Pillars – Pathways to Inclusive Labour Markets

Report

Job Training, Human Capital, and Labour Market Outcomes: The Role of Automation, Offshoring, and Digitization

December 2022

This project receives funding from the European Union's Horizon 2020 Research and Innovation Programme under Grant Agreement No. 101004703.

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Keywords: Job Training, Human Capital, Automation, Offshoring, Technological Change, Digital Skills, Age

★This project receives funding from the European Union's Horizon 2020 Resesarch and Innovation Programme under Grant Agreement No 101004703. See Falck et al. (2022) for a policy brief summarizing some of the main results and policy conclusions from this report.

1. Introduction

In recent decades, major secular trends in the labor market have significantly changed occupations and the skills demanded in occupations. In particular, advances in technologies and international outsourcing have decreased demand for certain types of tasks (Feenstra and Hanson, 1999; Acemoglu and Autor, 2011). A large body of literature suggests that routine occupations are particularly vulnerable to automation risks, i.e., the risk that their tasks will be replaced by robots and automation technologies (e.g., Autor et al., 2003; Arntz et al., 2016; Cortes, 2016; Frey and Osborne, 2017; Nedelkoska and Quintini, 2018). Further, workers in occupations performing tasks that can be outsourced abroad face similar changes in skill demand due to lower trade barriers and technological advances (Jensen et al., 2005; Blinder, 2009; Blinder and Krueger, 2013). Moreover, the ongoing digitization of workplaces and the increasing relevance of computers have likely increased digital skill requirements.

In light of these changing skill demands, the ability to work with computers and use the Internet — more generally, possessing digital skills — has become increasingly important in many occupations in recent decades (Deming and Noray, 2020). It has also been shown that workers with higher digital skills receive a wage premium (Falck et al., 2021). Thus, the increasing importance of digital skills raises the question of how workers who lack these skills can actually acquire them. One way to equip workers with digital skills is through job training. Thus, we investigate whether job training can improve workers' digital skills, and consequently labor market success.

While there is already a large literature on the returns of job training (e.g., Greenhalgh and Stewart, 1987; Pischke, 2001; Albert et al., 2010; Watanabe, 2010), most existing studies suffer from bias from omitted variables and unobserved selection into training.[1] Workers who participate in training arguably differ along many characteristics from workers who do not participate in training. For instance, if workers with higher (unobserved) ability are more likely to participate in training, and at the same time earn higher wages, a naive regression of wages on training will lead to upward-biased estimates of the returns to training. We propose a novel way of correcting for selection into training by controlling for tested numeracy skills as a powerful proxy for ability. We ensure that workers with and without training are similar in numeracy skills and a large set of additional individual-level control variables using entropy balancing (Hainmueller, 2012). This tech-

[1] Notable exceptions are Leuven and Oosterbeek (2008) or Goerlitz (2011), who provide quasi-experimental evidence on the returns to training.

nique applies a maximum entropy reweighting scheme that calibrates unit weights so that the reweighted treatment and control groups are statistically indistinguishable across a large set of covariates.

We use international survey data from 32 (mostly European) countries from PIAAC (Programme for the International Assessment of Adult Competencies). With respect to training, workers are asked about their training activities in the year before the survey. Importantly for us, PIAAC also provides an assessment of adults' proficiency in key information-processing skills, most notably, numeracy and problem-solving in technology-rich environments, which we refer to as digital skills. Moreover, PIAAC's rich background questionnaire contains detailed information on wages, workplace characteristics, and socio-demographic variables.

Controlling rigorously for selection into training using entropy balancing in combination with numeracy skills and additional background variables, we find that job training significantly affects digital skills and wages. First, digital skills of workers who participate in job training are 0.06 standard deviations higher than those of their "statistical twins" without training. This is an economically sizeable effect, similar to the difference in digital skills between Austria and the Netherlands or between the Czech Republic and Singapore. Intriguingly, using only numeracy skills as control already reduces the skill returns to training by 75%, indicating that ability-based selection into training leads to a severe upward bias in estimated training effectiveness when not properly accounted for. Such a model can already explain more than 50% of the total variation in digital skills. Reassuringly, adding further controls (including years of schooling as an alternative ability proxy) hardly changes the estimated training effectiveness, suggesting that numeracy skills can serve as a "sufficient statistic" for unobserved ability.

Not all individuals took part in the digital skill assessment. For instance, if PIAAC participants had no prior computer experience or failed a test of basic digital competencies such as using a keyboard/mouse or scrolling through a web page, their digital skills could not be assessed (see Falck et al., 2022). This implies sample selectivity since participation in the digital skill assessment is potentially correlated with (unobserved) variables such as ability, motivation, and effort. We propose several alternatives to impute missing digital skills, which always lead to very similar results: the effect of job training on digital skills almost doubles in these more encompassing samples, increasing to 0.10–0.11 standard deviations. Thus, we interpret the effect of job training in the baseline sample without imputed digital skills as a lower-bound of the true effect of job training on digital skills.

We also consider the mere fact of whether an individual participated in the digital skill assessment as informative about her basic digital skills — individuals without any computer experience or those failing a simple initial computer test likely have very little to zero digital skills. Intriguingly, we find that job training significantly increases the probability that individuals have at least basic digital skills by about 4.5 percentage points (pp).

Finally, following most of the previous economic literature on the returns to training, we also look at wages as a measure of overall productivity at the job. We find that job training leads to significantly higher hourly wages: workers participating in job training earn about 8% higher wages than their "statistical twins" without training.

The existing literature has not yet investigated to which extent the effectiveness of training differs between occupations that are differently affected by automation, offshoring, and digitization. Individuals working in occupations with higher exposure to automation or offshoring participate less often in employer- and self-organized job training; if they do participate in training, however, they are more likely to state career concerns (e.g., increasing employment chances in another occupation) as a main reason for participating in training. Moreover, job training in occupations more exposed to automation or offshoring is as effective (in terms of increasing digital skills and wages) as in other types of occupations. The pattern is noticeably different in occupations that experience faster increases in computerization: In such occupations, *more* (employer- and self-organized) training is taken up, but it is *less* effective in increasing digital skills. One potential explanation for this result is that it is more difficult to learn new skills when occupations are changing more rapidly.

Furthermore, we study how the returns of training vary with country features, such as union density, minimum wage regulations, employment protection, and pension generosity. We find that stricter labor market regulations are associated with lower returns to job training in terms of wages, as these country features may reflect a larger degree of wage compression (e.g., Hanushek et al., 2015).

We also study the effectiveness of job training particularly for the oldest worker generation (55 and older). Our most important result is that job training for older workers is as effective as for younger workers in increasing human capital and wages. Moreover, job training is even *more* effective for older workers when it comes to equipping workers with basic digital skills, particularly in workplaces that are becoming more reliant on computers. However, older workers receive less job training than their younger counterparts in all countries we study.

The remainder of this report proceeds as follows. Section 2 gives an overview of the related literature. Section 3 presents our identification strategy. Section 4 introduces our data and main variables. Section 5 presents our results on the effectiveness of job training. Section 6 investigates the frequency and effectiveness of training by the three major occupational trends of automation, offshoring, and digitization, as well as by country characteristics. Section 7 explores heterogeneities in training frequency and effectiveness by age groups and gender, with a particular focus on elderly workers. Section 8 concludes.

2. Related Literature

Labor Market Trends. Over the past decades, some phenomena have changed labor markets substantially. Progress in the development of labor-replacing technologies has advanced not only in production but in nearly all sectors, making automation and the use of computers at the workplace one of the most important developments in the labor market over the past years (Acemoglu and Autor, 2011). Simultaneously, workers — especially in the middle of the wage distribution — face an increasing risk of offshoring since technological advances have significantly lowered the costs of offshoring tasks (Jensen et al., 2005; Blinder, 2009; Blinder and Krueger, 2013; Schmidpeter and Winter-Ebmer, 2021).

The literature attributes this to routine jobs being more susceptible to technological change and offshoring because their tasks follow a structure that can easily be replaced by machines or cheaper labor abroad (Autor et al., 2003; Firpo et al., 2011; Cortes, 2016). Increasing automation, offshoring, and digitization lead to changing job tasks and thus changing skill requirements for workers. This affects workers at different stages of their careers differently and leaves them vulnerable to these developments. On the one hand, this might negatively affect workers through worse employment prospects, wages, or training opportunities. On the other hand, workers whose tasks are complementary to new technologies rather than substitutes face a competitive advance since the routine tasks they previously had to perform get replaced by machines, leaving them more time for tasks in which they are more productive (Acemoglu and Autor, 2011).

Job Training. Despite the importance of these labor market trends, both in workers' everyday lives and in the literature, surprisingly little is known about individual consequences for workers. We also know little about potential options to mitigate negative career concerns and to stay at the frontier of the task requirements at one's job, e.g., through job training. Schmidpeter and Winter-Ebmer (2021) show that increasing automation decreases the chances of finding a new job after an unemployment spell. However, training offered to unemployed workers seems to have a mitigating effect, reducing the negative impact of automation on the job-finding probability.[2] However, the literature thus far has not investigated the potential role of training at the workplace in counteracting the negative consequences of technological change and offshoring. Rather than providing training after a worker has already lost his or her job, job training could help to sustain the employability of workers by increasing their productive human capital.

Different worker groups might be differently affected by the three labor market trends outlined above, leading to heterogeneity in the frequency as well as the effectiveness of training. For instance, older workers often lack digital skills and are too hesitant to keep up with the rapid progress in this field (Falck et al., 2021). Recent literature has investigated potential determinants of training, but has not yet put it in the context of automation, offshoring, and digitization (e.g., Greenhalgh and Stewart, 1987; Pischke, 2001; Albert et al., 2010; Watanabe, 2010).[3] Previous literature points to differences in training frequency by gender, education, firm size, or age in general. These papers find that workers who are male, highly educated, employed in larger firms, or younger are more likely to participate in training (Oosterbeek, 1996, 1998; Watanabe, 2010). We add to this literature by investigating training frequency by gender and age in the context of automation, offshoring, and digitization.

Estimating Training Effectiveness. Participation in training is costly, thus the benefits of training should outweigh its costs. A further strand of literature thus examines the impact of job training (LaLonde, 1986; Lynch, 1992; Blundell et al., 1999; Lechner, 1999; Goux and Maurin, 2000; Pischke, 2001; Frazis and Loewenstein, 2005; Leuven and Oosterbeek, 2008; Goerlitz, 2011) and adult learning (Schwerdt et al., 2012; Hidalgo et al., 2014; Goerlitz and Tamm, 2016) on individuals' labor market outcomes. Other papers study the effectiveness of active labor market policies and training for unemployed workers (Hujer et al., 2006; Card et al., 2010; Kluve, 2010; McCall et al., 2016).[4]

However, a research design to study the relationship between training and economic outcomes has to address the endogeneity of training participation: Since we can never simultaneously observe individuals in a "treated" state, in which they receive training, and an "untreated" state without training, we need to resort to comparing workers with

[2]The effectiveness of active labor market policies for unemployed workers is also investigated in Hujer et al. (2006); Card et al. (2010); Kluve (2010); McCall et al. (2016). See Leuven (2005), Bassanini et al. (2007), and De Grip and Sauermann (2013) for overviews of this literature.

[3]See Hidalgo et al. (2014) for a literature overview on determinants of and returns to training.

[4]See Leuven (2005), Bassanini et al. (2007), De Grip and Sauermann (2013), and Hidalgo et al. (2014) for overviews of the literature.

and without training to estimate training effectiveness. However, workers receiving training are likely to be different from those who do not — both in terms of observed and unobserved characteristics. While we can control for observable characteristics, the probability to receive training may still be correlated to unobservable characteristics. If these unobservables are also related to our outcomes of interest (e.g., digital skills or wages), the typical omitted variable bias will result. In particular, we would overestimate the effectiveness of training if more productive workers are also more likely to receive training (De Grip and Sauermann, 2013). The literature addresses this endogeneity problem in several ways. For instance, Heckman et al. (1997, 1998) and Dehejia and Wahba (2002) suggest matching estimators to create counterfactual comparison groups.[5] However, matching does not solve the endogeneity problem in estimating training effectiveness if relevant variables that are correlated with both training participation and outcomes are unobserved and can thus not be included in the matching procedure.

Moreover, Haelermans and Borghans (2012) describe two other problems in the estimation of training effectiveness: First, studies often suffer from small sample sizes and this in turn leaves them prone to publication bias. Second, most studies fail to address heterogeneities in the wage effects of job training for certain groups. According to this study, the wage returns to job training are positive and of non-negligible magnitude. The authors further find that training is profitable only until the age of 55. However, the authors also explicitly state that their findings should be taken with caution until further causal research strengthens their findings. We add to the existing literature in several ways. First, we address the endogeneity issue in training participation by applying entropy balancing (following Hainmueller, 2012) in combinbation with using a powerful control for (unobserved) ability. Second, we investigate differences in training effectiveness by age, gender and also with respect to different dimensions of training (e.g., specific training for digital skills).

