Robots, Firms, and Workforce Composition in Germany

Liuchun Deng (YNC & IWH)
Steffen Müller (IWH)
Verena Plümpe (IWH)
Jens Stegmaier (IAB)

ProdTalk, CompNet
May 10, 2022

What is particularly interesting about robots today?

1. In contrast to previous technological revolutions
   - adoption of robots takes place much faster and
   - involves all industrial sectors
2. In contrast to other high-tech machines
   - robots are much more flexible and versatile
   - they can work autonomously, and
   - they can replace human labor to a much larger extent
3. Recent trends:
   - robotic innovations $\uparrow$
   - robot prices $\downarrow$
   - robot demand worldwide $\uparrow$
   - automation incentives due to COVID-19 $\uparrow$

How does robotization affect employment?

1. Economic theory: robots can be substitutes or complements to human labour (Acemoglu and Restrepo, 2018)
2. Evidence based on the industry-level IFR robot data is mixed (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2019; Dauth, et al., 2021). It cannot fully account for displacement and reallocation effects within industries
3. More recent work based on firm- or plant-level data shows positive employment effects for robot adopters (Bonfiglioli, et al., 2021; Acemoglu, et al., 2020; Koch, et al., 2021; Dixon, et al., 2020)

Research contribution

- First micro-level evidence from **Germany** – the most robot-intensive economy in Europe (IFR Report 2020)
- We link plant-level data with a **direct measure of robot use** to worker level data from social security records and task data
- We are first in analyzing **workforce composition effects** of robot adoption with respect to occupation and **age**
- Policy relevance:
  → socio-economic challenges for workers replaced by robots
  → human capital investment and occupational choice for young generations

A task-based model of robot adoption

- Task-based partial equilibrium model of robot adoption with heterogeneous labor Model Setup
- Key features:
  1. task content of jobs varies across occupations (robots replace routine manual tasks) Illustration
  2. within a given occupation, adaptation to robots varies across ages (vintage of human capital and experience) Illustration

Table: % of routine manual tasks across occupations BIBB

simple manual	qual manual	tech/engin	manager	service
49.04	40.49	22.64	17.34	40.90

Notes: BIBB/BAuA data 2012. Manufacturing sample.

Model implications

1. Robot adoption has ambiguous effects on total employment (replacement effect vs productivity and reinstatement effect)
2. Robot adoption increases worker flows (hirings $\uparrow$, separations $\uparrow$)
3. Robot adoption changes the workforce composition:
   - Less replaceable occupations (technical, managerial) see relative increase in employment.
   - Effects on age profile vary with occupation (initial task specialization vs new task adaptation).

Data

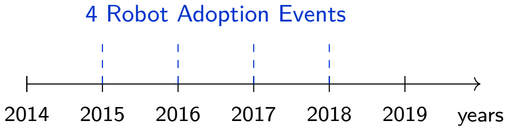
1. IAB Establishment Panel Survey 2019

A section dedicated to adoption and use of robots

A robot is an automatically controlled, programmable machine with multiple axes or directions of motion that performs certain tasks wholly or partially without human intervention.

Key survey question: How many robots were used in each of the last 5 years (2014–2018)?

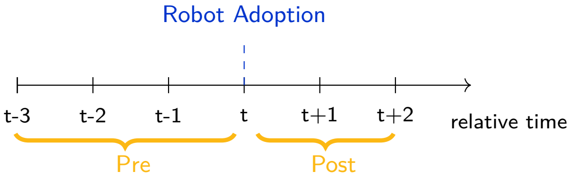
Robot adoption is identified as *the first time* a plant installed robots



Data

1. IAB Establishment Panel Survey 2019

   We randomize non-robot adopters (plants that never used robots) into 4 groups and assign each to one of the four adopter groups. We then define relative time for all plants w.r.t. the (artificial) adoption event. classification of plants



2. Plant-level employment from Establishment History Panel (BHP)
3. Task information from BIBB/BAuA Employment Survey 2012

