Highlights

The effect of automation technology on workers' training participation*

Pascal Heß, Simon Janssen, Ute Leber

- We combine detailed survey data on further training and the robot exposure measure from Webb (2019) to study the influence of automation technology on workers' training participation.
- Workers who are exposed to robots participate less often in training than those who are not exposed to it.
- Firms' willingness to support further training explains the lion share of the training gap.
- Highly exposed workers do particularly not train in fields that are correlated with future promotion.

The effect of automation technology on workers' training participation

Pascal Heß[a,*], Simon Janssen[a], Ute Leber[a]

[a]*Institute for Employment Research (IAB),*

Abstract

We use detailed survey data to study the influence of automation technology on workers' training participation. We find that workers who are exposed to substitution by automation are 15 percentage points less likely to participate in training than those who are not exposed to it. The gap is particularly pronounced for medium skilled and male workers, and largely driven by the lack of ICT training and training for soft-skills. We show that exposed workers select into firms that fare less generous training policies in general and for the individual worker. A detailed decomposition of the training gap reveals that the firms' financial and non-financial training support explains more than 50 percent of the training gap. In contrast, education, job, and firm characteristics only explain a small fraction of the gap.

Keywords: further training, technological change, firm support

JEL: : I20, M53, O33

[⋆]The authors gratefully acknowledge funding from the German Research Foundation (AN 1071/3-1).

[*]Corresponding author

1. Introduction

A large literature documents that technological change had a substantial impact on labor markets.[1] Particularly, leading automation technologies such as industrial robots have changed the wage and employment structure (e.g., Acemoglu, 2015; Acemoglu and Restrepo, 2017a,b, 2018; Dauth et al., 2021), and emerging technologies such as artificial intelligence (AI) might even disrupt labor markets more substantially in the future.[2] Therefore, many scholars and practitioners emphasize the growing importance of on-the-job training and life-long learning to prevent disruptive effects of technological change, and governments across the world invest heavily in training policies (OECD, 2019). For example, in 2019 the German government spent approximately 2.1 billion Euros to subsidize further training.

However, evidence on the relationship between automation and on-the-job training is scarce. Nedelkoska and Quintini (2018) find a large negative training gap for workers who are exposed to automation, but the results do not provide explanations for the lower training rate of affected workers. Instead, Innocenti and Golin (2022) show that workers who fear automation have a larger intention to participate in training.[3] Yet, firms — not workers

[1] See Autor (2013); Acemoglu and Autor (2011); Autor et al. (2003); Goos and Manning (2007); Goos et al. (2014); Michaels et al. (2014); Spitz-Oener (2006) for further evidence on the effects of technological change on labor markets.

[2] For example, Agrawal et al. (2019) argue that AI has particularly improved the quality of predictions that are involved in the decision making of many high-skilled workers.

[3] Similarly, Acemoglu (1997) argues that workers are more willing to invest in training if they expect many firms to innovate, because their returns to training increase with firms' innovation.

— initiate and finance most on-the-job training[4], and firms have different incentives than workers. On one hand, firms might invest in training to facilitate the implementation of new technologies or retain firm-specific human capital.[5] On the other hand, firms may refrain from investing in the training for workers whom they eventually substitute by technology. Without understanding whether and how technological change influences workers' training participation, designing efficient training policies that are tailored towards the most affected workers is difficult.

This paper sheds light on the relation between automation technology and training by analyzing whether and why workers whose jobs are at a high risk of being changed or automated by industrial robots invest more or less in training. Therefore, we combine the adult survey of the National Educational Panel Study (NEPS) with a novel technology exposure measure by Webb (2019).

The NEPS data contains detailed survey information about workers' demographics, firm characteristics, labor market careers, and — most importantly — training participation. More specifically, we have information about the training content, the training frequency and duration, and we know

[4]Booth and Bryan (2007) report that around 90 percent of all work-related training is firm-financed in Britain. Our data suggest a similar incidence of around 85 percent for Germany.

[5]A number of studies indeed show that technology implementation correlates with training investments on the firm level (e.g., Sieben et al., 2009; Bresnahan et al., 2002). Dixon et al. (2021) show that firms adopting robots train assembly workers to take over tasks from their former, laid-off managers. Others show that technology implementation leads to more job rotation (e.g., Caroli and Van Reenen, 2001).

whether and how firms support their workers' training. The technology exposure index of Webb (2019) allows us to identify the tasks compatible with the capabilities of current robot technology. It relies on the overlap between job task descriptions and patent applications to construct a measure of technology exposure on the occupational level.

We find a large negative training gap for workers who are strongly exposed to robot technology. Even if we account for a huge set of observable characteristics (i.e., worker, job, and firm characteristics) and unobserved worker heterogeneity, the training gap still amounts to 4.2 percentage points. This gap is almost as large as the conditional on-the-job-training gap between college- and non-college educated workers (Görlitz and Tamm, 2016b).

The training gap is particularly pronounced among males and medium skilled workers with an apprenticeship degree, and we find the strongest differences for training courses in information and communication technologies (ICT) and soft and business skills. Thus, workers who are exposed to robot technology lack training for skills that showed large and growing wage returns throughout the last decade and might be particularly useful for workers who have to change occupations or firms (e.g., Falck et al., 2021; Deming, 2017; Deming and Kahn, 2018).

Second, we exploit the detailed information of our data source to identify the most important factors that account for the training gap of workers who are exposed to robot technology. A detailed decomposition of the training gap reveals that education and other worker and job characteristics only account for less than 20 percent of the overall training gap. Common firm characteristics (e.g., firm size and industry) even only account for less than

5 percent of it. In contrast, the firms' training policy accounts for the lion share of 50 percent of the overall training gap. In more detail, we find that the firms' individual training support accounts for approximately 35 percent of the overall training gap, and the firms' general training support for another 15 percent of the training gap.

As Webb's measure is on the occupational level, our individual fixed effects models identify the training effect from variation of occupational switchers. More detailed analyses show that the effect is driven by workers who switch from high to lower robot exposure occupations and experience a quick and long-lasting surge in training participation. Workers who switch from high to low exposure experience a long lasting surge in training participation while workers who switch from low to high exposure experience a decline in their training participation, although their decline is smaller and not as long lasting. Nevertheless, these results contradict that the training gap is explained by self-selection of low-skilled workers in jobs with high robot exposure.

Overall, our results show that workers who are exposed to automation technology train significantly less than other workers do, and the lack of training support of their firms is the most important determinant for their low training participation — even within firms. These results suggest that firms have low incentives to support the training participation of workers who are working with or are likely to be replaced by modern technologies. In either case, the firm's expected returns to further training for workers who are exposed to automation technology are lower than the expected costs. At the same time, workers who are exposed to automation technology appear not to compensate the lack of their firms' training support by own investments in further training. Cavounidis and Lang (2020) formally show that this under-investment might be the result of a mix of a worker's credit constraints and low returns for new skills at the current job.

Our results contribute to at least two strands of the literature. First, we contribute to the literature on technological change. While previous studies have analyzed the wage and employment effects of technological change in general (Acemoglu and Restrepo, 2018) and robot technology in particular (e.g Acemoglu and Restrepo, 2017a; Dixon et al., 2021; Dauth et al., 2021), our study shows that automation has not only induced a polarization of the wage and employment structure, but is also related to a polarization of workers' training participation. Thus, our results provide evidence for a channel through which technological change translates into a polarization of wages and employment. Moreover, if workers who are most likely to be exposed to the negative consequences of technological change invest less in training and retraining than other workers, the polarization of workers' training participation may reinforce the polarization of the wage and employment structure in the long run.[6]

Second, we contribute to the literature on the determinants of further training. Previous studies have largely focused on the training gap between

[6]This claim holds for positive wage and employment returns to training. While there are several papers that find positive effects of training on wages, e.g. Görlitz and Tamm (2016a) and Schwerdt et al. (2012) find no effects on wages or employment for German voucher programs. Schmidpeter and Winter-Ebmer (2021) find that training improves the re-employment probabilities once workers have become unemployed.

low and highly educated workers (see e.g. Fouarge et al., 2013; Hidalgo et al., 2014; Kramer and Tamm, 2018). Instead, we show a large heterogeneity in the training participation of workers who have the same level of education but sorted into occupations that differ in their risk of automation. The automation training gap is almost as large as the gap between low and high skilled workers (Görlitz and Tamm, 2016b), and the results suggest that firms' financial and non-financial training support is the most important determinant for the gap.

As a result, we contribute to the literature on work-related further training by showing that firms act as gatekeeper if they expect potential returns to further training to be low. As most work-related training is firm-financed (Booth and Bryan, 2007), and previous results suggest that workers want to train when they fear automation (Innocenti and Golin, 2022), our results imply that firms prevent some workers from training by not supporting their training financially or non-financially. Our results corroborate the findings from, e.g., Görlitz and Tamm (2017) or van den Berg et al. (2020) that employees are not the primary decision maker.[7]

The remainder of this study is structured as follows. Section 2 describes our data and variables, and provides first descriptive evidence. Section 3 presents the methods, while Section 4 presents our results. Section 5 concludes.

