Pillars – Pathways to Inclusive Labour Markets

Report

Benchmark for Future Policies:

Studying the Effects of Training on the Adaptability to Technological Change

Worker-Level Evidence

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Training, Automation, and Wages: Worker-Level Evidence

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Abstract

This paper investigates the impact of job training on workers' susceptibility to automation. Using rich individual-level data from the Programme for the International Assessment of Adult Competencies (PIAAC) across 37 industrialized countries, we construct a unique individual-level measure of automation risk based on the tasks performed at work. We uncover substantial variation in automation risk within detailed occupations, which would have been overlooked by previous occupation-level automation measures. Job training is an important factor in explaining workers' susceptibility to automation within occupations. Our results show that workers who participate in job training witness a 4.7 percentage point reduction in their automation risk compared to observationally equivalent workers without training. Moreover, workers participating in training earn approximately 8 percent higher wages compared to their counterparts without training. While training is effective in reducing automation risk and increasing wages in almost all sample countries, there is a substantial heterogeneity in the magnitude of training effects. Our findings emphasize the need for comprehensive data on training participation and job tasks to better understand the efficacy of training programs in addressing automation risks.

Keywords: Job Training, Human Capital, Automation, Technological Change, Entropy Balancing

JEL: J24, J31, J61, O33

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1. Introduction

Over the past decades, we have witnessed significant advances in labor-replacing technologies not only in manufacturing, but across nearly all sectors in the economy. As a result, automation has emerged as one of the most transformative developments in the labor market (Acemoglu and Autor, 2011). In particular, workers in the middle of the wage distribution face an increasing risk of substitution by technology (Goos et al., 2014). The literature attributes this development to the fact that middle-wage workers often perform routine tasks, which are repetitive and follow a clearly defined structure, making them susceptible to be replaced by machines (Autor et al., 2003; Cortes, 2016). Thus, the composition of tasks a worker performs at the job determines her automation risk.

Generally, the literature resorts to expert surveys to measure the tasks workers perform in an occupation, such as O*NET in the United States (e.g., Autor et al., 2003; Goos et al., 2014), SOC in the United Kingdom (e.g., Arntz et al., 2016), and BERUFENET in Germany (e.g., Dengler and Matthes, 2015). These task measures are commonly used to construct occupation-level measures of automation risk (e.g., Acemoglu and Autor, 2011; Goos et al., 2014; Arntz et al., 2016; Cortes, 2016), which inform our understanding of aggregate wage developments of occupational groups. However, there might be substantial differences in the task composition and thus in the risk of automation between individual workers in the same occupation. For instance, workers who are employed at different firms with different production technologies or management practices may perform very different job tasks (e.g, Autor et al., 2003; Bloom et al., 2019). Occupation-level measures of automation risk overlook all heterogeneity in job tasks among workers within an occupation (Autor, 2013).

We suspect that job training is one important reason for within-occupational variation in job tasks – and thus automation risk. On the one hand, job training helps workers to acquire new skills and knowledge, enabling them to perform a wider range of tasks at their workplace. On the other hand, employers may recognize the need to adapt to technological progress to remain competitive, leading them to utilize job training as a strategic tool to align task requirements with advancing technology. By doing so, employers aim to optimize their labor inputs and ensure a better alignment between workforce skills and the evolving technological landscape.

However, surprisingly little is known about job training as a potential means to mitigate negative labor market effects of technological change and to ensure workers' ability to adapt to evolving task requirements.[1] More specifically, the existing literature does not provide evidence on the efficacy of training programs in changing the tasks workers perform and, consequently, their susceptibility to automation. This lack of evidence can be attributed to the scarcity of comprehensive data sets that encompass information on both individuals' participation in job training and the specific tasks they perform in their respective jobs. In this paper, we investigate the role of training for workers' susceptibility to automation across a wide range of developed countries.

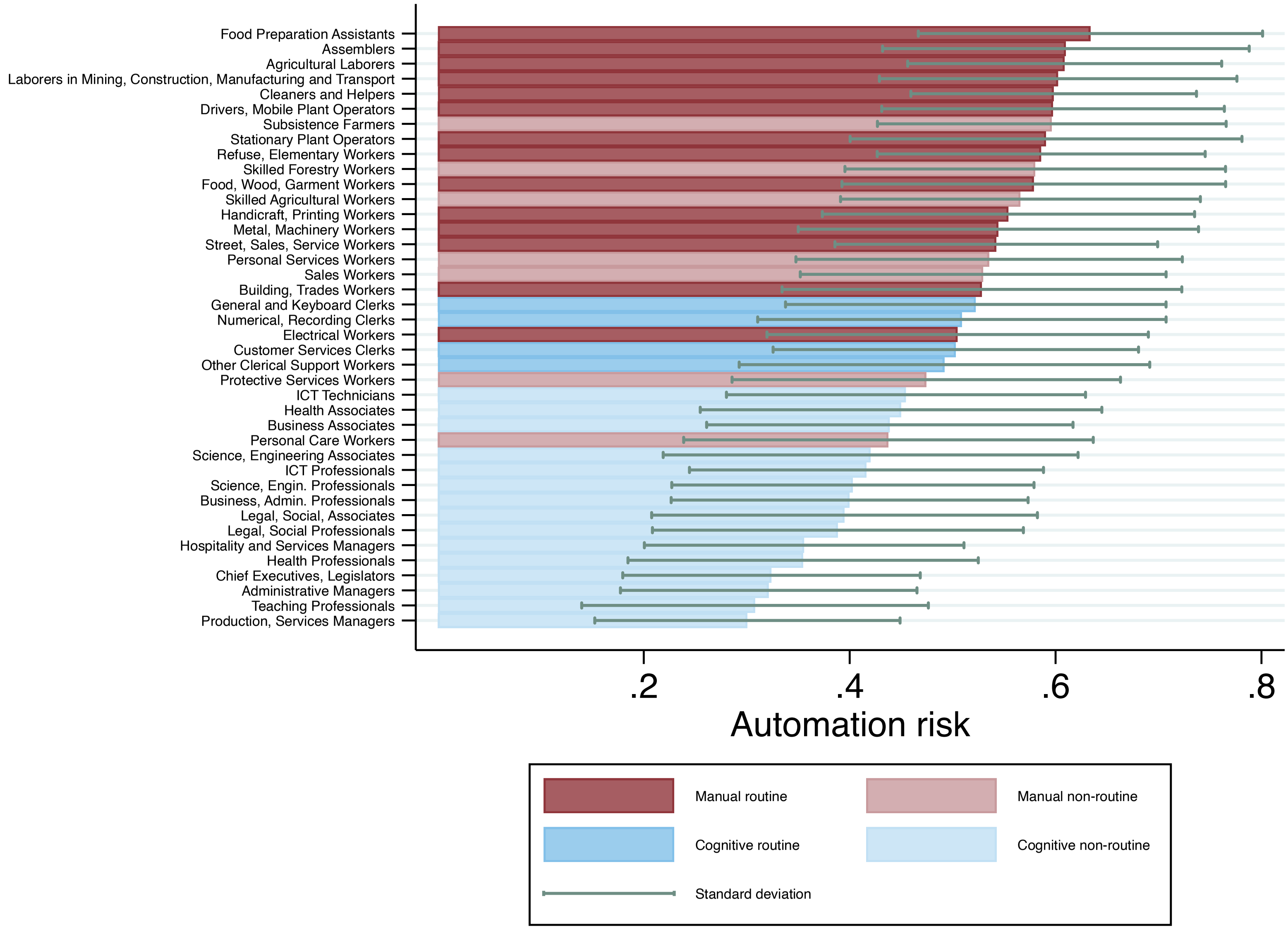
Our analysis leverages rich individual-level data from the Programme for the International Assessment of Adult Competencies (PIAAC), which offers comprehensive and internationally comparable information on training participation and job tasks for 37 countries (17 of them being European). With respect to training, workers are asked about their training activities in the year before the survey. PIAAC also elicits respondents' tasks use at work in the domains of manual, cognitive, digital, and social tasks. Specifically, PIAAC provides the opportunity to identify tasks that, based on current understanding, are difficult to automate. These tasks encompass social intelligence, involving adept navigation of complex social relationships; cognitive intelligence, such as complex reasoning; and perception and manipulation skills, involving the execution of physical tasks in unstructured work settings. By utilizing individual-level task information, we can construct an automation risk measure that varies at the level of each individual worker. This enables us to examine the impact of training on automation risk *within* occupations. Intuitively, our measure of automation risk is a weighted share of tasks workers perform with different degrees of susceptibility to automation.[2]

Before turning to the investigation of job training and automation risk, we highlight a number of descriptive patterns that are relevant for the subsequent analysis. First and perhaps most importantly, workers' automation risk differs widely both across and within occupations (Figure 1). In terms of between-occupation variation, we show that cognitive non-routine occupations have the lowest average automation risk across all occupations; for instance, the risk for production and service managers to get fully automated is only 32 percent. On the other side of the spectrum are manual routine occupations, which face the highest risk of automation; for instance, the automation risk for food preparation assistants is as large as 61 percent. Even more strikingly, however, there is also considerable variation in automation risk *within* occupations, as workers in the same occupation

[1] Nedelkoska and Quintini (2018) and Lergetporer et al. (2023) document that workers in occupations at a higher risk of automation actually have a lower propensity to participate in job training.

[2] See section 2.2 for details on the construction of the automation risk measure.

Figure 1: Automation risk across and within occupations



Notes: Figure shows the average automation risk by two-digit ISCO occupation across all countries in our sample. Whiskers indicate one standard deviation from the mean. See section 2.2 for details on the construction of the automation risk measure. *Data source*: PIAAC.

