Ref. Ares(2021)8018841 - 31/12/2021

Technequality

Understanding the relation between technological innovations and social inequality

Deliverable D3.5

Can Adults Learn Digital Skills in Non-formal and Informal Education? Cross-national Evidence from 25 countries.

Version 1.0

Funded by the Horizon 2020 Framework Programme of the European Union

Deliverable	:	3.5
Title	:	Can Adults Learn Digital Skills in Non-formal and Informal Education? Cross-national Evidence from 25 countries.
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Reviewer(s)	:	N/A
Document type	:	R
Document level	:	
Date	:	21-12-2021
Status	:	Final Version

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Description of deliverable

In this paper we analyse the relation between digital problem-solving skills and non-formal and informal learning environments. Are digital problem-solving skills systematically higher in countries with a certain type of non-formal and informal learning? We analyse PIAAC data and explore cross-national variation in the strength of the relationship between informal and non-formal learning and digital problem-solving skills. We find an association but conclude that it is mostly driven by selection into training by better skilled individuals or by confounding variables. We do find some evidence to suggest a causal effect of non-formal training of older workers. Cross-national analyses revealed that the effect of training on ICT skills does not vary systematically between countries.

Can Adults Learn Digital Skills in Non-formal and Informal Education? Cross-national Evidence from 25 countries.

1. Introduction

Against the background of technological innovations, digital problem-solving skills are becoming increasingly important for workers' productivity and performance in 21st century labour markets. The ubiquitous availability of information and communication technology (ICT) leads to a situation, in which digital skills are thought to be *key skills* for everybody (OECD, 2013a). The demand for such generic ICT skills increased in a majority of industrialised countries between 2011 and 2014 (OECD, 2016a). As technologies increasingly not only infuse into work but also everyday life, digital skills are not only key to ensure that workers remain productive and employable in labour markets but also included in societies (OECD, 2013a). Yet, many adults did not learn such skills sufficiently during initial education. Particularly if technological innovation evolves fast, a large part of the adult work force runs the risk of having obsolete skills because their initial education lags behind changes in skill demands. To keep up with changes, adult workers, who have left initial education, need to learn these skills. They can do so by participation in training courses (non-formal learning) or by learning at work (informal learning).

In theory, participation in non-formal and informal adult education and training intends to help adults to acquire, maintain, and restore skills and hereby prevent skills obsolescence (De Grip & Van Loo, 2002). The extent to which this is the case is still an open question. Empirical literature about the effects of formal and non-formal adult learning for acquiring skills is rather limited. One literature review on the extent to which to adult learning has improved literacy and numeracy is provided by Vorhaus et al. (2011). This review concludes that there "good evidence was found on adult basic skills levels", but "limited evidence was found on skills acquisition, retention and loss, and on adults' everyday practices in literacy and numeracy, including patterns of self-study" (*ibidem*: p. 11). Another study finds that British adults' reading comprehension skills can be improved by participation in workplace literacy courses, but the effects are small and only observed for those for whom English is second language (Wolf and Jenkins, 2014). However, the authors assume that this relation is not causal, and that the observed improvement is probably caused by the increased everyday contact with native speakers. The existing literature thus suggests that effects of adult learning on skills acquisition are rather modest at best. Our paper adds to this literature by providing empirical evidence on the relation between participation in non-formal and informal adult education and training and key information-processing skills in the skill domain of digital problem-solving, which is becoming increasingly important for workers' productivity, performance and employability. We aim to answer the following research questions:

RQ1: To what extent is participation in non-formal and informal adult learning related to higher proficiency in digital problem-solving skills?

RQ2: To what extent is this relationship plausible evidence for a causal relation between adult learning and problem-solving skills?

RQ3: In which national contexts (most notably: education systems) is the relation between adult learning and digital problem-solving skills stronger?

To answer these questions, we formulate hypotheses about the extent to which informal and non-formal learning can contribute to proficiency in ICT skills, and about potential explanations for cross-national differences. To test our hypotheses, we combine analyses on the individual and on the country level in a two-step multilevel design. On the individual level, we aim to assess whether the relation between training and problem solving skills is causal or driven by selection, using a comparison group approach. Thereafter, we assess cross-national differences. We use micro data from the Programme for the International Assessment of Adult Competencies (PIAAC) for 26 countries (OECD, 2013b). To identify technology-driven occupations, we enrich PIAAC micro data with information on occupational skills profiles. We combine PIAAC data with macro data on country characteristics, such as systems of (adult) education and training and indices on the digitalisation of societies and labour markets. We use these data to explore the cross-national variation in the strengths of the relationship between non-formal/informal learning and key information-processing and problem-solving skills.

Our analyses contribute to literature in four main ways. First, we introduce an innovative technique to assess whether the observed relationship between adult learning and ICT skills can be interpreted causally or is plausible driven by selection. The issue of causality has long since been at the core of research on training and informal learning (Gauly & Lechner, 2019). To solve it, randomised controlled trials would be best suited, but these are to the best of our knowledge non-existent. Alternatively, a range of quasi-experimental methods can be used for causal inference from observational data (Angrist and Pischke, 2009; Gangl, 2010). We supplement causal analyses already performed (Gauly & Lechner, 2019) with a new quasi-experimental identification strategy that allows us to scrutinize further whether observed relations can be interpreted causally. Secondly, we use data that have reliable information on training and learning activities and objective psychometric measures of ICT skills. Objective skill measures give a better and more valid picture of the ‘real’ skills and their relationship with outcomes (OECD, 2013), but only very few studies use such measures. Existing analyses of PIAAC data are limited by the lack of information on the content of training (Hämäläinen et al., 2015; Desjardins and Ederer, 2015; Gauly & Lechner, 2019). We posit plausible assumptions about the relation between skills use in jobs and the substance of informal and non-formal training and test these hypotheses empirically. Fourth, we explore explanations for cross-national differences the size of the (causal) relation between adult learning and problem solving skills, thereby providing insights in the extent to which national contexts can be conducive to the effectiveness of adult learning.

2. Theoretical considerations

2.1 Adult training and skills

It is received wisdom that early investments in education are most effective and provide the highest returns (Cunha and Heckman, 2007). However, the accumulation of human capital does not end with initial education, but also continues through participation in job-related and on-the-job non-formal training (Gauly and Lechner, 2019). The general theoretical assumption is that investment in non-formal adult learning increases general skills proficiencies, as well as proficiency in specific skills. Indeed, results based on the PIAAC data have previously indicated large differences in skills proficiency between individuals who had participated in training and those who had not (OECD, 2013a). In addition to formal and non-formal education, practical expertise can be acquired through informal learning, which is argued to be the most common form of job-related training at work (Fialho, Quintini, & Vandeweyer, 2019). There are two principal ways in which informal learning may occur: through the process of task activity itself or from knowledge sharing between the employees (Darrah, 1996). Informal learning can take place in different learning contexts which can affect skills acquisition. Results of Hämäläinen et al. (2015) on adults with vocational education and training and Desjardins and Ederer (2015) research on adults across four European countries have suggested that use of ICT skills at home and workplace is positively related to problem solving skills in technology-rich environments.

The practice engagement theory by Reder (1994) posits that whether at work or outside work context, engagement in reading, writing and maths activities in everyday life enhances literacy and numeracy proficiency development over time. Reder et al. (2020) research based on the PIAAC-L longitudinal data provided strong support for practice engagement theory. Desjardins and Ederer (2015) have found that those who use ICT at home or at work on a high level have higher odds of being proficient in problem solving skills relative to those who were using ICT skills on a low level. Research suggests that work environments that involve knowledge practice and literacy engagement provide an environment to develop or maintain cognitive abilities such as literacy and other cognitive skills (Desjardins, 2003; OECD & Statistics Canada, 2005). Following this reasoning, we would expect that ICT use and informal learning in the workplace may thus be also related to generally higher proficiency levels of problem-solving skills.

The extent to which these general relationships hold will strongly depend on the extent to which ICT skills are required in jobs. As a result of skill-biased technological changes, skill demands in the labour market are changing frequently in all sectors of the economy, and digital problem-solving skills increase in importance. According to CEDEFOP (2018: 5) about 85% of all jobs currently available in the EU require at least a basic level in digital skills. Recent studies also show that ICT skills are substantially rewarded at the labour market (Falck, Heimisch and Wiederhold, 2016; Lane and Conlon, 2016; Hanushek, Schwerdt, Wiederhold, and Woessmann, 2015b). Skill demands change especially in those sectors that are related to information technologies (De Grip 2015). De Grip (2015) argues that in dynamic jobs and high-performance workplace, the changing skill demands foster a continuous learning environment at work, because most workers learn the skills that are needed to work with a new technology in the workplace and workers learn particularly from engaging in new and challenging activities and from cooperating with more experienced colleagues. Especially mid-career workers have to learn these skills at work because the technologies were much less common when they went to school. For the adult population, the level of skills in technology-rich environments and the use of ICT is, in general, much lower than in the younger population (OECD, 2016b).