3. Identification Strategy

To investigate the effects of job training on human capital and wages, we estimate the following individual-level regression:

$$Y_i = \alpha + \beta_1 jobtraining_i + \varepsilon_i. \tag{1}$$

[5] Smith and Todd (2005) evaluate potential non-experimental estimators of training effectiveness and conclude that among these estimators a matching difference-in-difference estimator performs best.

where Y_i is the outcome of interest for individual i. We mainly focus on three outcome variables: digital skills, an indicator for having at least basic digital skills (i.e., whether the individual was able to participate in PIAAC in a computer-based mode),[6] and log hourly wages.[7] In this regression, β_1 estimates the association of job training with our outcomes of interest. However, the naive approach from Equation 1 only yields correlational evidence, since the coefficient on job training might be biased due to omitted variables.[8] In particular, we are concerned about omitted variables that affect who receives job training. For instance, if individuals with higher ability or work effort are more likely to organize or receive training, a positive coefficient of β_1 might simply reflect ability and motivation (also see Section 2 for a discussion).

To control for individual's ability and thus account for selection into training, previous literature mainly used measures of educational attainment, e.g., years of schooling (Lynch, 1992; Arulampalam and Booth, 1997; Leuven and Oosterbeek, 1999; Bassanini et al., 2007).[9] However, due to differences in the quality of schooling over time and across countries, measures of educational attainment might be poor approximations of actual human capital. Moreover, these measures just reflect an individual's human capital at the end of formal schooling, which may not be good indicators of human capital when individuals need to constantly adapt their skills to structural and technological change throughout their entire working life. Finally, educational attainment is very coarse, so individuals within the same attainment category may vary greatly in their actual human capital.[10] We introduce a novel control to capture an individual's ability in the training literature: numeracy skills. These come from PIAAC, a large-scale assessment of the skills

[6] Individuals did not participate in the computer-based mode for three reasons (Falck et al., 2021, 2022): (i) individuals had no prior computer experience; (ii) individuals failed a computer core test, which assessed basic digital competencies such as using a keyboard/mouse or scrolling through a web page; (iii) individuals refused to take part in the computer-based assessment.

[7] The PIAAC Public Use File reports hourly wages for Austria, Canada, Germany, Hungary, Sweden, Turkey, and the United States only in the form of a worker's decile rank in the country-specific wage distribution. For Germany, we obtained the Scientific Use File, which contains continuous wage information. For the remaining countries, we follow Hanushek et al. (2015) in assigning the decile median of hourly wages to each survey participant belonging to the respective decile of the country-specific wage distribution. Using wages in coarse categories in some countries is unlikely to affect our results as Hanushek et al. (2015) show that using decile medians instead of continuous wages has no substantive impact on their returns-to-skills estimates. Moreover, in each country, we trim the bottom and top 1% of the wage distribution to limit the influence of outliers.

[8] Reverse causality is less of a concern in our setting, as individuals are asked about training measures they finished in the last 12 months before the outcome are assessed.

[9] Moreover, standard (socio-economic) controls have also frequently been used, e.g., age (Oosterbeek, 1996, 1998) and firm size (Oosterbeek, 1996; Lynch and Black, 1998; Grund and Martin, 2012).

[10] See Hanushek and Woessmann (2008) for a discussion.

of the adult population. Tested numeracy skills are a more direct and precise measure of an individual's human capital than educational attainment.[11]

We thus estimate the following model to assess the effectiveness of training:

$$Y_{icoj} = \alpha + \beta_1 jobtraining_{icoj} + \beta_2 numeracy_{icoj} + \mathbf{X}'_{icoj}\gamma + \delta_c + \zeta_o + \eta_j + \varepsilon_{icoj}. \quad (2)$$

Here, Y_{icoj} is the outcome of interest for individual i who lives in country c and works in occupation o and industry j. X_{icoj} is a vector of controls, including years of schooling, the age group in four categories (25–34, 35–44, 45–54, 55–65 years), gender, migration status in three categories (first-generation, second-generation migrant, native), parental education in three categories (neither parent has attained upper secondary, at least one parent has attained secondary and post-secondary/non-tertiary, at least one parent has attained tertiary), an indicator whether the respondent has children, and the age group of the oldest child in four categories (0–2, 3–5, 6–12, 13+ years).

Importantly, we also control for self-organized training, i.e., training measures not offered or initiated by the employer. This should account for differences in motivation and effort between workers who participate in training and those who don't. Since workers in larger firms and those who are full-time employed generally get more training, we further include controls for firm size as measured by the number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+ employees) and an indicator for full-time employment. Finally, we include country fixed effects δ to account for differences in training provision and the general quality of training programs across countries. We also add two-digit occupation fixed effects, ζ, and two-digit industry fixed effects, η, which account for differences in training frequency or effectiveness across occupations and industries.

Standard errors in Equation 2 are robust to heteroskedasticity. When we investigate heterogeneity in training effectiveness or frequency by labor market trends (varying at the occupational level) or country characteristics (varying at the country level), standard errors are clustered at the occupational level or country level.

To get as close as possible to estimating a causal effect of job training on human capital and wages in the absence of experimental variation, we follow Hainmueller (2012) in

[11]Note that numeracy skills are elicited at the same time as the outcomes of training. If numeracy skills also increase due to participation in training, our estimates of training effectiveness have to be interpreted as lower-bounds.

applying entropy balancing.[12] Entropy balancing is a non-parametric data pre-processing method to obtain exact covariate balance in settings with a binary treatment (in our case, participation in job training). Given the treatment group covariate distribution, weights are calculated by minimizing a loss function to match the distribution of covariates in the control group. Thus, the weighted control group aligns with the treatment group along observable characteristics and differs only with respect to treatment status after reweighting. In our analysis, with a large number of included balancing covariates, we restrict the balancing to the first two moments (mean and variance) to avoid non-convergence. Thus, we balance the first and second moments of all variables specified in Equation 2 as balance variables for workers with and without job training. The identifying assumption that allows for a causal interpretation of our training estimates is that we have included all variables in the matching approach that identify the selection into training (i.e., selection on observables).[13] While the validity of this assumption cannot directly be tested, the inclusion of numeracy skills as a powerful proxy for ability and a wealth of additional background variables makes us confident that we have accounted for the most relevant selection variables.

4. Data

4.1. PIAAC

Our empirical analysis is based on data from the Programme for International Assessment of Adult Competencies (PIAAC). PIAAC is a survey administered by the Organisation for Economic Co-operation and Development (OECD) and comprises representative samples of working-age individuals (16–65 years). While a total of 39 countries have participated in PIAAC across the three rounds of data collection between 2011 and 2017, we focus on the 32 countries that have decided to implement a digital skill assessment.[14]

PIAAC assesses respondents' key workplace skills in literacy, numeracy, and problem-solving in technology-rich environments, which we refer to as digital skills.[15] The domains,

[12]We implement entropy balancing by using the *ebalance* command in Stata (Hainmueller and Xu, 2013).

[13]See Cunningham (2021) for a recent discussion.

[14]These are Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Ecuador, Estonia, Finland, Germany, Greece, Hungary, Ireland, Israel, Japan, Kazakhstan, Korea, Lithuania, Mexico, Netherlands, New Zealand, Norway, Peru, Poland, Singapore, Slovak Republic, Slovenia, Sweden, Turkey, United Kingdom, and United States.

[15]These skill data have been used to estimate returns to skills across countries (e.g., Hanushek et al., 2015; Falck et al., 2021).

described more completely in OECD (2013), refer to key information-processing competencies and are defined as:

> *Literacy*: ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals, and to develop oneâs knowledge and potential;
>
> *Numeracy*: ability to access, use, interpret, and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life;
>
> *Digital*: ability to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks.

PIAAC measures each of the three skill domains on a 500-point scale. For analytical purposes, we standardize scores in the subsequent regression analyses to have a mean of zero and a within-country standard deviation of one in the estimation sample.[16]

For our analysis, we also make use of detailed information on participation in job training in PIAAC's background questionnaire, where workers are asked about their training activities in the year before the survey. We define a training measure as *job training* if the training was either training on-the-job (i.e., organized sessions for on-the-job training or training by supervisors or co-workers) or when the training measure was job-related. Moreover, PIAAC also elicits information about self-organized training and the reasons for participating in training, such as to decrease the probability to lose one's job or increase one's possibility to change occupations. We subsume these responses as reasons related to career concerns. Finally, PIAAC contains a wealth of background characteristics of the respondents, such as gender, level of education, occupation at the ISCO two-digit level, and industry of employment at the ISIC two-digit level. We use these characteristics for the entropy balancing.

As we are interested in the effect of job training on human capital and wages, it is necessary to restrict the analysis to employees, as these can possibly receive such kind of training. We further restrict our sample to individuals aged 25–65, because younger individuals have often not finished their education and thus have not (fully) entered the labor market. Including individuals below the age of 25 who are already in employment would therefore introduce a selection issue. After implementing these restrictions, our

[16] Following Hanushek et al. (2015), we use the first plausible value of the PIAAC scores in each domain throughout.

final sample comprises a total of 102,844 individuals (79,728 with digital skill information and 92,008 with wage information).

4.2. Measurement of Labor Market Trends and Country-Level Factors

One main goal in this report is to investigate whether training effectiveness differs systematically by the degree of automation, offshoring, and computerization of occupations. Below, we describe how we measure these three labor market trends in our analysis.

Automation Risk. Our measure of automation risk stems from Nedelkoska and Quintini (2018), who construct a country and occupation-specific measure of automation risk using PIAAC data. This measure uses a task-based approach, ranging from 0 if none of the tasks in an occupation can be automated to 1 if all tasks in an occupation can be automated. The left panel of Figure 1 depicts the risk of automation by occupation in our sample. The most automatable occupation is agricultural workers, with an average automation risk of 61% (i.e., 61% of tasks in this occupation can be automated). At the other end of the spectrum, production and service managers as well as teaching professionals face the lowest automation risk, where less than one-third of the tasks can be automated. In total, the measure of automation risk is available at the two-digit occupational level for 26 out of 32 countries in our sample.[17] The average automation risk across all occupations and countries in our sample is 48%.

Offshorability. We draw on measures of the offshorability of occupations from Blinder and Krueger (2013). This measure is based on expert surveys and captures the degree to which the tasks in an occupation can be performed from abroad. As the original measures are based on data from the United States, we use the crosswalk between the Standard Occupational Classification (SOC) system to the ISCO (International Standard Classification of Occupations) occupational categories by Goos et al. (2014) to obtain an offshorability measure for the PIAAC countries.[18] As there is no one-to-one correspondence between SOC and ISCO, the measure of offshorability is available for 21 out of 32 occupations; however, the measure is available in all PIAAC countries. Our final measure of offshorability is normalized to have zero mean and standard deviation one across occupations, as in Goos et al. (2014). To illustrate, stationary plant operators have the highest offshoring risk with 1.6 standard deviations above the mean, while sales workers show the lowest offshorability with 0.6 standard deviations below the mean (see middle panel of Figure 1).

[17] We do not have information on the automation risk in Cyprus, Hungary, Indonesia, Kazakhstan, Mexico, and Peru.

[18] PIAAC only provides occupational information in the ISCO classification system.

Computer Use. To capture the increasing relevance of computers at the workplace, we exploit that the United States participated in two waves of the PIAAC survey, in 2012 and 2017.[19] In both waves, participants were asked how often they perform the following activities at work: create or read spreadsheets, use word-processing software, use programming language, and engage in computer-aided real-time discussions.[20] Following the procedure of Kling et al. (2007), the computer use index is constructed as an equally weighted average of the z-scores of the included items. The z-scores are computed by subtracting the mean and dividing by the standard deviation. We then calculate the average computer use index by occupation and survey year. Reassuringly, we find that ICT technicians and ICT professionals exhibit the highest computer use intensity in both years, while computers are least important in elementary occupations such as mining, construction, and cleaning (see Figure 1, right panel).

Our final measure of computer use change used in subsequent analyses is the difference in the occupation-level computer use index between 2012 and 2017, which indicates the speed of computerization or digitization.[21]

U.S. as Benchmark Country. Note that to construct our measures of offshorability and computer use, we rely on U.S. data to obtain proxies of global occupational characteristics.[22] The United States is a natural choice as a benchmark country both because of the detail and quality of U.S. statistics and because U.S. labor markets are less regulated than those of other developed countries. Observed differences in offshorability or computer use are therefore likely to better reflect technological characteristics of occupations. Using U.S. data to proxy for differences in occupational characteristics in other countries does have drawbacks, however. Most importantly, it could lead us to reject our hypotheses linking training effectiveness to occupation-level labor market trends not because they are false but because U.S. data do not yield good proxies for cross-occupational differences in offshorability or computer use in other countries. What matters for avoiding such a false negative is that differences in offshorability or computer use in the United States

[19] The United States is the only country that participated in several PIAAC waves.

[20] The response scale was: never; less than once a month; less than once a week but at least once a month; at least once a week but not every day; every day.

[21] Note that our measures of automation, offshoring, and computerization are missing for individuals without information on the occupation at the two-digit ISCO level.

