The effect of automation technology on workers' training participation

Pascal Heß
IAB, ROA

Simon Janssen
IAB

Ute Leber
IAB

November 29, 2022

AG BFN-Forum

R&R at the *Economics of Education Review*

Motivation and Literature

- Automation technology alters the wage and employment structure (e.g., Acemoglu and Restrepo, 2017, 2018; Dauth et al., 2021; Acemoglu and Autor, 2011; Autor, 2013; Autor et al., 2003; Bresnahan et al., 2002; Goos and Manning, 2007; Goos et al., 2014; Michaels et al., 2014)
- Public discussion on the importance of life-long learning and further training.
- Policies to promote further training (e.g., in 2019, the German government spent approximately 2.1 billion Euros to subsidize further training)

Motivation and Literature

- Why should workers train when they are exposed to automation?
  - Learn new tasks
  - Remain employable
- Why should firms' train workers who are exposed to automation?
  - Retain specific human capital; motivate workers
  - Forgone investments in workers who will be automated

Motivation and Literature

- Evidence on the relationship between automation and training is scarce and mixed
- Workers who fear automation have a larger intention to train (Innocenti and Golin, 2022)
    - Firms provide and finance between 85 and 90 percent of all training (Booth and Bryan, 2007)
- Nedelkoska and Quintini (2018) find large negative training gap for workers who are exposed to automation.
    - But why?

Contribution

- Workers who are exposed to automation train approximately 12 percent less than the average worker.
- Conditional automation-training gap is almost as large as education-training gap (Görlitz and Tamm, 2016)
- Education, worker and firm characteristics explain little of the training gap.
- Firms' financial and non-financial training support explains more than 50 percent of the automation-training gap.

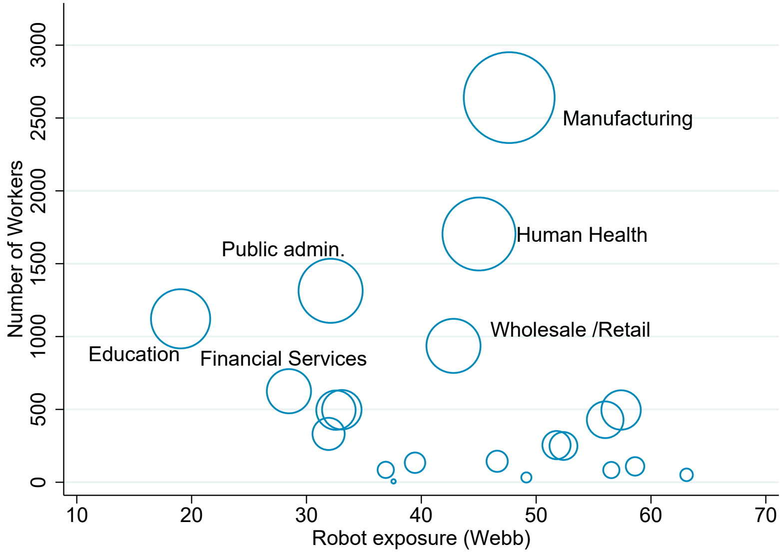
Data: National Educational Panel Study

- Starting cohort 6.
- $10,000$ adults between 2009 and 2017.
- Between 25 and 60.
- 43779 of 9594 adults.
- Detailed variables on training participation.
  - Frequency, duration, training content.
  - Detailed worker and firm characteristics: industry, occupation, part-time etc.
  - Information about firms′ training support

Data: Exposure to Automation Technology (Webb Measure)

- Combination of information from patent texts with job descriptions from O*Net
- Verb-noun pairs indicate overlap between tasks and the capabilities of new automation technologies according to patents
- Many studies validate Webb measure (e.g., Acemoglu et al., 2020)
- Crosswalk between the Standard Occupational Classification (SOC) from the U.S. and the German classification of occupations from 2010.