The nature of work, that one is employed in, is an important factor promoting the perceived need to invest in adult education (Desjardins & Rubenson, 2013). Previous research indicates that the skill content of jobs seems to have a stronger association with participation in employer supported adult education than educational attainment and skills proficiency (Desjardins 2014; Saar & Räis 2016; Reder, Gauly & Lechner 2020; see also Deliverable D3.6). Findings of Hämäläinen et al. (2019) signal that what people do at work is related with their problem-solving skills in technology-rich environments, as different job requirements may lead to different applications of problem-solving skills at work and thus skills proficiency can be influenced by the daily job tasks (see also Desjardins and Ederer, 2015). Based on the argument that the nature of work and skill content of jobs affect participation in employer supported adult education, we can also expect that the content of the courses that workers participate in, differ between the occupations. Problem solving skills in technology-rich environments are connected with using digital technology and communication tools to perform practical tasks. We could assume that in occupations where workers have higher rates of participation in ICT-related courses, we could see a stronger effect of non-formal education on acquisition of digital problem-solving skills. Based on the considerations in this section we expect the following:

H1. The participation in non-formal adult education is associated with higher digital problem-solving skills (1a), especially among older workers (1b) and if these skills are important in the job (1c).

H2. Informal learning is associated with higher digital problem-solving skills (2a), especially among older workers (2b) and if these skills are important in the job (2c).

2.2 Causal relation or selection?

The reasoning leading to hypotheses H1 and H2 assumes a causal relation between adult learning and digital skills proficiency. One outstanding question is whether this often reported positive relationship can indeed be interpreted causally, or that selection mechanisms may play a role. At least two alternative selection mechanisms can be at work. Firstly, there may be reverse causality: people who are more proficient in ICT skills are more likely to take part in training. For example, Desjardins and Ederer (2015) argue that the positive effect they report could also be interpreted the other way around: ICT proficiency could lead to using ICT skills at home and at work more often. Secondly and relatedly, selection intro training based on a wide variety of background characteristics may play a role. For example, people with higher cognitive abilities may be more likely to follow training, and also be associated with higher proficiency. Various empirical studies indeed suggest that the relation between training participation and skills is much more complex than the positive association presupposes. For example, research in Germany and in the UK showed that non-formal courses have only limited or no effect on general skills acquisition (Gauly and Lechner 2019; Vorhaus et al. 2011; Wolf and Jenkins 2014). Reder et al. (2015) argue that competency growth may not be caused by participating in training but due to practices, which may be triggered by training. Gauly and Lechner (2019) stated that the positive association that has previously been found between training and skills is the result of a selection effect, rather than a causal effect of training on proficiency.

While these plausible alternative mechanisms of course do not negate the possibility that people learn skills through informal or non-formal learning, their possibility shows that any observed association should be interpreted cautiously. To test whether the relationships we observe can plausibly be interpreted as evidence for a causal link between adult learning and skills proficiency, we test the following hypothesis:

H3 The associations between participation in non-formal (3a) and informal learning (3b) and ICT skills proficiency remain after controlling for observable and unobservable confounders

2.3 The relevance of national contexts

Previous research shows that there are large cross-country differences in the relevance of informal learning at work. Various explanations have been offered. For example, cross-national differences may be due to differences in the learning cultures in the workplace or to differences in other institutional settings between the countries (De Grip, 2015). Based on the notion of "adult learning systems", the acquisition of skills through further training can also depend on characteristics of educational systems and labour markets (Saar, Ure, and Desjardins 2013). The extent of adult education activity varies substantially across countries, as some countries feature much higher levels of participation in different forms of organized adult learning compared with other countries (Desjardins, 2015). Furthermore, there are differences in participation in adult education which suggests that learning cultures, learning opportunities at work, and also public policies, institutions and other structures relevant to adult education could differ between the countries (Desjardins & Rubenson, 2013). All these explanations ultimately revolve around the same basic mechanism: in some contexts, adult learning might be more effective than in others. For example, contextual characteristics may make adult learning more effective because they create an adult population that is better capable to learn. In this regard, one potentially important contextual characteristic is the formal education system: in countries that have education systems that produce a population that is better able to remain active learners, the effectiveness of adult learning activities should be higher. Another potentially important contextual trait is the extent to which a population is already familiar with ICT skills.

We test these assumptions with three hypotheses. Firstly, we focus on the level of differentiation of initial education systems. Differentiation refers to the extent to which pupils of different of ability levels are enrolled in different educational tracks, and is related to various educational system characteristics, including the number of tracks and the age of selection (Bol and Van der Werfhorst, 2011). Differentiation in upper secondary schooling might lead cumulative advantage or disadvantage of education over the life course (Blossfeld, Buchholz, Skopek, & Triventi, 2016; Blossfeld et al., 2014). One line of reasoning revolves around assumptions about the relevance of academic self-concept for adults' educational success. We assume that those adults with a higher academic self-concept and more educational success experiences are more likely to self-select into adult education and more likely to be effective learners. Indeed, a lower academic self-concept is associated with lower subsequent academic achievement and a range of other less desirable educational outcomes (Marsch and Martin, 2011). Much of adults' academic self-concept will be formed during initial education. In formal education, academic self-concept is formed because children compare their performance to the performance of their peers. As a consequence, equally able students develop lower academic self-concepts in high-ability schools than in low-ability schools (Marsh and Parker, 1984). This big-fish-little-pond-effect is observed in many countries and stable across age groups (Marsh and Hau, 2003; Seaton, Marsh and Craven, 2009). Salchegger (2016) demonstrated that this effect is stronger in more strongly differentiated systems. This may be an explanation for the higher achievement inequality and the slightly lower mean educational performance in more strongly differentiated systems (Hanushek and Woesmann, 2006).

In addition, educational differentiation may also be related to a less well-developed system of adult learning. In comprehensive school systems (for example, the US, the UK) adult education is used to compensate for the lack of occupationally specific skills obtained in initial education (Crouch, Finegold, & Sako, 1999; Brunello, 2003). In addition, in more strongly differentiated systems, employers better mold jobs and job tasks to the average skills of graduates from the various education levels (Marsden, 1999). Levels et al. (2014) showed that school-leavers in more strongly differentiated systems are indeed more likely to find a job at the right level of education. One consequence of the better initial education-to-job match may be that there would be less demand for on-the-job training, reskilling or upskilling in countries with more strongly differentiated initial education systems.

This reasoning leads us to posit the following hypothesis:

H4. The higher the level of external differentiation in education systems, the weaker the relationship between non-formal and informal adult learning and digital problem-solving skills.

As second potentially important trait of initial education systems is the extent to which a system is vocationally orientated. In many systems, general and vocational education tracks are offered, both in secondary and in post-secondary and tertiary education. In the general academic tracks, the emphasis lies on teaching general academic skills, Vocational education emphasizes occupationally specific skills.

In general, vocational systems ensure a smooth school-to-work transition for vocationally educated students, precisely because they teach students skills that are in demand (Wolbers, 2007; Levels et al., 2014). However, some evidence suggests there may be a downside to this. Krueger and Kumar (2002) argue that occupationally specific skills make VET students less likely to adopt technological skills. Recent studies have suggested that the effect of occupation specific skills varies over the life course (Hanushek and Woessmann, 2016; Forster et al., 2016; Forster and Bol, 2018), and suggest that the initial better starting position of vocationally educated school-leavers dwindles over time. One explanation is that over time, occupationally specific skills become outdated more rapidly than general skills, which erodes employment opportunities of those who do not update their skills through adult learning. Occupationally specific skills may make the vocationally educated less flexible than generally educated, who are probably also better equipped for learning new skills (Cedefop, 2013). This effect is observed to be stronger in more strongly vocationally oriented systems (Hanushek et al., 2017). However, this reasoning is not uncontroversial: at least one analysis suggests that the later-in-life disadvantages of vocational educated are not systematically related to vocational education systems (Forster et al., 2016) and Heisig and Solga (2015) find that the general skills of workers with upper-secondary education are about the same in systems with vocationally oriented and general education systems. To further explore this, we test the following hypothesis:

H5. The higher the level of vocational orientation in education systems, the weaker the relationship between non-formal and informal adult learning and digital problem-solving skills.