Employment, hiring, and separation

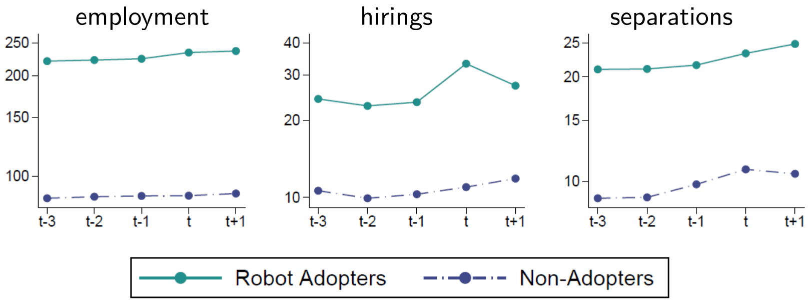


Figure: Employment, hiring and separation at plant level

Event study: baseline specification

TWFE

$$Y_{it} = \alpha_i + \sum_{t=-3}^{t=1} \beta_t \, T_t + \sum_{t=-3}^{t=1} \gamma_t \, Robot_i \, T_t + \epsilon_{it}, \tag{1}$$

where

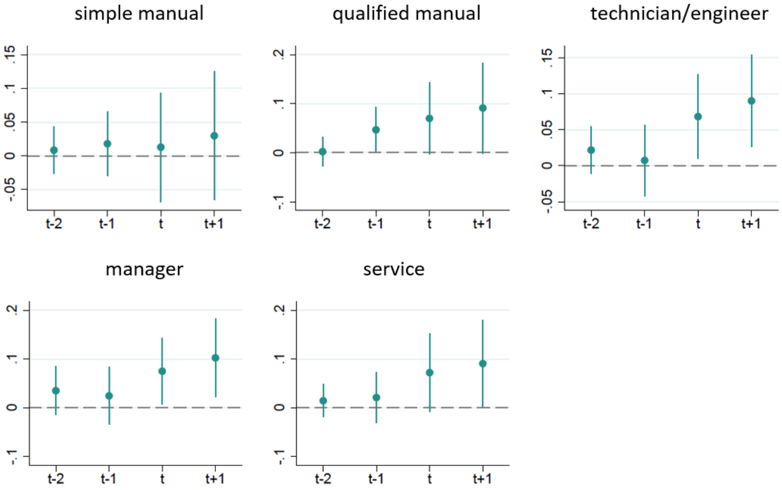
- Y_{it} is plant i's outcome variable in relative time t to the event of robot adoption.
- α_i is plant-level fixed effect.
- T_t is relative time dummy.
- $Robot_i$ is the time-invariant treatment dummy for robot adoption.
- ϵ_i is an idiosyncratic error term.

Employment and Worker Flows (event study results)

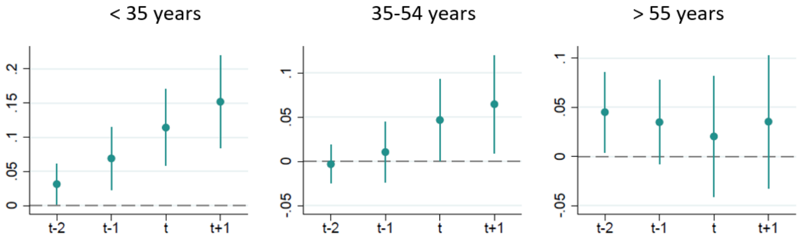
	Employment b/se	Hirings b/se	Separations b/se
t−2	0.0044	-0.0822***	0.0305
	(0.0036)	(0.0188)	(0.0186)
t−1	0.0076	-0.0517***	0.0543***
	(0.0048)	(0.0196)	(0.0188)
t	0.0102	-0.0174	0.0908***
	(0.0063)	(0.0201)	(0.0193)
t+1	-0.0019	-0.0393*	0.1186***
	(0.0091)	(0.0213)	(0.0200)
1.D_robot_adoption#t−2	0.0107	0.0615	0.0019
	(0.0102)	(0.0715)	(0.0621)
1.D_robot_adoption#t−1	0.0219	0.1018	0.0589
	(0.0152)	(0.0763)	(0.0610)
1.D_robot_adoption#t	0.0527**	0.2741***	0.0533
	(0.0232)	(0.0756)	(0.0671)
1.D_robot_adoption#t+1	0.0671**	0.2126***	0.1194*
	(0.0282)	(0.0796)	(0.0703)
Constant	yes	yes	yes
N	2096	2096	2096

