this setting, the random intercept at country level is 0 by construction and the main effect of country-level characteristics is not interpretable. And yet cross-level interactions between gender and SES with country-level characteristics are informative about whether gender and SES inequality align with these institutional features at the country level, which is the information we need to answer RQ 2. The inclusion of random slopes for gender and SES at the country and school level would offer additional insights on contextual variations in gender and SES inequality. However, this alternative strategy was computationally very intensive and not feasible in our context.

1.3.4 Empirical results on problem-solving skills

1.3.4.1 Variations across countries and schools

Figure 9 depicts differences in the raw average problem-solving scores across countries (red dots). Average scores in math, science, and reading are added for comparison. There is quite some variety across European countries in all domains. The figure shows some degree of correlation between problem-solving skills and other skill domains at the country level. Countries that score higher on problem solving also score higher on math, although with exceptions. The correlation with reading and especially science is less apparent, at least at the bottom of the distribution of problem-solving skills. The non-perfect overlap with the rankings in other skill domains calls for a closer attention to problem-solving as distinct outcome in cross-national comparison.

Figure 9. Average scores in problem-solving, math, science, and reading by country (PISA 2012).



Notes: multiple imputation techniques to average out estimates from the five sample plausible values. Raw scores. OECD average = 500; standard deviation = 100.

Looking at problem-solving skills, it is striking that most of the European countries we considered score higher than the OECD average (500). And yet some countries score lower, notably Eastern European countries. Top-scoring countries are quite heterogeneous in terms of their geographical position and overall welfare-state arrangements. Such heterogeneity is striking if we look at the five top-ranked countries: Finland, the United Kingdom, Spain, France, and Germany. The variation between the best (Finland) and the worst (Hungary) performing countries in problem-solving is considerable, around 60 points on the raw scale. This difference corresponds to more than half of a standard deviation across OECD countries (100).

Differences in the levels of problem-solving skills are even more pronounced between schools of the same country. Figure 10 plots the average problem-solving score across schools (green dots) grouped by country to ease comparison (countries are ranked according to the average proficiency level, as in Figure 1). It is apparent that country averages hide quite some variety in performance across schools. However, the variability across schools differs by countries. For example, in Finland or Estonia, the school averages are relatively homogeneous compared to Belgium, Slovenia, or Hungary, where there is quite a larger dispersion in the average school performance. And yet countries with the same average performance, for example Estonia and France (or Germany), may vary greatly in the amount of dispersion. Also, it is worth noting that there is no clear-cut relation between the average performance in a country and the dispersion across schools. While the top-performing country (Finland) shows the smaller variation across schools and the worst-performing countries the largest, the patterns for the countries in-between these two extremes are less clear-cut.

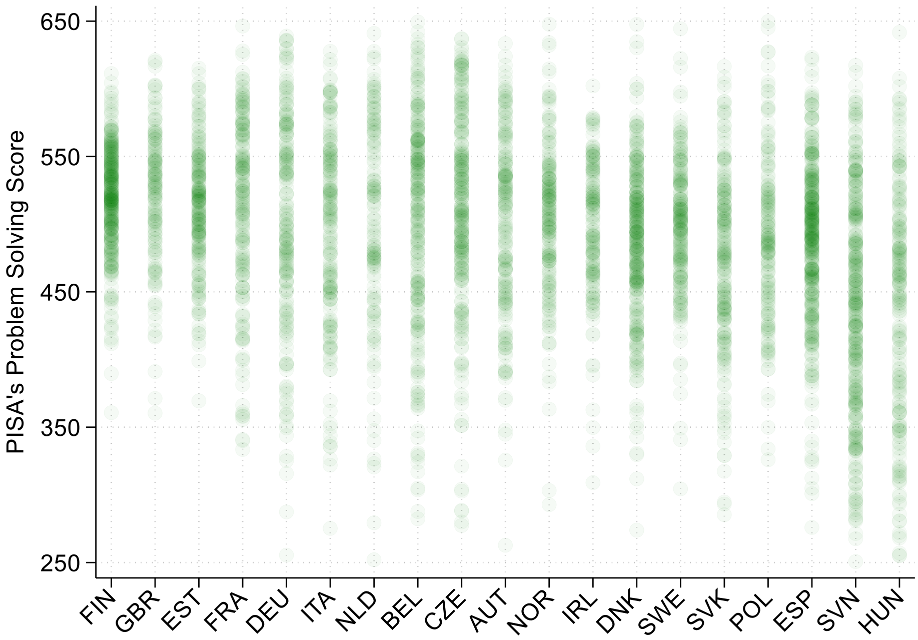
All in all, the two figures show a large variability in problem-solving scores across countries, and even more so across schools embedded in the same national context. In the next steps, we will try to explain such variability by national and school-level characteristics.

1.3.4.2 Explaining variations across countries and schools

Table 5 shows the results from the multilevel models (random intercept) regressing the raw problem-solving scores on a series of individual, school, and country-level characteristics. Model 1 is a null model that partitions the total variance of the outcomes across the three levels.

The examination of the variance components offers some initial insights on the contextual variety in problem-solving skills. First, there are substantially and statistically significant contextual variations across countries and schools. Schools seem to contribute to around 40% of the overall variation in problem-solving skills (3948 / [5789.8+3948+408] = .39). Instead, the variability attributable to the country-level is modest, around 4% (408 / [5789.8+3948+408] = .04). These results go in the direction of what we have shown in the previous paragraph: when it comes to contextual variations in problem-solving skills, the school context seems to matter more than the national context.

Figure 10. Average problem-solving score by school, grouped by country.



Notes: Raw scores. Multiple imputation techniques to average out estimates from the five sample plausible values.

Table 5. Multilevel models (random intercept) regressing raw problem-solving scores on individual, school, and country-level characteristics.

	PANEL A – Fixed and Random Effects									
	Model1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Individual-level										
Age at test		9.4***	9.5***	9.5***	9.5***	9.5***	9.5***	9.5***	9.5***	9.5***
Boys		11.2***	11.3***	11.3***	11.3***	11.3***	11.3***	11.3***	11.3***	11.3***
Migration (ref. Native)										
First gen.		-33.8***	-33.7***	-33.7***	-33.7***	-33.7***	-33.7***	-33.7***	-33.7***	-33.7***
Second gen.		-29.9***	-29.9***	-29.9***	-29.9***	-29.9***	-29.9***	-29.9***	-29.9***	-29.9***
SES (ESCS score)		18.0***	17.9***	17.9***	17.9***	17.9***	17.9***	17.9***	17.9***	17.9***
School-level										
Type (ref. Private)										
Private – Gov. depend.			-16.1	-16.1	-16.1	-16.2	-16.1	-16.2	-16.2	-16.1
Public			-30.9**	-30.5**	-30.7**	-30.9**	-30.7**	-30.8**	-30.9**	-30.8**
Autonomy			-0.7	-0.8	-0.7	-0.6	-0.7	-0.7	-0.8	-0.7
Extra-curricular creative activities			10.1***	10.1***	10.2***	10.1***	10.1***	10.2***	10.2***	10.1***
Student-Teacher Ratio			1.9**	1.9**	1.9**	1.9**	1.9**	1.9**	1.9**	1.9**
Country-level										
Input standardisation				-14.8*						
Output standardisation					-7.7					
R&D expenditure						7.1				
Income Inequality (Gini)							72.8			
Digital contact with the Gov.								0.3		
Vocational Enrolment									8.9	
Adult's Learning Strategies										11.2
Constant	495.7***	332.8***	320.2***	317.9***	325.2***	305.9***	299.3***	312.2***	314.4***	279.3**
Variance Intercept										
Country-level	408.0***	339.9***	340.5***	277.1***	328.0***	311.3***	334.5***	322.2***	305.1***	338.4***
School-level	3948.0***	3242.7***	3064.3***	3064.9***	3064.3***	3064.2***	3064.3***	3064.5***	3064.0***	3064.3***
Individual-level	5789.8***	5510.4***	5509.7***	5509.7***	5509.7***	5509.8***	5509.7***	5509.7***	5509.8***	5509.7***
	Panel B – % decrease variance components compared to									
Variance at		Model 1	Model 2	Model 3	Model 3	Model 3	Model 3	Model 3	Model 3	Model 3
Country-level	–	-16.8	–	-18.6	-3.7	-8.6	-1.8	-5.4	-10.4	-0.6
School-level	–	-17.9	-5.5	–	–	–	–	–	–	–
Individual-level	–	-4.8	–	–	–	–	–	–	–	–

Model 2 includes a series of individual characteristics that likely impact on problem-solving skills. The inspection of the single coefficients (Panel A) shows some expected patterns. Older students at the day of testing perform slightly better, while migrants (especially first-generation migrants) perform on average worse than natives. What is more, boys and children from higher SES perform better than girls and children from lower social background. We will be back on these gender and SES-based inequality in the next paragraph. For the time being, it is worth noting that even when including these individual characteristics significant variations across countries and schools remain (contextual variations across countries and schools decrease by 17–18%, see Panel B). This suggest that there are systematic differences across countries and schools that do not trace back to compositional effect in terms of individual characteristics.

Model 3 tries to explain the residual variation by including selected contextual indicators at the school level. Overall, the above-mentioned characteristics explain around 6% of the residual variation across schools (see Panel B). As one may suspect, the average performance of private schools is much higher compared to public schools. The average difference is astounding, around 30 points on the scale. This difference equals the one between the average performance in the top-performing country (Finland) and countries in the medium-lower tail of the distribution (for example, Ireland). Extracurricular activities seem to foster children's problem-solving abilities as expected. However, quite unexpectedly, the development of problem-solving skills seems to benefit from a higher number of students per teacher. And yet school autonomy does not seem to play any role for problem solving skills. This is a particularly surprising finding. We expected a larger flexibility would result in a better capacity of schools and teachers to adapt the content of teaching toward an increasingly important set of skills (like problem-solving skills) that are not yet embedded in national curricula. Additional analyses adding school-level indicators one by one confirm that the absence of association does not trace back to the possibility that the indicator for extra-curricular activities captured part of the role of school autonomy on problem-solving skills (see Table D2 in Appendix D).

Models 4 to 10 explore the role of selected national characteristics for problem-solving skills. Both the standardisation of instruction (input) and exams (output) are negatively associated with problem-solving skills (see Panel A, models 4 and 5). Input and output standardisation explain around 19 and 4% of the variability across national contexts (see Panel B). These results are consistent with the idea that, in more standardised education systems, the focus of learning is on classical subjects such as language or math rather other sets of skills. However, while the negative correlation between problem-solving skills and the standardisation of input is substantive statistically significant, the coefficient for output standardisation is smaller and within the range of estimation error.

Quite surprisingly one country's expenditure in research and development (model 6) seems not related to problem solving (though it reduces the country level variance with 9% approximately). The same holds for the index of income inequality (model 7), the digital contacts with the government (model 8), the rate of enrolment in vocational education (model 9), and the index of adult's learning strategies (model 10).

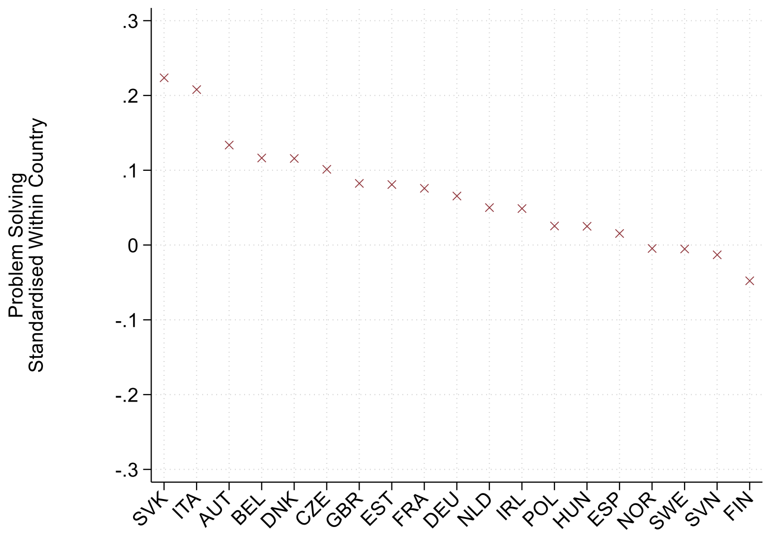
1.3.4.3 Gender and SES inequality in problem-solving skills: variation

Figure 11 shows the gender and SES gaps in problem solving skills (z-standardised within countries) across the 19 countries. Gender gaps are computed as the raw difference in the average z-score of boys and girls in each country; hence, positive gaps suggest boys perform better than girls on average. Boys outperform girls in the lion's share of countries. The extent of the girls' penalty varies greatly across national contexts; from more than 2SD in Slovakia and Italy to around .1 of SD in countries like Denmark, the UK, and France and a minimum of .05–.02SD in the Netherlands and Spain. Interestingly, in Slovenia, Sweden, and Norway the gender gap seems very limited while in Finland girls seem to slightly outperform boys. These cross-country variations are by far overcome by the differences in gender gaps across schools within countries.

Figure 12 plots the average gender gaps across schools grouped by countries (ranked according to the average gender gap at the country level). In all countries, the gender gap is positive in some schools (boys' advantage) and negative (girls' advantage) in others. In countries like Finland, Belgium, or Spain the gender gaps is more similar across schools compared to countries like Ireland or Austria, which are seem characterised by far larger dispersion at the school-level. Overall, the figure does not provide suggestive evidence for a relation between the average gender gap in a country and the variation of gender gaps across schools within the same countries.

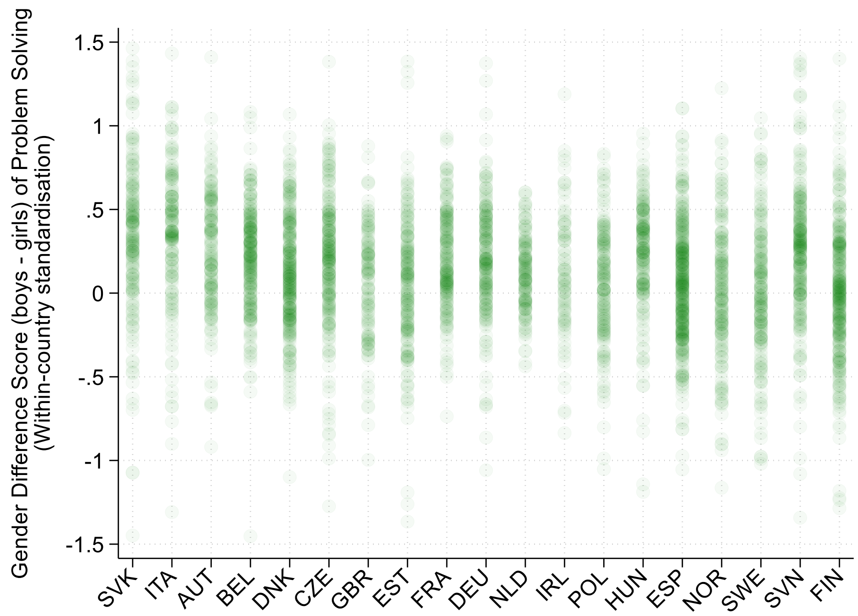
Figure 13 shows the SES gradient in problem-solving (z-standardised within countries) across the countries. Positive gradients indicate that children from higher social background perform on average better than children from lower social background. As the figure shows, this seems to be the case in all European countries we considered. The SES gradient ranges from a maximum of .5SD in Eastern European countries like Czech Republic, Slovakia, and Hungary, to a minimum of slightly less than .3SD in Southern European countries like Spain and Italy. These are meaningful differences. An estimated gradient of .5 implies that children whose social background (ESCS index) lies at the OECD average perform 50% of an SD below children whose social background lies one standard deviation above the OECD average.

Figure 11. Average gender gap (boys-girls) in problem-solving by country (PISA 2012).



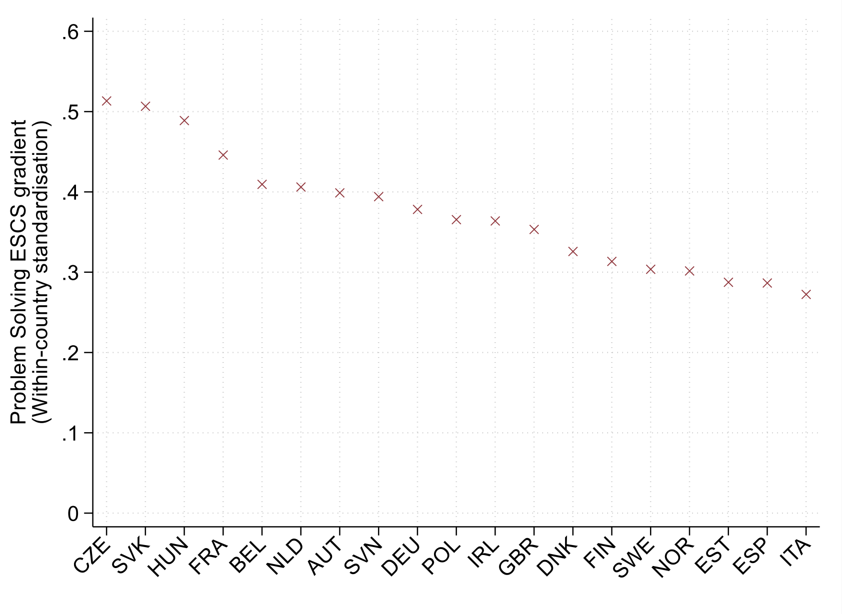
Notes: Scores are z-standardized within countries. Multiple imputation techniques to average out estimates from the five sample plausible values.

Figure 12. Average gender gap in problem solving by school, grouped by country.



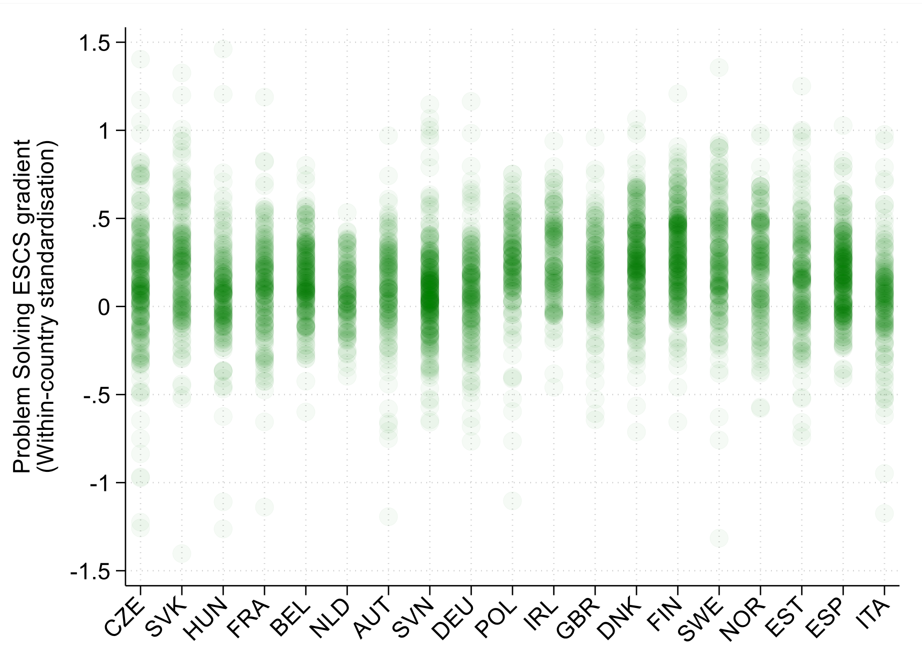
Notes: Scores are z-standardized within countries. Multiple imputation techniques to average out estimates from the five sample plausible values.

Figure 13. Average SES gradient (ESCS index) in problem solving by country (PISA 2012).



Notes: Scores are z-standardized within countries. Multiple imputation techniques to average out estimates from the five sample plausible values.

Figure 14. Average SES gradient (ESCS index) in problem solving by school, grouped by country.



Notes: Scores are z-standardized within countries. Multiple imputation techniques to average out estimates from the five sample plausible values.

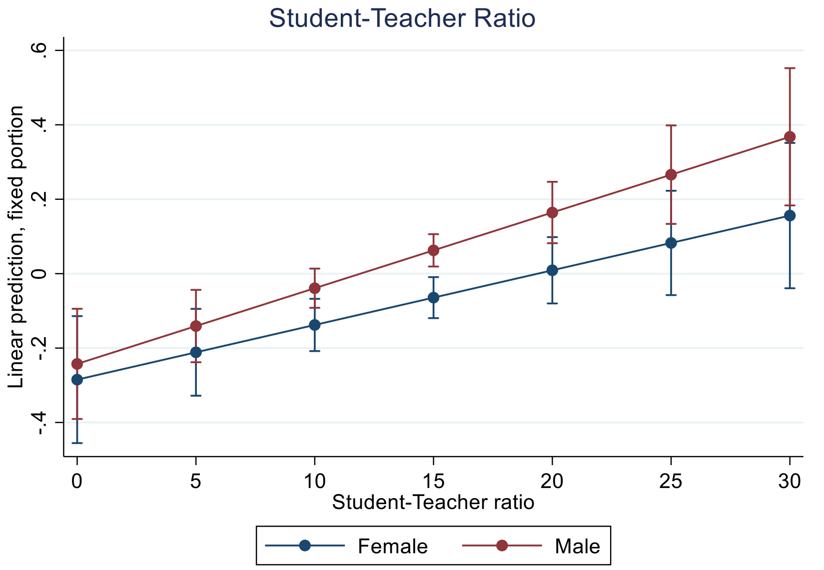
Figure 14 complement the picture by showing the variation in the social gradient across schools of the same countries (ranked according to the magnitude of the average SES gradient). Contrary to what we have seen before, the social gradients across schools seem much more homogeneous compared to differences between boys and girls and the average proficiency in problem solving. Still, while in most schools the social gradient is positive (high SES kids are advantaged), there are schools in which the gradient is negative (low SES are advantaged) in virtually all countries. And yet the variation across schools seems much larger compared to the variation across national contexts. Again, there is no apparent relation between the average SES gradient in a country and the heterogeneity of the SES gradients across schools within countries. All in all, akin what we have seen in the case of the average proficiency levels, the variability of both gender and SES-based inequality in problem solving skills seem larger across schools in the same national context than across countries. In the next paragraph. we will try to explain differences in gender and SES gaps by national and school-level characteristics.

1.3.4.4 Explaining variations across countries and schools

The previous paragraph has shown that the magnitude of gender SES gaps in problem-solving skills vary substantially across European countries and even more so across schools in the same country. But does such variation align with school and country-level characteristics? Table D3 in Appendix D reports the results from the models including the multiplicative terms between gender (Panel A) and SES (Panel B) with school-level characteristics (interactions terms are included one at a time). These models allow us to inspect whether the average gender and SES gaps (Benchmark model) increase or decrease according to school type, school autonomy, the extent of extra-curricular activities and the student teacher ratio in a school.

The benchmark model with no interaction confirms what we have shown by analysing problem-solving skills in absolute terms (Table 5, Model 3): on average, there is substantial gender and SES-based inequality in the countries and schools examined. Boys' average performance exceed girls' by 12% of an SD; while one SD positive difference in parental SES coincide with a 18% of an SD increase in achievement. However, models 1 to 8 in Table A3 generally shows that these average gender and SES gaps do not change substantially according to school characteristics. The only exception is that boys' advantage seems to increase with the student-teacher ratio. Figure 7 plots the predicted z-standardised scores of boys and girls at different levels of the student-teacher ratio: although there is strong uncertainty around the predictions, girls seem to lose more ground compared to boys as the number of teachers per students decreases. Worth noting is also that boys' advantage seems higher in public and semi-private schools compared to private, but such difference is within the range of estimation error. All other interaction terms between gender and SES with school-level characteristics are neither statistically not substantially significant, however.

Figure 15. Girls' penalty increases with the student-teacher ratio.



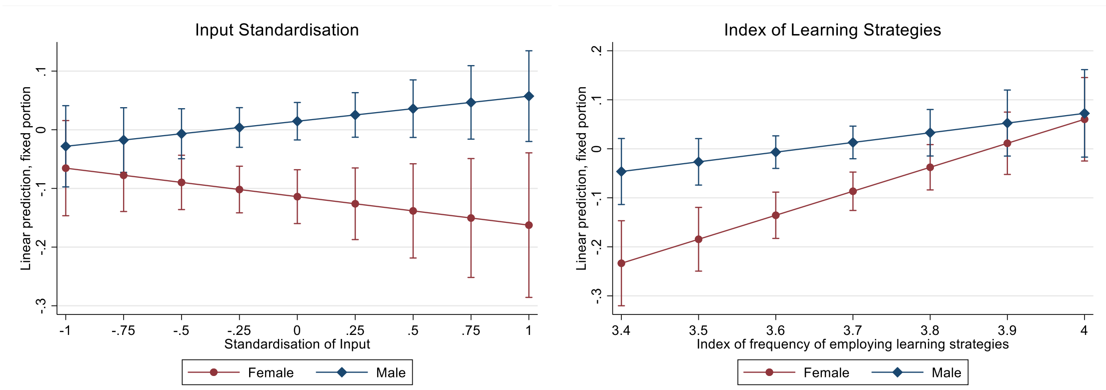
Note: Predictions from Table D3, Model 4.

Overall, these results suggest that school-level characteristics we considered do not to explain the large school-level differences in gender and SES inequality we see in the descriptive analyses. But do national characteristics we considered account for the variation in gender and SES gaps in problem-solving skills at the country-level? Table D5 and D6 in Appendix D show the results from the models interacting gender and SES with country-level characteristics. These models allow us to inspect whether the average gender and SES gaps (shown as a benchmark in Table A4) increase or decrease according to features of the education system (input and output standardization, vocational enrolment), the economic environment (Gini index and R&D expenditure), and some characteristics of the adult population in a country (motivation to learn [Adults' learning strategies] and the digital contacts with the government).

Table D3 reminds us that the average gender penalty is around .12 SD and the average SES advantage .18 SD per one SD increase in the ESEC index. These gender and SES-related gaps do not change dramatically along with national-level characteristics. Most of the interaction coefficients are not statistically significant or substantially relevant, although with exceptions (plotted in Figures 8 and 9). Boys' advantages in problem-solving skills seem stronger in countries with higher standardisation on instructional input, as shown if Figure 15. For example, the gender gap increases from 14% of an SD for countries with an average level of input standardisation (in the OECD countries) to even 23% for those countries scoring one standard deviation above the average. This result suggests that girls may lag behind boys in terms of problem-solving abilities especially when those skills are less likely embedded into formal teaching in the classroom. Conversely, as shown in Figure 16, boys' advantage decreases in countries where adults are keener to learn new things and apply new ideas to everyday life. The gap even disappears in countries where the frequency of these everyday learning activities is the highest. This very result suggests that everyday engagement with learning from the side of the parents, which likely shape learning environments at home, may compensate and even have the potential to close the girls' disadvantage in problem-solving skills.

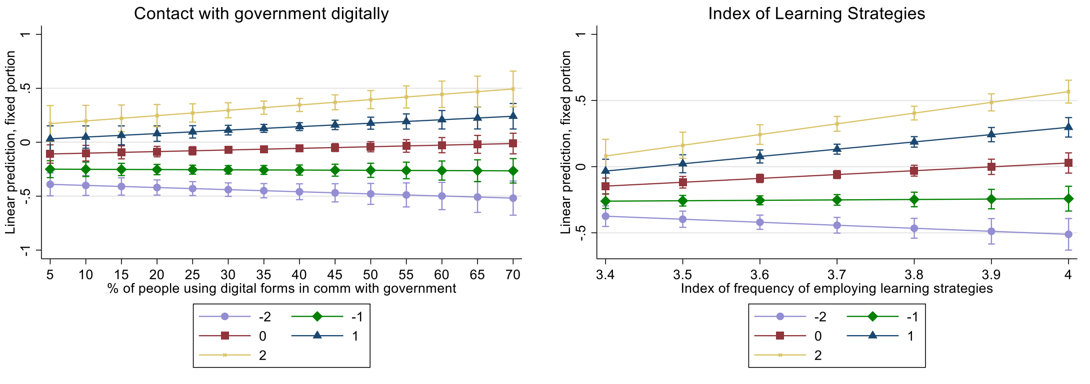
However, SES-gaps in problem-solving do seem to increase slightly in countries where adults employ more frequently strategies for learning, and much more so in countries where higher shares of adults interact digitally with the government. These results implies that stronger digitalisation and willingness to learn of the adult population increase only the problem-solving skills of those 15-years-olds from an advantages socioeconomic background.

Figure 16. Girls' penalty increases with input standardisation and decrease with the index of learning strategies.



Note: Predictions from Table D5, Models 1 and 7.

Figure 17. SES gaps increase with the digital contacts with the government and the index of learning strategies.



Note: Predictions from Table D6, Models 5 and 7.

1.4 Conclusions

In this chapter we studied determinants for the acquisition of relevant skills for tomorrow's labour markets. We focused on problem-solving skills, computer literacy skills and computational thinking as an important skill set of the future. We analysed the extent to which skill acquisition in these domains can be related to characteristics of the educational systems in different European countries. We focused on the individual level factors, on school level factors and country level factors. We analysed how groups of students in society are proficient in ICT-related skills. We focused on male and female adolescents on the one hand, and young people with high or low socio-economic background on the other hand. We studied how school- and country-level factors work differently for these groups. We ran multilevel random intercept models and allow for cross-level interaction effects in to test our hypotheses on the differential impact of school-level and country-level characteristics.

In a first step, we analysed determinants of ICT skills operationalised as computer and information literacy (CIL) and computational thinking (CT) skills across five European countries using data from the International Computer and Information Literacy Study (ICILS). In a second step, we used analysed problem-solving skills, i.e., an important example of higher-order cognitive skills and crucial prerequisites for ICT skills, across 19 European countries using the PISA data. The analyses with ICILS and PISA data are not directly comparable.

In our first analyses on determinants of ICT skills, we assessed the extent to which there is cross-country difference in the acquisition of those skills. Furthermore, we assessed which system characteristics can account for those differences and thus what we could do about the acquisition of those skills. Second, we assessed whether there were gaps in acquisition of CIL and CT skills between boys and girls and between students with different socio-economic backgrounds. If so, it might shed light on which groups should be targeted for policy.

With regard to the first question, we can conclude that although there are sizeable differences between countries, most of the variation in test scores hails from the school level. As our exploratory cross-country analysis shows, most differences between countries are not related to system characteristics. This too, albeit tentatively, implies that individual and school differences matter the most.

For computer and information literary skills (CIL), most of test-score variance is explained by the composition of the school, as sex, age, migration background and language spoken at home are used in our analyses. Noteworthy are the higher average scores of CIL skills for girls than for boys. As research into ICT skills shows, literacy is a very important prerequisite of ICT skills. The effect size of especially the language spoken at home is large in Germany, Finland and France. With regard to the school characteristics, most of CIL's variation across schools is explained by the composition of the students in the school. In larger schools, CIL is higher on average, while the same holds for the ratio between teachers and students. Lastly, school variance in test scores is explained by including information on the ICT resources at a school. The resources are positively associated with the CIL score. Compared to CIL, the analysis of CT shows that most of the individual-level variance is explained by the composition of the school too. Furthermore, the composition variables at the school level also explained most of the school-level variance. Another striking result for both CIL and CT is that only experience with computers helps in acquiring those skills, while experience with smartphone and tablets is most often negatively related with ICT skills. Contrary to CIL, for CT skills the boys have an advantage over girls.

Our results imply that substantial gains in both CIL and in CT skills come from the usage outside of the school environment. There is also a positive correlation between CIL and CT skills, on the one hand, and ICT use inside school and for school purposes on the other hand. Yet, for both CIL and CT skills, using ICT outside school for other than school purposes is what promotes these skills the most.

We systematically checked whether the determinants of ICT skills differ between boys and girls and across the socio-economic background of students in CIL and CT skills. ICT use outside of school for non-school purposes seem to play out less favourable with respect to CIL and CT skills for girls in Finland and Germany (and Luxembourg for CT skills only). Students from higher SES seem to benefit more from the use of ICT outside of school for school purposes in Germany and France, compared to students from low SES. However, this effect is not observable in Luxembourg, Portugal, and Finland. In general, the additional analyses show how different the moderation effects play out in the countries under consideration. Not only are there no moderation effects in some countries while there are in others, but there are opposite effects observed as well. This point thus to the importance of the national contexts when assessing schools.

Relying on the PISA data, we were able to analyse an additional aspect of relevant skills for future labour markets, i.e., the acquisition of problem-solving skills. We take advantage of the broad coverage of 19 European countries to focus more systematically on country differences. In line with our results for computer and information literacy and computational thinking skills, we find that the variation between countries is considerable, but that the variation within countries between schools is even larger. Subsequently, we inquired what kind of characteristics of individuals, schools and education system could explain those differences. The composition of students with their individual characteristics (gender, migration, SES, age) accounts for almost one sixth of the between-country variation and between-school variation in test scores. Once we take school characteristics into account as well, such as private/public school, autonomy, extra-curricular creative activities and the student-teacher-ratio, we account for some additional five percent of the between-school variation. Therefore, although we do find evidence that same of the school-level characteristics we considered explain the variation between schools, these characteristics are by far not exhaustive as most of the variation remains unexplained. We do find a considerable effect of the type of school: private schools have a higher average performance than public schools. Also, extra-curricular activities are associated with a higher problem-solving proficiency. But quite contrary to our expectations, higher problem-solving scores are (to a small degree) higher in schools with higher student-teacher ratios. Interestingly, our measure of autonomy does not contribute to between-school differences in students' problem-solving skills.

We also analysed whether characteristics of the educational systems and other country characteristics account for differences in problem-solving skills. We used measures of input and output standardization of the educational system, expenditures on research & development as well as the share of students in vocational programs in upper secondary education as features of the educational system in a country. In addition, we considered income inequality (measured by the GINI coefficient), the spread of digital behaviour in a country (measured by digital contact with the government), and an index of learning behaviour and strategies among adults.

Characteristics of the educational systems and other country characteristics we considered explain differences in average proficiency levels across countries only to a minor extent. The very impact of specific feature of the educational system is limited for development of problem-solving skills. Only input standardisation explains a substantial amount of variance across national contexts (about 19%). Problem solving scores seem on average substantially lower in standardised systems. This finding is compatible with the idea that, in standardised education systems, there is only limited scope for skills that fall outside the classical subjects that are part of the curricula. Output standardization works towards a similar direction (by decreasing problem-solving skills). However, more expenditures on research & development, higher shares of upper secondary students in vocational programmes, and a higher index of learning activities among adults do not contribute significantly to the variation of problem-solving skills across countries

We further found strong differences in the extent of gender and SES inequality across countries and schools. Males seem to perform better than females and so do children from higher SES, but the extent of those gaps seem large especially across different schools in the same country (rather than across countries). And yet the characteristics of the schools we considered seem not to moderate gender and SES inequality to a great extent. However, some characteristics of the education system at the country level seem to play a role for gender and social gradients in problem-solving skills. On the one hand, males advantage goes hand in hand with input standardisation and reduces when the willingness to learn of the adult population in a country increases. Yet, the socioeconomic gradient is exacerbated in countries having stronger digitalisation and parents with higher willingness to learn.

Bringing the ICILS and PISA results together, we draw similar take-home messages for the three different measures of ICT-related skills: computer and information literacy, critical thinking, and problem solving. Variation in ICT-related skills is larger between schools within countries than across countries. This considerable variation in ICT-related skills between schools holds even when accounting for compositional effects of the students' population in terms of gender, migration history, and socio-economic status of the families. Quite strikingly, our findings highlight the importance of extra-curricular activities or out-of-school activities for the development of ICT-related skills. This striking finding puts into question the contribution of education systems in fostering education for tomorrows' labour markets. Are education systems doing enough? Highly standardized educational systems seem inflexible to incorporate new curricula in a swift way. More expenditures on research and development may help to promote ICT skills among students, but our study cannot show whether these additional resources work directly through more funding of schools or indirectly through more research and more applications of digital procedures in everyday activities. Last, we unequivocally found differences between boys and girls and differences between students from high and low socio-economic statuses. Girls tend to perform somewhat better in computer and information literacy skills, whereas boys show better scores in computational thinking and problem-solving skills. Children from low SES families do face disadvantages in all three domains.

1.5 Policy implications

In Work Packages WP1 and WP2 of the TECHNEQUALITY project, we argued what kind of skills are becoming more important in future and technologically innovated labour markets. We consider ICT-related skills and problem-solving as decisive skills for the success on future labour markets. Thus, we need to think how our educational systems provide these kinds of skills, and about how to develop school instruction and educational systems in order to systematically train and support younger generations in the acquisition of ICT-related skills and problem-solving.

Our differentiation of three skill domains, i.e., computer and information skills, computational thinking and problem-solving skills, allows us to go beyond an assessment of a rather static measurements of competences. The three measures highlight a metacognitive aspect of future skill demands skills. In order to foster metacognitive skills, one should consider three mechanisms. First of all, *increase the exposure to ICT-related devices*. From the ICILS analyses, we know that internet access at home, computer experience as well as studying ICT in the current school year increase computer and information literacy as well as computational thinking in most of the observed countries. Hence, the provision of hardware is one important aspect. Though, our analyses also reveal that proving smartphone or tablets is not helping in acquiring ICT skills and that only computers do so as only experience with computers is positively related to the ICT skills. In most countries, most of the families do own a computer, but in some European countries, there are still differences in the distribution of hardware by socio-economic status to the disadvantage of children from low SES families. Educational institutions should think how to overcome these socio-economic disadvantages and provide hardware, and more specifically computers, for those who cannot afford these devices. This is certainly true for the secondary education, but arguably, this also relates to primary and pre-primary education.

Second, *allow for practice*. The provision of hardware is a necessary but not sufficient condition to improve ICT-related skills. All European countries offer instructions in ICT-related skills in schools for students to practise the use of computers. Yet, our analyses have shown that most of the skill acquisition does not happen in school or related to school. Thus, the countries should invest in more ICT-related curricula within educational institutions in order to train young students better for ICT-related skills. Again, this applies for all educational levels. ICT-related skills start to develop from very early on, similar to other competence domains such as literacy and numeracy. Thus, bringing more practice to the educational institutions should include programs in pre-school education as well. And yet the practice should be specifically tailored towards the use of computers as smartphone or tablets use seem unhelping.

Third, *expand problem-solving exercises to all fields of instruction*. Schneider and Stern (2010) have argued that direct training of domain-general competencies, such as metacognition, has very limit effects on the development of metacognitive skills (PISA 2012). Instead, it is necessary to contextualize problems and let instructors and students reflect on solution strategies. Having more practice in problem-solving in various situations and fields increase the set of potential problem-solving solutions. Students, together with instructors, should identify the underlying structures of subject-specific problems and reflect on previous solutions with similar underlying structures and become creative in the solution of a given problem. Applying problem-solving techniques to subject-specific problems enrich the set of potential problem-solving solutions. Hence, these techniques should be applied in all fields of instruction at all levels of education. Including subject-specific problem-solving tasks in the daily instruction will foster teaching techniques that focus on projects and include cooperative learning settings, using ICT devices if appropriate.

On the organizational level, our findings from PISA data suggest that private schools do better in the provision of problem-solving skills. Additional autonomy indicators do not further improve the problem-solving skills of students, however. For computer and information literacy skills, the ICILS data suggest better average scores if students are taught in public schools. Apparently, the evidence is mixed when it comes to organizational forms of ICT and problem-solving skills. What seem to matter most is involving students in ICT-related and/or problem-solving-related situations, regardless of the type of school. So far, exposure to problems and practice in ICT happens predominantly outside the curriculum. Educational institutions in Europe, from pre-school to higher education, need to catch up and create an environment in which all students can practise and develop these important ICT-related skills within the school environment.

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Appendix to Chapter 1

The materials in the appendix are referenced in the main text. As such, the set-up is the same as the main text. First, we show materials from the Computer Information and Literacy and Computational Thinking skills from the ICILS dataset. As that are quite some tables, the descriptive statistics are to be found in Appendix A. The CIL regressions that are not in the main text in Appendix B and the CT regression that are not in the main text are in Appendix C. Secondly, we show materials from the Problem Solving skills of the PISA dataset in Appendix D.