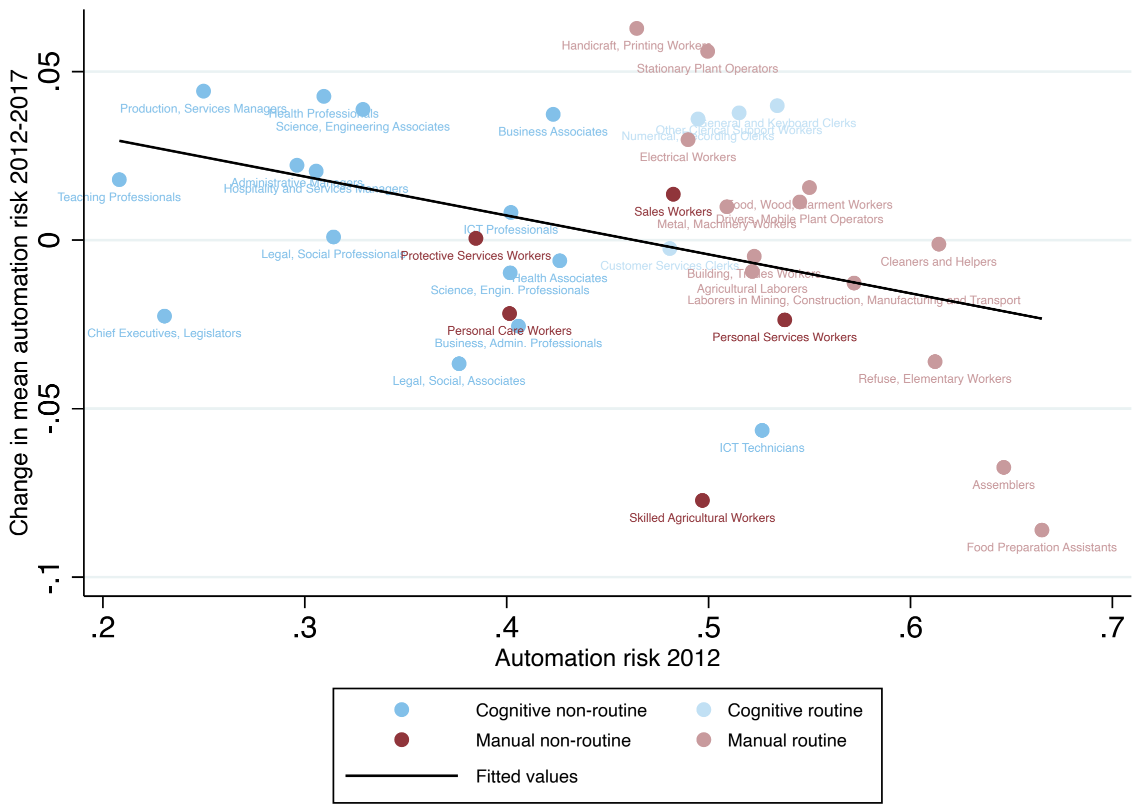
perform tasks with very different degrees of automatability. For instance, food preparation assistants at the 5th percentile are as automatable as an average production and service manager. Put differently, as many as 5 percent of workers in the most automatable occupation face an automation risk as low as the average risk in the least automatable occupation. When considering production and service managers with a somewhat higher automation risk than the average worker in their occupation, say, those at the 75th percentile, there are already 11th percent of food preparation assistants who have a similar automation risk. These examples illustrate that there is a non-negligible overlap in the automation risk of individual workers even when comparing occupations with the lowest vs. highest average automation risk.

Another way to show the amount of variation in within-occupation automation risk in Figure 1 is to consider the standard deviations. We observe that one standard deviation in the automation risk of food preparation assistants is 17 percent, being 14 percent for production and service managers. In general, we observe that the within-occupation variation in automation risk is substantial in *all* occupations, that is, the degree of variation is independent of an occupation's average automation risk. These comparisons show that simply looking at occupational averages masks considerable heterogeneity and can lead to misleading conclusions regarding workers' actual automation risk based on the tasks they perform at work.

We also document substantial shifts in the composition of tasks within occupations over time. Figure 2 shows that U.S. occupations with a higher average automation risk in 2012 experienced a larger decrease in automation risk between 2012 and 2017.[3] The observation that the automation risk is converging across occupations can help to explain recent findings in the literature. For instance, Bachmann et al. (2022) and Böhm et al. (2022) show that despite the decline of routine-intensive jobs in Germany, wages of workers staying in these occupations have not been decreasing. This result suggests that workers who remain to be employed in declining, more automatable occupations may be positively selected in terms of their productivity. At the same time, the occupational stayers may perform tasks at a lower risk of automation that cannot yet be replaced by automation technologies. Similarly, Atalay et al. (2020) show that the shift from routine tasks toward non-routine interactive and analytical tasks has been substantial in the United States over the period 1950–2000, with a large share of total changes occurring within narrowly

[3]To construct Figure 2, we make use of the fact that the United States were surveyed in PIAAC in 2012 and 2017. Unfortunately, the United States is the only country to date that participated twice in PIAAC.

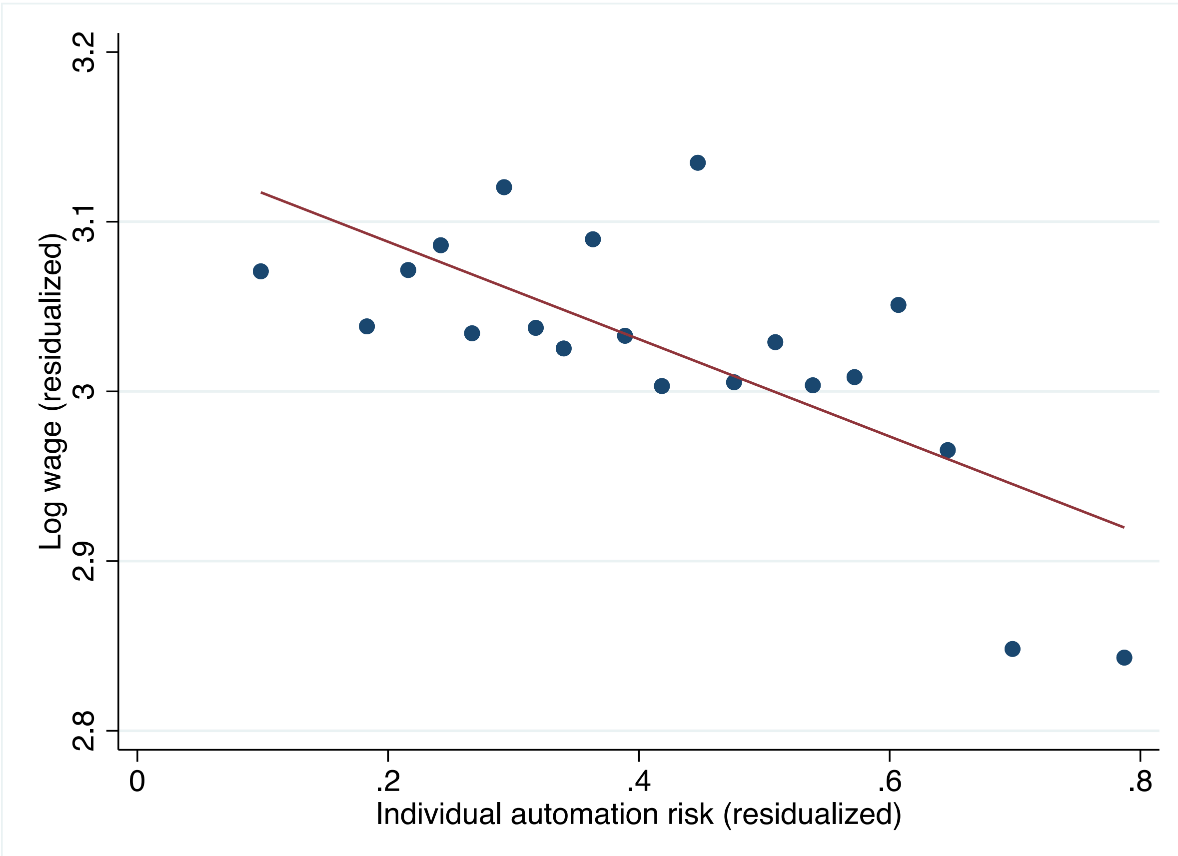
Figure 2: Change in mean automation risk over time in the United States



Notes: Figure plots the average automation risk in 2012 against the average change in automation risk between 2012 and 2017 by two-digit ISCO occupation for the United States. See section 2.2 for details on the construction of the automation risk measure. *Data source*: PIAAC.

defined job titles. Consequently, the task demands within occupations are evolving over time, emphasizing the importance for workers to adapt and respond to these changing requirements. Given the shifting skill demands in the labor market, it is crucial for workers to be able to meet these evolving needs.

Figure 3: Automation risk and wages



Notes: Figure displays a binned scatterplot showing the relationship between automation risk and wages. To construct the figure, we divided the average automation risk into 20 ranked equal-sized groups and plotted the mean of the log hourly wages against the mean of average automation risk in each bin. See section 2.2 for details on the construction of the automation risk measure. The figure shows the residualized relationship after accounting for country, industry, and occupation fixed effects. Industry fixed effects at the two-digit ISIC level and occupation fixed effects at the two-digit ISCO level. Best-fit line shown in red. *Data source*: PIAAC.

Our new worker-level measure of automation risk strongly predicts workers' wages, emphasizing its economic relevance. Figure 3 shows the residualized relationship between automation risk and wages after including country, industry, and occupation fixed effects. Clearly, workers in jobs that are less susceptible to automation earn higher wages, potentially due to the complementarity of their job tasks to automation technologies. The striking result is that the negative association between automation and wages also appears within occupations.

The evidence above illustrates the significant role that tasks performed at the workplace play for workers' adaptability to technological change and their labor market success – even within occupations. In this paper, we investigate whether job training affects the tasks workers perform at the job. More specifically, we ask whether participation in training allows workers to perform tasks that are complementary to new automation technologies, thereby reducing their automation risk.

Crucially, by utilizing task data at the individual worker level in PIAAC, we can analyze the impact of training on automation risk within occupations, rather than relying on occupational-level automation measures used in previous studies. This approach allows us to include occupation fixed effects, which help account for (unobserved) occupation characteristics that simultaneously influence both training participation and automation risk. For instance, occupations that rely heavily on advanced technology may have different training needs and also face different levels of automation risk compared to occupations that rely on less automated processes. Considering such occupation-specific confounders is crucial for properly estimating the effect of job training on automation risk and other worker outcomes.

Additionally, we account rigorously for selection into training based on observables by applying entropy balancing (Hainmueller, 2012). We make use of PIAAC's detailed background questionnaire to account for worker and firm characteristics that are likely associated with training participation, such as worker age, gender, migration status, education level, family background, and firm size. In contrast to previous studies on the effects of job training, we can also include a proxy for workers' unobserved ability, making use of PIAAC's internationally standardized numeracy skill assessments. Methodologically, entropy balancing ensures that the control group of workers who did not receive training are observational equivalent to the group of workers who receive training. Thus, among these groups of "statistical twins" with and without training, training is random conditional on the observable covariates. By combining entropy balancing on a rich set of work and firm characteristics with detailed controls for country, industry, and occupation fixed effects, we are better able to account for omitted variables and selection into job training than any prior international investigation.

We find that job training significantly decreases workers' automation risk. Workers who participate in job training witness a decrease in automation risk of 4.7 percentage points compared to their "statistical twins" without training in the same country, industry, and occupation. This is an economically sizeable effect, corresponding to 10 percent of the mean automation risk in our sample. The effect size is also equivalent to half of the difference in automation risk between a health associate (automation risk of 0.44) and a health professional (0.35). The reduced automation risk due to job training also translates into higher wages. Workers participating in job training earn about 8 percent higher wages than their "statistical twins" without training. This estimate is similar to the wage gradient associated with an additional year of schooling in developed countries (Hanushek et al., 2015).