[22] Using U.S. data to proxy for differences in industry or occupation characteristics in other countries is frequent in the literature (e.g., Rajan and Zingales, 1998; Nunn, 2007; Ciccone and Papaioannou, 2009; Akerman et al., 2015).

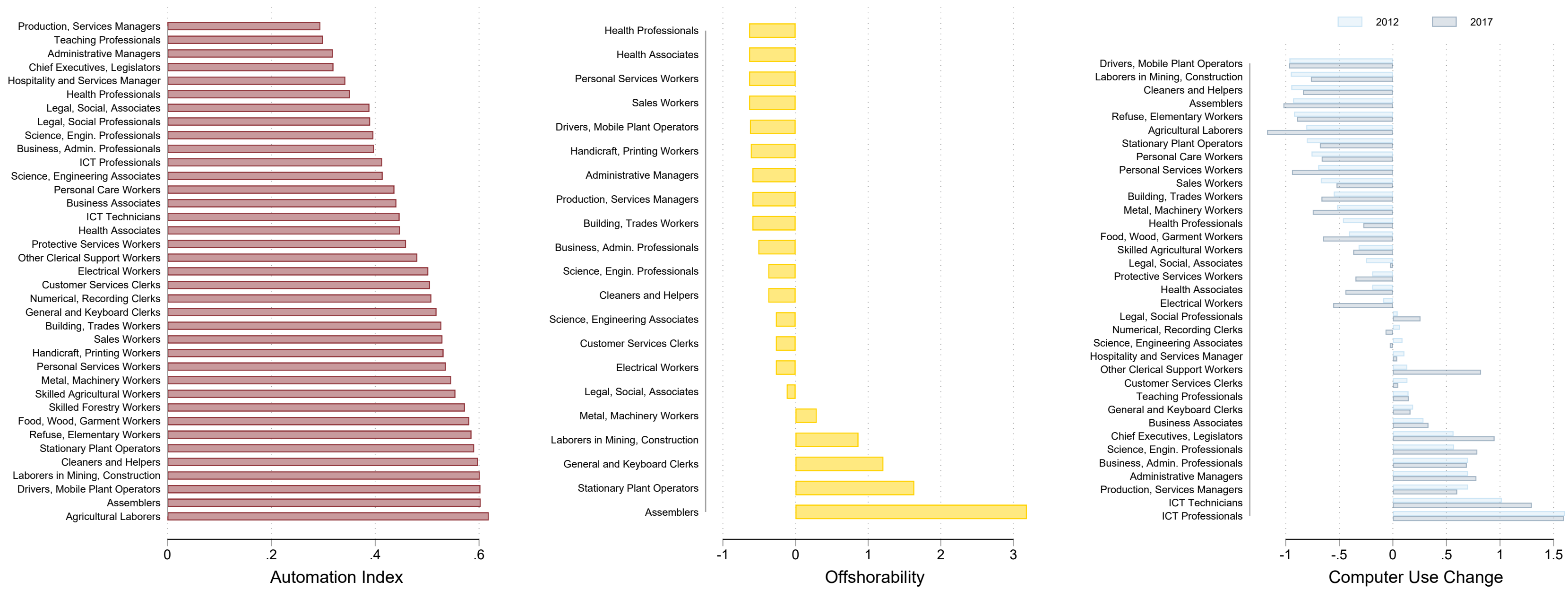
reflect inter-occupational differences in these labor market trends in the other countries in our sample (also see Ciccone and Papaioannou (2009) for a discussion).

Country-specific Factors. We further investigate how the effectiveness of training varies with country-specific characteristics, such as labor market institutions and pension systems. We obtain data on these factors from the OECD. We use the share of employees who are trade union members as a measure of union density. Further, we include a binary indicator for the existence of minimum wage regulations which takes the value 1 if a country has a statutory minimum wage, and zero otherwise. To measure the strength of employee protection, we use an index that captures the strictness of employment protection against individual and collective dismissal of employees. Data on these institutional characteristics are available for 26 countries in our sample.[23] Finally, we include a measure of pension generosity which is operationalized as the average present value of the flow of pension benefits expressed in terms of net annual individual earnings in the respective country. This measure is available for 24 countries in our sample.[24]

[23] These measures are not available for Cyprus, Ecuador, Kazakhstan, Lithuania, Peru, and Singapore.

[24] The following countries do not provide information on pension generosity: Cyprus, Ecuador, Kazakhstan, Lithuania, Peru, Singapore, Slovakia, and Turkey

Figure 1: Labor Market Trends by Occupation Across Countries



Notes: The figure shows the extent of automation (left), offshoring (middle), and computer use change (right) by occupation across all countries in our sample. See Section 4.2 for details on the construction of the measures. *Data source*: PIAAC.

5. Training, Human Capital, and Wages

This section investigates the relationship between job training and digital skills as our main measure of human capital. All results are estimated using entropy balancing. Table 1 presents our main results. Different columns show the association of job training with digital skills when gradually increasing the balancing variables. Column (1) provides the raw correlation between job training and digital skills within countries. Column (2) adds our main control variable, numeracy skills. Comparing Columns (1) and (2), the estimated coefficient on job training drops substantially from 0.33 to 0.08 once we control for numeracy skills. This indicates that ability-based selection into training leads to a severe upward bias in estimated training effectiveness when not properly accounted for. Intriguingly, just adding numeracy skills as an additional control boosts the R^2 from 0.03 to 0.53 — i.e., the share of explained variation in numeracy skills increases by as much as 50(!) pp by including numeracy skills. Column (3) replaces numeracy skills by years of schooling as the standard measure of human capital in the literature (Lynch, 1992; Arulampalam and Booth, 1997; Leuven and Oosterbeek, 1999; Bassanini et al., 2007). Compared to Column (2), the estimated coefficient on job training is twice as large and the share of explained variation in digital skills is notably smaller.

When including both numeracy skills and years of schooling in a "horse race" (Column (4)), we observe just a small additional drop in the job training coefficient compared to the specification with numeracy skills alone (Column (2)). Notably, the coefficient on numeracy skills hardly changes due to the inclusion of years of schooling, while the schooling coefficient decreases substantially by 82%. This suggests that the strong association between years of schooling and digital skills in Column (3) was mainly driven by the fact that individuals with higher educational attainment also have higher numeracy skills. Strikingly, when adding the complete set of socio-demographic and work-related control variables to the entropy balancing in Column (5), the estimated coefficient on job training remains virtually identical. This suggests that years of schooling and, in particular, numeracy skills already capture the differences in a large set of socio-demographic and work-related characteristics between individuals with and without training. We are thus confident that our identifying assumption that we have included all variables in the matching approach that identify the selection into training holds.

In the most demanding specification in Column (5) of Table 1, we find that job training increases digital skills by 0.056 standard deviations. In terms of magnitude, this is about the difference in digital skills between Austria (standardized score of 0.169) and the Netherlands (0.229) or between the Czech Republic (standardized score of 0.272) and

Table 1: Training and Human Capital: Digital Skills

Digital Skills	(1)	(2)	(3)	(4)	(5)
Job Training	0.3286***	0.0821***	0.1592***	0.0555***	0.0560***
	(0.0086)	(0.0059)	(0.0086)	(0.0062)	(0.0066)
Numeracy Skills		0.8611***		0.8313***	0.7746***
		(0.0039)		(0.0043)	(0.0049)
Years of Schooling			0.1252***	0.0224***	0.0134***
			(0.0019)	(0.0015)	(0.0017)
Observations	79728	79728	79728	79728	79728
R^2	0.03	0.53	0.11	0.53	0.58
Country FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	Yes

Notes: Least squares estimations with weights from entropy balancing. Dependent variable: digital skills standardized to standard deviation 1 across countries. Sample: employees aged 25–65 years. Job Training: indicator for participation in on-the-job training or job-related training in the 12 months before the survey. Controls: age group in four categories (25–34, 35–44, 45–54, 55–65 years), gender, migration status in three categories (first-generation, second-generation migrant, native), parental education in three categories (neither parent has attained upper secondary, at least one parent has attained secondary and post-secondary/non-tertiary, at least one parent has attained tertiary), indicator whether the respondent has children, age group of the oldest child in four categories (0–2, 3–5, 6–12, 13+ years), indicator for full-time employment, indicator of participation in self-organized training, firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+ employees), fixed effects for occupations (two-digit ISCO level) and industries (two-digit ISIC level). All regressions also control for country fixed effects. All control variables, including country fixed effects, were used for the entropy balancing. R^2 refers to within-country R^2. Robust standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Singapore (0.336). Given that we cannot rule out that job training also increases numeracy skills, we consider this a lower-bound estimate of the true causal effect of job training on the accumulation of digital skills.

Table 1 only includes workers for which digital skills could be assessed in PIAAC. As explained in Section 4, digital skills were not tested for individuals who had no prior computer experience or failed a simple initial computer test. This implies sample selectivity. In Appendix Table B.1, we show the results when imputing missing digital skills in various ways. Column (1) repeats the preferred specification from Column (5) of Table 1. In Column (2) (Column (3)), we impute missing digital skills with 0 (50). Column (4) imputes missing digital skills with the global minimum and Column (5) imputes missing digital skills with the country-specific minimum. As expected, the job training estimate increases in these more encompassing samples, as individuals with imputed (low) levels of digital skills are less likely to participate in training. Reassuringly, estimates are always very similar across the imputation methods. The sizeable increase in the skill returns to job training shown in Appendix Table B.1 corroborates our interpretation of the estimate in Column (5) of Table 1 as a lower-bound of the true effect of job training on digital skills.

In the remainder of the paper, we show the effects of job training on digital skills as tested in PIAAC ("intensive margin") as well as on an indicator of having participated in the computer-based mode, which we interpret as having at least basic digital skills ("extensive margin"). In Table 2, we replicate Table 1 using digital skills, basic digital skills, and log hourly wages (as an overall measures of training effectiveness) as outcomes. We find positive and statistically significant returns to training with respect to all three outcomes. Having participated in job training increases the probability to have at least basic digital skills by 4.3 pp (Column (3)) and hourly wages by 8.3% (Column (5)). While we are the first to investigate training effects on digital skills, we can benchmark our wage results using previous literature. The average wage effects of job training are estimated to be between 5–10% in the U.K. and U.S. (Leuven, 2005), about 9% as an unweighted average of the effect sizes across twelve European countries (Bassanini et al., 2007), and approximately 5% for Germany (Ruhose et al., 2019). Thus, our returns-to-training estimates are in a similar ballpark as previous estimates.[25]

We also show whether training effectiveness differs between EU and Non-EU countries by interacting the job training variable with an indicator for being an EU member state.[26] Overall, we find little difference in the training effectiveness between EU and Non-EU countries. Job training is similarly effective in increasing digital skills in developed countries within and outside the EU (Column (2)). While job training is slightly more effective in endowing workers with basic digital skills in EU countries (Column (4)), wage returns are slightly lower (albeit still significantly positive) (Column (6)). We will investigate potential institutional drivers for differences across countries below.

6. Automation, Offshorability, and Digitization

6.1. Training Frequency and Labor Market Trends

In this section, we investigate whether training frequency and effectiveness systematically varies with the extent to which workers are affected by labor-saving automation

[25] Note that the training-induced wage increase is of about the same magnitude as the wage return to an additional year of schooling in the PIAAC countries (Hanushek et al., 2015).

[26] In our sample, these are Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, Germany, Greece, Hungary, Ireland, Lithuania, Netherlands, Poland, Slovak Republic, Slovenia, and Sweden.

Table 2: Training, Human Capital, and Wages

	(1)	(2)	(3)	(4)	(5)	(6)
	Digital Skills		Basic Digital Skills		Log Wages	
Job Training	0.0560***	0.0613***	0.0431***	0.0384***	0.0827***	0.0899***
	(0.0066)	(0.0096)	(0.0029)	(0.0043)	(0.0038)	(0.0060)
Job Training × EU Member		-0.0117		0.0106*		-0.0159**
		(0.0130)		(0.0057)		(0.0075)
Observations	79728	79728	102844	102844	92008	92008
R^2	0.58	0.58	0.15	0.15	0.35	0.35
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Least squares estimations with weights from entropy balancing. Dependent variables: digital skills standardized to standard deviation 1 across countries, indicator for having at least basic digital skills, and log hourly wages. Sample: employees aged 25–65 years. Job Training: binary variable indicating whether the respondent participated in on-the-job training or job-related training in the 12 months before the survey. EU member: binary variable indicating whether country is a EU member. Controls: numeracy skills, years of schooling, age group in four categories (25–34, 35–44, 45–54, 55–65), gender, migration status in three categories (first-generation migrant, second-generation migrant, native), parental education in three categories (neither parent has attained upper secondary, at least one parent has attained secondary and post-secondary/non-tertiary, at least one parent has attained tertiary), an indicator whether the respondent has children, age group of the oldest child in four categories (0–2, 3–5, 6–12, 13+), an indicator for full-time employment, an indicator of participation in non-job-related training measures (e.g, self-organized training or seminar participation), firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+), as well as fixed effects for occupations (two-digit ISCO level) and industries (two-digit ISIC level). All regressions also control for country fixed effects. All control variables, including country fixed effects, were used for the entropy balancing. R^2 refers to within-country R^2. Robust standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

(i.e., automation risk), the reconfiguration of global value chains (i.e., offshoring), or digitization (i.e., computer use change). We begin with training frequency, shown in Table 3. Here, we condition on all control variables from our main empirical specification (see Section 3), while not including occupation fixed effects because this is the level at which the labor market trends vary.[27] Thus, to identify to job training coefficients in Table 3, we compare workers with the same numeracy skills, years of schooling, background characteristics, and in the same country and industry, who work in occupations with different exposure to automation, offshoring, and digitization.