Third, we focus on the way in which adult education and training is organised. This differs widely between countries (cf. Saar, Roosmaa and Martma, 2019). Institutional characteristics strongly shape participation in non-formal adult education (e.g. Saar and Helemäe, 2008; Roosmaa & Saar, 2010; Desjardins, 2017), and although evidence is scarce, it seems likely that the way adult education is organised also shapes the extent to which adults are effective in learning ICT skills through non-formal learning. One way in which it presumably does this is through formal instruction, by a tutor, a supervisor, or an experienced trainer. According to several classic theories about learning, the longer the time learners spend engaging with instruction, the better they learn (Anderson, 1981). For example, behaviourist theory focusses on observable learning behaviour (Foxall, 2008) and assumes that learning is achieved through conditioning learners to comply with external stimuli (Boghossian, 2006), which can for example be given during instruction. Cognitivist theory (Biniecki and Conceigao, 2016; Merriam et al., 2007; Rutherford-Hemming, 2012) focusses on understanding how minds learn, and assumes that engaging instruction can encourage students' attention and stimulate active learning. Constructivist theory assumes that learning involves a mental effort and social interaction (Altman, 2009; Merriam et al., 2007). Instruction is crucial, as it can promote enhanced learning (Altman, 2009; Biniecki and Conceigao, 2016; Jackson, 2009). Andragogy and other humanist theories stress that adults can and should take ownership of their learning process. For example, andragogy describes principles that are assumed generally applicable to adult learning situations, which ultimately should lead to self-actualisation and ownership over the learning process. During the learning process, adults will become increasingly independent; to evolve, guidance provided by instructors is essential (Henschke, 2011). Mutual respect and equality between learners and their educators is key (Knowles, 1980). These theories are fundamentally different in their approach and assumed mechanisms, but all these views, instruction time is key. And following these assumptions, we could expect that in non-formal systems that please a stronger emphasis on learning through instruction, learning of new skills (such as ICT skills) is more effective.

To test this reasoning, we postulate the following hypothesis:

H6. The higher the mean instruction time by participant in non-formal AET in a country, the stronger the relationship between non-formal adult learning and digital problem-solving skills.

As a final national contextual characteristic, we aim to assess whether the extent to which adult learning in countries is geared towards teaching adults ICT skills matters for the extent to which they learn these skills. Indeed, adult learning systems can host a plethora of different training topics. We assume that countries in which lifelong learning is more specifically intended for teaching ICT content are more effective in teaching adults these skills. As such, we postulate that:

H7. The higher share of non-formal courses with ICT content in a country, the stronger the relationship between non-formal adult learning and digital problem-solving skills.

3. Data and Methods

To test these hypotheses and answer our research questions, we make use of micro data from the OECD Programme of the International Assessment of Adult Competencies (PIAAC; see OECD, 2016a; 2016b). PIAAC samples adults between the age of 16 and 65 in highly industrialized countries. PAAC uses a combination of computer based assessment and paper-and-pencil data collection strategies. Participants take adaptive psychometric tests that directly assess their capacity to solve problems in technology-rich environments, and item response techniques were used to calculate 10 plausible values. These plausible values provide an unbiased estimate of the 'real' proficiency (OECD, 2013c). Respondents were further interviewed on key demographic and socio-economic background characteristics and skill use. PIAAC is cross-culturally and cross-nationally valid.

Not all countries that participated in PIAAC tested for digital problem-solving skills[1]. We use data for those 26 countries that participated in PIAAC and took part in the assessment of digital problem-solving skills. We exclude Russia and Australia due to data quality issues and administrative restrictions.

[1] Cyprus, France, Italy, Indonesia (Jakarta), and Spain did not offer the PS-TRE tests.

3.1 What are "digital problem-solving skills"?

Our dependent variables are objective measurements of digital problem-solving skills. In PIAAC data, digital problem-solving skills are defined as "using digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks" (PIAAC Expert Group, 2009: 9). The skill domain "problem solving in technology-rich environments" uses a scenario-based skill assessment. PIAAC-respondents work on nine response items that cover specific problems that people encounter when using PC or computer-based artefacts at the workplace. Thereby, the core feature of the problem-solving domain is that all tasks are specifically designed to avoid respondents reaching the goal using simple routine actions (PIAAC Expert Group, 2009: 7). We can therefore assume that digital problem-solving skills as measured in PIAAC capture more than routine computer skills in order to solve the so-called information-rich problems they are confronted with. On the contrary, this skill domain involves active strategies to set goals and the workers' endowment of capabilities to use strategies (and develop the mindset) needed to interact with databases. Digital problem-solving also involves the capabilities to navigate online and through digital interfaces, tools and folders as well as documents as well as the use of networks to acquire or process information and perform practical tasks and digital communication (Acemoglu and Autor, 2011: 1045; PIAAC Expert Group, 2009). The problem-solving scale has a range from zero to 500, with an OECD international average of 278 (OECD, 2016b).

Skills in PIAAC are provided as 10 plausible values to account for the complex measurement strategy. Therefore, we run our micro level models once for each plausible values and combine the estimates (Perry et al. 2017). Thereby, we avoid an underestimation of the variance of skills.

About 18% of the fulltime workers did not take the problem solving test (OECD, 2016c: 54). Test scores are missing for three groups of adults: (1) adults lacking computer experience, (2) respondents who failed the "ICT core" test implemented in PIAAC and thus lack the computer skills needed for computer-based competency testing, and (3) people who would have had the required skills but refused to use a computer for testing (OECD 2016c: 54 et seq.). While gender differences are rather small, non-respondents are a selective group that contains more migrants than non-immigrants, and that is, on average, older than the respondents who took the computer-based assessment, has lower levels of education and more often belongs to middle or lower socio-economic status groups as compared to higher socio-economic status. Therefore, the results have to be interpreted with caution because they are estimated on a sample that is selected positively on the above-mentioned factors.[2]

3.2 Measurement and operationalization of theoretical concepts

Below, we discuss the measurements we used. The relevant descriptive statistics are provided in section 5.1.

Informal adult education and training. Participation in informal learning activities is measured by combining three items on learning at the workplace using principal-component factor analysis. The three items used are “In your own job, how often do you learn new work-related things from co-workers or supervisors?”, “How often does your job involve learning-by-doing from the tasks you perform?”, and “How often does your job involve keeping up to date with new products or services?”. Respondents could choose between five answer categories ranging from “never” to “every day”. Table X shows that all three are strongly correlated with a common factor.

Table 1: Factor loadings from principal-component factor analysis of informal learning items on the first factor

	Factor 1
Learning from co-workers/supervisors	.8162108
Learning-by-doing	.8285385
Keeping up to date	.7236421

Source: PIAAC, own calculations

Non-formal learning. Participation in non-formal learning is measured with a dummy variable, indicating whether respondents had participated in (a) courses conducted through open or distance learning, (b) organized sessions for on-the-job training or training by supervisors or co-workers, (c) seminars or workshops, or (d) courses or private lessons in the 12 months before they were interviewed.

Gender: a dummy indicates whether respondents were male (1) or female (0)

Age: measured in years.

[2] We ran robustness checks with a categorical dependent variable that includes the non-respondents among the low achievers. Ther results remained largely comparable.

Migration background: For all respondents, the origin countries are their reported countries of birth. Respondents were also asked about the languages they had learned as a child and still understood. From this information, the native language of respondents was determined. The dummy variable is scored (1) if respondents' mother tongue is a language is different from the language in which the survey was performed, and (0) if it was the same. From this, we constructed a categorical variable that allows us to control for migrant backgrounds. The variable has four categories: (0) native-born and speaking a native language, (1) native-born and speaking a foreign language, (2) foreign-born and speaking a native language, and (3) foreign-born and speaking a foreign language.

Initial educational attainment: respondents were asked about their highest level of educational attainment in national education systems' classification. Information was then coded by the PIAAC consortium and country experts into the international standard classification of education (OECD, 2013b).

Field of study: a set of dummy variables indicating whether the main study field of respondents were (a) general programmes, (b) teacher training and education science, (c) humanities, (d) languages and arts, (e) social sciences, business and law, (f) science, mathematics and computing, (g) engineering, manufacturing and construction, (h) agriculture and veterinary, (i) health and welfare, or (j) services.

Working full-time: A dummy indicating whether respondents worked more than 32 hours/week.

Occupational groups: based on ISCO-08, we coded dummies indicating if respondents worked in one of the following occupational classifications: (a) armed forces, (b) legislators, senior officials and managers, (c) technicians and professionals, (d) technicians and associate professionals, (e) clerks, (f) service workers and shop and market sales workers, (g) skilled agricultural and fishery workers, (h) craft and related trades workers, (i) plant and machine operators and assemblers.

Importance if ICT Skills in jobs. This variable was constructed using data from CEDEFOPs occupational skill profiles. These data were merged to the PIAAC data on the occupational level (ISCO 2-digit). We the conducted a factor analysis of six skill variables: complexpsimp programmingimp electronicsimp processinginfoimp analyzingimp interactingpcimp. This yielded a single factor indicating the importance of ICT skills in the occupation. When using the CEFEFOP Data we lose all countries that did not provide ISCO on the 2digit level: Canada, Austria, Estonia, Finland. Therefore, we only use these data in the pooled models. In the comparative models, we do not use this variable to have a larger set of countries.