Notably, the effect of training on automation risk (wages) is negative (positive) in *all* 37 countries in our sample.[4] While there is considerable variation in effect sizes across countries, training effects are statistically significant at conventional levels in all but one (three) countries for automation (wages). We also observe that countries in which training is more effective in reducing automation risk are also those in which training has a stronger positive impact on wages.

Given that the labor force is aging in industrialized economies, a significant challenge arises in providing older workers with the skills that enable them to adapt to evolving task demands (Falck et al., 2022). One means to do so is job training. Previous literature has shown that training participation tends to decrease in age, with exit-age workers having by far the lowest training participation rate among all age groups (see PILLARS Deliverables 2.4 and 2.5). Making use of the fact that PIAAC provides cross-sectional information on individuals across their entire working lives, we provide evidence that training is equally effective in reducing automation risk for both older and younger workers. These results highlight the potential of training to assist workers of all ages in acquiring skills that cannot easily be replaced by technology.

Previous work by Black and Spitz-Oener (2010) has shown that gender differences in the skill content of jobs partly explain why labor market outcomes have been improving for women relative to those for men. Using German data, they find that women have witnessed stronger increases in abstract tasks and stronger decreases in routine tasks between 1979 and 1999, reducing their automation risk compared to men. However, we find that female workers still have a higher average automation risk than men based on their job tasks. At the same time, training is more effective in reducing the automation risk

[4]The wage analysis is conducted across 36 countries, as Peru did not provide wage information.

for female workers compared to male workers. This suggests that women may particularly benefit from training programs to adapt to technological change.[5]

Our paper relates to existing studies that examine the labor market effects 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). 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).[6] In the context of automation, Schmidpeter and Winter-Ebmer (2021) show that upon job loss, training offered to unemployed workers seems to be particularly effective in increasing the job-finding-probability for workers previously employed in a routine-intensive occupation.

Despite this large body of evidence on job training, the literature thus far has not investigated the potential role of training in counteracting the potentially negative consequences of technological change. Job training could help to sustain the employability of workers at their current job or in their current occupation by enabling them to upgrade to tasks that are complementary to evolving technologies. Our paper fills this gap by investigating the role of job training for the composition of tasks performed at the job and the resulting automation risk faced by workers. Moreover, we are also the first to provide an international investigation of how training affects workers' adaptability to technological change, showing that there is a wide heterogeneity in training effectiveness across countries.

Moreover, most existing studies on the effects of job training suffer from bias from omitted variables and unobserved selection into training.[7] Workers who participate in training arguably differ along many characteristics from workers who are not doing so. For instance, if workers with higher (unobserved) ability are more likely to receive training, and at the same time earn higher wages, a naive regression of wages on training will lead to upward-biased estimates of training impacts. Our study therefore also makes a methodological contribution to the literature on the returns of job training across countries by exploiting numeracy skills as a unique control for unobserved ability and by applying

[5]In PILLARS Deliverables 2.4 and 2.5, we show that there are no systematic differences in training participation between women and men across PIAAC countries.

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

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

entropy balancing on an extensive set of observable characteristics to account for selection into training.

The remainder of the paper proceeds as follows: Section 2 presents our data on job training and tasks from PIAAC and describes how we construct the automation risk measure. Section 3 discusses our empirical strategy. Section 4 presents the results. Section 5 concludes.

2. Data

2.1. International PIAAC data

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) in each sample country. A total of 38 countries[8] have participated in PIAAC across the three rounds of data collection between 2011 and 2017, including 17 European countries: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, Germany, Greece, Hungary, Ireland, Lithuania, Netherlands, Poland, Slovak Republic, Slovenia, Sweden, and the United Kingdom (England and Northern Ireland). From these 38 countries, we can use 37 for our analysis.[9]

We make use of detailed information on participation in job training (i.e., our treatment variable) in PIAAC's background questionnaire, where workers are asked about their training activities in the 12 months 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.

As the main outcome of interest in our analysis, we focus on task use at the workplace, also elicited in PIAAC's background questionnaire. For instance, subjects are asked to which extent they teach people, use dexterity, or negotiate with people.[10] In total, the PIAAC survey contains 73 items eliciting task use at work in the domains of manual, cognitive, digital, and social tasks. These items on task use at work allow us to construct

[8] We treat the England and Northern Ireland as one country (United Kingdom).

[9] We do not use data for the Russian Federation in our analysis. According to the OECD (2013), data for the Russian Federation are preliminary, may still be subject to change, and are not representative of the entire Russian population because they do not include the population of the Moscow municipal area.

[10] The responses are given on a 5-point Likert scale: 1 - Never, 2 - Less than once a month, 3 - Less than once a week but at least once a month, 4 - At least once a week but not every day, 5 - Every day.

a measure of automation risk at the individual level and to investigate the effect of training on this automation measure.

In addition to its effect on automation, we also consider the effect of training on hourly wages as a direct measure of labor market success.[11] PIAAC further assesses respondents' key workplace skills in literacy, numeracy, and problem-solving in technology-rich environments (which we refer to as digital skills).[12] The domains are described more completely in OECD (2013). These skill measures are defined as follows:

> *Literacy*: ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals, and to develop ones 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.

As a potential mechanism, we investigate the effect of job training on digital skill — as job training is frequently related to equipping workers with the skills to operate new hardware or software (e.g., OECD, 2017). In contrast, we treat numeracy skills as a *control* variable, accounting for selection into training based on ability.[13]

Finally, PIAAC contains a wealth of background characteristics of the respondents, such as age, gender, nationality, own education, parental education, number of children, employment status (full-time or part-time), occupation (two-digit ISCO level), industry (two-digit ISIC level), as well as the size of the firm in which the worker is employed.

[11] 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.

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

[13] PIAAC measures each of these 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. Moreover, following Hanushek et al. (2015), we use the first plausible value of the PIAAC scores in each domain throughout.

Finally, PIAAC also elicits training measures that are not directly job-related (e.g., participation in workshop, seminars, or private lessons). We exploit this rich set of observable worker characteristics for entropy balancing to account for selection into job training.

As we are interested in the effect of job training on automation based on the tasks performed at work 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. The main analysis also restricts the sample to workers who provide information on both workplace tasks and wages, so our automation and wage regressions are based on the same sample of workers. After implementing these restrictions, our final sample comprises a total of 91,474 individuals.

2.2. Individual-level automation risk

Our measure of automation risk is based on Nedelkoska and Quintini (2018), who construct a country-occupation-specific measure of automation risk using PIAAC data. Building on their approach, we construct an individual-level measure of automatability of a worker's job.

In general, we follow the approach by Nedelkoska and Quintini (2018) in predicting the probability that an individual's job tasks are fully automatable. While Nedelkoska and Quintini (2018) aggregate these individual predicted automation risk measures at the occupational level for each country, we are interested in the automation risk at the individual level based on the individual task use values to investigate the effect of training on a worker's job task composition and automation risk. The construction of their measure of automation risk proceeds in two steps. First, based on expert surveys in Frey and Osborne (2013) on engineering bottlenecks for the automation of tasks, they construct an automation variable that receives a value of 1 in occupations in which all tasks can be automated and a value of 0 in occupations that can only partially be automated.[14]

[14] At the heart of the occupational automation risk in Frey and Osborne (2013) lies the process of identifying the primary engineering bottlenecks encountered by mobile robotics and machine learning developers. To this end, Frey and Osborne (2013) conducted interviews with engineering scientists in 2013 during a workshop hosted by the Oxford University Engineering Sciences Department. Participants were presented with a comprehensive list of 70 occupations, accompanied with eleven job task descriptions from the U.S. ONET. The scientists were then asked to determine whether the tasks associated with each occupation could be automated and be executed by cutting-edge computer-controlled equipment.

Second, Nedelkoska and Quintini (2018) run a logistic regression with the occupational automation risk from Frey and Osborne (2013) as dependent variable and the task use items from PIAAC as independent variables.[15] The coefficients on the task use variables show the contribution of each task to the overall automation risk.

Table 1 gives an overview of the tasks used by Nedelkoska and Quntini (2018) to predict workers' automation risk with the respective coefficients from the logistic regression. For instance, if a worker's job activities involve influencing others, solving complex problems, or negotiating to a larger extent, this reduces her automation risk. Conversely, tasks such as solving simple problems or using dexterity increases her automation risk.[16]

To construct a measure of automation at the individual level, we borrow the estimated coefficients from Nedelkoska and Quintini (2018), which we treat as automatability weight. We multiply these by the corresponding task use values provided by the workers in PIAAC. Finally, we sum up the weighted values from all job tasks used in their exercise and plug this into a logistic function to predict a worker's individual automation risk. This approach gives an automation risk score that ranges from 0 (indicating a low probability that the individual is fully automated, based on the tasks performed at work) to 1 (indicating a high probability of that an individual is fully automated). Nedelkoska and Quintini (2018)

As shown in Figure 1, the occupation in the PIAAC sample with the highest average risk of automation is food preparation assistants, with an average automation risk of 61 percent — i.e., food preparation assistants have a 61 percent likelihood that their tasks are fully automated. At the other end of the spectrum, production and service managers as well as teaching professionals face the lowest automation risk, with less than one-third of the tasks that are fully automatable. The average automation risk across all occupations and countries in our sample is 46 percent.

Occupations in which all tasks were deemed automatable by all scientists received a value of 1, while occupations that could only be partially automated were assigned a value of 0.

[15] This relationship between tasks and the risk of automation is estimated using Canadian PIAAC data. According to Nedelkoska and Quintini (2018), the Canadian data have more detailed occupational information than provided by other PIAAC countries, allowing them to map directly into the occupational classification used by Frey and Osborne (2013). The estimation coefficients obtained from the regression using the Canadian PIAAC sample are applied to calculate the risk of automation of jobs at a more aggregate occupational classification within Canada and for countries other than Canada.

[16] In contrast to coefficients from a linear regression, the reported logit coefficients do not allow a straightforward interpretation beyond its sign and relative coefficient size.