Notes: Dependent variable is number of workers transformed using inverse hyperbolic sine. Standard errors clustered at plant level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Workforce composition by occupation (event study results)



Workforce composition by age (event study results)



Regression Tables

Unconditional Figures

Occupation-Age Workforce Composition (event study)

	simple manual	qualified manual	technician engineer	manager	service	total
18−35 years	$\uparrow\uparrow$	$\uparrow$	$\uparrow$	$\downarrow$	$\uparrow$	$\uparrow\uparrow$
35−54 years	$\rightarrow$	$\uparrow$	$\uparrow\uparrow$	$\rightarrow$	$\rightarrow$	$\uparrow$
55−65 years	$\uparrow$	$\uparrow$	$\rightarrow$	$\uparrow\uparrow$	$\uparrow$	$\rightarrow$
Total	$\rightarrow$	$\uparrow$	$\uparrow\uparrow$	$\uparrow\uparrow$	$\uparrow$	$\uparrow\uparrow$

Notes: $\uparrow\uparrow$ = significant increase. $\rightarrow$ = no change. $\downarrow$ = insignificant drop.

Conclusion

1. Employment gains are concentrated among younger workers and technicians/engineers and managers.
2. Young workers in low/middle skilled occupations are complements to robots.
   $\Rightarrow$ Could be related to high-quality dual apprentice ship training in German labor market.
   $\Rightarrow$ Shortage of them could hinder the large-scale adoption of robots.
   $\Rightarrow$ Demand for low/middle skilled older workers will decline.
3. Results suggest reallocation effects favoring robot adopters.
4. Future research: Complementarity between youth and robotics also in countries with other educational systems?

Thank you!

Descriptive statistics

		Robot Adopter (N=116)		Non User (N=1951)	
		Mean	SD	Mean	SD
Number of employees		222.67	251.01	102.64	193.49
Hirings		24.22	34.50	10.62	22.41
Separations		21.01	23.34	8.95	16.14
Occupational shares	simple manual	0.34	0.23	0.28	0.50
	qualified manual	0.29	0.22	0.33	0.71
	technician/engineer	0.12	0.09	0.14	0.55
	manager	0.03	0.03	0.03	0.05
	service	0.09	0.09	0.12	0.80
Age shares	younger (<35)	0.29	0.13	0.28	0.21
	midage (35-54)	0.50	0.11	0.51	0.34
	older (≥ 55)	0.20	0.08	0.20	0.12

Notes: Data from administrative social security data for plants identified as robot adopters or non users in the IAB establishment panel 2019 as described in the text. Manufacturing sample. Plant-level averages in $t-3$.

Replaceability of tasks by occupation and age

		Occupation					
		simple manual	qual manual	tech/engin	managers	occ svc	total
A	Younger (18–35)	48.76	41.71	22.84	17.97	36.00	34.25
G	Midage (35–54)	48.32	39.78	23.06	17.19	43.85	32.87
E	Older (55–65)	52.72	41.14	21.23	18.26	37.91	31.86
	Total	49.04	40.49	22.64	17.34	40.90	

Notes: BIBB/BAuA data 2012. Tasks potentially replaceable by robots (F303, F304, F305, F308, F320) as share of total tasks performed. Average on employee level in manufacturing sector. All tasks weighted with frequency of task performance (1 "often", .5 "sometimes", 0 "rarely"). Sampling weights used (Gew2012_hr).

back

Baseline model setting

- A partial equilibrium setting for a given industry
- Each firm is faced with the same iso-elastic demand with price elasticity $\eta > 1$
- Firm i combines a continuum of tasks to produce

$$y_i = A_i \left(\int_0^1 s_i(j)^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}},$$

where A_i is firm-specific productivity, $s_i(j)$ is supply of task j

- Fixed cost of robot adoption: F

back

Baseline model setting, cont'd

- Two occupations: h and ℓ
- Firm i's share of tasks performed by ℓ: α_i
- Occupation o's share of automatable tasks: β_o $(o = \ell, h)$
- Supply of each task j is specified as