Data: Exposure to Automation Technology



Descriptive statistics technology and training

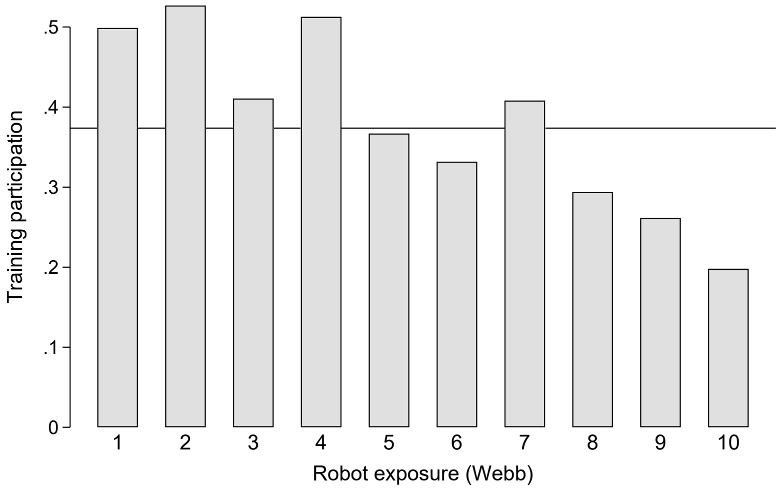


Figure: Relationship between robot exposure and training.

Methods: regular fixed effects estimation

$$T_{it} = \delta \cdot Robot_{it} + Educ_i \cdot \beta_1 + Individual_i \cdot \beta_2 + Job_{it} \cdot \beta_3 + Firm_{it} \cdot \beta_4 + \mu_i + \lambda_t + \epsilon_{it}$$

- T_{it}: Training measures
- $Robot_{it}$: Automation exposure
- $Educ_i$: 3 education categories
- $Individual_i$: gender, migration status, birth year
- Job_{it}: experience, working hours, part time, public employment
- $Firm_{it}$: firm size, industry
- μ_i: individual fixed effects
- λ_t: time fixed effects

Methods: decomposition

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

- LE: Low exposure; HE: High exposure
- $(E(X_{LE}) - E(X_{HE}))' \beta_{LE}$: explained part
- $E(X_{HE})' (\beta_{LE} - \beta_{HE})$: unexplained part
- Focus on firms' financial and non-financial support
- Restriction on waves $2011/12$, $2018/19$ and $2019/20$

Results: fixed effects regressions

Table: Effect of robot exposure on training participation

	I	II	III	IV	V
Robot exposure	-0.028***	-0.022***	-0.021***	-0.010***	-0.006**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
High robot exposure	-0.153***	-0.121***	-0.109***	-0.060***	-0.042***
	(0.007)	(0.007)	(0.008)	(0.014)	(0.014)
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
R^2	0.033	0.039	0.041	0.015	0.019
Observations	43779	43779	43779	43779	43779

Data: Exposure to Automation Technology

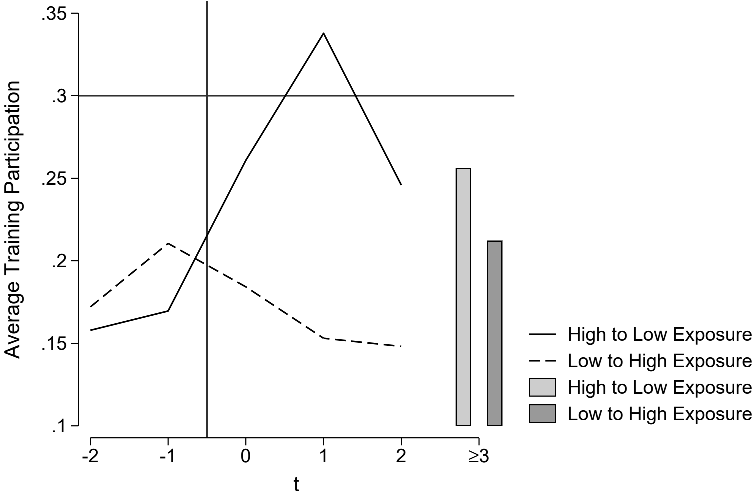


Figure: Switchers and stayers

Results: intensive vs extensive margin

Table: Intensive and Extensive Margin of Training Intensity

	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

Results: heterogeneity

Table: Heterogeneity Analysis

	Education			Male	Female
	Low	*Medium*	*High*		
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