Firm size: set of dummy variables indicating if respondents work in firms with (a) 1 to 10 people, (b) 11 to 50 people, (c) 51 to 250 people, (d) 251 to 1000 people, or (e) 1000 people and more.

Economic sector: Dummies indicating if respondents were working in the (a) public sector, or in (b) commerce, transport or services.

Vocational orientation Bol and Van der Werfhorst (2011) combined two data sources measuring the percentage of students enrolled in upper secondary vocational programs (from the OECD and UNESCO).

Differentiation. We use a measure constructed by Bol and Van de Werfhorst (2011). This measure is the result of a principal factor analysis on three country level variables: the age of first selection, the percentage of the total curriculum in primary and secondary education that is stratified, and the number of tracks. The variables that comprise the factor scores each refer to different characteristics of differentiated systems. The age of selection indicates at what point in the educational career differentiation starts, the length of the differentiated curriculum specifies what proportion of the education system is tracked, and the number of tracks available for 15-year olds shows how much differentiation education systems have. Combined, the indicators give a fairly good and cross-nationally comparable indicator of the level of differentiation (Bol and Van der Werfhorst, 2013). Principal factor analyses resulted in a relative score on the differentiation index for all countries.

Mean instruction hours by participant in non-formal AET (Standardized): We obtained this measure from the Eurostat online database (code: trng_aes_151). It was calculated from the Adult Education Survey by summing up the instruction hours for all participants and then calculating an average for the whole country. Thus, it shows how much instruction time the average training participant in a country had.

Share of non-formal courses with ICT content: We use the 2011 Adult Education Survey data, that provides information about the content of the non-formal learning activities, to calculate the mean participation rates in ICT-related courses in different occupations, which we thereafter include to the analysis. When using this data, we lose all countries that did not provide ISCO on the 2digit level: Canada, Austria, Estonia, Finland. Therefore, we only use these data in the pooled models. In the comparative models, we do not use this variable to have a larger set of countries.

4. Analytical strategy

To answer our research questions, we combine analyses on the individual and on the country level in a two-step multilevel design. On the individual level, we aim to estimate the causal relation between training and problem solving skills. Then, we compare the individual level effect estimates across countries. Below, we describe our methods in detail.

The estimation of causal effects of training participation on skills on the individual level is difficult because participation is highly selective on factors that are also likely to affect skills. Moreover, causality may also run in the opposite direction: high skills may cause training participation. In order to answer our research question, we have to address both issues. We apply two different strategies to control for selection and reverse causality that are feasible with our cross-sectional data. First, we make use the wide range of observable characteristics in the PIAAC data and control for possible confounding factors. However, this strategy has limitations, which we will describe below. Second, we also compare individuals who wanted to take a course but involuntarily missed it with those who took part. This resembles a quasi-experiment where those who involuntarily missed a course are a control group (see Görlitz 2011; Leuven and Oosterbeek 2008). Yet, there are also some limitations associated with the approach. Comparing the results of the two methods, we hope to gain some insights about the effect of training on ICT problem solving skills on the individual level. Below, we describe the two methods.

PIAAC provides a wide range of variables that we can use to control for selection using ordinary least squares regression. However, with this strategy there is the danger of collider bias, that may for example arise if the control variables are caused by the outcome (Elwert and Winship 2014). Job tasks and skill use at the workplace may be both a confounder or a collider, i.e. caused by both training and skills. Therefore, we have to be cautious to include only variables that are unlikely to be caused by skills. Ultimately, we decided to use age, gender, initial education, place of birth, language, occupational groups, field of study, firm size, service sector, and public sector as control variables. Still, this strategy has the limitation that there may be further selection on unobserved variables. Also, we cannot rule out reverse causality.

The quasi-experimental strategy using involuntarily missed courses potentially gets closer to a causal effect. The basic idea of this “comparison group” approach is that involuntarily missing a planned course may resemble random assignment of training courses (Leuven and Oosterbeek 2008; Görlitz 2011). To resemble a quasi-experiment, the reason for missing the course should be randomly distributed or at least not related to confounding factors. If this (conditional) independence holds, we can recover the causal effect of training on skills from the comparison of participants and involuntary non-participants. Thereby, we can control for both selectivity and reverse causality. To identify involuntary non-participants, we use two variables from the PIAAC survey. Each respondent was asked “In the last 12 months, were there more/any learning activities you wanted to participate in but did not?” If they replied yes, they were asked for the reasons for non-attendance. We coded the following reasons as “random” events: “I was too busy at work”, “The course or programme was offered at an inconvenient time or place”, “I did not have time because of childcare or family responsibilities”, and “Something unexpected came up that prevented me from taking education or training”. Clearly, all categories except the last one do not always occur at random and may even be correlated with factors that are associated with both training and skills. This regards work organization in the first two cases and family structure in the third one. Therefore, we add the same control variables used in the regression approach to adjust for remaining heterogeneity.[3]

To explore whether the impact of training on skills varies across countries, we apply a two-step approach. We first estimate the micro level effects for each country and then use the coefficients for each country as a dependent variable in a model on the macro level. We then explain the differences in the estimated effects between countries with our macro level predictors. In the model on the macro level, we have to account for the fact that the coefficients are estimated and come with uncertainty. To do this we use a model for estimated dependent variables developed by Lewis and Linzer (2005).

[3] Please note that we only have this information for non-formal learning. We cannot test Hypothesis H3b with quasi-experimental methods.

5. Results

5.1 Descriptive results

Table 2 shows the selectivity of training on the mentioned control variables and the improvement in balance that the comparison group approach entails. The comparison of those who take training and those who do not in the full sample (columns 1 to 3 in Table 2) shows strong selection on education, field of study and occupation. This mirrors the finding from previous literature that the higher educated are more likely to receive further training because they are more often in training intensive occupations. The comparison group approach reduces this selectivity as columns 4 to 6 show. The differences between the educational groups, fields of study, and occupations are either reduced or disappear completely. At the same time, differences between men and women as well as between migrants and natives become larger. In the case of gender, this may be due to the inclusion of family issues as a reason for not taking part in training, which is more common among women. The comparison clearly shows that involuntarily missing a course is not randomly distributed. Therefore, we also use all control variables when applying this approach. Also, Table 2 shows that the number of cases is reduced from about 50,000 to about 7,000 individuals when using the comparison group approach. Especially the control group becomes much smaller.

Table 2: Descriptive results

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample			Comparison groups		
Variable	No Training	Training	Difference	No Training	Training	Difference
Age	39.673	40.608	0.935**	38.641	39.740	1.099*
	(11.787)	(11.138)	(0.389)	(10.572)	(11.940)	(0.549)
Male	0.488	0.498	0.011	0.443	0.523	0.079***
	(0.500)	(0.500)	(0.010)	(0.497)	(0.500)	(0.022)
Native-born and native-language	0.865	0.862	-0.003	0.806	0.876	0.069***
	(0.341)	(0.345)	(0.011)	(0.395)	(0.330)	(0.024)
Native-born and foreign-language	0.038	0.038	0.000	0.048	0.035	-0.012
	(0.192)	(0.192)	(0.005)	(0.213)	(0.185)	(0.008)
Foreign-born and native-language	0.030	0.036	0.006	0.044	0.029	-0.015**
	(0.171)	(0.187)	(0.005)	(0.206)	(0.167)	(0.006)
Foreign-born and foreign-language	0.066	0.063	-0.003	0.102	0.060	-0.041**
	(0.249)	(0.244)	(0.006)	(0.302)	(0.238)	(0.015)
ISCED 0-2: Lower sec. education & below	0.133	0.069	-0.064***	0.118	0.122	0.004
	(0.340)	(0.254)	(0.009)	(0.322)	(0.327)	(0.019)
ISCED 3a: Upper sec. general education	0.176	0.117	-0.059***	0.168	0.157	-0.011
	(0.381)	(0.322)	(0.013)	(0.374)	(0.364)	(0.017)
ISCED 3b: Upper sec. vocational education	0.237	0.173	-0.064***	0.204	0.269	0.065***
	(0.425)	(0.379)	(0.013)	(0.403)	(0.443)	(0.019)
ISCED 4/5: Short, post-sec & low. tert. education	0.333	0.428	0.095***	0.390	0.338	-0.053*
	(0.471)	(0.495)	(0.015)	(0.488)	(0.473)	(0.026)
ISCED 5/6: Higher tert. education	0.120	0.212	0.091***	0.119	0.114	-0.005
	(0.325)	(0.409)	(0.010)	(0.324)	(0.318)	(0.014)
General programmes	0.133	0.075	-0.058***	0.129	0.114	-0.015
	(0.340)	(0.263)	(0.011)	(0.335)	(0.318)	(0.020)
Teacher training and education science	0.062	0.102	0.041***	0.071	0.070	-0.001
	(0.240)	(0.303)	(0.006)	(0.257)	(0.255)	(0.009)
Humanities, languages and arts	0.066	0.070	0.004	0.074	0.058	-0.016
	(0.249)	(0.255)	(0.003)	(0.262)	(0.233)	(0.011)
Social sciences, business and law	0.174	0.213	0.040***	0.197	0.175	-0.022
	(0.379)	(0.410)	(0.006)	(0.398)	(0.380)	(0.013)
Science, mathematics and computing	0.079	0.093	0.013***	0.087	0.077	-0.010
	(0.270)	(0.290)	(0.003)	(0.282)	(0.266)	(0.009)
Engineering, manufacturing and construction	0.208	0.197	-0.010	0.190	0.238	0.048**
	(0.406)	(0.398)	(0.011)	(0.393)	(0.426)	(0.020)
Field of Study: Agriculture and veterinary	0.028	0.022	-0.006*	0.024	0.029	0.005
	(0.165)	(0.145)	(0.003)	(0.153)	(0.168)	(0.005)
Field of Study: Health and welfare	0.067	0.123	0.056***	0.060	0.079	0.019
	(0.250)	(0.328)	(0.005)	(0.238)	(0.270)	(0.011)
Field of Study: Services	0.072	0.050	-0.022***	0.062	0.069	0.007
	(0.259)	(0.218)	(0.007)	(0.241)	(0.253)	(0.006)