$$s_i(j) = \begin{cases} \ell_i(j) + \lambda k_i(j) & 0 \leq j \leq \beta_\ell \alpha_i \\ \ell_i(j) & \beta_\ell \alpha_i < j \leq \alpha_i \\ h_i(j) + \lambda k_i(j) & \alpha_i < j \leq \alpha_i + \beta_h(1 - \alpha_i) \\ h_i(j) & \alpha_i + \beta_h(1 - \alpha_i) < j \leq 1 \end{cases},$$

where $\ell_i(j)$ and $h_i(j)$ are labor input and $k_i(j)$ is robot input

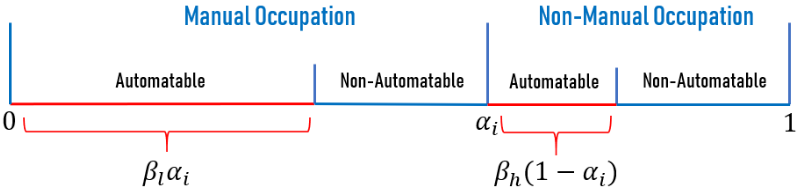
back

Extended model setting with age dimension

- Workers partitioned into G different age groups: $\{1, 2, ..., G\}$
- For any task i by occupation o ($o = \ell, h$), there exists an ideal age group $g_o(i)$ to perform that task
- Share of tasks automatable for age g and occupation o: $\beta_o(g)$
- How $\beta_o(g)$ changes with g varies with o
    - initial task specialization and new task adaptation
- Employment effects more positive (or less negative) for smaller $\beta_o(g)$

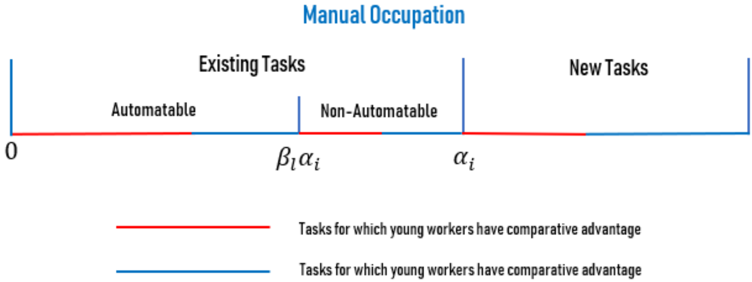
back

Replaceability across occupations: illustration



back

Replaceability across ages: illustration



back

Data

1. IAB Establishment Panel Survey 2019

2014	2015	2016	2017	2018

Examples:

0	0	0	0	0	→ non-user
0	1	3	5	5	→ robot adopter
2	2	10	10	8	→ incumbent user

back

Workforce composition by occupation (event study results)

	Occupation				
	(1) simple manual b/se	(2) qual manual b/se	(3) techn/engin b/se	(4) manager b/se	(5) svc occ b/se
2.rel_time	0.0152**	0.0017	0.0156***	0.0053	0.0029
	(0.0069)	(0.0060)	(0.0060)	(0.0055)	(0.0065)
3.rel_time	0.0187**	0.0049	0.0290***	0.0192***	0.0126
	(0.0095)	(0.0078)	(0.0077)	(0.0071)	(0.0087)
4.rel_time	0.0315***	0.0051	0.0439***	0.0373***	0.0247**
	(0.0117)	(0.0096)	(0.0094)	(0.0088)	(0.0107)
5.rel_time	0.0411***	-0.0130	0.0458***	0.0426***	0.0219*
	(0.0142)	(0.0122)	(0.0108)	(0.0105)	(0.0121)
1.D_robot_adoption#2.rel_time	0.0068	0.0020	0.0216	0.0353	0.0161
	(0.0215)	(0.0183)	(0.0197)	(0.0303)	(0.0203)
1.D_robot_adoption#3.rel_time	0.0165	0.0461*	0.0066	0.0243	0.0213
	(0.0290)	(0.0278)	(0.0299)	(0.0359)	(0.0312)
1.D_robot_adoption#4.rel_time	0.0097	0.0662	0.0669*	0.0740*	0.0715
	(0.0491)	(0.0445)	(0.0357)	(0.0412)	(0.0489)
1.D_robot_adoption#5.rel_time	0.0225	0.0841	0.0841**	0.0990**	0.0887
N	2067	2067	2067	2067	2067

back

Workforce composition by age (event study results)

