Adjusting to Robots

Wolfgang Dauth (University of Würzburg; IAB)
Sebastian Findeisen (University of Mannheim; CEPR)
Jens Suedekum (DICE Düsseldorf; CEPR; CESifo)
Nicole Woessner (DICE Düsseldorf)

Supported by the DFG Priority Program 1764:
The German Labour Market in a Globalised World

14th joint ECB/CEPR Labour Market Workshop
Frankfurt, 7 December 2018

Motivation: Automation and Employment

- Media routinely portrays a future where robots will "take all our jobs"

The New York Times

The Long-Term Jobs Killer Is Not China. It's Automation.

theguardian

Robots will destroy our jobs - and we're not ready for it

The Economist

The impact on jobs

Automation and anxiety

Will smarter machines cause mass unemployment?

Automation is a real threat. How can we slow down the march of the cyborgs?

Motivation: Automation and Employment

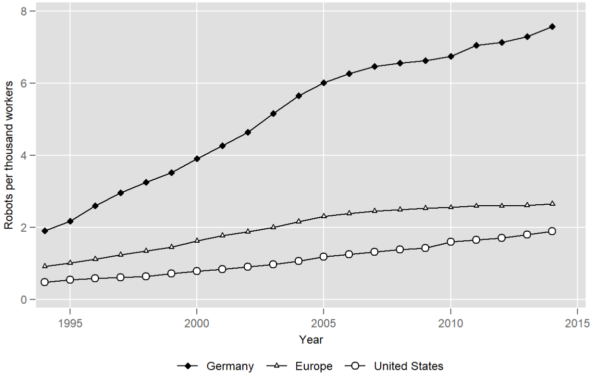
- Media routinely portrays a future where robots will "take all our jobs"
- The more sophisticated view – based on introspection and also based on theory – is that
    1. automation *displaces* labor from certain tasks...Displacement Effect
    2. but also raises productivity, which can potentially increase labor demand in other tasks or create new tasks....Productivity and Reallocation Effect
- We don't know whether the first or the second effect dominates...and need more evidence

What we do

- In this paper, we focus on a particular episode of automation:
  the rise of industrial robots between 1994 and 2014, used in manufacturing

What we do

- In this paper, we focus on a particular episode of automation: **the rise of industrial robots** between 1994 and 2014, used in manufacturing



  - Pervasive global increase. Germany, South Korea, and Japan have adopted the most

What we do

- In this paper, we focus on a particular episode of automation: **the rise of industrial robots** between 1994 and 2014, used in manufacturing
- First, we ask how strong displacement and reallocation effects of labor are in the German context
- Second, what is behind the worker displacement and worker reallocation effects?
  - Who gets displaced? Who gets re-allocated? Where does new labor demand arise? Across firms, industries, occupations?
- Third, beyond employment, we look at wages and distributional issues:
  - In particular, labor versus capital: does the labor share decrease?
  - Labor share has been documented to fall in most countries in last 30 years [Autor, Dorn, Katz, Patterson, Van Reenen 2018], [Karabarbounis and Neiman, 2013], but causes of decline remain uncertain

Research Design

- Before previewing results, a few words on the research design
- In our main analysis, we compare the impact of robots across local labor markets
- This motivated by past research, which has found that much of the adjustment to comparable shocks, both in the short run and the medium run, takes place locally, e.g.
  - Moretti (2011) surveys older literature
  - Computers: Autor and Dorn (2013)
  - Trade: Autor, Dorn, Hanson (2013)
- We identify relative effects as in a differences-in-differences analysis.
  - Mapping to aggregate effects needs a model. We use a model by Acemoglu and Restrepo (2018) to calibrate some of the aggregate impacts

Preview: Results

1. We find sizeable *displacement effects* exactly offset by *reallocation effects*. Summing up to zero total employment effects.
   - Each robot killed 2 manufacturing jobs but offsetting job growth in service jobs
2. Who is displaced from manufacturing?
   - Incumbent workers are not displaced. All action is on the hiring margin of new cohorts.
3. Reallocation takes partly place within firms across occupations.
   - Re-training within firms. Legislative firing costs.
4. Labor share goes down, wages go down, labor productivity goes up

Literature

- Technology (ICT) and Labor Markets
  - Autor, Levy, and Murnane 2003; Goos and Manning, 2007; Acemoglu and Autor 2011; Autor and Dorn 2013; Goos, Manning, and Salomons 2014; Michaels, Natraj and Van Reenen 2014; Frey and Osborne 2013; Gregory, Salomons and Zierahn 2018
- Trade and Labor Markets
  - Autor, Dorn, Hanson 2013; Autor, Dorn, Hanson, Song 2014; Dauth, Findeisen, Suedekum 2014
- Automation (Robots) in Theory
  - Acemoglu and Restrepo 2018 a; b; c
- Graetz and Michaels 2018: Across industries across countries. No total employment effects. Positive effect on labor productivity.
- Acemoglu and Restrepo 2018: Across local labor markets, robots dreadful for US workers. We add results 2 – 4 to this literature.