Working full-time: More than 32 hours/week	0.776	0.845	0.069***	0.766	0.802	0.036*
	(0.417)	(0.362)	(0.013)	(0.424)	(0.399)	(0.019)
Armed Forces	0.006	0.006	0.000	0.005	0.005	0.000
	(0.074)	(0.077)	(0.001)	(0.069)	(0.071)	(0.002)
Legislators, senior officials and managers	0.067	0.112	0.045***	0.078	0.065	-0.013
	(0.250)	(0.315)	(0.005)	(0.269)	(0.247)	(0.013)
Technicians and Professionals	0.170	0.317	0.148***	0.192	0.180	-0.012
	(0.375)	(0.465)	(0.011)	(0.394)	(0.384)	(0.014)
Technicians and associate professionals	0.144	0.191	0.046***	0.143	0.169	0.026*
	(0.351)	(0.393)	(0.007)	(0.351)	(0.375)	(0.012)
Clerks	0.142	0.103	-0.039***	0.150	0.136	-0.014
	(0.350)	(0.304)	(0.008)	(0.357)	(0.343)	(0.010)
Service workers and shop and market sales workers	0.185	0.131	-0.054***	0.186	0.175	-0.010
	(0.388)	(0.337)	(0.005)	(0.389)	(0.380)	(0.017)
ISCO-08: Skilled agricultural and fishery workers	0.009	0.005	-0.004***	0.013	0.009	-0.003
	(0.094)	(0.068)	(0.001)	(0.111)	(0.096)	(0.003)
ISCO-08: Craft and related trades workers	0.112	0.065	-0.047***	0.096	0.116	0.019*
	(0.316)	(0.247)	(0.009)	(0.295)	(0.320)	(0.011)
ISCO-08: Plant and machine operators and assemblers	0.082	0.045	-0.036***	0.057	0.086	0.029**
	(0.274)	(0.208)	(0.004)	(0.233)	(0.281)	(0.013)
Working in public sector	0.228	0.368	0.141***	0.189	0.273	0.083***
	(0.419)	(0.482)	(0.012)	(0.392)	(0.445)	(0.016)
Working in commerce, transport or services	0.706	0.782	0.076***	0.711	0.704	-0.007
	(0.456)	(0.413)	(0.011)	(0.453)	(0.456)	(0.016)
Firmsize: 1 to 10 people	0.313	0.171	-0.142***	0.360	0.246	-0.115***
	(0.464)	(0.376)	(0.011)	(0.480)	(0.430)	(0.016)
Firmsize: 11 to 50 people	0.305	0.292	-0.012	0.287	0.308	0.021
	(0.460)	(0.455)	(0.007)	(0.453)	(0.462)	(0.014)
Firmsize: 51 to 250 people	0.212	0.270	0.058***	0.211	0.243	0.032**
	(0.409)	(0.444)	(0.005)	(0.408)	(0.429)	(0.013)
Firmsize: 251 to 1000 people	0.103	0.148	0.045***	0.083	0.126	0.043***
	(0.304)	(0.355)	(0.005)	(0.276)	(0.332)	(0.011)
Firm size: 1000 people and more	0.068	0.119	0.051***	0.058	0.076	0.018**
	(0.252)	(0.324)	(0.006)	(0.234)	(0.266)	(0.008)
Observations	20,486	28,875	49,487	1,674	5,155	6,829

Table 3 Descriptive statistics of the macro indicators

	count	mean	sd	min	max
Index of vocational enrollment	19	.31	.89	-1.8	1.7
Index of external differentiation	20	.09	.98	-1.32	1.86
Mean instruction hours per participant in non-formal education	21	81.90	30.59	51	190
Share of non-formal courses with ICT content	12	.16	.05	.09	.23

5.2 Pooled analyses

We now turn to exploring whether digital skills are associated with participation in non-formal and informal training and gauging how plausible it is that observed associations can be interpreted causally. Table 4 presents the results of the OLS regressions of job-related non formal training on ICT skills. We present the bivariate regressions, the regressions with full controls, and a regression for older workers, respectively.

Table 4: OLS estimates of the association between non-formal training and ICT skills

	(1) Raw	(2) + Controls	(3) + Controls & age > 40
Job-related non-formal training	14.53***	6.353***	5.534***
	(13.56)	(6.19)	(5.16)
Observations	48963	48963	24725

t statistics in parentheses
Controls: age, gender, education, foreign-born, foreign language, part-time, occupation (ISCO 08 main group), field of study, public sector, service sector, firm size
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The analyses confirm what is often found in the literature, and what we expected with Hypothesis H1a: there is a strong association between participating in job-related non-formal training and skills (Model 1: *b*=14.53). However, the association is reduced strongly by controlling for possible confounders, which implies that a large part of the observed association is driven by selection, and not by causal effects. Still there is a positive and significant association between training and skills in Model 2 with controls. Among older workers, the association is smaller. This is evidence against hypothesis 1b stating that training should become more important for older worker's ICT skills because they did not learn them at school. This may be evidence that the OLS model does not yield plausible results. In Table 5 we explore this further with the control group analysis.

Table 5: Comparison group estimates of the association between non-formal training and ICT skills

	(1) Raw	(2) + Controls	(3) + Controls & age > 40
Non-formal training (Comp. group)	0.472	2.143	4.745*
	(0.25)	(1.38)	(2.34)
Observations	6756	6756	3228

t statistics in parentheses
Controls: age, gender, education, foreign-born, foreign language, part-time, occupation (ISCO 08 main group), field of study, public sector, service sector, firm size
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table strongly suggests that most of the originally observed association between non-formal training participation and ICT skills should not be interpreted causally. We observe much smaller and non-significant associations in both Models 1 and 2, without and with controls. Standard errors are considerably larger, which is also due to the much lower sample size. Interestingly, the association is larger and significant among older workers in Model 3. This is in line with hypothesis 1b. We take this as evidence that the comparison group model yields more plausible estimates. We also interpret this as evidence suggesting a causal effect for older workers. Thus, we interpret this as evidence in favor of Hypothesis 3a stating that there is an effect net of observable and unobservable confounders.

Table 6: OLS estimates of the association between informal training and ICT skills

	(1) Raw	(2) + Controls	(3) + Controls & age > 40
Job-related informal training	-4.207***	0.134	-0.364
	(-3.96)	(0.13)	(-0.32)
Observations	48798	48798	24627

t statistics in parentheses
Controls: age, gender, education, foreign-born, foreign language, part-time, occupation (ISCO 08 main group), field of study, public sector, service sector, firm size
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 6, we test the relationship for informal learning. Contrary to what we expected with Hypothesis H2a, we observe a large negative association without controls. This may be due to selectivity of work-related informal training as surveyed in PIAAC: it may well be the case that many of the activities included in the scale of job-related training are more likely among low-skilled workers. This would indeed explain why the negative association disappears once controls are entered into the equation. With controls, there is only a very small and non-significant association. The estimates among older workers are not much different indicating that Hypothesis 2b also is not supported. This may again indicate that the model does not estimate the unbiased effect of training on skills. All in all, we conclude that there is little evidence of causal effects of informal learning on ICT skills and refute Hypothesis H3b.