Table 1: Factor loadings from Nedelkoska and Quinitini (2018)

Task	Logit Coefficient
Plan Work of Others	-0.308***
Influence Others	-0.235***
Advise	-0.199***
Teach	-0.0691***
Complex Problems	-0.0691**
Negotiate	-0.0463*
Simple Problems	0.0573*
Dexterity	0.105***
Sell	0.160***
Communicate	0.214***

Notes: Coefficients from a logistic regression with the occupational automation risk from Frey and Osborne (2013) as dependent variable and the task use items from PIAAC as independent variables. Dependent variable is based on expert surveys asking for engineering bottlenecks; occupations for which all tasks can be automated receive a value of 1 and occupations that can only be partially automated receive a value of 0. Regressors: PIAAC task items corresponding to engineering bottlenecks identified in Frey and Osborne (2013); PIAAC asks for frequency of task use, with answers given on a Likert scale ranging from 1 (never) to 5 (every day). Coefficients estimated on the Canadian PIAAC sample, which provides a high level of disaggregation allowing to identify 4-digit ISCO occupations. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

3. Empirical Strategy

To investigate the effect of job training on labor market outcomes, we estimate the following individual-level OLS regression:

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

Here, Y_i is the outcome of interest for individual i. We mainly focus on two outcome variables: automation risk and log hourly wages.[17] The binary variable $jobtraining_i$ receives a value of 1 if a respondent participated in on-the-job training (i.e., organized sessions or training by supervisors or co-workers) or other job-related training in the 12 months prior to the survey, and 0 otherwise.[18]

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.[19] In particular, we are concerned about omitted variables that affect who receives job training.

[17] We investigate digital skills as a potential channel in Table A.5.

[18] See section 2 for details about the measurement of job training in PIAAC.

[19] 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.

For instance, if individuals with higher ability or work effort are more likely to organize or receive training, a positive β_1 might simply indicate that more able or more motivated workers receive higher wages.

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).[20] However, there are several reasons why measures of educational attainment might be poor approximations of actual human capital: First, the quality of schooling greatly differs over time and across countries, Second, acquired years of schooling just reflect an individual's human capital at the end of formal schooling, which may not be a good indicator of human capital when individuals need to constantly adapt their skills to cope with 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 (for recent evidence, see Langer and Wiederhold, 2023). We introduce a novel control variable to the training literature that arguably better captures an individual's ability than previously used variables: cognitive skills from PIAAC's numeracy assessment. Tested numeracy skills are a more direct and precise measure of an individual's human capital than educational attainment (see Hanushek and Woessmann (2008) for a discussion).[21]

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

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

Here, Y_{icoj} is the outcome of interest for individual i who lives in country c and works in occupation o and industry j. Our regressions 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 industry fixed effects, η, which account for differences in training frequency or effectiveness across industries.

Our measure of automation risk is based on individual-level task data instead of being measured at the occupational level as in previous literature. Crucially, this allows us to include occupation fixed effects, ζ. As suggested by a large literature (e.g., Acemoglu and

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

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

Autor, 2011; Goos et al., 2014) and as illustrated in Figure 1, occupations differ substantially in the task composition and thus in their average automation risk. At the same time, the literature documents large differences in the demand for training (Lergetporer et al., 2023) and in the take-up of training (Nedelkoska and Quintini, 2018) across occupations. Thus, the occupation fixed effects ζ account for (unobserved) occupation characteristics that affect both differences in automation risk and training between two-digit occupations and allow us to identify training effects just from within-occupation variation.

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 receive 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 of full-time employment. Standard errors are robust to heteroskedasticity in our main analysis.

To get as close as possible to estimating a causal effect of job training on the task composition and wages in the absence of experimental variation, we follow Hainmueller (2012) in applying entropy balancing.[22] Entropy balancing is a non-parametric data preprocessing method to obtain exact covariate balance in settings with a binary treatment (in our case, participation in job training). Given the covariate distribution in the treatment group, 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

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

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).[23] 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.

Table A.1 shows the full balancing table with respect to our covariates. Before weighting, the workers without training have on average lower numeracy skills, are less educated and less likely to be employed full-time, and are less likely to work at larger firms. However, after entropy balancing, workers with and without training are perfectly balanced along all these dimensions.

4. Results

4.1. Training and automation

This section investigates the relationship between job training and individual-level automation risk as our main outcome of interest. Table 2 presents our main results. Different columns show the association of job training with automation risk in gradually more demanding specifications. Column (1) provides the raw correlation between job training and automation risk within countries and industries. In this specification, training is associated with at 8.4 percentage points lower risk of automation. However, the coefficient on training decreases to -5.6 percentage points when we include occupation fixed effects in column (2) to account for (unobserved) occupation characteristics affecting both training and automation risk. Adding occupation fixed effects is also powerful in terms of explanatory power, as the R^2 increases from 0.11 to 0.22 — i.e., the share of explained variation in automation risk doubles by including occupation fixed effects. However, we can estimate a precise and sizable training coefficient even when just exploiting within-occupation variation.

Including numeracy skills to control for (unobserved) ability in column (3) of Table 2 further reduces on the size of the training, however not by much. Strikingly, when adding the complete set of socio-demographic and work-related control variables in column (4) and applying entropy balancing in column (5), the estimated coefficient on job training

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

remains very similar to the coefficient in column (3).[24] This suggests that occupational selection and numeracy skills can be seen as a sufficient statistic for other socio-demographic and work-related characteristics that differ between workers with and without training. We are thus confident that our identifying assumption that we have included all variables that drive the selection into training in the entropy balancing approach holds.

Table 2: Training and automation risk

Automation Risk	(1)	(2)	(3)	(4)	(5)
Job Training	-0.0839***	-0.0559***	-0.0511***	-0.0464***	-0.0467***
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0012)
Numeracy Skills			-0.0229***	-0.0175***	-0.0129***
			(0.0009)	(0.0010)	(0.0008)
Observations	91470	91470	91470	91470	91470
R^2	0.11	0.22	0.22	0.24	0.20
Country FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes
Entropy Balancing	No	No	No	No	Yes

Notes: Ordinary least squares estimation in columns (1)-(4), least squares estimation with weights from entropy balancing in column (5). Dependent variable: automation risk index, ranging from 0 (indicating a low probability that a worker is fully automated) to 1 (indicating a high probability that a worker is fully automated); automation risk is predicted using items on task use at work from PIAAC, applying the automatability weights from Nedelkoska and Quintini (2018). Sample: employees aged 25–65 years with information on automation risk and log hourly wages. 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 (standardized to unit standard deviation across countries), 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 (e.g, self-organized training or seminar participation), and firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+). Industry fixed effects at the two-digit ISIC level and occupation fixed effects at the two-digit ISCO level. All regressions also control for country fixed effects. All control variables were used for the entropy balancing in column (5). R^2 refers to within-country R^2. Robust standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

In the most demanding specification in column (5) of Table 2, we find that job training decreases automation risk by 4.7 percentage points. In terms of magnitude, this is about one-third of a standard deviation in individual automation risk in our sample, or 10 percent of the mean automation risk. Another way to see the magnitude of the training coefficient is to relate it to the difference in the average automation risk between professional occupations — which typically involve a rather large amount of complex tasks and

[24]The coefficients from column (4) and column (5) are not statistically different from the coefficient in column (3) at conventional levels.

thus have a low automation risk — and technician or associate occupations in the same field. For instance, the magnitude of the training estimate is equivalent to the difference in automation risk between an information and communication technology (ICT) technician (0.44) and an ICT professional (0.40) or to half of the difference between a health associate (0.44) and a health professional (0.35).[25]

The United States is the only country that participated twice in PIAAC, allowing us to assess how the effectiveness of training in reducing the automation risk has changed over time.[26] Table A.3 exploits the time dimension and estimates column (5) of Table 2 in the US for 2012 (column (2)) and 2017 (column (3)).[27] We observe that training has become more effective in reducing the automation risk between 2012 and 2017. This may be attributed to sampling variation between the two survey waves (e.g., Meager, 2019). However, an increasing coefficient can also stem from true heterogeneity over time related to factors such as changes in labor market dynamics or changes in the training content over time related to an evolving technological landscape. For instance, a shrinking labor force due to demographic change (e.g., Acemoglu and Restrepo, 2022), declining labor force participation (e.g., Dotsey et al., 2017), or a tighter labor market resulting from a longer recovery period from the Great Recession in the United States (e.g., Cunningham, 2018) may increase employers' incentives to invest in more effective training in order to enable incumbent employees to adjust to changing task requirements. At the same time, the content of training may have changed over time, as more recent technologies require different task inputs (e.g., Atalay et al., 2020) that are at a lower risk of automation.

Our automation risk in Table 2 is a composite measure of different tasks workers perform at their jobs. Estimating our baseline specification from column (5) of Table 2, Figure 4 shows the role of training for individual task items. For exposition, these items are shown in decreasing order of their contribution to automation risk.[28] While workers

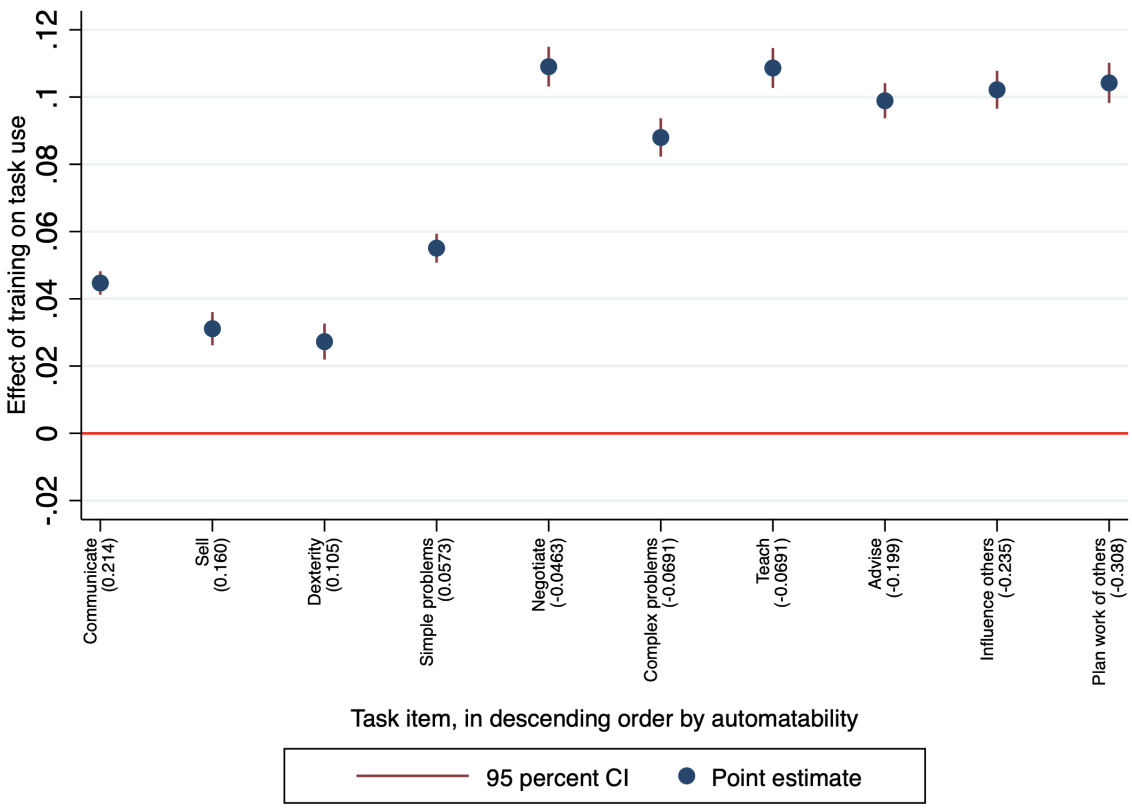
[25]Our results are robust to not limiting the sample to observations that possess complete information on both automation and wages (see Table A.2).