[7]Both Görlitz and Tamm (2017) and van den Berg et al. (2020) provide information to employees about different training programs. Both programs increase the awareness of the programs, but not the take-up rate. However, van den Berg et al. (2020) find small increases in the take-up rate of not-subsidized training.

2. Data and variables

This section describes our data and variables. The first subsection describes the adult starting cohort of the National Educational Panel Study (NEPS) containing training measures and variables on individual worker characteristics and firms. The second subsection describes the technology exposure data by Webb (2019) that we use to measure the workers' exposure to automation by robots.

2.1. The National Educational Panel Study (NEPS)

The adult starting cohort of the NEPS is a longitudinal study that surveys educational and labor market trajectories of about $10,000$ adults between 2009 and 2017. We restrict our data to working individuals who do not undergo a vocational training at the time of the interview and are between 25 and 60 years old. Finally, we delete all observations with missing values in our main variables of interest. Theses restrictions leave us with $43,779$ observations of $9,594$ individuals.

Our dependent variables measure the workers' participation in non-formal training courses that are labor-related and occur throughout the workers' employment spells.[8] In more detail, our main dependent variable is a dummy variable indicating whether a worker participated in at least one training course throughout the last 12 months before the interview. In addition, we analyse the frequency and duration of training to uncover effects at the

[8] We exclude training that is not employment-related, informal training that is not organized in courses or seminars, formal training such as apprenticeship training, and training courses that occur during periods of non-employment.

intensive margin. Finally we analyze the effects for different fields of training (e.g., ICT or soft skills training), and we provide evidence for the workers' formal training participation.

In addition to our training measures the NEPS contains a wide variety of individual and firm characteristics that have a strong influence on the training participation of workers according to many previous studies (e.g., Nelen and de Grip, 2009; Kramer and Tamm, 2018; Tamm, 2018). First, we have detailed information about the workers' gender, migration background, education, part-time employment, work experience, tenure, and wages. Second, in contrast to virtually all other large panel data sources, we have detailed information about their firms financial and non-financial training support. In more detail, we know whether the workers' firms have an official training agreement, an official unit responsible for on-the-job training, and we know whether a firm has offered the individual worker financial or non-financial training support (see Appendix C for the detailed survey questions. More detailed descriptions of the variables and descriptive statistics of all variables appear in A.9.

2.2. Exposure to robot automation

The main goal of our study is to analyze the influence of robot exposure on workers' training participation. To measure robot exposure, we use a new index by Webb (2019) quantifying the share of tasks for each occupation that might be performed by robots. To create this measure, Webb (2019) combined information from patent texts with job descriptions from O*Net. He used both data sources to find verb-noun pairs indicating an overlap between occupational tasks and the capabilities of new robot technologies according to patent texts. Thus, the measure considers occupations with a larger fraction of overlapping tasks as more exposed to robot technology than those with a lower fraction.

Many recent papers have used and validated Webb's measure for technology exposure (e.g., Acemoglu et al., 2020). For example, Webb (2019) himself finds displacement effects of robot exposure on wages and employment that are similar to those found in studies using data from the International Federation of Robotics (IFR) (e.g., Acemoglu and Restrepo, 2018). Acemoglu et al. (2020) validated Webb's measure by comparing it with a variety of other technology exposure measures.

As Webb created the robot exposure measure for U.S. occupations, we had to use a crosswalk between the Standard Occupational Classification (SOC) from the U.S. and the German classification of occupations from 2010 (see Appendix B). One concern might be that the tasks of German occupations differ from the tasks of U.S. occupations. Therefore, Appendix D replicates our analysis with an index from Dengler et al. (2014). This index measures to which extend automation technology can replace occupational tasks. Dengler et al. (2014) designed the measure explicitly for the German occupational structure using the German task data base BERUFENET. Although the BERUFENET measure does not exclusively focus on robots, it is reassuring that both measures significantly correlate (0.34).[9]

Webb's measure assigns each occupation to its exposure percentile. For

[9] The measure by Dengler et al. (2014) does not directly relate to industrial robots, and tasks are classified based on the judgment by a small set of experts. Thus, we decided to remain with Webb's measure for our main analysis.

example, a value of 50 indicates that the occupation is the median occupation of being likely to be automated by robots. A value of 100 or 0 indicates that the occupation is among the most likely or the least likely occupation to be automated by robots. Table 1 shows the sample composition along the distribution of robot exposure in our sample. In more detail, we compare the shares of gender, education, and age groups within quartiles for the first NEPS wave in 2009.

Table 1: Sample statistics along the robot exposure distribution

	$< p25$	$[p25; p50)$	$[p50; p75)$	$\geq p75$
Gender				
Men	.455	.449	.401	.653
Women	.545	.551	.599	.347
Education				
No Vocational Degree	.028	.065	.073	.146
Apprenticeship Degree	.364	.604	.789	.788
University Degree	.608	.331	.138	.066
Age				
Born 1980 and above	.162	.171	.156	.152
Born 1970 - 1979	.203	.174	.187	.189
Born 1960 - 1969	.254	.266	.287	.261
Born 1950 - 1959	.381	.389	.371	.398
Observations	745	753	820	815

This Table shows the sample composition for gender, education, and age for different quartiles of the distribution of Webb(2019)'s robot exposure measure for the first wave. Source: NEPS-SC6 12.1.0, own calculation.

Table 1 shows that women are working in fewer robot exposed jobs than men do. For example, 54.5 percent of all workers in occupations that are below 25^{th} percentile in the Webb measure are women, but only 34.7% in occupations that are above the 75^{th} percentile. A great share of workers that are highly exposed to robots are men. This holds true for workers without a vocational degree or an apprenticeship degree. While workers without vocational degree are disproportionately often working in jobs with very high robot exposure ($\geq p75$), there are only very few workers with university degree. Surprisingly, we do not find any ageing effect on whether or not a worker is highly exposed to robots. Table A.8 replicates Table 1 using the latest wave (12) instead of the first to show that the composition of the workforce in our sample has not changed throughout the observation period. The results are indeed qualitatively the same.

Figure 1 shows the distribution of robot exposure across industries relative to the size of the industries in our data. The y-axis shows the number of observations in each industry, and the x-axis the average robot exposure scores within each industry. The figure reveals that the average robot exposure is relatively high in the manufacturing sector—the largest sector in our data. In contrast, the sectors of education, public administration, and financial services have on average lower robot exposure scores. The wholesale and retail sector lie in the middle of the exposure distribution, and a number of small industries have on average even larger exposure scores than the manufacturing sector. For example, the relatively small sector of professional cleaning services has an average exposure score of 65, because the innovation of robot technology for cleaning has accelerated throughout recent years, i.e., the robot technology cleaning surfaces of large buildings (Zhang et al., 2007).

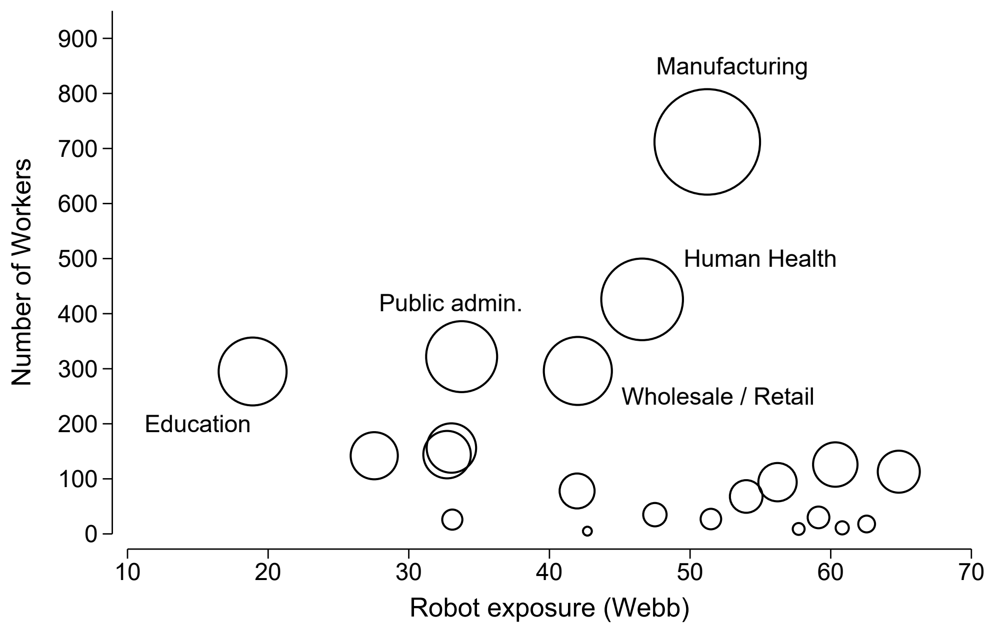

Figure 1: Distribution of robot exposure across industries

The Figure shows the distribution of robot exposure across industries. Bubbles indicate the number of workers where a larger bubble means more workers. The five largest industries' names are shown in the figure. Source: NEPS-SC6 12.1.0, own calculation.