In Panel A of Table 3, we investigate whether workers in occupations that are more exposed to automation have a different probability to participate in job training. One may think that such workers participate in training more often, as they need to guard themselves against technology-related displacements or wage cuts. Moreover, as shown below (e.g., Table 6), they also benefit more from job training in terms of wages. However, our data suggest that workers who are more exposed to automation actually participate significantly *less* in job training. In Column (1) of Panel A, workers in occupations with a 10 pp higher exposure to automation[28] are 11.4 pp less likely to receive job training.

In principle, if workers in occupations that are exposed to higher automation risk receive less training from their employers, they might compensate for this by organizing training themselves. However, Column (2) of Panel A shows that these workers are also significantly less likely to participate in self-organized training. However, if workers in occupations with higher automation risk do participate in training, there are significantly more likely than workers in other occupations to do so for career reasons, i.e., to decrease the probability of losing their jobs or to increase their possibilities to change occupations (Column (3) of Panel A).[29] This suggests that these workers might be particularly worried about their labor market prospects in light of advancing technological change (e.g., Kaihovaara and Im, 2020).[30]

[27]Our measure of automation risk varies at the country-occupation level. Thus, while it would be possible to include occupation fixed effects, we refrain from doing so for consistency with the other specifications.

[28]For instance, the difference in the automation risk between food and garment workers (64%) and sales workers (54%) in Greece amounts to 10 pp.

[29]Other reasons to participate in training elicited in PIAAC are: to do my job better and/or improve career prospects; to start my own business; I was obliged to participate; to increase my knowledge or skills on a subject that interests me; to obtain a certificate; other.

[30]Exploiting data from the European Social Survey, Kaihovaara and Im (2020) find that attitudes toward immigration become considerably more negative as occupational routine task content increases, as these workers are most worried about their job market prospects.

Table 3: Relationship between Training and Automation, Offshoring, and Digitization

	Job Training	Self-Organized Training	Reason for Participating: Career Concerns
	(1)	(2)	(3)
Panel A: Automation Risk			
Automation Risk	-1.1403***	-0.3140***	0.1205***
	(0.0209)	(0.0141)	(0.0114)
Observations	59377	59377	31253
R^2	0.18	0.05	0.02
Panel B: Offshoring			
Offshorability	-0.0613***	-0.0136**	0.0063**
	(0.0164)	(0.0056)	(0.0024)
Observations	45606	45606	21521
R^2	0.19	0.05	0.03
Panel C: Computer Use			
Computer Use Change	0.0509**	0.0347***	-0.0227***
	(0.0226)	(0.0084)	(0.0046)
Observations	75639	75639	37885
R^2	0.18	0.05	0.02
Country FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Least squares estimation. Job training: binary variable indicating whether the respondent participated in on-the-job training or job-related training in the 12 months before the survey. Self-organized training: binary variable indicating whether the respondent participated in training that was not organized by employer in the 12 months before the survey. Reason for participating, career concerns: if stated reason for participating in training is to be less likely to lose ones job or to increase ones possibilities of changing a job or profession. Sample: employees aged 25–65 years. Automation Risk: country-occupation-specific measure ranging from 0 (no tasks in an occupation can be automated) to 1 (all tasks in an occupation can be automated), obtained from Nedelkoska and Quintini (2018). Offshorability: occupation-specific measure of the degree to which work can be performed from abroad, obtained from Blinder and Krueger (2013); offshorability index is standardized to standard deviation 1 across occupations. Computer Use Change: change in computer use within an occupation between 2012 and 2017, calculated using the PIAAC data from the United States (sampled in PIAAC in 2012 and 2017); computer use index is based on questions indicating how often a person performs the following activities at work: create or read spreadsheets, use word-processing software, use programming language, and engage in computer-aided real-time discussions; answers are combined to a single index following the procedure described in Kling et al. (2007) and then aggregated to the occupation (two-digit ISCO) level. See Section 4.2 for a discussion of data availability. Automation risk, offshorability, and computer use change are de-meaned. Controls: numeracy skills, years of schooling, age group in four categories (25–34, 35–44, 45–54, 55–65), gender, migration status in three categories (first-generation migrant, second-generation migrant, native), parental education in three categories (neither parent has attained upper secondary, at least one parent has attained secondary and post-secondary/non-tertiary, at least one parent has attained tertiary), an indicator whether the respondent has children, age group of the oldest child in four categories (0–2, 3–5, 6–12, 13+), an indicator for full-time employment, an indicator of participation in non-job-related training measures (e.g, self-organized training or seminar participation), firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+), as well as fixed effects for industries (two-digit ISIC level) and countries. Panel C additionally includes the baseline level of computer use in 2012. R^2 refers to within-country R^2. Robust standard errors (adjusted for clustering at two-digit occupation level) in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

The association of training frequency with offshorability, shown in Panel B of Table 3, looks strikingly similar to that for automation risk. Workers in occupations more affected by offshoring are less likely to receive job training, less likely to initiate training by themselves, and more likely to state career concerns as a reason for participating in training. This result suggests that workers in more offshorable occupations are aware of the risk of becoming replaced by workers abroad, and invest in training to reduce this displacement risk. While automation risk and offshorability show very similar associations with training frequency, the pattern for the third labor market trend, digitization, is noticeably different. Panel C of Table 3 shows the relationship between job training and digitization, measured by the change in the computer use index between 2012 and 2017. We find that occupations that became more computer-intense over time are associated with significantly *higher* training participation — both for employer-provided training and for self-organized training. However, mitigating career concerns does not seem to be the main reason for these workers to participate in the training measures. The latter may be due to the fact that the positive relationship between job training and computer use change is driven by older workers (see Table 8 below), who are less prone to change occupations.

6.2. Training Effectiveness

We now investigate how the effectiveness of training in terms of developing digital skills (Table 4), endowing workers with basic digital skills (Table 5), and increasing wages (Table 6) differs by the extent to which workers are exposed to the secular labor market trends described above. To this end, we estimate the following individual-level regression:

$$Y_{icoj} = \alpha + \beta_1 jobtraining_{icoj} + \beta_2 jobtraining_{icoj} \times T_o + \mathbf{X}'_{icoj}\gamma + \mu_{icoj}, \tag{3}$$

where $jobtraining_{icoj} \times T_o$ is the interaction term between job training and each labor market trend.[31] Since these trends, with the exception of automation risk, vary only at the occupation level, the main effects of the trends are absorbed in the occupation fixed effects.[32] β_2 shows how training effectiveness varies with the labor market trends. For ease of interpretation, we de-mean the trend variables, so β_1 shows the effect of job training at

[31] In the specifications with computer use change, we always control for the initial level of computer use in 2012 to account for a potential correlation between level and change.

[32] X_{icoj} contains all control variables from our main specification, including country, occupation, and industry fixed effects.

the average of the respective trend variable (in the sample for which the respective trend variable is available).

Columns (1) and (2) of Table 4 suggest that training effectiveness does not systematically vary with automation risk or offshoring. That is, while workers in occupations that are more exposed to automation or offshoring receive less training (see Table 3), the training is not less effective than in occupations that are less affected by these trends. When it comes to digitization, Column (3) shows that job training is less effective in occupations that became more computer intense over time. One explanation for this result could be decreasing marginal returns to training, as workers in more computer-intense occupations participate in more training measures (see Table 3).[33] It could also be that occupations which become more computer intense in nature tend to offer training not targeting digital skills or it may be particularly difficult for workers in these occupations to accumulate digital skills, perhaps because these skills have been less relevant in the past.[34]

When considering basic digital skills in Table 5, we find that job training is more effective for workers in occupations with higher exposure to automation risk. An increase in the automation risk by 10 pp increases the positive effect of job training on having at least basic digital skills by 1.1 pp. One potential reason for this could be that workers exposed to higher risks of automation have a stronger incentive to improve their basic digital skills in anticipation of future challenges related to automation. The interactions of job training with our indices of offshorability and computer use change are small and statistically insignificant.

Finally, in line with the results on basic digital skills, Table 6 shows that workers in occupations with higher exposure to automation risk also benefit more from training in terms of wages (Column (1)). For a 10 pp increase in the automation risk, the positive effect of job training on hourly wages increases by an additional 1.5%. The wage increase due to job training does not systematically vary by an occupation's degree of offshorability or speed of digitization.

Country-Specific Labor Market Features. Appendix Figures A.1, A.2, and A.3 show the effect of job training on digital skills, basic digital skills, and wages for each country

[33]Workers in more computer-intense occupations also tend to have higher digital skills, as we find a positive correlation of 0.19 between digital skills and computer use change at the occupational level.

[34]Note that, due to limited data availability, we do not include all trend variables simultaneously, as these would severely reduce sample size.

Table 4: Effectiveness of Training and Technological Content of Occupations: Digital Skills

	(1)	(2)	(3)
Job Training	0.0499***	0.0534***	0.0526***
	(0.0066)	(0.0063)	(0.0052)
Job Training × Automation Risk	0.1206		
	(0.0868)		
Job Training × Offshorability		0.0045	
		(0.0073)	
Job Training × Computer Use Change			-0.1028***
			(0.0386)
Observations	47640	34115	58176
R^2	0.59	0.58	0.57
Country FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Least squares estimation with weights from entropy balancing. Dependent variable: digital skills standardized to standard deviation 1 across countries. Sample: employees aged 25–65 years. Job Training: binary variable indicating whether the respondent participated in on-the-job training or job-related training in the 12 months before the survey. Automation Risk: country-occupation-specific measure ranging from 0 (no tasks in an occupation can be automated) to 1 (all tasks in an occupation can be automated), obtained from Nedelkoska and Quintini (2018). Offshorability: occupation-specific measure of the degree to which work can be performed from abroad, obtained from (Blinder and Krueger, 2013); offshorability index is standardized to standard deviation 1 across occupations. Computer Use Change: change in computer use within an occupation between 2012 and 2017, calculated using the PIAAC data from the United States (sampled in PIAAC in 2012 and 2017); computer use index is based on questions indicating how often a person performs the following activities at work: create or read spreadsheets, use word-processing software, use programming language, and engage in computer-aided real-time discussions; answers are combined to a single index following the procedure described in Kling et al. (2007) and then aggregated to the occupation (two-digit ISCO) level. See Section 4.2 for a discussion of data availability. Automation risk, offshorability, and computer use change are de-meaned. Controls: numeracy skills, years of schooling, age group in four categories (25–34, 35–44, 45–54, 55–65), gender, migration status in three categories (first-generation migrant, second-generation migrant, native), parental education in three categories (neither parent has attained upper secondary, at least one parent has attained secondary and post-secondary/non-tertiary, at least one parent has attained tertiary), an indicator whether the respondent has children, age group of the oldest child in four categories (0–2, 3–5, 6–12, 13+), an indicator for full-time employment, an indicator of participation in non-job-related training measures (e.g, self-organized training or seminar participation), firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+), as well as fixed effects for occupations (two-digit ISCO level) and industries (two-digit ISIC level). All regressions also control for country fixed effects. Column (3) additionally includes the baseline level of computer use in 2012, interacted with job training. All control variables, including country fixed effects, were used for the entropy balancing. R^2 refers to within-country R^2. Robust standard errors (adjusted for clustering at two-digit occupation level) in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 5: Effectiveness of Training and Technological Content of Occupations: Basic Digital Skills

	(1)	(2)	(3)
Job Training	0.0399***	0.0406***	0.0445***
	(0.0045)	(0.0056)	(0.0037)
Job Training × Automation Risk	0.1138***		
	(0.0304)		
Job Training × Offshorability		-0.0022	
		(0.0062)	
Job Training × Computer Use Change			-0.0296
			(0.0219)
Observations	59377	45606	75639
R^2	0.20	0.22	0.22
Country FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Table replicates Table 4 using an indicator for having at least basic digital skills as dependent variable. R^2 refers to within-country R^2. Robust standard errors (adjusted for clustering at two-digit occupation level) in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 6: Effectiveness of Training and Technological Content of Occupations: Wages

	(1)	(2)	(3)
Job Training	0.0772***	0.0727***	0.0778***
	(0.0049)	(0.0078)	(0.0030)
Job Training × Automation Risk	0.1478***		
	(0.0484)		
Job Training × Offshorability		0.0124	
		(0.0076)	
Job Training × Computer Use Change			0.0229
			(0.0170)
Observations	54899	40955	67751
R^2	0.39	0.41	0.38
Country FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Table replicates Table 4 using log hourly wages as dependent variable. R^2 refers to within-country R^2. Robust standard errors (adjusted for clustering at two-digit occupation level) in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

individually, showing a large international heterogeneity in the effectiveness of training.[35] To explain these cross-country differences, we consider various institutional features at the country level. In particular, Europe has implemented far-reaching changes in labor market policies and pension systems over the last decades, which may affect workers' incentives to participate in job training as well as firms' incentives to offer or reward training. In particular, we consider whether training effectiveness varies systematically with the following institutional features: union density, minimum wage regulation, employment protection legislation, and pension generosity.