[26]However, for consistency with the other PIAAC countries, we include only the first survey wave for our baseline results.

[27]column (1) of Table A.3 provides the results when pooling the 2012 and 2017 waves.

[28]The values of the responses to the task items elicited in PIAAC represent the frequency of task use, which respondents provide on a Likert scale ranging from 1 (never) to 5 (every day). For ease of interpretation, we dichotomize this variable for the analysis in . To this end, we define a binary task variable equal to 1 if the respondent performs the task at least once a week (values 4 and 5 of the original task item); accordingly, the binary task variable takes a value of 0 if a task is performed less than once a week (values of 1, 2, or 3). This allows us to obtain OLS estimates analogous to those in Table 2 that have a more straightforward interpretation compared to coefficients from a ordered logit estimation usually applied to categorical Likert-responses (Cameron and Trivedi, 2005). The results in Figure 4 are robust to different specifications of the task-use cut-off.

Figure 4: Training and task use



Notes: Figure shows how job training affects job tasks. Estimates are based on our baseline specification in column (5) of Table 2. The values of the responses to the task items elicited in PIAAC represent the frequency of task use given on a Likert scale ranging from 1 (never) to 5 (every day). For ease of interpretation, we binarize the task items (1: task is performed at least once a week; 0: task is performed less than once a week). Training coefficients are shown in descending order by automatability; automatability weights (i.e., factor loadings from Table 1) are shown on the horizontal axis in parentheses.

who receive training perform all tasks to a larger extent than those without training, the increase in the intensity of performing a task is particularly pronounced for tasks associated with a lower risk of automation. Notably, these tasks include solving complex problems as well as interaction-intensive activities such as negotiating and influencing others. This is in line with prior work by Deming (2017), who argues that social interaction tasks currently cannot be easily replaced by automation, leading to a growing significance of these tasks in the labor market. At the same time, these tasks are likely to be complementary to automation technology (Acemoglu and Autor, 2011) and are thus associated with a lower automation risk. For instance, workers who receive training perform dexterity tasks that are associated with a higher automation risk, 2.6 percent more often than workers who did not receive training. By contrast, planning the work of others which is associated with a lower automation risk, is performed 10.2 percent more often by workers who received training.

Appendix Table A.5 explores digital skills as a potential channel through which training enables workers to perform more complex, less automatable tasks. Applying the same empirical strategy as in Table 2, column (1) of Table A.5 provides the raw correlation between job training and digital skills within countries and industries. We find that the digital skills of workers who receive training are by 0.29 standard deviations larger than those of workers without training. The estimated training coefficient decreases from 0.29 to 0.21 once we include occupation fixed effects in column (2). However, the most significant drop in the training coefficient is observed when adding numeracy skill in column (3), which is not surprising give the high correlation coefficient between numeracy skills and digital skills of 0.74. In the most demanding specification that also adds further controls and applies entropy balancing in column (5) of Table A.5, we find that job training increases digital skills by 0.051 standard deviations. In terms of magnitude, this is about 15 percent of the average difference in digital skills between an information and communication technology professional (standardized digital skill score of 0.847) and a business and administration professional (0.472). Alternatively, this corresponds to about 30 percent of the difference in digital skills between a worker in the age group 25-34 (standardized digital skill score of 0.241) and a worker in the age group 35-44 (0.085). 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.[29]

[29]PILLARS Deliverables 2.4 and 2.5 provide a detailed analysis of the relationship between job training and digital skills by occupation, age and gender.

Our results suggest that improving digital skills through job training might enable workers to perform more complex tasks associated with a lower risk of automation. For instance, the literature suggests that new technologies, in particular, ICT, are complementary to human labor (e.g., Krueger, 1993; Acemoglu and Pischke, 1998; Caunedo et al., 2023). At the same time, there is growing evidence that social and interaction intensive tasks are growing in importance. Thus, digital technologies might be particularly complementary to tasks requiring social interaction. By developing proficiency in digital skills, job training may also help workers to perform certain social tasks, such as planning the work of others (with computer-aided technologies).

4.2. Training and wages

Table 3 shows the relationship between training and log hourly wages. Similar to the discussion of the automation results above, column (1) shows the association between training and wages when only including country and industry fixed effects. In this specification, wages of workers with training are by 20.8 percent higher than those of workers without training. Similarly to Table 2, the coefficient drops substantially after including occupation fixed effects in column (2) and further decreases when adding numeracy skills as controls (column 3). Including further worker and firm characteristics changes the training coefficient only little (column 4). Applying entropy balancing in column (5), we find that training increases wages by 8.2 percent.[30] This coefficient corresponds to the difference in wages between a business administration professional (4.23 log points) and a business administration associate (4.15 log points). Moreover, a wage increase of 8 percent is similar to the wage gradient associated with an additional year of schooling in developed countries (see Table A.2 in Hanushek et al., 2015). This corroborates the idea that the upgrade in task composition towards tasks that are more complementary to new technologies in Table 2 and Figure 4 raises workers' marginal product of labor, resulting in higher wages.[31]

4.3. Heterogeneity

Figure B.1 and Figure B.2 show the the effect of job training on automation risk and wages for each country individually, revealing substantial cross-country heterogeneity in

[30] Our results are robust to not limiting the sample to observations that possess complete information on both automation and wages (see Table A.4).

[31] In fact, when adding automation risk as an additional control to the wage regression, the estimate on training decreases by almost one-fifth. This suggests that a non-negligible fraction of the wage effect of training is due to training reducing workers' automation risk.

Table 3: Training and wages

Log Wages	(1)	(2)	(3)	(4)	(5)
Job Training	0.2082***	0.1336***	0.1131***	0.1035***	0.0824***
	(0.0044)	(0.0042)	(0.0042)	(0.0041)	(0.0025)
Numeracy Skills			0.0972***	0.0878***	0.0716***
			(0.0025)	(0.0025)	(0.0018)
Observations	91470	91470	91470	91470	91470
R^2	0.16	0.27	0.29	0.34	0.35
Country FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes
Entropy Balancing	No	No	No	No	Yes

Notes: Ordinary least squares estimation in columns (1)-(4), least squares estimation with weights from entropy balancing in column (5). Dependent variable: log hourly wages. Sample: employees aged 25–65 years with information on automation risk and log hourly wages. 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 (standardized to unit standard deviation across countries), 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 (e.g, self-organized training or seminar participation), and firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+). Industry fixed effects at the two-digit ISIC level and occupation fixed effects at the two-digit ISCO level. All regressions also control for country fixed effects. All control variables were used for the entropy balancing in column (5). R^2 refers to within-country R^2. Robust standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

the effectiveness of training. In particular, the effect size of training varies between -0.01 in Turkey to -0.07 in Canada for automation risk and between 0.01 in France and 0.21 in Mexico for wages.[32] However, both the effect of training on automation risk and wages are significant for the majority of countries all countries in our sample.[33]

Moreover, Figure 5 shows that countries in which training is more effective in decreasing workers' susceptibility to automation also tend to be those where training is more effective in raising wages. The correlation between the training coefficients for automation and wages is -1.10 (significant at the 5 percent level). This suggests that the effectiveness of training on the shift towards tasks that are less automatable and more

[32]Similarly, Bassanini et al. (2007) find a spread in the wage returns to training between 3.7 and 21.6 percent across European countries. PILLARS Deliverables 2.4 and 2.5 investigate the role of country-specific institutions and labor-market characteristics for the effectiveness of training on wages in detail.

[33]For automation risk, the effect of training on automation risk is not significant for Kazakhstan and Turkey. For wages, the effect is not significant for France, New Zealand, and Turkey.

complementary to new technologies may play an important role for the impact of training in improving success on the labor market.[34]

In light of demographic change and ageing labor forces in industrialized countries, it is a key challenge to equip older workers with the necessary skills to enable them to upgrade their tasks and to keep up with changing task requirements (e.g., Falck et al., 2022). Figure 6 investigates the effectiveness of training by age group.[35] Specifically, panel (a) shows that the effect of training on automation risk is not significantly different across age groups. This suggests that elderly workers benefit as much as younger workers from training in terms their susceptibility to automation. Similarly, training effects on wages are also similar for younger and older workers. 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. Rather, 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 in terms of automation risk and wages.

Figure 7 shows the effectiveness of training on automation risk and wages by gender. First, we find that women perform on average tasks with a higher risk of automation (see Table A.7). However, while women have a higher risk of automation on average, female workers benefit significantly more from training in terms of automation, as Figure 7, panel (a) shows and Table A.7, column 1 show. Moreover, Figure 7, panel (b) illustrates that women also benefit more from training in terms of wages relative to men (see also Table A.7 column 2). Thus, women might particularly benefit from training as a means to adapt to technological change and improve labor market outcomes.