	Age		
	(6) young b/se	(7) midage b/se	(8) older b/se
2.rel_time	-0.0138*	-0.0055	0.0505***
	(0.0080)	(0.0049)	(0.0075)
3.rel_time	-0.0179*	-0.0149**	0.1005***
	(0.0106)	(0.0066)	(0.0098)
4.rel_time	-0.0264**	-0.0275***	0.1616***
	(0.0126)	(0.0081)	(0.0117)
5.rel_time	-0.0515***	-0.0514***	0.2014***
	(0.0147)	(0.0107)	(0.0132)
1.D_robot_adoption#2.rel_time	0.0294	-0.0037	0.0459*
	(0.0181)	(0.0130)	(0.0247)
1.D_robot_adoption#3.rel_time	0.0653**	0.0110	0.0346
	(0.0277)	(0.0208)	(0.0259)
1.D_robot_adoption#4.rel_time	0.1098***	0.0441	0.0196
	(0.0338)	(0.0282)	(0.0370)
1.D_robot_adoption#5.rel_time	0.1449***	0.0568*	0.0284
	(0.0412)	(0.0334)	(0.0408)
N	2067	2067	2067

back

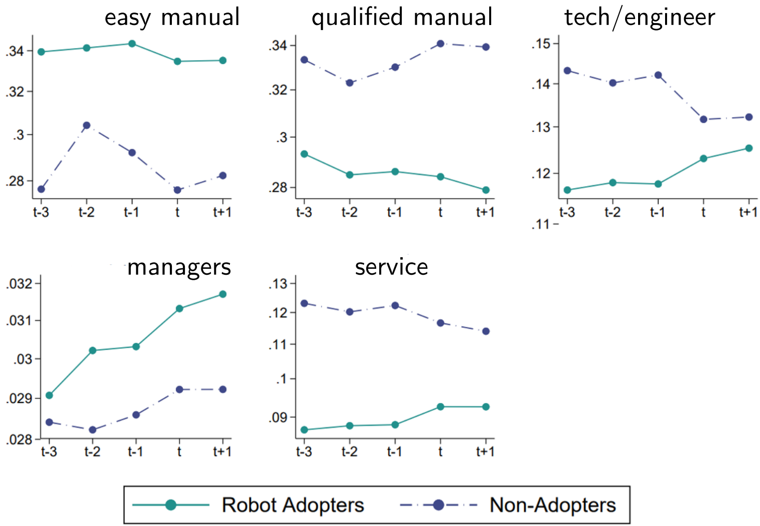


Figure: Share of employees per occupation (in % of total employment)

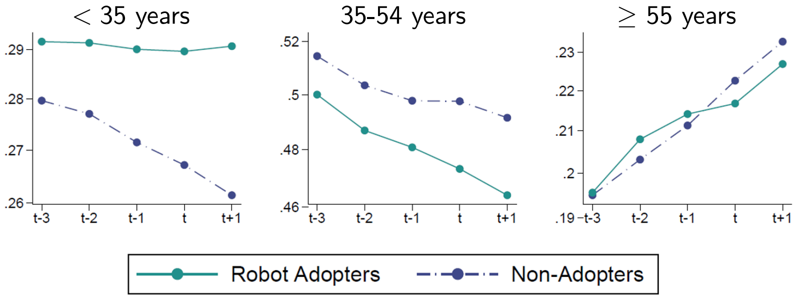


Figure: Share of employees per age group (in % of total employment)

back

TWFE and multiple events

The TWFE setting can be decomposed into several simple DiD settings. Goodman-Bacon (2021) shows that an OLS estimation of a TWFE model with several treatment events includes undesirable comparisons.

- But we deviate from the two-way fixed effect model: randomized control group to match exactly the pre and post period of adopter group. We then pool across the treatment to control comparisons in a relative time setting. The staggered diff-in-diff setting is effectively turned into a standard diff-in-diff setting.
- W.r.t. Goodman-Bacon (2021) we exclude two of the simple DiD comparisons: later adopters as control to earlier adopters (wanted), earlier adopters as control to to late adopters (unwanted). But we only lose 4% of observations by not including the wanted comparison above. Thus, we still consider our estimate to be efficient.