In Equation 3, we provide results of a specification analogous to Equation 3, while replacing the interactions with the occupation-level labor market trends by interactions with the country features. As the institutional variables vary only at the country level, standard errors in this model are clustered at the country level. In Columns (1) and (2), we find little evidence that training effectiveness with respect to digital skill accumulation varies systematically with the country features. The only exception is that job training in countries with higher union density is less able to endow workers with basic digital skills (Column (2)).

However, when repeating the same exercise with wages as the outcome variable in Column (3) of Equation 3, we find an interesting pattern of results: union density, minimum wage regulations, and employment protection have significant negative interactions with training effectiveness. That is, countries with a larger share of unionized workers, minimum wages, and stricter employment protection have systematically lower returns to training on the labor market. This is in line with the results presented in Hanushek et al. (2015), which show that these labor market regulations are negatively related to wage returns to skills. In our context, these negative interactions may be due to the fact that employers have less leeway for setting wages and compensate workers for additional training. It may also be that these results reflect that wage distributions are generally more compressed in countries with stronger labor market institutions, putting an upper-bound on training returns. Finally, countries with more generous pension benefits appear to have higher wage returns of training. However, the interaction is only marginally significant.

The pension system may be particularly relevant for the training of older workers. In the second part of the report, we investigate whether training participation and effectiveness differ by age.

[35] Similarly, Bassanini et al. (2007) find a spread in the wage returns to training between 3.7 and 21.6% across European countries.

Table 7: Effectiveness of Training and Country Features: All Outcomes

	(1) Digital Skills	(2) Basic Digital Skills	(3) Log Wages
Job Training	0.0530***	0.0650***	0.1131***
	(0.0127)	(0.0124)	(0.0120)
Job Training × Union Density	0.0538	-0.0932***	-0.1266***
	(0.0419)	(0.0252)	(0.0271)
Job Training × Minimum Wage Regulation	-0.0155	-0.0174	-0.0268**
	(0.0170)	(0.0143)	(0.0119)
Job Training × Employment Protection	-0.0153	0.0079	-0.0317***
	(0.0151)	(0.0092)	(0.0084)
Job Training × Pension Generosity	0.0017	-0.0008	0.0040*
	(0.0048)	(0.0024)	(0.0023)
Observations	56046	68840	63849
R^2	0.61	0.14	0.32
Country FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Least squares estimation with weights from entropy balancing. Dependent variables: digital skills standardized to standard deviation 1 across countries, indicator for having at least basic digital skills, and log hourly wages. Sample: employees aged 25–65 years. Job Training: binary variable indicating whether the respondent participated in on-the-job training or job-related training in the 12 months before the survey. Union density: share of employees in a country who are trade union members. Minimum wage regulation: binary variable indicating whether country has a statutory minimum wage. Employment protection: composite indicator measuring strictness of employment protection for individual and collective dismissals. Pension generosity: average net present value of the flow of pension benefits expressed in terms of average net annual individual earnings. See Section 4.2 for a discussion of data availability. Union density, minimum wage regulation, employment protection, and pension generosity are de-meaned. Controls: numeracy skills, years of schooling, age group in four categories (25–34, 35–44, 45–54, 55–65), gender, migration status in three categories (first-generation migrant, second-generation migrant, native), parental education in three categories (neither parent has attained upper secondary, at least one parent has attained secondary and post-secondary/non-tertiary, at least one parent has attained tertiary), an indicator whether the respondent has children, age group of the oldest child in four categories (0–2, 3–5, 6–12, 13+), an indicator for full-time employment, an indicator of participation in non-job-related training measures (e.g, self-organized training or seminar participation), firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+), as well as fixed effects for occupations (two-digit ISCO level) and industries (two-digit ISIC level). All regressions also control for country fixed effects. All control variables, including country fixed effects, were used for the entropy balancing. R^2 refers to within-country R^2. Robust standard errors (adjusted for clustering at the country level) in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

7. Job Training across Age Cohorts

After we have provided international evidence on how training affects digital skills and wages in the overall population, the second part of the report investigates potential heterogeneities by subgroup. Our discussion focuses on age, but we also consider differences by gender.[36]

7.1. Training Frequency

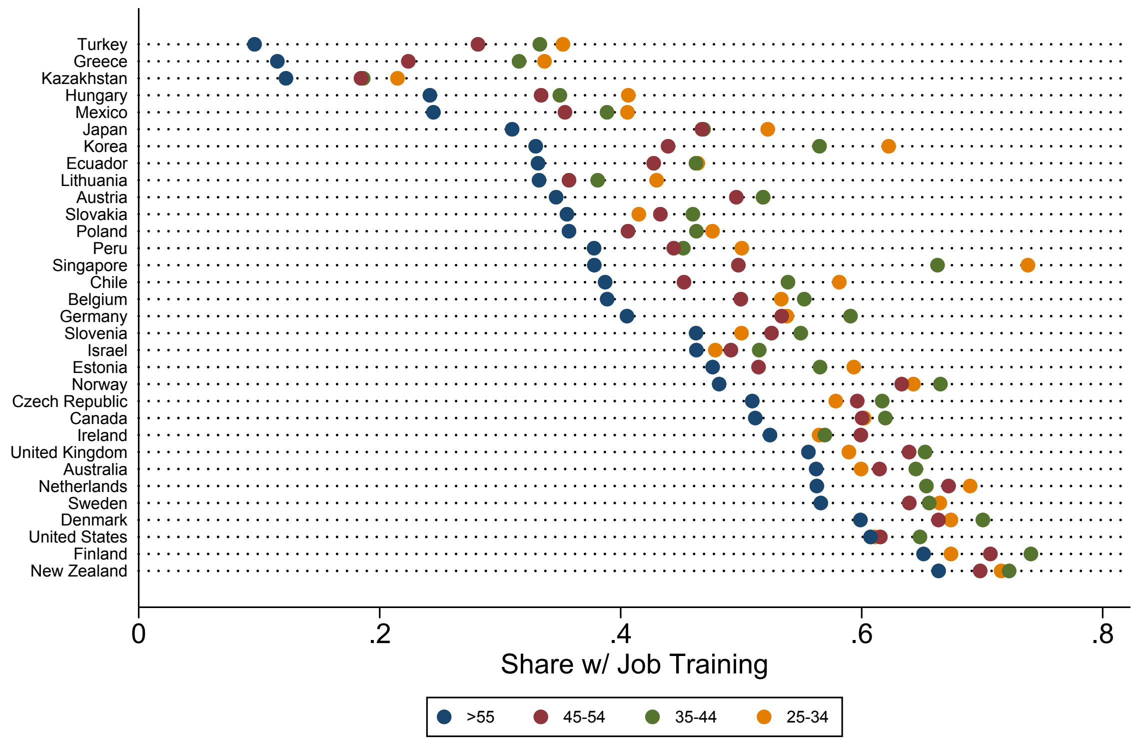
Previous literature shows that participation in job training differs by worker age and gender (Oosterbeek, 1998). However, little is known to which extent workers of different ages and genders (differently) use training to cope with labor market challenges, such as the arrival of new technologies and offshoring. Thus, we start with presenting descriptive differences in training participation by country across age groups and gender before estimating the relation between training take-up and automation, offshoring, and digitization for different age groups.

Figure 2 shows the distribution of job training by age group across countries. For exposition, we group workers in four age categories: 25–34, 35–44, 45–54, and 55–65. In most countries, the training frequency clearly decreases in age. Notably, the oldest worker generation receives the least job training in *each* country. Some countries such as New Zealand and Isreal exhibit only small differences in job training between age groups. In particular, New Zealand achieves high rates of training participation across all age groups. However, in most countries, there is a large disparity between the job training frequency in the oldest age group and that in all other age groups. The gap in training frequency between the oldest age group and the group with the next-lower frequency, typically age group 45–54, is largest (> 10 pp) in Turkey, Greece, Mexico, Japan, Korea, Austria, Singapore, Belgium, Germany, and Norway.

Turning to gender, we observe only small differences in training participation between females and males (Figure 3). In particular, there are almost as many countries where females take up more training than males (15) as there are countries where the opposite is true (17). We also observe that in countries in the middle of the international ranking in training participation, there tends to be a wider gap in favor of males.

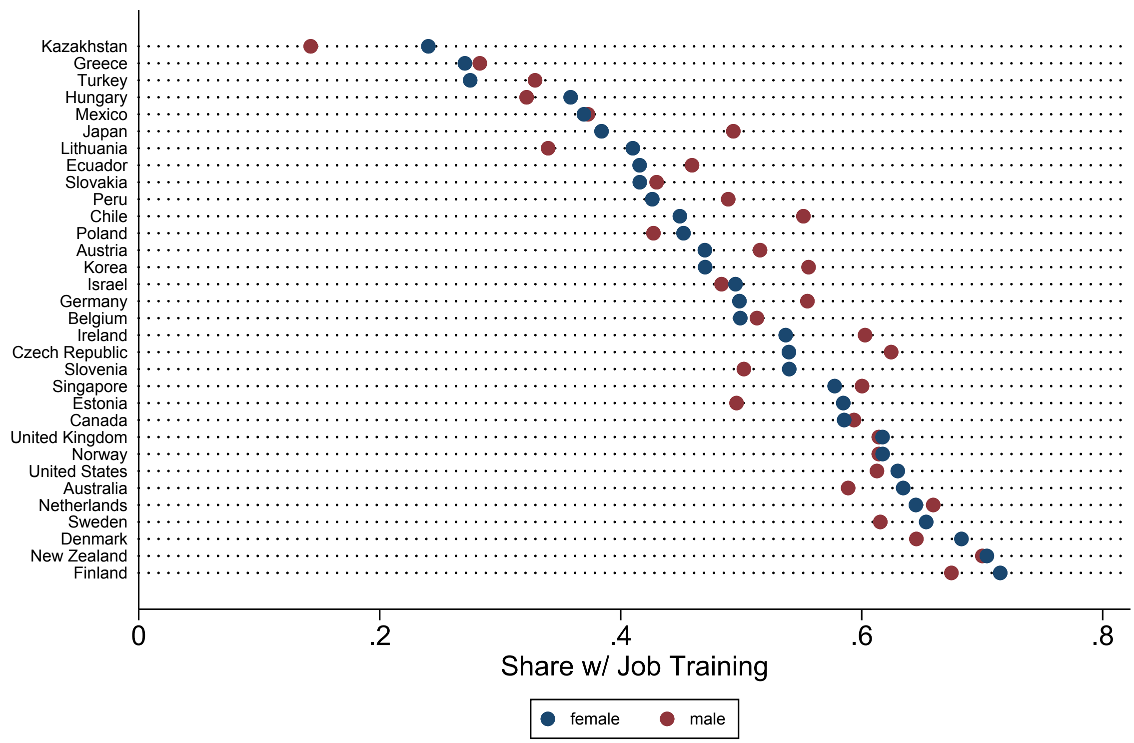
[36]Doing so, we complement the analysis in Falck et al. (2022), who show that digital skills of older workers differ substantially across countries and that these differences contribute to the international inequality in wages and employment of elderly workers.

Figure 2: Job Training by Age Group across Countries



Notes: Share of workers participating in job training by age group and country. Only countries which tested digital skills are included in the sample. Job training: binary variable indicating whether the respondent participated in on-the-job training or job-related training in the 12 months before the survey.

Figure 3: Job Training by Gender across Countries



Notes: Share of workers participating in job training by gender and country. Only countries which tested digital skills are included in the sample. Job training: binary variable indicating whether the respondent participated in on-the-job training or job-related training in the 12 months before the survey.

The observation that older workers participate less in job training is problematic particularly when considering the importance of training to cope with technology- or trade-induced changes in the labor market. Thus, we now investigate how the relationship between job training and automation, offshoring, and digitization differs by worker age.[37]

Panel A of Table 8 shows that higher automation risk is significantly related to lower job training participation for workers of all ages. However, this negative relationship tends to become stronger in worker age, suggesting that training efforts of older workers are particularly negatively affected by automation. Panel B repeats the same exercise for offshoring. The pattern is similar to what we observe for automation risk: there is a negative relationship between offshoring and job training in all age groups. The relationship is also weakest for the youngest age group, but — in contrast to the evidence above — does not become stronger with age for workers aged 35 onward.