3. Methods

A large number of observable and unobservable characteristics are likely to influence both the workers' training participation and their exposure to robot technology. Unfortunately, robot exposure is a function of occupational tasks, and workers do not tend to choose their jobs randomly. As a result, finding quasi-experimental variation to identify the causal effect of robot exposure on workers training participation is very difficult, if not impossible.

Therefore, we have to rely on panel data estimators and control variables to capture as many observable and unobservable confounding factors as possible.

To do so, we regress the workers' training participation on Webb's robot exposure according to the following equation:

$$T_{it} = \delta Robot_{it} + Job_{it}\beta_1 + Firm_{it}\beta_2 + Individual_i\beta_3 + \mu_i + \lambda_t + \epsilon_{it} \qquad (1)$$

The dependent variable T_{it} measures, first, whether workers undertook at least one training course throughout the last 12 months. Second, T_{it} measures training intensity, e.g., hours in training or number of training. Third, T_{it} measures special types of training, e.g., IT training or soft/business skill training. Fourth, in one specification T_{it} measures formal further training—that is, trainees receive a diploma afterwards—instead of non-formal further training. The main explanatory variable $Robot_{it}$ is Webb's robot exposure score, and δ is our main coefficient of interest.

In this paper, we use both a continuous and a dichotomous version of the robot exposure measure. Webb (2019) uses the continuous measure throughout his analyses, where each occupation's score equals its percentile in the distribution of robot exposure. The dummy version of the variable equals to 1 if an occupation is above the $70th$ percentile, and 0 otherwise.

Variables Job_{it} and $Firm_{it}$ comprise several job and firm characteristics that are not directly related to a firm's training policy. Job_{it} displays a set of time-varying job characteristics including dummy variables for part-time and public employment, a quadratic function for experience, and a categorical variable for working hours. $Firm_{it}$ contains industry fixed effects on the one-digit level and a categorical variable for firm size. $Individual_i$ contains time-constant individual characteristics such as education, gender, migration background and year of birth. We leave $Indiviual_i$ out if we use individual worker fixed effects. μ_i displays individual worker fixed effect to capture time-constant unobserved heterogeneity on the worker level , λ_t are time fixed effects, and ϵ_{it} is the error term. Standard errors are clustered at the individual level.

4. Results

This section presents the results of our paper in five subsections. The first subsection shows our main results. The second subsection presents heterogeneous effects for different groups of workers. The third subsection analyzes the effects for different training contents, the fourth one for formal training. The fifth subsection shows results from a decomposition analysis.

4.1. Main results

For our sample, Figure 2 shows the relationship between workers' training participation on the y-axis and the percentiles of robot exposure on the x-axis.

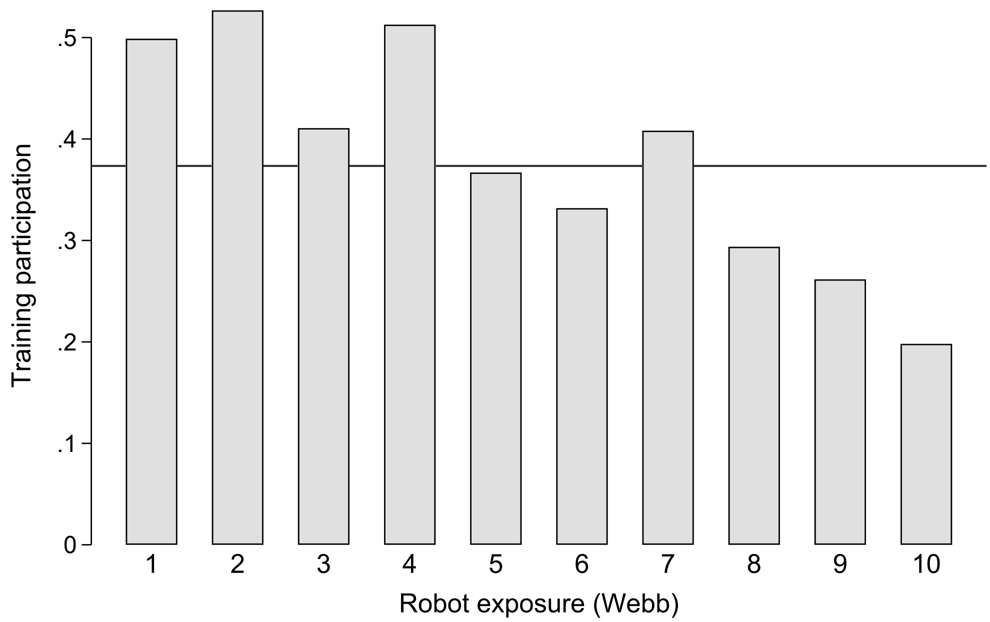

Figure 2: Relationship between robot exposure and training.

The Figure shows the training participation rate along the robot exposure distribution. The horizontal line indicates the sample average training participation across all waves. Source: NEPS-SC6 12.1.0, own calculation.

The figure reveals that specifically workers who are highly exposed to substitution by robot technology train on average substantially less than those who are less exposed to it. More specifically, workers below the 70^{th} percentile of robot exposure have an average rate of training participation that is close to the mean training participation rate of approximately 30 percent or substantially above (e.g., approximately 40 percent). In contrast, workers in the highest percentiles of robot exposure (i.e., above the 70^{th}

percentile) have substantially lower participation rates of less than 25 percent on average.

To be able to quantify the visual correlation from Figure 2, Table 2 shows a set of results from regression equation (1). Panel A of Table 2 displays the results from a specification with the continuous measure for robot exposure, and Panel B displays the training gap between workers in jobs with high robot exposure (i.e., above the $70th$ percentile) and lower robot exposure.

Table 2: Effect of robot exposure on training participation

	Dependent variable: Training participation				
	I	II	III	IV	V
Panel A					
Robot exposure	-0.0028***	-0.0022***	-0.0021***	-0.0010***	-0.0006**
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0003)
R^2	0.033	0.039	0.041	0.015	0.019
Panel B					
High robot exposure	-0.1527***	-0.1205***	-0.1093***	-0.0603***	-0.0420***
	(0.0069)	(0.0073)	(0.0075)	(0.0141)	(0.0144)
R^2	0.027	0.036	0.039	0.015	0.019
Education	No	Yes	Yes	No	No
Individual controls	No	No	Yes	No	No
Individual FE	No	No	No	Yes	Yes
Job Characteristics	No	No	No	No	Yes
Firm Characteristics	No	No	No	No	Yes
Observations	43779	43779	43779	43779	43779

Dependent variable: training participation (yes/no). Column I shows results for an OLS version of Equation 1 without individual fixed effects and other controls. Column II includes Education. Column III includes Education and other Individual controls (gender, migration background, age). Columns IV and V use individual fixed effects as specified in Equation (1). Column IV shows results without Job and Firm Characteristics. Column V shows results with Job and Firm Characteristics. All regressions include time fixed effects. Standard errors in parentheses are clustered on the individual level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Source: NEPS-SC6 12.1.0, own calculation.

Column I shows the raw OLS results containing only year dummies to control for non-linear time trends. The coefficient estimate for robot exposure is -0.028, and it is precisely estimated at the one percent level. Thus, a

10 point increase in the percentile of robot exposure is associated with a reduced training participation of approximately three percentage points. The training gap between those with high and low levels of robot exposure is approximately 15 percentage points. In other words, workers who are strongly exposed to substitution by robot technology train approximately 50 percent less than the average worker.

Column II additionally accounts for education. Previous literature shows that low educated workers on average train less than high educated workers (e.g. Fouarge et al., 2013; Bassanini et al., 2007). As low educated workers are also more likely to work in occupations with higher robot exposure, the negative effect of Column I might be the consequence of low educated workers self-selecting into occupations with higher robot exposure. However, the coefficient estimate for the continuous measure in Column II is still -0.022 and the training gap between high and low exposed workers' remains at 12 percentage points. These results suggest that educational differences only account for a small share of the training gap. Similarly, accounting for time-constant individual worker characteristics, such as gender and migration status, does not change the results substantially.

In contrast, if we account for unobserved time-constant heterogeneity by adding individual worker fixed-effects the effects declines by more than half to approximately 1 percentage point for the continuous measure and 6 percentage points for the training gap between low and highly exposed workers.[10] Although unobserved heterogeneity reduces the effect, we still find a

[10]This fixed effects regression does not control for education and individual characteristics, because these variables are time-constant.

sizable gap. Adding job and firm characteristics further reduces the absolute value of the coefficient estimates, but the results are precisely estimated at conventional levels. A training gap of approximately 4 percentage points is economically significant. First, the training gap amounts to 12 percent of the average training participation. Second, the training gap is approximately half as large as the unconditional training gap between high- and medium- or medium- and low- skilled workers in Germany (Kramer and Tamm, 2018).