Appendix A. Descriptive statistics

Table A1. Descriptive statistics of complete analytical sample

	N	mean	sd	min	max
Computer and Information Literacy	9449	522.480	73.339	176.339	745.778
Computational Thinking	9449	501.150	89.982	79.919	807.931
Age (in years)	9449	14.303	0.662	12	17.920
Sex (1=girl)	9449	0.499	0.500	0	1
Born Abroad	9449	0.231	0.544	0	2
Language spoken at home same as test language	9449	0.774	0.418	0	1
Socioeconomic background	9449	0.046	0.982	-3.273	2.567
Internet access at home	9449	0.990	0.098	0	1
Computer experience in years	9449	2.466	1.241	0	4
Smartphone experience in years	9449	2.330	1.109	0	4
Tablet experience in years	9449	2.007	1.186	0	4
ICT studies in current school year	9449	0.561	0.496	0	1
Learning of ICT coding tasks at school	9449	47.356	9.314	23.932	75.045
Learning of ICT tasks at school	9449	48.638	9.782	21.298	72.898
Use of ICT at school for school purposes	9449	3.097	1.151	1	5
Use of ICT at school for other purposes	9449	3.132	1.613	1	5
Use of ICT outside school for school purposes	9449	3.324	1.187	1	5
Use of ICT outside school for other purposes	9449	4.542	0.996	1	5
Ratio of school size and teachers	9449	0.095	0.059	0.020	1.250
Number of students in school (School size)	9449	2.749	0.969	1	4
School composition	9449	2.018	0.905	1	3
Availability of ICT resources at school	9449	50.390	9.408	9.320	73.858
Ratio of school size and number of ICT devices	9449	4.872	4.656	0.320	42.430
Availability of computer resources at school	9449	50.031	2.384	38.783	57.021
ICT experience in years in the school	9449	2.508	0.673	0	3
ICT experience with ICT use during lessons	9449	2.434	0.109	2.098	3
Use of ICT for teaching practices in class	9449	49.163	1.616	42.571	53.452

Table A2. Descriptive statistics by country

	DEU (N=1892)				FIN (N=2056)				FRA (N=1764)				LUX (1713)				PRT (2024)			
	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
Computer and Information Literacy	531.601	75.197	201.647	727.039	539.625	72.494	189.668	739.249	513.800	71.827	236.786	719.434	495.996	75.885	189.478	693.022	526.518	63.728	270.614	711.986
Computational Thinking	500.642	98.242	102.903	803.215	518.237	88.859	198.076	791.575	518.419	83.707	220.012	768.020	473.147	97.324	97.019	767.788	492.917	73.083	221.367	702.021
Age (in years)	14.443	0.575	12.830	17.170	14.796	0.341	13.830	17.420	13.791	0.428	12.250	15.830	14.467	0.615	12.580	16.670	13.976	0.717	12	17.920
Sex (1=girl)	0.495	0.500	0	1	0.504	0.500	0	1	0.501	0.500	0	1	0.500	0.500	0	1	0.496	0.500	0	1
Born Abroad	0.272	0.561	0	2	0.043	0.264	0	2	0.169	0.480	0	2	0.631	0.754	0	2	0.098	0.375	0	2
Language spoken at home same as test language	0.819	0.385	0	1	0.948	0.222	0	1	0.895	0.306	0	1	0.176	0.381	0	1	0.954	0.210	0	1
Socioeconomic background	0.036	0.989	-2.567	2.207	0.041	0.986	-3.273	2.567	0.072	0.988	-2.840	2.563	0.033	0.965	-2.527	1.944	0.047	0.979	-2.398	1.950
Internet access at home	0.993	0.085	0	1	0.993	0.081	0	1	0.994	0.078	0	1	0.984	0.126	0	1	0.987	0.114	0	1
Computer experience in years	2.104	1.160	0	4	2.939	1.132	0	4	2.329	1.239	0	4	2.092	1.227	0	4	2.759	1.202	0	4
Smartphone experience in years	2.276	0.927	0	4	2.965	0.855	0	4	1.857	1.214	0	4	2.183	1.138	0	4	2.271	1.089	0	4
Tablet experience in years	1.653	1.195	0	4	2.118	1.092	0	4	1.981	1.213	0	4	2.044	1.225	0	4	2.217	1.137	0	4
ICT studies in current school year	0.376	0.484	0	1	0.299	0.458	0	1	0.824	0.381	0	1	0.411	0.492	0	1	0.895	0.306	0	1
Learning of ICT coding tasks at school	46.395	9.083	23.932	75.045	48.360	8.711	23.932	75.045	47.980	8.811	23.932	75.045	46.003	10.346	23.932	75.045	47.834	9.411	23.932	75.045
Learning of ICT tasks at school	45.854	8.782	21.298	72.898	49.353	9.239	21.298	72.898	46.251	8.365	21.298	72.898	46.649	9.837	21.298	72.898	54.277	9.855	21.298	72.898
Use of ICT at school for school purposes	2.642	1.104	1	5	3.618	0.827	1	5	2.883	1.196	1	5	3.150	1.291	1	5	3.136	1.088	1	5
Use of ICT at school for other purposes	2.525	1.517	1	5	4.036	1.336	1	5	2.391	1.468	1	5	3.351	1.503	1	5	3.241	1.639	1	5
Use of ICT outside school for school purposes	3.122	1.148	1	5	3.331	1.123	1	5	3.568	1.240	1	5	3.429	1.316	1	5	3.204	1.069	1	5
Use of ICT outside school for other purposes	4.712	0.801	1	5	4.611	0.925	1	5	4.571	0.991	1	5	4.322	1.184	1	5	4.475	1.023	1	5
Ratio of school size and teachers	0.074	0.025	0.040	0.230	0.098	0.027	0.020	0.230	0.068	0.014	0.040	0.160	0.108	0.018	0.080	0.190	0.126	0.110	0.030	1.250
Number of students in school (School size)	2.723	0.890	1	4	2.201	0.805	1	4	2.303	0.656	1	4	3.594	0.655	2	4	3.004	1.046	1	4
School composition	2.118	0.909	1	3	1.784	0.848	1	3	2.077	0.878	1	3	1.893	0.922	1	3	2.216	0.897	1	3
Availability of ICT resources at school	42.757	8.366	9.320	56.468	59.679	7.967	31.298	73.858	49.556	8.058	29.075	73.858	49.503	6.442	39.935	63.395	49.565	6.896	29.075	73.858
Ratio of school size and number of ICT devices	6.842	4.180	1.120	30.380	2.228	1.315	0.450	6.840	4.100	2.094	0.650	14.440	2.772	1.340	0.940	6.760	8.168	7.207	0.320	42.430
Availability of computer resources at school	50.402	2.763	38.783	57.021	50.120	2.104	45.252	56.454	50.071	1.943	43.464	55.420	50.082	1.629	46.755	54.037	49.516	2.994	39.583	57.021
ICT experience in years in the school	2.500	0.665	0	3	2.546	0.674	1	3	2.604	0.584	1	3	2.521	0.725	1	3	2.382	0.687	0	3
ICT experience with ICT use during lessons	2.432	0.120	2.104	2.752	2.435	0.084	2.196	2.640	2.440	0.088	2.196	2.631	2.426	0.085	2.265	2.557	2.439	0.148	2.098	3
Use of ICT for teaching practices in class	49.391	1.905	42.571	53.452	49.268	1.417	45.815	53.327	49.457	1.379	45.815	53.327	48.852	0.946	47.329	50.950	48.851	2.006	42.571	53.452

Table A3. Correlation matrix of individual characteristics within analytical sample.

	Computer and Information Literacy	Computational Thinking	Age (in years)	Sex (1=girl)	Born Abroad	Language spoken at home same as test language	Socioeconomic background	Internet access at home	Computer experience in years	Smartphone experience in years	Tablet experience in years	ICT studies in current school year	Learning of ICT coding tasks at school	Learning of ICT tasks at school	Use of ICT at school for school purposes	Use of ICT at school for other purposes	Use of ICT outside school for school purposes
Computational Thinking	0.796																
Age (in years)	-0.112	-0.155															
Sex (1=girl)	0.119	-0.056	-0.077														
Born Abroad	-0.169	-0.144	0.111	-0.018													
Language spoken at home same as test language	0.213	0.197	-0.145	0.002	-0.444												
Socioeconomic background	0.321	0.331	-0.183	0.012	-0.137	0.082											
Internet access at home	0.063	0.043	-0.021	0.011	-0.041	0.032	0.044										
Computer experience in years	0.172	0.122	0.084	-0.011	-0.052	0.104	0.064	0.059									
Smartphone experience in years	-0.066	-0.104	0.260	-0.011	-0.005	0.026	-0.100	0.006	0.368								
Tablet experience in years	-0.013	-0.023	0.015	-0.025	-0.018	-0.022	0.084	0.043	0.429	0.388							
ICT studies in current school year	-0.043	0.000	-0.232	-0.099	-0.044	0.112	-0.042	-0.004	0.016	-0.094	0.040						
Learning of ICT coding tasks at school	-0.092	-0.091	0.021	-0.047	-0.045	0.030	-0.037	0.001	0.013	0.045	0.035	0.107					
Learning of ICT tasks at school	0.070	0.004	-0.041	0.054	-0.071	0.100	0.043	-0.005	0.093	0.049	0.065	0.120	0.407				
Use of ICT at school for school purposes	0.060	0.024	0.061	0.029	-0.055	0.032	0.030	-0.005	0.149	0.123	0.133	0.013	0.138	0.164			
Use of ICT at school for other purposes	0.073	0.041	0.125	-0.046	-0.055	-0.009	0.008	-0.013	0.164	0.172	0.145	-0.054	0.041	0.101	0.356		
Use of ICT outside school for school purposes	0.091	0.061	-0.077	0.105	-0.005	-0.041	0.097	0.014	0.067	0.022	0.080	0.013	0.095	0.103	0.351	0.211	
Use of ICT outside school for other purposes	0.250	0.228	-0.062	-0.019	-0.079	0.087	0.118	0.047	0.127	0.082	0.080	-0.028	-0.001	0.004	0.147	0.274	0.304

Table A4. Correlation matrix of school characteristics within analytical sample.

	Computer and Information Literacy	Computational Thinking	Ratio of school size and teachers	Number of students in school (School size)	School composition	Availability of ICT resources at school	Ratio of school size and number of ICT devices	Availability of computer resources at school	ICT experience in years in the school	ICT experience with ICT use during lessons
Computational Thinking	0.796									
Ratio of school size and teachers	-0.037	-0.069								
Number of students in school (School size)	0.014	-0.012	-0.182							
School composition	-0.203	-0.201	0.136	-0.122						
Availability of ICT resources at school	0.036	0.046	0.060	-0.072	-0.015					
Ratio of school size and number of ICT devices	0.036	0.005	-0.120	0.234	0.056	-0.314				
Availability of computer resources at school	0.033	0.023	-0.010	0.008	-0.029	0.121	-0.146			
ICT experience in years in the school	0.039	0.059	-0.088	0.003	0.012	0.140	-0.035	0.073		
ICT experience with ICT use during lessons	0.020	0.022	0.028	-0.014	-0.008	0.015	-0.004	0.010	0.006	
Use of ICT for teaching practices in class	0.013	0.012	0.037	-0.157	0.025	0.075	-0.099	0.496	0.031	0.161

Table A5. Country level characteristics

	Input standardisation	Output standardisation	OECD Research and Development	Income Inequality	Digital contact with government	% Public Schools	Index of autonomy governance	Index of autonomy of assessment in ICT
DEU	0.018	0.440	2.882	0.292	18.617	89	0.685	0.685
FIN	-0.614	1.000	3.398	0.265	64.735	96	0.667	0.833
FRA	-0.008	1.000	2.227	0.295	58.784	78	0.778	0.5
LUX	2.079	1.000	1.273	0.317	31.378			.
PRT	-0.041	1.000	1.379	0.323	29.912	85	0.794	0.889

Appendix B. Regression results CIL

Table B1. CIL Regression analysis for each country

A	DEU		FIN		FRA		LUX		PRT	
Constant	527.338	***	538.339	***	511.318	***	496.474	***	521.865	***
	0.825		1.041		1.396		0.588		1.095	
School variance	3.849	***	3.103	***	3.241	***	3.417	***	3.280	***
	0.028		0.060		0.052		0.033		0.055	
Individual variance	4.056	***	4.233	***	4.205	***	4.235	***	4.062	***
	0.017		0.015		0.016		0.013		0.009	
B	DEU		FIN		FRA		LUX		PRT	
Age (in years)	-6.197	***	-14.721	***	-26.389	***	-12.188	***	-5.971	***
	1.806		2.123		1.989		1.422		1.191	
Sex (1=girl)	12.239	***	19.778	***	15.872	***	16.719	***	4.109	
	2.550		1.577		1.338		1.830		2.193	
(At least) one parent born abroad	6.017		-9.801		-0.936		-10.701	***	-5.675	
	4.431		7.446		3.042		2.444		3.789	
Born abroad	4.990		-9.462		5.966		0.088		-23.110	***
	4.166		8.107		4.436		1.432		5.437	
Language spoken at home same as test language	26.092	***	33.873	***	24.254	***	7.770	**	0.528	
	4.273		3.672		2.380		2.560		4.415	
Socioeconomic background	9.843	***	18.073	***	19.959	***	15.386	***	13.727	***
	1.240		0.640		1.154		1.316		0.856	
Constant	588.442	***	714.328	***	845.152	***	665.833	***	603.725	***
	29.627		31.394		26.900		20.907		18.075	
School variance	3.668	***	2.908	***	2.906	***	2.923	***	3.128	***
	0.031		0.073		0.069		0.073		0.058	
Individual variance	4.040	***	4.182	***	4.133	***	4.204	***	4.037	***
	0.016		0.018		0.015		0.010		0.009	
C	DEU		FIN		FRA		LUX		PRT	
Internet access at home	22.784		36.122	**	51.606	***	24.149	**	30.368	***
	12.037		13.264		7.674		7.414		4.508	
Constant	504.670	***	502.453	***	460.094	***	472.840	***	491.991	***
	11.823		13.936		6.973		6.975		4.811	
School variance	3.848	***	3.102	***	3.223	***	3.407	***	3.273	***
	0.028		0.058		0.054		0.036		0.053	
Individual variance	4.055	***	4.232	***	4.204	***	4.235	***	4.060	***
	0.016		0.015		0.016		0.013		0.009	
D	DEU		FIN		FRA		LUX		PRT	
Computer experience	11.151	***	16.008	***	11.911	***	10.490	***	12.645	***
	0.956		0.593		0.718		0.543		0.567	
	0.000		0.000		0.000		0.000		0.000	
Smartphone experience	-6.062	***	-9.250	***	-13.731	***	-11.867	***	-7.847	***
	1.137		0.899		1.083		0.704		0.983	
	0.000		0.000		0.000		0.000		0.000	
Tablet experience	-6.683	***	-1.503		-0.393		-0.019		-2.390	**
	1.009		0.859		0.469		0.726		0.781	
	0.000		0.080		0.402		0.979		0.002	
Constant	529.490	***	521.553	***	510.008	***	500.092	***	510.179	***
	2.910		3.608		2.043		1.825		1.909	
School variance	3.822	***	3.127	***	3.181	***	3.352	***	3.255	***
	0.033		0.056		0.049		0.038		0.053	
Individual variance	4.034	***	4.196	***	4.171	***	4.216	***	4.033	***
	0.015		0.016		0.013		0.012		0.008	
E	DEU		FIN		FRA		LUX		PRT	
Studies ICT in current school year	6.631	**	7.586	***	-8.910	***	-28.959	***	22.088	***
	2.302		1.769		2.499		1.979		4.015	
Learning coding tasks	-0.337	*	-1.449	***	-1.165	***	-0.955	***	-1.142	***
	0.138		0.111		0.109		0.089		0.134	
Learning ICT tasks	-0.000		1.887	***	1.237	***	0.424	***	-0.275	
	0.118		0.099		0.087		0.072		0.222	
Constant	540.583	***	513.262	***	517.320	***	533.427	***	571.698	***
	4.856		5.557		3.835		2.313		9.612	
School variance	3.855	***	3.022	***	3.202	***	3.385	***	3.257	***
	0.030		0.049		0.055		0.032		0.052	
Individual variance	4.053	***	4.206	***	4.191	***	4.210	***	4.040	***
	0.016		0.014		0.015		0.013		0.010	

F	DEU		FIN		FRA		LUX		PRT	
Use ICT at school for school purposes	0.883		2.824	**	1.467		-0.004		-3.191	**
	0.901		1.044		0.788		0.761		1.235	
Use ICT at school for other purposes	-1.118	*	2.854	***	-3.934	***	1.439	**	-0.393	
	0.475		0.736		0.553		0.539		0.332	
Use ICT outside school for school purposes	-1.929	*	3.684	***	1.081		-1.915	***	1.638	*
	0.765		0.708		0.607		0.549		0.653	
Use ICT outside school for other purposes	18.579	***	15.177	***	14.918	***	12.477	***	10.932	***
	1.383		0.864		0.858		0.851		0.946	
Constant	446.387	***	434.436	***	444.946	***	444.006	***	479.256	***
	8.752		4.351		3.151		3.399		6.286	
School variance	3.799	***	3.048	***	3.150	***	3.327	***	3.218	***
	0.026		0.060		0.054		0.039		0.055	
Individual variance	4.028	***	4.196	***	4.182	***	4.214	***	4.046	***
	0.016		0.015		0.016		0.012		0.010	

Source: ICILS 2018. Repetitive weights are applied.

Panel A is the null model, panel B the composition variables, panel C the structural individual access to internet, panel D experience with devices. In panel E, we include the learning at school variable, whereas in panel F the purpose of the ICT use is included.

Panel B also reveals that the computer information literacy score is lower for older student and higher for girls (though in Portugal there is no gender difference). The country in which one is born does not matter, but a language spoken at home different than the test matters as that is associated with a lower CIL score (but again for Portugal it is the other way around). A higher socio-economic status is associated with a higher CIL score.

Whether being connected to the internet at home matter for the CIL score varies over countries. It does not matter in Germany, but is positively related to CIL in Finland, France, Luxembourg and Portugal. In Panel D the amount of experience with a laptop, smartphone or tablet is estimated and reveals that computer and information literacy is positively related to experience on a computer, but negatively with a smartphone and tablet, though the latter only for certain countries: Germany and Portugal.

In panel E, we estimate the effect of studying ICT in school, resulting in a mixed bag. For Germany, Finland and Portugal this effect is positive, while in France and Luxembourg it is negative. The indicators on the content of the subject also shows a mixed bag: learning coding tasks is negatively correlated, while more general ICT tasks are positively related in Finland, France and Luxembourg.

Using ICT at school for school related purposes is negatively related to CIL in Portugal and is not associated in CIL in other countries. Using ICT at school for other purposes is a mixed bag: positive in Finland and Luxembourg, while negatively related to CIL in Germany and France. Using ICT outside school for school related purposes is negatively related to CIL in Germany and Luxembourg, while positively related to CIL in Finland and Portugal. However, the biggest effects are using ICT outside school for other purposes: across the board positively related to CIL.

Model 1 in the main text reveals that for the composition indicators, there are no substantial differences with the model in panel B, the effects of being connected to the internet are explained by other individual level characteristics, as the effect is not associated with CIL. For the experience with devices, the effects of the tablet are most influenced by other characteristics as they are now also negatively related in France and Luxembourg. Learning general ICT tasks is not negatively related anymore in the complete individual level model. Lastly, the use of ICT at school for other purposes and the use of ICT outside school for school purposes are more often not significant anymore, whereas the use of ICT outside school for other purposes remains strongly related to CIL.

Table B2. Variance reduction for CIL regression models

	A					B					C				
	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT
Constant	527.34	538.34	511.32	496.47	521.86	588.44	714.33	845.15	665.83	603.72	504.67	502.45	460.09	472.84	491.99
School variance	3.85	3.10	3.24	3.42	3.28	3.67	2.91	2.91	2.92	3.13	3.85	3.10	3.22	3.41	3.27
Individual variance	4.06	4.23	4.20	4.24	4.06	4.04	4.18	4.13	4.20	4.04	4.06	4.23	4.20	4.23	4.06
ICC	0.49	0.42	0.44	0.45	0.45	0.48	0.41	0.41	0.41	0.44	0.49	0.42	0.43	0.45	0.45
%Δ Null model (school level)						4.68	6.28	10.32	14.44	4.63	0.02	0.03	0.55	0.30	0.21
%Δ Null model individual level)						0.39	1.21	1.70	0.75	0.60	0.01	0.02	0.02	0.02	0.04

	D					E					F				
	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT
Constant	529.49	521.55	510.01	500.09	510.18	540.58	513.26	517.32	533.43	571.70	446.39	434.44	444.95	444.01	479.26
School variance	3.82	3.13	3.18	3.35	3.26	3.86	3.02	3.20	3.39	3.26	3.80	3.05	3.15	3.33	3.22
Individual variance	4.03	4.20	4.17	4.22	4.03	4.05	4.21	4.19	4.21	4.04	4.03	4.20	4.18	4.21	4.05
ICC	0.49	0.43	0.43	0.44	0.45	0.49	0.42	0.43	0.45	0.45	0.49	0.42	0.43	0.44	0.44
%Δ Null model (school level)	0.69	-0.77	1.85	1.90	0.74	-0.17	2.60	1.19	0.93	0.68	1.29	1.76	2.81	2.62	1.89
%Δ Null model individual level)	0.53	0.87	0.80	0.47	0.70	0.07	0.64	0.32	0.60	0.53	0.68	0.87	0.54	0.50	0.39

	Model 1					Model 2					Model 3				
	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT
Constant	543.87	572.33	699.97	613.83	570.26	552.65	554.45	729.38	624.30	551.67	452.15	499.01	698.38	549.82	546.67
School variance	3.63	2.88	2.78	2.88	3.07	3.27	2.78	2.60	2.44	3.02	3.57	2.87	2.78	2.74	3.06
Individual variance	3.99	4.10	4.07	4.15	3.98	3.99	4.10	4.07	4.15	3.98	3.99	4.10	4.07	4.15	3.98
ICC	0.48	0.41	0.41	0.41	0.44	0.45	0.40	0.39	0.37	0.43	0.47	0.41	0.41	0.40	0.43
%Δ Null model (school level)	5.64	7.21	14.11	15.79	6.41	14.94	10.38	19.75	28.52	8.00	7.27	7.51	14.33	19.85	6.57
%Δ Null model individual level)	1.62	3.19	3.15	2.05	2.01	1.68	3.19	3.18	2.05	2.05	1.63	3.19	3.15	2.05	2.01
%Δ Individual model (school level)						9.85	3.42	6.57	15.11	1.70	1.73	0.33	0.26	4.82	0.16
%Δ Individual model individual level)						0.06	0.01	0.03	0.00	0.04	0.01	0.00	0.00	0.00	0.00

	Model 4					Model 5					Model 6				
	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT
Constant	542.16	537.37	666.91	456.68	572.66	667.80	543.24	710.43	506.62	522.71	588.05	511.00	898.20	638.39	491.99
School variance	3.61	2.88	2.77	2.81	3.07	3.62	2.88	2.78	2.87	3.06	3.20	2.77	2.53	-0.93	3.00
Individual variance	3.99	4.10	4.07	4.15	3.98	3.99	4.10	4.07	4.15	3.98	3.99	4.10	4.07	4.15	3.98
ICC	0.47	0.41	0.41	0.40	0.44	0.48	0.41	0.41	0.41	0.43	0.44	0.40	0.38	-0.29	0.43
%Δ Null model (school level)	6.24	7.30	14.47	17.66	6.44	5.94	7.23	14.16	15.89	6.62	16.95	10.60	21.90	127.15	8.60
%Δ Null model individual level)	1.62	3.19	3.15	2.05	2.01	1.62	3.19	3.15	2.05	2.01	1.70	3.20	3.18	2.01	2.04
%Δ Individual model (school level)	0.64	0.10	0.42	2.22	0.03	0.31	0.02	0.06	0.11	0.21	11.99	3.66	9.07	132.24	2.34
%Δ Individual model individual level)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.01	0.03	-0.04	0.04

Table B3. Interaction effect of CIL with Sex

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT	
Sex (1=girl)	30.602		33.776	***	-15.965	*	-22.783		-19.991	**	8.255	*	20.980	***	21.929	***	25.452	***	3.936	
	19.619		6.940		7.597		12.683		7.721		3.719		2.511		3.189		5.251		2.578	
Availability of ICT 75esource at school (ICT Coordinator)	1.827	***	0.237		-0.386	**	-1.603	***	-0.244											
	0.303		0.154		0.119		0.195		0.129											
Sex (1=girl) # Availability of ICT 75esource at school (ICT Coordinator)	-0.451		-0.201		0.639	***	0.812	**	0.489	***										
	0.444		0.126		0.160		0.252		0.144											
Ratio of school size and number of ICT devices											-0.291		-0.178		0.179		4.233	*	0.185	
											0.403		1.140		0.539		1.648		0.138	
Sex (1=girl) # Ratio of school size and number of ICT devices											0.467		0.369		-1.521	*	-3.039		0.040	
											0.475		1.076		0.628		1.789		0.251	
Constant	470.760	***	558.578	***	720.552	***	689.019	***	581.989	***	546.016	***	573.117	***	702.494	***	598.830	***	569.188	***
	41.990		34.515		33.949		14.410		23.391		35.792		33.555		31.883		18.968		18.044	
School variance	3.578	***	2.879	***	2.774	***	2.798	***	3.069	***	3.632	***	2.878	***	2.773	***	2.849	***	3.068	***
	0.044		0.050		0.069		0.080		0.053		0.043		0.053		0.071		0.067		0.050	
Individual variance	3.988	***	4.098	***	4.071	***	4.148	***	3.979	***	3.990	***	4.098	***	4.072	***	4.148	***	3.980	***
	0.013		0.018		0.013		0.009		0.010		0.013		0.018		0.013		0.009		0.010	

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT	
Sex (1=girl)	-3.095		166.766	***	54.419		135.653	**	44.339		13.132	***	22.835	***	14.287	***	16.610	***	7.214	**
	39.167		22.689		43.278		52.366		36.944		2.560		2.498		1.724		1.661		2.622	
Availability of computer resources at school (Teachers)	0.641		2.887	***	0.668		2.096	**	0.854											
	0.513		0.312		0.539		0.650		0.485											
Sex (1=girl) # Availability of computer resources at school (Teachers)	0.290		-2.895	***	-0.773		-2.371	*	-0.810											
	0.776		0.455		0.870		1.059		0.760											
10 or more years ICT experience in the school											13.947	***	0.442		-2.603		5.391		-4.899	*
											2.233		1.957		2.551		3.571		2.032	
Sex (1=girl) # 10 or more years ICT experience in the school											-3.963		-2.966		4.180		2.125		-5.789	**
											3.390		3.478		3.228		2.673		1.765	
Constant	512.069	***	430.739	***	665.442	***	510.242	***	526.558	***	536.084	***	571.614	***	701.126	***	610.497	***	571.809	***
	42.178		36.551		38.043		24.954		32.575		35.914		33.845		30.771		19.266		18.213	
School variance	3.631	***	2.873	***	2.784	***	2.863	***	3.065	***	3.608	***	2.881	***	2.775	***	2.865	***	3.070	***
	0.045		0.047		0.069		0.076		0.054		0.041		0.053		0.072		0.080		0.051	
Individual variance	3.990	***	4.097	***	4.072	***	4.148	***	3.980	***	3.990	***	4.098	***	4.072	***	4.149	***	3.980	***
	0.014		0.018		0.013		0.009		0.010		0.014		0.018		0.013		0.009		0.010	

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT	
Sex (1=girl)	76.382		44.087		-118.703	**	-92.565		44.422		-46.028		31.349		-120.221		314.698	***	72.918	*
	51.262		22.556		45.057		62.869		31.941		41.353		28.474		76.480		83.520		34.861	
ICT experience with ICT use during lessons	12.124		18.547	*	-15.966		38.072	*	8.220											
	13.289		8.111		19.481		18.640		7.951											
Sex (1=girl) # ICT experience with ICT use during lessons	-26.730		-9.139		55.097	**	45.098		-16.481											
	21.121		9.497		18.477		26.108		12.938											
Use of ICT for teaching practices in class											-3.054	***	0.682		-1.576		5.304	***	1.721	**
											0.744		0.486		1.196		1.574		0.630	
Sex (1=girl) # Use of ICT for teaching practices in class											1.166		-0.194		2.748		-6.088	***	-1.406	
											0.863		0.556		1.541		1.698		0.728	
Constant	515.749	***	527.836	***	738.658	***	521.696	***	549.632	***	690.816	***	538.423	***	778.791	***	355.598	***	485.555	***
	61.492		37.990		49.034		48.290		32.538		45.923		36.390		56.345		77.785		41.552	
School variance	3.635	***	2.876	***	2.776	***	2.822	***	3.070	***	3.620	***	2.878	***	2.779	***	2.878	***	3.063	***
	0.043		0.054		0.069		0.081		0.051		0.042		0.053		0.074		0.077		0.055	
Individual variance	3.989	***	4.098	***	4.071	***	4.148	***	3.980	***	3.990	***	4.098	***	4.072	***	4.147	***	3.980	***
	0.014		0.018		0.012		0.009		0.010		0.014		0.018		0.013		0.009		0.010	

Note: the analyses are also controlling for the individual level factors.

Table B4. Interaction effect of CIL with NISB

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT	
Socioeconomic background (NISB)	18.536	**	19.424	***	3.620		18.428	***	2.759		8.620	***	13.060	***	18.923	***	18.652	***	9.319	***
	6.698		3.986		5.296		5.599		4.785		2.299		1.213		1.638		1.922		1.198	
Availability of ICT resources at school (ICT Coordinator)	1.604	***	0.138		-0.073		-1.245	***	0.005											
	0.132		0.118		0.069		0.124		0.098											
NISB # Availability of ICT resources at school (ICT Coordinator)	-0.270		-0.085		0.284	*	-0.138		0.159											
	0.156		0.063		0.111		0.125		0.095											
Ratio of school size and number of ICT devices											-0.060		-0.044		-0.646		3.050		0.205	
											0.316		0.772		0.495		1.011		0.102	
NISB # Ratio of school size and number of ICT devices											-0.274		0.576		-0.294		-2.495		0.167	
											0.327		0.527		0.335		0.494		0.120	
Constant	481.579	***	564.791	***	705.982	***	675.524	***	570.307	***	545.442	***	572.806	***	702.711	***	604.797	***	568.350	***
	38.011		33.101		30.757		16.010		21.321		36.061		34.176		32.379		19.576		17.976	
School variance	3.567	***	2.879	***	2.790	***	2.786	***	3.075	***	3.633	***	2.880	***	2.776	***	2.843	***	3.061	***
	0.039		0.050		0.067		0.080		0.053		0.044		0.052		0.071		0.067		0.054	
Individual variance	3.989	***	4.098	***	4.071	***	4.148	***	3.980	***	3.990	***	4.098	***	4.072	***	4.148	***	3.980	***
	0.014		0.018		0.012		0.009		0.010		0.013		0.018		0.013		0.009		0.010	

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT	
Socioeconomic background (NISB)	60.277	*	0.302		48.561		39.771		2.207		8.841	***	15.201	***	16.699	***	9.332	***	12.142	***
	23.514		18.123		29.437		49.360		14.132		2.042		0.896		1.703		2.059		0.855	
Availability of computer resources at school (Teachers)	0.672		1.337	***	0.241		1.289	*	0.465	*										
	0.436		0.387		0.324		0.615		0.218											
NISB # Availability of computer resources at school (Teachers)	-1.062	*	0.281		-0.617		-0.561		0.169											
	0.473		0.362		0.588		1.000		0.278											
10 or more years ICT experience in the school											15.826		1.939		-4.812		4.188		-1.997	
											1.782		0.890		1.655		2.478		1.477	
NISB # 10 or more years ICT experience in the school											-3.494		-1.299		1.394		3.812		-3.068	
											3.430		1.042		2.409		1.862		1.768	
Constant	508.700	***	504.147	***	687.570	***	549.472	***	547.512	***	537.341	***	570.830	***	701.870	***	611.126	***	570.309	***
	45.467		35.334		30.656		29.664		20.827		35.795		33.320		31.036		19.687		18.303	
School variance	3.622	***	2.868	***	2.788	***	2.883	***	3.066	***	3.605	***	2.876	***	2.777	***	2.848	***	3.073	***
	0.042		0.049		0.069		0.085		0.054		0.039		0.054		0.071		0.081		0.050	
Individual variance	3.989	***	4.098	***	4.072	***	4.148	***	3.980	***	3.990	***	4.098	***	4.072	***	4.148	***	3.979	***
	0.014		0.018		0.012		0.009		0.010		0.013		0.018		0.012		0.009		0.010	

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT	
Socioeconomic background (NISB)	59.836	**	49.821	**	-30.213		15.984		-6.256		82.193	**	66.479	***	-16.751		49.013		-42.081	
	20.955		16.307		18.346		32.444		16.257		29.424		16.439		35.900		31.927		28.459	
ICT experience with ICT use during lessons	-1.991		13.861	*	10.214		63.545	***	-0.414											
	9.497		6.571		11.823		8.749		4.114											
NISB # ICT experience with ICT use during lessons	-21.736	*	-14.578	*	19.639	**	-1.801		6.941											
	8.851		6.699		7.575		13.147		6.681											
Use of ICT for teaching practices in class											-2.712		0.511		-0.255		2.282		1.149	
											0.571		0.367		0.660		0.931		0.441	
NISB # Use of ICT for teaching practices in class											-1.530		-1.059		0.697		-0.765		1.080	
											0.602		0.332		0.726		0.655		0.574	
Constant	552.711	***	540.079	***	676.060	***	458.503	***	570.342	***	673.882	***	546.805	***	711.705	***	502.574	***	513.696	***
	49.728		38.157		36.243		29.469		23.745		47.574		34.457		37.073		51.076		32.541	
School variance	3.627	***	2.873	***	2.772	***	2.831	***	3.076	***	3.611	***	2.883	***	2.774	***	2.874	***	3.073	***
	0.041		0.056		0.069		0.082		0.048		0.039		0.051		0.075		0.077		0.052	
Individual variance	3.989	***	4.098	***	4.072	***	4.148	***	3.980	***	3.990	***	4.098	***	4.072	***	4.148	***	3.979	***
	0.014		0.018		0.013		0.009		0.010		0.014		0.018		0.013		0.009		0.009	

Note: the analyses are also controlling for the individual level factors.

First, the availability of ICT resources at school according to the ICT coordinator interacted with sex shows that in France, Luxembourg and Portugal the more ICT coordinator indicated that there are resources available at the school the smaller the gender gap is (a negative main effect combined with the positive interaction effect).

Second, in France the interaction of student-teacher ratio with sex shows that the gender gap becomes smaller the higher the student-teacher ratio is. Meaning that the advantage that girls have declines with higher the ratio. Third, in Finland and Luxembourg the effect of the teacher indicating availability of computer resources at school differs between boys and girls. The effect of computer availability on CIL is positive for boys, while around zero for girls (the positive main effect and the interaction effect are about equal in size).

Fourth, the experience of ICT coordinator in school does vary over gender Portugal only. The experience of ICT in school effect is larger for girls than for boys. Fifth, the effect of ICT experience with ICT use during lessons is positive for girls in France, but not for boys. In other countries, this effect does not vary by gender. Sixth, the use of ICT for teaching practices in class is negative for girls and positive for boys in Luxembourg (combing a positive main effect with a negative interaction effect).

With regard to the moderation effect of the school characteristics with the socioeconomic background, as shown in Table 3, it holds that only the teachers ICT experience during the lessons has a structural interaction effect over multiple countries. For Germany and Finland it holds that the socioeconomic effect on CIL is lower when the teacher has a lot of ICT experience during classes. For France, the opposite holds: there students with a high socioeconomic background seem to profit more from an experienced teacher than those with a low socioeconomic background.

Appendix C. Regression Results CT

Table C1. CT Regression analysis for each country

A	DEU		FIN		FRA		LUX		PRT	
Constant	497.293	***	516.656	***	516.660	***	473.265	***	490.712	***
	1.146		1.259		0.968		1.100		0.917	
School variance	4.073	***	3.311	***	3.344	***	3.657	***	3.334	***
	0.023		0.059		0.039		0.038		0.048	
Individual variance	4.356	***	4.437	***	4.364	***	4.490	***	4.208	***
	0.010		0.014		0.014		0.016		0.007	
B	**DEU**		**FIN**		**FRA**		**LUX**		**PRT**	
Age (in years)	-8.989	**	-15.685	***	-27.881	***	-19.324	***	-14.607	***
	2.922		2.394		2.162		2.009		1.354	
Sex (1=girl)	-14.070	**	1.308		-17.071	***	-15.083	***	-28.210	***
	4.978		1.998		1.297		2.665		2.606	
(At least) one parent born abroad	8.635		-29.732	**	-16.041	***	-0.439		-5.955	
	5.537		9.583		4.082		1.392		3.332	
Born abroad	-4.827		-9.853		16.975	*	10.008	***	-22.784	***
	7.137		9.912		7.852		2.851		4.484	
Language spoken at home same as test language	31.725	***	22.776	***	29.958	***	10.910	***	-18.044	**
	5.416		4.426		3.992		3.307		5.577	
Socioeconomic background	15.103	***	23.345	***	25.251	***	17.351	***	17.996	***
	1.539		0.887		1.506		1.082		0.987	
Constant	607.195	***	727.001	***	882.742	***	755.877	***	726.753	***
	45.537		32.322		28.515		28.800		19.447	
School variance	3.875	***	3.121	***	3.006	***	3.245	***	3.113	***
	0.032		0.085		0.043		0.069		0.049	
Individual variance	4.339	***	4.400	***	4.285	***	4.466	***	4.146	***
	0.014		0.014		0.013		0.016		0.011	
C	**DEU**		**FIN**		**FRA**		**LUX**		**PRT**	
Internet access at home	10.840		-13.391		46.425	***	29.799	***	13.841	*
	14.508		16.189		7.572		7.463		6.519	
Constant	486.509	***	529.959	***	470.561	***	444.105	***	477.091	***
	14.550		16.755		7.410		6.703		7.054	
School variance	4.073	***	3.311	***	3.334	***	3.645	***	3.332	***
	0.023		0.059		0.040		0.040		0.047	
Individual variance	4.356	***	4.437	***	4.363	***	4.489	***	4.208	***
	0.010		0.014		0.014		0.016		0.008	
D	**DEU**		**FIN**		**FRA**		**LUX**		**PRT**	
Computer experience	8.171	***	17.816	***	11.647	***	11.681	***	11.902	***
	0.928		0.560		0.654		0.925		0.848	
Smartphone experience	-9.951	***	-7.779	***	-15.663	***	-16.202	***	-9.940	***
	1.102		1.031		1.280		1.474		1.368	
Tablet experience	-5.982	***	-5.153	***	-0.787		0.620		0.153	
	1.155		1.135		0.491		0.609		1.331	
Constant	513.504	***	497.880	***	520.319	***	482.520	***	480.257	***
	3.477		3.909		2.343		2.864		1.261	
School variance	4.042	***	3.344	***	3.287	***	3.589	***	3.307	***
	0.027		0.055		0.039		0.044		0.047	
Individual variance	4.346	***	4.408	***	4.335	***	4.471	***	4.186	***
	0.010		0.014		0.012		0.014		0.007	
E	**DEU**		**FIN**		**FRA**		**LUX**		**PRT**	
Studies ICT in current school year	21.963	***	17.108	***	-4.608		-25.100	***	15.118	***
	5.343		1.890		2.747		2.376		4.154	
Learning coding tasks	-0.708	***	-1.430	***	-1.209	***	-1.076	***	-1.072	***
	0.206		0.149		0.107		0.150		0.177	
Learning ICT tasks	-0.359		1.488	***	0.763	***	0.373	*	-0.381	
	0.218		0.117		0.091		0.187		0.211	
Constant	538.616	***	507.472	***	543.124	***	516.502	***	549.234	***
	7.799		7.651		4.565		7.242		7.675	
School variance	4.093	***	3.263	***	3.320	***	3.623	***	3.311	***
	0.024		0.053		0.040		0.041		0.042	
Individual variance	4.344	***	4.421	***	4.356	***	4.476	***	4.194	***
	0.012		0.014		0.014		0.016		0.007	

F	DEU		FIN		FRA		LUX		PRT	
Use ICT at school for school purposes	-2.151	*	4.593	***	3.186	***	-1.359		-8.003	***
	0.916		1.066		0.837		1.141		1.562	
Use ICT at school for other purposes	-2.491	**	6.742	***	-5.867	***	2.416	***	-0.389	
	0.940		1.264		0.629		0.499		0.607	
Use ICT outside school for school purposes	-6.731	***	0.402		-2.247	***	-4.258	***	-1.447	*
	1.818		0.841		0.588		0.889		0.630	
Use ICT outside school for other purposes	18.585	***	16.496	***	17.240	***	15.020	***	16.992	***
	1.513		1.319		0.766		1.080		0.882	
Constant	442.615	***	395.524	***	451.154	***	418.822	***	445.928	***
	9.672		5.053		3.103		4.142		6.906	
School variance	4.058	***	3.269	***	3.253	***	3.586	***	3.256	***
	0.020		0.056		0.043		0.041		0.047	
Individual variance	4.338	***	4.401	***	4.343	***	4.472	***	4.174	***
	0.010		0.014		0.014		0.016		0.007	

Source: ICILS 2018. Repetitive weights are applied.

Panel B also reveals that the computational thinking score is lower for older student as with the CT, but lower for girls, which is contrary to the CIL score (but in Finland there is no gender difference). If the language spoken at home is different than the test is associated with a lower CIL score. A higher socio-economic status is associated with a higher CT score.

Being connected to the internet at home matter for the CT score in some countries. It does not matter in Germany and Finland, but is positively related to CT in France, Luxembourg and Portugal. The amount of experience with a laptop, smartphone or tablet shown in panel D, shows that computational thinking is positively related to experience on a computer, but negatively for a smartphone. With regard to experience on a tablet, only in Germany and Finland it is negatively related to CT.

The effect of studying ICT in school, estimated in panel E, shows mixed results as it did with CIL. For Germany, Finland and Portugal this effect is positive, while in Luxembourg it is negative and in France uncorrelated with CT. The indicators on code learning is negative across the board, whereas learning general ICT tasks negatively related in Germany and Finland.

