# Robots and the income distribution

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

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The German Labour Market in a Globalised World

DG ECFIN – Brussels, 19 November 2018

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?

# Robots will steal your job: Over time


(a) 1964


(b) 1978


(c) 2016

# The next industrial revolution

An imminent fear of technological unemployment ... again!

- Famous fore-runners: Aristotle (300 b.c.), Elizabeth I. (1589), Keynes (1930), Leontief (1983): Analogy to horses in the early 20th century
- Frey and Osborne (2017), World Development Report (2016), Ford (2015): Almost 50% of all jobs can be replaced by machines
- Based on projections which tasks *could be* replaced, given current technology

So far: the labor markets in good shape, despite steam engines, computers, ...

# The next industrial revolution

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So far: the labor markets in good shape, despite steam engines, computers, ...

Robots: Is **this time** different?

- Little systematic analysis of *general equilibrium* impact of robots
- Not everything that *could* be replaced *will* be replaced
- Acemoglu/Restrepo (2016): *displacement effect* vs. *productivity effect*

# What we do

- What is the impact of *industrial robots* on the German labor market?
- *Individual* perspective, tracing employment biographies of $\sim$1 million workers with a varying robot exposure over time
  - How did individual workers adjust to this technology?
  - Were workers displaced because of robots?
  - How were wages affected?
- *Aggregate* perspective, using a local labor market approach in spirit of Acemoglu/Restrepo (2017)
  - Regions are sub-economies that are differently exposed to robots
  - What is the equilibrium impact of robots on local labor markets in Germany?
  - How do robots affect the (functional) income distribution?

# What we find

- Robots have **no effect** on the **total number of jobs**, but on their **composition**
  - Robots reduce manufacturing employment, but this is compensated new jobs in the service sector!
- Robots do not destroy existing jobs, but they reduce the creation of new manufacturing jobs for labor market entrants
- Low/medium skilled production workers experience earnings losses, while high-skilled workers gain.
- Robots raise labor productivity, but not average wages. Contribute to the falling labour income share.

# Literature

**Robots**

- Graetz/Michaels (2016): Panel of country/industry cells. Support for productivity. Negative employment effects only for low-skilled
- Acemoglu/Restrepo (2016): displacement vs. productivity. Possibly skilled biased, depends on how quickly low skilled adapt
- Acemoglu/Restrepo (2017): US local labor markets. 1 robot eats 3-6 jobs!

**Skill-biased technological change:** Katz/Murphy 1992; Autor et al. 2003; Michaels et al. 2014

- Information/communication technology replaces medium skilled routine labor but is complementary to high skill labor

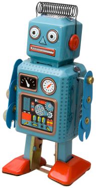
**Falling labor share:** Autor et al. 2017; Kehring/Vincent 2017

- Globalization or technological change lead to reallocation of production to "superstar firms", having increasingly high profits and a low share of labor

# What is a robot?

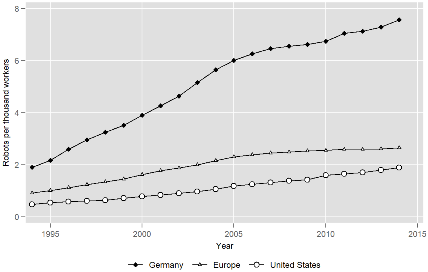
### Industrial robot (ISO 8373)

An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications

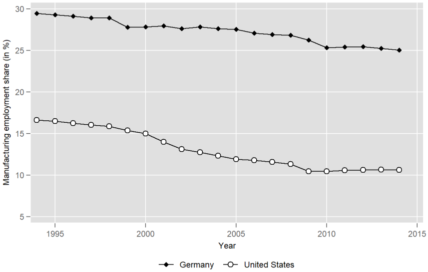


- International Federation of Robotics (IFR): *World Robotics Industrial Robots*
  - Based on yearly surveys of robot manufacturers

# German robots




(f) Industrial robots




(g) Manufacturing employment

- Germany has *substantially* more robots and manufacturing jobs p.c. than US
- 130,428 robots installed in 1994–2014
- Among the 20 largest robotic producers in the world, 5 are German (1 US)

# Robot data

- International Federation of Robotics (IFR): *World Robotics Industrial Robots*
  - Installations and operational stock of industrial robots for 50 countries and ISIC Rev. 4 industries (2- or 3-digit)
  - Based on yearly surveys of robot manufacturers
  - Stocks estimated from flows using perpetual inventory approach