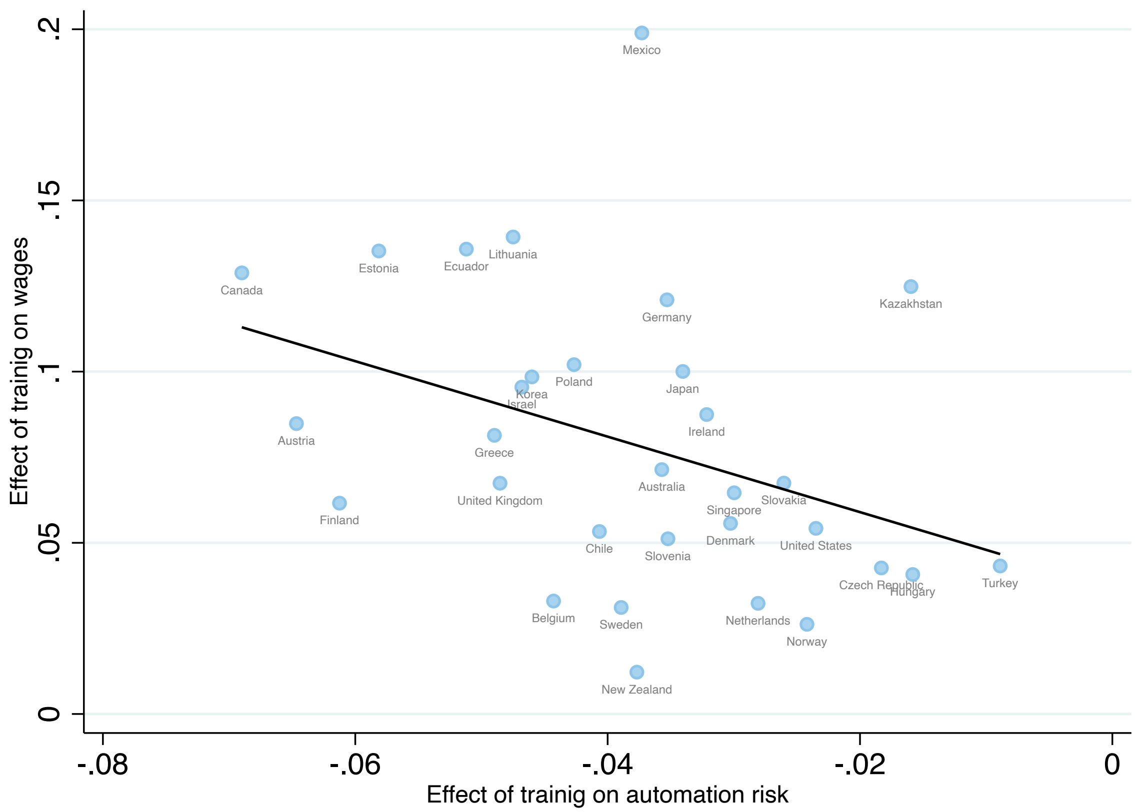
5. Conclusions and Policy Debate

Automation has emerged as a transformative development in the labor market, posing a significant risk to workers in jobs that heavily involve routine tasks. While the susceptibility to automation is primarily determined by the task composition of a worker's job, previous literature relied on occupation-level measures of automation risk, thus overlooking within-occupation variation in job tasks and associated automation risk. Our study overcomes this limitation by utilizing individual-level task data to construct a measure of

[34]Figure B.1 and Figure B.2 provide more detailed results, showing the estimated training coefficients in the automation risk and wage regressions alongside the relevant confidence intervals.

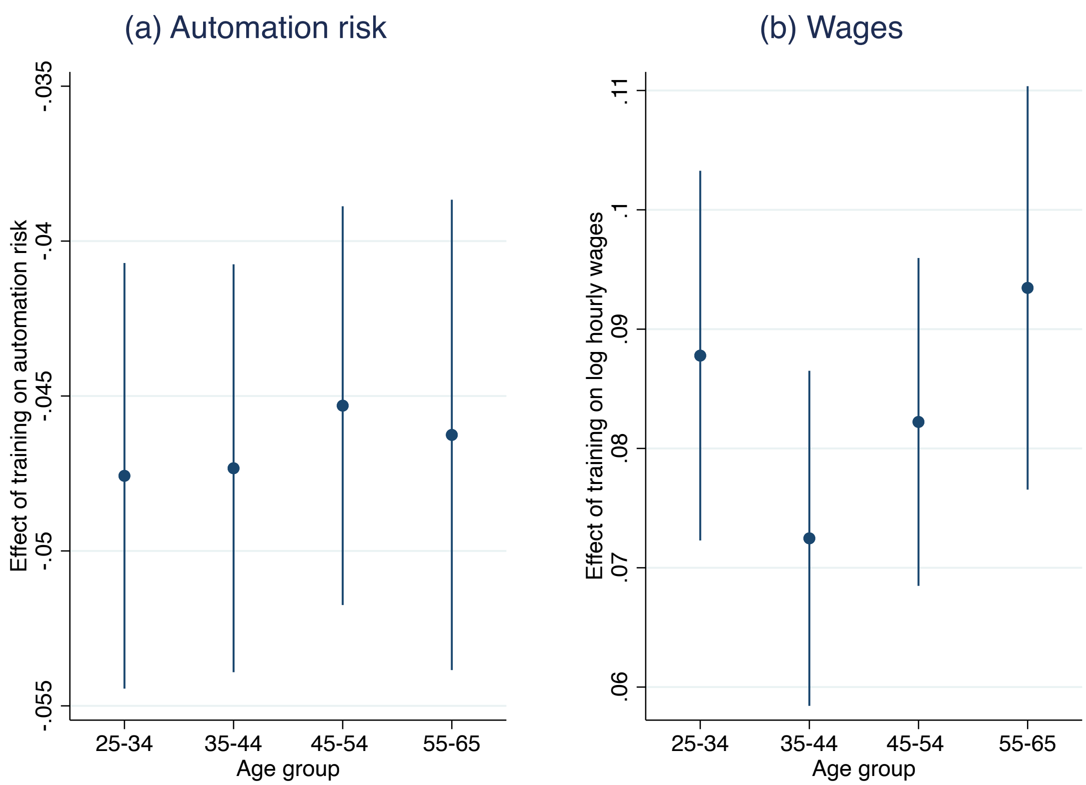
[35]See Table A.6 for the full regression results.

Figure 5: Training effects on automation and wages by country



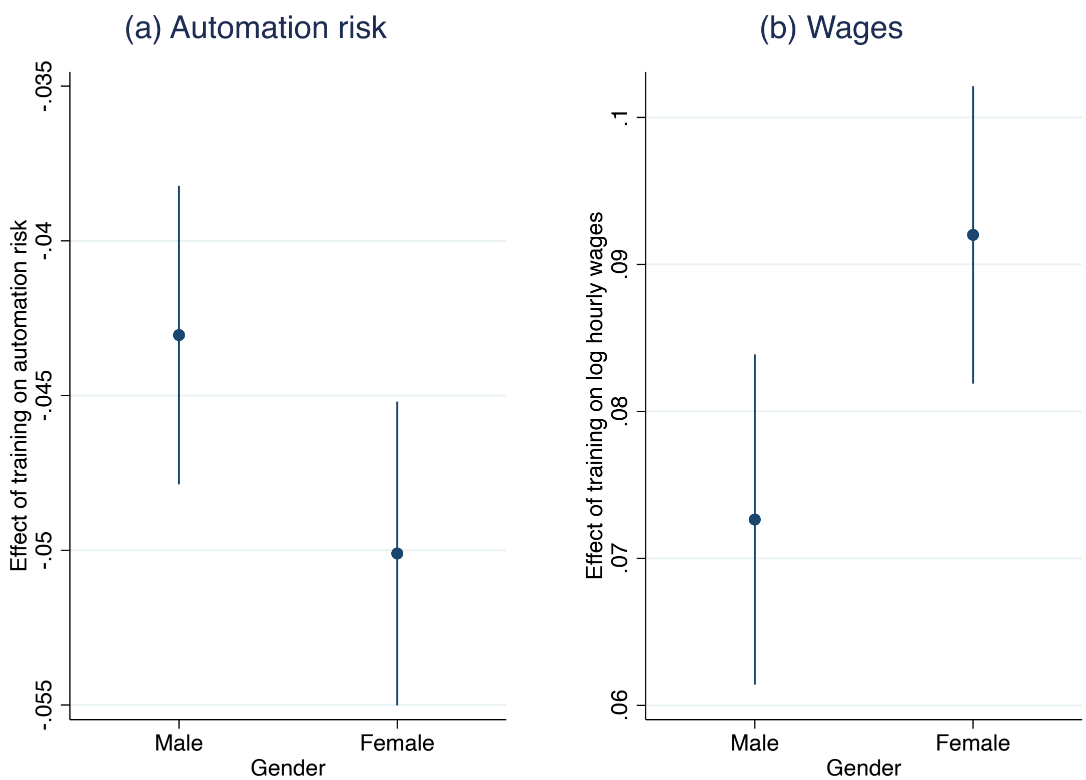
Notes: Figure plots the training coefficients from regressing automation risk or wages on training in our baseline specification (see column (5) of Table 2 and Table 3, respectively), separately by country. Least squares estimation with weights from entropy balancing. Dependent variable on the horizontal axis: automation risk index, ranging from 0 (indicating a low probability that a worker is fully automated) to 1 (indicating a high probability that a worker is fully automated); automation risk is predicted using items on task use at work from PIAAC, applying the automatability weights from Nedelkoska and Quintini (2018). Dependent variable on the vertical axis: log hourly wages. Sample: employees aged 25–65 years with information on automation risk and log hourly wages. 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 and variables used for entropy balancing: numeracy skills (standardized to unit standard deviation across countries), 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 (e.g, self-organized training or seminar participation), and firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+). Industry fixed effects at the two-digit ISIC level and occupation fixed effects at the two-digit ISCO level.

Figure 6: Training effects on automation and wages by age group



Notes: Figure plots the training coefficients and corresponding 95% confidence intervals from regressing automation risk or wages on training using our baseline specification (see columns (5) of Table 2 and Table 3) by age group. Least squares estimation with weights from entropy balancing. Dependent variable in Panel (a): automation risk index, ranging from 0 (indicating a low probability that a worker is fully automated) to 1 (indicating a high probability that a worker is fully automated); automation risk is predicted using items on task use at work from PIAAC, applying the automatability weights from Nedelkoska and Quintini (2018). Dependent variable in Panel (b): log hourly wages. Sample: employees aged 25–65 years with information on automation risk and log hourly wages. 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 and variables used for entropy balancing: numeracy skills (standardized to unit standard deviation across countries), 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 (e.g, self-organized training or seminar participation), and firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+). Industry fixed effects at the two-digit ISIC level and occupation fixed effects at the two-digit ISCO level. Confidence intervals based on robust standard errors.

Figure 7: Training effects on automation and wages by gender



Notes: Figure plots the training coefficients and corresponding 95% confidence intervals from regressing automation risk or wages on training using our baseline specification (see columns (5) of Table 2 and Table 3) by gender. Least squares estimation with weights from entropy balancing. Dependent variable in Panel (a): automation risk index, ranging from 0 (indicating a low probability that a worker is fully automated) to 1 (indicating a high probability that a worker is fully automated); automation risk is predicted using items on task use at work from PIAAC, applying the automatability weights from Nedelkoska and Quintini (2018). Dependent variable in Panel (b): log hourly wages. Sample: employees aged 25–65 years with information on automation risk and log hourly wages. 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 and variables used for entropy balancing: numeracy skills (standardized to unit standard deviation across countries), 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 (e.g, self-organized training or seminar participation), and firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+). Industry fixed effects at the two-digit ISIC level and occupation fixed effects at the two-digit ISCO level. Confidence intervals based on robust standard errors.

automation risk. This individual-level measure allows us to capture the heterogeneity in automation risk among workers within the same occupation.

We investigate the role of job training in adapting to evolving task requirements across 37 industrialized countries, including 17 European countries. To address the potential endogeneity of training participation, we apply entropy balancing on a rich set of worker and firm background characteristics, including numeracy skills as a control for unobserved ability. Moreover, we identify training effects just from within-country, within-industry, and within-occupation variation.