Using ICT at school for school related purposes is negatively related to CT in Germany and Portugal and positive in France and Portugal. Using ICT at school for other purposes shows mixed results across countries as well: positive in Finland and Luxembourg, while negatively related to CIL in Germany and France. Using ICT outside school for school related purposes is negatively related to CT except for Finland. Again, the biggest effects are for using ICT outside school for other purposes, which is positively related to CT in all countries.

Model 1 reveals that for the composition indicators, there are no substantial differences with the model in panel B. For Portugal, the effects of being connected to the internet are explained by other individual level characteristics, as the effect is not associated with CT. For the experience tablet, it holds that it is now also negatively related in France. Learning coding tasks is not related anymore in Luxembourg.

Table C2. Variance reduction for CT regression models

	A					B					C				
	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT
Constant	497.29	516.66	516.66	473.27	490.71	607.20	727.00	882.74	755.88	726.75	486.51	529.96	470.56	444.10	477.09
School variance	4.07	3.31	3.34	3.66	3.33	3.88	3.12	3.01	3.24	3.11	4.07	3.31	3.33	3.65	3.33
Individual variance	4.36	4.44	4.36	4.49	4.21	4.34	4.40	4.28	4.47	4.15	4.36	4.44	4.36	4.49	4.21
ICC	0.48	0.43	0.43	0.45	0.44	0.47	0.41	0.41	0.42	0.43	0.48	0.43	0.43	0.45	0.44
%Δ Null model (school level)						4.86	5.73	10.10	11.27	6.61	0.01	-0.01	0.30	0.32	0.07
%Δ Null model individual level)						0.41	0.82	1.80	0.52	1.46	0.00	0.00	0.01	0.02	0.00

	D					E					F				
	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT
Constant	513.50	497.88	520.32	482.52	480.26	538.62	507.47	543.12	516.50	549.23	442.61	395.52	451.15	418.82	445.93
School variance	4.04	3.34	3.29	3.59	3.31	4.09	3.26	3.32	3.62	3.31	4.06	3.27	3.25	3.59	3.26
Individual variance	4.35	4.41	4.33	4.47	4.19	4.34	4.42	4.36	4.48	4.19	4.34	4.40	4.34	4.47	4.17
ICC	0.48	0.43	0.43	0.45	0.44	0.49	0.42	0.43	0.45	0.44	0.48	0.43	0.43	0.44	0.44
%Δ Null model (school level)	0.75	-1.01	1.69	1.85	0.81	-0.49	1.45	0.71	0.92	0.69	0.37	1.26	2.71	1.95	2.32
%Δ Null model individual level)	0.24	0.65	0.66	0.42	0.52	0.28	0.35	0.17	0.32	0.34	0.43	0.80	0.48	0.39	0.80

	Model 1					Model 2					Model 3				
	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT
Constant	615.08	624.61	748.21	688.34	697.92	640.65	608.15	762.07	719.30	683.09	489.12	571.25	768.75	653.92	693.20
School variance	3.88	3.12	2.90	3.17	3.06	3.54	3.03	2.80	2.82	3.04	3.83	3.11	2.89	3.06	3.05
Individual variance	4.30	4.33	4.23	4.43	4.09	4.30	4.33	4.23	4.43	4.08	4.30	4.33	4.23	4.43	4.09
ICC	0.47	0.42	0.41	0.42	0.43	0.45	0.41	0.40	0.39	0.43	0.47	0.42	0.41	0.41	0.43
%Δ Null model (school level)	4.79	5.81	13.31	13.22	8.22	13.19	8.55	16.22	22.94	8.86	5.89	5.93	13.48	16.30	8.43
%Δ Null model individual level)	1.19	2.34	2.96	1.42	2.90	1.27	2.35	2.96	1.43	2.94	1.20	2.34	2.96	1.43	2.91
%Δ Individual model (school level)						8.82	2.91	3.37	11.19	0.70	1.15	0.13	0.20	3.55	0.23
%Δ Individual model individual level)						0.08	0.00	0.01	0.00	0.04	0.01	0.00	0.00	0.00	0.00

	Model 4					Model 5					Model 6				
	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT	DEU	FIN	FRA	LUX	PRT
Constant	608.75	558.37	625.12	465.48	750.97	758.55	634.83	845.29	484.42	654.37	712.50	579.98	887.56	811.68	668.72
School variance	3.87	3.11	2.87	3.10	3.05	3.87	3.12	2.88	3.16	3.06	3.47	3.01	2.70	0.04	3.00
Individual variance	4.30	4.33	4.23	4.43	4.09	4.30	4.33	4.23	4.43	4.09	4.30	4.33	4.23	4.43	4.08
ICC	0.47	0.42	0.40	0.41	0.43	0.47	0.42	0.40	0.42	0.43	0.45	0.41	0.39	0.01	0.42
%Δ Null model (school level)	5.10	6.01	14.30	15.25	8.59	5.04	5.82	13.88	13.53	8.34	14.87	9.15	19.33	98.88	9.98
%Δ Null model individual level)	1.19	2.34	2.96	1.42	2.90	1.19	2.34	2.95	1.42	2.90	1.28	2.35	2.95	1.38	2.94
%Δ Individual model (school level)	0.32	0.22	1.14	2.33	0.41	0.26	0.01	0.66	0.35	0.13	10.58	3.55	6.94	98.71	1.92
%Δ Individual model individual level)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.09	0.01	0.00	-0.04	0.04

Table C3. Interaction of CT with Sex

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT	
Sex (1=girl)	-5.962		45.787	***	-42.327	***	-59.244	**	-70.437	***	-17.462	***	2.443		-6.744		-5.497		-22.347	***
	17.830		10.137		11.872		19.263		10.862		5.032		2.164		3.637		5.934		2.521	
Availability of ICT resources at school (ICT Coordinator)	1.920	***	0.615	***	-0.163		-1.743	***	-0.521	***										
	0.287		0.184		0.143		0.156		0.154											
Sex (1=girl) # Availability of ICT resources at school (ICT Coordinator)	-0.167		-0.671	***	0.503	*	0.903	*	0.881	***										
	0.391		0.172		0.248		0.409		0.181											
Ratio of school size and number of ICT devices											-0.562		-1.344		0.655		8.406	***	0.625	***
											0.343		1.023		0.639		1.291		0.096	
Sex (1=girl) # Ratio of school size and number of ICT devices											0.656		1.531		-2.605	***	-3.499	*	-0.533	*
											0.561		1.434		0.775		1.384		0.225	
Constant	536.840	***	588.865	***	757.267	***	769.936	***	722.858	***	619.534	***	629.400	***	750.329	***	660.056	***	694.908	***
	52.967		36.909		37.941		31.628		30.565		48.603		35.119		34.864		28.224		24.330	
School variance	3.837	***	3.116	***	2.894	***	3.135	***	3.060	***	3.879	***	3.119	***	2.887	***	3.086	***	3.054	***
	0.038		0.063		0.049		0.071		0.038		0.037		0.064		0.051		0.067		0.036	
Individual variance	4.304	***	4.332	***	4.234	***	4.425	***	4.084	***	4.304	***	4.333	***	4.234	***	4.426	***	4.085	***
	0.015		0.013		0.010		0.015		0.013		0.015		0.013		0.010		0.015		0.013	

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT	
Sex (1=girl)	-103.525	*	215.454	***	-0.400		121.241	**	17.660		-12.206	**	4.686		-20.094	***	-16.114	***	-24.091	***
	42.354		36.326		52.528		38.178		43.364		3.839		2.940		2.035		1.948		4.004	
Availability of computer resources at school (Teachers)	0.570		3.128	***	-0.105		1.189	*	0.525											
	0.807		0.244		0.788		0.606		0.452											
Sex (1=girl) # Availability of computer resources at school (Teachers)	1.800	*	-4.184	***	-0.339		-2.722	***	-0.897											
	0.867		0.718		1.053		0.772		0.888											
10 or more years ICT experience in the school											15.975	***	0.677		4.820		6.822	*	-4.513	
											3.065		2.632		3.103		3.233		3.116	
Sex (1=girl) # 10 or more years ICT experience in the school											-1.670		3.346		7.766		4.481		-5.217	
											3.125		4.533		4.280		4.831		3.975	
Constant	585.095	***	472.799	***	753.051	***	630.694	***	670.513	***	606.216	***	624.585	***	745.275	***	683.828	***	699.325	***
	63.930		36.698		42.934		41.544		33.757		47.329		35.125		32.414		26.722		24.373	
School variance	3.876	***	3.120	***	2.897	***	3.167	***	3.059	***	3.865	***	3.117	***	2.900	***	3.166	***	3.060	***
	0.039		0.063		0.049		0.078		0.038		0.035		0.066		0.049		0.080		0.039	
Individual variance	4.304	***	4.331	***	4.235	***	4.426	***	4.085	***	4.304	***	4.333	***	4.234	***	4.426	***	4.085	***
	0.015		0.013		0.010		0.016		0.013		0.015		0.013		0.011		0.015		0.012	

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT	
Sex (1=girl)	80.623		45.612		-125.759	**	-160.830	**	-65.653	**	-79.989		69.391		-192.650	*	468.458	***	-25.432	
	73.821		30.423		48.032		59.011		20.437		69.745		49.833		86.495		105.469		30.173	
ICT experience with ICT use during lessons	19.530		35.664	***	29.277		56.713	***	-29.260	***										
	18.328		10.651		19.189		11.760		4.768											
Sex (1=girl) # ICT experience with ICT use during lessons	-38.525		-16.303		44.437	*	60.003	*	15.945											
	29.707		12.593		19.815		24.774		8.225											
Use of ICT for teaching practices in class											-3.541	***	0.439		-3.702	*	9.227	***	0.909	
											1.070		0.679		1.617		1.240		0.524	
Sex (1=girl) # Use of ICT for teaching practices in class											1.360		-1.289		3.543	*	-9.890	***	-0.028	
											1.450		0.985		1.743		2.120		0.633	
Constant	569.566	***	538.947	***	678.499	***	551.405	***	769.806	***	785.365	***	602.867	***	933.290	***	238.977	***	653.642	***
	54.161		42.223		58.188		42.040		22.850		55.220		42.474		68.825		66.548		31.469	
School variance	3.881	***	3.112	***	2.861	***	3.098	***	3.048	***	3.868	***	3.118	***	2.879	***	3.171	***	3.056	***
	0.035		0.068		0.054		0.085		0.044		0.033		0.066		0.061		0.077		0.040	
Individual variance	4.304	***	4.333	***	4.234	***	4.426	***	4.086	***	4.304	***	4.333	***	4.234	***	4.424	***	4.086	***
	0.015		0.013		0.010		0.015		0.012		0.015		0.013		0.010		0.015		0.012	

Note: the analyses are also controlling for the individual level factors.

Table C4. Interaction of CT with NISB

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT	
Socioeconomic background (NISB)	23.142	*	12.166	**	9.481	*	17.677		7.522		17.920	***	17.282	***	26.258	***	17.944	***	14.310	***
	10.177		3.967		4.562		11.283		5.555		2.641		1.710		2.151		2.210		1.106	
Availability of ICT resources at school (ICT Coordinator)	1.819	***	0.255	*	0.080		-1.338	***	-0.087											
	0.176		0.126		0.075		0.162		0.095											
NISB # Availability of ICT resources at school (ICT Coordinator)	-0.255		0.140	*	0.279	**	-0.094		0.143											
	0.265		0.067		0.097		0.219		0.101											
Ratio of school size and number of ICT devices											-0.236		-0.712		-0.751		6.874	***	0.378	***
											0.348		0.829		0.489		1.063		0.090	
NISB # Ratio of school size and number of ICT devices											-0.857	**	1.406	*	-0.709		-1.727		0.033	
											0.323		0.689		0.407		0.895		0.148	
Constant	543.609	***	609.234	***	746.547	***	754.935	***	702.330	***	620.363	***	627.278	***	749.769	***	667.029	***	695.790	***
	47.158		34.592		33.758		27.571		27.676		48.196		35.657		34.616		28.877		24.239	
School variance	3.831	***	3.115	***	2.906	***	3.125	***	3.062	***	3.883	***	3.120	***	2.896	***	3.092	***	3.055	***
	0.037		0.064		0.047		0.079		0.038		0.038		0.062		0.049		0.065		0.038	
Individual variance	4.304	***	4.333	***	4.234	***	4.426	***	4.086	***	4.303	***	4.332	***	4.234	***	4.426	***	4.086	***
	0.015		0.013		0.010		0.016		0.012		0.015		0.013		0.010		0.015		0.013	

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT	
Socioeconomic background (NISB)	119.709	*	-50.912		46.140		77.273		35.280	*	13.819	***	22.613	***	20.897	***	9.573	***	14.090	***
	52.114		27.053		29.719		50.284		15.005		2.130		1.572		2.088		1.626		1.363	
Availability of computer resources at school (Teachers)	1.186	*	0.865	*	-0.301		0.488		0.028											
	0.565		0.441		0.488		0.691		0.173											
NISB # Availability of computer resources at school (Teachers)	-2.137	*	1.430	**	-0.456		-1.281		-0.415											
	1.061		0.549		0.604		1.000		0.293											
10 or more years ICT experience in the school											16.728	***	-0.948		0.600		4.351	*	-1.935	
											2.661		1.043		1.769		1.825		1.709	
NISB # 10 or more years ICT experience in the school											-3.043		-3.334	*	3.798		5.823	**	1.082	
											2.882		1.551		2.809		1.826		3.205	
Constant	552.198	***	577.862	***	763.186	***	664.683	***	695.290	***	607.631	***	624.885	***	746.149	***	685.416	***	698.879	***
	54.265		29.071		33.111		47.690		27.517		46.536		34.417		32.982		26.936		24.718	
School variance	3.868	***	3.106	***	2.897	***	3.197	***	3.061	***	3.863	***	3.115	***	2.896	***	3.148	***	3.060	***
	0.036		0.067		0.048		0.079		0.038		0.034		0.067		0.048		0.082		0.040	
Individual variance	4.303	***	4.332	***	4.234	***	4.426	***	4.086	***	4.304	***	4.333	***	4.234	***	4.426	***	4.086	***
	0.014		0.013		0.010		0.016		0.012		0.015		0.013		0.010		0.015		0.012	

	DEU		FIN		FRA		LUX		PRT		DEU		FIN		FRA		LUX		PRT	
Socioeconomic background (NISB)	83.871	**	1.642		-8.407		-42.173		35.403	***	159.931	*	62.219	**	-3.853		38.129		36.409	
	29.668		19.686		26.108		26.822		10.035		73.899		23.980		38.203		48.857		39.600	
ICT experience with ICT use during lessons	-0.692		27.680	***	50.533	***	84.903	***	-20.913	***										
	11.074		7.543		12.292		10.189		5.124											
NISB # ICT experience with ICT use during lessons	-29.403	*	7.725		12.986		22.860	*	-8.553	*										
	12.623		7.944		10.849		11.018		4.034											
Use of ICT for teaching practices in class											-3.274	***	-0.265		-1.978	*	4.227	***	0.822	***
											0.783		0.464		0.903		0.525		0.248	
NISB # Use of ICT for teaching practices in class											-3.000	*	-0.848		0.554		-0.512		-0.446	
											1.531		0.482		0.781		0.989		0.802	
Constant	622.225	***	556.950	***	627.579	***	481.285	***	749.986	***	770.541	***	637.677	***	846.191	***	481.689	***	658.147	***
	47.166		37.941		48.278		42.848		22.480		50.689		34.522		34.151		30.320		26.603	
School variance	3.871	***	3.115	***	2.862	***	3.089	***	3.042	***	3.856	***	3.120	***	2.878	***	3.163	***	3.054	***
	0.034		0.067		0.053		0.080		0.045		0.031		0.066		0.062		0.078		0.040	
Individual variance	4.304	***	4.333	***	4.235	***	4.426	***	4.086	***	4.303	***	4.333	***	4.235	***	4.426	***	4.086	***
	0.015		0.013		0.010		0.016		0.012		0.015		0.013		0.010		0.016		0.012	

Note: the analyses are also controlling for the individual level factors.

First, in France, Luxembourg and Portugal the effect of ICT coordinator indicating that degree of resources available at the school is less negative or positive for girls and non-existent or negative for boys. For Finland, the positive availability effect is almost zero for girls.

Second, the interaction of student-teacher ratio with sex appears to be negative in France, Luxembourg and Portugal though to a varying degree of significance, meaning that girls have a less positive or even negative ratio-effect. Third, in Finland and Luxembourg the effect of the teacher indicating availability of computer resources at school makes the advantage for girls in those countries smaller. In Germany the disadvantage of girls becomes smaller the more ICT resources there are available.

Fourth, the experience of ICT coordinator in school does not vary over gender in any country. Fifth, the effect of ICT experience with ICT use during lessons is larger for girls in France and Luxembourg. Sixth, the use of ICT for teaching practices in class effect is smaller for girls in Luxembourg, and larger in France.

In Table 6, the interaction effect of NISB is shown for the school level variables with Computational Thinking. All the effects are under control of individual level effects. First, in Finland and France the effect of the availability of ICT resources according to the ICT coordinator is larger for student with a high socioeconomic status. Second, In Luxembourg and Portugal, the positive effect of student-teacher ratio is larger the higher the socioeconomic status. The availability of ICT resources according to teachers is smaller for high socioeconomic status in Germany, but larger in Finland. Fourth, the experience with ICT in the school effect is smaller the higher the socioeconomic status in Finland, but larger in Luxembourg. Fifth, the socioeconomic gap in the effect of teacher experience in class is smaller in Germany and Portugal, but larger in Luxembourg. Lastly, the use of ICT in the classroom effect is smaller for those with a higher socioeconomic status in Germany.

Appendix D. Materials for PISA analyses.

Table D1. Descriptive statistics of analytical variables (N = 91512).

	Mean	Sd	Min	Max
Individual level				
Problem-solving scores (raw)	500.79	98.20	6.92	877.94
Age	15.77	0.29	15.25	16.33
Sex (boys = 1)	1.5	0.5	1	2
SES (ESCS index)	0.1	0.89	-4.68	3.01
Migration background				
Non-migrants	0.91	0.28	0	1
First-generation mig.	0.04	0.2	0	1
Second-generation mig.	0.05	0.2	0	1
School level				
Extra-curricular creative activities	1.56	1.05	0	3
Student-teacher ratio	11.92	4.04	0.17	50
School autonomy	0.12	0.90	-2.87	1.6
School type				
Public	0.79	0.41	0	1
Private – Gov. dependent	0.19	0.4	0	1
Private	0.02	0.14	0	1
Country level				
Digital contacts with the Government	30.66	16.22	8.27	69.41
Income inequality (Gini)	0.29	0.03	0.25	0.35
R&D expenditure	2.08	0.8	0.8	3.4
Index of learning strategies (adults)	3.67	0.15	3.40	3.95
Input standardisation	-0.19	0.55	-0.84	1.29
Output standardisation	0.62	0.48	0	1
Vocational Enrolment	0.63	0.65	-0.70	1.74

Table D2. Multilevel models (random intercept) regressing raw problem-solving scores on school level characteristics one by one.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Individual-level						
Age at test		9.405***	9.375***	9.405***	9.492***	9.429***
Boys		11.18***	11.19***	11.18***	11.24***	11.20***
Migration (ref. Native)						
First gen.		-29.90***	-29.90***	-29.90***	-29.89***	-29.94***
Second gen.		-33.77***	-33.72***	-33.76***	-33.79***	-33.69***
SES (ESCS score)		18.04***	17.97***	18.04***	17.99***	17.98***
School-level						
Type (ref. Private)						
Private – Gov. depend.			-15.99*			
Public			-32.98***			
Autonomy				2.765		
Extra-cur. creative activities					10.73***	
Student-teacher ratio						2.064**
Constant	495.7***	332.8***	362.3***	332.3***	314.2***	307.8***
Variance Intercept						
Country-level	408.4***	339.9***	322.0***	344.6***	361.2***	319.2***
School-level	3948.0***	3242.7***	3200.5***	3238.7***	3144.7***	3189.9***
Individual-level	5789.8***	5510.4***	5510.3***	5510.4***	5510.3***	5509.9***

Notes: raw scores

Table D3. Multilevel models (random intercept) regressing z-standardised problem-solving scores on individual, school, and country-level characteristics: Models with and without (benchmark) cross-level interactions between gender and SES with school-level characteristics.

	Benchmark Model:	PANEL A: Gender interactions				PANEL B: SES interactions			
	No interactions	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Individual-level									
Age at test	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***
Boys	0.12***	0.07*	0.12***	0.11**	0.05	0.12***	0.12***	0.12***	0.12***
Migration (ref. Native)									
First gen.	-0.35***	-0.35***	-0.35***	-0.35***	-0.35***	-0.35***	-0.35***	-0.35***	-0.35***
Second gen.	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***
SES (ESCS score)	0.18***	0.18***	0.18***	0.18***	0.18***	0.18***	0.18***	0.19***	0.20***
School-level									
Type (ref. Private)									
Private – Gov. depend.	-0.18	-0.21*	-0.18	-0.18	-0.18	-0.18	-0.17	-0.18	-0.17
Public	-0.32**	-0.34**	-0.32**	-0.32**	-0.32**	-0.32**	-0.31**	-0.32**	-0.32**
Autonomy	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
Extra-cur. creative activities	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***
Student-teacher ratio	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**
Interaction School x Boys									
Boys *x* Private – Gov. dep.		0.07							
Boys *x* Public		0.04							
Boys *x* Autonomy			0						
Boys *x* Extra-curric. creative act.				0.01					
Boys *x* Student-teacher ratio					0.01*				
Interaction School x SES									
SES *x* Private – Gov. Dep.						-0.01			
SES *x* Public School						0.01			
SES *x* School Autonomy							0.01		
SES *x* Extra-curric. creative act.								0	
SES *x* Student-teacher ratio									0
Constant	-1.84***	-1.69***	-1.72***	-1.71***	-1.68***	-1.83***	-1.84***	-1.84***	-1.84***
Variance Intercept									
Country-level	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
School-level	0.32***	0.32***	0.32***	0.32***	0.32***	0.32***	0.32***	0.32***	0.32***
Individual-level	0.59***	0.59***	0.59***	0.59***	0.59***	0.59***	0.59***	0.59***	0.59***

Notes: scores z-standardized within countries (country-level variance is not exactly 0 due to school-level variance parameter).

Table D4. Multilevel models (random intercept) regressing z-standardised problem-solving scores on individual, school, and country-level characteristics: Benchmark models without cross-level interactions between gender and SES with school-level characteristics.

	Benchmark models: no interaction						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Individual-level							
Age at test	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***
Boys	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***
Migration (ref. Native)							
First gen.	-0.35***	-0.35***	-0.35***	-0.35***	-0.35***	-0.35***	-0.35***
Second gen.	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***
SES (ESCS score)	0.18***	0.18***	0.18***	0.18***	0.18***	0.18***	0.18***
School-level							
Type (ref. Private)							
Private – Gov. depend.	-0.18	-0.18	-0.18	-0.18	-0.18	-0.18	-0.17
Public	-0.32**	-0.32**	-0.32**	-0.32**	-0.32**	-0.32**	-0.32**
Autonomy	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
Extra-curricular creative activities	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***
Student-teacher ratio	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**
Country-level							
Input standardisation	0.01						
Output standardisation		-0.01					
R&D expenditure			0.04				
Income Inequality (Gini)				-0.95			
Digital contact with the Gov.					0.003*		
Vocational Enrolment						0.01	
Adult's Learning Strategies							0.41***
Constant	-1.83***	-1.83***	-1.91***	-1.56***	-1.90***	-1.84***	-3.32***
Variance Intercept							
Country-level	0.01***	0.01***	0.01***	0.01***	0.0049***	0.01***	0.0036***
School-level	0.32***	0.32***	0.32***	0.32***	0.32***	0.32***	0.32***
Individual-level	0.59***	0.59***	0.59***	0.59***	0.59***	0.59***	0.59***

Notes: scores z-standardized within countries (country-level variance is not exactly 0 due to school-level variance parameter, main effects of country-level characteristics are meaningless).

Table D5. Multilevel models (random intercept) regressing z-standardised problem-solving scores on individual, school, and country-level characteristics: Models with cross-level interactions between gender and school-level characteristics.

	Gender interactions						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Individual-level							
Age at test	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***
Boys	0.14***	0.14**	0.20*	0.19	0.21***	0.09**	1.19**
Migration (ref. Native)							
First gen.	-0.35***	-0.35***	-0.35***	-0.35***	-0.35***	-0.35***	-0.35***
Second gen.	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***
SES (ESCS score)	0.18***	0.18***	0.18***	0.18***	0.18***	0.18***	0.18***
School-level							
Type (ref. Private)							
Private – Gov. depend.	-0.18	-0.18	-0.18	-0.18	-0.18	-0.18	-0.17
Public	-0.32**	-0.32**	-0.32**	-0.32**	-0.32**	-0.32**	-0.32**
Autonomy	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
Extra-curricular creative activities	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***
Student-teacher ratio	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**
Country-level							
Input standardisation	-0.04						
Output standardisation		0.02					
R&D expenditure			0.06				
Income Inequality (Gini)				-0.83			
Digital contact with the Gov.					0.004**		
Vocational Enrolment						-0.01	
Adult's Learning Strategies							0.56***
Interaction Country x Boys							
Boys *x* Input standardisation	0.09*						
Boys *x* Output standardisation		-0.04					
Boys *x* R&D expenditure			-0.04				
Boys *x* Income Inequality (Gini)				-0.24			
Boys *x* Digital contact with the Gov.					-0.00		
Boys *x* Vocational Enrolment						0.05	
Boys *x* Adult's Learning Strategies							-0.29*
Constant	-1.73***	-1.73***	-1.83***	-1.48**	-1.84***	-1.71***	-3.74***
Variance Intercept							
Country-level	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.004***
School-level	0.33***	0.32***	0.32***	0.32***	0.33***	0.32***	0.32***
Individual-level	0.59***	0.59***	0.59***	0.59***	0.59***	0.59***	0.59***

Notes: scores z-standardized within countries (country-level variance is not exactly 0 due to school-level variance parameter, main effects of country-level characteristics are meaningless).

Table D6. Multilevel models (random intercept) regressing z-standardised problem-solving scores on individual, school, and country-level characteristics: Models with cross-level interactions between SES and school-level characteristics.

	SES interactions						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Individual-level							
Age at test	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***
Boys	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***
Migration (ref. Native)							
First gen.	-0.35***	-0.35***	-0.35***	-0.35***	-0.34***	-0.35***	-0.34***
Second gen.	-0.31***	-0.31***	-0.31***	-0.31***	-0.30***	-0.31***	-0.31***
SES (ESCS score)	0.18***	0.18***	0.17***	0.22	0.13***	0.20***	-0.77***
School-level							
Type (ref. Private)							
Private – Gov. depend.	-0.17	-0.18	-0.18	-0.18	-0.19*	-0.17	-0.17
Public	-0.32**	-0.32**	-0.32**	-0.33**	-0.33***	-0.32**	-0.32**
Autonomy	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
Extra-curricular creative activities	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***
Student-teacher ratio	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**
Country-level							
Input standardisation	0.01						
Output standardisation		0					
R&D expenditure			0.04				
Income Inequality (Gini)				-0.94			
Digital contact with the Gov.					0.002*		
Vocational Enrolment						0.01	
Adult's Learning Strategies							0.35***
Interaction Country x SES							
SES *x* Input standardisation	-0.04						
SES *x* Output standardisation		0					
SES *x* R&D expenditure			0.01				
SES *x* Income Inequality (Gini)				-0.11			
SES *x* Digital contact with the Gov.					0.002*		
SES *x* Vocational Enrolment						-0.023	
SES *x* Adult's Learning Strategies							0.26***
Constant	-1.84***	-1.83***	-1.90***	-1.56***	-1.88***	-1.84***	-3.13***
Variance Intercept							
Country-level	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.003***
School-level	0.33***	0.324**	0.32***	0.32***	0.33***	0.33***	0.33***
Individual-level	0.59***	0.59***	0.59***	0.59***	0.59***	0.59***	0.59***

Notes: scores z-standardized within countries (country-level variance is not exactly 0 due to school-level variance parameter, main effects of country-level characteristics are meaningless).

Chapter 2

Determinants of individual differences in adults' ICT skills across 18 European countries

Per Bles, Lynn-Malou Lutz, Nora Müller

2.1 Workplace technologization and ICT skills

Throughout the last two decades, workplaces have been increasingly technologized (OECD, 2019b). Studies show that with technological change, the demand for skilled labour increases (O'Mahony et al., 2008; Spitz-Oener, 2006). This increase includes the demand for general cognitive skills – like literacy and numeracy – as a basis to pursue lifelong learning. In addition, it includes specific cognitive – like ICT skills or analytical skills – and non-cognitive skills – like creativity, problem-solving, critical thinking, interpersonal and communication skills – to cope with the demands of the digital transition (Morandini et al., 2020; OECD, 2017a). We focus on ICT skills as the ability set most directly related to the demand of technologized workplaces and their potential determinants.

ICT skills form a relevant analysis object because they were found to be positively related to numerous micro- and macro-level outcomes. These outcomes include individuals' employability (Picatoste et al., 2018; Walton et al., 2009), earnings (Buchmann et al., 2020 ; Grundke et al., 2018; Lane & Conlon, 2016), and online (older individuals) and offline (older individuals with dementia) social participation (Pinto-Bruno et al., 2017; Sims et al., 2016; Yu et al., 2016), but also societies' economic growth (Fernández-Portillo et al., 2020; Niebel, 2018). Consequently, several scholars suggest that differences in ICT skills reinforce existing social inequalities (Helsper, 2012; Witte & Mannon, 2010).

Research on determinants of ICT skills suffers from two major shortcomings. First, previous research has almost exclusively concentrated on young students (e.g., Aesaert & van Braak, 2015; Hargittai & Hinnant, 2008; Owens & Lilly, 2017), while empirical evidence on determinants of adults' ICT skills is scarce (for exceptions see: Falck et al., 2016; Wicht et al., 2021). Second, almost nothing is known about determinants of adults' ICT skills on the country level (exception: Falck et al., 2016). These shortcomings are unfortunate because it is crucial for policy- and decision-makers to know which context variables can predict and influence individual ICT skills, not only of the future but also of the current working and non-working population. Making use of such knowledge, countries can remain competitive or can even increase their competitiveness. On the individual level, they can achieve to integrate their inhabitants into the technologized labour market, services, and consumption of public and private everyday life (OECD, 2013).

We use existing micro-level theories to explain individual differences in adults' ICT skills and extend them to explanatory factors at the contextual (country) level. Our macro-level variables include indicators of a country's ICT infrastructure, governmental and private ICT usage, technical skills demand, adult education infrastructure, and level of gender equality. Applying large-scale data from the first cycle of the "Programme for the International Assessment of Adult Competencies" (PIAAC), we put our hypotheses to an empirical test across 18 OECD countries.

2.2 Previous research on individual differences in adults' ICT skills

While differences in individuals internet access – also known as the "first digital divide"— have diminished in most developed countries, significant disparities persist or have even increased concerning ICT skills, also known as the "second digital divide" (DiMaggio et al., 2004; Hargittai & Hinnant, 2008; Scheerder et al., 2017; van Dijk, 2006). Researchers conducted a bulk of studies to identify determinants of ICT skills, though with inconsistent use of terminology and measures (Scheerder et al., 2017; van Dijk, 2006). Many of these studies analysed individuals' subjectively assessed ICT skills (e.g., Martzoukou et al., 2020; Tijdens & Steijn, 2005). Yet, subjectively and objectively assessed ICT skills were shown to correlate only moderately (Bradlow et al., 2002; Hargittai & Shafer, 2006). Consequently Palczyńska & Rynko (2021) advocate using objective standardized measures, especially in international comparative studies.

In general, previous studies identified three groups of factors to determine individual ICT skills: socio-demographic characteristics, practice-oriented factors, and life contexts. Regarding socio-demographic characteristics, determinants of ICT skills (second digital divide) do largely overlap with those already found for internet usage (first digital divide) (van Deursen & van Dijk, 2014). These include age, gender, ethnicity, migration status, and socioeconomic status. On average, female, older, lower-educated, immigrated individuals show lower ICT skills (Aesaert & van Braak, 2015; Gnambs, 2021; Hargittai, 2010; Owens & Lilly, 2017; van Dijk, 2006). These studies, however, almost exclusively focus on the populations of pupils or young students, ignoring differences in ICT skills of the current working population that mainly did not acquire these skills during their education.

Regarding practice-oriented factors, studies point out that the use of ICT skills as well as of general competencies at work and in daily life positively correlate with the individuals level of ICT skills (e.g., Claro et al., 2012; Desjardins & Ederer, 2015; Hämäläinen et al., 2015, 2017; Livingstone & Helsper, 2010; Wicht et al., 2021). These studies argue and empirically show that the usage of ICT skills but also more general competencies (reading and writing) are prerequisites to acquiring and maintaining ICT skills.

The third group of factors – life contexts – includes micro-level contexts (e.g., home and workplace) as well as macro contexts (regional or country contexts). Previous research, for example, showed a large urban-rural gap in ICT access (Salemink et al., 2017; Schleife, 2010). Wicht et al. (2021) analyze internet domain registration rates as a proxy for regional digital cultures in Germany and find a positive though very small impact on individuals' ICT skills. Research on country-level determinants of adults' ICT skills, however, is largely missing so far. Although Desjardins & Ederer (2015) conducted an international comparative analysis on determinants of adults' ICT skills, they concentrated on only four exemplary countries (Finland, Norway, Germany, UK). Thus, they could not include any contextual level variables in their analyses. In a similar vein, Bynner et al. (2008) compare Portland (USA) and London (UK). They find

ICT use at home to be positively related to individuals' ICT skills in London and ICT use at work to be positively associated with individuals' ICT skills in Portland. Falck et al. (2016) is the only study we found to analyse country-level determinants of adults' ICT skills. Although the authors focus on returns to ICT skills, they also study the relationship between ICT infrastructure and adults' ICT skills across 19 OECD countries. Their analyses show a positive and statistically significant relationship between the two measures.

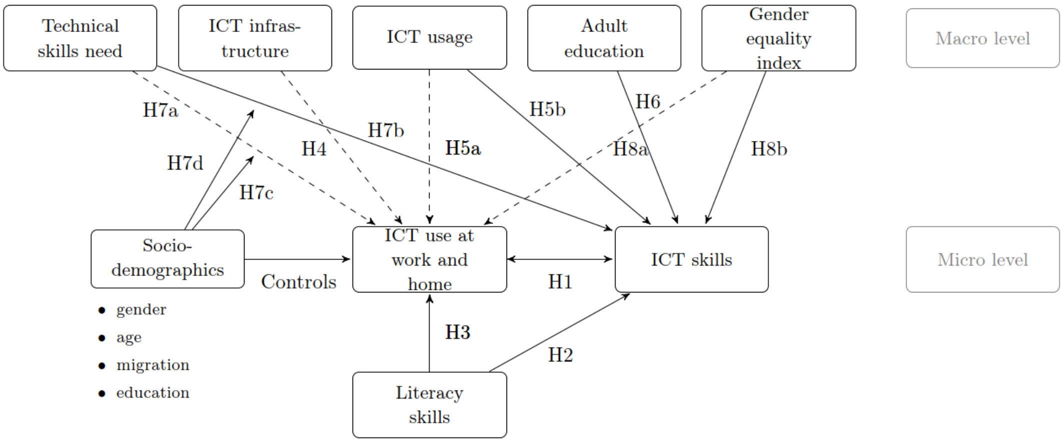
While studies on macro-level determinants on adults' ICT skills are rare, at the same time, countries differ quite remarkably in their adult populations' levels of ICT skills. The OECD (2019a) differentiates between four levels of ICT proficiency. They report New Zealand and Sweden as the countries with the highest share of adults among the highest ICT proficiency group (about 40% of the adult population). The remaining Scandinavian countries and the Netherlands show similarly high levels of adults within the highest ICT proficiency group. In contrast, Turkey, Greece, and Chile show the lowest number of adults (15% or less) within this group. Across all countries, the largest proportion of adults is found within the two lowest ICT proficiency groups (with each group containing about a third of all adults). Knowledge about macro-level determinants of differences in adults' ICT skills can be relevant information, especially for the low-scoring countries to catch up.

2.3 Theoretical model

To answer the lack of theoretical coherence of most previous studies, Wicht et al. (2021) developed a unified conceptual framework to explain individual differences in ICT skills, consolidating previous theoretical models and research. The theoretical framework of Wicht et al. (2021) brings together elements from major theories of skill acquisition – practice engagement theory (Reeder, 1994), constructivist learning theories (Bandura, 1971; Piaget, 1969), social cognitive theory (Bandura, 1986; Compeau & Higgins, 1995), and Bronfenbrenner's ecological systems theory (Bronfenbrenner, 1979; Herselman et al., 2018) – with the so-called literacy hypothesis (Olson, 1977; Vlieghe, 2015).

We apply this integrative theoretical framework and contribute to previous research on determinants of adults' ICT skills by extending the contextual or macro-level to include country-level variables, as illustrated in Figure 1.

Figure 1: Conceptual framework and hypotheses



Own illustration.

2.3.1 Micro-level

Practice engagement theory argues that a stronger involvement of a certain skill – including literacy (for which it was originally developed), but also numeracy (Reder et al., 2020) and ICT skills (Wicht et al., 2021) – in an individual's daily life (work, leisure) gives rise to a reciprocal interaction between the individual and the individual's engagement. The resulting circle of (self-)reinforcement, practice, and skill acquisition leads to a constant improvement of the specific skill.

In a similar vein, constructivist learning theories (e.g., Dewey, 1916; Piaget, 1969) highlight the role of non-formal and informal learning for skill acquisition and improvement for skills that have not been learned in formal settings. In other words, if adults have not acquired ICT skills during their formal education, they can still acquire (or improve) such skills through non-formal and informal learning.

Social cognitive theory, also called social practice view, precedes practice engagement theory and constructivist learning theories and understands human functioning, including ICT skills, as a result of personal, behavioural, and environmental determinants. In line with practice engagement theory and constructivist learning theories, social cognitive theory stresses the role of ICT use (ICT usage and experience) as a behavioural determinant for adults' ICT skills. Personal determinants include personal factors such as ICT self-efficacy, ICT attitudes, or privacy concerns. Environmental determinants include factors such as ICT and training access (cf. Bandura, 1986; Hoffmann et al., 2015).

Summing up these three theories, Wicht et al. (2021) argue that the most relevant micro-level determinants of ICT skills among adults are their ICT use at the workplace and in everyday life because older cohorts did most likely not receive any formal ICT training. Based on these considerations, we derive our first hypothesis: The more intense an individual's ICT use at work and in everyday life, the higher his or her ICT skills.

ICT use, in turn, depends on several prerequisites understood as opportunities and encouragements to engage with ICT as offered by individuals' multi-layered living contexts (Bronfenbrenner, 1979) and their endowment with literacy skills. The so-called literacy hypothesis claims that specialized skills, such as ICT skills, strongly depend on more general cognitive skills, including numeracy, problem-solving, critical thinking, and literacy. In this regard, literacy skills – i.e., the ability to decode and comprehend written language – are regarded as the most crucial ones for and a prerequisite of ICT skills, as digital technologies are heavily based on text and abstract symbols that individuals need to process and decode (Olson, 1977; Vlieghe, 2015; Wicht et al., 2021). From these considerations, we derive two more hypotheses: The higher an individual's literacy skills, the higher his or her ICT skills (hypothesis 2). The positive association between literacy skills and ICT skills is partly mediated by ICT use at work and in everyday life (hypothesis 3).

2.3.2 Macro-level

In his 'Ecological Systems Theory' – originally developed to understand child development – Bronfenbrenner (1979) argues that individuals' micro-contexts are embedded in a series of more distant contexts – including the country context – that shape and are in turn shaped by different micro-contexts. Both contexts are understood as opportunities and encouragements for the individual actors to engage with ICT, with the micro context being the most influential one.

As illustrated in Figure 1, individuals' literacy skills and educational level, and other socio-demographic characteristics represent our individual level. Our theoretical model also includes micro-contexts represented by the settings in which ICT use occurs (workplace and daily life). As an example for distant contexts, previous research included, for example, regional differences (Wicht et al. 2021). As our analysis focuses on the cross-country level, we refrain from taking the regional context into account. On our contextual level, we consider economic, technological, institutional, and cultural factors as examples for distant contexts on the country level. We expect these factors to be related to individual differences in adults' ICT skills either directly or indirectly through restricting or encouraging their ICT use.

A country's ICT infrastructure – understood to consist of hardware, software, networks, and media for the collection, storage, processing, transmission, and presentation of information (The World Bank Group, 2003) – lays the foundation for individuals' possibilities of ICT usage. Analyzing adults' ICT skills across 19 OECD countries, Falck et al. (2016) find that access to ICT infrastructure promotes individuals' ICT skills through ICT usage at work or home. Moreover, they show that these acquired ICT skills reap substantial rewards in the labour market. We hypothesize that the better a countries ICT infrastructure, the more intense the individuals' ICT use at work and in everyday life, resulting in higher ICT skills (hypothesis 4).