In Table 7, we explore whether non-formal and informal learning are more important for ICT skills in jobs in which these skills are more important. Overall, the models confirm that ICT use in occupations is associated with higher ICT skills. However, the interaction effect differs between the estimation methods and the type of training. We expect that training in occupations with higher ICT-use contains more ICT content. We can also show this using the AES data, there is a positive correlation between the ICT intensity in a job and the share of ICT content in training courses. Therefore, we would expect higher effects of training on ICT skills in occupations with high importance of ICT. Our models show that we do not find this interaction when using the standard OLS specification among older workers. If anything, the interaction even seems to be negative. This may again indicate that the OLS model is not suited to estimate the effects of training correctly. In the comparison group approach, we find a positive interaction as expected. The interaction is not significant, but quite sizeable. For informal training we also find a positive interaction, but it is small and not significant. We do not see this as strong evidence for hypotheses H1c and H2c.

Table 7: The interaction between training and ICT use in explaining ICT problem solving skills among older workers (40+)

	(1) OLS	(2) Comp. group	(3) OLS
Job-related non-formal training	5.571^{***}		
	(7.16)		
Importance of ICT skills in occupation	8.645^{***}	4.508	8.356^{***}
	(5.09)	(1.84)	(5.30)
Training * Importance	-0.516		
	(-0.77)		
Non-formal training (Comp. group)		4.647^{*}	
		(2.28)	
Training * Importance		2.892	
		(1.34)	
Job-related informal training			-0.287
			(-0.76)
Inf. Training * Importance			0.322
			(0.91)
Observations	24725	3228	24627

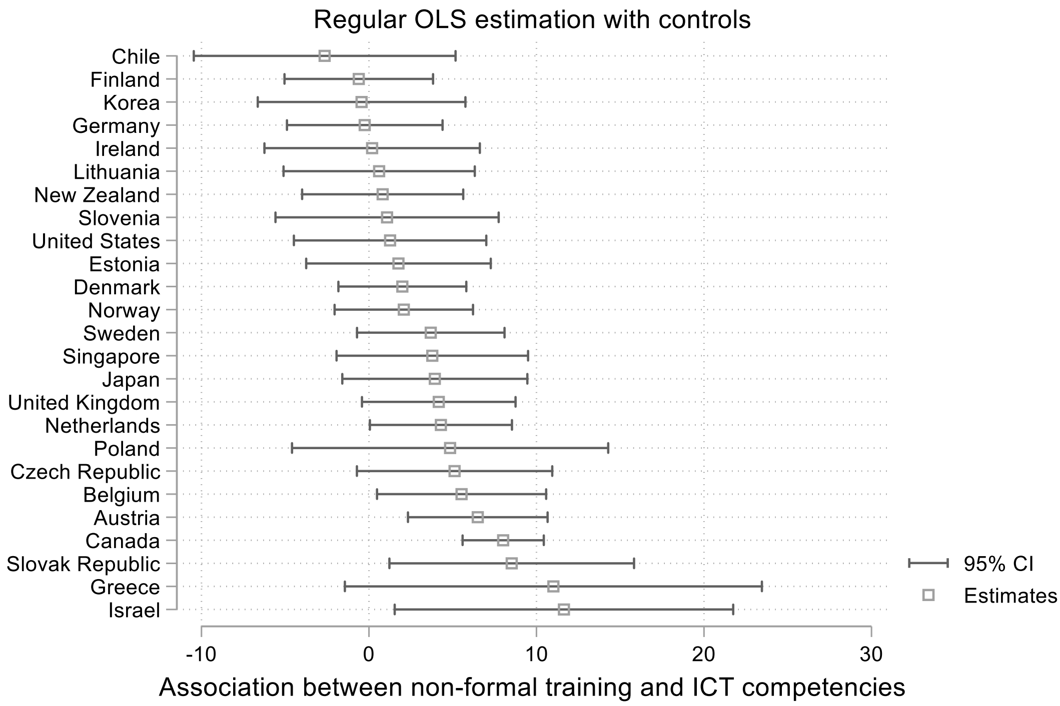
t statistics in parentheses

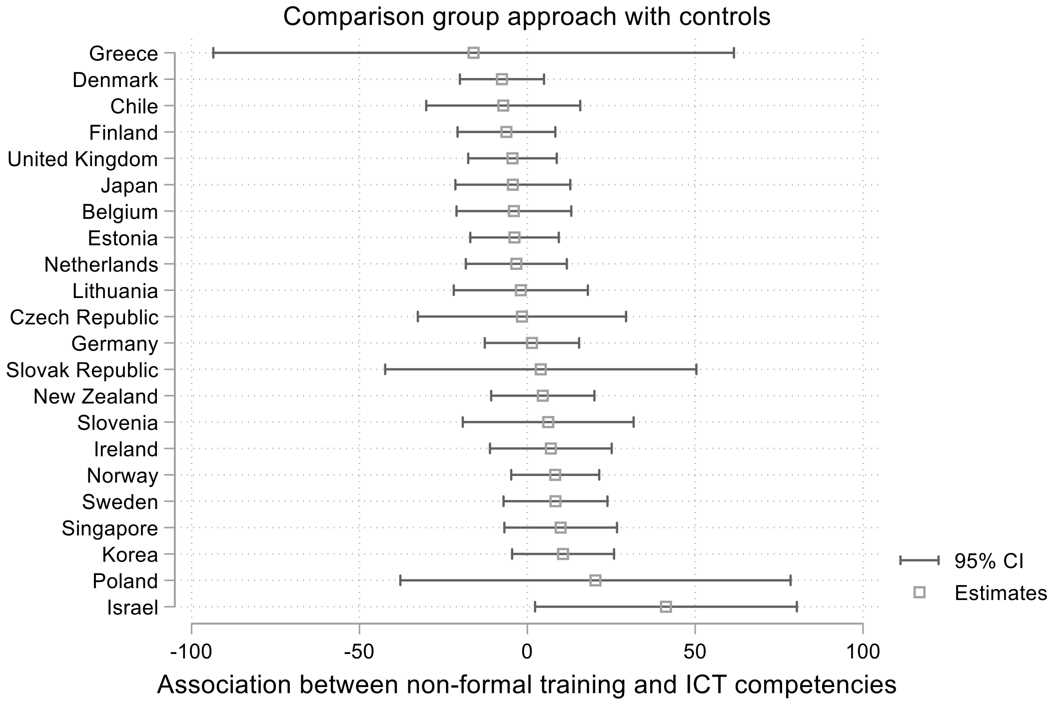
Controls: age, gender, education, foreign-born, foreign language, part-time, occupation (ISCO 08 main group), field of study, public sector, service sector, firm size
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

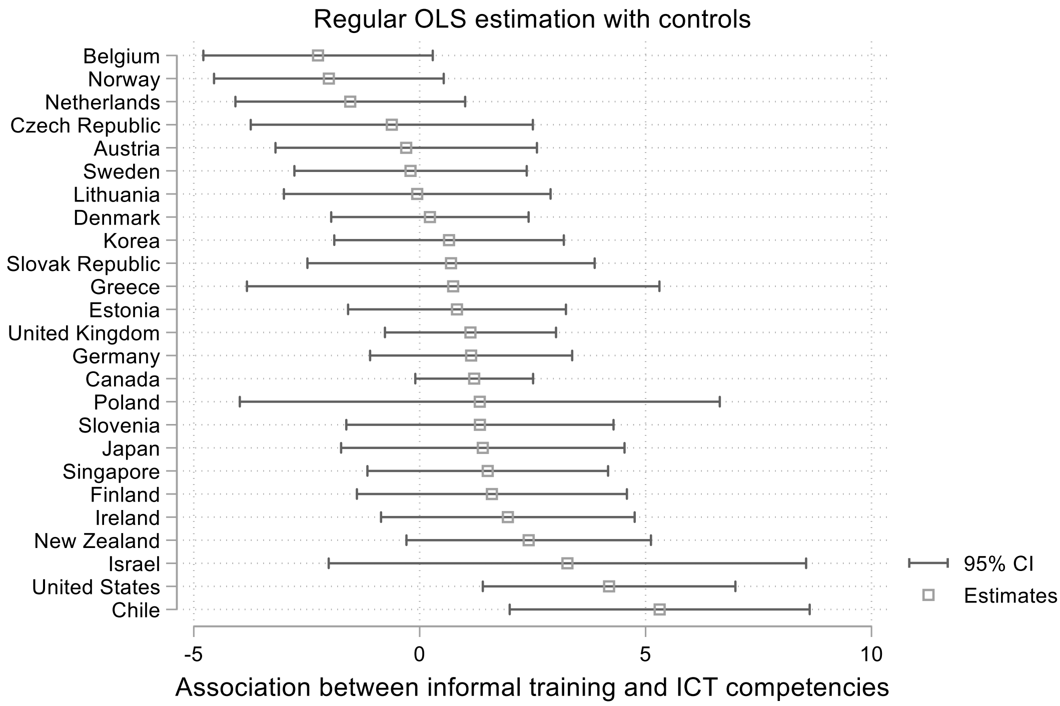
5.3 Cross-country analyses

We now turn to testing cross-national hypotheses. To do so, we first explore whether there are cross-national differences in the strength and direction of the relation between adult education and training (either through informal or non-formal training) and ICT skills. They are depicted in Figure 1. We focus on the estimated association between adult learning and skills among older workers (40+), controlled for observable confounders.