Rest of Talk

1. Data, Research Design, and Identification Issues

2. Results
    2.1 Displacement and Reallocation/Productivity Effects
    2.2 Decomposition
    2.3 Productivity and the Labor Share

3. Comparison to the US and Conclusion

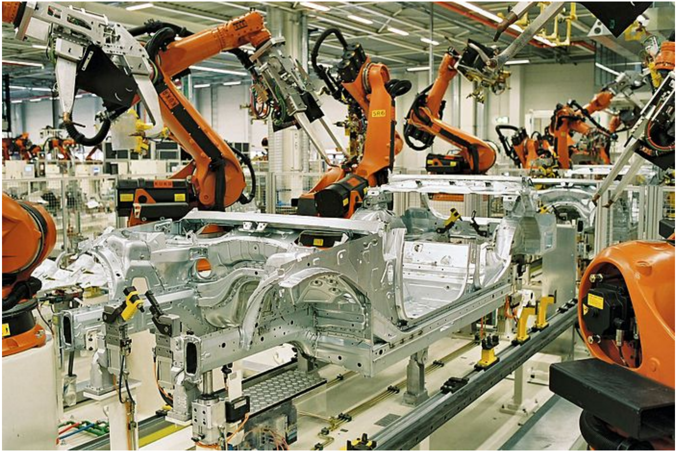
Definition of an Industrial Robot

Industrial Robot (ISO 8373)

An automatically controlled and multipurpose machine for use in industrial applications.

- Do not need a human operator and can be used for different tasks
- For example, cranes or transportation bands are not industrial robots
  - They cannot be reprogrammed to perform other tasks, and/or require a human operator.
- Typical tasks that used to be labor intensive:
  - Welding, assembling, packaging, inspecting...

Robot tasks



- Welding of a car

Robot tasks

- Palletizing food in a bakery

Robot Data

- Data comes from International Federation of Robotics (IFR)
  - Lobby: "promote, strengthen and protect the robotics industry worldwide"
  - Has built a detailed data base on robot adoption across countries and industries
  - First used and probed by Graetz and Michaels (2018)
  - Installations and stock of industrial robots at 2 or 3 digit industry level (25 industries; use crosswalks to assign to 75 NACE Rev.1 2/3 digit industries)
  - Based on yearly surveys of robot suppliers (over 90% of the world market)
- Auto industry (35%), electrical equipment, household appliances (dishwasher etc.), furniture, games and toys, musical instruments
- Started to be used on some scale in 1980 and then accelerated in 1990's

Distribution by industry

Labor market data

- Integrated Employment Biographies (IEB), provided by the Employment Research (IAB) of the German Federal Employment Agency
  - Full employment biographies of *all* German employees except for civil servants and self-employed
  - Daily data on employment, earnings, occupation, location, industry, education, demographics
- Establishment History Panel (BHP) by the IAB
  - Employee information of IEB, aggregated to plant level
  - Further aggregated to 402 NUTS-3 level counties (*Landkreise*)
  - Information on level and composition of employment (in full-time equivalents), industry structure, characteristics of the workforce
- Federal Statistical Office
  - National accounts broken down to local labor markets
  - Information on population size, GDP, income and productivity measures, etc.

Research Design

- Local labor market shift-share design with Bartik-instrument:
  - Exposure to ICT: Autor and Dorn (2013)
  - Exposure to trade: Autor, Dorn, and Hanson (2013) and others
  - Immigration: Card, Peri and others
  - Exposure to robots: Acemoglu and Restrepo (2018)

Research Design

- Local labor market shift-share design with Bartik-instrument:
- In detail: How strongly is a local labor market affected?

$$\Delta \text{robots}_r = \frac{1}{\text{emp}_{r,1994}} \sum_{j=1}^{72} \left(\frac{\text{emp}_{jr,1994}}{\text{emp}_{j,1994}} \times \Delta \text{robots}_j \right)$$