Countries strategically invest in the adoption of ICT to spur economic growth and improve the efficiency of their public services (Shrivastava et al., 2021). Moreover, governments can reduce costs for administrative tasks and increase social inclusion through the effective use of ICT services (Chohan & Hu, 2020). Private businesses even created a whole new economy based on the internet and the development of high-speed networks, Big Data, and new forms of mobile devices offering internet access at all times and in all places (Degryse, 2016). Examples for resulting private services include online marketplaces for passenger transportation (such as Uber), lodging (such as Airbnb), or immediate help with everyday tasks (such as TaskRabbit). Based on constructivist learning theories, we expect individuals to train their ICT skills to the level necessary to use public and private ICT services, such as administrative procedures, banking services, or health services. We, therefore, expect to find a positive relationship between ICT use by the government and private businesses and ICT skills (hypothesis 5a). At the same time, based on social practice theory, we expect ICT use by the government and private businesses to directly motivate or even force individuals' ICT usage (hypothesis 5b) in order to save time and money or to be socially integrated.

A country's adult education system is a crucial contextual variable for our study because it is the major relevant institution where adults – who have most likely not acquired ICT training in school – can acquire and develop their ICT skills. We argue that a high participation rate in adult education is positively related to adults' skill formation in general (including literacy, numeracy, problem-solving) and ICT skills in particular. We thus expect a positive relationship between participation in adult education and ICT skills (hypothesis 6).

We expect a high labour market demand for technical skills to be positively related to ICT skills (hypothesis 7a) because individuals can be expected to train their ICT skills to the levels demanded at the labour market (constructivist learning theory). At the same time, we expect a high labour market demand for technical skills to be positively related to individuals' ICT usage (hypothesis 7b), because many individuals should be expected to apply ICT skills in their jobs (social practice theory). Yet, a high demand for ICT skills could very well mean a high demand for high-educated workers (at the cost of medium-educated workers and with little effect on low-educated workers) in general (polarized skill demand: e.g., Michaels et al., 2014). In this respect, the suggested positive relationships between demand for technical skills need and ICT usage and ICT skills should be driven by the highly educated (hypothesis 7c and 7d).

With a country's level of gender equality, we try to capture cultural factors on the macro-level. Previous research found that in countries with high(er) levels of gender inequality, women are likely to be less exposed to ICT and have thus fewer possibilities to train and use ICT skills (Doney & Canon, 1997; Frenkel, 1990; Wei et al., 2011). We, therefore, understand the level of gender inequality as an indicator for potential discrimination of a specific gender in their exposure to ICT. We expect to find a positive relationship between a country's level of gender equality and its level of ICT skills (hypothesis *8a)* and ICT use *(hypothesis 8b)*.

2.4 Data

We use the first cycle of the OECD's Programme of the International Assessment of Adult Competencies (OECD, 2017b: ZA6712), surveyed between 2011 and 2018. PIAAC was initiated by the Organisation for Economic Cooperation and Development (OECD) and aims to provide internationally comparable measures of key competencies, such as literacy, numeracy, and adaptive problem-solving – including a measure for ICT skills – in OECD countries among adults aged 16-65 years. We combine the individual-level PIAAC data with country-level data from the OECD, the World Bank, the UN, Eurostat, and the European Commission (see also the variable section below).

The overall sample of the first PIAAC cycle includes 232,686 respondents. However, ICT skills are assessed only for 149,582 persons who reported previous experience using computers, consented to a computer-based skills assessment, and demonstrated basic capability using the computer keyboard and mouse. After only selecting European countries (but excluding Russia), we are left with 81,736 respondents in 18 countries. Being interested in ICT use in everyday life and work, we further restricted our sample to the working population, i.e., respondents who do not define themselves as students or apprentices, leaving our analytical sample at 55,082. Lastly, we listwise delete on our individual level control variables, ending up with 52,392 working respondents across 18 European countries. Table A1.1 in the Appendix shows our case numbers by country and survey year; Table A1.2. shows the number of cases we lose due to our list-wise deletion.

We adjust the final full sample weight to our analytical sample, considering our population of working adults as well as our listwise deletion on independent variables. We make sure to normalize the weights so that their sum equals the number of respondents in our sample. In this way, we circumvent the problem that the weights after listwise deletion deviate from the number of respondents used in our analyses, and we ensure between-model comparisons (similar to what OECD's PISA advices: OECD, 2009).

2.4.1 Variables

2.4.1.1 Independent variable

In the assessment framework of PIAAC ICT skills are referred to as problem-solving in technology-rich environments and defined as "using digital technology, communication tools, and networks to acquire and evaluate information, communicate with others and perform practical tasks" (OECD, 2019c). The ICT skill domain is measured using computer-based assessments based on near real-life problems. Because the real proficiency can only be inferred from their assessment responses, in the surveys, plausible values are used to make a correct inference. A plausible value is a likely score of proficiency drawn from the marginal posterior of the latent distribution. The ten plausible values that are drawn yield unbiased estimates of the real proficiency scores (OECD, 2019b, 2019a). The items were scaled using item response theory (Davier et al., 2009). Scores range from zero to 500 points, with an average of 250 points and a standard deviation of 50 points. Following Bol et al. (2014) and Jacobs and Wolbers (2018) we average out the 10 estimates from the 10 plausible values via a multiple imputation procedure. We calculated the standard errors taking into account the within and between variance of the plausible values.

2.4.1.2 Dependent variables

At the individual level, we include gender, age, age squared, educational attainment in four categories (lower secondary or less, upper secondary, post-secondary, tertiary), parental education attainment in four categories (neither parent obtained upper secondary degree, at least one parent obtained upper secondary degree, at least one parent obtained tertiary degree, don't know), migration status (non-migrants and migrants) and literacy proficiency. The latter is obtained in the same manner as the ICT skills with the PIAAC questionnaire, though we use the posterior mean of the literacy domain of the test (see OECD, 2019c). Furthermore, we construct an index of ICT use in daily life and an index of ICT use at work. For the former index, we average seven Lickert scored items (from 1=never to 5=every day) on the question how often one uses the computer to have real-time discussions, program language, Word, spreadsheets, and the internet to conduct transactions, to look up information on health, finances or environmental issues or for e-mail (Cronbach's Alpha: 0.6741). With regard to our index on ICT at work, the items are using the same wording, except for item on the searching for information that now is on searching for issues related to work (Cronbach's Alpha: 0.7477). As these questions on job-related ICT use require to have used a computer at the job (and about 20% did not use a computer at one's job), we still include the latter group of people by giving them a 1 on this scale ("never" category). Lastly, participation in formal or non-formal adult education or training is derived from separate questions on participation in either type of education or training in the last 12 months before they set out the survey. The elements are later combined, having either not participated (=0), participated (=1), or for those in the last 12 months who were (partly) still in formal education (=2). All our individual-level variables are derived from the PIAAC data.

Our macro-level variables we derived from different data sources, as indicated below[5]. For ICT infrastructure and ICT services, we built indices consisting of several variables. For adult education, we

[5] Most country-level characteristics are a yearly statistic and are matched with the year in which the survey has been administered. This could be different between respondents, as the PIAAC rounds are administered in different years . For some indicators this was not possible and a statistics from a different year has been matched. As digitally applying for a job was surveyed every other year, the percentage has been averaged over the adjacent two years (e.g. for 2012, the average of 2011 and 2013 has been taken). The same holds for internet access in 2014, whereas the internet access for those surveyed in 2017 have also been used for those surveyed in 2018. One underlying variable in the factor score of the country's daily ICT use, about making an online appointment with a practitioner, uses the statistics for both the year prior as the year in which PIAAC has been administered. For the indicator about the countries training participation the statistic for 2011 is used for countries that administered their PIAAC survey in 2011, 2012 and 2013. The statistic in 2016 has been used for survey years 2014, 2015, 2016, 2017 and 2018.

use a single indicator, and for gender equality we use an already existing index. For the technical skill demand, we use three separate indicators all measuring different aspects of skill demand.

ICT infrastructure (standardized index). To capture a country's ICT infrastructure, we use three indicators derived from OECD Statistics that we combined to an index: broadband subscriptions per 100 inhabitants (OECD, 2021c), computer access and internet access (OECD, 2021a). We construct a standardised index with a mean of 0 and a standard deviation of 1 (Cronbach's Alpha 0.9395).

Governmental and private ICT services (standardized index; usage). To capture ICT usage on the macro-level we used four variables derived from the European Commission (2021a, 2021b, 2021c, 2021d) that we combined into an index: the extent to which people (aged 16-74) use a digital form in contact with public authorities in the last 12 months, used online banking in the last 3 months, make an online appointment with a practitioner via a website in the last 3 months and search and apply for a job digitally in the last 3 months. All four underlying factors, just as the averaged index (Cronbach's Alpha: 0.8056) are expressed as a percentage ranging from 0 to 100.

Adult education. We use one indicator to capture the participation in a country's adult education system: derived from the Adult Education Survey by Eurostat (2021b), we use the percentage of formal and non-formal education and training of adults between 25-64 years old in the 12 months prior to the interview.

Technical skills demand. To capture a country's technical skills demand, we use three indicators. First, the average index of shortage of engineering and technology knowledge and technical skills at the labour market (OECD, 2021b) and has a theoretical range from -1 to +1, whereby the maximum value reflects the strongest shortage observed across OECD countries. Second, we create five quintiles of employment in the high- and medium-high technology manufacturing and knowledge-intensive services (Eurostat, 2021a). Third, we use the percentage of ICT-related imports of all imported goods (Worldbank, 2021).

Gender equality. To capture broader cultural differences between countries, we include the Gender Inequality Index as derived by the United Nations Development Programme (2021), which comprises inequality in achievements between women and men in three dimensions: reproductive health, empowerment, and the labour market. A 0 reflects the situation in which women and men are equal, and a 1 reflects the situation where one gender is maximally unequal in all measured dimensions.

2.5 Analytical strategy

To test our hypotheses, we proceed in four general steps: estimation of (1) a null model, (2) individual-level indicators, (3) step-wise models of country-level indicators, and (4) cross-level interaction models. Second, we estimate proficiency in ICT skills using multilevel mixed-effects models and whether the proficiency differs on individual-level characteristics. Third, we estimate the effect of different country-level contexts on individuals' ICT skills. We do this by estimating the country-level coefficients separately before a model with all indicators together. Fourthly, we assess whether the effect of various country-level characteristics vary over composition indicators, including education to test our hypothesis 6c (the positive relationships between demand for technical skills need and ICT usage and ICT skills should be driven by the highly educated) (for a detailed analytical strategy see Appendix 2).

2.6. Results

2.6.1 Descriptive results

In Table 1 we show descriptive statistics of the variables that we include in our analyses, for all countries separate and for the complete analytical sample. These variables are obtained by using replicate weighted adjustments. The correlation matrix and the matrices for each country separately are found in Appendix 3 and 4.

Our overall average ICT skill score is 281.96 for the countries and the respondents in our analytical sample. Compared to the average of all countries which administered the ICT skill test, which is 276.38, the average of our sample is higher. This is both due to country selection and due to respondents in the countries that have a job. The average age of our sample is 40.03 years, and our sample consists of 47% of women. About 40% obtained an upper secondary degree, 43% obtained a form of a tertiary degree, and 28% of the respondents indicate that at least one parent obtained a tertiary degree as well. About 10% of the sample are migrants. The factor score of ICT use in daily life on a scale from 1 to 5 was 2.74, and the factor score of ICT at work on a scale from 1 to 5 was 2.54. Assessing these numbers, our sample is a positive selection of the general population. With regard to the differences in ICT skills across countries, one can see in Figure 2 that Sweden is on top equalling the average proficiency over all countries, while Greece is at the bottom.

Table 1. Descriptive statistics of the variables concerned in the multivariate analyses.

	TOTAL	(N=52392)			AUT	(N=2726)	BELL	(N=2794)	CZE	(N=2499)	DEU	(N=2988)	DNK	(N=4158)
	mean	sd	min	max	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Age	40.03	11.35	16.00	65.00	38.91	11.10	41.03	10.85	38.79	10.76	41.72	11.15	42.88	11.32
Age squared	1730.88	935.10	256.00	4225.00	1637.39	872.90	1800.90	901.21	1620.14	882.44	1865.27	928.03	1966.44	967.88
Lower secondary or less (ISCED 1.2. 3C short or less)	0.10	0.30	0	1	0.10	0.30	0.08	0.27	0.04	0.19	0.06	0.23	0.13	0.34
Upper secondary (ISCED 3A-B. C long)	0.40	0.49	0	1	0.53	0.50	0.39	0.49	0.66	0.47	0.46	0.50	0.38	0.49
Post-secondary. non-tertiary (ISCED 4A-B-C)	0.07	0.25	0	1	0.14	0.34	0.04	0.20	0.03	0.18	0.08	0.27	0.02	0.13
Tertiary (ISCED 5/6)	0.43	0.50	0	1	0.24	0.43	0.50	0.50	0.27	0.44	0.41	0.49	0.47	0.50
Participated in formal or non-formal AET in 12 months preceding survey (No)	0.34	0.47	0	1	0.37	0.48	0.39	0.49	0.33	0.47	0.35	0.48	0.23	0.42
Participated in formal or non-formal AET in 12 months preceding survey (Yes)	0.63	0.48	0	1	0.60	0.49	0.60	0.49	0.65	0.48	0.63	0.48	0.75	0.43
Participated in formal or non-formal AET in 12 months preceding survey (Still in formal initial education)	0.03	0.18	0	1	0.03	0.17	0.02	0.13	0.02	0.13	0.02	0.15	0.02	0.14
Gender (=1 female)	0.47	0.50	0	1	0.47	0.50	0.46	0.50	0.40	0.49	0.44	0.50	0.48	0.50
Factor score ICT use daily life	2.74	0.65	1	5	2.60	0.64	2.70	0.60	2.87	0.61	2.66	0.63	2.93	0.62
Factor score ICT use at work	2.54	1.08	1	5	2.51	1.02	2.58	1.02	2.50	1.10	2.46	1.02	2.75	1.02
Migration status (= 1 migrants)	0.10	0.30	0	1	0.15	0.36	0.06	0.24	0.04	0.21	0.17	0.37	0.08	0.27
Neither parent has attained upper secondary	0.25	0.43	0	1	0.19	0.40	0.32	0.47	0.05	0.23	0.07	0.25	0.29	0.45
At least one parent has attained secondary and post-secondary. non-tertiary	0.44	0.50	0	1	0.57	0.49	0.38	0.49	0.76	0.43	0.52	0.50	0.38	0.49
At least one parent has attained tertiary	0.28	0.45	0	1	0.22	0.41	0.27	0.45	0.17	0.38	0.37	0.48	0.32	0.47
Parental education: Don't know	0.03	0.18	0	1	0.02	0.13	0.03	0.17	0.02	0.14	0.04	0.20	0.01	0.08
Literacy scale score - Posterior mean	282.91	38.79	121.68	412.19	280.66	35.03	287.36	37.96	280.77	35.67	279.16	40.19	282.44	36.20
ICT Skill Score - Replicate sampling	281.96	42.83	73.06	488.72	285.76	36.34	283.58	42.07	284.85	44.81	283.96	42.66	285.53	40.50
ICT infrastructure (standardized index)	0.01	0.95	-1.62	1.54	-0.52		-0.07		-1.10		0.55		1.31	
Governmental and private ICT services (standardized index; usage)	30.46	10.92	14.44	51.16	24.68		27.75		17.77		21.84		50.40	
Adult education: % participate in adult learning	45.86	13.84	16.70	71.80	48.20		37.70		37.10		50.20		58.50	
Technical skills demand 1: Average index of shortage of engineering and technology knowledge and technical skills at the labour market	0.04	0.10	-0.15	0.18	0.02		-0.11		0.18		0.06		0.13	
Technical skills demand 2: Quintiles of working in the high- and medium-high technology manufacturing and knowledge-intensive services	2.97	1.41	1.00	5.00	4.00		3.00		5.00		5.00		3.46	
Technical skills demand 3: % of ICT goods of all the country's import	8.40	3.25	3.10	15.82	5.01		3.29		15.34		7.98		7.99	
Gender equality index	0.11	0.06	0.05	0.26	0.10		0.09		0.12		0.05		0.06	

Source: PIAAC First Cycle

Table 1. Descriptive statistics of the variables concerned in the multivariate analyses (continued)

	EST	(N=3613)	FIN	(N=3132)	GBRE	(N=2786)	GBRN	(N=1786)	GRC	(N=1643)	HUN	(N=2764)	IRL	(N=2404)
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Age	38.69	11.25	41.42	11.61	39.78	11.94	37.93	11.60	38.59	10.04	40.66	11.14	37.61	10.60
Age squared	1623.44	920.50	1850.10	971.18	1724.81	974.87	1573.32	926.89	1589.77	798.47	1777.79	931.60	1527.14	850.18
Lower secondary or less (ISCED 1.2. 3C short or less)	0.08	0.27	0.07	0.26	0.14	0.35	0.17	0.38	0.14	0.35	0.08	0.27	0.09	0.29
Upper secondary (ISCED 3A-B. C long)	0.35	0.48	0.37	0.48	0.38	0.49	0.37	0.48	0.32	0.47	0.35	0.48	0.20	0.40
Post-secondary. non-tertiary (ISCED 4A-B-C)	0.06	0.24	0.05	0.21	0.00	0.05	0.00	0.00	0.10	0.30	0.16	0.36	0.17	0.38
Tertiary (ISCED 5/6)	0.51	0.50	0.52	0.50	0.47	0.50	0.46	0.50	0.43	0.50	0.42	0.49	0.53	0.50
Participated in formal or non-formal AET in 12 months preceding survey (No)	0.30	0.46	0.21	0.40	0.30	0.46	0.31	0.46	0.63	0.48	0.51	0.50	0.30	0.46
Participated in formal or non-formal AET in 12 months preceding survey (Yes)	0.65	0.48	0.77	0.42	0.65	0.48	0.63	0.48	0.35	0.48	0.47	0.50	0.66	0.48
Participated in formal or non-formal AET in 12 months preceding survey (Still in formal initial education)	0.04	0.20	0.03	0.16	0.05	0.22	0.06	0.24	0.02	0.15	0.02	0.15	0.05	0.21
Gender (=1 female)	0.52	0.50	0.50	0.50	0.46	0.50	0.48	0.50	0.40	0.49	0.47	0.50	0.51	0.50
Factor score ICT use daily life	2.81	0.62	2.76	0.57	2.74	0.66	2.60	0.68	2.39	0.73	2.70	0.72	2.73	0.68
Factor score ICT use at work	2.56	1.16	2.61	0.96	2.65	1.10	2.54	1.09	2.12	1.09	2.48	1.16	2.59	1.11
Migration status (= 1 migrants)	0.20	0.40	0.03	0.17	0.17	0.38	0.07	0.26	0.06	0.25	0.03	0.18	0.19	0.39
Neither parent has attained upper secondary	0.17	0.38	0.36	0.48	0.18	0.39	0.28	0.45	0.55	0.50	0.19	0.39	0.39	0.49
At least one parent has attained secondary and post-secondary. non-tertiary	0.40	0.49	0.42	0.49	0.39	0.49	0.45	0.50	0.27	0.45	0.54	0.50	0.33	0.47
At least one parent has attained tertiary	0.39	0.49	0.20	0.40	0.24	0.43	0.19	0.39	0.17	0.38	0.27	0.44	0.25	0.43
Parental education: Don't know	0.04	0.19	0.02	0.12	0.18	0.39	0.08	0.26	0.00	0.02	0.00	0.07	0.03	0.17
Literacy scale score - Posterior mean	281.09	38.72	298.87	38.99	284.73	40.76	281.45	38.72	253.98	39.98	279.21	33.84	282.51	37.85
ICT Skill Score - Replicate sampling	276.44	42.53	290.26	40.79	287.53	39.90	282.31	38.89	257.59	51.44	281.76	40.29	281.19	38.99
ICT infrastructure (standardized index)	-0.91		0.36		0.43		0.49		-1.22		0.07		-0.41	
Governmental and private ICT services (standardized index; usage)	37.56		44.20		22.87		24.60		16.55		28.23		25.51	
Adult education: % participate in adult learning	49.90		55.70		35.80		35.80		16.70		55.70		24.40	
Technical skills demand 1: Average index of shortage of engineering and technology knowledge and technical skills at the labour market	-0.15		0.13		0.12		0.12		-0.04		-0.10		0.11	
Technical skills demand 2: Quintiles of working in the high- and medium-high technology manufacturing and knowledge-intensive services	2.00		4.00		2.00		2.00		1.00		5.00		3.00	
Technical skills demand 3: % of ICT goods of all the country's import	11.10		7.08		8.04		7.88		4.31		12.52		8.32	
Gender equality index	0.16		0.08		0.21		0.21		0.14		0.26		0.12	

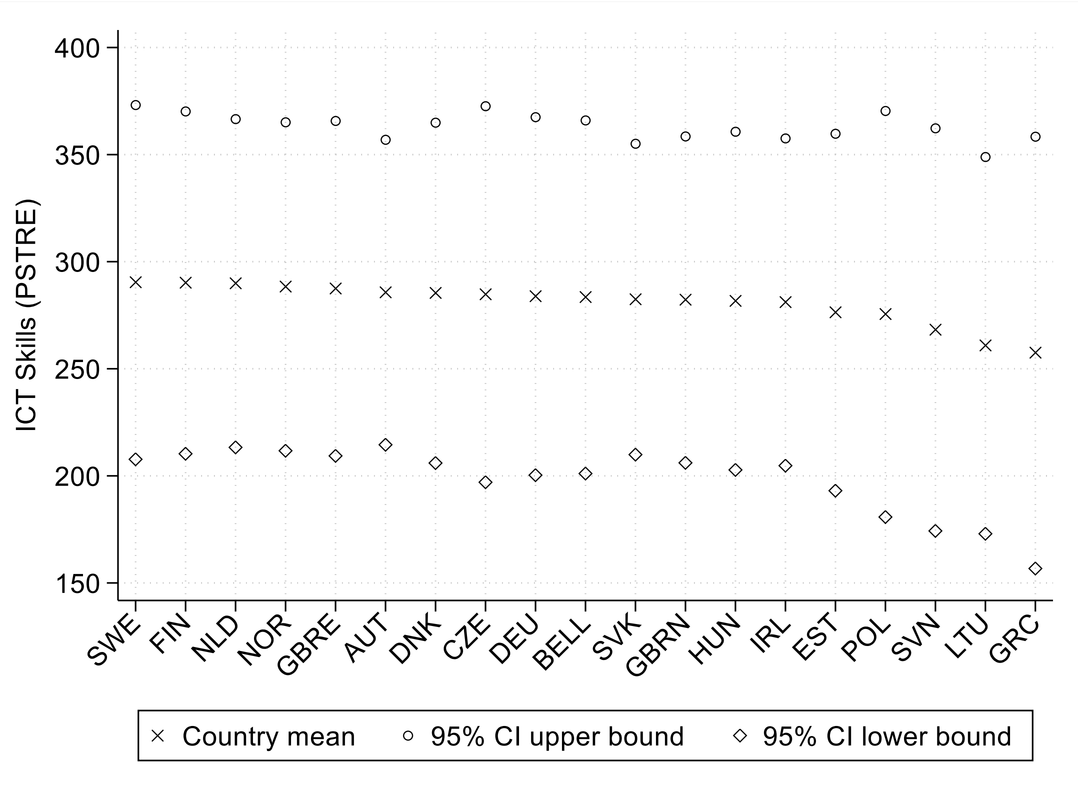
Source: PIAAC First Cycle

Table 1. Descriptive statistics of the variables concerned in the multivariate analyses (continued)

	LTU	(N=2509)	NLD	(N=3255)	NOR	(N=3168)	POL	(N=2887)	SVK	(N=2097)	SVN	(N=2367)	SWE	(N=2816)
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Age	38.91	11.78	41.25	11.74	41.46	11.86	35.93	10.25	37.97	10.55	40.12	9.56	41.76	12.18
Age squared	1653.11	945.31	1839.53	977.74	1859.57	1000.84	1395.85	810.84	1552.81	845.74	1700.76	789.34	1892.36	1026.18
Lower secondary or less (ISCED 1.2. 3C short or less)	0.04	0.20	0.20	0.40	0.16	0.36	0.03	0.17	0.03	0.17	0.07	0.26	0.12	0.32
Upper secondary (ISCED 3A-B. C long)	0.33	0.47	0.40	0.49	0.28	0.45	0.39	0.49	0.62	0.48	0.54	0.50	0.43	0.49
Post-secondary. non-tertiary (ISCED 4A-B-C)	0.20	0.40	0.00	0.00	0.10	0.31	0.06	0.24	0.01	0.09	0.00	0.00	0.09	0.29
Tertiary (ISCED 5/6)	0.42	0.49	0.40	0.49	0.46	0.50	0.52	0.50	0.34	0.47	0.39	0.49	0.36	0.48
Participated in formal or non-formal AET in 12 months preceding survey (No)	0.48	0.50	0.24	0.43	0.26	0.44	0.38	0.48	0.46	0.50	0.36	0.48	0.25	0.43
Participated in formal or non-formal AET in 12 months preceding survey (Yes)	0.46	0.50	0.72	0.45	0.71	0.45	0.57	0.50	0.52	0.50	0.64	0.48	0.72	0.45
Participated in formal or non-formal AET in 12 months preceding survey (Still in formal initial education)	0.06	0.23	0.03	0.18	0.03	0.17	0.05	0.22	0.02	0.16	0.01	0.08	0.03	0.17
Gender (=1 female)	0.51	0.50	0.46	0.50	0.47	0.50	0.45	0.50	0.44	0.50	0.46	0.50	0.47	0.50
Factor score ICT use daily life	2.54	0.72	2.82	0.58	2.83	0.56	2.73	0.69	2.79	0.71	2.78	0.65	2.74	0.59
Factor score ICT use at work	2.13	1.16	2.68	0.99	2.71	0.96	2.43	1.11	2.43	1.14	2.55	1.11	2.55	0.96
Migration status (= 1 migrants)	0.03	0.18	0.10	0.31	0.11	0.31	0.00	0.07	0.02	0.15	0.14	0.35	0.15	0.36
Neither parent has attained upper secondary	0.25	0.43	0.47	0.50	0.24	0.43	0.11	0.31	0.14	0.34	0.24	0.43	0.36	0.48
At least one parent has attained secondary and post-secondary. non-tertiary	0.21	0.41	0.27	0.44	0.41	0.49	0.67	0.47	0.69	0.46	0.54	0.50	0.24	0.43
At least one parent has attained tertiary	0.53	0.50	0.25	0.43	0.35	0.48	0.21	0.41	0.17	0.38	0.20	0.40	0.36	0.48
Parental education: Don't know	0.01	0.10	0.01	0.12	0.01	0.11	0.01	0.12	0.00	0.06	0.01	0.12	0.04	0.19
Literacy scale score - Posterior mean	273.56	36.95	293.75	38.96	288.34	37.91	281.41	38.31	284.72	30.69	267.58	40.15	292.64	38.51
ICT Skill Score - Replicate sampling	260.96	44.89	290.03	39.10	288.44	39.13	275.52	48.37	282.57	37.01	268.31	47.97	290.54	42.16
ICT infrastructure (standardized index)	-1.24		1.51		1.17		-1.52		-1.02		-0.49		0.93	
Governmental and private ICT services (standardized index; usage)	29.13		39.96		42.64		14.95		19.25		19.99		41.48	
Adult education: % participate in adult learning	27.90		59.30		60.00		24.20		41.60		46.10		71.80	
Technical skills demand 1: Average index of shortage of engineering and technology knowledge and technical skills at the labour market	0.06		0.00		0.13		0.08		0.10		-0.06		-0.09	
Technical skills demand 2: Quintiles of working in the high- and medium-high technology manufacturing and knowledge-intensive services	1.00		1.00		1.00		3.00		5.00		4.00		2.00	
Technical skills demand 3: % of ICT goods of all the country's import	4.24		12.71		6.96		7.63		12.92		3.75		10.35	
Gender equality index	0.16		0.05		0.07		0.14		0.17		0.08		0.06	

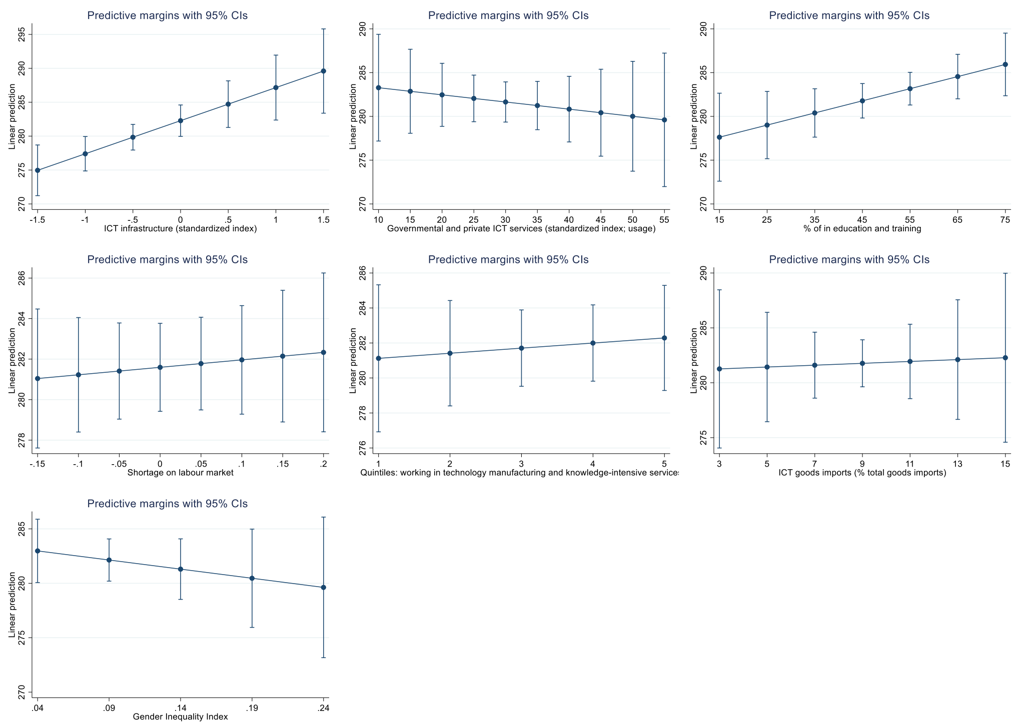
Source: PIAAC First Cycle

Figure 2. Country ICT skills averages



Source: PIAAC First Cycle

Figure 3. Country Level Effects



Source: PIAAC First Cycle

2.6.2 Multivariate results

Our multilevel random intercept regression analyses (see Table 2) show a grand mean of ICT skills estimated within the null model of 280.80, with a country level variance of about 87.83 and an individual (or residual) level variance of 1762.30. Calculating the intraclass correlation – (87.83 / (87.83 + 1762.30)) = 0.047 – shows that there is reason to assume clustering and thus a need for multilevel modelling.

In all our models, we run one estimation with and one without including ICT use at home and the workplace, as our theoretical model indicates (see hypothesis 3: The positive association between literacy skills and ICT skills is partly mediated by ICT use at work and in everyday life). As the individual level composition indicators are estimated in the second model, both the variance at the individual level and at the country level are reduced. The individual-level variance has been reduced by 59.8%, and the country-level variance by 70.6%. This means that there are composition effects that explain differences between countries in ICT skills.

Hypothesis 1: The more intense an individual's ICT use at work and in everyday life, the higher his or her ICT skills In Model 3, we include individual ICT use at home and at work, resulting in a further variance reduction: at the country level, a further 17.3% of the variance is explained compared to Model 2, and at the individual level, a further 3.4%. The positive correlation between ICT use at home and at work with ICT skills (b=4.833 and b=3.537, respectively) supports our first hypothesis.

In line with previous findings reported above, the composition variables itself show higher ICT skills for men and younger respondents. We find no relationship between the respondents' own educational level and their ICT skills, but a positive relationship between the respondents' parental education and ICT skills.

Hypothesis 2: The higher an individual's literacy skills, the higher his or her ICT skills. In model 2, we see that literacy proficiency does correlate positively with ICT skills (b=0.778), supporting our second hypothesis.

Hypothesis 3: The positive association between literacy skills and ICT skills is partly mediated by ICT use at work and in everyday life In addition, model 3 indicates that literacy proficiency is mediated by the inclusion of ICT use (b=0.737), supporting our third hypothesis. In Appendix 5, a regression with ICT use at home and work is positively related, thus completing the mediation.

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Table 2. Main Regression Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gender (=1 Female)		-3.246***	-2.596***	-3.240***	-2.594***	-3.246***	-2.595***	-3.248***	-2.598***
		(0.631)	(0.623)	(0.632)	(0.624)	(0.631)	(0.624)	(0.631)	(0.623)
Age		-0.505***	-0.606***	-0.509***	-0.608***	-0.505***	-0.606***	-0.505***	-0.605***
		(0.147)	(0.157)	(0.147)	(0.157)	(0.147)	(0.157)	(0.147)	(0.157)
Age squared		-0.000449	0.000744	-0.000408	0.000767	-0.000448	0.000748	-0.000462	0.000733
		(0.00180)	(0.00190)	(0.00181)	(0.00191)	(0.00181)	(0.00191)	(0.00181)	(0.00191)
Upper secondary (ISCED 3A-B, C long)		1.579	0.607	1.623	0.651	1.576	0.597	1.584	0.612
		(1.451)	(1.425)	(1.443)	(1.418)	(1.452)	(1.428)	(1.450)	(1.424)
Post-secondary, non-tertiary (ISCED 4A-B-C)		2.476	0.580	2.561	0.663	2.475	0.573	2.486	0.591
		(2.031)	(1.885)	(2.030)	(1.883)	(2.031)	(1.885)	(2.030)	(1.884)
Tertiary (ISCED 5/6)		4.314***	0.412	4.382***	0.489	4.312***	0.402	4.326***	0.425
		(1.288)	(1.244)	(1.288)	(1.238)	(1.290)	(1.247)	(1.290)	(1.245)
At least one parent has attained secondary and post-secondary, non-tertiary		2.374**	1.705*	2.386**	1.721*	2.373**	1.702*	2.376**	1.706*
		(0.804)	(0.789)	(0.800)	(0.786)	(0.803)	(0.788)	(0.807)	(0.793)
At least one parent has attained tertiary		4.021***	2.582**	4.000***	2.572**	4.022***	2.584**	4.017***	2.578**
		(1.086)	(0.958)	(1.086)	(0.958)	(1.089)	(0.960)	(1.087)	(0.959)
Parental education: Don't know		1.671	1.562	1.672	1.564	1.667	1.552	1.676	1.566
		(1.778)	(1.773)	(1.760)	(1.760)	(1.778)	(1.777)	(1.774)	(1.770)
Migration status (= 1 migrants)		-1.243	-1.413	-1.279	-1.443	-1.241	-1.407	-1.247	-1.417
		(1.468)	(1.654)	(1.474)	(1.658)	(1.471)	(1.657)	(1.468)	(1.654)
Literacy scale score - Posterior mean		0.778***	0.737***	0.777***	0.737***	0.778***	0.737***	0.778***	0.737***
		(0.0156)	(0.0170)	(0.0154)	(0.0169)	(0.0156)	(0.0170)	(0.0155)	(0.0170)
FNF AET in 12 months preceding survey (Yes)		2.980***	1.256	2.997***	1.273	2.980***	1.255	2.973***	1.249
		(0.691)	(0.694)	(0.687)	(0.690)	(0.691)	(0.694)	(0.690)	(0.694)
FNF AET in 12 months preceding survey (Still in formal initial education)		4.639**	3.155	4.672**	3.184	4.638**	3.151	4.636**	3.152
		(1.707)	(1.912)	(1.720)	(1.920)	(1.705)	(1.906)	(1.708)	(1.913)
Factor score ICT use daily life			4.833***		4.814***		4.836***		4.830***
			(0.741)		(0.740)		(0.742)		(0.741)
Factor score ICT use at work			3.537***		3.521***		3.539***		3.537***
			(0.392)		(0.387)		(0.393)		(0.392)
ICT infrastructure (standardized index)				6.046***	4.880**				
				(1.678)	(1.557)				
Governmental and private ICT services (standardized index; usage)						-0.0290	-0.0816		
						(0.161)	(0.147)		
Adult education: % participate in adult learning								0.166*	0.139*
								(0.0718)	(0.0662)
Technical skills demand 1: Average index of shortage of engineering and technology knowledge and technical skills at the labour market									
Technical skills demand 2: Quintiles of working in the high- and medium-high technology manufacturing and knowledge-intensive services									
Technical skills demand 3: % of ICT goods of all the country's import									
Gender inequality index									
_cons	280.8***	77.33***	72.28***	78.21***	73.01***	78.18***	74.67***	69.99***	66.15***
	(2.290)	(5.858)	(5.902)	(5.346)	(5.475)	(7.478)	(7.402)	(7.594)	(7.335)
Var(_cons)	87.83***	25.83***	21.36***	25.10***	19.25***	26.63***	23.08***	20.08***	17.32***
	(34.59)	(11.29)	(8.555)	(10.09)	(7.191)	(11.74)	(9.359)	(7.383)	(5.732)
Var(Residual)	1762.3***	709.2***	685.0***	708.4***	684.5***	709.2***	685.0***	709.2***	685.0***
	(70.42)	(53.94)	(51.74)	(53.68)	(51.53)	(53.94)	(51.73)	(53.95)	(51.74)
N	52392	52392	52392	52392	52392	52392	52392	52392	52392

Standard errors in parentheses; Models are weighted - PSTRE proficiency obtained by normalized final weights; Plausible values are estimated with multiple imputation techniques; * p<0.05; ** p<0.01; *** p<0.001; Source: PIAAC First Cycle

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Table 2. Main Regression Models (continued)

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Gender (=1 Female)	-3.246***	-2.596***	-3.246***	-2.596***	-3.246***	-2.596***	-3.247***	-2.596***	-3.236***	-2.589***
	(0.631)	(0.623)	(0.631)	(0.623)	(0.631)	(0.623)	(0.631)	(0.623)	(0.634)	(0.627)
Age	-0.505***	-0.606***	-0.505***	-0.606***	-0.505***	-0.606***	-0.505***	-0.606***	-0.511***	-0.611***
	(0.147)	(0.156)	(0.147)	(0.157)	(0.147)	(0.157)	(0.147)	(0.157)	(0.148)	(0.158)
Age squared	-0.000450	0.000744	-0.000449	0.000743	-0.000447	0.000742	-0.000450	0.000743	-0.000391	0.000794
	(0.00180)	(0.00190)	(0.00180)	(0.00191)	(0.00181)	(0.00191)	(0.00180)	(0.00190)	(0.00182)	(0.00192)
Upper secondary (ISCED 3A-B, C long)	1.579	0.606	1.579	0.604	1.581	0.605	1.581	0.608	1.598	0.620
	(1.451)	(1.425)	(1.450)	(1.425)	(1.449)	(1.423)	(1.451)	(1.426)	(1.446)	(1.422)
Post-secondary, non-tertiary (ISCED 4A-B-C)	2.477	0.580	2.477	0.578	2.479	0.579	2.481	0.584	2.555	0.661
	(2.031)	(1.885)	(2.031)	(1.886)	(2.029)	(1.885)	(2.031)	(1.886)	(2.032)	(1.884)
Tertiary (ISCED 5/6)	4.315***	0.412	4.315***	0.411	4.316***	0.411	4.318***	0.416	4.361***	0.464
	(1.288)	(1.244)	(1.288)	(1.244)	(1.287)	(1.243)	(1.290)	(1.246)	(1.287)	(1.240)
At least one parent has attained secondary and post-secondary, non-tertiary	2.373**	1.704*	2.374**	1.702*	2.374**	1.704*	2.377**	1.708*	2.382**	1.710*
	(0.804)	(0.790)	(0.802)	(0.789)	(0.805)	(0.790)	(0.804)	(0.790)	(0.793)	(0.779)
At least one parent has attained tertiary	4.021***	2.581**	4.021***	2.580**	4.020***	2.582**	4.022***	2.583**	4.008***	2.578**
	(1.086)	(0.958)	(1.084)	(0.956)	(1.085)	(0.957)	(1.086)	(0.958)	(1.085)	(0.957)
Parental education: Don't know	1.670	1.561	1.671	1.560	1.670	1.562	1.677	1.568	1.627	1.515
	(1.779)	(1.774)	(1.776)	(1.771)	(1.777)	(1.774)	(1.776)	(1.772)	(1.774)	(1.774)
Migration status (= 1 migrants)	-1.242	-1.412	-1.243	-1.410	-1.243	-1.413	-1.245	-1.415	-1.253	-1.418
	(1.468)	(1.655)	(1.470)	(1.656)	(1.468)	(1.654)	(1.468)	(1.654)	(1.479)	(1.665)
Literacy scale score - Posterior mean	0.778***	0.737***	0.778***	0.737***	0.778***	0.737***	0	0	0.777***	0.737***
	(0.0156)	(0.0170)	(0.0156)	(0.0170)	(0.0156)	(0.0170)	(.)	(.)	(0.0154)	(0.0169)
FNF AET in 12 months preceding survey (Yes)	2.979***	1.255	2.980***	1.256	2.981***	1.254	4.638**	3.153	3.011***	1.286
	(0.692)	(0.694)	(0.691)	(0.694)	(0.690)	(0.694)	(1.708)	(1.913)	(0.689)	(0.691)
FNF AET in 12 months preceding survey (Still in formal initial education)	4.639**	3.154	4.639**	3.154	4.639**	3.155	0.778***	0.737***	4.670**	3.184
	(1.707)	(1.912)	(1.707)	(1.912)	(1.708)	(1.911)	(0.0156)	(0.0170)	(1.708)	(1.904)
Factor score ICT use daily life		4.833***		4.834***		4.833***		4.833***		4.815***
		(0.741)		(0.741)		(0.741)		(0.741)		(0.738)
Factor score ICT use at work		3.537***		3.537***		3.537***		3.537***		3.527***
		(0.392)		(0.392)		(0.390)		(0.392)		(0.387)
ICT infrastructure (standardized index)									8.421***	7.431***
									(1.944)	(1.893)
Governmental and private ICT services (standardized index; usage)									-0.322*	-0.342**
									(0.131)	(0.123)
Adult education: % participate in adult learning									-0.0930	-0.0677
									(0.160)	(0.156)
Technical skills demand 1: Average index of shortage of engineering and technology knowledge and technical skills at the labour market	5.030	3.684							-5.457	-5.862
	(9.140)	(8.637)							(11.27)	(10.59)
Technical skills demand 2: Quintiles of working in the high- and medium-high technology manufacturing and knowledge-intensive services			0.0241	0.291					0.833	0.764
			(0.894)	(0.747)					(0.720)	(0.612)
Technical skills demand 3: % of ICT goods of all the country's import					-0.0849	0.0848			0.223	0.234
					(0.693)	(0.607)			(0.407)	(0.403)
Gender inequality index							-19.92	-16.77	8.690	4.514
							(22.87)	(21.27)	(16.73)	(15.36)
_cons	77.17***	72.16***	77.26***	71.40***	78.04***	71.58***	79.64***	74.22***	86.92***	81.85***
	(5.760)	(5.801)	(6.537)	(6.610)	(8.924)	(8.540)	(5.702)	(5.764)	(7.438)	(7.473)
Var(_cons)	25.58***	21.22***	26.04***	20.46***	26.97***	21.04***	24.52***	20.43***	12.60***	10.32***
	(11.55)	(8.706)	(13.21)	(8.681)	(13.80)	(8.693)	(10.09)	(7.629)	(5.946)	(5.132)
Var(Residual)	709.2***	685.0***	709.2***	685.0***	709.2***	685.0***	709.2***	685.0***	708.1***	684.2***
	(53.94)	(51.74)	(53.95)	(51.74)	(53.95)	(51.73)	(53.94)	(51.74)	(53.62)	(51.46)
N	52392	52392	52392	52392	52392	52392	52392	52392	52392	52392

Standard errors in parentheses; Models are weighted - PSTRE proficiency obtained by normalized final weights; Plausible values are estimated with multiple imputation techniques; * p<0.05; ** p<0.01; *** p<0.001; Source: PIAAC First Cycle

Hypothesis 4: The better a countries ICT infrastructure, the more intense the individuals' ICT use at work and in everyday life. In models 4 and 5, we include our index for the countries' ICT infrastructure. Comparing the variance of model 3 – only composition variables – and model 5 – including the technical conditions – we see a reduction at the country-level (about 10%) but not at the individual level. The coefficients of our ICT infrastructure index are in both models positive, though smaller when we include ICT use at the individual level (b=6.046 and b=4.880). Moreover, the table in Appendix 5 showing the regression on the use of ICT also shows a positive association with ICT infrastructure. We understand this as support for our fourth hypothesis.