Our fixed-effects specifications identify the effect from variation of job switchers, because robot exposure is measured on the occupational level. However, workers tend to train more upon jobs changes, because they have to acquire new skills. Thus, if the majority of workers switches from jobs with high robot exposure to jobs with low robot exposure, we might simply measure an artifact that arises because workers train more when they switch jobs.

Therefore, Figure 3 analyzes the training pattern of job switchers over time and distinguishes between occupational switchers who switch from high to low robot exposure, and vice versa. The Figure shows the average training participation of job switchers relative to the time of their switch ($t = 0$). The time ranges from two years before the switch, to three years and more after the switch. It is visually evident that both groups of switchers develop in a similar way before they switch occupations, but switchers who initially work in highly exposed occupations train on average less often than those who initially work in low exposed occupations do.

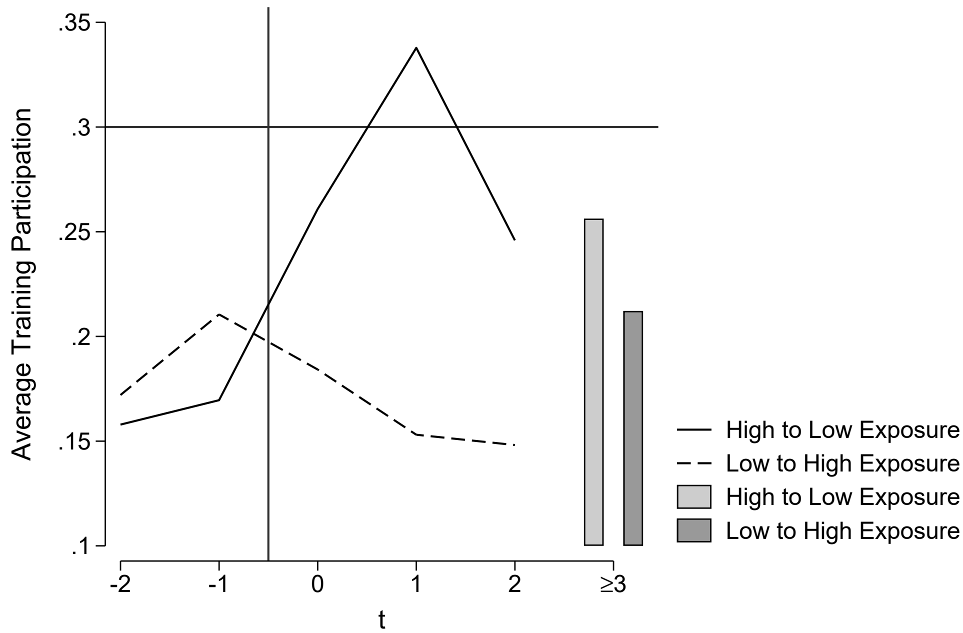

Figure 3: Training participation of occupational switchers

The Figure shows the training participation rate of occupational switchers before and after they switch between $t = -1$ and $t = 0$. The dashed line indicates switchers from high to low robot exposure. The dotted line indicates switchers from low to high robot exposure. The horizontal line indicates the sample average training participation across all waves. The vertical line indicates the timing of the switch. Source: NEPS-SC6 12.1.0, own calculation.

Although the training participation of workers who switch from high to low robot exposure surges immediately after the job change, Figure 3 clearly shows that workers who switch from high to low exposure also train more in the long run while those who switch from low to high exposure train less in the long run. If we would measure an artifact stemming from higher training rates upon job switching, both types of job switchers should train more immediately after the switch, and we should not observe long term differences in the workers training participation.

Table 3 exploits our data in more detail by analyzing the intensive margin of workers' training participation—i.e., their hours spent in training courses and the number of courses per year. Column I shows the effect for working hours on a sample that includes all workers, i.e., also those who do not train. Column II shows the effect on a sample that only includes workers who train. Columns III and IV replicate this analysis for the number of training courses. All specifications show a negative effect of robot exposure on the training intensity. However, only column three shows an effect that is precisely estimated at conventional levels. This result might suggests that robot exposure has a larger effect on the workers' decision of whether to train or not than on their training intensity.

Table 3: Extensive and Intensive Margin of Training Intensity

	I	II	III	IV
	Ext. Hours	Int. Hours	Ext. Number	Int. Number
High robot exposure	-2.266	-2.721	-0.111***	-0.158
	(1.415)	(5.840)	(0.043)	(0.203)
R^2	0.009	0.014	0.017	0.023
Observations	43779	13344	43779	13344

Dependent variables: Hours spent in training courses, number of courses. All columns show results for a version of Equation (1) using different dependent variables. Columns I and II show results for the hours spent in training as dependent variable. Columns III and IV show results for the number of courses as dependent variable. Columns I and III show results for the extensive margin, i.e. unconditional on training participation. Columns II and IV show results for the intensive margin, i.e. conditional on training participation. All regressions include individual fixed effects and time fixed effects. Standard errors in parentheses are clustered on the individual level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Source: NEPS-SC6 12.1.0, own calculation.

4.2. Heterogeneous effects

Exposure to automation might have different effects for different types of workers. For example, high skilled workers might be less exposed to the negative consequences of automation and more capable to train and re-train than low skilled workers. Men might be more exposed to automation then women, because they are more likely to work in production.

To get a more nuanced view on who exactly is affected by high robot exposure, Table 4 shows results of regression equation (1) separately for low (no degree), medium (apprenticeship degree), and high-skilled workers (university degree) and for men and women. The results show a small negative effect of robot exposure on training participation for low (Column I) and high-skilled workers (Column III) that is not statistically significant at conventional levels. In contrast, they reveal a large negative effect for medium skilled workers with an apprenticeship degree that is precisely estimated (Column II).[11] Columns IV and V reveal that the training gap is much larger for men than for women.

Table 4: Heterogeneity Analysis

	Education			Gender	
	I	II	III	IV	V
	Low	*Medium*	*High*	*Male*	*Female*
High robot exposure	-0.026	-0.050***	-0.024	-0.068***	-0.021
	(0.038)	(0.016)	(0.039)	(0.021)	(0.019)
R^2	0.026	0.019	0.029	0.021	0.021
Observations	2661	28124	12994	21170	22609

Dependent variable: training participation. All columns show results for Equation 1 for different subsamples. Columns I, II, and III show results for the groups of low (no vocational degree), medium (apprenticeship degree), and highly (university degree) educated. Columns IV and V show results for male and female workers. All regressions include individual fixed effects and time fixed effects. Standard errors in parentheses are clustered on the individual level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Source: NEPS-SC6 12.1.0, own calculation.

Overall, the results reveal that the negative effect of robot exposure on

[11] Apprenticeship graduates are skilled workers with a dual education that alternates between firm and class room training. Apprenticeship training programs usually last three years and are comparable to U.S. four year colleges that provide high-skilled vocational education. Approximately 60 percent of all workers in Germany hold an apprenticeship degree.

training participation is strongest for medium skilled and male workers. We can contradict concerns that the results are driven by low skilled workers who generally train less often than other workers do. However, workers who are highly exposed to robots learn on-the-job rather than off-the-job but face a high risk of unemployment when robots become further independent of a worker's input. Training may then help to bridge transition from worker to, e.g., manager or climb the promotion ladder to other jobs. Not participating in further training, however, can have devastating effects on individuals' careers. Not only are these workers less likely to climb the promotion ladder, but also more likely to become unemployed or taking wage cuts if robots render their skills obsolete. Therefore, the next section exploits the detailed information about the training content to explore whether workers with high robot exposure invest in specific types of training.

4.3. Training content

This subsection analyzes the influence of robot exposure on the training participation in four different training categories. The first category contains IT training courses that include training for IT, computer, and data processing skills. Many view IT skills as the new literacy (e.g., Neelie Kroes, former Vice President of the European Commission) and IT skills are related to substantial wage returns for individual workers (e.g., Falck et al., 2021). Thus, IT skills appear to be important for career development in times of fundamental technological change. The second training category contains training for production technologies and processes. These comprise innovations in production technologies and potential adaptions rather than learning how to collaborate with a robot. Thus, these production training courses may be beneficiary for supervisory employees rather than assembly line workers, though they may be used as preparation for a later promotion.

The third category contains courses for soft skills and business administration including courses for presentation skills, courses for linguistic proficiency, and courses in business administration. An emerging literature shows the rising importance of soft and management skills including communication, teamwork, presentation, customers relation and leadership skills. Throughout the recent decades, the wage returns to soft-skills even rose more strongly than the returns to analytical or IT skills (e.g., Deming, 2017; Deming and Kahn, 2018). The fourth category contains all other training courses.