Finally, Panel C of Table 8 displays the results for the speed of digitization, measured by the change in computer use over time. We find that the positive relationship between training frequency and computer use change, shown in Table 3 for the overall sample, is driven by older workers. One explanation for this result is that older workers may be more in need than younger workers to participate in training for coping with the digital transformation and a changing work environment.

7.2. Training Effectiveness

The psychological literature stresses that older individuals suffer more often from computer anxiety and have less computer self-efficacy (Czaja et al., 2006). Moreover, Falck et al. (2021) and Falck et al. (2022) show that older workers have less digital skills than younger workers and are often even incapable of performing simple tasks using computers or the Internet. Given the importance of having digital skills to cope with technological change, it is paramount to investigate whether job training increases (basic) digital skills for elderly workers.[38] Table 9 shows how training effectiveness differs by age. Columns (2), (4), and (6) show training effects on digital skills, basic digital skills, and hourly wages, always using the oldest worker group (aged 55–65) as reference group; Columns (1), (3), and (5) show results in the whole sample as a benchmark (see Table 2). First, the large, significantly positive coefficients on *Age* in the bottom of the table indicate that younger workers have substantially higher levels of digital skills (up to half a standard

[37] See Table 3 for results in the overall population.

[38] Note that technological change will not only raise demand for digital skills at the workplace, but also in other areas of life, e.g., digital public services and Internet voting.

Table 8: Relationship between Training and Automation, Offshoring, and Digitization by Age

Age group:	(1) 25–34	(2) 35–44	(3) 45–54	(4) 55+
Panel A: Automation Risk				
Automation Risk	-1.0263***	-1.1176***	-1.2315***	-1.2097***
	(0.0421)	(0.0396)	(0.0395)	(0.0476)
Observations	16592	16798	15594	10393
R^2	0.17	0.20	0.21	0.22
Panel B: Offshoring				
Offshorability	-0.0499***	-0.0668***	-0.0654***	-0.0664***
	(0.0163)	(0.0165)	(0.0164)	(0.0206)
Observations	13030	13121	11863	7592
R^2	0.17	0.21	0.19	0.20
Panel C: Computer Use				
Computer Use Change	0.0235	0.0367	0.0720*	0.0896***
	(0.0231)	(0.0233)	(0.0366)	(0.0302)
Observations	21434	21711	19450	13044
R^2	0.16	0.19	0.19	0.20
Country FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: Least squares estimation. Dependent variable: job training, binary variable indicating whether the respondent participated in on-the-job training or job-related training in the 12 months before the survey. Sample: employees in the age group indicated in the column header. Automation Risk: country-occupation-specific measure ranging from 0 (no tasks in an occupation can be automated) to 1 (all tasks in an occupation can be automated), obtained from Nedelkoska and Quintini (2018). Offshorability: occupation-specific measure of the degree to which work can be performed from abroad, obtained from Blinder and Krueger (2013); offshorability index is standardized to standard deviation 1 across occupations. Computer Use Change: change in computer use within an occupation between 2012 and 2017, calculated using the PIAAC data from the United States (sampled in PIAAC in 2012 and 2017); computer use index is based on questions indicating how often a person performs the following activities at work: create or read spreadsheets, use word-processing software, use programming language, and engage in computer-aided real-time discussions; answers are combined to a single index following the procedure described in Kling et al. (2007) and then aggregated to the occupation (two-digit ISCO) level. See Section 4.2 for a discussion of data availability. Controls: numeracy skills, years of schooling, gender, migration status in three categories (first-generation migrant, second-generation migrant, native), parental education in three categories (neither parent has attained upper secondary, at least one parent has attained secondary and post-secondary/non-tertiary, at least one parent has attained tertiary), an indicator whether the respondent has children, age group of the oldest child in four categories (0–2, 3–5, 6–12, 13+), an indicator for full-time employment, an indicator of participation in non-job-related training measures (e.g, self-organized training or seminar participation), firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+), as well as fixed effects for industries (two-digit ISIC level) and countries. Panel C additionally includes controls for the baseline level of computer use in 2012. R^2 refers to within-country R^2. Robust standard errors (adjusted for clustering at two-digit occupation level) in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

deviation) and a higher likelihood of having at least basic digital skills (up to 14 pp). This mimics previous findings from Falck et al. (2021) and Falck et al. (2022). Can job training help to reduce these gaps, or does it even widen them?

The main result of the analysis in Table 9 is that there are significantly positive training effects across *all* age groups. When it comes to digital skills, training is as effective in increasing digital skills for older workers as for younger workers (Column (2)) — the interaction terms between job training and age groups below 55 are positive, but not statistically significant. Intriguingly, job training is even more effective for older than for younger workers in equipping workers with basic digital skills (Column (4)); thus, job training tends to close the age gap in such basic skills. Finally, the effect of training on wages does not differ strongly by age (Column (6)). While point estimates of the training-age interactions are negative, only the interaction of training with age group 35-44 reaches statistical significance (albeit only at the 10% level).

Our results are in line with Picchio and van Ours (2013) and Berg et al. (2017), who document that job training is effective in improving productivity for both younger and older workers. However, they find a decline in training effectiveness with age, which we do not observe in our data. Our results regarding the wage effects of training are in contrast to Goebel and Zwick (2013), who find no positive wage effects of job training for older workers in Germany using linked employer-employee panel data.

In Appendix Tables B.2 and B.3, we investigate gender-specific age heterogeneity in training effectiveness. There are some noteworthy patterns: First, job training is generally more effective for males than for females in increasing digital skills (Columns (1)). For female workers in the oldest age group, job training does actually not lead to a significant increase in digital skills (Column (2) of Table B.3). This suggests that male workers receive more training to increase digital skills than female workers, perhaps because females are typically underrepresented in digital-intense or Science, Technology, Engineering and Mathematics (STEM) occupations (see, e.g., National Science Foundation, 2016, 2017).[39] Second, the effect of job training on basic digital skills is qualitatively similar for female and male workers, both in the overall sample and in the various age groups (Columns (3)

[39]For instance, there is a gender gap in STEM fields in the EU, with women being underrepresented in both education and employment in these fields (Brett, 2022). For instance, only 34% of graduates in STEM fields in the EU are women. Additionally, in 2018, just 41% of the EU's scientists and engineers were women, and just 5 EU Member States had more female scientists than male scientists: Lithuania, Bulgaria, Latvia, Portugal, and Denmark. As STEM occupations also generally pay higher wages, the lack of women working in such occupations contributes to the widening of the gender wage gap (e.g., Black et al., 2008; Duflo, 2012; Blau and Kahn, 2017).

and (4)). Third, wage returns to job training are even larger for females than for males (Columns (5)), particularly in the oldest age group (Columns (6)). These results suggest that while the content of training seems to differ between female and male workers, training is at least as effective in increasing overall work productivity (measured by wages) for females as for males.

Job training for older workers may pay off differently in occupations that are differently affected by automation, offshoring, and digitization — as their younger peers often have a competitive advantage in (basic) digital skills. Thus, we now investigate whether the effectiveness of job training in the oldest worker generation differs by occupations' automation risk, offshorability, and computer use. Table 10 provides results using digital skills as outcome. Columns (1) and (2) indicate that training effects for older workers do not differ systematically by automation or offshoring.[40] However, this pattern is noticeably different for computer use (Column (3)): the more relevant computers become in an occupation, the less effective is job training in increasing the digital skills of elderly workers. This suggests that it is difficult for older workers to reap the benefits of training when technological change is rapid.

Tables 11 and 12 repeat the same exercise with basic digital skills and log wages as the outcomes. The pattern in both tables is qualitatively similar: the effectiveness of job training for older workers does not differ systematically by risk of automation, offshorability, or digitization. However, we do observe that the wage effects of job training tend to increase in an occupation's reliance on computers. The fact that such positive interaction could not be observed in the overall sample (see Table 6) suggests that employers particularly reward training efforts by older workers when occupations are rapidly changing.

[40]The main effects of job training drop slightly compared to the interacted model in Column (2) of Table 9 and also lose precision, as our measures of automation risk and offshorability are not available for the full set of countries and occupations.

Table 9: Effectiveness of Training by Age

	(1)	(2)	(3)	(4)	(5)	(6)
	Digital Skills		Basic Digital Skills		Log Wages	
Job Training	0.0560***	0.0405**	0.0431***	0.0737***	0.0827***	0.0935***
	(0.0066)	(0.0163)	(0.0029)	(0.0077)	(0.0038)	(0.0086)
Job Training × Age: 25-34		0.0161		-0.0499***		-0.0062
		(0.0208)		(0.0090)		(0.0117)
Job Training × Age: 35-44		0.0205		-0.0343***		-0.0211*
		(0.0200)		(0.0093)		(0.0111)
Job Training × Age: 45-54		0.0172		-0.0242**		-0.0104
		(0.0205)		(0.0098)		(0.0110)
Age						
25-34	0.5068***	0.4987***	0.1489***	0.1738***	-0.1840***	-0.1809***
	(0.0115)	(0.0194)	(0.0051)	(0.0083)	(0.0066)	(0.0108)
35-44	0.3434***	0.3331***	0.1135***	0.1306***	-0.0409***	-0.0304***
	(0.0106)	(0.0183)	(0.0048)	(0.0081)	(0.0058)	(0.0098)
45-54	0.1633***	0.1547***	0.0624***	0.0744***	0.0054	0.0106
	(0.0104)	(0.0184)	(0.0049)	(0.0085)	(0.0056)	(0.0097)
Observations	79728	79728	102844	102844	92008	92008
R^2	0.58	0.58	0.15	0.15	0.35	0.35
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Least squares estimations with weights from entropy balancing. Dependent variables: digital skills standardized to standard deviation 1 across countries, indicator for having at least basic digital skills, and log hourly wages. Sample: employees aged 25–65 years. Job Training: binary variable indicating whether the respondent participated in on-the-job training or job-related training in the 12 months before the survey. EU member: binary variable indicating whether country is a EU member. Controls: numeracy skills, years of schooling, gender, migration status in three categories (first-generation migrant, second-generation migrant, native), parental education in three categories (neither parent has attained upper secondary, at least one parent has attained secondary and post-secondary/non-tertiary, at least one parent has attained tertiary), an indicator whether the respondent has children, age group of the oldest child in four categories (0–2, 3–5, 6–12, 13+), an indicator for full-time employment, an indicator of participation in non-job-related training measures (e.g, self-organized training or seminar participation), firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+), as well as fixed effects for occupations (two-digit ISCO level) and industries (two-digit ISIC level). All regressions also control for country fixed effects. All control variables, including country fixed effects, were used for the entropy balancing. R^2 refers to within-country R^2. Robust standard errors in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 10: Effectiveness of Training by Labor Market Trends in the Oldest Age Group: Digital Skills

	(1) Digital Skills	(2) Digital Skills	(3) Digital Skills
Job Training	0.0217 (0.0174)	0.0314 (0.0193)	0.0367*** (0.0120)
Job Training × Automation Risk	-0.0780 (0.2111)		
Job Training × Offshorability		0.0101 (0.0376)	
Job Training × Computer Use Change			-0.2940*** (0.0489)
Observations	6997	4610	8282
R^2	0.58	0.59	0.57
Country FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Least squares estimation with weights from entropy balancing. Dependent variable: digital skills standardized to standard deviation 1 across countries. Sample: employees aged 55–65 years. Job Training: binary variable indicating whether the respondent participated in on-the-job training or job-related training in the 12 months before the survey. Automation Risk: country-occupation-specific measure ranging from 0 (no tasks in an occupation can be automated) to 1 (all tasks in an occupation can be automated), obtained from Nedelkoska and Quintini (2018). Offshorability: occupation-specific measure of the degree to which work can be performed from abroad, obtained from Blinder and Krueger (2013); offshorability index is standardized to standard deviation 1 across occupations. Computer Use Change: change in computer use within an occupation between 2012 and 2017, calculated using the PIAAC data from the United States (sampled in PIAAC in 2012 and 2017); computer use index is based on questions indicating how often a person performs the following activities at work: create or read spreadsheets, use word-processing software, use programming language, and engage in computer-aided real-time discussions; answers are combined to a single index following the procedure described in Kling et al. (2007) and then aggregated to the occupation (two-digit ISCO code) level. See Section 4.2 for a discussion of data availability. Automation risk, offshorability, and computer use change are de-meaned. Controls: numeracy skills, years of schooling, age group in four categories (25–34, 35–44, 45–54, 55–65), gender, migration status in three categories (first-generation migrant, second-generation migrant, native), parental education in three categories (neither parent has attained upper secondary, at least one parent has attained secondary and post-secondary/non-tertiary, at least one parent has attained tertiary), an indicator whether the respondent has children, age group of the oldest child in four categories (0–2, 3–5, 6–12, 13+), an indicator for full-time employment, an indicator of participation in non-job-related training measures (e.g, self-organized training or seminar participation), firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+), as well as fixed effects for occupations (two-digit ISCO level) and industries (two-digit ISIC level). All regressions also control for country fixed effects. Column (3) additionally includes controls for the baseline level of computer use in 2012, interacted with job training. All control variables, including country fixed effects, were used for the entropy balancing. R^2 refers to within-country R^2. Robust standard errors (adjusted for clustering at two-digit occupation level) in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 11: Effectiveness of Training by Labor Market Trends in the Oldest Age Group: Basic Digital Skills