- Δrobots_j = increase in number of robots in industry j
- Distribute across regions according to national employment share of local industry $\frac{\text{emp}_{jr,1994}}{\text{emp}_{j,1994}}$
- For each region r, we sum over all 72 industries j
- Finally: normalize by size of local labor market to get a per worker measure
- Variation comes purely from regions' initial industry specialization in 1994
- Microfoundation: Acemoglu and Restrepo (2018)

Research Design

- Local labor market shift-share design with Bartik-instrument:
- In detail: How strongly is a local labor market affected?

$$\Delta\text{robots}_r = \frac{1}{\text{emp}_{r,1994}} \sum_{j=1}^{72} \left(\frac{\text{emp}_{jr,1994}}{\text{emp}_{j,1994}} \times \Delta\text{robots}_j \right)$$

- Δrobots_j = increase in number of robots in industry j
- Distribute across regions according to national employment share of local industry $\frac{\text{emp}_{jr,1994}}{\text{emp}_{j,1994}}$
- For each region r, we sum over all 72 industries j
- Finally: normalize by size of local labor market to get a per worker measure
- Variation comes purely from regions' initial industry specialization in 1994
- Microfoundation: Acemoglu and Restrepo (2018)

Research Design

- Local labor market shift-share design with Bartik-instrument:
- In detail: How strongly is a local labor market affected?

$$\Delta \text{robots}_r = \frac{1}{\text{emp}_{r,1994}} \sum_{j=1}^{72} \left(\frac{\text{emp}_{jr,1994}}{\text{emp}_{j,1994}} \times \Delta \text{robots}_j \right)$$

- Δrobots_j = increase in number of robots in industry j
- Distribute across regions according to national employment share of local industry $\frac{\text{emp}_{jr,1994}}{\text{emp}_{j,1994}}$
- For each region r, we sum over all 72 industries j
- Finally: normalize by size of local labor market to get a per worker measure
- Variation comes purely from regions' initial industry specialization in 1994
- Microfoundation: Acemoglu and Restrepo (2018)

Research Design

- Local labor market shift-share design with Bartik-instrument:
- In detail: How strongly is a local labor market affected?

$$\Delta \text{robots}_r = \frac{1}{\text{emp}_{r,1994}} \sum_{j=1}^{72} \left(\frac{\text{emp}_{jr,1994}}{\text{emp}_{j,1994}} \times \Delta \text{robots}_j \right)$$

- Δrobots$_j$ = increase in number of robots in industry j
- Distribute across regions according to national employment share of local industry $\frac{\text{emp}_{jr,1994}}{\text{emp}_{j,1994}}$
- For each region r, we sum over all 72 industries j
- Finally: normalize by size of local labor market to get a per worker measure
- Variation comes purely from regions' initial industry specialization in 1994
- Microfoundation: Acemoglu and Restrepo (2018)

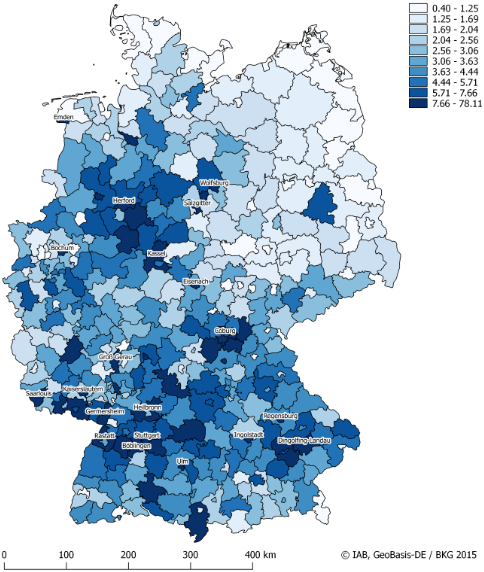
Research Design

- Local labor market shift-share design with Bartik-instrument:
- In detail: How strongly is a local labor market affected?

$$\Delta \text{robots}_r = \frac{1}{\text{emp}_{r,1994}} \sum_{j=1}^{72} \left(\frac{\text{emp}_{jr,1994}}{\text{emp}_{j,1994}} \times \Delta \text{robots}_j \right)$$

- Δrobots_j = increase in number of robots in industry j
- Distribute across regions according to national employment share of local industry $\frac{\text{emp}_{jr,1994}}{\text{emp}_{j,1994}}$
- For each region r, we sum over all 72 industries j
- Finally: normalize by size of local labor market to get a per worker measure
- Variation comes purely from regions' initial industry specialization in 1994
- Microfoundation: Acemoglu and Restrepo (2018)