Our findings demonstrate that job training significantly reduces workers' automation risk. Workers who participate in job training experience a decrease in automation risk by 4.7 percentage points compared to their counterparts without training, which is equivalent to 10 percent of the mean automation risk in our sample. Furthermore, training participation is associated with higher wages, as workers with training earn approximately 8 percent higher wages.

The general pattern of results is similar across all 37 countries in our sample, indicating the widespread effectiveness of training in reducing automation risk and increasing wages. At the same time, the magnitude of the training effects is notably different across countries, suggesting the need for context-specific policies and interventions. We also show that training is similarly effective for both older and younger workers, suggesting that it is a powerful tool for developing skills that are complementary to new technologies, regardless of age. Additionally, female workers benefit particularly from training programs in reducing automation risk, indicating its potential to address gender-related disparities in the modern labor market.

Our study contributes to the existing literature by examining the role of job training in mitigating the negative consequences of technological change and ensuring workers' adaptability to evolving task requirements. By considering occupation fixed effects and controlling for selection into training using entropy balancing, we account for the most daunting threats to causal identification, which particularly plague cross-country studies that typically lack quasi-experimental variation in training.

Overall, our findings emphasize the importance of job training as a means to enhance workers' skills, reduce automation risk, and improve labor market outcomes. Policymakers and employers should prioritize investing in training programs to equip workers with the skills necessary to adapt to technological advancements and secure their future in an evolving labor market.

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Appendix A. Tables

Table A.1: Balancing table

Variable	(1) Training Mean/(SE)	(2) No Training Mean/(SE)	(3) No Training (Entropy Weighted) Mean/(SE)	Difference (1)-(2) P-value	Difference (1)-(3) P-value
Numeracy Skills	0.249	-0.228	0.249	0.000***	1.000
	(0.004)	(0.005)	(0.004)		
Share Age Group 25-34	0.281	0.263	0.281	0.000***	1.000
	(0.002)	(0.002)	(0.002)		
Share Age Group 35-44	0.295	0.270	0.295	0.000***	1.000
	(0.002)	(0.002)	(0.002)		
Share Age Group 45-54	0.266	0.263	0.266	0.298	1.000
	(0.002)	(0.002)	(0.002)		
Share Age Group 55-65	0.157	0.203	0.157	0.000***	1.000
	(0.002)	(0.002)	(0.002)		
Share Female	0.515	0.507	0.515	0.019**	1.000
	(0.002)	(0.002)	(0.002)		
Share Immigrant	0.154	0.156	0.154	0.450	1.000
	(0.002)	(0.002)	(0.002)		
Share Neither Parent Has Attained Upper Secondary Education	0.296	0.418	0.296	0.000***	1.000
	(0.002)	(0.002)	(0.002)		
Share At Least One Parent Has Attained Secondary and Post-Secondary Education	0.371	0.342	0.371	0.000***	1.000
	(0.002)	(0.002)	(0.002)		
Share At Least One Parent Has Attained Tertiary Education	0.293	0.182	0.293	0.000***	1.000
	(0.002)	(0.002)	(0.002)		
Share Has Children	0.170	0.186	0.170	0.000***	1.000
	(0.002)	(0.002)	(0.002)		
Share Full Time	0.876	0.805	0.876	0.000***	1.000
	(0.001)	(0.001)	(0.001)		
Training (Other)	0.043	0.078	0.043	0.000***	1.000
	(0.001)	(0.001)	(0.001)		
Share Firm Size 1 to 10 People	0.184	0.359	0.184	0.000***	1.000
	(0.002)	(0.002)	(0.002)		
Share Firm Size 11 to 50 People	0.299	0.298	0.299	0.720	1.000
	(0.002)	(0.002)	(0.002)		
Share Firm Size 51 to 250 People	0.264	0.194	0.264	0.000***	1.000
	(0.002)	(0.002)	(0.002)		
Share Firm Size 251 to 1000 People	0.142	0.086	0.142	0.000***	1.000
	(0.001)	(0.001)	(0.001)		
Share Firm Size More than 1000 People	0.105	0.050	0.105	0.000***	1.000
	(0.001)	(0.001)	(0.001)		

Notes: Balancing table showing covariate means and standard deviations (in parentheses) in the training group (column 1), the no-training group (column 2), and the no-training group after entropy weighting (column 3). Entropy balancing follows Hainmueller (2012). Covariates used for entropy balancing: numeracy skills (standardized to unit standard deviation across countries), age group in four categories (25–34, 35–44, 45–54, 55–65), gender, migration status, 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 (e.g, self-organized training or seminar participation), and firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+). Entropy balancing also includes fixed effects for countries, industries (two-digit ISIC level) and occupations (two-digit ISCO level) (not shown in the balancing table for expositional reasons).

Table A.2: Training and automation risk, unrestricted sample

Automation Risk	(1)	(2)	(3)	(4)	(5)
Job Training	-0.0829***	-0.0556***	-0.0508***	-0.0458***	-0.0460***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0011)
Numeracy Skills			-0.0219***	-0.0166***	-0.0126***
			(0.0009)	(0.0009)	(0.0007)
Observations	101949	101949	101949	101949	101949
R^2	0.11	0.21	0.22	0.23	0.20
Country FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	Yes	Yes
Entropy balancing	No	No	No	No	Yes

Notes: Table replicates Table 2 when not restricting the sample to individuals with non-missing wages. Ordinary least squares estimation in columns (1)-(4), least squares estimation with weights from entropy balancing in column (5). Dependent variable: automation risk index, ranging from 0 (indicating a low probability that a worker is fully automated) to 1 (indicating a high probability that a worker is fully automated); automation risk is predicted using items on task use at work from PIAAC, applying the automatability weights from Nedelkoska and Quintini (2018). 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 (standardized to unit standard deviation across countries), 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 (e.g, self-organized training or seminar participation), and firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+). Industry fixed effects at the two-digit ISIC level and occupation fixed effects at the two-digit ISCO level. All regressions also control for country fixed effects. All control variables were used for the entropy balancing in column (5). R^2 refers to within-country R^2. Robust standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.3: Training and automation risk in 2012 and 2017, United States

	(1) Automation Risk (2012 and 2017)	(2) Automation Risk (2012)	(3) Automation Risk (2017)
Job training	-0.0288***	-0.0223***	-0.0404***
	(0.0053)	(0.0067)	(0.0086)
Numeracy Skills	0.0034	0.0010	0.0056
	(0.0035)	(0.0045)	(0.0056)
Observations	4073	2430	1643
R^2	0.27	0.31	0.26
Country FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Entropy Balancing	Yes	Yes	Yes

Notes: Least squares estimation with weights from entropy balancing in all specifications. Dependent variable: automation risk index, ranging from 0 (indicating a low probability that a worker is fully automated) to 1 (indicating a high probability that a worker is fully automated); automation risk is predicted using items on task use at work from PIAAC, applying the automatability weights from Nedelkoska and Quintini (2018). Sample: employees aged 25–65 years in the United States, survey waves 2012 and 2017 in column (1), survey wave 2012 in column (2), and survey wave 2017 in column (3). 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 and variables used for entropy balancing: numeracy skills (standardized to unit standard deviation across countries), 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 (e.g, self-organized training or seminar participation), and firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+). Industry fixed effects at the two-digit ISIC level and occupation fixed effects at the two-digit ISCO level. R^2 refers to within-country R^2. Robust standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.4: Training and wages, unrestricted sample

Log Wages	(1)	(2)	(3)	(4)	(5)
Job Training	0.2085***	0.1339***	0.1133***	0.1038***	0.0827***
	(0.0044)	(0.0042)	(0.0042)	(0.0041)	(0.0025)
Numeracy Skills			0.0971***	0.0878***	0.0713***
			(0.0025)	(0.0025)	(0.0017)
Observations	92008	92008	92008	92008	92008
R^2	0.16	0.26	0.29	0.34	0.35
Country FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	Yes	Yes
Entropy balancing	No	No	No	No	Yes

Notes: Table replicates Table 3 when not restricting the sample to individuals with information on automation risk. Ordinary least squares estimation in columns (1)-(4), least squares estimation with weights from entropy balancing in column (5). Dependent variable: 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. Controls: numeracy skills (standardized to unit standard deviation across countries), 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 (e.g, self-organized training or seminar participation), and firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+). Industry fixed effects at the two-digit ISIC level and occupation fixed effects at the two-digit ISCO level. All regressions also control for country fixed effects. All control variables were used for the entropy balancing in column (5). R^2 refers to within-country R^2. Robust standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.5: Training and digital skills

Digital Skills					
Job Training	0.2999***	0.2116***	0.0879***	0.0770***	0.0509***
	(0.0100)	(0.0098)	(0.0076)	(0.0074)	(0.0045)
Numeracy Skills			0.8213***	0.7778***	0.7762***
			(0.0048)	(0.0048)	(0.0032)
Observations	72180	72180	72180	72180	72180
R^2	0.08	0.14	0.54	0.58	0.59
Country FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes
Entropy Balancing	No	No	No	No	Yes

Notes: Ordinary least squares estimation in columns (1)-(4), least squares estimation with weights from entropy balancing in column (5). Dependent variable: digital skills standardized to standard deviation 1 across countries. Sample: employees aged 25–65 years with information on digital skills, automation risk, and log hourly wages. 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 (standardized to unit standard deviation across countries), 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 (e.g, self-organized training or seminar participation), and firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+). Industry fixed effects at the two-digit ISIC level and occupation fixed effects at the two-digit ISCO level. All regressions also control for country fixed effects. All control variables were used for the entropy balancing in column (5). R^2 refers to within-country R^2. Robust standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.6: Effectiveness of training by age

	(1) Automation Risk	(2) Log Wages
Job Training	-0.0476***	0.0878***
	(0.0035)	(0.0079)
× Age 35-44	0.0002	-0.0153
	(0.0049)	(0.0107)
× Age 45-54	0.0023	-0.0056
	(0.0048)	(0.0106)
× Age 55 plus	0.0013	0.0057
	(0.0052)	(0.0117)
Age 35-44	-0.0213***	0.1509***
	(0.0045)	(0.0099)
Age 45-54	-0.0202***	0.1925***
	(0.0045)	(0.0099)
Age 55 plus	-0.0127***	0.1807***
	(0.0047)	(0.0108)
Numeracy Skills	-0.0130***	0.0722***
	(0.0012)	(0.0026)
Observations	91470	91470
R^2	0.20	0.35
Country FE	Yes	Yes
Occupation FE		
Controls	Yes	Yes