Hypothesis 5a and 5b: We expect to find ICT use by the government and private businesses to be positively related to ICT skills and individuals' ICT usage. In models 6 and 7, we include our country indicator of ICT use by the government and private businesses. The variances are virtually the same, if not higher, thus not contributing to explaining variance at either country or individual level. The indicator of ICT use by the government and private businesses also does not show any meaningful or statistically significant effect (b=-0.029 and b=-0.082). However, in the full models (18/19), this indicator shows statistical significance for ICT skills and ICT use supporting our hypotheses 5a and 5b. ICT use by the government and private businesses does show, however, a positive relationship with the governmental and private ICT services use (see Appendix 5), supporting our hypothesis 5b (usage).

Hypothesis 6: We expect to find a positive relationship between participation in adult education and ICT skills. In models 8 and 9 we include our indicator for participation in adult education and training. The variance at the country level shows a drop (18.9% compared to model 3), which translates in a positive association between a country's participation rate in adult education and ICT skills (b=0.139), supporting our sixth hypothesis.

Hypothesis 7a and 7b: We expect to find a high labour market demand for technical skills to be positively related to ICT skills and to individuals' ICT usage. Model 10 to 15 include our country-level indicators for the technical skills demand. A shortage of engineering and technology knowledge or a technical skills shortage at the labour market do not correlate with individuals' ICT skills, neither does the employment of people working in the high- and medium-high technology manufacturing and knowledge-intensive services, nor the import of ICT goods. The variance at the country and individual level compared to model 3 drops 6%, 4.2%, and 1.4%, respectively. We thus find no support for our hypothesis 7a. We also find no relationship between a country's technical skills demand and individuals' ICT usage (see Appendix 5) when it comes to the shortage of skills and employment in technological fields, therewith not supporting our hypothesis 7b. Moreover, for ICT goods import, a negative coefficient is found, thus contradicting the hypothesis.

Hypothesis 8a and 8b: We expect to find a country's level of gender equality to be positively related to ICT skills and to individuals' ICT usage. In models 16 and 17, we take the broader cultural context into account by adding the country's gender equality index score. Though the country level variance drops somewhat (4.3%), the indicator does not show any statistically significant association with ICT skills nor ICT use (Appendix 5), and hence no support for our hypotheses 8a and b[6].

2.6.3 All models combined

In our final models (18 and 19), we include all country-level variables at once. Compared to a composition model only (model 3), the variance drops by more than half (51.6%), and the indices for ICT infrastructure and public and private ICT usage show a meaningful and statistically significant association with ICT skills. The same holds for the gender inequality index. For the inclusion of a countries daily ICT use, the relationship is contrary to expectation negative, meaning that the more people on average in a country make daily use of ICT services, the lower the ICT skills on average, conditional on all other country-level variables. We have to interpret this with caution, as the degrees of freedom at the country level are limited as we only include 18 countries.

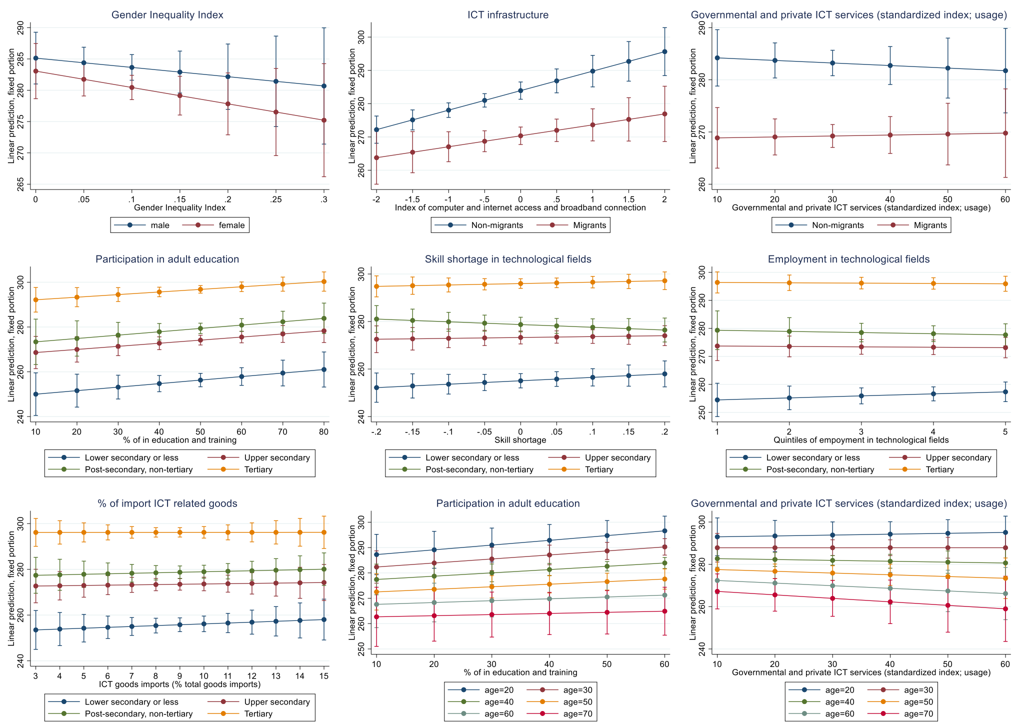
2.6.4 Cross-level interaction models

As can be seen in Appendix 6 and illustrated in Figures 4 below, our interaction models are showing little traction. The effect of the country's gender equality index does not differ over the respondent's gender, nor does a country's ICT infrastructure differ over the respondents' migration status. Our index for public and private ICT services does not vary across migration status either.

The country's average adult education participation does not differ over the educational level of the individual. The technical skills demand at the labour market also does not differ over the individuals' educational level and is thus not supporting our *hypotheses 7c (The positive relationships between demand for technical skills need and ICT usage and ICT skills should be driven by the highly educated.*). Whether there is a shortage of engineering and technology knowledge or technical skills shortage at the labour market, or the percentage of people working in the high- and medium-high technology manufacturing and knowledge-intensive services or the percentage ICT-related import does not vary over educational level. Lastly, a country's adult education participation and daily ICT use do not vary over age either. Our results indicate that our macro-level relationships with ICT skills and usage as presented in Table 2 are not group-specific.

[6] Conditional on all other country level indicators, the gender equality index shows a positive sign. However, we refrain from overinterpreting this effect as the degrees of freedom at the country level are limited.

Figure 4. Graphs of interaction effects



Source: PIAAC First Cycle

2.6.5 Robustness checks

In Appendix 7, we show a complete model, only without literacy proficiency. It reveals that the null effect of the educational level and migration status reported in Table 2 is due to the inclusion of literacy proficiency. The size of the coefficients for gender, age and the respondent's education are substantially smaller when literacy scores are included. For age it even flips the coefficient that was negative before ICT skills are lower among the older on given levels of literacy). Without the inclusion of literacy scores, older respondents show higher ICT skills, which seems to be driven by their higher literacy scores. Country-level indicators do not show much difference, indicating to the robustness of our macro-level analyses as presented in Table 2.

To test for country outliers, in Appendix 8, we re-ran our regression model 19 from Table 2 selecting one country out at a time. We found no major differences caused by one country. The country-level indicator on public and private ICT usage shows the most inconsistency, sometimes (close to) being statistically insignificant.

2.7 Summary and discussion

Even though an increase in ICT use and the relevance of ICT skills in work and everyday life are observable worldwide, individuals' ICT proficiency differs considerably across countries. While previous research extensively investigated individual-level determinants of differences in individuals' ICT skills, determinants on the country-level have been either ignored or analysed only for young individuals, missing out on knowledge about the current working population. Our paper contributes to previous research by analysing micro- and macro-level determinants of the working populations' ICT skills across 18 European countries.

Our findings on the micro-level support our predictions derived from practice engagement theory, constructivist learning theories, and social cognitive theory and corroborate with previous research (e.g., Wicht et al., 2021; van Deursen & van Dijk, 2014; Aesaert & van Braak, 2015; Claro et al., 2012; Schleife, 2010): (1) ICT skills are positively related to ICT use at home and the workplace: (2) literacy skills can be considered to be an essential prerequisite of ICT skills; and (3) they partly mediate the positive relationship between ICT skills and ICT use. (2) and (3) further support the literacy hypothesis claiming that specialized skills, such as ICT skills, strongly depend on more general cognitive skills. Our findings once again underline the necessity of literacy skills' incorporation to develop and improve ICT skills.

On the macro-level, we analysed five groups of indicators as potential direct or indirect (through individuals ICT usage) determinants of adults' ICT skills: a country's ICT infrastructure, governmental and private ICT usage, technical skills demand, participation in adult education, and the level of gender equality. Our findings partly support our theoretical expectations: (4) A country's ICT infrastructure is positively related to adults' ICT skills both directly (unexpected) and indirectly through ICT use (expected). In line with our expectations, (5) governmental and private ICT usage is positively related to ICT skills directly and indirectly. The same holds for (6) participation rates in adult education and ICT skills, for which we expected to find a direct, but no indirect relationship (through ICT usage) to ICT skills. In contrast, (7) a high labour market demand for technical skills shows no relationship to adults' ICT skills. Also, our analyses do not show any meaningful relationship between (8) a country's level of gender equality and their working populations' ICT skills.

Our results give a first hint to where policymakers could start in order to promote their working population's ICT skills. Just as on the micro-level, education seems to play a key role in developing ICT skills, as indicated by the positive relationship between a country's participation rate in adult education and the working population's ICT skills. While we could not analyse which type of classes adults participate in, our findings indicate the importance of general (adult) education to develop general cognitive skills as a prerequisite for developing more specialized skills on the macro-level. The permanent interaction of different competencies to foster another one is in line with the ideas of practice engagement theory. The specific role of adult education in developing ICT skills of the younger generation, who could already develop these skills during their school years, remains an open question. In addition to promoting general cognitive competencies, it seems promising for policymakers to provide a good ICT infrastructure that, based on our findings, can foster adults ICT usage and ICT skills. Also, an extensive usage of public and private ICT services – including the use of digital forms with public authorities, making online appointments with practitioners, or searching and applying for a job digitally – can be a fruitful approach not only to reduce costs for administrative tasks but also to foster adults ICT skills. For our indicator of gender equality, we could not find any effect on ICT use or skills, which could be due to the low variance in gender equality across our country sample (our sample values range between 0.045 and 0.256, whereas the average world value equals 0.463).

Our findings must be considered in the light of several shortcomings: first, we had to limit our sample to the working population because only for them could we observe all our skill variables. This means that we ignore the currently or permanently inactive population in the labour market, including unemployed persons and homemakers. Yet, ICT skills of these groups might systematically differ from those of employed adults. It could be, for instance, that a shortage of ICT skills is a determinant of unemployment. Further research on studying the ICT skills of the non-working-population is needed. Second, we did not have information about the courses offered in adult education across countries. Even though participation in adult education indicates a high relevance of education and competencies in general; the importance of specific ICT training remains unclear. Thirdly, our analyses focus on 18 European countries, comprising a relatively small and homogenous sample concerning our macro variables. It is likely to expect that the relationships between our macro-variables and the working populations' ICT skills show up even stronger in a larger and more heterogeneous sample. Finally, we want to emphasize that this research is only descriptive in its nature. A promising avenue for future research is to focus on the causal mechanisms underlying the relationships between country-level variables and adults ICT skills

To sum up, our findings are in line with previous research on the individual level, but even though individual-level variables explain a large amount of differences in adults' ICT skills, our study points to the relevance of further including country factors to understand these differences better. Expanding our research to more countries and collecting and analyzing longitudinal data can help formulate more specific policies and interventions to foster adults ICT skills and help countries compete in our ever-increasing digitalized realities.

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Appendix to Chapter 2

Appendix 1. Information on number of respondents.

Table A1.1. Number of respondents in year of survey administering by country

	Interview year						
	2011	2012	2014	2015	2017	2018	Total
AUT	1791	935	0	0	0	0	2726
BELL	1737	1057	0	0	0	0	2794
CZE	1402	1097	0	0	0	0	2499
DEU	2548	440	0	0	0	0	2988
DNK	1922	2236	0	0	0	0	4158
EST	2280	1333	0	0	0	0	3613
FIN	2391	741	0	0	0	0	3132
GBRE	2212	574	0	0	0	0	2786
GBRN	1107	679	0	0	0	0	1786
GRC	0	0	1327	316	0	0	1643
HUN	0	0	0	0	1315	1449	2764
IRL	1650	754	0	0	0	0	2404
LTU	0	0	2098	411	0	0	2509
NLD	1993	1262	0	0	0	0	3255
NOR	2512	656	0	0	0	0	3168
POL	1904	983	0	0	0	0	2887
SVK	769	1328	0	0	0	0	2097
SVN	0	0	2367	0	0	0	2367
SWE	1533	1283	0	0	0	0	2816
Total	27751	15358	5792	727	1315	1449	52392

Source: PIAAC First Cycle

Table A1.2. Number of listwise deleted cases per country

	Listwise deletion	In sample	Total		Listwise deletion	In sample	Total		Listwise deletion	In sample	Total
AUT	123	2726	2849	GBRE	243	2786	3029	NOR	64	3168	3232
	4.32	95.68	100.00		8.02	91.98	100.00		1.98	98.02	100.00
BELL	120	2794	2914	GBRN	254	1786	2040	POL	103	2887	2990
	4.12	95.88	100.00		12.45	87.55	100.00		3.44	96.56	100.00
CZE	243	2499	2742	GRC	58	1643	1701	SVK	132	2097	2229
	8.86	91.14	100.00		3.41	96.59	100.00		5.92	94.08	100.00
DEU	179	2988	3167	HUN	200	2764	2964	SVN	94	2367	2461
	5.65	94.35	100.00		6.75	93.25	100.00		3.82	96.18	100.00
DNK	111	4158	4269	IRL	224	2404	2628	SWE	125	2816	2941
	2.60	97.40	100.00		8.52	91.48	100.00		4.25	95.75	100.00
EST	186	3613	3799	LTU	96	2509	2605	Total	2690	52392	55082
	4.90	95.10	100.00		3.69	96.31	100.00		4.88	95.12	100.00
FIN	64	3132	3196	NLD	71	3255	3326				
	2.00	**98.00**	**100.00**		**2.13**	**97.87**	**100.00**				

Source: PIAAC First Cycle

Appendix 2: Analytical strategy

In order to test our hypotheses, we proceed in four general steps: estimation of (1) a null model, (2) individual level indicators, (3) step-wise models of country-level indicators and (4) cross-level interaction models.

First, we assess the variance at the country and individual level by estimating a null model, with only allowing random intercept at the country level, as denoted in equation [1].

$$PSTRE_{ic} = \alpha_c + \upsilon_{ic} + \omega_c \quad [1]$$

Second, we estimate proficiency in ICT skills using multilevel mixed-effects models and whether the proficiency differs on individual level characteristics. As our theoretical model emphasizes that ICT skills are mostly related via ICT use at home and at work, we denote two equations [2a and 2b]:

$$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_5 AET_{ic} + \beta_6 LIT_{ic} + \beta_7 C_{ic} + \upsilon_{ic} + \omega_c \quad [2a]$$

$$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 ICTUSE\_HOME_{ic} + \beta_7 ICTUSE\_WORK_{ic} + \beta_8 C_{ic} + \upsilon_{ic} + \omega_c \quad [2b]$$

for each individual i in country c; AET_{ic} is the indicator on adult education, and LIT_{ic} is the literacy proficiency, C_{ic} is a vector of control variables consisting of age, age squared and parental education attainment, υ_{ic} and ω_c are error terms at the individual and country levels. ICT at home (ICTUSE_HOME) and at work (ICTUSE_WORK) are estimated in a separate model to check whether it mediates relationships of individual characteristics on ICT skills.

Third, we estimate the effect of different country-level contexts on individual's ICT skills. We do this by estimating the country-level coefficients separately before a model with all indicators together. First, we look at the country's ICT infrastructure ($INFRA_c$). Our model is based on the following equations [3a and 3b]:

$$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 C_{ic} + \beta_7 INFRA_c + \upsilon_{ic} + \omega_c \quad [3a]$$

$$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 ICTUSE\_HOME_{ic} + \beta_7 ICTUSE\_WORK_{ic} + \beta_8 C_{ic} + \beta_9 INFRA_c + \upsilon_{ic} + \omega_c \quad [3b]$$

Our next group of country-level characteristics represents public and private ICT services $ICTSERVICE_c$:

$$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 C_{ic} + \beta_7 ICTSERVICE_c + \upsilon_{ic} + \omega_c \quad [4a]$$

$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 ICTUSE\_HOME_{ic} + \beta_7 ICTUSE\_WORK_{ic} + \beta_8 C_{ic} + \beta_9 ICTSERVICE_c + \upsilon_{ic} + \omega_c$ [4b]

We then analyse the participation rate in adult aducation - $TRNG\_PART_c$ –, estimated in the following equations [5a and 5b]:

$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 C_{ic} + \beta_7 TRNG\_PART_c + \upsilon_{ic} + \omega_c$ [5a]

$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 C_{ic} + \beta_7 ICTUSE\_HOME_{ic} + \beta_8 ICTUSE\_WORK_{ic} + \beta_9 TRNG\_PART_c + \upsilon_{ic} + \omega_c$ [5b]

A fourth group of country-level characteristics contains indicators for the technical skills demand, es estimated in equation [6.1 to 6.3]:

$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 C_{ic} + \beta_7 SKILL\_SHORT_c + \upsilon_{ic} + \omega_c$ [6.1a]

$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 C_{ic} + \beta_7 ICTUSE\_HOME_{ic} + \beta_8 ICTUSE\_WORK_{ic} + \beta_9 SKILL\_SHORT_c + \upsilon_{ic} + \omega_c$ [6.1b]

$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 C_{ic} + \beta_7 EMPL\_TECH_c + \beta_9 ICT\_IMPORT_c + \upsilon_{ic} + \omega_c$ [6.2a]

$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 C_{ic} + \beta_7 ICTUSE\_HOME_{ic} + \beta_8 ICTUSE\_WORK_{ic} + \beta_9 EMPL\_TECH_c + \upsilon_{ic} + \omega_c$ [6.2b]

$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 C_{ic} + \beta_7 ICT\_IMPORT_c + \upsilon_{ic} + \omega_c$ [6.3a]

$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 C_{ic} + \beta_7 ICTUSE\_HOME_{ic} + \beta_8 ICTUSE\_WORK_{ic} + \beta_9 ICT\_IMPORT_c + \upsilon_{ic} + \omega_c$ [6.3b]

Our last country-level estimation is the countries gender equality index (GENDER_INDEX):

$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 C_{ic} + \beta_7 GENDER\_INDEX_c + \upsilon_{ic} + \omega_c$ [7a]

$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 C_{ic} + \beta_7 ICTUSE\_HOME_{ic} + \beta_8 ICTUSE\_WORK_{ic} + \beta_9 GENDER\_INDEX_c + \upsilon_{ic} + \omega_c$ [7b]

Fourthly, we assess whether the effect of various country-level characteristics vary over composition indicators, including education to test our hypothesis 6c (the positive relationships between demand for technical skills need and ICT usage and ICT skills should be driven by the highly educated). This is depicted in a generalized manner in equation [8].

$PSTRE_{ic} = \alpha_c + \beta_1 GENDER_{ic} + \beta_2 IMMIG_{ic} + \beta_3 EDUC_{ic} + \beta_4 AET_{ic} + \beta_5 LIT_{ic} + \beta_6 C_{ic} + \beta_7 ICTUSE\_HOME_{ic} + \beta_8 ICTUSE\_WORK_{ic} + \beta_9 COUNTRY\text{-}LEVEL_c + \beta_{10} COUNTRY\text{-}LEVEL_c * INDIVIDUAL\ LEVEL_{ic} + \upsilon_{ic} + \omega_c$ [8]

where the β_{10} is the coefficient that lets the country level variable change the individual level effect for that country.

Appendix 3. Correlation Matrix

	ICT Skill Score - Replicate sampling	Gender	Age	Age squared	Education	Parental Education	Migrant	Literacy scale score - Posterior mean	Factor score ICT use daily life	Factor score ICT use at work	Participated in formal or non-formal AET	Average index of shortage	Quintiles working in technology sector	% of ICT goods of all the country’s import	ICT infrastructure (standardized index)	Governmental and private ICT services (standardized index; usage)	% participate in adult learning
Gender	-0,040																
Age	-0,235	0,018															
Age squared	-0,243	0,015	0,989														
Education	0,306	0,110	0,047	0,031													
Parental Education	0,134	-0,011	-0,175	-0,173	0,095												
Migrant	-0,088	-0,002	-0,013	-0,016	0,020	0,024											
Literacy scale score - Posterior mean	0,758	-0,004	-0,125	-0,139	0,392	0,113	-0,127										
Factor score ICT use daily life	0,367	-0,040	-0,174	-0,173	0,244	0,105	0,027	0,325									
Factor score ICT use at work	0,388	0,000	0,086	0,067	0,422	0,075	-0,044	0,399	0,433								
Participated in formal or non-formal AET	0,184	0,048	-0,256	-0,216	0,104	0,085	-0,013	0,158	0,194	0,103							
Average index of shortage	0,053	-0,011	-0,002	0,001	-0,011	0,036	-0,052	0,042	0,045	0,027	0,048						
Quintiles working in technology sector	0,032	-0,016	0,001	-0,005	-0,024	-0,017	-0,048	-0,010	0,023	-0,001	-0,046	0,133					
% of ICT goods of all the country’s import	0,077	-0,009	-0,005	-0,002	-0,047	0,006	-0,005	0,070	0,083	0,027	0,021	0,051	0,209				
ICT infrastructure (standardized index)	0,140	0,004	0,133	0,137	-0,038	0,000	0,047	0,122	0,081	0,105	0,068	0,132	-0,193	0,087			
Governmental and private ICT services (standardized index; usage)	0,086	0,030	0,108	0,114	0,011	-0,058	0,016	0,120	0,089	0,082	0,077	-0,013	-0,303	0,072	0,701		
% participate in adult learning	0,125	0,011	0,120	0,124	-0,054	-0,035	0,036	0,123	0,088	0,081	0,051	-0,185	0,046	0,298	0,733	0,741	
Gender equality index	-0,059	0,003	-0,082	-0,081	0,035	0,111	-0,020	-0,066	-0,045	-0,047	-0,050	-0,130	0,085	0,201	-0,495	-0,458	-0,452

Source: PIAAC First Cycle

Appendix 4. Correlation matrix by country

See document PIAAC_corr_w_sel_reshaped.xlsx (on request)

Appendix 5 Regression with averaged ICT use at home and at work as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender (=1 Female)	-0.0782***	-0.0784***	-0.0784***	-0.0783***	-0.0783***	-0.0783***	-0.0783***	-0.0782***
	(0.0157)	(0.0157)	(0.0157)	(0.0157)	(0.0157)	(0.0157)	(0.0157)	(0.0157)
Age	0.0174***	0.0175***	0.0175***	0.0175***	0.0175***	0.0174***	0.0175***	0.0174***
	(0.00257)	(0.00258)	(0.00258)	(0.00258)	(0.00258)	(0.00257)	(0.00258)	(0.00256)
Age squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Upper secondary (ISCED 3A-B, C long)	0.129***	0.129***	0.128***	0.128***	0.128***	0.129***	0.128***	0.129***
	(0.0217)	(0.0216)	(0.0218)	(0.0217)	(0.0217)	(0.0216)	(0.0218)	(0.0216)
Post-secondary, non-tertiary (ISCED 4A-B-C)	0.251***	0.250***	0.249***	0.249***	0.249***	0.250***	0.249***	0.251***
	(0.0410)	(0.0410)	(0.0410)	(0.0411)	(0.0410)	(0.0406)	(0.0410)	(0.0409)
Tertiary (ISCED 5/6)	0.510***	0.510***	0.509***	0.509***	0.509***	0.510***	0.509***	0.511***
	(0.0475)	(0.0474)	(0.0476)	(0.0475)	(0.0475)	(0.0474)	(0.0475)	(0.0475)
At least one parent has attained secondary and post-secondary, non-tertiary	0.0812***	0.0812***	0.0811***	0.0810***	0.0811***	0.0808***	0.0811***	0.0810***
	(0.0130)	(0.0129)	(0.0130)	(0.0130)	(0.0129)	(0.0130)	(0.0129)	(0.0130)
At least one parent has attained tertiary	0.175***	0.176***	0.176***	0.176***	0.176***	0.176***	0.176***	0.175***
	(0.0235)	(0.0234)	(0.0234)	(0.0235)	(0.0234)	(0.0234)	(0.0234)	(0.0234)
Parental education: Don't know	0.0127	0.0134	0.0128	0.0127	0.0129	0.0124	0.0129	0.0128
	(0.0185)	(0.0188)	(0.0187)	(0.0187)	(0.0185)	(0.0187)	(0.0187)	(0.0185)
Migration status (= 1 migrants)	0.00358	0.00375	0.00423	0.00440	0.00414	0.00419	0.00432	0.00350
	(0.0416)	(0.0417)	(0.0419)	(0.0418)	(0.0418)	(0.0418)	(0.0419)	(0.0415)
Literacy scale score - Posterior mean	0.00505***	0.00507***	0.00506***	0.00507***	0.00507***	0.00507***	0.00507***	0.00506***
	(0.000283)	(0.000282)	(0.000282)	(0.000281)	(0.000281)	(0.000281)	(0.000281)	(0.000284)
FNF AET in 12 months preceding survey (Yes)	0.218***	0.218***	0.218***	0.218***	0.218***	0.218***	0.218***	0.219***
	(0.0196)	(0.0196)	(0.0197)	(0.0198)	(0.0198)	(0.0196)	(0.0197)	(0.0196)
FNF AET in 12 months preceding survey (Still in formal initial education)	0.168**	0.168***	0.168**	0.168**	0.168**	0.168**	0.168**	0.169***
	(0.0512)	(0.0508)	(0.0514)	(0.0514)	(0.0514)	(0.0512)	(0.0514)	(0.0508)
ICT infrastructure (standardized index)	0.116***							0.110***
	(0.0207)							(0.0224)
Governmental and private ICT services (standardized index; usage)		0.00680**						0.00351***
		(0.00223)						(0.00103)
Adult education: % participate in adult learning			0.00323*					-0.000596
			(0.00153)					(0.00299)
Technical skills demand 1: Average index of shortage of engineering and technology knowledge and technical skills at the labour market				0.149				0.274
				(0.186)				(0.375)
Technical skills demand 2: Quintiles of working in the high- and medium-high technology manufacturing and knowledge-intensive services					-0.0195			-0.00629
					(0.0228)			(0.0244)
Technical skills demand 3: % of ICT goods of all the country's import						-0.0324**		-0.0177
						(0.0112)		(0.0107)
Gender inequality index							-0.381	1.080*
							(0.358)	(0.504)
_cons	0.370***	0.154	0.210*	0.348***	0.412***	0.622***	0.397***	0.324**
	(0.0848)	(0.124)	(0.102)	(0.0760)	(0.0957)	(0.113)	(0.0773)	(0.119)
Var(_cons)	0.0118***	0.0116***	0.00796***	0.00992***	0.0124***	0.0312***	0.00966***	0.0197***
	(0.00431)	(0.00500)	(0.00246)	(0.00386)	(0.00683)	(0.0230)	(0.00321)	(0.0162)
Var(Residual)	0.377***	0.377***	0.377***	0.377***	0.377***	0.377***	0.377***	0.377***
	(0.0127)	(0.0127)	(0.0127)	(0.0127)	(0.0127)	(0.0127)	(0.0127)	(0.0127)
N	52392	52392	52392	52392	52392	52392	52392	52392

Standard errors in parentheses; Models are weighted; * p<0.05; ** p<0.01; *** p<0.001; Source: PIAAC First Cycle

Appendix 6. Interaction effects

Gender (=1 Female)	-1.617	-2.993**	-2.599***	-3.246***	-2.599***	-3.250***	-2.599***	-3.246***	-2.594***
	(0.893)	(0.928)	(0.623)	(0.631)	(0.625)	(0.632)	(0.618)	(0.626)	(0.626)
Age	-0.607***	-0.505***	-0.601***	-0.504***	-0.608***	-0.508***	-0.602***	-0.499***	-0.604***
	(0.156)	(0.147)	(0.158)	(0.148)	(0.158)	(0.148)	(0.157)	(0.148)	(0.157)
Age squared	0.000760	-0.000447	0.000644	-0.000502	0.000775	-0.000419	0.000701	-0.000516	0.000731
	(0.00190)	(0.00180)	(0.00193)	(0.00183)	(0.00192)	(0.00182)	(0.00191)	(0.00182)	(0.00191)
Upper secondary (ISCED 3A-B, C long)	0.613	1.583	0.657	1.631	0.584	1.563	1.684	3.452	0.913
	(1.423)	(1.449)	(1.420)	(1.444)	(1.428)	(1.449)	(6.722)	(7.087)	(1.572)
Post-secondary, non-tertiary (ISCED 4A-B-C)	0.596	2.485	0.710	2.601	0.551	2.451	1.250	3.505	1.000
	(1.887)	(2.032)	(1.882)	(2.027)	(1.883)	(2.026)	(7.664)	(8.370)	(2.106)
Tertiary (ISCED 5/6)	0.416	4.320***	0.534	4.427***	0.378	4.286***	2.804	9.319	0.533
	(1.245)	(1.288)	(1.239)	(1.287)	(1.251)	(1.285)	(5.708)	(6.335)	(1.422)
At least one parent has attained secondary and post-secondary, non-tertiary	1.707*	2.377**	1.690*	2.365**	1.683*	2.354**	1.700*	2.358**	1.716*
	(0.789)	(0.804)	(0.787)	(0.800)	(0.781)	(0.796)	(0.803)	(0.823)	(0.790)
At least one parent has attained tertiary	2.574**	4.021***	2.545**	3.984***	2.568**	4.005***	2.572**	3.993***	2.587**
	(0.960)	(1.088)	(0.961)	(1.087)	(0.949)	(1.077)	(0.955)	(1.078)	(0.964)
Parental education: Don't know	1.547	1.672	1.516	1.638	1.518	1.631	1.597	1.744	1.588
	(1.794)	(1.793)	(1.764)	(1.759)	(1.773)	(1.770)	(1.771)	(1.763)	(1.769)
Migration status (= 1 migrants)	-1.412	-1.244	-1.109	-1.033	-3.874	-3.831	-1.423	-1.259	-1.425
	(1.655)	(1.468)	(1.555)	(1.451)	(3.889)	(4.045)	(1.651)	(1.464)	(1.656)
Factor score ICT use daily life	4.839***		4.833***		4.835***		4.817***		4.842***
	(0.743)		(0.737)		(0.741)		(0.734)		(0.744)
Factor score ICT use at work	3.545***		3.536***		3.539***		3.525***		3.534***
	(0.394)		(0.387)		(0.393)		(0.390)		(0.388)
FNF AET in 12 months preceding survey (Yes)	1.255	2.978***	1.267	2.997***	1.259	2.983***	1.236	2.929***	1.265
	(0.692)	(0.688)	(0.690)	(0.686)	(0.692)	(0.691)	(0.690)	(0.678)	(0.693)
FNF AET in 12 months preceding survey (Still in formal initial education)	3.172	4.643**	3.223	4.705**	3.147	4.634**	3.133	4.584**	3.146
	(1.921)	(1.715)	(1.920)	(1.722)	(1.915)	(1.715)	(1.913)	(1.713)	(1.910)
Literacy scale score - Posterior mean	0.737***	0.778***	0.736***	0.776***	0.738***	0.778***	0.737***	0.778***	0.737***
	(0.0170)	(0.0155)	(0.0167)	(0.0153)	(0.0171)	(0.0157)	(0.0170)	(0.0154)	(0.0169)
Gender inequality index	-12.77	-18.89							
	(21.90)	(23.87)							
Female # Gender inequality index	-8.519	-2.206							
	(9.808)	(10.49)							
ICT infrastructure (standardized index)			5.131**	6.239***					
			(1.579)	(1.695)					
Female # ICT infrastructure (standardized index)			-2.416	-1.773					
			(1.890)	(1.774)					
Governmental and private ICT services (standardized index; usage)					-0.0918	-0.0396			
					(0.151)	(0.165)			
Migrant # Governmental and private ICT services (standardized index; usage)"					0.0796	0.0835			
					(0.147)	(0.141)			
Adult education: % participate in adult learning							0.170	0.227	
							(0.114)	(0.129)	
Upper secondary (ISCED 3A-B, C long) # % participate in adult learning							-0.0215	-0.0370	
							(0.129)	(0.134)	
Post-secondary, non-tertiary (ISCED 4A-B-C) # % participate in adult learning							-0.0111	-0.0156	
							(0.154)	(0.165)	
Tertiary (ISCED 5/6) # % participate in adult learning							-0.0497	-0.105	
							(0.113)	(0.121)	
Average index of shortage of engineering and technology knowledge and technical skills at the labour market									10.03
									(14.45)
Upper secondary (ISCED 3A-B, C long) # Average index of shortage of engineering and technology knowledge and technical skills at the labour market									-8.993
									(12.72)
Post-secondary, non-tertiary (ISCED 4A-B-C) # Average index of shortage of engineering and technology knowledge and technical skills at the labour market									-15.75
									(17.24)
Tertiary (ISCED 5/6) # Average index of shortage of engineering and technology knowledge and technical skills at the labour market									-3.706
									(12.08)
_cons	73.72***	79.51***	73.24***	78.40***	74.96***	78.49***	64.62***	66.92***	71.90***
	(5.530)	(5.453)	(5.413)	(5.271)	(7.470)	(7.566)	(9.606)	(10.11)	(5.636)
Var(_cons)	20.40***	24.52***	19.35***	25.23***	23.32***	26.85***	17.37***	20.16***	21.02***
	(7.610)	(10.08)	(7.244)	(10.22)	(9.438)	(11.80)	(5.725)	(7.348)	(8.635)
Var(Residual)	685.0***	709.2***	684.1***	708.2***	684.9***	709.1***	684.9***	708.8***	684.9***
	(51.74)	(53.95)	(51.69)	(53.81)	(51.68)	(53.87)	(51.69)	(53.81)	(51.68)
N	52392	52392	52392	52392	52392	52392	52392	52392	52392

Standard errors in parentheses; Models are weighted; * p<0.05; ** p<0.01; *** p<0.001; Source: PIAAC First Cycle

Appendix 6. Interaction effects (continued)

Gender (=1 Female)	-3.251***	-2.593***	-3.245***	-2.595***	-3.245***	-2.602***	-3.252***	-2.598***	-3.250***
	(0.635)	(0.625)	(0.634)	(0.622)	(0.630)	(0.623)	(0.631)	(0.626)	(0.633)
Age	-0.504***	-0.604***	-0.502***	-0.601***	-0.501***	-0.496**	-0.418*	-0.514**	-0.435**
	(0.148)	(0.155)	(0.146)	(0.156)	(0.148)	(0.171)	(0.163)	(0.167)	(0.157)
Age squared	-0.000472	0.000726	-0.000479	0.000692	-0.000497	0.00118	-0.000117	0.00124	-0.0000862
	(0.00181)	(0.00189)	(0.00179)	(0.00190)	(0.00181)	(0.00191)	(0.00181)	(0.00189)	(0.00180)
Upper secondary (ISCED 3A-B, C long)	1.998	2.704	3.377	4.913	5.748	0.630	1.601	0.597	1.579
	(1.591)	(3.247)	(3.351)	(3.748)	(3.923)	(1.433)	(1.462)	(1.428)	(1.454)
Post-secondary, non-tertiary (ISCED 4A-B-C)	3.001	2.857	3.660	4.287	5.914	0.584	2.485	0.631	2.524
	(2.236)	(4.132)	(4.639)	(4.703)	(5.292)	(1.919)	(2.062)	(1.913)	(2.060)
Tertiary (ISCED 5/6)	4.628**	1.782	4.998	3.730	7.806*	0.488	4.384**	0.461	4.366***
	(1.467)	(2.701)	(3.200)	(3.079)	(3.672)	(1.277)	(1.331)	(1.264)	(1.315)
At least one parent has attained secondary and post-	2.372**	1.724*	2.402**	1.709*	2.376**	1.694*	2.367**	1.634*	2.323**
	(0.806)	(0.787)	(0.799)	(0.789)	(0.804)	(0.782)	(0.799)	(0.779)	(0.795)
At least one parent has attained tertiary	4.013***	2.595**	4.034***	2.579**	4.017***	2.542**	3.991***	2.464*	3.934***
	(1.092)	(0.952)	(1.077)	(0.957)	(1.083)	(0.967)	(1.095)	(0.960)	(1.086)
Parental education: Don't know	1.673	1.555	1.659	1.571	1.679	1.522	1.641	1.463	1.600
	(1.792)	(1.779)	(1.791)	(1.772)	(1.775)	(1.761)	(1.768)	(1.764)	(1.768)
Migration status (= 1 migrants)	-1.247	-1.428	-1.251	-1.383	-1.213	-1.411	-1.243	-1.406	-1.241
	(1.462)	(1.661)	(1.477)	(1.658)	(1.469)	(1.655)	(1.470)	(1.672)	(1.482)
Factor score ICT use daily life		4.833***		4.833***		4.832***		4.839***	
		(0.741)		(0.735)		(0.739)		(0.739)	
Factor score ICT use at work		3.542***		3.540***		3.549***		3.554***	
		(0.392)		(0.389)		(0.394)		(0.393)	
FNF AET in 12 months preceding survey (Yes)	2.984***	1.258	2.981***	1.260	2.984***	1.237	2.967***	1.248	2.978***
	(0.691)	(0.693)	(0.691)	(0.693)	(0.688)	(0.692)	(0.690)	(0.690)	(0.690)
FNF AET in 12 months preceding survey (Still in formal	4.621**	3.119	4.602**	3.190	4.673**	3.144	4.631**	3.057	4.569**
	(1.706)	(1.912)	(1.703)	(1.908)	(1.704)	(1.918)	(1.710)	(1.920)	(1.705)
Literacy scale score - Posterior mean	0.778***	0.737***	0.778***	0.738***	0.778***	0.737***	0.777***	0.737***	0.777***
	(0.0156)	(0.0170)	(0.0156)	(0.0170)	(0.0156)	(0.0172)	(0.0157)	(0.0172)	(0.0157)
Average index of shortage of engineering and technology	15.06								
	(14.65)								
Upper secondary (ISCED 3A-B, C long) # Average index of	-12.07								
	(12.30)								
Post-secondary, non-tertiary (ISCED 4A-B-C) # Average	-18.04								
	(17.54)								
Tertiary (ISCED 5/6) # Average index of shortage of	-8.886								
	(11.83)								
Quintiles of working in the high- and medium-high		0.884	0.429						
		(1.083)	(1.217)						
Upper secondary (ISCED 3A-B, C long) # Quintiles of		-0.785	-0.653						
		(0.933)	(0.935)						
Post-secondary, non-tertiary (ISCED 4A-B-C) # Quintiles of		-0.857	-0.458						
		(1.166)	(1.267)						
Tertiary (ISCED 5/6) # Quintiles of working in the high- and		-0.548	-0.286						
		(0.881)	(0.938)						
% of ICT goods of all the country's import				0.504	0.332				
				(0.710)	(0.825)				
Upper secondary (ISCED 3A-B, C long) # % of ICT goods of				-0.513	-0.496				
				(0.361)	(0.370)				
Post-secondary, non-tertiary (ISCED 4A-B-C) # % of ICT				-0.445	-0.410				
				(0.498)	(0.549)				
Tertiary (ISCED 5/6) # % of ICT goods of all the country's				-0.397	-0.417				
				(0.327)	(0.363)				
Adult education: % participate in adult learning						0.262**	0.263**		
						(0.0797)	(0.0834)		
% participate in adult learning # Age						-0.00313	-0.00246		
						(0.00210)	(0.00220)		
Governmental and private ICT services (standardized								0.0895	0.100
								(0.173)	(0.183)
Governmental and private ICT services (standardized								-0.00429	-0.00324
								(0.00253)	(0.00256)
_cons	76.83***	69.85***	76.20***	67.91***	74.41***	61.26***	66.14***	70.42***	74.97***
	(5.535)	(7.536)	(7.406)	(9.286)	(9.835)	(7.425)	(7.385)	(7.794)	(7.708)
Var(_cons)	25.37***	20.80***	26.30***	21.15***	27.09***	17.24***	20.01***	23.03***	26.61***
	(11.47)	(8.969)	(13.44)	(8.754)	(13.90)	(5.745)	(7.403)	(9.374)	(11.79)
Var(Residual)	709.0***	684.9***	709.0***	684.8***	709.0***	684.8***	709.0***	684.7***	709.0***
	(53.87)	(51.61)	(53.85)	(51.65)	(53.85)	(51.62)	(53.84)	(51.66)	(53.88)
N	52392	52392	52392	52392	52392	52392	52392	52392	52392

Standard errors in parentheses; Models are weighted; * p<0.05; ** p<0.01; *** p<0.001; Source: PIAAC First Cycle

Appendix 7. Models without literacy proficiency.