Robot Exposure: Regional Variation County Level



- Strong regional variation of robot exposure
- Most exposed regions are Wolfsburg and Dingolfing-Landau (factory towns of *Volkswagen* and *BMW*)
- Substantially lower exposure in East Germany

Identification Issues

- Local labor markets that specialize in industries more exposed to this shock may be systematically different
  - Identification conditional on local demographic characteristics and broad industry structures, and within broad regions

Identification Issues

- Local labor markets that specialize in industries more exposed to this shock may be systematically different
  - Identification conditional on local demographic characteristics and broad industry structures, and within broad regions
- Pattern of robot adoption in German industries correlated with unobservables
  - A confounder:
    Maybe German industries face unobserved shocks at the same time affecting their robot demand and other outcomes

Identification Issues

- Local labor markets that specialize in industries more exposed to this shock may be systematically different
  - Identification conditional on local demographic characteristics and broad industry structures, and within broad regions
- Pattern of robot adoption in German industries correlated with unobservables
  - A confounder:
    Maybe German industries face unobserved shocks at the same time affecting their robot demand and other outcomes
  - Step back: What is the experiment? Robot prices fall or robots become better
  - Industries differ in the suitability for robot use, and this generates differences in robot adoption across industries
  - Instrument German adoption with adoption in other countries
    - Remaining cross-industry variation in adoption that is correlated across countries is likely to be due to the robot supply shock

Identification Issues: Three Additional Tools

1. We conduct Placebo exercises to see if pre-treatment outcomes are correlated with future exposure
2. We check if 2SLS and OLS estimates are sensitive to the inclusion of controls
3. Standard errors clustered at the level of 50 aggregate labor market regions

Empirical Model

- Change in log employment over the period 1994–2014

$$\Delta Y_r = \boldsymbol{\alpha} \cdot \mathbf{x}_r' + \beta_1 \cdot \Delta \text{robots}_r + \beta_2 \cdot \Delta \text{trade}_r + \beta_3 \cdot \Delta \text{ICT}_r + \phi_{REG(r)} + \epsilon_r$$

- $\mathbf{x}_r'$: workforce and industry characteristics in levels which influence the employment trend in the region
  - Contains % female, % foreign, % age $\geq$ 50, % medium skilled (percentage of workers with completed apprenticeship), and % high skilled (percentage of workers with a university-degree) in 1994
  - Manufacturing share
  - Industry shares cover the percentage of workers in nine broad industry groups: agriculture; food products; consumer goods; industrial goods; capital goods; construction; maintenance, hotels and restaurants; education, social work, other organizations
- Δtrade_r, ΔICT_r: other shift share variables, control for trade exposure and ICT investment
- $\phi_{REG(r)}$: dummies for North, South, West, East Germany

Aggregate: Total Employment

	(1)	(2)	(3)	(4)	(5)
IV: Robots in other countries	2SLS: 100 × Log-△ in total employment between 1994 and 2014				
△ robots per 1000 workers	-0.0072	-0.0918	-0.0270	-0.0019	0.0023
	(0.111)	(0.108)	(0.118)	(0.112)	(0.119)
△ net exports in 1000 € per worker		0.8954**	0.7297**	0.7449**	0.6322*
		(0.366)	(0.330)	(0.313)	(0.375)
△ ICT equipment in € per worker			0.0178	0.0139	0.0045
			(0.012)	(0.014)	(0.014)
Broad region dummies	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes
Manufacturing share	No	No	No	Yes	No
Broad industry shares	No	No	No	No	Yes

Notes: $N = 402$. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

- Zero aggregate effects (point estimate is 0.0023%)...but this masks offsetting displacement and reallocation

Manufacturing versus non-manufacturing

	Employment		
	(1)	(2)	(3)
	Total	Manuf.	Non-manuf.
[A] Baseline: 100 x Log-△ in employment between 1994 and 2014			
△ robots per 1000 workers	0.0023	-0.3832**	0.4257**
	(0.119)	(0.149)	(0.205)
[B] Alternative employment measure: 100 x △ in e/pop 1994 and 2014			
△ robots per 1000 workers	-0.0177	-0.0594**	0.0417
	(0.065)	(0.027)	(0.050)
N	402	402	402

- Effect of 1 additional robot on manufacturing jobs: -2.12 (=-0.0595/100 x 1000/0.2812)
  US: -6.2 (Acemoglu/Restrepo 2018)
- Adds up to 276,507 manufacturing jobs $\hat{=}$ 23% of manufacturing decline in 1994–2014
- But: Fully compensated by additional jobs in non-manufacturing!