Notes: Least squares estimation with weights from entropy balancing in both columns. Dependent variable in column (1): automation risk index, ranging from 0 (indicating a low probability that a worker is fully automated) to 1 (indicating a high probability that a worker is fully automated); automation risk is predicted using items on task use at work from PIAAC, applying the automatability weights from Nedelkoska and Quintini (2018). Depenent variable in column (2): log hourly wages. Sample: employees aged 25–65 years with information on automation risk and log hourly wages. Reference for the main effect of job training is the youngest age group (25-34). 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 (standardized to unit standard deviation across countries), 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 (e.g, self-organized training or seminar participation), and firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+). Industry fixed effects at the two-digit ISIC level and occupation fixed effects at the two-digit ISCO level. All regressions also control for country fixed effects. All control variables were used for the entropy balancing in column (5). R^2 refers to within-country R^2. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

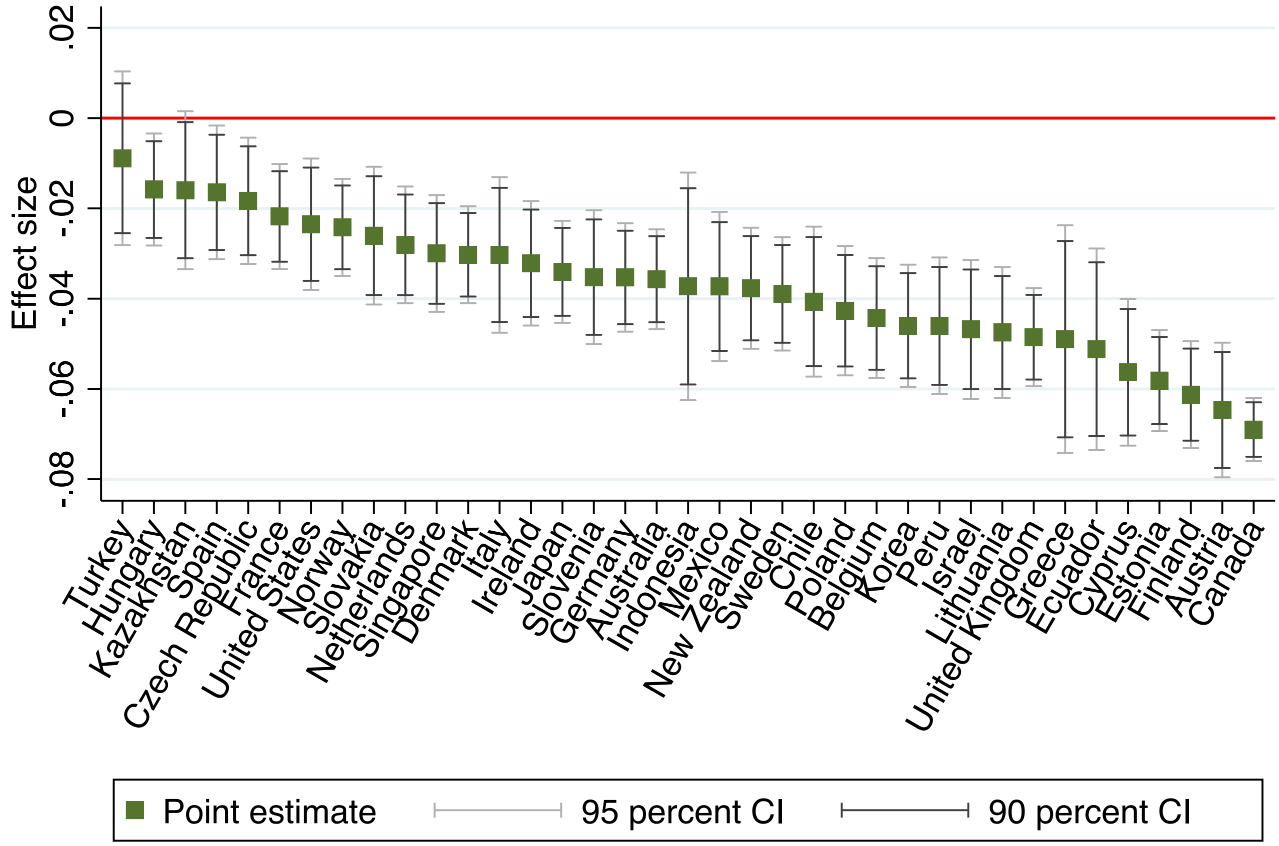
Table A.7: Effectiveness of training by gender

	(1) Automation Risk	(2) Log Wages
Job Training	-0.0430***	0.0726***
	(0.0025)	(0.0057)
× Female	-0.0071**	0.0194**
	(0.0034)	(0.0074)
Female	0.0213***	-0.1453***
	(0.0035)	(0.0077)
Numeracy Skills	-0.0131***	0.0723***
	(0.0012)	(0.0026)
Observations	91470	91470
R^2	0.20	0.35
Country FE	Yes	Yes
Occupation FE	Yes	Yes
Controls	Yes	Yes
Entropy balancing	Yes	Yes

Notes: Least squares estimation with weights from entropy balancing in both columns. Dependent variable in column (1): automation risk index, ranging from 0 (indicating a low probability that a worker is fully automated) to 1 (indicating a high probability that a worker is fully automated); automation risk is predicted using items on task use at work from PIAAC, applying the automatability weights from Nedelkoska and Quintini (2018). Depenent variable in column (2): log hourly wages. Sample: employees aged 25–65 years with information on automation risk and log hourly wages. Reference for the main effect of job training are male workers. 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 (standardized to unit standard deviation across countries), 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 (e.g, self-organized training or seminar participation), and firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+). Industry fixed effects at the two-digit ISIC level and occupation fixed effects at the two-digit ISCO level. All regressions also control for country fixed effects. All control variables were used for the entropy balancing in column (5). R^2 refers to within-country R^2. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

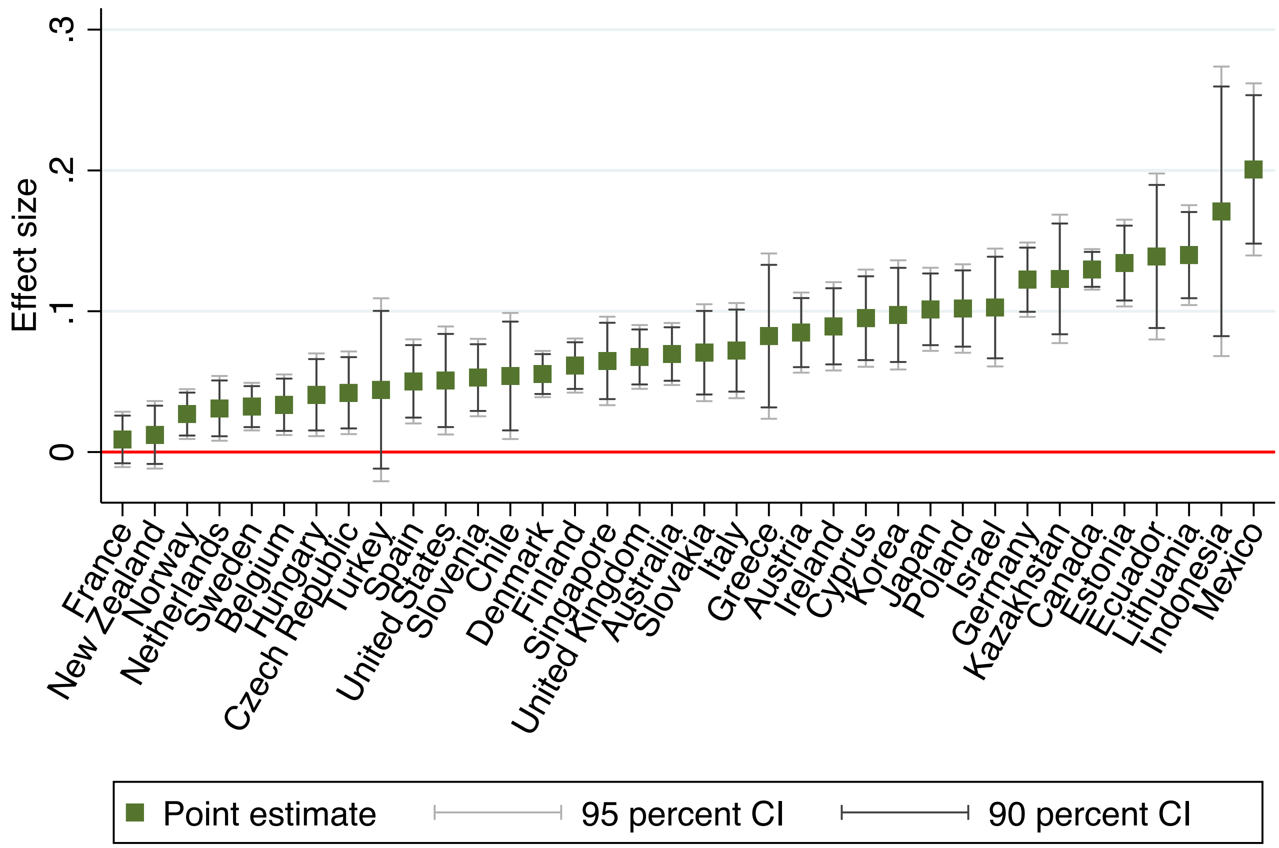
Appendix B. Figures

Figure B.1: Training and automation risk by country



Notes: Figure shows the effect of training on automation risk separately for each PIAAC country. Least squares estimation with weights from entropy balancing. Dependent variable: automation risk index, ranging from 0 (indicating a low probability that a worker is fully automated) to 1 (indicating a high probability that a worker is fully automated); automation risk is predicted using items on task use at work from PIAAC, applying the automatability weights from Nedelkoska and Quintini (2018). Sample: employees aged 25–65 years with information on automation risk and log hourly wages. 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 and variables used for entropy balancing: numeracy skills (standardized to unit standard deviation across countries), 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 (e.g, self-organized training or seminar participation), and firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+). Industry fixed effects at the two-digit ISIC level and occupation fixed effects at the two-digit ISCO level. Confidence intervals based on robust standard errors.

Figure B.2: Training effects on wages by country



Notes: Figure shows the effect of training on wages separately for each PIAAC country. Least squares estimation with weights from entropy balancing. Dependent variable: log hourly wages. Sample: employees aged 25–65 years with information on automation risk and log hourly wages. 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 and variables used for entropy balancing: numeracy skills (standardized to unit standard deviation across countries), 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 (e.g, self-organized training or seminar participation), and firm size measured by number of employees in five categories (1–10, 11–50, 51–250, 251–1000, 1000+). Industry fixed effects at the two-digit ISIC level and occupation fixed effects at the two-digit ISCO level. Confidence intervals based on robust standard errors.