Table 5: Effect of robot exposure on training by content

	I	II	III	IV
	IT	Production	Soft/Business	Other
High robot exposure	-0.016**	-0.004	-0.031***	-0.017
	(0.007)	(0.009)	(0.010)	(0.014)
R^2	0.009	0.006	0.013	0.011
Observations	32659	32061	35109	43779

Dependent variable: training participation. All columns show results for Equation 1 for different types of training content. The indicator for training participation is 1 if the respondent has participated in a course in the last 12 months specified as IT (Column I), Production (Column II), Soft / Business (Column III), or others (Column IV), and 0 if the respondent has not participated in any course in the last 12 months. All regressions include individual fixed effects and time fixed effects. Standard errors in parentheses are clustered on the individual level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Source: NEPS-SC6 12.1.0, own calculation.

Table 5 reveals that workers who are strongly exposed to robot technology are significantly less likely to invest in IT training and training for soft and business skills than other workers. IT and soft skills are general and can be transferred across firms, occupations, and industries. While IT training benefits individual productivity, social skills reduce coordination costs and benefit team productivity (Deming, 2017). Moreover, as mentioned above, recent literature suggests that firms demand a complementary cognitive and social skill set (Deming and Kahn, 2018). Thus, these skills are important for the workers' career development. However, firms should have relatively low incentives to invest in these skills—particularly, when workers are inclined to be replaced by technology. In contrast, individual workers should have a high incentive to do so. However, the results of Table 5 rather suggest that workers do not compensate the potential lack of their firms' training support by individually investing in further training. We investigate this relationship in more detail below.

For training in production technologies and other training fields we find no significant negative effects. Training in specific production technologies includes security training for production purposes. Even if firms want to displace a worker in the near future, work protection regulation forces firms to train their workforce with respect to security issues of the production process.

4.4. Formal training

If workers are likely to be replaced by robot technology in the near future, both workers and firms might have very low incentives to invest in non-formal on-the-job training, because workers are very likely to change their firm and occupation. However, workers who are likely to be displaced from their current job, might have high incentives to invest in formal training (i.e., to undertake a second apprenticeship training or to acquire a University degree) so that they can switch their occupation.

Table 6: Effect of robot exposure on formal further training participation

	I	II	III	IV	V
High robot exposure	-0.002***	-0.001*	-0.001	-0.002	-0.000
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
R^2	0.0011	0.0014	0.0056	0.00087	0.0027
Education	No	Yes	Yes	No	No
Individual controls	No	No	Yes	No	No
Individual FE	No	No	No	Yes	Yes
Job Characteristics	No	No	No	No	Yes
Firm Characteristics	No	No	No	No	Yes
Observations	43779	43779	43779	43779	43779

Dependent variable: formal training participation. All columns show results for Equation 1 with formal further training as dependent variable. Formal training is defined as undergoing regular vocational education (apprenticeship / university degree). The indicator for formal training participation is 1 if the respondent has started formal further training in the last 12 months, and 0 if the respondent has not started formal further training in the last 12 months. Columns I, II and III show results for an OLS version of Equation 1 without individual fixed effects and other controls. Column II includes Education. Column III includes Education and other Individual controls (gender, migration background, age). Columns IV and V use individual fixed effects as specified in Equation 1. Column IV shows results without Job and Firm Characteristics. Column V shows results with Job and Firm Characteristics. All regressions include time fixed effects. Standard errors in parentheses are clustered on the individual level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Source: NEPS-SC6 12.1.0, own calculation.

Therefore, Table 6 replicates the results of Table 2 for the workers' formal training participation, i.e., the dependent variable is a dummy variable indicating whether the worker undertook a apprenticeship or university degree. The raw OLS results in the first column of Table 6 reveal a significant negative gap in the workers' formal training participation of approximately 0.2 percentage points, which amounts to around 40% of the control group mean. However the gap disappears once we control for education and individual characteristics (Column III).Thus, the results do not suggest that workers who are likely to be replaced by robot technology are more likely to invest in formal training to be able to switch jobs. However, they are also not less likely to do so.

4.5. Decomposition results

The previous sections exploited the panel nature of our data to account for unobserved heterogeneity. However, the most important advantage of our data is that it contains a substantial amount of information about workers' training participation that allows us to explain the training gap by observable characteristics that are commonly not available in other data sources.

Thus, we estimate the following Oaxaca-Blinder decomposition:

$$E(T_{LE}) - E(T_{HE}) = (E(X_{LE}) - E(X_{HE}))'\beta_{LE} + E(X_{HE})'(\beta_{LE} - \beta_{HE}) \quad (2)$$

The left-hand side of equation 2 shows the difference in the expected training participation between workers who are not highly exposed to robot technology—i.e., low exposure (LE) below the 70^{th} percentile—and those who are highly exposed to them—i.e., high exposure (HE) above the 70^{th} percentile.

The right-hand side shows two terms. The first term $((E(X_{LE})-E(X_{HE}))'\beta_{LE})$ denotes the cumulative mean difference of all explanatory variables between the two groups weighted by the slope of the low-exposed group.

This term is usually referred to as the explained part of the decomposition. Thus, in our case, the first term indicates the part of the difference in the training participation between high- and low-exposed workers that is related to observable individual and firm characteristics in our data set.

The second term of the right-hand side $(E(X_{HE})'(\beta_{LE} - \beta_{HE}))$ denotes the cumulative average of the explanatory variables of the reference group of high-exposed workers weighted by the differences of the slopes between low- and high-exposed workers. This term is usually referred to as the unexplained part of the decomposition. In our case, this term can be interpreted as the difference in the training participation of high and low exposed workers that is not related to observable worker and firm characteristics. For the purpose of the Oaxaca-Blinder decomposition, we again have to restrict our sample to the waves 2011/12, 2018/19, and 2019/20. Standard errors are clustered at the individual level.

Table 7 shows the results. The first row of the upper panel shows the raw training gap between low- and highly-exposed workers. The second row shows the explained part, and the third row shows the unexplained part. The lower panel shows the detailed decomposition of the explained part as a fraction of the overall gap. Therefore, we summarized the explanatory variables in six categories. Education (1) contains two dummy variables for medium and high education. Individual characteristics (2) contain dummies for the workers' gender and migration status, and a variable capturing the workers' birth year. Job characteristics (3) include variables for part-time and public employment, working hours, experience and experience squared. Firm characteristics (4) contain industry dummies and firm size. The category general support (5) contains dummy variables that indicate whether the workers' firms have implemented human resource practices for the workers' training support. The category individual support (6) contains dummy variables indicating whether a worker generally receives financial support for his or her training, and whether he or she is generally allowed to reduce working hours for training purposes. The detailed questions appear in Appendix C.

Table 7: Oaxaca blinder decomposition

	I	II	III	IV
	Overall	IT	Soft/business	Age-Training-Gap
Raw difference	-0.169***	-0.080***	-0.142***	-0.072***
Explained	-0.113***	-0.042***	-0.092***	0.005
Unexplained	-0.057***	-0.038***	-0.050***	-0.077***
Detailed decomposition of explained part in percent of the overall gap				
Education	9%***	4%	11%***	4%
Ind. characteristics	5%***	8%***	5%**	-10%***
Job characteristics	2%	0%	-1%	-18%
Firm characteristics	2%	8%	9%***	-8%***
General support	15%***	10%***	11%***	4%
Individual support	35%***	28%***	32%***	26%***
Observations	12224	8801	9597	12224

Dependent variable: training participation. All columns show results for Equation 2 with further training as dependent variable. Column I shows results for overall training participation. Columns II and III show results for IT and soft-skill training, respectively. Column IV shows results for a decomposition using age as the discriminatory variable instead of robot exposure. The upper panel describes the raw difference, explained, and unexplained share. The lower panel shows the contribution to the explained share by group of variables. Education contains indicators for medium and high education. Individual characteristics contain indicators for the workers' gender and migration status, and a variable capturing the workers' birth year. Job characteristics include variables for part-time and public employment, working hours, experience and experience squared. Firm characteristics contain industry dummies and firm size. The category general support contains indicators whether the workers' firms have implemented human resource practices for the workers' training support. The category individual support contains indicators whether a worker generally receives financial support for his or her training, and whether he or she is generally allowed to reduce working hours for training purposes. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Source: NEPS-SC6 12.1.0, own calculation.

The first column of Table 7 shows an unconditional training gap of approximately 17 percentage points. Thus, the raw training gap in this restricted sample is very similar to the raw training gap in the overall sample (see Table 2). The second row of the first column shows that we can explain approximately 11 percentage points (approximately 67 percent) of the entire gap with the available worker and firm characteristics. Only, approximately 6 percentage points of the training gap remain unexplained.