Where do offsetting job gains come from?

Table: Decomposing services

	Dependent variable: 100 x Log-△ in employment between 1994 and 2014				
	(1) Non-Manuf.	(2) Constr.	(3) Consumer serv.	(4) Business serv.	(5) Public sector
△ robots per 1000 workers	0.4257**	-0.0476	0.2114	0.7572*	0.0656
	(0.205)	(0.192)	(0.234)	(0.390)	(0.120)

- Business services: consulting, advertising, temporary work.
- Firms spend locally on these services
- Consistent with "freed-up labor" theory:
  workers increasingly used in other tasks as output expands

Who is Displaced and Reallocated?

- A large literature has documented dreadful and long-lasting effects of displacement for workers
  - Plant closure literature: Jacobson, LaLonde, and Sullivan (1993), Schmieder, Wachter, and Heining (2018), Autor, Dorn, Hanson, and Song (2014)
- Does automation induce similar effects?

Who is Displaced and Reallocated?

- A large literature has documented dreadful and long-lasting effects of displacement for workers
  - Plant closure literature: Jacobson, LaLonde, and Sullivan (1993), Schmieder, Wachter, and Heining (2018), Autor, Dorn, Hanson, and Song (2014)
- Does automation induce similar effects?
- We look at incumbent manufacturing workers in 1994 and see how robots affected their employment biographies Summary statistics
- Focus on total employment measured in days over 20 year period. Decompose it precisely.
- Run similar models as before at worker level using industry exposure

Worker Adjustment

[A] Industry mobility	(1)	(2)	(3)	(4)	(5)
	all employers		same sector		other sector
Same industry		yes	yes	no	no
Same employer		yes	no	no	no
Δ robots per 1000 workers	0.8003**	11.4410***	-4.6514***	-2.0260	-3.9632***
	(0.349)	(2.124)	(1.475)	(1.669)	(1.029)

[B] Occupational mobility	(1)	(2)	(3)	(4)	(5)
	all jobs	same employer		other employer	
Same occupational field		yes	no	yes	no
Δ robots per 1000 workers	0.8003**	6.3888***	5.0522***	-7.5556***	-3.0850***
	(0.349)	(1.584)	(0.744)	(1.692)	(0.559)

Notes: Based on 993,184 workers. 2SLS results including the full set of control variables. The outcome variables are cumulated days of employment.

- Coefficients from models in column 2-5 add up to column 1

Worker Adjustment

[A] Industry mobility	(1)	(2)	(3)	(4)	(5)
	all employers		same sector		other sector
Same industry		yes	yes	no	no
Same employer		yes	no	no	no
Δ robots per 1000 workers	0.8003**	11.4410***	-4.6514***	-2.0260	-3.9632***
	(0.349)	(2.124)	(1.475)	(1.669)	(1.029)

[B] Occupational mobility	(1)	(2)	(3)	(4)	(5)
	all jobs	same employer		other employer	
Same occupational field		yes	no	yes	no
Δ robots per 1000 workers	0.8003**	6.3888***	5.0522***	-7.5556***	-3.0850***
	(0.349)	(1.584)	(0.744)	(1.692)	(0.559)

Notes: Based on 993,184 workers. 2SLS results including the full set of control variables. The outcome variables are cumulated days of employment.

- Robot exposure increases total employment duration

Worker Adjustment

[A] Industry mobility	(1)	(2)	(3)	(4)	(5)
	all employers		same sector		other sector
Same industry		yes	yes	no	no
Same employer		yes	no	no	no
Δ robots per 1000 workers	0.8003**	11.4410***	-4.6514***	-2.0260	-3.9632***
	(0.349)	(2.124)	(1.475)	(1.669)	(1.029)

[B] Occupational mobility	(1)	(2)	(3)	(4)	(5)
	all jobs	same employer		other employer	
Same occupational field		yes	no	yes	no
Δ robots per 1000 workers	0.8003**	6.3888***	5.0522***	-7.5556***	-3.0850***
	(0.349)	(1.584)	(0.744)	(1.692)	(0.559)

Notes: Based on 993,184 workers. 2SLS results including the full set of control variables. The outcome variables are cumulated days of employment.