	(1)	(2)
Gender (=1 Female)	-6.095***	-4.349***
	(0.781)	(0.677)
Age	0.711***	0.301
	(0.169)	(0.160)
Age squared	-0.0190***	-0.0138***
	(0.00224)	(0.00224)
Upper secondary (ISCED 3A-B, C long)	13.97***	10.30***
	(1.409)	(1.328)
Post-secondary, non-tertiary (ISCED 4A-B-C)	22.44***	15.79***
	(2.572)	(2.103)
Tertiary (ISCED 5/6)	34.68***	22.28***
	(1.525)	(1.482)
At least one parent has attained secondary and post-secondary, non-tertiary	8.165***	6.026***
	(1.082)	(0.950)
At least one parent has attained tertiary	16.47***	11.88***
	(1.466)	(1.104)
Parental education: Don't know	-1.000	-0.933
	(2.314)	(2.211)
Migration status (= 1 migrants)	-15.50***	-14.07***
	(2.197)	(2.502)
FNF AET in 12 months preceding survey (Yes)	9.069***	4.499***
	(0.658)	(0.689)
FNF AET in 12 months preceding survey (Still in formal initial education)	11.35***	7.430***
	(1.579)	(1.711)
Average index of shortage of engineering and technology knowledge and technical skills at the labour market	3.009	-0.884
	(18.69)	(20.27)
Quintiles of working in the high- and medium-high technology manufacturing and knowledge-intensive services	1.447	1.284
	(0.915)	(1.079)
% of ICT goods of all the country's import	0.832	0.937
	(0.619)	(0.727)
Standardized index of technical conditions	12.84***	10.44***
	(3.040)	(3.132)
Average % that use ICT daily	-0.473**	-0.516**
	(0.161)	(0.155)
% participate in adult learning	0.0737	0.0830
	(0.247)	(0.260)
Gender inequality index	-5.292	-17.11
	(36.87)	(34.14)
Factor score ICT use daily life		9.760***
		(0.958)
Factor score ICT use at work		8.410***
		(0.447)
_cons	254.6***	227.3***
	(10.31)	(10.82)
Var(_cons)	36.35***	33.57***
	(15.17)	(16.53)
Var(Residual)	1349.8***	1222.3***
	(67.64)	(67.11)
N	52392	52392

Standard errors in parentheses; Models are weighted; * p<0.05; ** p<0.01; *** p<0.001; Source: PIAAC First Cycle

Appendix 8. One-country-out regression models

	AUT	BEL	CZE	DEU	DNK	EST	FIN	GBRE	GBRN
Gender (=1 Female)	-2.538***	-2.575***	-2.560***	-2.670***	-2.596***	-2.726***	-2.510***	-2.226***	-2.583***
	(0.660)	(0.659)	(0.641)	(0.646)	(0.680)	(0.647)	(0.659)	(0.532)	(0.624)
Age	-0.629***	-0.619***	-0.534***	-0.599***	-0.669***	-0.601***	-0.610***	-0.603***	-0.608***
	(0.167)	(0.167)	(0.144)	(0.165)	(0.160)	(0.166)	(0.167)	(0.167)	(0.158)
Age squared	0.00101	0.000988	-0.000191	0.000681	0.00161	0.000638	0.000849	0.000759	0.000763
	(0.00202)	(0.00203)	(0.00172)	(0.00203)	(0.00192)	(0.00203)	(0.00204)	(0.00202)	(0.00192)
Upper secondary (ISCED 3A-B, C long)	0.208	0.649	0.809	0.672	0.732	0.638	0.653	1.197	0.638
	(1.410)	(1.480)	(1.461)	(1.495)	(1.556)	(1.488)	(1.478)	(1.440)	(1.419)
Post-secondary, non-tertiary (ISCED 4A-B-C)	0.244	0.732	0.855	0.768	0.849	0.636	0.650	1.075	0.674
	(1.962)	(1.958)	(1.920)	(1.934)	(1.987)	(2.006)	(1.919)	(1.959)	(1.882)
Tertiary (ISCED 5/6)	0.299	0.648	0.723	0.426	0.460	0.560	0.411	0.762	0.477
	(1.288)	(1.280)	(1.222)	(1.295)	(1.351)	(1.286)	(1.264)	(1.347)	(1.239)
At least one parent has attained secondary and post-secondary, non-tertiary	1.758*	1.673*	1.699*	1.704*	1.878*	1.562	1.408	1.726*	1.707*
	(0.818)	(0.828)	(0.780)	(0.800)	(0.848)	(0.812)	(0.794)	(0.840)	(0.781)
At least one parent has attained tertiary	2.652**	2.579*	2.334*	2.627**	2.960**	2.443*	2.371*	2.771**	2.575**
	(1.006)	(1.018)	(0.931)	(0.995)	(0.980)	(1.012)	(0.991)	(1.008)	(0.960)
Parental education: Don't know	1.578	1.334	1.686	1.236	1.665	0.915	1.169	3.428*	1.496
	(1.826)	(1.816)	(1.892)	(1.783)	(1.844)	(1.721)	(1.762)	(1.722)	(1.794)
Migration status (= 1 migrants)	-1.208	-1.393	-1.500	-1.151	-1.127	-2.890**	-1.437	-1.191	-1.414
	(1.771)	(1.722)	(1.696)	(1.786)	(1.740)	(1.013)	(1.707)	(1.820)	(1.668)
ict_use_dailylife	4.782***	4.849***	4.977***	4.736***	4.971***	4.935***	4.812***	4.738***	4.809***
	(0.782)	(0.771)	(0.749)	(0.786)	(0.783)	(0.778)	(0.775)	(0.790)	(0.739)
ict_use_work_cmpl_smpl	3.612***	3.511***	3.330***	3.576***	3.563***	3.560***	3.550***	3.435***	3.525***
	(0.397)	(0.408)	(0.346)	(0.406)	(0.399)	(0.413)	(0.405)	(0.389)	(0.388)
Literacy scale score - Posterior mean	0.738***	0.736***	0.733***	0.736***	0.732***	0.732***	0.738***	0.747***	0.737***
	(0.0176)	(0.0177)	(0.0174)	(0.0177)	(0.0173)	(0.0176)	(0.0180)	(0.0142)	(0.0169)
FNF AET in 12 months preceding survey (Yes)	1.304	1.212	1.369	1.466*	1.234	1.358	1.447*	1.438*	1.290
	(0.740)	(0.728)	(0.732)	(0.717)	(0.743)	(0.740)	(0.702)	(0.725)	(0.691)
FNF AET in 12 months preceding survey (Still in formal initial education)	3.333	3.079	2.857	3.759*	3.160	3.175	3.336	1.840	3.178
	(1.991)	(1.983)	(1.934)	(1.884)	(1.999)	(2.069)	(1.996)	(1.558)	(1.907)
ICT infrastructure (standardized index)	7.546***	7.660***	6.137***	7.811***	7.321***	7.842***	8.015***	7.302***	7.437***
	(1.825)	(1.958)	(1.695)	(1.998)	(1.918)	(1.948)	(2.027)	(1.973)	(1.891)
Governmental and private ICT services (standardized index; usage)	-0.311**	-0.339**	-0.239**	-0.362**	-0.351**	-0.375**	-0.331**	-0.430*	-0.341**
	(0.115)	(0.121)	(0.0803)	(0.130)	(0.129)	(0.131)	(0.121)	(0.193)	(0.125)
Adult education: % participate in adult learning	-0.117	-0.0901	-0.0558	-0.0809	-0.0731	-0.0634	-0.107	-0.0240	-0.0683
	(0.143)	(0.164)	(0.158)	(0.160)	(0.155)	(0.157)	(0.170)	(0.190)	(0.156)
Technical skills demand 1: Average index of shortage of engineering and technology knowledge and technical skills at the labour market	-7.168	-8.532	-8.317	-6.558	-8.016	-0.399	-7.388	-5.389	-5.821
	(9.828)	(12.19)	(8.958)	(11.11)	(10.09)	(11.92)	(12.40)	(12.33)	(10.59)
Technical skills demand 2: Quintiles of working in the high- and medium-high technology manufacturing and knowledge-intensive services	0.718	0.838	0.700	0.881	1.017	0.836	0.877	0.500	0.766
	(0.527)	(0.650)	(0.570)	(0.678)	(0.676)	(0.656)	(0.637)	(0.714)	(0.614)
Technical skills demand 3: % of ICT goods of all the country's import	0.404	0.218	0.248	0.241	0.218	0.137	0.252	0.277	0.232
	(0.365)	(0.410)	(0.456)	(0.419)	(0.405)	(0.408)	(0.450)	(0.416)	(0.403)
Gender inequality index	2.760	2.741	1.688	1.210	3.906	3.924	5.867	0.725	4.739
	(14.44)	(16.86)	(15.16)	(17.54)	(14.17)	(14.19)	(16.71)	(18.36)	(15.31)
_cons	81.65***	83.32***	77.93***	82.98***	83.17***	83.81***	82.24***	79.71***	81.74***
	(7.593)	(8.049)	(7.117)	(8.121)	(7.547)	(7.604)	(8.100)	(7.499)	(7.428)
Var(_cons)	6.992***	10.99***	8.916***	11.05***	9.985***	10.11***	11.84***	11.66***	10.31***
	(3.843)	(5.452)	(5.893)	(5.565)	(4.774)	(5.019)	(6.494)	(5.918)	(5.121)
Var(Residual)	693.6***	688.3***	675.2***	687.0***	697.5***	689.4***	693.3***	692.2***	684.5***
	(53.72)	(54.42)	(53.04)	(54.59)	(54.63)	(55.03)	(54.22)	(55.59)	(51.54)
N	49666	49598	49893	49404	48234	48779	49260	49606	50606

Standard errors in parentheses; Models are weighted; * p<0.05; ** p<0.01; *** p<0.001; Source: PIAAC First Cycle

	GRC	HUN	IRL	LTU	NLD	NOR	POL	SVK	SVN	SWE
Gender (=1 Female)	-2.710***	-2.629***	-2.636***	-2.748***	-2.663***	-2.647***	-2.319***	-2.628***	-2.612***	-2.631***
	(0.627)	(0.662)	(0.664)	(0.627)	(0.658)	(0.651)	(0.597)	(0.641)	(0.656)	(0.667)
Age	-0.646***	-0.642***	-0.600***	-0.637***	-0.613***	-0.542***	-0.616***	-0.620***	-0.585***	-0.630***
	(0.158)	(0.163)	(0.164)	(0.166)	(0.168)	(0.150)	(0.163)	(0.164)	(0.160)	(0.170)
Age squared	0.00117	0.00106	0.000657	0.00106	0.000737	0.0000644	0.000893	0.000749	0.000474	0.00114
	(0.00193)	(0.00200)	(0.00200)	(0.00203)	(0.00204)	(0.00188)	(0.00199)	(0.00199)	(0.00194)	(0.00206)
Upper secondary (ISCED 3A-B, C long)	-0.0372	0.947	0.280	0.797	0.882	0.336	0.646	0.740	0.928	0.125
	(1.309)	(1.442)	(1.421)	(1.449)	(1.552)	(1.520)	(1.458)	(1.450)	(1.451)	(1.426)
Post-secondary, non-tertiary (ISCED 4A-B-C)	-0.240	1.217	0.331	1.350	0.818	0.415	0.730	0.782	0.848	-0.0780
	(1.795)	(1.867)	(1.983)	(1.818)	(1.963)	(2.058)	(1.953)	(1.886)	(1.929)	(1.837)
Tertiary (ISCED 5/6)	-0.137	0.912	0.0963	0.604	0.521	0.251	0.594	0.508	0.629	0.0769
	(1.169)	(1.186)	(1.232)	(1.267)	(1.355)	(1.354)	(1.271)	(1.269)	(1.275)	(1.263)
At least one parent has attained secondary and post-secondary, non-tertiary	2.252***	1.675*	1.715*	1.619*	1.850*	1.649*	1.846*	1.638*	1.517	1.605
	(0.599)	(0.814)	(0.842)	(0.809)	(0.837)	(0.835)	(0.769)	(0.786)	(0.787)	(0.828)
At least one parent has attained tertiary	3.103***	2.489*	2.478*	2.187*	2.780**	2.685**	2.549**	2.538**	2.380*	2.474*
	(0.854)	(0.994)	(1.020)	(0.928)	(1.030)	(1.021)	(0.975)	(0.975)	(0.959)	(1.026)
Parental education: Don't know	1.907	1.453	1.632	1.275	1.871	1.481	1.553	1.445	1.078	1.197
	(1.754)	(1.807)	(1.894)	(1.812)	(1.874)	(1.816)	(1.814)	(1.789)	(1.697)	(1.801)
Migration status (= 1 migrants)	-1.056	-1.366	-1.589	-1.590	-1.616	-1.337	-1.508	-1.508	-1.213	-0.983
	(1.658)	(1.706)	(1.821)	(1.683)	(1.778)	(1.764)	(1.679)	(1.708)	(1.745)	(1.706)
ict_use_dailylife	4.487***	4.833***	4.743***	4.483***	4.823***	4.919***	5.112***	5.055***	4.715***	4.712***
	(0.687)	(0.782)	(0.768)	(0.686)	(0.778)	(0.773)	(0.711)	(0.739)	(0.763)	(0.763)
ict_use_work_cmpl_smpl	3.506***	3.642***	3.558***	3.453***	3.665***	3.501***	3.477***	3.505***	3.495***	3.550***
	(0.388)	(0.393)	(0.410)	(0.405)	(0.384)	(0.413)	(0.416)	(0.400)	(0.396)	(0.410)
Literacy scale score - Posterior mean	0.741***	0.733***	0.740***	0.737***	0.738***	0.738***	0.730***	0.737***	0.735***	0.739***
	(0.0170)	(0.0171)	(0.0175)	(0.0177)	(0.0179)	(0.0178)	(0.0165)	(0.0175)	(0.0177)	(0.0176)
FNF AET in 12 months preceding survey (Yes)	1.364	1.211	1.390	1.403*	1.265	1.167	1.375	0.967	1.188	0.988
	(0.714)	(0.720)	(0.710)	(0.707)	(0.727)	(0.707)	(0.720)	(0.632)	(0.722)	(0.632)
FNF AET in 12 months preceding survey (Still in formal initial education)	3.488	2.865	3.403	3.585	3.388	3.204	3.678	2.718	3.324	3.047
	(1.909)	(1.971)	(2.021)	(1.982)	(1.981)	(2.001)	(1.973)	(1.926)	(1.915)	(2.021)
ICT infrastructure (standardized index)	6.722***	7.580***	7.579***	7.701***	7.858***	7.475***	6.422***	7.583***	7.379***	7.462***
	(1.686)	(1.978)	(2.025)	(2.257)	(1.864)	(1.935)	(1.741)	(2.013)	(1.886)	(1.895)
Governmental and private ICT services (standardized index; usage)	-0.329**	-0.357**	-0.336**	-0.339**	-0.347**	-0.341**	-0.364**	-0.344**	-0.352**	-0.335**
	(0.123)	(0.121)	(0.121)	(0.127)	(0.118)	(0.126)	(0.132)	(0.123)	(0.127)	(0.121)
Adult education: % participate in adult learning	0.0343	-0.0369	-0.0935	-0.0962	-0.0961	-0.0863	0.00675	-0.0756	-0.0569	-0.0756
	(0.124)	(0.155)	(0.180)	(0.169)	(0.153)	(0.179)	(0.143)	(0.163)	(0.159)	(0.160)
Technical skills demand 1:	0.584	-7.655	-6.250	-6.310	-10.64	-7.738	-0.587	-5.845	-7.065	-4.512
	(8.520)	(11.54)	(10.86)	(12.71)	(9.507)	(13.13)	(9.615)	(11.06)	(10.33)	(11.28)
Technical skills demand 2:	0.919	0.844	0.793	0.677	0.403	0.854	0.600	0.801	0.835	0.823
	(0.581)	(0.713)	(0.646)	(0.699)	(0.528)	(0.744)	(0.603)	(0.621)	(0.641)	(0.652)
Technical skills demand 3: % of ICT goods of all the country's import	0.135	0.239	0.258	0.302	0.528	0.268	-0.00140	0.266	0.173	0.179
	(0.367)	(0.403)	(0.436)	(0.505)	(0.408)	(0.430)	(0.321)	(0.413)	(0.436)	(0.407)
Gender inequality index	9.893	16.26	3.474	4.974	-11.55	3.615	8.150	5.072	2.594	7.133
	(13.11)	(24.42)	(16.78)	(19.34)	(12.66)	(15.67)	(13.35)	(16.61)	(14.88)	(16.01)
_cons	76.63***	80.91***	82.08***	84.35***	83.73***	80.41***	82.01***	81.90***	82.85***	82.27***
	(6.845)	(8.085)	(8.244)	(7.255)	(7.739)	(7.593)	(7.657)	(7.761)	(7.615)	(7.749)
Var(_cons)	7.611***	10.65***	11.13***	11.08***	8.010***	10.92***	9.186***	11.08***	10.08***	10.80***
	(4.631)	(5.006)	(5.613)	(7.530)	(4.800)	(5.617)	(3.748)	(5.751)	(5.131)	(5.141)
Var(Residual)	651.2***	685.3***	688.7***	680.2***	694.8***	696.5***	660.1***	680.3***	672.9***	688.2***
	(39.08)	(54.34)	(53.97)	(53.91)	(54.10)	(53.71)	(47.30)	(53.38)	(52.24)	(54.43)
N	50749	49628	49988	49883	49137	49224	49505	50295	50025	49576

Standard errors in parentheses; Models are weighted; * p<0.05; ** p<0.01; *** p<0.001; Source: PIAAC First Cycle

Appendix 9: Variables

Variable	Item	Operationalization	Source
Micro-level			
Literacy proficieny		0 – 500 (a higher number indicates a h	PIAAC
Gender		0 - male 1 - female	PIAAC
Age		in years (16-65)	PIAAC
Educational attainment		0 - lower secondary or less 1 - upper secondary 2 - post-secondary 3 - tertiary	PIAAC
Parental educational attainment		0 - neither parent obtained upper secondary degree 1 - at least one parent obtained upper secondary degree 2 - at least one parent obtained tertiary degree 3 - don't know	PIAAC
Migration status		0 - no migration status 1 - migration status	PIAAC
ICT use daily	How often one uses (at home) - the computer to have real-time discussion - program language - word - spreadsheets -internet to conduct transactions - look up information on health, finances or environmental issues - for e-mail	1 - never 5 - every day	PIAAC
ICT use at work	How often one uses (at work) - the computer to have real-time discussion - program language - word - spreadsheets -internet to conduct transactions - look up information on health, finances or environmental issues - for e-mail	1 - no computer is required for the job 1 - never 5 - every day	PIAAC
Macro-level			
ICT infrastructure	- Broadband subscriptions per 100 inhabitants - Computer access -Internet access	Standardised (mean: 0; standard deviation 1)	OECD
Adult education	Percentage of formal and non-formal education and training of adults in the last 12 months	0 - 100%	Eurostat
Techniqual skills demand	-average index of shortage of engineering and technology knowledge and technical skills at the labour market - quintile groups of the percentage of employment in the high- and medium-high technology manufacturing and knowledge-intensive services - percentage of ICT related import goods	-1 – + 1 - 1 through 5 - 0 – 100%	-OECD -Eurostat -Worldbank
Governmental and private ICT services	- use a digital form in contact with public authorieties in the last 12 months -used online banking in the last 3 months - make an online appointment with a practitioner in the last 3 months	0 - 100%	Digital Agenda Data
Gender equality index	inequality in achievemnts between women and men in reproductive health, empowerment, labour market	0 - women and men are equal 1 - one gender is maximally inequal in all measured dimensions	Human Development Report

Chapter 3

Education expansion, technical change, and job complexity

Tomas Korpi

3.1 Educational policy and technical change

In recent decades, education has advanced to one of the top political priorities in almost all industrialized countries. The reasons are myriad, but among the most prominent are the arrival of the knowledge society, an intensified competition from developing countries for low skill jobs, or a combination of the two. As outlined by Saar et al. (2019), when the European Union set its goal of becoming "the most competitive and dynamic knowledge-based economy in the world" it urged its member states to pursue an e labourate reform strategy in which educational policy played an important part (EU 2000). In the revised European Employment Strategy (EES), the EU thus stated an ambition to increase the level of education in the union (EU 2003). This has also taken place, and the increase in educational attainment in Europe has been extraordinary. In the period between 2002 and 2019, the share of young workers with a tertiary degree thus almost doubled from roughly 20 to 40 % (Eurostat 2020). Such an ambitious educational policy was however not an exclusively European phenomenon, other countries such as the USA have also given increased weight to the question of education. Education in other words appears to be the only social policy area in which there is unanimous support for welfare state expansion, resisting the tendency for welfare state retrenchment so predominant in the industrialized world.

One striking aspect of the EU's educational goals is that educational reform is necessary because of changes in the labour market. When discussing the revamped EES, the European Commission thus makes reference to factors such as the pace of technological change and the increasing share of services in the economy. Educational reform in other words comes as a response to exogenous changes in the structure of employment and jobs.

This view of structural change reflects an older debate on structural change in industrialized economies and changes in skill requirements on the labour market. However, there is also a somewhat more recent literature on the causes of technological change, or more precisely the skill-bias of technological change. In this literature on endogenous growth and directed technical change, education is seen as a factor that in itself changes the structure of production. This alternative view in other words gives educational policy a dynamic and constructive role, a role in which social policy becomes a true engine in the transformation of the economy.

The purpose of this paper is to examine the relationship between educational expansion and job content. Section 2 of the paper contains a brief overview of theories of changes in the production process and what causes them, followed in Section 3 by a review of the existing empirical evidence. Section 4 presents the data and the methods used for the analysis of the link between educational reform and job complexity, the dimension of job requirements central to much of the current debate. The results from the analyses are presented in Section 5, while Section 6 concludes.

3.2 Jobs and the production process

There is a longstanding discussion of the evolution of the production process in the industrialized world. Much of this debate has been carried out under the heading of skills, as in the debate on de- vs. upskilling trends in the economy. Skills, or rather skill requirements, is here simply a shorthand for the type of tasks carried out in various forms of production, whether a job primarily involves physical power in the form of heavy lifting as in the case of a dockhand or conscious decision making processes such as those carried out by skilled craftsmen. The cognitive processes exemplified by the latter are here generally regarded as being high skilled, whereas the former are not. Visions of deskilling therefore project an increase in the number of single task job involving little discretion, whereas upskilling implies an increase in jobs with decision making latitude and multitasking.

Of particular interest is in this case how the forces generating a transformation of the production process are conceived, and in particular whether any role is accorded to education and educational policy. Some of the classical texts dealing with the deskilling vs. upskilling debate adopted a technologically deterministic approach to the evolution of jobs were technological change simply arrives in the form of various technical innovations. This is for example the case with Fuchs (1968) and Blauner (1964), who argued that the arrival of the post-industrial service society and the concomitant increase in skill requirements is the result of the elimination of routine work through technological change. Similar ideas are also present in Clark (1948), Kerr et al. (1960), Bell (1973), and Kern and Schumann (1984).

In this scenario, technological change is taken as exogenous. In contrast, Braverman (1974) argued that the "labour process" is not determined by such independent technological developments. Rather technological developments are the outcome of employers' conscious search for technological alternatives that answer to their need for control over the production process (see also Crompton and Jones, 1984). However, although technological change now is endogenous, it is nevertheless the case that it is this change that determines the evolution of job content. Thus, while Braverman predicted de- rather than upskilling, technological change was once again the key ingredient in the transformation of work.

Between these two extremes one finds the dualization/polarization thesis of Doeringer and Piore (1971) and Edwards (1979). In contrast to the theories above, which predicted an either increasingly complex or an increasingly simplified production process, the labour market was here seen as becoming more and more divided. While some jobs were indeed becoming more and more involved, others were less and less so. We would in other words have both worlds, rather than the one or the other.

These rather disparate views of economic development do however share a complete indifference with regard to public policy in general and educational policy specifically. Very little, if anything, is said regarding a potential role of education and skills as causal factors in the determination of modes of production.

A potentially greater role for education is on the other hand implicit in standard economic production theory. This starts from the assumption that employers adjust the production process to the available factors of production and their relative prices, including the available human capital in the labour force and wages. Nonetheless, although this allows for an effect of education on job content this is not been spelled out in any greater detail. The economic theory of production simply assumes that the various factors of production are transformed into output using some specific production function but without analysing the choice of production function, i.e. the production process.

This leads over to another strand of literature that potentially could have some bearing on the problem: endogenous growth theory. Education (at times labelled human capital or knowledge) is here linked to economic growth (Aghion and Howitt 1998), opening up the possibility of there being a link between education and specific forms of economic growth (i.e. choice of production function). Nevertheless, endogenous growth theory is not very limpid when it comes to what type(s) of education is important, or what type of production may be furthered. The only statements of this kind (in models of what has been called heterogeneous or two-stage innovation) deal with the distinction between high and low education and between high and low production in a rather confabulatory manner (Maré 2004).

This is also partly true of the related literature on endogenous skill-biased technical change (SBTC), a.k.a. directed technical change. Recall that the early upskilling literature discussed above took exogenous technical change as its starting point. This is also the dominant assumption in the literature on SBTC. However, the SBTC strand has been developed so that technical change (i.e. the choice of production function) can be endogenous in the sense that it is seen as a function of the skill level of the labour force (Acemoglu 1998, 2002a, 2002b; Kiley 1999). As in the case of endogenous growth theory, the models simplify and only discuss high- and low-skilled workers and how changes in the composition of the labour force might affect the wage distribution.

The basic idea is that employers respond to incentives, including incentives regarding what innovative adventures to support and which innovations to introduce. As always, the primary incentive is the price, in this case the price of various factors of production, something largely determined by their relative supply. When it comes to labour, the wages paid to different types of workers is in other words largely a result of their relative supply. An increase in the supply of highly educated workers could be expected to lead to a reduction in their relative wages. This would in turn make it more profitable for employers to make use of this particular category of workers, and stimulate the development and introduction of work processes that employ highly educated workers. Although it is not entirely clear what work processes could be conceived as complementary to education, it is generally argued that this is independent analytical work. These types of jobs, or tasks, have for instance been said to involve interpreting the increased information flow associated with computerization (Autor et al. 2002, see also Caroli and Van Rennen 2001).

This literature thus posits a general association between educational change and changes in production, yet in some of the more recent literature these claims are contextualized. Particularly interesting in this case is the discussion by Blundell et al (2018) in which employers' choice of production method is related to both the level and the rate of change in the qualifications of the labour force. They discussed a scenario with technological leaders and followers, the former being settings (in their case countries) with a highly qualified labour force and the latter with a less qualified workforce. In their model, a given change in educational attainment of the labour force induces different changes in production depending on the initial level of education in the labour force. This literature thus modifies the general association between education and production posited in the literature on directed technical change, arguing that the relationship will depend on the starting levels.

3.3 Empirical literature

The up- and deskilling debates have generated a substantial literature. There are a number of national studies, focusing mainly on the five countries Great Britain, Sweden, USA, Netherlands, and Canada. The general conclusion from these analyses, covering roughly the time period 1970 to 2000, is that there is a weak trend towards upskilling. This conclusion holds irrespective of whether the analyses focus on changes in the occupational structure or on more direct measures of job requirements. Although it is somewhat difficult to assess the strength of the upskilling trend, as it lacks an intuitive yardstick, the changes in the educational requirements suggest that the change is rather moderate.

In contrast, the quantitative empirical literature on how education may impact on job content is still very limited. Even such an intensely debated issue as the rising skill premium provides relatively little in terms of pertinent evidence, i.e. in how rising educational attainment has influenced production technology in turn affecting wage levels and dispersions.

In one of the early overviews of the literature on directed technical change, Acemoglu (2002a) thus referred to the analysis by Autor et al. (1998) in his discussion of the link between the supply of human capital and changes in the demand for skills. Their study examined the link between the relative supply of college and non-college workers and wage inequality in the USA. Despite a dramatic increase in the relative supply of college educated labour, they found an equally marked increase in the relative wages of this group.

This line of work remains the dominant approach to the analysis of the links between education and production, or, in the words of Goldin and Katz (2008), the "race between education and technology". Their book explored how changes in labour supply have interacted with changes in labour demand in the evolution of wage and earnings inequality in the USA over the last century. Their main conclusion was that changes in supply have been the major determinant of US inequality. Educational policy in the form of the high school movement around 1910 was thus the prime mover in the reduction in inequality that started at that time and continued into the 1980's.

The above literature focuses on the link between education and wages, or more specifically on educational attainment and wage inequality. Similar evidence is also available from large scale educational reforms in Norway, Sweden, Switzerland, and the UK. These studies differ in both the type of reform that is examined and in the outcome variables studied. Albrecht et al (2009) analysed a Swedish program intended to raise the qualifications of all low skill workers in the country, around 10 percent of the labour force. They examined the impact of the reform on the whole economy, and not on the employment and wages of the participating workers as in a more traditional evaluation. Their conclusion was that the reform did lead to an increase in wages for the large treatment group. They explicitly discussed this in terms of employers' changes in production as a response to the change in labour supply.

In contrast, Blundell et al. (2018), Carneiro et al (2019), and Schultheiss et al (2019) all examined expansion of higher education. Using both with- and between industry and regional variation Blundell et al. (2018) looked at the wage inequality effects of university expansion in the UK. Carneiro et al (2019) also utilized regional variation to analyse the impact of the introduction of Norwegian universities of applied sciences on wage inequality. The results from the two studies were similar in that neither country experienced a decrease in inequality following university expansion. In fact, in Norway inequality even increased something the authors attribute to employer changes to the production process producing increased demand for high skilled labour. Another interesting finding in the Norwegian case was also that the increases appeared to be concentrated to areas in which universities with science, technology, engineering and mathematics (STEM) programs. Moving beyond wages, Schultheiss et al (2019) may be said to provide some indirect evidence of changes in production in their analysis of the task content of Swiss job postings, analyses showing that the content of postings in regions with an expansion of universities of applied sciences shifted towards R&D and became more similar to academic postings.

Striking is nevertheless that there seems to be little direct empirical evidence on the relationship between educational expansion and what people actually do at work. Although the studies mentioned above all discuss their results in terms of changes to the production process in response to the increased supply of highly educated workers, the evidence provided is mainly circumstantial. The most direct evidence to date seems to be the supportive evidence on worker decision latitude provided by Blundell et al (2018). Using a few standard indicators of discretion, they examined how variation in education across regions had impacted on worker job control. This type of analysis will here be extended by using a more extensive set of indicators of job content and by accounting for the nested structure of the data through the use of multilevel regression. This will provide new information on the link between educational reform and the extent to which workers' carry out different types of tasks in their daily work.

3.4 Data and method

The theoretical debate on the potential consequences of an expansion of education for the labour market has focused on the impact of the changing supply of skills on employers' choice of production methods. Specifically, the idea in the literature on directed technical change has been that "complex" skills (self-directed work) to an increasing extent have come to supplant the use of "simple" skills (physical prowess) in the production process. Against this background we will here focus on job indicators dealing with the performance of various tasks that might indicate the type of skills utilized in production.

To study the changing nature of work overtime we would thus need rather detailed indicators of the type of tasks performed at work, indicators preferably covering a variety of skills. This type of information is available in many different national surveys of working conditions, some of them very comprehensive. They would provide us with in-depth information, yet for our purposes these have the drawback of having been conducted only intermittently making it difficult to link any observed changes in task composition to changes in the educational qualifications of the country's labour force in a rigorous manner.

In our analysis of the link between education and job complexity we will therefore make use of the European Working Conditions Survey (EWCS), which has been conducted in 1991, 1995, 2000, and 2005, 2010, and 2015. The number of countries taking part in the EWCS has grown over time, from an initial 11 to the most recent 31. We here make use of a balanced panel of 14 countries; Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and the UK. Sample sizes for the different countries and surveys are listed in Table A1 in the Appendix.

The survey was designed to cover many different aspects of working conditions, including the performance of certain tasks. Although the available indicators are not without problems, the use of the EWCS also gives us additional leverage when it comes to the key independent variable education. A data set with a selection of countries thus gives us much greater variation in the educational composition of the labour force than we would have in a country study.

The number of indicators included in the EWCS has also grown dramatically over time, from a limited set of 20 questions in 1991 to around 100 in 2015. This successive expansion of the questionnaire does pose a problem in that the information in the initial survey is much more limited than in latter rounds. We will therefore work with the surveys from 1995 to 2015, using the information from twelve indicators to construct and index of job tasks.

The central idea has been to try to capture aspects of job complexity, to track trends away from the stereotypical manufacturing line jobs. The measures include two indicators of job autonomy; "can choose or change order of tasks" and "can choose or change speed or rate of work". Furthermore, there is an indicator of whether or not the job "involves short repetitive tasks of less than 10 minutes", and finally an indicator of the use of “computer equipment”. In addition, there is also information based on the following questions; whether the job involves “repetitive hand or arm movements”, “dealing directly with people who are not employees at your workplace”, “assessing the quality of your own work”, “monotonous tasks”, “complex tasks”, “learning new things”, “solving unforeseen problems on your own”, and whether one is able to “choose or change methods of work”.

Although further detail would undoubtedly have been desirable, for instance regarding management or computer related tasks, these variables would nonetheless seem to measure key dimensions of job complexity. Individually, they have also been used to track changes in job quality and skill usage in many earlier reports (e.g. Handel 2012).

Most of the questions were answered with simply “Yes” or “No”. Exceptions were the questions relating to computer usage, dealing with people and repetitive movements which all were answered using a seven-point time-based scale (from “all of the time” to “never”). The first set of questions have been naturally coded as zero-one response, while the latter have been recoded to a zero-one scale with the breakpoint lying at “around half of the time”. To capture increasing complexity, answers to the questions regarding repetitive tasks, repetitive movements, and monotonous tasks have been reverse coded.

To explore the relationships between the various dummy indicators we have conducted a series of factor analyses. The purpose has been to ascertain what types of skill profiles are captures by the various indicators, and if the skill profiles are stable over time. The results from the analysis based on the 2005 wave can be seen in Table 1, Panel A. The indicators clearly distinguish one dominant work dimension, and separate out two other job types relatively clearly as well (see also the scree plot of the eigenvalues in Figure 1). The first component scores low on indicators capturing monotonous or repetitive tasks, and highly on measures of flexibility, complexity, and self-direction. The other two components are both quite distinct from the main component. Component no. 2 thus scores lower on indicators of task flexibility, and much higher on the repetitive dimensions. In contrast, component no. 3 scores lower on complexity and self-directedness, and somewhat higher on monotonicity. This also implies that the components 2 and 3 are distinct from each other, despite the fact that their eigenvalues are relatively similar. Interesting is also that the three components load very differently on the indicator of computer usage. Component 1 thus scores high, component 3 low, and component 2 in between.

Table 1. Factor analysis of job complexity

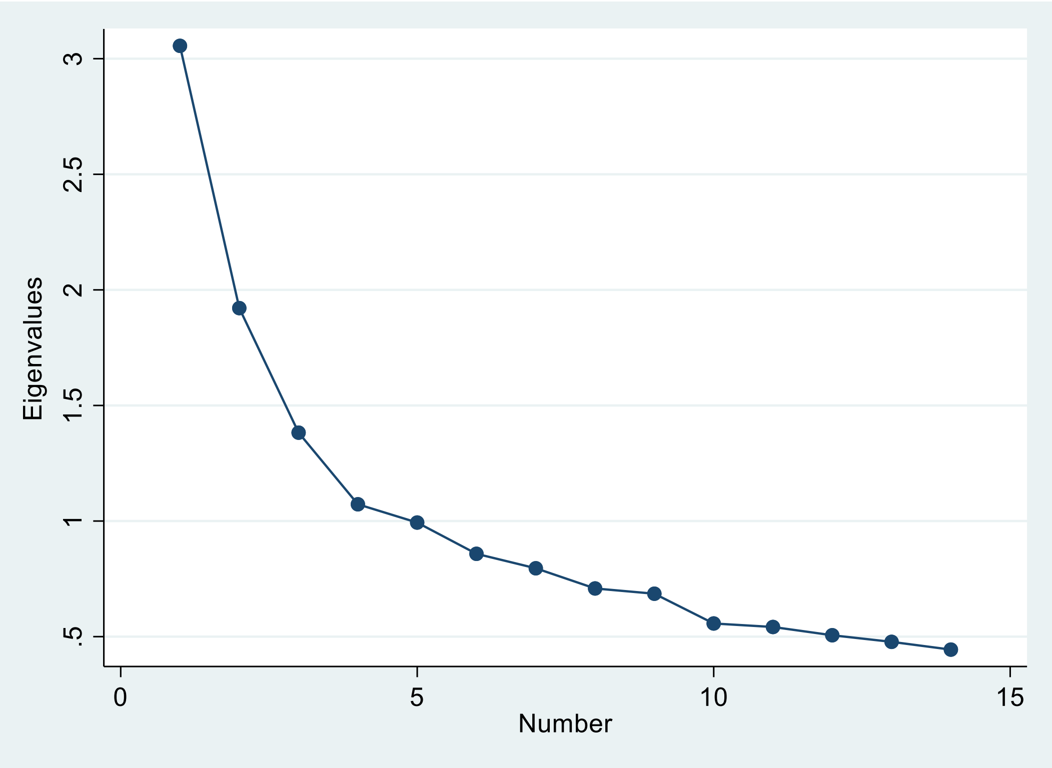
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,840	23,667	23,667	2,840	23,667	23,667
2	1,506	12,552	36,219	1,506	12,552	36,219
3	1,388	11,563	47,782	1,388	11,563	47,782
4	,986	8,219	56,002			
5	,917	7,638	63,640			
6	,815	6,793	70,432			

Extraction Method: Principal Component Analysis.

	Component		
	1	2	3
Does your main paid job involve – repetitive hand or arm movements?	-0,298	0,658	0,232
Does your main paid job involve: monotonous tasks?	-0,279	0,524	0,193
Does your job involve short repetitive tasks of less than 10 minutes?	-0,156	0,674	0,156
Does your main paid job involve - dealing directly with people who are not employees at your workplace?	0,279	-0,036	-0,142
Does your main paid job involve: assessing yourself the quality of your own work?	0,425	0,367	-0,080
Does your main paid job involve - working with computers: PCs, network, mainframe?	0,452	-0,008	-0,396
Does your main paid job involve: complex tasks?	0,501	0,311	-0,400
Does your main paid job involve: solving unforeseen problems on your own?	0,570	0,223	-0,165
Does your main paid job involve: learning new things?	0,581	0,227	-0,430
Are you able to choose or change your speed or rate of work?	0,585	-0,033	0,545
Are you able to choose or change your order of tasks?	0,680	-0,069	0,443
Are you able to choose or change your methods of work?	0,684	-0,065	0,474

Source: European Working Conditions Survey 2005. Own calculations.