The lower panel of Table 7 reveals that differences in the workers' education account for approximately 9 percent of the entire training gap while individual, job, and firm characteristics together only account for less than 10 percent of it. In contrast, differences in the firms' support for workers' training participation account for the lion share of the training gap, i.e., the firms' general support for workers' training participation accounts for 15 percent and the firms' individual support accounts for 35 percent of the overall training gap. In other words, the training participation of workers who are exposed to substitution by robot technology would be approximately 50 percent higher if they would receive the same training support by their firms as other workers. Additional analyses shown in Figures A.5 and A.6 present visual evidence that the increase in training for high-to-low switchers corresponds to an increase in individual support of the firms as well as better general HR policies.

Columns II and III decompose the training gap for different types of training. Column II shows the decomposition of the training gap for IT courses. For the gap in IT training, observable individual and job characteristics barely explain anything of the training gap. General firm characteristics and the general support within a firm explain 8 percent and 10 percent, respectively. The lion share of the gap is explained by the individual support explaining 28 percent of the training gap. Similar to the previous results column III reveals that the firms general and individual training support accounts for the largest share of the training gap for soft-skills and business courses.

Workers who have low preferences for training might be more likely to claim that they do not receive support, even if they do. Moreover, they might be less informed about their firms' training support than other workers. As a result, firms' training support might not only explain the automation gap, but also any other training gap.

To analyze this argument, the last column presents a decomposition of the training gap between young and old workers (i.e., workers who were born between 1950 and 1959). As for workers who are exposed to automation, firms should have relatively low incentives to train old workers who will retire soon. Nevertheless, the average old worker should have lower individual incentives to train than the average worker who is exposed to automation, i.e., workers who are close to their retirement have less time to collect the returns to their training investments. As a result, we should expect firms' training support to matter more for the automation-training gap than for the age-training gap. Indeed, the last column reveals that firms' general and individual training support accounts for less of the age training gap than of the automation-training gap.

5. Conclusion

Policymakers around the world are concerned about potential negative effects of automation. This paper shows that workers who are strongly exposed to robot technology train substantially less than other workers, and neither common observable characteristics, such as education and experience, nor time-constant heterogeneity can entirely explain the training gap. The effect is mainly driven by medium-skilled and male workers and cannot be explained with training substitution strategies towards formal further training (catching up on, for example, university degrees).

We show that the training gap does not persist into the intensive margin (hours and number of training incidences)—that is, the bottleneck for workers in occupations with high robot exposure is the initial training decision. Moreover, analyzing occupational switchers reveals that workers who switch from high to low robot exposure train significantly more often after their switch in both the short- and longer-term than workers who switch from low to high exposure occupations.

Our detailed survey data shows that the lower training participation rate is concentrated among relevant skills, such as IT (Falck et al., 2021) or soft- and business-skills (Deming, 2017; Deming and Kahn, 2018). This may be problematic as it magnifies inequalities resulting from the worker selection process. Workers who select into high robot exposure occupations are less likely to receive typical promotion training. A detailed decomposition reveals that the training gap for workers who are strongly exposed to robot technology is largely related to their firms' training support and to a much lesser extend to variables that commonly drive workers' training participation, e.g., education, age, experience, gender, or migration background.

Overall, our results suggest that firms reduce their training investments for workers whom they plan to substitute by technology, and workers appear not to compensate the lack of their firms' training support by individual training investments. This lack of training investment might have negative effects for the workers' careers in the long run. Therefore, our results help to understand why workers who are replaced by modern technologies experience long lasting negative consequences and do not adjust immediately (e.g., Cortes, 2016).

Appendix A. Figures and Tables

Table A.8: Sample statistics along the robot exposure distribution for the last wave

	$< p25$	$[p25; p50)$	$[p50; p75)$	$\geq p75$
Gender				
Men	.453	.455	.433	.648
Women	.547	.545	.567	.352
Education				
No Vocational Degree	.030	.040	.050	.092
Apprenticeship Degree	.340	.604	.749	.855
University Degree	.630	.355	.201	.054
Age				
Born 1980 and above	.190	.140	.102	.094
Born 1970 - 1979	.225	.193	.208	.182
Born 1960- 1969	.390	.464	.460	.476
Born 1950 - 1959	.195	.203	.230	.248
Observations	1014	1041	943	818

This Table shows the sample composition for gender, education, and age for different quartiles of the distribution of Webb's (2019) robot exposure measure for wave 12. Source: NEPS-SC6 12.1.0, own calculation.

Table A.9: Baseline characteristics by robot exposure

	Robot Exposure		
	High	Low	Difference
Training Outcomes			
Training participation	0.23	0.42	0.19***
Number of courses	0.59	1.15	0.56***
Hours in courses	12.85	22.64	9.78***
IT course	0.03	0.11	0.08***
Production course	0.06	0.07	0.01
Soft & Business Skills course	0.06	0.21	0.16***
Other course	0.66	0.55	-0.11**
Individual Characteristics			
Female	0.36	0.56	0.20***
Migration Background	0.21	0.11	-0.10***
Education = No Vocational Degree	0.15	0.06	-0.10***
Vocational Degree	0.78	0.60	-0.18***
University Degree	0.06	0.35	0.28***
Year of Birth	1964.98	1965.33	0.36
Job Characteristics			
Part Time Employment	0.28	0.34	0.07***
Employed in the public sector	1.80	1.69	-0.12***
Working Hours = <15 hours	0.10	0.07	-0.02*
Between 15 and 30 hours	0.12	0.20	0.08***
Between 30 and 40 hours	0.31	0.24	-0.07***
Between 40 and 50 hours	0.43	0.42	-0.01
> 50 hours	0.05	0.07	0.02*
Labor Market Experience(Years)	20.34	18.01	-2.34***
Firm Characteristics			
Industry = Agriculture	0.02	0.01	-0.02***
Mining and quarrying	0.01	0.00	-0.00*
Manufacturing	0.33	0.20	-0.13***

Table continues on next page

Table A.9 continued

	Robot Exposure		
	High	Low	Difference
Energy supply	0.01	0.01	-0.00
Water supply	0.01	0.00	-0.01***
Construction	0.08	0.03	-0.05***
Retail	0.06	0.10	0.04***
Transportation and storage	0.09	0.02	-0.07***
Accommodation	0.03	0.02	-0.00
ICT	0.01	0.06	0.04***
Finances and insurances	0.00	0.06	0.06***
Real estate activities	0.00	0.01	0.01
Prof., scient. and techn. activities	0.02	0.06	0.04***
Administrative services	0.06	0.02	-0.04***
Public admin. and defence	0.04	0.12	0.09***
Education	0.01	0.12	0.10***
Human health and social work	0.18	0.12	-0.05***
Arts, entertain. and recreation	0.01	0.01	-0.01
Other service activities	0.03	0.02	-0.00
Households as employers	0.01	0.00	-0.00
Extraterritorial organisations	0.00	0.00	0.00
Firm Size = Below 10	0.17	0.20	0.02
Between 10 and 50	0.31	0.31	-0.00
Between 50 and 200	0.25	0.22	-0.03
Between 200 and 500	0.10	0.11	0.01
More than 500	0.17	0.16	-0.00

This Table shows averages for training outcomes as well as individual, job, and firm characteristics by Webb's (2019) robot exposure measure. The first column shows averages for workers working in highly exposed occupations. The second column shows averages for workers working in low exposed occupations. The third column shows the differences (low vs. high) and the significance of a t-test. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Source: NEPS-SC6 12.1.0, own calculation.

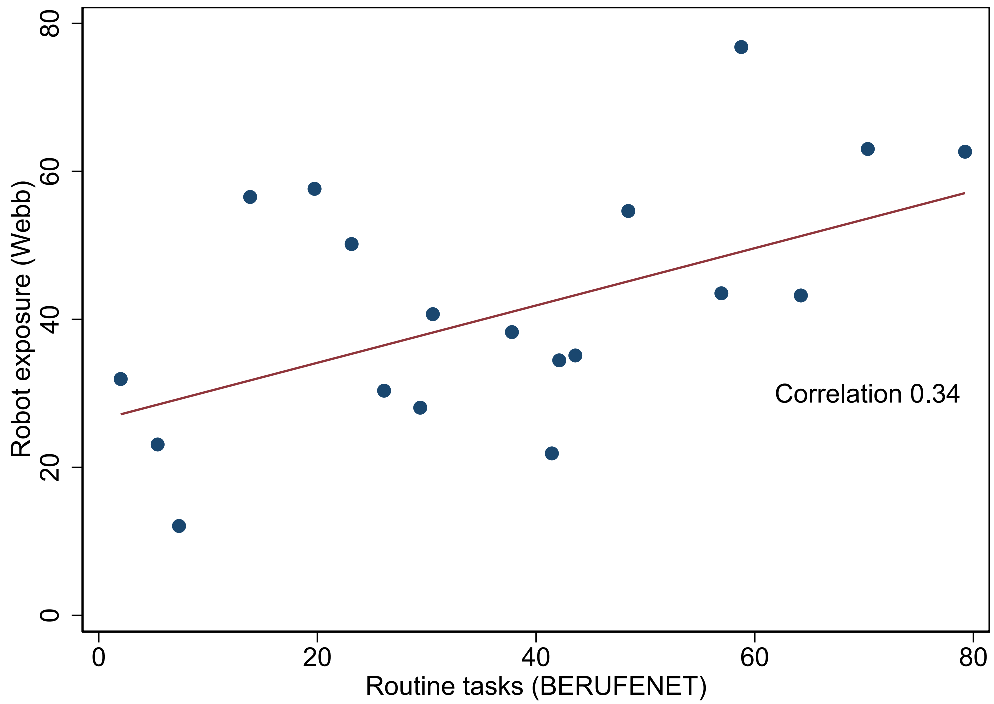

Figure A.4: Correlation between robot exposure and routine tasks

The Figure shows the correlation between the share of routine tasks and Webb's (2019) robot exposure measure. The solid line indicates fitted values. Scatterplot is binned. Source: NEPS-SC6 12.1.0, own calculation.