Figure 1 Cross-national variation in relation between adult training and skills







The upper panel in Figure 1 invites three conclusions. First, cross-national variation indeed exists in the relationship between non-formal training and ICT skills. Second, this variation is not very large, and, given the rather wide and overlapping confidence intervals, may well be even smaller. Third, that in most countries, the relationship does not deviate significantly from zero: the relation is only statistically significant in the Netherlands, Belgium, Austria, Canada, Slovak Republic, and Israel). The bottom panel shows that this is also true for the relation between informal learning and ICT skills, However, here, a small group of countries (including Belgium, Norway, the Netherlands, Czech Republic, Austria, and Sweden) exhibit a negative relationship. Interestingly, it seems that the stronger the relation between informal learning and skills is in a country, the weaker the relation between non-formal learning and skills.

Next, we turn to exploring if these relationships vary systematically by country and show that we find only weak evidence of systematic differences. Table 8 shows the coefficients from two-step multilevel models. The dependent variables in these models are the nation-specific coefficients of training on ICT skills. We show the OLS estimates with controls and the comparison group estimates with controls for non-formal training and the OLS estimates with control for informal learning. All models are estimated for workers ages 40 and older because we assume that the effect is more meaningful for this group (see above). The coefficients can thus be interpreted like interaction effects between the macro level variable and the training indicator.

Panels A and B in Table 8 show that in our preferred models school systems interact with the effect of training in the expected direction. Nevertheless, only one of the coefficients is statistically significant: The effect of informal learning on ICT skills decreases with higher vocational enrolment. Still, we also find a negative coefficient using non-formal training and the comparison group approach. The OLS estimates for non-formal training on the other hand point in the opposite direction. Clearly, the latter model did not provide plausible estimates earlier. Overall, this is some weak evidence in favor of Hypothesis 5 stating that the effect of training should be lower in systems with a strong vocational component. Yet, if anything this only holds for informal learning. The results about external differentiation of schools go into the same direction. Yet, since we find no significant coefficients we have to reject Hypotheses 4, which stated that school systems with higher external differentiation (i.e., more tracks) lead to lower effects of training on ICT skills.

Table 8: explaining cross-national variation

A

	(1) Non-formal OLS	(2) Non-formal Comp. group	(3) Informal OLS
Index of vocational enrolment	0.929	-2.060	-1.429*
	(1.15)	(-0.62)	(-3.53)
Constant	2.671*	2.384	1.236*
	(3.43)	(0.91)	(3.26)
Observations	18	17	18

B

	(1) Non-formal OLS	(2) Non-formal Comp. group	(3) Informal OLS
External differentiation	0.400	-0.523	-0.411
	(0.59)	(-0.25)	(-0.93)
Constant	2.936*	1.609	0.815^{+}
	(4.30)	(0.80)	(1.85)
Observations	19	18	19

C

	(1) Non-formal OLS	(2) Non-formal Comp. group	(3) Informal OLS
Mean instruction hours per participant in non-formal education	0.484	-2.452	0.159
	(0.41)	(-0.98)	(0.32)
Constant	3.170*	-1.850	0.344
	(4.52)	(-1.26)	(1.13)
Observations	16	15	16

D

	(1) Non-formal OLS	(2) Non-formal Comp. group	(3) Informal OLS
Share of non-formal courses with ICT content	1.111	-1.968	-0.840*
	(1.75)	(-1.02)	(-2.44)
Constant	2.614*	1.611	-0.0199
	(4.21)	(0.84)	(-0.06)
Observations	12	12	12

Comp. group: Participation in one course vs. none and one involuntarily missed. All estimates controlled for age, gender, education, foreign-born, foreign language, part-time, occupation (ISCO 08 main group), field of study, public sector, service sector, firm size

$^{+}$ $p < 0.10$, * $p < 0.05$

The influence of the current lifelong learning system in the country shown in panels C and D of Table 8 show even less systematic results. Here, the only significant relationship is a negative between the effect of informal learning and the share of non-formal courses with ICT content in panel D. This is unexpected and against the prediction of Hypothesis 7 stating that more ICT courses in a country should lead to a higher effect. We do find this for our OLS estimates of non-formal training. Yet, these are the least reliable estimates based on our earlier analyses. Thus, Hypothesis 7 has to be rejected in our data. Also, we find no significant relationship between the average training intensity in the country and the effect of training on ICT skills. Therefore, Hypothesis 6 is also not supported.

6. Conclusion and discussion

In this paper, we aimed to investigate a) to what extent participation in non-formal and informal adult learning is related to higher proficiency in digital problem-solving skills, b) whether any observed relations are plausibly causal in nature, and c) which national education system characteristics are associated with a stronger relation between adult learning and digital problem-solving skills. Our findings are mostly in line with common findings in literature: there is a correlation between participation in learning and ICT skills, particularly in non-formal learning participation of older workers. Just like other papers (Vorhaus et al., 2011; Gauly and Lechner, 2019) we conclude that most of this association is driven by selection into training by better skilled individuals or by confounding variables. We do find some evidence to suggest a causal effect of non-formal training of older workers.

Whether this causal inference is correct hinges on the extent to which our identification strategy is plausible. Our comparison group strategy has several important problems and drawbacks. First, there are several overlapping comparison groups: involuntary non-participants and participants in one course, participants in one course who involuntarily missed another course and participants in two courses etc. Since the intensities of courses may differ, one course for one person could be much more relevant than two courses for others. Arguably, only the first comparison is clear-cut and theoretically sensible for our research question. Hence, we only use this one in the analyses. Thus, the comparison group approach only estimates a local effect in our analyses, namely the difference between non-participation and participation in one course. Second, in any case the number of cases and hence the power of the analyses is greatly reduced because the number of people involuntarily missing courses is low. This is even more the case since we restrict to only the first comparison. We furthermore lost three countries (Canada, the US, and Austria) because they do not provide all variables necessary to implement the strategy. All in all, we evaluate that our identification, while not without flaws, produces evidence that suggests a causal relationship might exist between training participation and ICT skills among adults, With these data, we could not provide better evidence, but follow-up papers may use field experiments or instrumental variables to better control for unobserved heterogeneity and provide stronger evidence.

Our cross-national analyses revealed that the effect of training on ICT skills does not vary systematically between countries. We found some weak evidence that comprehensive school systems without vocational components are associated with higher skill acquisition through training. This supports our theoretical argument that school systems focusing on general skills may enable more efficient learning during adulthood. Yet, given the high uncertainty of our estimates and the large variation between our model specifications we are hesitant to draw strong conclusions from this. If anything, the impact is not very strong indicating that workers in both general and vocational systems can learn ICT skills later on.

Interestingly, we found no systematic impact of our variables measuring the impact of the current adult education system. Neither training intensity nor the relative importance of ICT training courses in a country seems to be related to the effect of training on ICT skills. This may be due to imprecise measures and future research should work on providing better indicators of the efficiency of adult education regimes.

References

Altman, B.A. (2009). Determining US workers' training: history and constructivist paradigm, Journal of European Industrial Training, 33(6):480-491.

Anderson, L.W. (1981) Instruction and Time-on- Task: a Review, Journal of Curriculum Studies, 13(4):289-303.

Angrist, J. D., & Pischke, J. S. (2008). Mostly harmless econometrics. Princeton university press.

Biniecki, S.M.Y. & Conceigao, S.C.O. (2016). Using concept maps to engage adult learners in critical analysis, Adult Learning, 27(2):51-59.

Boghossian, P. (2006). Behaviorism, constructivism, and Socratic pedagogy, Educational Philosophy and Theory, 38 (6):713-722,

Brunello G. (2003). 'On the Complementarity between Education and Training in Europe', D. Checchi, C. Lucifora (eds.): Education, Training and Labour Market Outcomes in Europe, London: MacMillan.

Cedefop. (2013). Labour market outcomes of vocational education in Europe. Evidence from the European Union labour force survey. Luxembourg: Publications Office of the European Union.

Cedefop. (2020). On the way to 2020: data for vocational education and training policies. Indicator overviews: 2019 update. Luxembourg: Publications Office of the European Union.

Chyul-Young, J., Yoowoo, L., Sunyoung, P., Eunhye, C., & Romi, C. (2020). Factors Affecting Employees' Problem-Solving Skills in Technology-Rich Environments in Japan and Korea. Sustainability, 12(17).