- Strongly driven by increased job stability with original firm. p90 versus p10: 3 years

Worker Adjustment

[A] Industry mobility	(1) all employers	(2)	(3) same sector	(4)	(5) other sector
Same industry		yes	yes	no	no
Same employer		yes	no	no	no
Δ robots per 1000 workers	0.8003**	11.4410***	-4.6514***	-2.0260	-3.9632***
	(0.349)	(2.124)	(1.475)	(1.669)	(1.029)

[B] Occupational mobility	(1) all jobs	(2) same employer	(3)	(4) other employer	(5)
Same occupational field		yes	no	yes	no
Δ robots per 1000 workers	0.8003**	6.3888***	5.0522***	-7.5556***	-3.0850***
	(0.349)	(1.584)	(0.744)	(1.692)	(0.559)

Notes: Based on 993,184 workers. 2SLS results including the full set of control variables. The outcome variables are cumulated days of employment.

- Coefficients of column 2 and 3 from Panel B add up to column 2 from Panel A

Worker Adjustment

[A] Industry mobility	(1) all employers	(2)	(3) same sector	(4)	(5) other sector
Same industry		yes	yes	no	no
Same employer		yes	no	no	no
Δ robots per 1000 workers	0.8003**	11.4410***	-4.6514***	-2.0260	-3.9632***
	(0.349)	(2.124)	(1.475)	(1.669)	(1.029)

[B] Occupational mobility	(1) all jobs	(2) same employer	(3)	(4) other employer	(5)
Same occupational field		yes	no	yes	no
Δ robots per 1000 workers	0.8003**	6.3888***	5.0522***	-7.5556***	-3.0850***
	(0.349)	(1.584)	(0.744)	(1.692)	(0.559)

Notes: Based on 993,184 workers. 2SLS results including the full set of control variables. The outcome variables are cumulated days of employment.

- 45% of increased tenure in original firm happens in different occupation

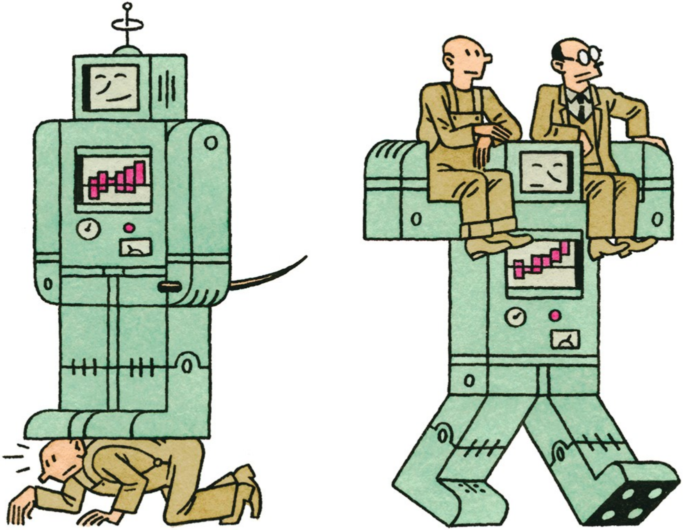
Automation and Firing Costs

- What explains this?
- Firing costs for individual workers are high in Germany especially if the firm is doing well
- Firms have to plead the case that worker cannot take another job in the firm
- Firing restrictions seem to encourage re-training at the firm level
- Job stability is no free lunch: negative effect of robots on wage in original firm! (Earnings/wage effect is skill-biased) Heterogenous effects

Automation and Firing Costs

- What explains this?
- Firing costs for individual workers are high in Germany especially if the firm is doing well
- Firms have to plead the case that worker cannot take another job in the firm
- Firing restrictions seem to encourage re-training at the firm level
- Job stability is no free lunch: negative effect of robots on wage in original firm! (Earnings/wage effect is skill-biased) ▸ Heterogenous effects
- We show replacement and reallocation across sector incidence is purely on entering labor market cohorts
- Labor market entrants start their careers in non-manufacturing industries in exposed regions

Who profits from the robots? Labor versus Capital



Productivity and the Labor Share

- Going back to local labor market level

	Dependent variable: Change between 2004 and 2014		
	(1) Labor productivity	(2) Labor share	(3) Population
△ robots per 1000 workers	0.5345**	-0.4380**	0.0242
	(0.268)	(0.192)	(0.191)
N	402	372	402

Notes: The dependent variable in column (1) is the log change in output per worker x 100, in column (2) the percentage point change in gross pay per employee over output per worker x 100, and in column (3) the log change in population x 100. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

- Regions with higher robot exposure see stronger increases in labor productivity (GDP per employee)...
- ... but no increasing average wages...
- Thus, stronger decline in labor income share