Figure 1. Scree plot of eigenvalues from factor analysis of job complexity



Source: European Working Conditions Survey 2005. Own calculations.

We will here focus on the first dimension, as this seems to capture the type of work tasks and jobs that are at the core of the idea of skilled biased technical change. Analyses of the other four waves of the survey (i.e. 1995, 2000, 2010 and 2015) display very similar results, with the factor loadings of the different indicators yielding basically the same “ranking.” The twelve indicators have then been used to construct a simple additive index of job complexity, a so-called factor-based index in which all items are given equal weight and the factor analysis only determines which items are to be included in the index.

In addition to the validity stemming from the frequent use of these and similar questions in previous work, an additional check of the validity of the index may be conducted by listing the mean complexity scores for different types of jobs. The EWCS contains information on the job title of the respondents (2-digit ISCO88), and although these represent rather broad job categories they may still be used to examine the index' face validity. In Table 2, the various job titles contained in the 2005 EWCS are ranked according to increasing mean complexity score, and it is obvious that there is a fairly strong relationship between complexity and any sort of hierarchical job ranking. The lowest scores thus include job titles such as labourer and machine operator, medium scores encompass various associate professionals, and the highest scores are obtained for various professional categories. This suggests that the index even in this simple form does capture core dimensions of work complexity.

Table 2. Mean job complexity score by job title

Job title	Job compl. score	Job title, cont	Job compl. score, cont
Labourers in mining, constr., manufact. & transport	6,72	Life science and health associate professionals	9,34
Machine operators and assemblers	6,85	Armed forces	9,45
Agricultural, fishery and related labourers	6,89	Office clerks	9,82
Stationary plant and related operators	6,89	Managers of small enterprises	10,06
Drivers and mobile plant operators	7,44	Life science and health professionals	10,08
Sales and services elementary occupations	7,70	Physical and engineering science associate professionals	10,11
Extraction and building trades workers	7,77	Other associate professionals	10,18
Other craft and related trades workers	8,11	Teaching associate professionals	10,45
Skilled agricultural and fishery workers	8,26	Teaching professionals	10,50
Precision, handicraft, craft printing and related trades wor	8,27	Legislators and senior officials	10,71
Metal, machinery and related trades workers	8,38	Other professionals	10,76
Models, salespersons and demonstrators	8,64	Physical, mathematical and engineering science professionals	10,76
Personal and protective services workers	8,70	Corporate managers	10,91
Customer services clerks	8,89		
Source: European Working Conditions Survey, 2005. Own calculations.			

The other central variable pertains to educational attainment in the workforce. As just noted, the data on job complexity spans the period 1995 to 2015, yet uncertainty in how rapid any technological adjustment process might be also makes us interested in examining the links over an even longer time period. We therefore require data on educational attainment from ca. 1985.

Detailed comparative and historical data on educational attainment in the labour force is however surprisingly rare, and quality issues have been abundant. We here use data on educational attainment from Goujon et al (2016), with updates obtained from the Wittgenstein Centre for Demography and Global

Human Capital (2018), on the share of the adult population (25 to 64 years-of-age) with tertiary education (ISCED 4, 5 or 6). As theory provides no clear guidance on the speed at which employers might adapt the production process we have examined the importance of the share of university educated using lags of either zero, five or ten years.

The data from the EWCS consists of repeated cross sections of the European population and therefore has a three-level structure, with individuals nested in years nested in countries. In addition to simple descriptive analyses, 3-level random effects regression will consequently be used in exploring the link between educational expansion and technical change. Such a model can be written a

$$y_{ipc} = \beta_0 + X_{ipc}\beta_1 + Z_{pc}\beta_2 + e_{ipc} + u_{pc} + u_c, \qquad (1)$$

where y_{ipc} is the outcome variable, β_0 an intercept, X_{ipc} a vector of level-1 variables, β_1 a corresponding vector of parameters, Z_{pc} a vector of level-2 variables, β_2 a corresponding vector of parameters and sub-indexes i, p and c denote observations at level-1 (here individuals), level-2 (periods) and level-3 (countries) respectively. e_{ipc} is the level-1 residual with $e_{ipc} \sim N(0,\sigma^2_e)$, u_{pc} is the level-2 residual with $u_{pc} \sim N(0,\sigma^2_u)$, and u_c is the level-3 residual with $u_c \sim N(0,\sigma 2_u)$. In this setting, there are no level-3 variables.

However, as pointed out by Fairbrother (2014), when there are involve time-varying variables involved, specification (1) runs the risk of conflating the effects of long-term trends in a variable with the effects of short-term variations in the same variable. He proposed to de-mean the time related variables, so that (1) becomes

$$y_{ipc} = \beta_0 + X_{ipc}\beta_1 + (Z_{pc} - \dot{Z}_c)\beta_2 + \dot{Z}_c\beta_3 + W_{pc}\beta_4 + e_{ipc} + u_{pc} + u_c, \qquad (2)$$

where Z_{pc} is the time-varying level-2 variable, and $\dot{Z}_c$ is the mean of the same variable. β_2 here indicates the effects of within and β_3 the effects of between variation in Z, that is variation over time in Z within a country and long-term differences between countries. In addition, Fairbrother (2014) suggested to include a time variable, W, in the model to capture any trends in y unrelated to Z.

In their analysis of similar questions, Blundell et al. (2018) were concerned that reverse causality and omitted variable bias, e.g. either of which could generate selective migration of higher educated workers to areas with greater job complexity. An association between education and complexity would then not indicate adaptation by employers to changing worker skills, but rather adaptations by workers to employers' production decisions. To address this possibility, they suggested including a lagged measure of the dependent variable, a measure which would capture initial differences in production technologies.[7] We follow this suggestion here, leading to the equation

$$y_{ipc} = \beta_0 + X_{ipc}\beta_1 + (Z_{pc} - \dot{Z}_c)\beta_2 + \dot{Z}_c\beta_3 + W_{pc}\beta_4 + y_c{*}\beta_5 + e_{ipc} + u_{pc} + u_c, \quad (3)$$

where y_{c*} is the mean job complexity in each country in 1995 and β_5 the corresponding parameter. This specification is then estimated using only observations from the subsequent waves of the EWCS, implying that the calculation $\dot{Z}_c$ changes to only encompass the last three waves of the survey.

Finally, the starting point for the analyses of Blundell et al. (2018), was the idea that the speed at which production technologies adapt in response to educational reforms may be dependent on the technologies used initially. This is what Fairbrother (2014) labelled a "societal" growth model, i.e. a model in which some time-invariant independent variable is associated with different rates of change in the dependent variable. In our case, such a model can be written as

$$y_{ipc} = \beta_0 + X_{ipc}\beta_1 + (Z_{pc} - \dot{Z}_c)\beta_2 + \dot{Z}_c\beta_3 + W_{pc}\beta_4 + y_c{*}\beta_5 + W_{pc*}y_{c*}\beta_6 + e_{ipc} + u_{pc} + u_c, \quad (4)$$

and differs from the previous ones in that it includes an interaction term between the initial, country-specific, production technology y_{c*} and time W_{pc}.

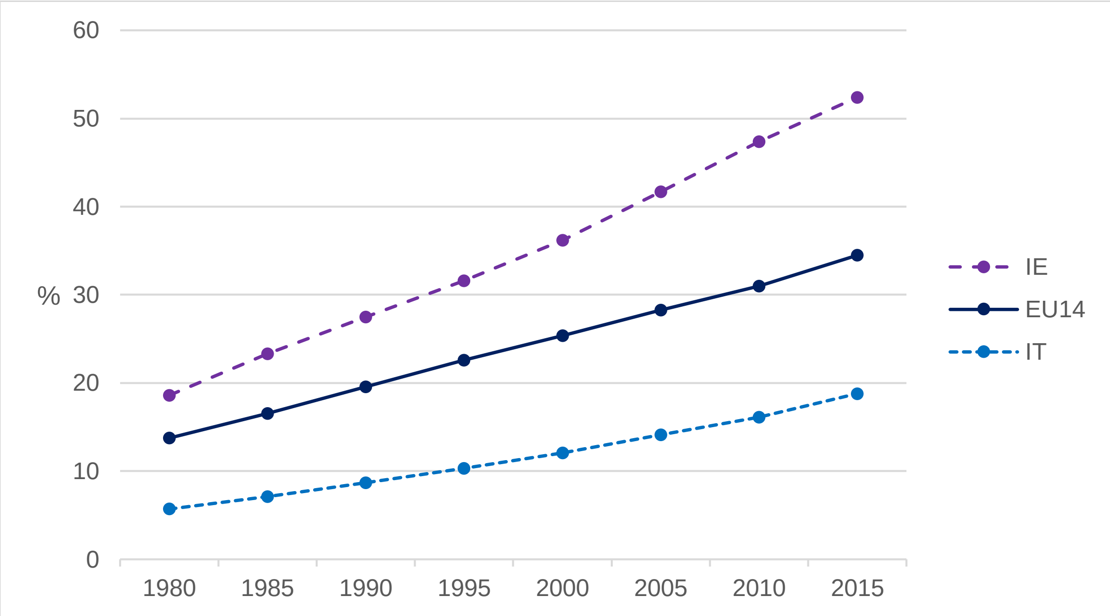
3.5 Education and job complexity in Europe 1995 to 2015

An indication of the development of educational attainment is provided in Figure 2, which shows the share of the adult population with degrees from higher education for Ireland, Italy as well as the mean share for our 14 countries. Ireland and Italy are here shown as they in 2015 are the countries with the highest respectively the lowest share of the population with university degrees. As illustrated by the figure, educational attainment has tended to increase at a relatively steady pace in all countries. However, the figure also shows that there are notable differences between countries. In 1980, university education was for instance around three times more common in Ireland than in Italy, with shares of 19 and 6 % respectively. The absolute difference was in other words 13 percentage points. University enrolment then grew in both countries, in 2015 reaching 52 % in Ireland and 19 % in Italy. Although educational attainment more than doubled in Ireland, it increased even more in Italy. However, despite the faster Italian growth,

[7] Blundell et al. (2018) also suggested accounting for additional heterogeneity through the use of instrumental variables. We have attempted to implement this suggestion as well, using variations of the instruments utilized by Blundell et al. (2018), but none of the specifications turned out be satisfactory.

the absolute difference between the countries increased to 33 percentage points. There are in other words substantial variation in educational attainment between and within countries, i.e. in our central independent variable.

Figure 2. Educational attainment in Europe. Share of adult population with higher education degree (ISCED 4, 5 or 6).



Source: Wittgenstein Centre for Demography and Global Human Capital (2018). Wittgenstein Centre Data Explorer Version 2.0.

What could then be said about the link between the changes in the educational qualifications of the labour force and the work process? A first impression of the evolution of job complexity in Europe is given by Table 3, showing descriptive statistics for the job complexity scores by year. As is evident from the table, there is little indication of any dramatic changes in the distribution over time, the measures mean, standard deviation, skewness, and kurtosis all remain relatively stable. Overall, job complexity during this twenty year-period is characterized more by stability than by change.

Table 3. Job complexity in Europe, 1995 – 2015. Descriptive statistics

Year	Mean	Std. Dev.	Skewness	Kurtosis
1995	9.17	2.47	-0.59	2.86
2000	8.79	2.56	-0.54	2.75
2005	9.09	2.50	-0.58	2.86
2010	9.17	2.76	-0.55	2.79
2015	9.36	2.69	-0.55	2.78

Source: European Working Conditions Survey, own calculations.

Table 4. Job complexity in Europe, 1995 - 2015. 3-level random effects regression. Robust standard errors in parenthesis.

	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed effects coefficients					
Tertiary ed. % (mean)		0.035*** (0.014)	0.035*** (0.014)	0.005 (0.007)	0.006 (0.007)
Tertiary ed. % (diff.)		0.032*** (0.007)	-0.016 (0.017)	-0.010 (0.014)	-0.016 (0.018)
Year 2000	-0.380*** (0.081)		-0.336*** (0.110)		
Year 2005	-0.097 (0.088)		-0.006 (0.136)	0.311*** (0.095)	3.430*** (1.315)
Year 2010	0.088 (0.108)		0.222 (0.210)	0.522*** (0.114)	2.046 (1.534)
Year 2015	0.286*** (0.076)		0.476** (0.244)	0.754*** (0.154)	2.082** (1.057)
Job compl. 1995 (country)				1.146*** (0.105)	1.304*** (0.138)
Job compl. 1995 * year 2005					-0.338** (0.147)
Job compl. 1995 * year 2010					-0.162 (0.164)
Job compl. 1995 * year 2015					-0.138 (0.110)
Constant	9.215*** (0.162)	8.195*** (0.440)	8.122*** (0.456)	-1.889* (0.953)	-3.360*** (1.276)
Random effects variances					
Country-year	0.037 (0.007)	0.074 (0.008)	0.037 (0.006)	0.032 (0.008)	0.027 (0.007)
Country	0.390 (0.132)	0.325 (0.131)	0.333 (0.131)	0.046 (0.020)	0.047 (0.020)
Log pseudo-likelihood	-202272.98	-202289.06	-202271.61	-170313.73	-170310.64
No. of units of analysis	Respondents = 85 847, country-years = 70, countries = 14			Respondents = 72 010, country-years = 56, countries = 14.	

Notes: European Working Conditions Survey, own calculations. Maximum likelihood estimation, standard errors clustered on country. *** = p < 0.01, ** = p < 0.05, * = p < 0.10. Models 4 and 5 using only waves 2000, 2005, 2010 and 2015.

Nevertheless, closer inspection of the means reveals that the distribution seems to have shifted slightly to the left between 1995 and 2000 followed by successive rightwards shifts after 2000. However, these shifts would appear rather minor given the massive changes in the qualifications of the labour force shown in Figure 2. There, the share of the adult labour force with a degree from higher education on average almost doubled, from 14 to 35 %. Despite the large and more or less continuous increase in educational attainment, the measure of job complexity suggests rather limited changes in work organization.

A more systematic take on this problem is presented in Table 4, containing the results from the 3-level random effects regressions of the job complexity index on mean educational attainment, variations in educational attainment, and time. The models have here been kept simple, as theory does not provide any clear guidance regarding model specification.

Model 1 shows the relationship between time and job complexity, and the results replicate the pattern in the means observed above. We in other words see a marked decrease in mean complexity between 1995 and 2000, subsequent minor increases, and final increase between 2010 and 2015. While the initial decrease in complexity seems difficult to align with the theoretical expectations, the ensuing evolution in job complexity would at least coincide with the expansion of educational attainment.

An attempt at exploring this more directly seen in Model 2, showing the relationship between long- and short-term differences in educational attainment and job complexity. Both estimates are positive and significant, suggesting that increasing attainment indeed is associated with greater complexity. Interesting is here also that the two coefficients are relatively similar, indicating that the effect of variations in attainment within a country is about as large as the effect of the much larger differences between countries.

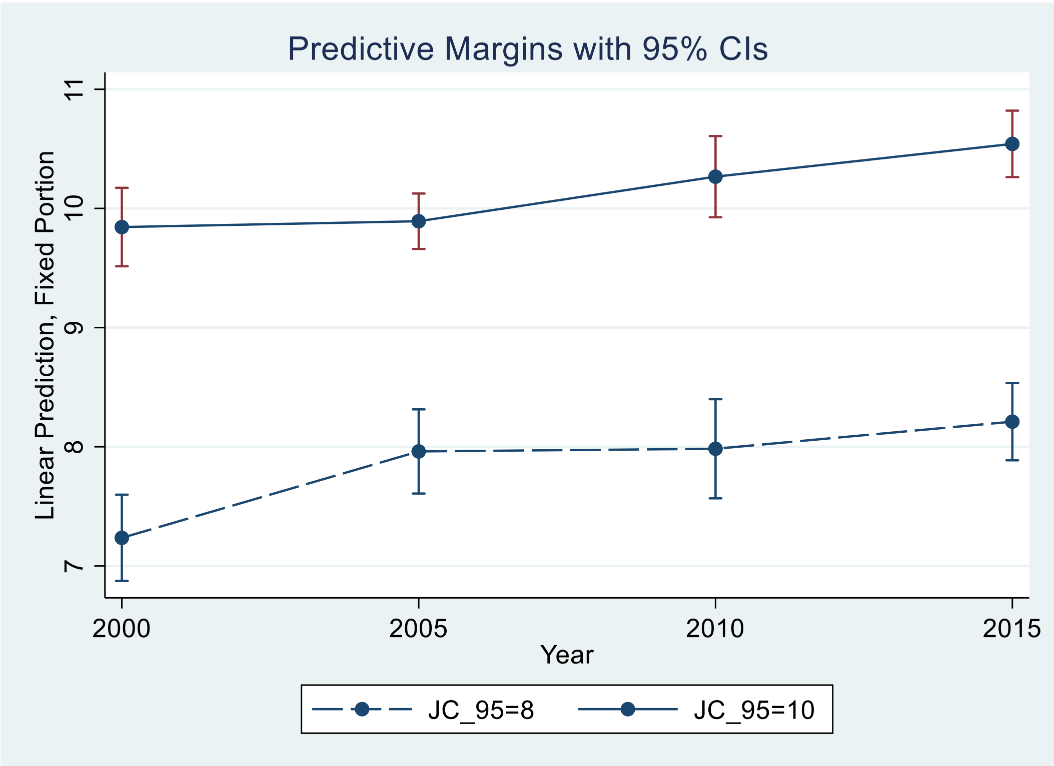
However, as noted earlier time trends such as the one evident in Model 1 may confound substantive relationships, and Model 3 therefore includes both sets of variables at once. As in Model 1 there are clear indications that job complexity initially drops and then increases steadily over time. More importantly, even after taking this time trend into account, the between effect of education remains almost unchanged and clearly significant. This, in contrast, does not apply to the within effect. It would consequently seem as if long-term differences in educational attainment are crucial to country differences in job complexity, while changes in attainment within countries over time are of little importance.[8]

That variations between countries matter but that variations within countries don’t, would however seem to suggest that it may not be education per se that influences the choice of production technology, but rather some other unobserved country-specific factor. This is explored further in Model 4 in which the

[8] As it is unclear how quickly employers might respond to changing educational attainment in the workforce, the analyses in Models 2 and 3 have been repeated using 5- and 10-year lagged values of the educational variables. However, the results from these analyses (not shown) did not differ substantively from those presented in Table 4.

initial level of job complexity in each country (i.e. mean job complexity in 1995) is included in the model. This model can thus be said to take production technology in 1995 as the baseline and examine how differences in educational attainment are related to subsequent changes over time. While the time trend is largely unchanged, showing a steady increase in complexity from 2000 onwards, none of the estimates for the educational variables are now significant. This again indicates that the expansion of education that has taken place within our 14 countries after 1995 has had no impact on job complexity, and also that our suspicion that the between country differences observed earlier may be more related to some unobserved background factor than to the observed differences in educational attainment.

Figure 3. Predicted evolution of job complexity by level of job complexity in 1995 (JC_95). Confidence intervals in whiskers.



Source: European Working Conditions Survey, own calculations. Figure based on results in Table 4, Model 5.

What this unobserved factor may be is of course unclear, but Model 5 nonetheless explores the notion that starting point itself impacts on the changes in job complexity by introducing an interaction term between time and the countries initial level of job complexity. As the estimates in the table are difficult to interpret, Figure 3 presents the predicted evolution of job complexity for two levels of initial complexity. The two levels illustrated, JC_95 = 8 and 10, are equal to the highest and lowest values observed in the data.

As is clear from the figure, there are in these data only very weak indications of such an effect. The difference between the predicted values for the high and low complexity countries does decreases from 2,6 in 2000 to 2,3 in 2015, yet the overall impression is that the two lines run roughly parallel to each other.

There is thus little sign of initial laggards drawing upon the choices and experiences made by the leaders, or of the leaders being able to build upon their initial advantage. While technological adaptation may be a slow process, the 15-year period examined here would nonetheless seem sufficiently long for any such processes to occur.

3.6 Conclusion: is education a trigger?

Much has been made of the importance of education as a vehicle for social change. It has among other things often been said to be of vital importance for individual life chances, and educational reform was thus a centrepiece of social policy in many countries. Lately, it has also been regarded as crucial for the success of nations in the global marketplace. The arrival of the IT cum knowledge society has here been said to require a substantial increase in the educational attainment of the citizens of industrial nations. However, education has also been portrayed as the driver of the transformation of the workplace, with employers responding to the increasing supply of highly educated workers by introducing changes in the organization of work.

This paper has explored the validity of this second view, examining the link between educational expansion and job complexity at the societal level. All in all, we find basically no support for the view that education is the transformative force it has been made out to be. The simple descriptive analysis of changes in job complexity provides no indications that the continuous educational expansion observed in the 14 countries has produced a general increase in complexity. This conclusion is also borne out by the multivariate analyses showing no relationship between changes in educational attainment and job complexity once the starting level of complexity has been taken into account.

This conclusion is nevertheless accompanied by a number of caveats. First, both the time span examined and the measures used may leave something to be desired. The period examined stretches from 1995 to 2015, with the educational data encompassing the years 1985 to 2015. While this may seem like quite an extensive period, it may nonetheless be located between the breakthrough of the personal computer in the 1980s and the recent introduction of artificial intelligence. This may be the reason for the lack of change in job complexity, with most change occurring either before or after the period examined here. Moreover, despite strong face validity, the measure of job complexity may still be unable to capture changes in certain aspects of job complexity, mainly in more complex jobs, something that further complicates the identification of changes over time. Most importantly, the multivariate analysis focuses exclusively on means, rather than on the distribution of skill requirements that is the centrepiece of much of the debate.

Nonetheless, this analysis presents one of the more comprehensive analyses of this question to date. The conclusion that education is not a driver of changes in job complexity would in turn imply that technological change is an exogenous process.

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Appendix to Chapter 3

Table A1. European Working Conditions Survey, sample sizes by survey and selected countries.

	1995	2000	2005	2010	2015
Austria	393	510	1009	1003	1028
Belgium	407	562	1003	4001	2587
Denmark	281	374	1006	1069	1002
Finland	224	312	1059	1028	1001
France	2374	3220	1083	3046	1527
Germany	3817	4984	1018	2133	2093
Greece	404	550	1001	1037	1007
Ireland	138	226	1009	1003	1057
Italy	2137	2837	1005	1500	1402
Netherlands	743	1072	1025	1017	1028
Portugal	480	654	1000	1000	1037
Spain	1349	2099	1017	1008	3364
Sweden	429	567	1059	1004	1002
United Kingdom	2792	3710	1058	1575	1623

Chapter 4

How important are general skills for vocationally educated?

Rolf van der Velden, Ineke Bijlsma, Marie-Christine Fregin and Mark Levels

4.1. Introduction

The question to what extent education systems in Europe effectively support the acquisition of skills that maximize the future employability of students is an important theme for national and international policymakers. The concern is that education fails to develop those skills that students need to help them succeed in a globalised economy, where knowledge and innovation have become more important and where flexibility on the labour market increasingly requires workers to assume responsibility for their own employability (Autor, 2010; Levy, 2010; Allen and Van der Velden, 2013; Oesch, 2013; Arntz, Gregory and Zierahn, 2016). This is concerning as education plays a central role in preparing future workers for these increasing demands in knowledge, innovation capacity, flexibility, and entrepreneurship (OECD, 2010; CEDEFOP, 2015; Humburg and Van der Velden, 2017).

The debate is especially relevant for vocational education. Here the discussion focusses traditionally on whether education should primarily teach occupation-specific skills (Bishop, 1998) or whether more attention should be paid to incorporating general skills in the curriculum. Over the years, many curricula in vocational education have been redesigned to incorporate key skills like literacy and numeracy, but also so-called 21st century skills (e.g., OECD 2013a: 94). Still, the empirical research gives mixed signals. On the one hand there is clear evidence that in many countries, vocationally educated school-leavers from upper-secondary education experience better quality school-to-work transitions than their generally educated peers (Arum and Shavit, 1995; Shavit and Muller, 1998, 2000; Ryan, 2001, 2003; Van der Velden and Wolbers, 2003; Iannelli, and Raffe, 2007; Levels, Van der Velden and DiStasio, 2014a; for an overview see Blommaert et al., 2020). And this seems to be driven by the comparative advantage that vocationally educated have in terms of relevant occupation-specific skills.

On the other hand, there is evidence that general skills are key in driving success on the labour market. So-called key information-processing skills such as numeracy and literacy are strong predictors of unemployment risks, wages, job stability, career opportunities etc. (Levels, Van der Velden and Allen, 2014b; Hanushek et al. 2015; 2017a; Hampf, Wiederhold, and Woessmann, 2017). Moreover, occupational task demands change during careers, and occupation-specific skills that were acquired in education may be more at risk of becoming obsolete than general skills (Gould, Moav, and Weinberg, 2001; De Grip, Van Loo, and Mayhew, 2002; Hanushek et al., 2017b).

A major problem with some of the empirical studies so far, is that they rely on subjective self-ratings to measure general and occupation-specific skills (e.g., Allen and Van der Velden, 2001; Green, 2013; Ramos et al. 2013; Livingstone, 2017; Muja, Gesthuizen, and Wolbers, 2021). However, these subjective ratings are prone to social bias (Verhaest and Omey, 2006; Van der Velden and Bijlsma, 2019) and might not be a good indicator of the actual skill level. The strongest evidence therefore seems to come from studies using direct tests to measure skills (e.g., OECD, 2013b; Levels et al., 2014b; Hanushek et al., 2015). However, an association between general skills and wages does not imply that these skills are used and thus lead to a high productivity.

To scrutinise the relation between general skills and wages, we use the recently developed concept of effective skills (Van der Velden and Bijlsma, 2019). The underlying idea of effective skills is that skills can only affect wages if they are put to productive use. It is the combination of possessing key skills and at the same time using them at work, that affects productivity. By combining skill proficiency and skill use in one concept, the resulting association with wages is arguably an effect of using these general skills in the work context.

We use data from the Programme for the International Assessment of Adult Competencies (PIAAC) to explore the relationship between general skills and wages for 20-55-year-old workers in 25 countries with advanced economies. Focusing on people who completed education at ISCED levels 3 or 4, we assess the effect of general skills on wages for vocationally educated workers. To put this into perspective, we compare the results for workers who followed a general track in upper secondary education. We run analyses separately for male and female workers, from different age groups and working in sectors of different R&D intensity. Moreover, we explore whether characteristics of the educational system moderate this relation between general skills and wages for the vocationally educated. The PIAAC data also allows us to assess how much people trained in vocational or general tracks differ in their skill proficiency and which characteristics of the education system are most associated with a high proficiency level.

In sum, we address the following two research questions:

1. Do general skills affect the wages of vocationally educated? Is this effect comparable to the effect for those educated in general tracks? Does this differ by gender, age, and sector? To what extent do the effects for vocationally educated differ between countries with different characteristics of the education system?
2. Which characteristics of the education system are associated with a higher proficiency level of general skills of the vocationally educated?

The results indicate that general skills strongly affect wages of vocationally educated workers and are not less important than for generally educated workers. For vocationally educated males these effects are specifically salient for prime age and older workers (36 and above). For vocationally educated females, general skills are most important in the beginning of their career (20-35) and at prime age (36-45). The associations vary with characteristics of the educational system, with stronger associations for vocationally educated male workers in countries where the vocational orientation is high. We further show that a strong vocational orientation of the educational system is not associated with the skill proficiency levels of vocationally educated, but they are systematically related to the skills levels of those educated in general tracks. A strong vocational orientation of the educational system leads to a more selective group of students who follow the general tracks. This characteristic is thus associated with an increasing gap between the vocationally and generally educated. Skill proficiency levels of vocationally educated are not systematically related to whether vocational programs in a country are primarily school-based or workplace-based.

4.2. Theory

A recent meta-analysis by Blommaert et al. (2020) shows that the vocational orientation of a country's education system is generally associated with positive labour market outcomes, although the magnitude of the effect is modest at best and the effect is mainly driven by the vocational specificity of the underlying vocational programs. The results of the meta-analysis confirm previous research showing that vocationally educated have relatively smooth education-to-work transitions (Shavit and Muller, 1998; Ryan, 2001, 2003; Van der Velden and Wolbers, 2003; Levels et al., 2014a).

There are two complementary explanations for the positive effect of vocational education on labour market outcomes. The human capital explanation is that vocationally educated school-leavers are equipped with skills directly deployable at the labour market, thus making them relatively attractive for employers (Ryan, 2001, 2003; Hoffman, 2011). Indeed Muja et al. (2021) show that occupation-specific rather than general skills drive the labour market success of upper secondary vocationally educated. And Humburg and Van der Velden (2015) show that employers value occupation-specific skills much more than general skills when hiring tertiary education graduates. The social network explanation is that vocationally educated often have close contacts with prospective employers during their initial training (e.g., via an internship or an apprenticeship), which leads to a smooth transition to the labour market (Ryan, 2001, 2003; Van der Velden and Wolbers, 2003. Baert et al., 2021; Muja et al., 2021). For example, Baert et al. (2021) show that job applicants with an internship experience have a higher probability to be invited to a job talk.

At the same time, there is clear evidence that general skills such as literacy and numeracy are very strong predictors of unemployment risks, wages, job stability, career opportunities etc. (OECD, 2013b; Levels et al, 2014b; Hanushek et al. 2015; 2017a; Hampf et al., 2017; Verhaest et al., 2018). Moreover, there is evidence that the better employment prospects associated with a vocational qualification in the school-to-work transition seem to reverse later in life (Hanushek et al., 2017a; Forster, Bol and Van de Werfhorst, 2016).

Some of the previous studies on the effect of general skills rely on indirect measures of skill proficiency, such as self-ratings by workers (Allen and Van der Velden, 2001; Muja et al., 2021; Green, 2013). However, self-ratings are prone to biases such as boasting (Hartog, 2000; Verhaest and Omey, 2006) and are unlikely to provide a valid estimate of a worker's actual skill level. The empirical support for the relevance of general skills therefore seems to rely primarily on studies that use direct skill measures (tests) to assess the worker's proficiency level (e.g., OECD, 2013b; Hanushek et al., 2015; Levels et al., 2014b). But these studies are not entirely convincing either. The fact that certain skills are associated with wages, does not imply that they are causing an increase in the productivity and thus to wages.

A simple example may illustrate the point. In most jobs, piano playing skills will not have any impact on the work productivity (except of course in the case of a professional pianist). Suppose we would have a test in which we measure the piano playing skills of workers and correlate that with wages. Most probably, these piano playing skills would show a significant correlation with wages, simply because they are correlated with other skills that are relevant in the job. If these other skills are not controlled for, one could wrongly conclude that piano playing skills affect wages. This is known as the omitted variable bias. The same might hold for the above-mentioned studies on the effect of general skills. The omitted variable bias implies that in those studies, the effect of general skills on wages might be overestimated. This situation might hold even stronger for the vocationally educated as relevant occupation-specific skills are usually not measured (Baetghe et al., 2006), although they are arguably important for the productivity in the job.

Recently, an approach has been developed that provides a more solid theoretical foundation for the effect of skills on wages: the effective skill concept (Van der Velden and Bijlsma, 2019). The basic idea is the following. Employers reward employees only for skills that are being used in the job, not for skills that are never used.[9] In other words, it is the combination of having a high skill proficiency level and the ability to use those skills in the job which makes a worker productive. Put alternatively, it is the product of skills proficiency and skill use that affects the productivity in a job. Returning to the example of the piano playing skills: the wage effects of piano playing skills are best modelled as the piano playing proficiency multiplied with the actual use of these skills in the job. This would lead to an impact on wages for professional pianists but not for workers who have piano playing skills, but do not have to use them at work.

Van der Velden and Bijlsma (2019) demonstrate the application and usefulness of the concept in an empirical analyse using PIAAC data. PIAAC does not only measure the proficiency of a worker in domains like numeracy and literacy, but also the use of these skills in the work context. They construct two scales based on items that reflect the use of numeracy and literacy skills at work: five items on the use of numeracy skills at work (e.g., “In your job, how often do you usually a) calculate prices, costs, or budgets, b) use or calculate fractions, decimals, or percentages”) and seven items on the use of reading skills at work (e.g., “In your job, how often do you usually a) read directions or instructions, b) read letters, memos, or e-mails”). First, they use a standard Mincerian wage regression to show the main effects of skill proficiency and skill use. Next, they include the interaction term, and show that only the interaction term is significant (Van der Velden and Bijlsma, 2019: Table 1). In other words: *there is no effect of numeracy or literacy on wages, other than by using these skills*. They then define the concept of effective skill as the multiplicative function of skill proficiency and skill use and take this up in the other analyses, instead of the separate variables of skill proficiency and skill use. They show that this concept is superior to other concepts in defining skills or skill mismatches. Note that the concept of effective skill also reduces concerns about the omitted variable bias. If we find an effect of effective numeracy or effective literacy on wages, we have a stronger case that these skills really affect the productivity, because they can only affect wages by being used at work.

4.2.1 Individual level hypotheses

We use the effective skill concept, to estimate the effect of general skills for the vocationally educated workers and compare this estimate with the effect for workers trained in general tracks. Given the relative importance of occupation-specific skills for the vocationally educated, we might expect that general skills are somewhat less important for the vocationally educated than for those educated in general tracks.

H1. General skills are important for the wages of vocationally educated, but relatively less than for the generally educated.

We have no a priori reason to expect that the wage effects of general skills are different for female or male workers. However, we do expect that these effects might change over the career. In the beginning of a worker’s career, an employer has no information yet on the skills that a worker possesses, as these cannot be easily observed. Research has shown that young age workers are paid primarily based on signals (e.g., credentials) rather than actual skills (Spence, 1973; Weiss, 1995; Altonji and Pierret, 2001). We can therefore assume that general skills will be more relevant for the wages of prime age and old age workers

[9] Van der Velden and Bijlsma (2019) argue that this holds for most skills, except for certain very specific skills that are required at a high proficiency level, but are seldom used, e.g., an aircraft pilot’s ability to deal with emergency situations.

compared to young age workers (cf. Van der Velden and Bijlsma, 2019). Given the possible obsolescence of occupation-specific skills over time, we expect this to be stronger for vocationally educated workers:

H2. The wage effects of general skills are stronger for prime age and old age workers than for young age workers. This should hold stronger for the vocationally educated.

We may also assume that general skills are more important in sectors that are rapidly changing. In times of change, workers need to adapt to new situations as their occupation-specific skills have become obsolete (De Grip et al., 2002). In such a situation general skills become more important for a worker's productivity. This will be specifically relevant in sectors with a high R&D intensity, as occupations in these sectors change more rapidly, e.g., when new technologies or knowledge are adapted. We therefore expect the effect of general skills on wages to be more relevant in sectors characterised by a high R&D intensity.

H3. General skills are more important for the wages of workers in sectors with a high R&D intensity. This should hold for vocationally and generally educated.

4.3.2 Education-system level hypotheses

As Levels et al. (2014b) have demonstrated, the role of skills in explaining wages differs between countries. Depending on institutional characteristics of the education system, we therefore expect that general skills are likely to differ in their relevance for the wage setting. Two characteristics of an educational system are specifically relevant for the vocationally educated. One is the vocational orientation often operationalized as the share of vocationally educated in upper secondary education (Allmendinger, 1989; Lavrijsen and Nicaise, 2012; Bol and Van de Werfhorst, 2016). One can argue that countries with a strong vocational oriented educational system can often be characterized as Occupational Labour Markets (OLMs, see Maurice, Sellier & Silvestre, 1986; Marsden, 1990). In OLMs, workers are recruited based on their skills, rather than their trainability (Estévez-Abe, Iversen, and Soskice, 2001; Hall and Soskice, 2001; Gangl, 2004). These skills affect the worker's productivity and relate to occupation-specific skills as well as more general skills. We thus expect that:

H4. General skills are more important for the wages of vocationally educated when the vocational orientation of the educational system is high.

The reverse is true for the vocational specificity of the system. This characteristic refers to the share of vocationally educated pupils that follows a workplace-based program (dual education) instead of a school-based program (Bol and Van der Werfhorst, 2016; Muja, 2021). In workplace learning, the emphasis is more on occupation- and firm-specific skills, while in school-based vocational programs there is more emphasis on acquiring general skills (Deissinger, 2018). We thus expect that the relevance of general skills for wages is less important in countries where the vocational programs are workplace-based rather than school-based. We expect that:

H5. General skills are less important for the wages of vocationally educated when the vocational specificity is high.

Under the assumption that general skills are indeed relevant for the wages of vocationally educated, it is interesting to explore which characteristics of educational systems are most strongly associated with high levels of such skills. In line with the literature (OECD, 2013b), we expect that skill proficiency levels are positively associated with the years of schooling and negatively with having followed a vocational track instead of a general track. This means that we should control for these individual characteristics when looking at the effect of system characteristics. Heisig and Solga (2015), also using PIAAC data, find that the mean skills of intermediate-educated adults are higher in countries with a stronger vocational orientation and that higher degrees of vocational orientation of upper-secondary education are associated with smaller skills gaps between low educated (ISCED 1 or 2) and intermediate educated (ISCED 3 and 4). However, they do not differentiate between those who followed a vocational track versus those people who followed a general track. But this distinction is relevant and not controlling for having followed a vocational track may lead to wrong conclusions. This is because on the one hand a strong vocational oriented system may lead more students to follow a vocational track, which in itself is associated with lower skill proficiency levels. But at the same time, in countries with a strong vocational orientation, the choice for such a vocational track is a positive selection rather than a negative selection (Shavit and Müller, 1998). And the curricula might include more general skills than the curricula of vocational tracks in countries where a vocational track is an exception rather than the rule. If one compares the vocationally educated in strong and weak vocational oriented systems, the former will have higher skill proficiency levels. A similar argument holds for those who followed a general track. The choice for a general track in countries that are more vocationally oriented, is even more selective and based on a higher initial level of general academic skills. We therefore expect:

H6. Controlling for years of schooling, general skill proficiency levels of vocationally educated are higher in countries where the vocational orientation is high. The same should hold for the generally educated.

As indicated before, workplace learning is more associated with the acquisition of occupation- and firm-specific skills than with the acquisition of general skills. As OECD (2010: 60) indicates, countries in which workplace-learning is the dominant mode of teaching in vocational education, generally pay little attention to general skills like numeracy and literacy. We therefore expect that:

H7. Controlling for years of schooling, general skill proficiency levels of people with a vocational degree are lower in countries where the vocational specificity is high.

4.3 Data and model of analysis

4.3.1 The PIAAC data

We make use of the PIAAC data set (OECD, 2013b, 2013c), which assesses the proficiency of the adult population in key information-processing skills in OECD countries. The survey is designed to be cross-culturally and cross-nationally valid. We make use of the 1st and 2nd wave, carried out in 2011/2012 and 2014/2015 respectively, totalling 32 countries and some 216,000 respondents. The national samples are representative samples of non-institutionalized persons aged 16-65. Most countries have around 5.000 respondents in the sample, except for Canada which has more than 27,000 respondents. We took a random sample of some 20% from the Canadian dataset to avoid an overrepresentation of the Canadian sample in the total data set. We further excluded Australia from our analyses, because of data protection rules, and the Russian Federation because of data quality issues. Moreover, we excluded countries with missing information on the educational system characteristics. This was the case for Cyprus, Estonia, Lithuania, New Zealand, and Singapore. For all analyses, we only selected respondents whose highest achieved level of education is ISCED 3 or 4, as we would like to concentrate on those educated in vocational and general tracks in upper secondary education. Moreover, we leave out the 16-19-year-olds as they will not have finished a full upper secondary qualification yet.

The next selection steps are different for the first part of the analyses (concentrating on the effect of general skills on wages) and the second part of the analysis (concentrating on the relation between education system characteristics and the achieved proficiency levels). For the wage analyses, we selected all employees aged 20-55 with a minimum working week of twelve hours or more.[10] The reason to leave out workers aged 56 or older is because countries differ strongly in retirement age. We also dropped self-employed, workers who are employed as an apprentice or still in education as well as non-paid family workers and armed forces. This is because for these workers the relation between skills and income or wages is more arbitrary. Finally, we only selected respondents for whom we have valid information on skill proficiency, skill use and hourly wages and the control variables. Note that the item non-response in PIAAC is very low. This leaves us with an analytical sample for the wage analyses of 26,835 observations in 25 countries.

For the analysis on achieved proficiency levels, we selected all respondents aged 20-35 (whether working or not) and examine whether characteristics of the education system are associated with cross-national differences in skill proficiency levels. The reason to select only young people is because we are interested in the relation between characteristics of the education system and the achieved skill proficiency levels, which would be more obscured if the time since leaving education is too long. Ideally, we would like to have respondents who just finished their study program and had no labour market experience yet. Unfortunately, that would leave only a handful of observations. The focus on 20-35-year-olds seems to provide a good balance between having a sample that left education not too long ago, and an analytical sample with enough observations per country. This leaves us with an analytical sample for the skill proficiency analyses of 22,516 observations in 25 countries.