	(1) Basic Digital Skills	(2) Basic Digital Skills	(3) Basic Digital Skills
Job Training	0.0605***	0.0628***	0.0705***
	(0.0092)	(0.0099)	(0.0078)
Job Training × Automation Risk	-0.0106		
	(0.0943)		
Job Training × Offshorability		-0.0075	
		(0.0141)	
Job Training × Computer Use Change			0.0024
			(0.0427)
Observations	10393	7592	13044
R^2	0.22	0.24	0.23
Country FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Table replicates Table 10 using an indicator for having at least basic digital skills as dependent variable. R^2 refers to within-country R^2. Robust standard errors (adjusted for clustering at two-digit occupation level) in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 12: Effectiveness of Training by Labor Market Trends in the Oldest Age Group: Hourly Wages

	(1) Log Wages	(2) Log Wages	(3) Log Wages
Job Training	0.0715***	0.0769***	0.0754***
	(0.0109)	(0.0135)	(0.0092)
Job Training × Automation Risk	0.1353		
	(0.0937)		
Job Training × Offshorability		0.0024	
		(0.0158)	
Job Training × Computer Use Change			0.0861*
			(0.0515)
Observations	6394	4163	7449
R^2	0.40	0.44	0.39
Country FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Table replicates Table 10 using log hourly wages as dependent variable.. R^2 refers to within-country R^2. Robust standard errors (adjusted for clustering at two-digit occupation level) in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Finally, Table 13 explores how the training effectiveness for older workers differs by countries' institutional features, replicating Table 7 for workers aged 55–65. First, the effectiveness of training on digital skills does not differ between countries with different labor market institutions and pension systems (Column (1)).[41] Second, training has a larger impact on basic digital skills for older workers in countries with higher levels of employment protection (Column (2)). This may reflect that — as job separations from less productive workers are more costly with stricter dismissal protection (e.g., Mortensen and Pissarides, 1994) — employers have a higher incentive to offer training to increase the skills and thus productivity of the incumbent workers. In contrast, training has a weaker impact on basic skills for older workers in countries with a higher union density and more generous pensions. A potential explanation for this result is that in labor markets with higher wage rigidity and higher pension benefits, respectively, older workers have a reduced incentive to invest in training to keep their skills up-to-date, as the perceived returns to training in terms of job security and wages are lower. Indeed, Column (3) shows that the effect of job training on wages is more muted in countries with stronger labor market regulations (see Table 7 for similar evidence in the full sample).

8. Conclusion

In the last decades, labor markets have undergone substantial changes due to automation, offshoring, and increasing computer use. As a consequence, workers face changing skill demands, especially when it comes to digital skills. In this report, we investigate how job training might help workers to cope with the consequences of these recent developments that significantly altered their working life.

For this purpose, we draw on large-scale survey data for 32 countries from PIAAC, which provide tested digital skills. PIAAC also includes rich information on participation in job training, on worker characteristics, work environment, and wages. These detailed data allow us to examine whether training participation and effectiveness vary (1) between occupations differently affected by automation, offshoring, and digitization, (2) by country features such as union density or minimum wage regulations, and (3) by worker age and gender. Moreover, PIAAC also has information on tested numeracy skills as a proxy for worker ability, allowing us to rigorously control for ability-based selection into training.

[41] The main effect decreases and is less precisely estimated (as was already seen in Table 9), since in this analysis we can only consider the smaller subset of workers in countries for which data on labor market institutions and pension systems are available.

Table 13: Effectiveness of Training by Country Features in the Oldest Age Group

	(1) Digital Skills	(2) Basic Digital Skills	(3) Log Wages
Job Training	0.0216	0.0748***	0.1022***
	(0.0173)	(0.0054)	(0.0094)
Job Training × Union Density	0.1488	-0.1254**	-0.2362***
	(0.1550)	(0.0575)	(0.0668)
Job Training × Minimum Wage Regulation	-0.0060	-0.0192	-0.0736**
	(0.0703)	(0.0316)	(0.0310)
Job Training × Employment Protection	-0.0717	0.0352**	-0.0519**
	(0.0488)	(0.0179)	(0.0213)
Job Training × Pension Generosity	0.0099	-0.0083*	0.0003
	(0.0050)	(0.0052)	(0.0066)
Observations	8947	13137	11836
R^2	0.59	0.17	0.34
Country FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Least squares estimation with weights from entropy balancing. Dependent variables: digital skills standardized to standard deviation 1 across countries, indicator for having at least basic digital skills, and log hourly wages. Sample: employees aged 55–65 years. Job Training: binary variable indicating whether the respondent participated in on-the-job training or job-related training in the 12 months before the survey. Union density: share of employees in a country who are trade union members. Minimum wage regulation: binary variable indicating whether country has a statutory minimum wage. Employment protection: composite indicator measuring strictness of employment protection for individual and collective dismissals. Pension generosity: average net present value of the flow of pension benefits expressed in terms of average net annual individual earnings. See Section 4.2 for a discussion of data availability. Union density, minimum wage regulation, employment protection, and pension generosity are de-meaned. Controls: numeracy skills, years of schooling, age group in four categories (25–34, 35–44, 45–54, 55–65), gender, migration status in three categories (first-generation migrant, second-generation migrant, native), parental education in three categories (neither parent has attained upper secondary, at least one parent has attained secondary and post-secondary/non-tertiary, at least one parent has attained tertiary), an indicator whether the respondent has children, age group of the oldest child in four categories (0–2, 3–5, 6–12, 13+), an indicator for full-time employment, an indicator of participation in non-job-related training measures (e.g, self-organized training or seminar participation), firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+), as well as fixed effects for occupations (two-digit ISCO level) and industries (two-digit ISIC level). All regressions also control for country fixed effects. All control variables, including country fixed effects, were used for the entropy balancing. R^2 refers to within-country R^2. Robust standard errors (adjusted for clustering at the country level) in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

We find that job training increases digital skills by 0.06 standard deviations. While this is already an economically sizable magnitude, we interpret it as a lower-bound of the true causal effect of job training on digital skills. We also show that by just accounting for numeracy skills, we can already explain more than half of the total variation in digital skills, severely reducing the scope for other omitted variables plaguing our estimates. Moreover, we also show that job training increases an indicator of having at least basic digital skills (by 4 pp), e.g., being able to use a keyboard/mouse or to scroll through a website, which seem as an absolute necessity in an ever more digital labor market. Finally, job training increases hourly wages by 9%, which is about the same magnitude as the wage returns of an additional year of schooling.

Our results further suggest that workers in occupations that are more susceptible to automation and offshoring are less likely to participate in training on-the-job or off-the-job, while workers in occupations that are increasingly digitized exhibit higher training frequencies. If workers in occupations with higher automation risk do receive training, it tends to be more effective than in other types of occupations. We do not observe such higher training effectiveness by occupations' levels of offshorability or digitization. In addition, countries with labor market institutions leading to a more compressed pay schedule tend to exhibit lower returns to job training.

Comparing the training effectiveness by various worker characteristics, we observe little systematic difference by gender. However, some noticeable differences emerge with respect to worker age. In particular, older workers — who are most likely to struggle in keeping up with the pace of technological change — benefit more from job training than younger workers in terms of their basic digital skills.

In sum, our results point to job training as a potential channel to keep especially older employees up to speed with new technologies at the workplace. Endowing workers with (basic) digital skills through job training is an opportunity to close the large age gaps in digital skills, and seems essential to sustain the employability of workers at all ages in the face of accelerating technology- or trade-induced changes in the labor market.

However, the fact that there is systematically less training in occupations that are more susceptible to automation and offshoring, i.e., where work environments are changing most rapidly, calls for additional policies to afford workers the opportunity to undertake training. One option would be to establish accounts for labor market entrants, which individuals can use to fund training throughout their careers. Such a credit system has already been piloted in Singapore (Economist, 2018). However, a large-scale roll-out, e.g., in Europe, would require that companies participate to ensure that the training offered meets employers' needs.

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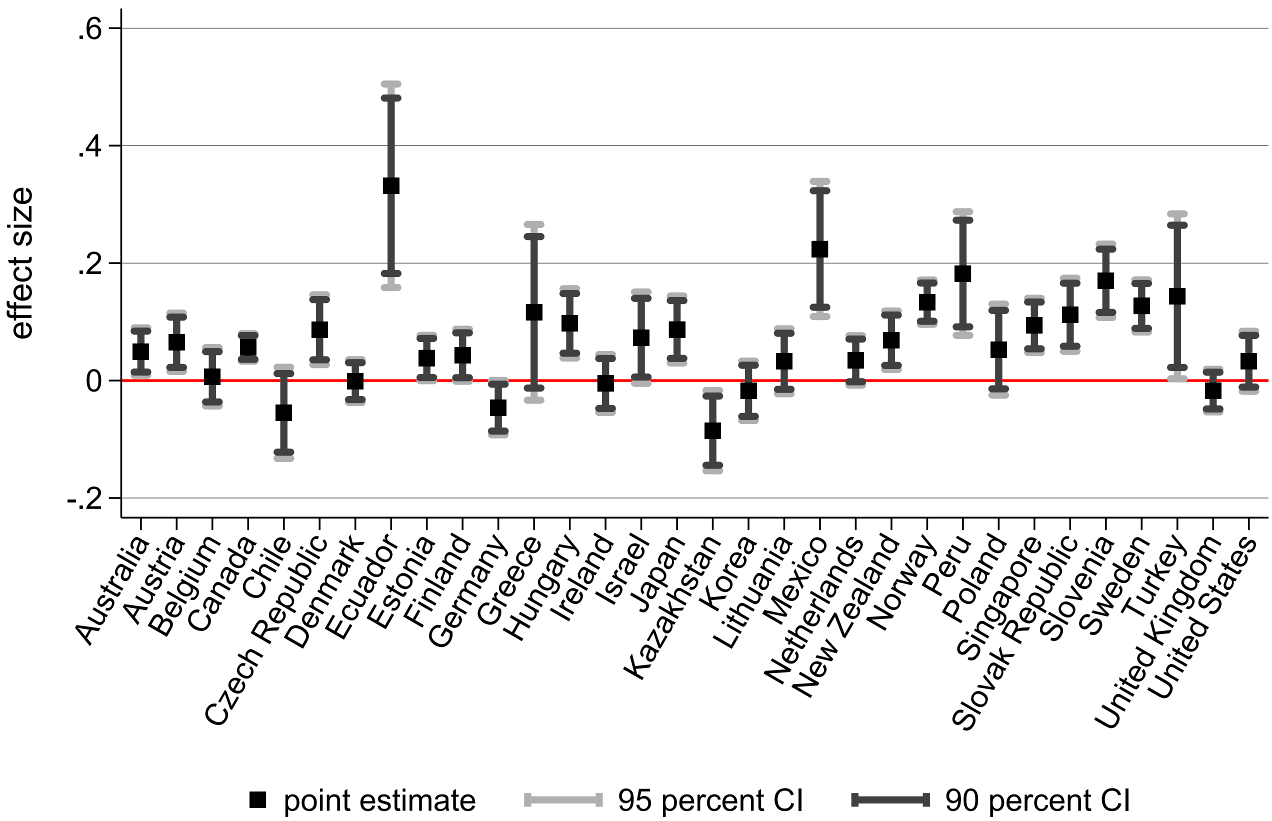
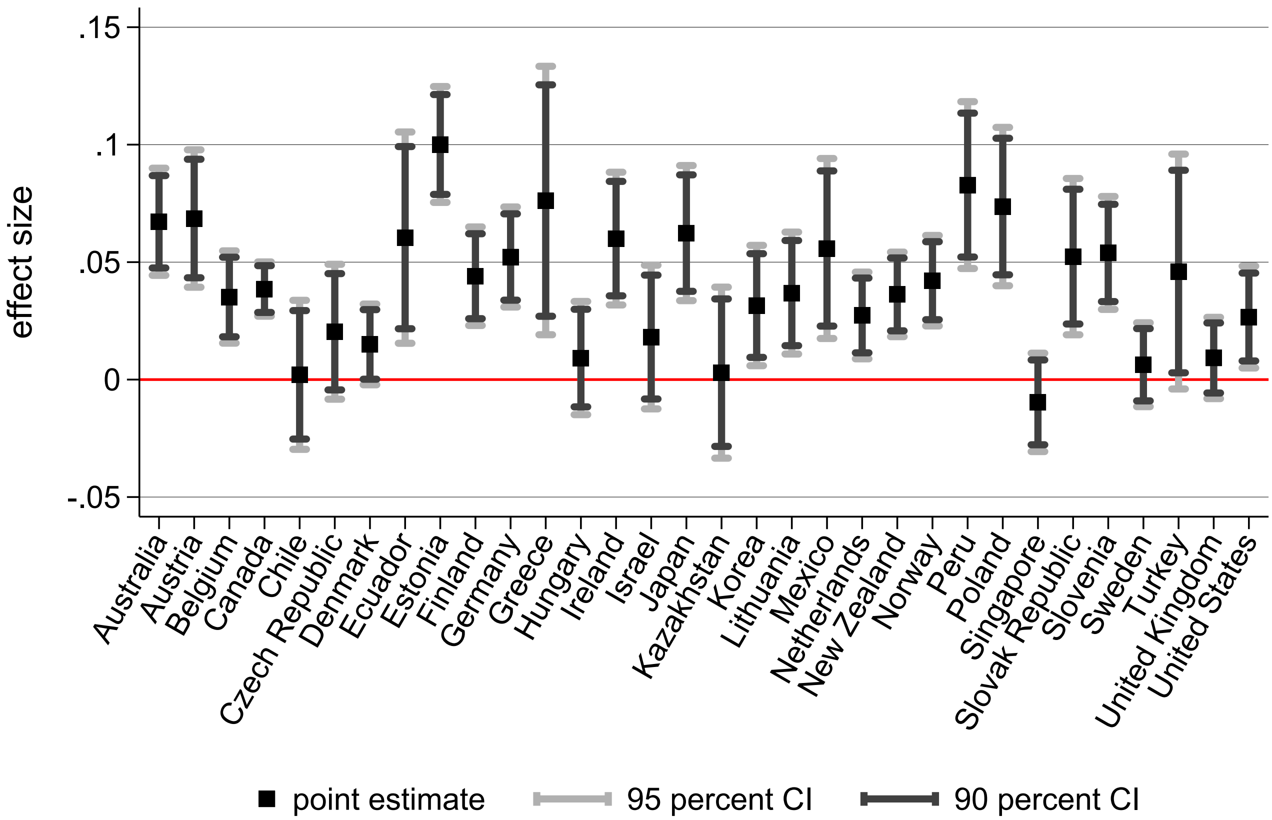
Appendix A. Figures