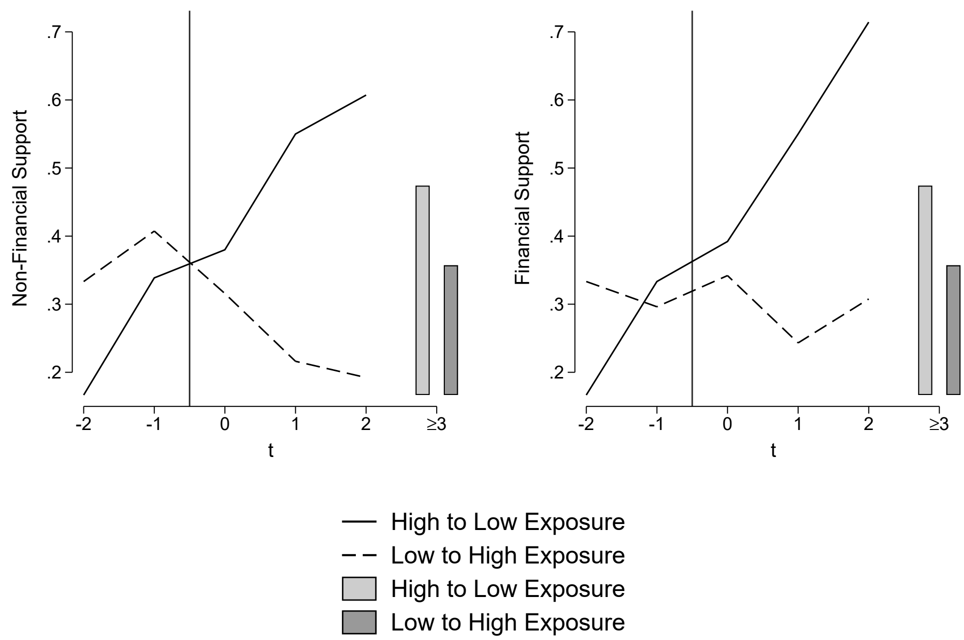

Figure A.5: Individual training support of occupational switchers

The Figure shows the training participation rate of occupational switchers before and after they switch between $t = -1$ and $t = 0$ for individual financial and non-financial training support. The dashed line indicates switchers from high to low robot exposure. The dotted line indicates switchers from low to high robot exposure. The vertical line indicates the timing of the switch. Source: NEPS-SC6 12.1.0, own calculation.

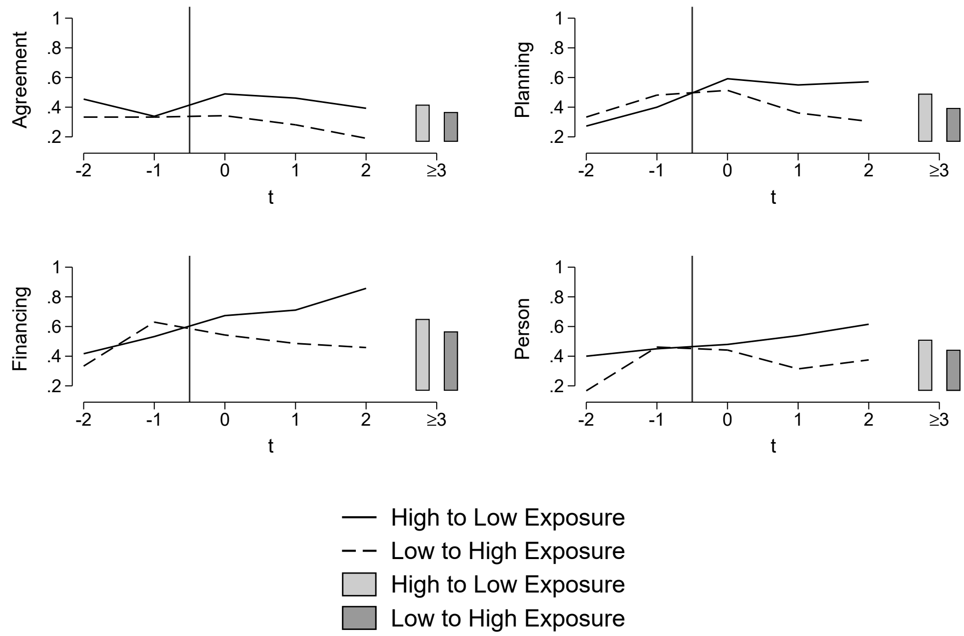

Figure A.6: General training policies of the firm of occupational switchers

The Figure shows the training participation rate of occupational switchers before and after they switch between $t = -1$ and $t = 0$ for general training policies of the firm. The dashed line indicates switchers from high to low robot exposure. The dotted line indicates switchers from low to high robot exposure. The vertical line indicates the timing of the switch. Source: NEPS-SC6 12.1.0, own calculation.

Appendix B. Webb Scores - Crosswalk

Webb (2019) delivers raw scores of the exposure level of occupations to software, robots, and AI, alongside with the percentiles of each occupation. To crosswalk the raw data from Webb to the German classification of occupations, we first create a crosswalk for the Standard Occupational Classification (SOC) 2010 to the German Classification of Occupations (KldB) 2010 by using the International Standard Classification of Occupations (ISCO) 2008. Hardy et al. (2018) provide data on the crosswalk from SOC2010 to ISCO08. We use the official crosswalk data from the Federal Employment Agency (BA) in Germany to crosswalk ISCO08 to KLDB2010.

We then take the raw data obtained from Webb (2019) and trim the the 8-digit O*NET SOC-Code to 6 digits. Since several occupations have the same 6-digit code, we take the median exposure score of the duplicates. Afterwards, we merge the 6-digit SOC to 5-digit KLDB2010 using the crosswalk created in the first step and aggregate the data to the KLDB2010 level taking the median exposure score for each 5-digit KLDB2010 level.

The following occupations do not receive any exposure score: Occupations of the armed forces, coach drivers, chimney sweepers, professions in money and pawn lending, members of legislative bodies, professions in community work, members of religious orders and mother houses, professions in theology and congregational work, professions in moderation and entertainment, comedians and cabaret artists, magicians and illusionists.

Appendix C. Survey questions on individual and general firm support for training investments

The NEPS provides detailed information about their firms' financial and non-financial training support for workers. One set of questions addresses the firms' general support for training participation in terms of human resource practices. The survey questions are as follows:

- Does your company have a shop agreement governing continuing education?
- Is there continuing education planning on a regular basis for the employees there?
- Does your company finance or provide classes or training courses?
- Is there a staff member, unit or department responsible for training or continuing education?

Another set of questions addresses the firms' individual support for further training. The detailed survey questions are as follows:

- Has your current employer offered to release you from work to attend training sessions and courses?
- Has your current employer offered to pay for you to attend courses and training sessions, give you aid or other kinds of financial support?

Appendix D. Replication with BERUFENET

Table D.10: Effect of task composition on training participation

	Dependent variable: Training participation				
	I	II	III	IV	V
Panel A					
Share of routine tasks	-0.026***	-0.021***	-0.0019***	-0.010***	-0.0009**
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
R^2	0.021	0.034	0.037	0.014	0.019
Panel B					
High routine intensity	-0.095***	-0.081***	-0.060***	-0.034	-0.036
	(0.011)	(0.011)	(0.011)	(0.026)	(0.027)
R^2	0.011	0.028	0.031	0.014	0.019
Education	No	Yes	Yes	No	No
Individual controls	No	No	Yes	No	No
Individual FE	No	No	No	Yes	Yes
Job Characteristics	No	No	No	No	Yes
Firm Characteristics	No	No	No	No	Yes
Obs.	43779	43779	43779	43779	43779

Dependent variable: training participation (yes/no). Column I show results for an OLS version of Equation 1 without individual fixed effects and other controls. Column II includes Education. Column III includes Education and other Individual controls (gender, migration background, age). Columns IV and V use individual fixed effects as specified in Equation 1. Column IV shows results without Job and Firm Characteristics. Column V shows results with Job and Firm Characteristics. All regressions include time fixed effects. Standard errors in parentheses are clustered on the individual level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Source: NEPS-SC6 12.1.0, own calculation.