4.3.2 Dependent variables

The dependent variable in the wage analyses is the *log hourly wage*, excluding bonuses and PPP converted to US dollars. Wages were trimmed per country leaving out the 1st and 99th percentile of the respondents in each country (the wage trimming was done on the full sample, not the selected sample).

The dependent variable in the skill proficiency analyses is the *numeracy and literacy proficiency score*. PIAAC assesses the proficiency of respondents in three key information-processing areas: numeracy, literacy and problem solving in technology-rich environments. In this paper we only focus on numeracy and literacy.[11] Adaptive testing and item response techniques were used to calculate 10 plausible values for each of these two domains. Together, these plausible values on numeracy and literacy provide an unbiased estimate of the 'real' score if the respondent would have taken all the numeracy and literacy

[10] We ran similar analyses for fulltime working employees (fulltime defined as working 32 hours or more) and the results are substantially the same.

[11] The reason to leave out problem solving is that around one third of the respondents did not take the test, because they lacked computer skills or because they choose to only use paper-and-pencil tests (which was not available for the problem-solving domain). Moreover, some countries (France, Cyprus, Spain, and Italy) decided not to have the test at all.

related items (OECD, 2013c). The numeracy scale has a range from 0 to 500 with an OECD international average of 273 and the literacy scale has a similar range with an OECD average of 270.

4.3.3 Main predictors

The main predictors in the wage analysis are the *effective numeracy* and *effective literacy*. This is calculated as the product of the standardised skill proficiency and the standardised skill use in the same domain. Before calculating the product term, both variables were weighted according to their relevance for wages (see Van der Velden and Bijlsma, 2019, for details). The use of numeracy and literacy skills is calculated as the average score of five (numeracy) respectively seven (literacy) items. Example items are: "In your job, how often do you usually a) calculate prices, costs, or budgets" and "In your job, how often do you usually read letters, memos, or e-mails", with response categories ranging from "1. Never" to "5. Every day". After calculating the *effective numeracy* and *effective literacy* score, these were standardised again (on the whole sample).

In the analysis, we differentiate between respondents who followed a *general track* or a *vocational track*. This information was based on the coding by national experts of the national programs into either vocational or general (OECD, 2013c). Some programs however could not be assigned to either vocational or general, as they might be both, depending on the specific curriculum followed. This was the case in seven countries (Belgium, Denmark, Italy, Japan, Sweden, the UK, and the US). For these countries, we used information on the field of study to assign respondents to either vocational or general. If the field of study was Engineering, Agriculture or Services, the respondent was assumed to have followed a vocational course. In all other cases, we assigned respondents to a general program.

As the relations are expected to differ between age groups (see section on hypotheses), we differentiate the wage analyses by *age group*, differentiating young age workers (20-35), prime age workers (36-45) and old age workers (46-55).

R&D intensity is a taxonomy of industries developed by the OECD according to their level of R&D intensity, i.e., the ratio of R&D to value added within an industry (Galindo-Rueda and Verger, 2016). Manufacturing and non-manufacturing activities are clustered into 5 groups (high, medium-high, medium, medium-low, and low R&D intensity industries). Note that in this classification, public sectors such as government, education and health care are excluded. We therefore added 'missing classification' as a sixth category

4.3.4 Control variables

We have the following control variables

- *years of schooling*: This is taken up because the qualifications at ISCED level 3 and 4 vary in length and level. Research has shown that this affects the wage returns (Friedrich and Hirtz, 2021). The scores range from 9 to 18 years.
- *Gender*: male vs female
- *Age* and *age square*
- *Parttime worker:* distinguishing between fulltime workers (32 hours or more per week; coded as 0) and parttime workers (12-31 hours per week; coded as 1)

- *Labour market status:* three dummies distinguishing between fulltime workers (32 hours or more per week), part time workers (up to 32 hours per week) and non-working (this control is taken up in the analysis with skill proficiency as dependent variable).

Table A1 and A2 in the Appendix provide the descriptive statistics of the individual level variables.

4.3.5 Country characteristics

For the characteristics of the education system, we use two measures. For the *vocational orientation*, we use two data sources measuring the percentage of students enrolled in upper secondary vocational programs (OECD, 2006; UNESCO, 2011). For the *vocational specificity*, we use the percentage of upper secondary vocational education that takes place in a dual system (OECD, 2007). To compare the impact, both variables are standardized. Table A3 in the Appendix provides the descriptive statistics for the 25 countries in question.

4.3.6 Statistical model

All analyses are done separately for males and females. This is because both the choice of educational programs at the upper secondary level and the allocation to certain occupations, is highly segregated by gender (e.g., Kriesi and Imdorf, 2019; Sinclair, Nilsson, and Cederskär, 2019). This has an impact on the acquisition of literacy and numeracy skills at school, as well as on the effect of these skills on wages. We also run all analyses separately for numeracy and literacy.

For the wage analysis, we start with the following basic model:

$$LnW_{ic} = \alpha_c + \beta_1 ES_{ic} + \beta_2 VOC_{ic} + \beta_3 YoS_{ic} + \beta_4 C1_{ic} + \upsilon_{ic} + \omega_c \qquad [1]$$

where LnW_{ic} is the natural log of the hourly wage of individual i in country c; α_c is the country-specific constant; ES_{ic} the effective skill, VOC_{ic} is a dummy for having followed a vocational track, YoS_{ic} the years of schooling, and $C1_{ic}$ a vector with control variables (age, age square, parttime dummy). The idiosyncratic error term at the individual level is represented by υ_{ic} whereas ω_c refers to the country-level error term.

Next, we run Eq. 1 separately for generally and vocationally educated; young age, prime age and old age workers; and workers in sectors of different R&D intensity.

Then we add characteristics of the country's vocational education system:

$$LnW_{ic} = \alpha_c + \beta_1 ES_{ic} + \beta_2 VOC_{ic} + \beta_3 YoS_{ic} + \beta_4 C_{ic} + \beta_5 E_c + \beta_6 ES_{ic} * E_c + \upsilon_{ic} + \omega_c \qquad [2]$$

where E_c is a vector of vocational education characteristics (vocational orientation, vocational specificity).

In the second part of the analyses, we look at the skill proficiency level and how that is related to characteristics of the country's vocational education system. The specified model is:

$$SP_{ic} = \alpha_c + + \beta_1 VOC_{ic} + \beta_2 YoS_{ic} + \beta_3 C2_{ic} + \beta_4 E_c + \beta_5 SP_{ic} * E_c + \upsilon_{ic} + \omega_c \qquad [3]$$

In which SP_{ic} is the skill proficiency level individual, and $C2_{ic}$ a vector with control variables (age, age square, labour market status). Next, we run Eq. 3 separately for vocationally educated and those educated in general tracks.

4.4 Results

Table 1 presents the results of Eq. 1 estimating the general wage effects of effective key skills for all male and female working employees with an ISCED 3 or 4 qualification level. We observe strong wage effects for effective numeracy and effective literacy for both male and female workers. In general, the wage returns to effective key skills are similar for male and female workers. The effect of one standard deviation increase in effective numeracy or literacy is associated with a wage increase of 15% for male workers and with 16% for female workers. But this similar wage effect hides strong differences between the generally and vocationally educated male and female workers. In the case of vocationally educated workers, the wage effects of one standard deviation increase in effective numeracy or literacy is 17% for the female workers and 11% for the male workers.

For the generally educated workers, we find the opposite. Here the wage effects of one standard deviation increase in effective numeracy or literacy is 19% for the male workers and 13% resp. 14% for the female workers We can therefore conclude that in line with H1 general skills affect the wages of vocationally educated. For males we conclude that, again in line with H1, these effects are less strong than for those educated in general tracks. However, for female workers the opposite is true. General skills are even more important for vocationally educated female workers than for female workers educated in general tracks. This holds for effective numeracy (17% versus 13%) and for effective literacy (17% versus 14%). This is probably because females with a vocational ISCED 3 or 4 qualification, work in other occupations than their male counterparts, e.g., in health care, retail, or personal services. These occupations more often require higher levels of general skills. Note however that the confidence intervals overlap. A separate analysis, not shown here, with an interaction term, indicates no significant difference.

When we look at the different age groups, we observe some interesting results. Concentrating on male workers first, we see no significant effect of effective general skills for young age workers. This confirms earlier findings that young age workers are paid based on signals rather than their real skills (Altonji and Pierret, 2001). For prime age workers, we do observe a significant effect for both the generally and the vocationally educated male worker. This effect is – as expected – stronger for the generally educated worker than for the vocationally educated male worker. Note however, that the effects are significant at the 5% level only. The strongest effects are observed for the older workers, where the wage effects for the generally educated male workers are stronger than for the vocationally educated male workers. It thus seems that in the first phase of the working career of male vocationally educated workers, general skills are not so important yet. However, after age 35 these skills increasingly determine the productivity of these workers. This might have to do with the fact that they must deal with technological changes that increasingly require general skills to cope with. For female workers, the picture is quite different. Here we

Table 1a: Effective numeracy and earnings by age: male employees

VARIABLES	1 all	1a general	1b vocational	2a young age general	2b young age vocational	3a prime age general	3b prime age vocational	4a old age general	4b old age vocational
Vocational degree	-5.953								
	(7.572)								
Effective numeracy (mean 0, sd 1)	14.542***	19.148***	11.207***	6.699	4.428	21.238**	12.875**	38.230***	21.601***
	(3.213)	(5.575)	(3.953)	(9.346)	(8.008)	(9.264)	(5.873)	(11.051)	(7.351)
Observations	14,412	4,400	10,012	1,567	2,982	1,631	3,947	1,086	2,810
Number of groups	25	24	25	23	25	23	25	24	25

Standard errors in parentheses; coefficients multiplied by 100
*** p<0.01, ** p<0.05, * p<0.1
Controls include age, age2, years of schooling, dummy parttime plus country dummies
Selection on male employees (with working week of 12 hour or more), aged 20-55 with ISCED 3 or 4

Table 1b: Effective literacy and earnings by age: male employees

VARIABLES	1 all	1a general	1b vocational	2a young age general	2b young age vocational	3a prime age general	3b prime age vocational	4a old age general	4b old age vocational
Vocational degree	-5.852								
	(7.574)								
Effective literacy (mean 0, sd 1)	14.667***	19.071***	11.485***	7.966	5.873	20.723**	13.742**	37.558***	20.180***
	(3.210)	(5.551)	(3.956)	(9.226)	(7.905)	(9.222)	(5.898)	(11.130)	(7.410)
Observations	14,412	4,400	10,012	1,567	2,982	1,631	3,947	1,086	2,810
Number of groups	25	24	25	23	25	23	25	24	25

Standard errors in parentheses; coefficients multiplied by 100
*** p<0.01, ** p<0.05, * p<0.1
Controls include age, age2, years of schooling, dummy parttime plus country dummies
Selection on male employees (with working week of 12 hour or more), aged 20-55 with ISCED 3 or 4

Table 1c: Effective numeracy and earnings by age: female employees

VARIABLES	1 all	1a general	1b vocational	2a young age general	2b young age vocational	3a prime age general	3b prime age vocational	4a old age general	4b old age vocational
Vocational degree	2.971								
	(8.190)								
Effective numeracy (mean 0, sd 1)	16.102***	13.379**	17.457***	14.657*	29.334***	17.200*	13.878*	12.186	14.314
	(3.603)	(5.303)	(4.888)	(8.022)	(9.542)	(9.078)	(7.786)	(10.722)	(8.843)
Observations	12,423	4,780	7,643	1,398	1,956	1,847	3,036	1,358	2,413
Number of groups	25	24	25	23	25	23	25	24	25

Standard errors in parentheses; coefficients multiplied by 100
*** p<0.01, ** p<0.05, * p<0.1
Controls include age, age2, years of schooling, dummy parttime plus country dummies
Selection on female employees (with working week of 12 hour or more), aged 20-55 with ISCED 3 or 4

Table 1d: Effective literacy and earnings by age: female employees

VARIABLES	1 all	1a general	1b vocational	2a young age general	2b young age vocational	3a prime age general	3b prime age vocational	4a old age general	4b old age vocational
Vocational degree	2.791								
	(8.185)								
Effective literacy (mean 0, sd 1)	16.087***	14.083***	16.898***	12.799	24.904***	18.171**	15.203**	15.041	13.851
	(3.604)	(5.319)	(4.875)	(7.937)	(9.396)	(9.125)	(7.736)	(10.897)	(8.969)
Observations	12,423	4,780	7,643	1,398	1,956	1,847	3,036	1,358	2,413
Number of groups	25	24	25	23	25	23	25	24	25

Standard errors in parentheses; coefficients multiplied by 100
*** p<0.01, ** p<0.05, * p<0.1
Controls include age, age2, years of schooling, dummy parttime plus country dummies
Selection on female employees (with working week of 12 hour or more), aged 20-55 with ISCED 3 or 4

find the strongest effects of effective numeracy and literacy for vocationally educated young age workers. In the case of literacy, these skills are also relevant for both generally and vocationally educated prime age workers, but at the 5% significant level only. For older female workers, we observe no wage effects of effective skills. We can thus only partly confirm H2. The wage effects of effective literacy and numeracy are stronger for old age workers compared to young age workers, but this only holds for males. For female workers, the results are rather the opposite and for them H2 must be refuted.

Table 2a: Effective numeracy and earnings by R&D intensity: male fulltime employees

	1a	1b	2a	2b	3a	3b	4a	4b	5a	5b	6a	6b
VARIABLES	R&D = low (1)	R&D = low (1)	R&D = 2	R&D = 2	R&D = 3	R&D = 3	R&D = 4	R&D = 4	R&D = high (5)	R&D = high (5)	R&D = missing	R&D = missing
	general	vocational	general	vocational	general	vocational	general	vocational	general	vocational	general	vocational
Effective numeracy (mean 0, sd 1)	27.497***	14.529***	19.433	8.062	12.086	25.169**	18.753	-8.139	-4.329	-0.278	-9.579	14.698
	(7.976)	(5.603)	(13.552)	(9.433)	(23.281)	(11.043)	(16.247)	(12.642)	(21.662)	(25.111)	(13.877)	(11.163)
Observations	2,444	5,380	531	1,388	194	616	391	1,071	97	211	743	1,346
Number of groups	23	25	24	25	21	25	23	25	18	22	23	25

Standard errors in parentheses; coefficients multiplied by 100
*** p<0.01, ** p<0.05, * p<0.1
Controls include age, age2, years of schooling, dummy parttime plus country dummies
Selection on male employees (with working week of 12 hour or more), aged 20-55 with ISCED 3 or 4

Table 2b: Effective literacy and earnings by R&D intensity: male fulltime employees

	1a	1b	2a	2b	3a	3b	4a	4b	5a	5b	6a	6b
VARIABLES	R&D = low (1)	R&D = low (1)	R&D = 2	R&D = 2	R&D = 3	R&D = 3	R&D = 4	R&D = 4	R&D = high (5)	R&D = high (5)	R&D = missing	R&D = missing
	general	vocational	general	vocational	general	vocational	general	vocational	general	vocational	general	vocational
Effective literacy (mean 0, sd 1)	24.246***	9.442	-2.915	18.852	12.056***	46.851	7.881	0.032	-20.911	0.271	4.345	23.255***
	(8.127)	(8.350)	(15.699)	(14.212)	(3.955)	(29.780)	(5.142)	(16.680)	(28.060)	(23.268)	(10.095)	(7.949)
Observations	2,460	3,407	434	787	64	121	173	373	86	116	1,563	2,839
Number of groups	24	25	22	25	20	23	23	24	17	20	23	25

Standard errors in parentheses; coefficients multiplied by 100
*** p<0.01, ** p<0.05, * p<0.1
Controls include age, age2, years of schooling, dummy parttime plus country dummies
Selection on male employees (with working week of 12 hour or more), aged 20-55 with ISCED 3 or 4

Table 2c: Effective numeracy and earnings by R&D intensity: female fulltime employees

	1a	1b	2a	2b	3a	3b	4a	4b	5a	5b	6a	6b
VARIABLES	R&D = low (1)	R&D = low (1)	R&D = 2	R&D = 2	R&D = 3	R&D = 3	R&D = 4	R&D = 4	R&D = high (5)	R&D = high (5)	R&D = missing	R&D = missing
	general	vocational	general	vocational	general	vocational	general	vocational	general	vocational	general	vocational
Effective numeracy (mean 0, sd 1)	27.570***	14.625***	19.787	8.213	7.433	21.870**	19.056	-6.250	-0.821	7.884	-10.545	14.111
	(7.963)	(5.599)	(13.300)	(9.510)	(23.395)	(11.035)	(15.957)	(12.716)	(21.918)	(25.327)	(13.907)	(11.088)
Observations	2,444	5,380	531	1,388	194	616	391	1,071	97	211	743	1,346
Number of groups	23	25	24	25	21	25	23	25	18	22	23	25

Standard errors in parentheses; coefficients multiplied by 100
*** p<0.01, ** p<0.05, * p<0.1
Controls include age, age2, years of schooling, dummy parttime plus country dummies
Selection on female employees (with working week of 12 hour or more), aged 20-55 with ISCED 3 or 4

Table 2d: Effective literacy and earnings by R&D intensity: female fulltime employees

	1a	1b	2a	2b	3a	3b	4a	4b	5a	5b	6a	6b
VARIABLES	R&D = low (1)	R&D = low (1)	R&D = 2	R&D = 2	R&D = 3	R&D = 3	R&D = 4	R&D = 4	R&D = high (5)	R&D = high (5)	R&D = missing	R&D = missing
	general	vocational	general	vocational	general	vocational	general	vocational	general	vocational	general	vocational
Effective literacy (mean 0, sd 1)	24.155***	7.263	1.298	23.431*	11.885***	54.881*	8.130	3.093	-16.105	-0.138	4.620	21.853***
	(8.150)	(8.349)	(15.996)	(14.172)	(3.864)	(29.755)	(5.156)	(16.685)	(28.264)	(22.966)	(10.078)	(7.892)
Observations	2,460	3,407	434	787	64	121	173	373	86	116	1,563	2,839
Number of groups	24	25	22	25	20	23	23	24	17	20	23	25

Standard errors in parentheses; coefficients multiplied by 100
*** p<0.01, ** p<0.05, * p<0.1
Controls include age, age2, years of schooling, dummy parttime plus country dummies
Selection on female employees (with working week of 12 hour or more), aged 20-55 with ISCED 3 or 4

Table 2 shows whether the results are heterogeneous according to the R&D intensity of the sector. In general, we see no clear association between the effect size of our effective skill measures and the R&D intensity of the sector in which one is working. Moreover, the effects are not the same for male and female workers. The only sector in which both male and female workers experience a strong effect of general skills are the sectors with the lowest R&D intensity (this includes e.g., Construction, Wholesale and retail trade, Transportation and storage, Accommodation and food service activities, and Financial and insurance activities). This holds for generally educated workers in the case of both effective numeracy and literacy and for vocationally educated workers only for numeracy. All other effects are not systematically the same for male and female workers or for effective numeracy and literacy. Overall, we conclude that the wage effects of effective numeracy and literacy are not systematically related to the R&D intensity of the sector. We therefore refute H3.

Tables 3a-b present the results of Eq.2. Here we are interested whether the wage effects of general skills are context dependent. Do characteristics of the education system, affect this relation? In H4, we postulated that: '*General skills are more important for the wages of vocationally educated when the vocational orientation is high*'. We can confirm this for the male workers. Both for numeracy and literacy, we find a significant interaction effect of effective skill with the strength of the vocational orientation.[12] In an educational system with an average vocational orientation, the effect size of effective numeracy (literacy) is 4.7 (6.0). This means that in such countries, a one standard deviation increase in effective numeracy (literacy) yields a non-significant wage increase of 5% (6%). However, in countries in which this vocational orientation is one standard deviation higher, the corresponding wage increase is 15% (14%)[13].

For vocationally educated female workers, the interaction effect is not significant. Here we observe that in educational systems with an average vocational orientation, the effect size of effective numeracy (literacy) is already much higher than for males. In such countries, a one standard deviation increase in effective numeracy (literacy) yields a significant wage increase of 14% (13%). In countries in which the vocational orientation is one standard deviation higher, the corresponding wage increase for females is 19% (19%). Although the effect size is larger, the difference is not significant. We thus conclude that H4 is confirmed for males, but not for females. For vocationally educated males, general skills are more important in countries with a strong vocational orientation. For vocationally educated females, general skills are always important regardless of the level of vocational orientation.

As a side note, we find a negative interaction effect of vocational orientation for the generally educated female workers. In educational systems with an average vocational orientation, a one standard deviation increase in effective numeracy or literacy yields a wage increase for these workers of 16% and 17% respectively. In countries in which the vocational orientation is one standard deviation higher, the wage drops with 12% and 13% respectively. We did not postulate any hypothesis for this, and we also have no post-hoc explanation why this would be the case.

In H5 we postulated that: *'General skills are less important for the wages of vocationally educated when the vocational specificity is high.'* The results do not confirm this hypothesis. None of the models show a significant interaction effect of effective skill with the specificity of the vocational system. This means that for vocationally educated workers, general skills are always important, regardless of whether they were trained in countries where the vocational program is primarily school-based or workplace-based.

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[12] In this equation we looked at vocational orientation as a continuous variable. We ran similar analyses using a dummy distinguishing weak and strong vocational oriented systems and the results are substantially the same.

[13] Calculated as 4.732+10.119 and 6.033+8.458 respectively.

Table 3a: Earnings and effective numeracy by context

	Males			Females		
	1a	1b	2a	1a	1b	2a
VARIABLES	general	vocational	vocational	general	vocational	vocational
Effective numeracy (mean 0, sd 1)	19.333***	4.732	9.798**	16.118***	13.562**	16.998***
	(5.678)	(5.050)	(4.062)	(5.447)	(6.138)	(5.091)
educ characteristics (z-scores)						
vocational orientation (zvoc)	-16.556*	-6.019		-5.881	-8.163	
	(9.404)	(9.637)		(14.787)	(13.346)	
zvoc * effective numeracy	3.177	10.119**		-12.132**	5.903	
	(6.000)	(4.943)		(5.713)	(5.649)	
vocational specificity (zspec)			-1.362			2.173
			(8.329)			(12.173)
zspec * effective numeracy			5.350			1.401
			(3.583)			(4.318)
Observations	4,400	10,012	10,012	4,780	7,643	7,643
Number of groups	24	25	25	24	25	25

Standard errors in parentheses; coefficients multiplied by 100
*** p<0.01, ** p<0.05, * p<0.1
Controls include age, age2, years of schooling, dummy parttime plus country dummies
Selection on employees (with working week of 12 hour or more), aged 20-55 with ISCED 3 or 4

Table 3b: Earnings and effective literacy by context

	Males			Females		
	1a	1b	2	1a	1b	2
VARIABLES	general	vocational	vocational	general	vocational	vocational
Effective literacy (mean 0, sd 1)	19.086***	6.033	10.488***	16.929***	12.856**	16.309***
	(5.649)	(5.082)	(4.065)	(5.457)	(6.121)	(5.074)
educ characteristics (z-scores)						
vocational orientation (zvoc)	-16.684*	-5.839		-5.850	-8.189	
	(9.418)	(9.644)		(14.777)	(13.343)	
zvoc * effective literacy	4.241	8.458*		-12.931**	6.137	
	(5.938)	(4.982)		(5.717)	(5.637)	
vocational specificity (zspec)			-1.417			2.177
			(8.344)			(12.172)
zspec * effective literacy			3.788			1.814
			(3.593)			(4.309)
Observations	4,400	10,012	10,012	4,780	7,643	7,643
Number of groups	24	25	25	24	25	25

Standard errors in parentheses; coefficients multiplied by 100
*** p<0.01, ** p<0.05, * p<0.1
Controls include age, age2, years of schooling, dummy parttime plus country dummies
Selection on employees (with working week of 12 hour or more), aged 20-55 with ISCED 3 or 4

Table 4a: Acquisition of numeracy

	Males				Females			
	1a	2a	2b	3	1a	2a	2b	3
VARIABLES	all	general	vocational	vocational	all	general	vocational	vocational
years of schooling	23.357***	22.698***	27.400***	27.393***	18.286***	21.893***	21.272***	21.284***
	(1.072)	(3.313)	(1.268)	(1.268)	(1.108)	(3.049)	(1.307)	(1.307)
Vocational track (VET)	-39.851***				-36.056***			
	(1.854)				(1.902)			
educ characteristics (z-scores)								
vocational orientation (zvoc)		16.060***	2.835			15.286***	-1.048	
		(4.295)	(7.659)			(4.028)	(7.115)	
vocational specificity (zspec)				-2.852				-2.460
				(6.664)				(6.206)
Observations	11,591	4,638	6,953	6,953	10,925	5,060	5,865	5,865
Number of groups	25	24	25	25	25	24	25	25

Standard errors in parentheses; coefficients multiplied by 100
*** p<0.01, ** p<0.05, * p<0.1
Controls include age, age2, labour market status plus country dummies
Selection on respondents, aged 20-35 with ISCED 3 or 4

Table 4b: Acquisition of literacy

	Males				Females			
	1a	2a	2b	3	1a	2a	2b	3
VARIABLES	all	general	vocational	vocational	all	general	vocational	vocational
years of schooling	21.973***	24.562***	25.561***	25.553***	17.937***	23.949***	19.697***	19.720***
	(1.085)	(3.356)	(1.292)	(1.291)	(1.122)	(3.093)	(1.336)	(1.335)
Vocational track (VET)	-40.977***				-33.456***			
	(1.880)				(1.927)			
educ characteristics (z-scores)								
vocational orientation (zvoc)		16.656***	2.416			15.605***	-1.824	
		(4.497)	(7.119)			(4.342)	(6.647)	
vocational specificity (zspec)				-2.788				-2.471
				(6.170)				(5.791)
Observations	11,591	4,638	6,953	6,953	10,925	5,060	5,865	5,865
Number of groups	25	24	25	25	25	24	25	25

Standard errors in parentheses; coefficients multiplied by 100
*** p<0.01, ** p<0.05, * p<0.1
Controls include age, age2, labour market status plus country dummies
Selection on respondents, aged 20-35 with ISCED 3 or 4

In Tables 4a-b we present the results of Eq.3. What are the characteristics of the vocational education system that are associated with a high skill proficiency level for young people aged 20-35? In model 1a we show that – as expected - the skill proficiency level of young people with an ISCED 3 or 4 qualification is positively associated with the years of schooling of their ISCED 3 or 4 program and negatively with the fact whether this program was vocational instead of general. Each year of schooling at this level is associated with 23 points (males) or 18 points (females) increase in numeracy proficiency and with 22 points (males) or 18 points (females) increase in literacy proficiency. Having followed a vocational instead of a general program decreases the skill proficiency with between 33 points (literacy for females) to 41 points (literacy for males). Given that one standard deviation in proficiency scores corresponds to some

50 points, these effects are quite substantial ranging between 0.67 and 0.82 of a standard deviation. These results do not change substantially if we include the vocational orientation of a country in the model (Models 1b and 1c). In other words, regardless of the vocational orientation of the educational system, vocationally educated always have lower proficiency levels than generally educated. Moreover, model 1b shows that the vocational orientation of a country's educational system is not associated with higher or lower proficiency levels.

In H6 we postulated that: *'Controlling for years of schooling, general skill proficiency levels of vocationally educated are higher in countries where the vocational orientation is high. The same should hold for the generally educated.'* This is confirmed when we look at the results for the generally educated (Model 2a) but not for the vocationally educated (Model 2b).[14] The average numeracy proficiency level of generally educated males (females) is 16% (15%) higher in countries that have an educational system that is one standard deviation more vocational oriented. For the average literacy proficiency level, these numbers are 17% (males) and 16% (females) respectively. The higher proficiency levels for the generally educated are associated with the fact that in such countries, the selection into a general track is very selective. H6 is therefore partly confirmed.

We find no significant negative effect of the specificity of the vocational programs in a country on the skills of the vocationally educated (Model 3). This means that we refute H7, where such an effect was predicted. Although the effect is in the expected direction, it is small and insignificant. We can conclude that apparently there are no major differences in the skill proficiency levels of vocationally educated that were trained in countries where these programs are primarily school-based versus countries where such programs are predominantly workplace-based.

4.5 Conclusions

The world is changing rapidly, and key information-processing skills are becoming more and more important in determining success in the world of work as well as in life in general (OECD, 2013b). Still there is a debate to what extent these skills should be a prime focus in vocational education. The vocationally educated have a 'protected' position on the labour market because they have acquired occupation-specific skills that their generally educated peers lack. The whole idea of vocational education as a safety net (Shavit and Müller, 2000) assumes that vocationally educated students are equipped with skills that are different from those with a general education, and not just lower (Lutz and Sengenberger, 1974; Shavit and Müller, 2000). This difference will give them some protection when competing with their generally educated peers on the labour market. Without these occupation-specific skills, they would lose this comparative advantage and be worse off. This is confirmed in earlier research: young people with a vocational degree have little trouble entering the labour market, even though they have lower general skills than their competitors (Ryan, 2001; 2003; Van der Velden and Wolbers, 2003; Levels et al., 2014a). The problem is that this initial advantage peters out over the life course and can even reverse at older age (Forster et al. 2016; Hanushek et al. 2017a). This is because their occupation-specific skills are rendered obsolete, and they increasingly need general skills to stay employable. The conclusions from earlier research seem to indicate that general skills are important for vocationally educated, but mainly to help adjust to changes in the job requirements and work tasks later in life (Hanushek et al., 2017b).

[14] In this equation we looked at vocational orientation as a continuous variable. We ran similar analyses using a dummy distinguishing weak and strong vocational oriented systems and the results are substantially the same.

The key problem in earlier empirical analyses is that it is not easy to assess the effect of general skills. Research has often relied on weak instruments to measure such skills (such as worker self-assessments). And if they used test scores, they fail to specify how these skills would affect the productivity. These estimates are therefore prone to omitted variable bias, and the effects might be overestimated. This is even a bigger concern when estimating the effect of general skills for the vocationally educated, as their productivity is largely determined by occupation-specific rather than general skills.

In this paper we use the recently developed concept of effective skills (Van der Velden and Bijlsma, 2019) to identify the association between general skills and wages. The basic idea of effective skills is that skills can only affect wages if they are put to productive use. It is the combination of possessing key skills and at the same time using them at work, that affects productivity. By combining skill proficiency and skill use in one concept, the resulting association with wages is less obscured by the omitted variable bias, as the effect of the skills can only be observed if they are used at work. The fact that these skills are used is a strong indication that they are related to a worker's productivity.

We use PIAAC data to explore the relationship between general skills and wages for 20-55-year-old workers in 25 countries with advanced economies. We concentrated on employees in jobs of at least 12 hours per week. We focus on workers with a completed qualification at the upper-secondary level (ISCED 3 or 4) and looked at the effect of effective numeracy and effective literacy. The analyses were done separately for male and female workers, as they are often working in different occupations that require different types of skills. Although the focus of this paper is on vocationally educated workers, we compare the results to workers who completed a general track.[15]

The main conclusion, and an answer to the question in this paper's title, is that general skills are important for vocationally educated workers. The effect of one standard deviation increase in effective numeracy or literacy is associated with a wage increase of 17% for the female vocationally educated workers and 11% for the male vocationally educated workers. This is an important finding, as it solves a long-lasting debate on the relevance of general skills for the vocationally educated.

This is not to imply that the occupation-specific skills are not important. For vocationally educated male workers who are often working in sectors that require technical skills (e.g., construction). these general skills start getting important at prime age and older age (age 36 and above). The increasing relevance of general skills for vocationally educated male workers could be driven by two different factors. First, older workers might move to jobs in which they must use these general skills more often, e.g., in supervisory jobs. Second, older workers might be confronted with technological developments that render their vocational skills obsolete. in which case they need more general skills. This means that in the beginning of their occupational career, their occupation-specific skills are still more important to be successful. For the vocationally educated female workers, who more often work in sectors that require general skills (such as health care, retail, or personal services), the general skills are relevant right from the beginning of their career (up until age 45). And at young age (20-35) they seem even more important than for their generally educated counterparts.

We do not find any systematic relation between the R&D intensity of a sector and the relevance of general skills. For some workers, these skills are most important in sectors that have low R&D intensity, for others

[15] In most countries, this is a rather selective group, as most students in general tracks in secondary education move on to tertiary education. Although this group is thus negatively selected, it is the most relevant comparison with the vocationally educated, which takes place at this level.

general skills are more important in sectors that have medium R&D intensity. We conclude that the relevance of general skills for vocationally educated workers is not driven by the R&D intensity of the sector, but rather by occupation-specific factors.

We also looked at whether the wage effects of general skills differ with characteristics of the education system. First, we expected the effect of general skills to be stronger for vocationally educated in countries with a strong vocational orientation, i.e., with a larger share of people following a vocational instead of a general track. The reason was that in such countries, following a vocational track is not a negative selection. This was true for male workers but not for female workers. For vocationally educated males, general skills are more important in countries with a strong vocational orientation. For vocationally educated females, however, general skills are always important regardless of the level of vocational orientation. Second, we expected the effect of general skills to be weaker for vocationally educated in countries with a strong vocational specificity, i.e., a larger share of vocational programs that are workplace-based instead of school-based. The reason is that workplace-based programs more often focus on firm-specific skills. The results do not confirm this hypothesis. This means that for vocationally educated workers, general skills are always important, regardless of whether they were trained in a primarily school-based program or in a workplace-based program.

Now that we have demonstrated that general skills are important for vocationally educated workers with a qualification at the upper-secondary level, it is interesting to see which characteristics of the education system are associated with a high proficiency level in numeracy or literacy. For this analysis, we looked at all young people aged 20-35 (whether working or not) with an ISCED 3 or 4 qualification. The analyses show that following a vocational track and tracks that require less years of schooling is associated with lower proficiency levels than general tracks or tracks that require more years of schooling. This holds regardless of the level of vocational orientation in a country. Moreover, school-leavers with an ISCED 3 or 4 qualification in countries where the system is more strongly vocational oriented, have similar proficiency levels as their peers in countries that have more general oriented systems. This suggests that vocational orientation in itself does not affect the overall proficiency level in upper secondary education. Nevertheless, in each country those who followed a vocational track have acquired fewer general skills.

Next, we expected general skill proficiency levels of vocationally educated to be higher in countries where the vocational orientation is high and the same would hold for those who followed a general track. This is confirmed only for the generally educated young people. The underlying mechanism is that in such countries, the selection into a general track is very selective. This characteristic is thus associated with an increasing gap between the vocationally educated and those educated in general tracks. Second, contrary to our expectation we found no negative effect of the specificity of a vocational program on the skills of the vocationally educated: there are no major differences in the skill proficiency levels of vocationally educated that were trained in countries where these programs are primarily school-based versus countries where such programs are predominantly workplace-based.

What does this imply for vocational programs in upper-secondary education? General skills are important, and the development of such skills should also be addressed in vocational programs. The reassuring message is that the average skill proficiency level for the vocational educated in a country is not affected by whether these programs are primarily school-based or workplace-based. The countries with primarily workplace-based programs seem just as good in achieving certain proficiency levels as countries that have primarily school-based programs. Moreover, the average proficiency level of all school-leavers with an

ISCED 3 or 4 qualification is not associated with the vocational orientation of a country's educational system.

Nevertheless, there is a gap in the proficiency levels between the vocationally educated and the generally educated at the upper secondary level and this gap is bigger when the general tracks are more selective (or conversely the vocational tracks are more popular: high vocational orientation). One of the worries is that there might be a price to be paid if the acquisition of more general skills in these vocational programs comes at the expense of acquiring occupation-specific skills. These specific skills are typically the skills that protect vocationally educated workers in the beginning of their career. Specifically for males these specific skills are important in the beginning of their career. For females we see that general skills are important right from the start. Of course, this is related to the different programs that are followed in upper-secondary vocational education and the stronger gender occupational segregation at this level. This might imply that in vocational programs that are typically female-dominated like health care, retail, secretarial work, and personal service, the role of general skills in the curriculum might be less of a problem than in vocational programs that are typically male-dominated like construction, or engineering. However, even in these programs a foundation should be laid for the future acquisition of such skills, as they will be crucial in the later career.

The fear of a trade-off or crowding-out effect of general versus vocational-specific skills in initial education might look like a choice between Scylla and Charybdis. What is needed however is that the acquisition of general and occupation-specific skills is developed in a more symbiotic way. This could be achieved by viewing these two types of skills not as two separate components in the curriculum, but by integrating them in (authentic) teaching materials that combine the acquisition of general skills with occupation-specific tasks (Middleton, 2002).

The results also suggest that laying this foundation in initial education is not enough. For male vocationally educated workers, the general skills become most relevant after age 35. This means that these skills should have an important place in adult training as well. Just like for initial education, the research in adult education shows that embedding literacy and numeracy into vocational training improves the likelihood of retention, but only if the content is connected to real-life vocational contexts (Alkema and Rean, 2014).

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Appendix to Chapter 4

Table A1 Descriptive statistics wage analyses

Male

	N	Min	Max	Mean	Std. Dev
LnWage	13608	0,28	27,63	3,08	3,66
Effective numeracy (std)	13608	-0,08	0,84	-4,46	2,80
Effective literacy (std)	13608	-0,17	0,90	-4,79	2,78
Vocational track	13608	0	1	0,70	0,46
Years of schooling	13608	9	18	12,18	1,17
Age	13608	20	55	37,37	10,23
Young age (20-35)	13608	0	1	0,31	0,46
Prime age (36-45)	13608	0	1	0,39	0,49
Old age (46-55)	13608	0	1	0,27	0,45
Low R&D intensity (1)	13608	0	1	0,54	0,50
Medium-Low R&D intensity (2)	13608	0	1	0,14	0,34
Medium R&D intensity (3)	13608	0	1	0,06	0,23
Medium-High R&D intensity (4)	13608	0	1	0,11	0,31
High R&D intensity (5)	13608	0	1	0,02	0,15
Missing R&D intensity	13608	0	1	0,14	0,35

Female

	N	Min	Max	Mean	Std. Dev
LnWage	8832	0,09	27,63	2,96	4,00
Effective numeracy (std)	8832	-4,29	2,60	-0,26	0,78
Effective literacy (std)	8832	-4,63	2,68	-0,26	0,91
Vocational track	8832	0	1	0,62	0,49
Years of schooling	8832	9	18	12,22	1,14
Age	8832	20	55	38,28	10,31
Young age (20-35)	8832	0	1	0,28	0,45
Prime age (36-45)	8832	0	1	0,38	0,49
Old age (46-55)	8832	0	1	0,31	0,46
Low R&D intensity (1)	8832	0	1	0,46	0,50
Medium-Low R&D intensity (2)	8832	0	1	0,11	0,32
Medium R&D intensity (3)	8832	0	1	0,02	0,14
Medium-High R&D intensity (4)	8832	0	1	0,05	0,23
High R&D intensity (5)	8832	0	1	0,02	0,14
Missing R&D intensity	8832	0	1	0,33	0,47

Table A2 Descriptive statistics proficiency analyses					
Male					
	N	Min	Max	Mean	Std. Dev
Numeracy (/100)	11220	-4,6	2,8	-0,07	0,90
Literacy (/100)	11220	-5,0	2,7	-0,06	0,91
Vocational track	11220	0	1	0,60	0,49
Years of schooling	11220	9	18	12,24	1,10
Age	11220	20	35	26,42	4,72
Fulltime worker	11220	0	1	0,62	0,49
Partime worker	11220	0	1	0,07	0,25
Non-working	11220	0	1	0,31	0,46
Female					
	N	Min	Max	Mean	Std. Dev
Numeracy (/100)	10689,0	-4,6	2,6	-0,14	0,89
Literacy (/100)	10689,0	-5,5	2,6	-0,13	0,91
Vocational track	10689	0	1	0,54	0,50
Years of schooling	10689	9	18	12,31	1,08
Age	10689	20	35	26,51	4,81
Fulltime worker	10689	0	1	0,36	0,48
Partime worker	10689	0	1	0,17	0,38
Non-working	10689	0	1	0,47	0,50

Table A3: Number of respondents and per country cluster

	N total	N general	N vocational	Voc orientation	Voc specificity
Austria	1232	80	1152	1,70	1,32
Belgium (Flanders)	881	381	500	0,95	-0,61
Canada	759	398	361	-1,72	-0,82
Chili	751	357	394	-0,16	-0,82
Czech Republic	1543	96	1447	1,74	1,50
Denmark	1023	203	820	0,45	2,30
Finland	910	160	750	0,74	-0,13
France	1221	304	917	0,39	-0,08
Germany	1098	20	1078	0,89	2,12
Greece	515	234	281	-0,31	-0,49
Ireland	596	300	296	-0,35	-0,57
Israel	716	462	254	-0,27	-0,55
Italy	796	460	336	0,95	-0,82
Japan	771	464	307	-0,73	-0,82
Korea	875	456	419	-0,55	-0,82
Netherlands	652	113	539	1,26	0,49
Norway	856	201	655	0,89	0,05
Poland	1953	473	1480	0,30	-0,40
Slovak Republic	1574	865	709	1,49	1,25
Slovenia	1242	3	1239	1,06	-0,58
Spain	411	348	63	0,00	-0,64
Sweden	950	367	583	0,69	-0,82
Turkey	388	0	388	-0,14	-0,34
United Kingdom	1231	596	635	0,47	-0,82
United States	635	470	165	-1,84	-0,82