Figure A.1: Job Training and Digital Skills by Country



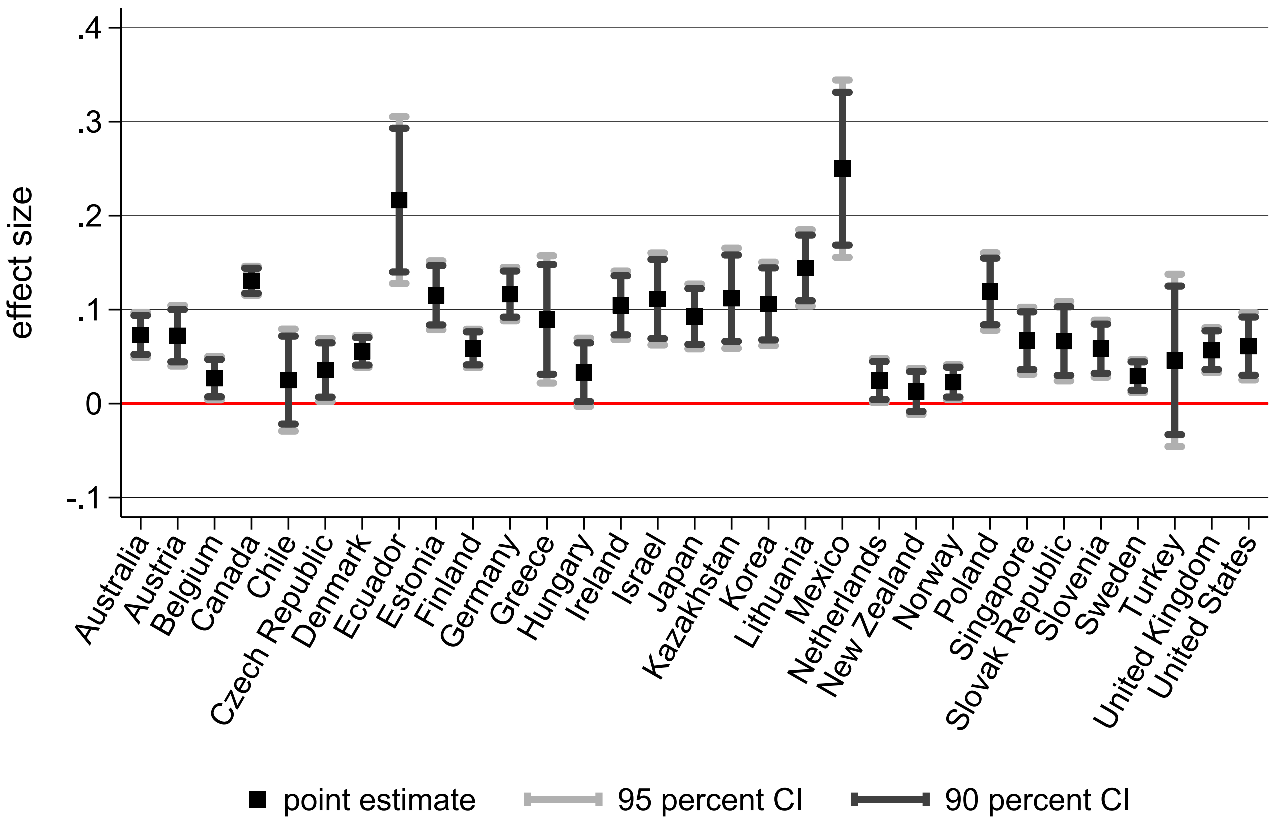
Notes: Outcome: Digital skills standardized to standard deviation 1 across countries. Sample: employees aged 25â-65 years. Job Training: indicator for participation in on-the-job training or job-related training in the 12 months before the survey. Main specification (see Equation 2) repeated for each country individually. Robust standard errors.

Figure A.2: Job Training and Basic Digital Skills by Country



Notes: Outcome: indicator for having at least basic digital skills. Sample: employees aged 25â-65 years. Job Training: indicator for participation in on-the-job training or job-related training in the 12 months before the survey. Main specification (see Equation 2) repeated for each country individually. Robust standard errors.

Figure A.3: Job Training and Wages by Country



Notes: Outcome: log hourly wage. Sample: employees aged 25â-65 years. Job Training: indicator for participation in on-the-job training or job-related training in the 12 months before the survey. Main specification (see Equation 2) repeated for each country individually. Robust standard errors.

Appendix B. Tables

Table B.1: Robustness: Imputing Missing Digital Skills

	(1) Digital Skills	(2) Imputed with 0	(3) Imputed with 50	(4) Imputed with global min	(5) Imputed with country min
Job Training	0.0560***	0.1096***	0.1094***	0.1096***	0.0999***
	(0.0066)	(0.0067)	(0.0066)	(0.0067)	(0.0065)
Observations	79728	102844	102844	102844	102844
R^2	0.58	0.32	0.35	0.32	0.40
Controls	Yes	Yes	Yes	Yes	Yes

Notes: Least squares estimations with weights from entropy balancing. Dependent variables: digital skills with different imputations for missing skills (as indicated in the column header). Sample: employees aged 25–65 years. Job Training: binary variable indicating whether the respondent participated in on-the-job training or job-related training in the 12 months before the survey. Controls: numeracy skills, years of schooling, age group in four categories (25–34, 35–44, 45–54, 55–65), gender, migration status in three categories (first-generation migrant, second-generation migrant, native), parental education in three categories (neither parent has attained upper secondary, at least one parent has attained secondary and post-secondary/non-tertiary, at least one parent has attained tertiary), an indicator whether the respondent has children, age group of the oldest child in four categories (0–2, 3–5, 6–12, 13+), an indicator for full-time employment, an indicator of participation in non-job-related training measures (e.g, self-organized training or seminar participation), firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+), as well as fixed effects for occupations (two-digit ISCO level) and industries (two-digit ISIC level). All regressions also control for country fixed effects. All control variables, including country fixed effects, were used for the entropy balancing. R^2 refers to within-country R^2. Robust standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table B.2: Effectiveness of Training by Age: Females

	(1)	(2)	(3)	(4)	(5)	(6)
	Digital Skills		Basic Digital Skills		Log Wages	
Job Training	0.0435***	0.0226	0.0450***	0.0774***	0.0932***	0.1124***
	(0.0090)	(0.0233)	(0.0043)	(0.0111)	(0.0051)	(0.0115)
Job Training × Age: 25-34		0.0372		-0.0524***		-0.0133
		(0.0288)		(0.0131)		(0.0151)
Job Training × Age: 35-44		0.0235		-0.0321**		-0.0310**
		(0.0282)		(0.0136)		(0.0152)
Job Training × Age: 45-54		0.0118		-0.0320**		-0.0233
		(0.0288)		(0.0143)		(0.0152)
Age						
25-34	0.4982***	0.4796***	0.1393***	0.1655***	-0.1680***	-0.1612***
	(0.0158)	(0.0270)	(0.0078)	(0.0125)	(0.0089)	(0.0141)
35-44	0.3429***	0.3311***	0.1050***	0.1211***	-0.0461***	-0.0305**
	(0.0147)	(0.0259)	(0.0069)	(0.0120)	(0.0079)	(0.0135)
45-54	0.1686***	0.1628***	0.0623***	0.0782***	-0.0039	0.0077
	(0.0146)	(0.0263)	(0.0072)	(0.0127)	(0.0077)	(0.0134)
Observations	41405	41405	52569	52569	47113	47113
R^2	0.58	0.58	0.14	0.14	0.34	0.34
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Least squares estimations with weights from entropy balancing. Dependent variables: digital skills standardized to standard deviation 1 across countries, indicator for having at least basic digital skills, and log hourly wages. Sample: female employees aged 25–65 years. Job Training: binary variable indicating whether the respondent participated in on-the-job training or job-related training in the 12 months before the survey. Controls: numeracy skills, years of schooling, gender, migration status in three categories (first-generation migrant, second-generation migrant, native), parental education in three categories (neither parent has attained upper secondary, at least one parent has attained secondary and post-secondary/non-tertiary, at least one parent has attained tertiary), an indicator whether the respondent has children, age group of the oldest child in four categories (0–2, 3–5, 6–12, 13+), an indicator for full-time employment, an indicator of participation in non-job-related training measures (e.g, self-organized training or seminar participation), firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+), as well as fixed effects for occupations (two-digit ISCO level) and industries (two-digit ISIC level). All regressions also control for country fixed effects. All control variables, including country fixed effects, were used for the entropy balancing. R^2 refers to within-country R^2. Robust standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table B.3: Effectiveness of Training by Age: Males

	(1)	(2)	(3)	(4)	(5)	(6)
	Digital Skills		Basic Digital Skills		Log Wages	
Job Training	0.0695***	0.0563**	0.0396***	0.0682***	0.0737***	0.0739***
	(0.0095)	(0.0230)	(0.0038)	(0.0109)	(0.0056)	(0.0124)
Job Training × Age: 25-34		0.0006		-0.0438***		0.0057
		(0.0291)		(0.0126)		(0.0173)
Job Training × Age: 35-44		0.0222		-0.0352***		-0.0072
		(0.0285)		(0.0129)		(0.0156)
Job Training × Age: 45-54		0.0255		-0.0207		0.0013
		(0.0292)		(0.0135)		(0.0158)
Age						
25-34	0.5074***	0.5071***	0.1574***	0.1793***	-0.2140***	-0.2168***
	(0.0167)	(0.0274)	(0.0068)	(0.0110)	(0.0095)	(0.0158)
35-44	0.3417***	0.3305***	0.1222***	0.1398***	-0.0445***	-0.0409***
	(0.0157)	(0.0264)	(0.0067)	(0.0112)	(0.0083)	(0.0137)
45-54	0.1569***	0.1442***	0.0651***	0.0755***	0.0115	0.0108
	(0.0149)	(0.0260)	(0.0068)	(0.0115)	(0.0080)	(0.0137)
Observations	38323	38323	50275	50275	44895	44895
R^2	0.58	0.58	0.18	0.18	0.34	0.34
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Least squares estimations with weights from entropy balancing. Dependent variables: digital skills standardized to standard deviation 1 across countries, indicator for having at least basic digital skills, and log hourly wages. Sample: male employees aged 25–65 years. Job Training: binary variable indicating whether the respondent participated in on-the-job training or job-related training in the 12 months before the survey. Controls: numeracy skills, years of schooling, gender, migration status in three categories (first-generation migrant, second-generation migrant, native), parental education in three categories (neither parent has attained upper secondary, at least one parent has attained secondary and post-secondary/non-tertiary, at least one parent has attained tertiary), an indicator whether the respondent has children, age group of the oldest child in four categories (0–2, 3–5, 6–12, 13+), an indicator for full-time employment, an indicator of participation in non-job-related training measures (e.g, self-organized training or seminar participation), firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+), as well as fixed effects for occupations (two-digit ISCO level) and industries (two-digit ISIC level). All regressions also control for country fixed effects. All control variables, including country fixed effects, were used for the entropy balancing. R^2 refers to within-country R^2. Robust standard errors in parentheses. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.