Table D.11: Oaxaca blinder decomposition – High routine intensity

	I Overall training	II IT	III Production	IV Soft/business
Raw difference	0.101***	0.039***	-0.034***	0.063***
Explained	0.091***	0.016***	-0.016***	0.051***
Unexplained	0.010	0.023**	-0.017	0.012
Detailed decomposition of explained part in percent of the overall gap				
Education	7%***	8%***	0%	11%***
Ind. characteristics	21%***	28%***	0%	22%***
Job characteristics	1%	-5%	12%	-6%
Firm characteristics	31%***	-23%*	47%***	25%***
General support	6%**	3%	0%	5%
Individual support	25%***	21%***	-9%**	27%***
Observations	12223	8800	8515	9597

Dependent variable: training participation. All columns show results for Equation 2 with further training as dependent variable. Column I shows results for overall training participation. Columns II, III, and IV show results for IT, production, and soft-skill training, respectively. The upper panel describes the raw difference, explained, and unexplained share. The lower panel shows the contribution to the explained share by group of variables. Education contains indicators for medium and high education. Individual characteristics contain indicators for the workers' gender and migration status, and a variable capturing the workers' birth year. Job characteristics include variables for part-time and public employment, working hours, experience and experience squared. Firm characteristics contain industry dummies and firm size. The category general support contains indicators whether the workers' firms have implemented human resource practices for the workers' training support. The category individual support contains indicators whether a worker generally receives financial support for his or her training, and whether he or she is generally allowed to reduce working hours for training purposes. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Source: NEPS-SC6 12.1.0, own calculation.

References

Acemoglu, D., 1997. Training and innovation in an imperfect labour market. Review of Economic Studies 64, 445–464.

Acemoglu, D., 2015. Localised and biased technologies: Atkinson and stiglitz's new view, induced innovations, and directed technological change. The Economic Journal 125, 443–463.

Acemoglu, D., Autor, D., 2011. Skills, Tasks and Technologies: Implications for Employment and Earnings. volume 4. pp. 1043–1171.

Acemoglu, D., Autor, D., Hazell, J., Restrepo, P., 2020. Ai and jobs: Evidence from online vacancies. NBER Working Paper .

Acemoglu, D., Restrepo, P., 2017a. Robots and Jobs: Evidence from US Labor Markets. Report. NBER Working Paper No. 23285.

Acemoglu, D., Restrepo, P., 2017b. Secular stagnation? the effect of aging on economic growth in the age of automation. American Economic Review 107, 174–179.

Acemoglu, D., Restrepo, P., 2018. The race between man and machine: Implications of technology for growth, factor shares, and employment. American Economic Review 108, 1488–1542.

Agrawal, A., Gans, J., Goldfarb, A., 2019. Artificial intelligence: The ambiguous labor market impact of automating prediction. Journal of Economic Perspectives 33, 31–50.

Autor, D., 2013. The "task approach" to labor markets: an overview. Journal for Labour Market Research 46, 185–199.

Autor, D., Levy, F., Murnane, R., 2003. The skill content of recent technological change: An empirical exploration. The Quarterly Journal of Economics 118, 1279–1333.

Bassanini, A., Booth, A.L., Brunello, G., de Paola, M., Leuven, E., 2007. Worplace training in europe, in: Brunello, G., Garibaldi, P., Wasmer, E. (Eds.), Education and Training in Europe. Oxford University Press.

Booth, A.L., Bryan, M.L., 2007. Who pays for general training in private sector britain?, in: Polachek, S., Bargain, O. (Eds.), Aspects of Worker Well-Being. Emerald Group Publishing Limited, Bingley. Research in Labor Economics, pp. 85–123.

Bresnahan, T., Brynjolfsson, E., Hitt, L., 2002. Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. Quarterly Journal of Economics 117, 339–376.

Caroli, E., Van Reenen, J., 2001. Skill-biased organizational change? evidence from a panel of british and french establishments. The Quarterly Journal of Economics 116, 1449–1492.

Cavounidis, C., Lang, K., 2020. Ben-porath meets lazear: Microfoundations for dynamic skill formation. Journal of Political Economy 128, 1405–1435.

Cortes, G.M., 2016. Where have the middle-wage workers gone? a study of polarization using panel data. Journal of Labor Economics 34, 63–105.

Dauth, W., Findeisen, S., Suedekum, J., Woessner, N., 2021. The adjustment of labor markets to robots. Journal of the European Economic Association .

Deming, D., 2017. The growing importance of social skills in the labor market*. The Quarterly Journal of Economics 132, 1593–1640.

Deming, D., Kahn, L.B., 2018. Skill requirements across firms and labor markets: Evidence from job postings for professionals. Journal of Labor Economics 36, S337–S369.

Dengler, K., Matthes, B., Paulus, W., 2014. Occupational tasks in the german labour market. FDZ Methodenreport .

Dixon, J., Hong, B., Wu, L., 2021. The robot revolution: Managerial and employment consequences for firms. Management Science 67, 5586–5605.

Falck, O., Heimisch-Roecker, A., Wiederhold, S., 2021. Returns to ict skills. Research Policy 50.

Fouarge, D., Schils, T., de Grip, A., 2013. Why do low-educated workers invest less in further training? Applied Economics 45, 2587–2601.

Goos, M., Manning, A., 2007. Lousy and lovely jobs: The rising polarization of work in britain. The Review of Economics and Statistics 89, 118–133.

Goos, M., Manning, A., Salomons, A., 2014. Explaining job polarization: Routine-biased technological change and offshoring. American Economic Review 104, 2509–2526.

Görlitz, K., Tamm, M., 2016a. The returns to voucher-financed training on wages, employment and job tasks. Economics of Education Review 52, 51–62.

Görlitz, K., Tamm, M., 2016b. Revisiting the complementarity between education and training – the role of job tasks and firm effects. Education Economics 24, 261–279.

Görlitz, K., Tamm, M., 2017. Information, financial aid and training participation: Evidence from a randomized field experiment. Labour Economics 47, 138–148.

Hardy, W., Keister, R., Lewandowski, P., 2018. Educational upgrading, structural change and the task composition of jobs in europe. Economics of Transition 26, 201–231.

Hidalgo, D., Oosterbeek, H., Webbink, D., 2014. The impact of training vouchers on low-skilled workers. Labour Economics 31, 117–128.

Innocenti, S., Golin, M., 2022. Human capital investment and perceived automation risks: Evidence from 16 countries. Journal of Economic Behavior & Organization 195, 27–41.

Kramer, A., Tamm, M., 2018. Does learning trigger learning throughout adulthood? evidence from training participation of the employed population. Economics of Education Review 62, 82–90.

Michaels, G., Natraj, A., Van Reenen, J., 2014. Has ict polarized skill demand? evidence from eleven countries over twenty-five years. Review of Economics and Statistics 96, 60–77.

Nedelkoska, L., Quintini, G., 2018. Automation, skills use and training. OECD Social, Employment, and Migration Working Papers , 1–124.

Nelen, A., de Grip, A., 2009. Why do part-time workers invest less in human capital than full-timers? LABOUR 23, 61–83.

OECD, 2019. The future of work. volume 2019 of *OECD employment outlook*. OECD Publishing, Paris.

Schmidpeter, B., Winter-Ebmer, R., 2021. Automation, unemployment, and the role of labor market training. European Economic Review 137, 103808.

Schwerdt, G., Messer, D., Woessmann, L., Wolter, S., 2012. The impact of an adult education voucher program: Evidence from a randomized field experiment. Journal of Public Economics 96, 569–583.

Sieben, I., De Grip, A., Longen, J., Sørensen, O., 2009. Technology, selection, and training in call centers. Industrial and Labor Relations Review 62, 553–572.

Spitz-Oener, A., 2006. Technical change, job tasks, and rising educational demands: looking outside the wage structure. Journal of labor economics 24, 235–270.

Tamm, M., 2018. Training and changes in job tasks. Economics of Education Review 67, 137–147.

van den Berg, G., Dauth, C., Homrighausen, P., Stephan, G., 2020. Informing employees in small and medium sized firms about training: Results of a randomized field experiment. volume 2020, 3 of *Working paper / Institute* *for Evaluation of Labour Market and Education Policy*. IFAU Institute for Evaluation of Labour Market and Education Policy, Uppsala.

Webb, M., 2019. The impact of artificial intelligence on the labor market. SSRN 3482150 .

Zhang, H., Zhang, J., Wang, W., Liu, R., Zong, G., 2007. A series of pneumatic glass–wall cleaning robots for high–rise buildings. Industrial Robot: An International Journal 34, 150–160.