Comparison to US

- Automation has caused substantial displacement effects in Germany
- But only around 50% of the displacement effects in the US and, in sharp contrast, zero aggregate effects [Acemoglu and Restrepo, 2018]
- Why are displacement effects smaller here?
- Legislative firing costs
  - Reduces displacement for incumbent workers
- Strong unions and worker councils
- German skilled workers probably can be re-trained more easily [Janssen and Mohrenweiser, 2018]

Conclusion

- Robots have not been job killers
- No total job losses, but effect on composition of aggregate employment
  - Channel: Robots *foreclose* entry into manufacturing for labor market entrants
- Incumbent workers are not displaced, but many earn lower wages
  - Direct evidence for skill-biased technological change
- Positive effect on labor productivity, but not on labor income
  - Contributing to the declining labor share

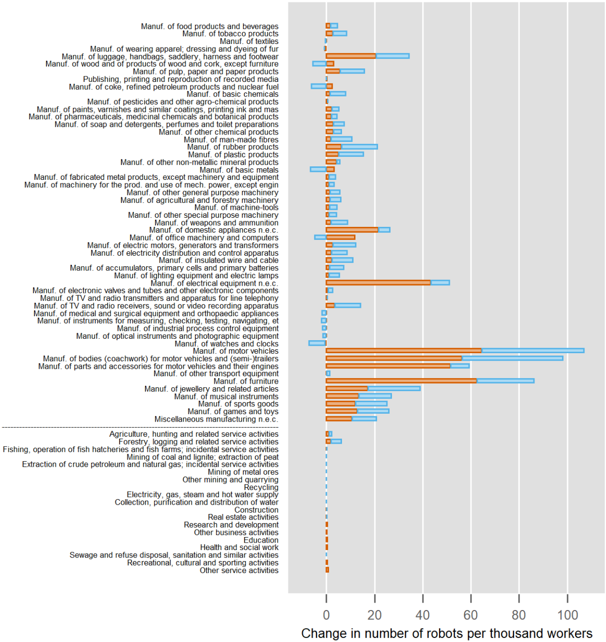
Bottom line

- No need to panic about mass unemployment
- Worry about income distribution!