Results: training content

Table: Effect of robot exposure on training content

	IT	Production	Soft/Business	Other
High robot exposure	-0.016**	-0.004	-0.031***	0.027
	(0.007)	(0.009)	(0.010)	(0.056)
R^2	0.009	0.006	0.013	0.008
Observations	32659	32061	35109	13344

Formal training

Table: 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)
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
R^2	0.0011	0.0014	0.0056	0.00087	0.0027
Observations	43779	43779	43779	43779	43779

Decomposition results

Table: Oaxaca blinder decomposition

	Overall training	Production	ICT	Soft/business
Raw difference	-0.188***	-0.019***	-0.083***	-0.136***
Explained	-0.133***	-0.013***	-0.045***	-0.093***
Unexplained	-0.055***	-0.006	-0.037***	-0.043***
Detailed decomposition of explained part in percent of the overall gap				
Education	12% ***	16%	1%	10%***
Ind. characteristics	3%*	-5%	4%	7%***
Job characteristics	-2%	-5%	-1%	-7%**
Firm characteristics	5%*	-37%***	10%**	10%***
General support	19%***	52%***	11%***	16%***
Individual support	36%***	84%***	30%***	33%***
Observations	10983	7801	7978	8780

Conclusion

- Firms' do not invest in training of workers' whom they substitute
- Impact on the key training fields (IT, soft and business skills)
- Firms training support explains largest share of training gap

Firm support

Firms′ general training support

- 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?

Firms′ individual support for further training.

- 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?

Literature

Acemoglu, Daron and David Autor, *Skills, Tasks and Technologies: Implications for Employment and Earnings*, Vol. 4,

___ **and Pascual Restrepo**, ``Robots and Jobs: Evidence from US Labor Markets,'' Report, NBER Working Paper No. 23285 2017.

___ **and** ___ , ``The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment,'' *American Economic Review*, 2018, *108* (6), 1488--1542.

___ **, David Autor, Jonathon Hazell, and Pascual Restrepo**, ``AI and Jobs: Evidence from Online Vacancies,'' *NBER Working Paper*, 2020.

Autor, David H., ``The \task approach" to labor markets: an overview,'' *Journal for Labour Market Research*, 2013, *46* (3), 185--199.

___ **, Frank Levy, and Richard J. Murnane**, ``The Skill Content of Recent Technological Change: An Empirical Exploration,'' *The Quarterly Journal of Economics*, 2003, *118* (4), 1279--1333.

Booth, Alison L. and Mark L. Bryan, ``Who Pays for General Training in Private Sector Britain?,'' in Simon Polachek and Oliver Bargain, eds., *Aspects of Worker Well-Being*, Research in Labor Economics, Bingley: Emerald Group Publishing Limited, 2007, pp. 85--123.

Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt, ``Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence,'' *Quarterly Journal of Economics*, 2002, *117* (1), 339--376.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner, ``The Adjustment of Labor Markets to Robots,'' *Journal of the European Economic Association*, 2021.

Goos, Maarten, Alan Manning, and Anna Salomons, ``Explaining Job Polarization: Routine-Biased Technological Change and Offshoring,'' *American Economic Review*, 2014, *104* (8), 2509--2526.

___ **and** ___ , ``Lousy and Lovely Jobs: The Rising Polarization of Work in Britain,'' *The Review of Economics and Statistics*, 2007, *89* (1), 118--133.

Görlitz, Katja and Marcus Tamm, ``The returns to voucher-financed training on wages, employment and job tasks,'' *Economics of Education Review*, 2016, *52*, 51--62.

Innocenti, Stefania and Marta Golin, ``Human capital investment and perceived automation risks: Evidence from 16 countries,'' *Journal of Economic Behavior & Organization*, 2022, *195*, 27--41.

Michaels, Guy, Ashwini Natraj, and John Van Reenen, ``Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years,'' *Review of Economics and Statistics*, 2014, *96* (1), 60--77.

Nedelkoska, Ljubica and Glenda Quintini, ``Automation, skills use and training,'' *OECD Social, Employment, and Migration Working Papers*, 2018, (38), 1--124.