Crouch, C., Finegold, D., & Sako, M. (1999). Are skills the answer? The political economy of skill creation in advanced industrial economies. Oxford: Oxford University Press.

Cunha, F., & Heckman, J. (2007). The Technology of Skill Formation. American Economic Review, 97(2):31-47.

De Grip, A. (2015). The importance of informal learning at work. IZA World of Labor, 162

De Grip, A. & Van Loo, J. (2002). The economics of skills obsolescence: a review. In A. de Grip, J. van Loo & K. Mayhew (eds.) The Economics of Skills Obsolescence, Research in Labor Economics 21, JAI Press, 1-26.

Darrah, C.N. (1996). Learning and work: An exploration in industrial ethnography. New York, NY: Garland Publishing.

Desjardins, R. (2014). Rewards to Skill Supply, Skill Demand and Skill-mismatch. Studies Using the Adult Literacy and Lifeskills Survey. Lund: Lund University.

Desjardins, R. (2015). Participation in adult education opportunities: Evidence from PIAAC and policy trends in selected countries. Paris: UNESCO.

Desjardins, R. (2017). Political Economy of Adult Learning Systems. Comparative Study of Strategies, Policies and Constraints. London: Bloomsbury Academic.

Desjardins, R., & Ederer, P. (2015). Socio-demographic and practice-oriented factors related to proficiency in problem solving: a lifelong learning perspective. International Journal of Lifelong Education, 34(4):468-486.

Desjardins, R., & Rubenson, K. (2013). Participation Patterns in Adult Education: the role of institutions and public policy frameworks in resolving coordination problems. European Journal of Education, 48(2).

Ehlert, M. (2020). No Future, No Training? Explaining Cross-national Variation in the Effect of Job Tasks On Training Participation, KZfSS - Kölner Zeitschrift für Soziologie und Sozialpsychologie, 72, S1, 483-510

Elwert, F., and Winship, C. (2014). Endogenous Selection Bias: The Problem of Conditioning on a Collider Variable. Annual Review of Sociology 40(1):31–53.

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

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

Foxall, G.R. (2008). Intentional behaviorism revisited, Behavior and Philosophy, 36:113-155.

Gauly, B., & Lechner, C. M. (2019). Self-perfection or self-selection? Unraveling the relationship between job-related training and adults' literacy skills. PLoS ONE, 14(5).

Gangl, M. (2010). Causal Inference in Sociological Research. Annual Review of Sociology, 36:21-47.

Görlitz, K. (2011). Continuous Training and Wages: An Empirical Analysis Using a Comparison-Group Approach."Economics of Education Review 30(4):691–701.

Hämäläinen, R., De Wever, B., Malin, A., & Cincinnato, S. (2015). Education and working life: VET adults' problem-solving skills in technology-rich environments. Computers & Education, 88:38–47.

Hämäläinen, R., De Wever, B., Nissinen, K., & Cincinnato, S. (2017). Understanding adults' strong problem-solving skills based on PIAAC. Journal of Workplace Learning, 29(7/8):537–553.

Hämäläinen, R., De Wever, B., Nissinen, K., & Cincinnato, S. (2019). What makes the difference – PIAAC as a resource for understanding the problem-solving skills of Europe's higher-education adults. Computers & Education, 129, 27-36.

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

Hanushek, E.A. & Wößmann, L. (2006). Does Educational Tracking Affect Performance and Inequality? Differences- in-Differences Evidence Across Countries, The Economic Journal, 116(510):C63–C76

Henschke, J.A. (2011). Considerations regarding the future of andragogy, Adult Learning, 22 (1): 34-37.

Jackson, L.D. (2009). Revisiting adult learning theory through the lens of an adult learner, Adult Learning, 20(3):20-22,

Knowles, M.S. (1980). The Modern Practice of Adult Education: From Pedagogy to Andragogy, Cambridge Books, New York, New York.

Knowles, M.S., Holton, E.F., III. & Swanson, R.A. (2014). The Adult Learner: The Definitive Classic in Adult Education and Human Resource Development, Routledge, Abingdon.

Krueger, D., & Kumar, K. (2004). Skill-specific rather then General Education: A Reason for USEurope Growth Differences? Journal of Economic Growth, 9(2):167–207.

Leuven, E. |& Oosterbeek, H. (2008). An Alternative Approach to Estimate the Wage Returns to Private-Sector Training. Journal of Applied Econometrics, 23(4):423–34.

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

Lewis, J.B. & Linzer, D.A. (2005). Estimating Regression Models in Which the Dependent Variable Is Based on Estimates. Political Analysis, 13(4):345–64.

Marsh, H.W. & Hau, K.T. (2003). Big-Fish--Little-Pond effect on academic self-concept: A cross-cultural (26-country) test of the negative effects of academically selective schools. American Psychologist, 58 (5):364–376.

Marsh, H.W. & Parker, J.W. (1984). Determinants of student self-concept: Is it better to be a relatively large fish in a small pond even if you don't learn to swim as well?. Journal of Personality and Social Psychology, 47 (1):213–231

Marsh, H.W., & Martin, A.J. (2011). Academic self-concept and academic achievement: Relations and causal ordering. British Journal of Educational Psychology, 81(1):59-77.

Merriam, S.B., Caffarella, R.S. & Baumgartner, L.M. (2007). Learning in Adulthood: A Comprehensive Guide, Jossey-Bass, San Francisco, CA.

OECD. (2013a). OECD skills outlook 2013: First results from the survey of adult skills. Paris, France: OECD Publishing.

OECD. (2013b). PIAAC Data, Paris: OECD.

OECD. (2013c). Technical Report of the OECD Survey of Adult Skills (PIAAC). Paris: OECD Publishing.

OECD. (2014). Indicator C6: How many adults participate in education and learning? Paris: OECD Publishing.

OECD. (2016a). Skills Matter. Further results from the Survey of Adult Skills. Paris: OECD Publishing.

OECD. (2016b). What does age have to do with skills proficiency? Adult Skills in Focus, no 3, Paris.

Perry, A., Helmschrott, S., Konradt I., & Maehler, D.B. (2017). User Guide for the German PIAAC Scientific Use File. GESIS Papers 2017/23. Köln: GESIS - Leibniz-Institut für Sozialwissenschaften.

Reder, S., Gauly, B., & Lechner, C. (2020). Practice makes perfect: Practice engagement theory and the development of adult literacy and numeracy profciency. International Review of Education, 66: 267-288.

Roosmaa, E.-L., & Saar, E. (2010). Participating in Non-Formal Learning: Patterns of Inequality in EU-15 and the New EU-8 Member Countries. Journal of Education and Work, 23:179–206.

Rutherford-Hemming, T. (2012). Simulation methodology in nursing education and adult learning theory, Adult Learning, 23(3):129-137

Saar, E., & Helemäe, J. (2008). Estonia on the backdrop of the European Union states: countryspecific institutional context and lifelong learning. Studies for Learning Society, 1:7−16

Saar, E., & Räis, M. (2016). Participation in job-related training in European countries: the impact of skill supply and demand characteristics. Journal of Education and Work, 30(5):531-551.

Saar, E., Odd B.U., & R. Desjardins. (2013). The Role of Diverse Institutions in Framing Adult Learning Systems. European Journal of Education 48(2):213–32.

Saar, E., Roosmaa, E.L. & Martma, L. (2019). Report on recent changes in European education systems (literature review). Maastricht University: Technequality Deliverable 2.1.

Salchegger, S. (2016). Selective school systems and academic self-concept: How explicit and implicit school-level tracking relate to the big-fish-–little-pond effect across cultures. Journal of Educational Psychology, 108(3):405–423.

Seaton, M., Marsh, H. W., & Craven, R. G. (2009). Earning its place as a pan-human theory: Universality of the big-fish-little-pond effect across 41 culturally and economically diverse countries. Journal of Educational Psychology, 101(2):403–419.

Vorhaus, J., Litster J., Frearson, M. & Johnson, S. (2011). Review of Research and Evaluation on Improving Adult Literacy and Numeracy Skills. Research Paper. 61. London: Department for Business, Innovation and Skills.

Wolbers, M. (2007). Patterns of Labour Market Entry: A Comparative Perspective on Schoolto-Work Transitions in 11 European Countries. Acta Sociologica, 50(3):189–210.

Wolf, A. & Jenkins, A. (2014). Do 'Learners' Always Learn? The Impact of Workplace Adult Literacy Courses on Participants' Literacy Skills. British Educational Research Journal 40(4):585–609.

Yilmaz, K. (2011). The cognitive perspective on learning: its theoretical underpinnings and implications for classroom practices, The Clearing House: A Journal of Educational Strategies, Issues and Ideas, 84(5):204-212