woessner@dice.uni-duesseldorf.de

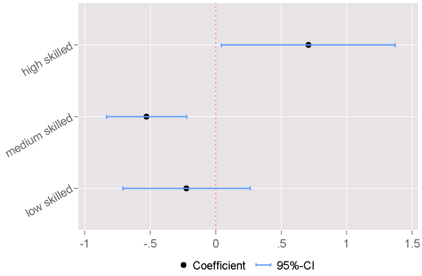
APPENDIX

back

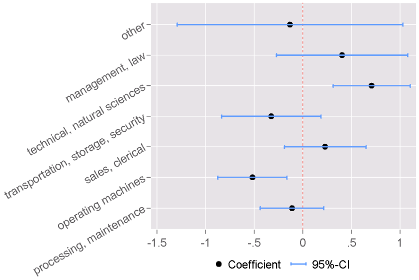

Manuf. of food products and beverages
Manuf. of tobacco products
Manuf. of textiles
Manuf. of wearing apparel; dressing and dyeing of fur
Manuf. of luggage, handbags, saddlery, harness and footwear
Manuf. of wood and of products of wood and cork, except furniture
Manuf. of pulp, paper and paper products
Publishing, printing and reproduction of recorded media
Manuf. of coke, refined petroleum products and nuclear fuel
Manuf. of basic chemicals
Manuf. of pesticides and other agro-chemical products
Manuf. of paints, varnishes and similar coatings, printing ink and mas
Manuf. of pharmaceuticals, medicinal chemicals and botanical products
Manuf. of soap and detergents, perfumes and toilet preparations
Manuf. of other chemical products
Manuf. of man-made fibres
Manuf. of rubber products
Manuf. of plastic products
Manuf. of other non-metallic mineral products
Manuf. of basic metals
Manuf. of fabricated metal products, except machinery and equipment
Manuf. of machinery for the prod. and use of mech. power, except engin
Manuf. of other general purpose machinery
Manuf. of agricultural and forestry machinery
Manuf. of machine-tools
Manuf. of other special purpose machinery
Manuf. of weapons and ammunition
Manuf. of domestic appliances n.e.c.
Manuf. of office machinery and computers
Manuf. of electric motors, generators and transformers
Manuf. of electricity distribution and control apparatus
Manuf. of insulated wire and cable
Manuf. of accumulators, primary cells and primary batteries
Manuf. of lighting equipment and electric lamps
Manuf. of electrical equipment n.e.c.
Manuf. of electronic valves and tubes and other electronic components
Manuf. of TV and radio transmitters and apparatus for line telephony
Manuf. of TV and radio receivers, sound or video recording apparatus
Manuf. of medical and surgical equipment and orthopaedic appliances
Manuf. of instruments for measuring, checking, testing, navigating, et
Manuf. of industrial process control equipment
Manuf. of optical instruments and photographic equipment
Manuf. of watches and clocks
Manuf. of motor vehicles
Manuf. of bodies (coachwork) for motor vehicles and (semi-)trailers
Manuf. of parts and accessories for motor vehicles and their engines
Manuf. of other transport equipment
Manuf. of furniture
Manuf. of jewellery and related articles
Manuf. of musical instruments
Manuf. of sports goods
Manuf. of games and toys
Miscellaneous manufacturing n.e.c.
Agriculture, hunting and related service activities
Forestry, logging and related service activities
Fishing, operation of fish hatcheries and fish farms; incidental service activities
Mining of coal and lignite; extraction of peat
Extraction of crude petroleum and natural gas; incidental service activities
Mining of metal ores
Other mining and quarrying
Recycling
Electricity, gas, steam and hot water supply
Collection, purification and distribution of water
Construction
Real estate activities
Research and development
Other business activities
Education
Health and social work
Sewage and refuse disposal, sanitation and similar activities
Recreational, cultural and sporting activities
Other service activities
0
20
40
60
80
100
Change in number of robots per thousand workers

Heterogeneous effects

back



(a) by education



(b) by occupation

- Earnings losses: Medium-skilled workers performing routine and manual tasks
- Earnings gains: High-skilled workers in non-routine occupations

Summary statistics, worker level

back

	1994-2014		1994-2004		2004-2014	
observations	993,184		1,431,576		1,246,414	
	mean	(sd)	mean	(sd)	mean	(sd)
[A] Outcomes, cumulated over years following base year						
days employed	5959	(2014)	3015	(1001)	3261	(802)
average daily wage	120.7	(71.6)	121.7	(74.4)	126.8	(73.9)
100 x earnings / base year earnings	1925	(1001)	940	(449)	950	(353)
[B] control variables, measured in base year						
base year earnings	38880	(20775)	40273	(22441)	44862	(28322)
dummy, 1=female	0.239	(0.426)	0.237	(0.425)	0.215	(0.411)
dummy, 1=foreign	0.100	(0.301)	0.110	(0.312)	0.086	(0.280)
birth year	1960	(6)	1955	(9)	1963	(8)
dummy, 1=low skilled	0.153	(0.360)	0.170	(0.375)	0.118	(0.323)
dummy, 1=medium skilled	0.756	(0.430)	0.740	(0.438)	0.757	(0.429)
dummy, 1=high skilled	0.091	(0.288)	0.090	(0.286)	0.125	(0.331)
dummy, 1=tenure 2-4 yrs	0.405	(0.491)	0.357	(0.479)	0.285	(0.451)
dummy, 1=tenure 5-9 yrs	0.315	(0.464)	0.270	(0.444)	0.287	(0.452)
dummy, 1=tenure $\geq$10 yrs	0.243	(0.429)	0.338	(0.473)	0.387	(0.487)
dummy, 1=plant size $\leq$9	0.059	(0.236)	0.056	(0.230)	0.045	(0.207)
dummy, 1=plant size 10-99	0.232	(0.422)	0.230	(0.421)	0.251	(0.434)
dummy, 1=plant size 100-499	0.287	(0.453)	0.288	(0.453)	0.320	(0.466)
dummy, 1=plant size 500-999	0.121	(0.326)	0.122	(0.328)	0.118	(0.322)
dummy, 1=plant size 1000-9999	0.219	(0.414)	0.222	(0.415)	0.189	(0.392)
dummy, 1=plant size $\geq$10000	0.079	(0.269)	0.080	(0.271)	0.075	(0.263)
dummy, 1=food products	0.084	(0.277)	0.083	(0.276)	0.085	(0.279)
dummy, 1=consumer goods	0.123	(0.328)	0.124	(0.330)	0.099	(0.299)
dummy, 1=industrial goods	0.362	(0.480)	0.362	(0.481)	0.363	(0.481)
dummy, 1=capital goods	0.432	(0.495)	0.430	(0.495)	0.453	(0.498)