## Industrial robot (ISO 8373)

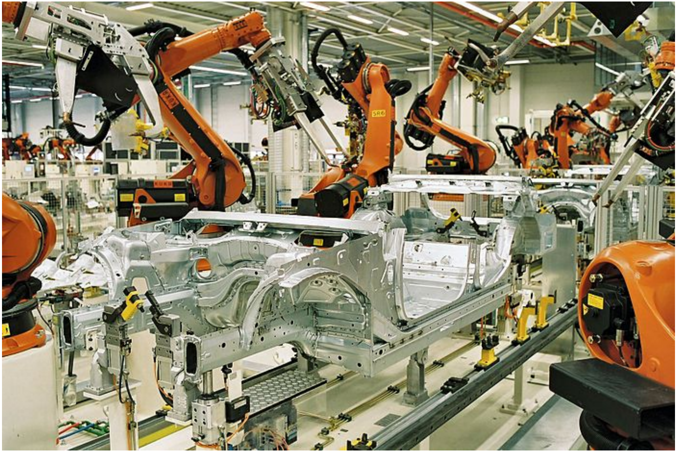
An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications

- Industrial robots in Germany

Distribution

  - Industries can be mapped into 72 NACE Rev. 1 codes using cross-walks provided by EUROSTAT
  - Change in number of robots per 1000 workers (1994–2014):
    Manuf. of motor vehicles, auto bodies, and parts (60-100), furniture (80), electrical equipment (50)

# Robot Tasks



- Welding of a car

# Robot Tasks

- Palletizing food in a bakery

# Robot Tasks


- Flat-glass handling, heavy duty robot with 1,000 kg payload

# Robot Tasks

- Foundry automation with a heat-resistant robot

# Individual workers and local labor markets

- 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

  Summary statistics
  - 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, unemployment rates

# Robot exposure

How strongly is an individual worker in industry $j$ exposed to robots?

$$\Delta\text{robots}_j = \frac{[\text{Robot count}]_{j,2014} - [\text{Robot count}]_{j,1994}}{\text{emp}_{j,1994}/1000}$$

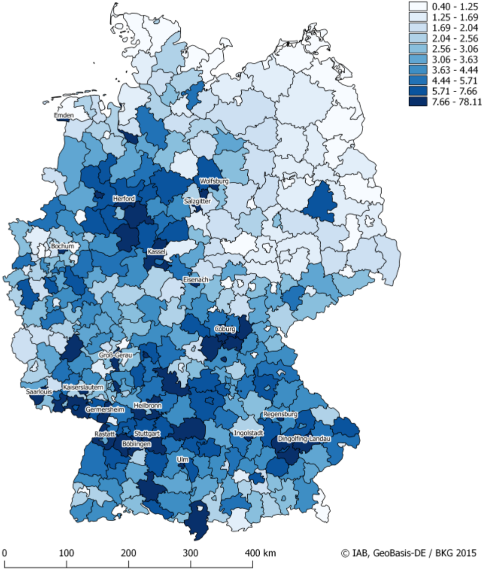
How strongly are all workers in county $r$ exposed to robots?

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

| | **1994-2014** | | **1994-2004** | | **2004-2014** | |
|---|---|---|---|---|---|---|
| | mean | ( sd ) | mean | ( sd ) | mean | ( sd ) |
| $\Delta$robots$_j$ | 16.976 | ( 30.942 ) | 10.620 | ( 20.373 ) | 6.915 | ( 12.158 ) |
| p10-p90 interval | [ -1.748 ; 77.141 ] | | [ 0.020 ; 56.468 ] | | [ -1.886 ; 23.650 ] | |
| p25-p75 interval | [ 3.369 ; 9.606 ] | | [ 1.079 ; 4.337 ] | | [ 1.502 ; 7.829 ] | |
| $\Delta$robots$_r$ | 4.644 | ( 6.921 ) | 3.044 | ( 4.297 ) | 1.723 | ( 2.585 ) |
| p10-p90 interval | [ 1.249 ; 7.659 ] | | [ 0.796 ; 5.543 ] | | [ 0.440 ; 2.602 ] | |
| p25-p75 interval | [ 1.871 ; 4.898 ] | | [ 1.187 ; 3.374 ] | | [ 0.741 ; 1.832 ] | |

$\Rightarrow$ Variation due to regions *initial* industry specialization in 1994

# Robot exposure




- 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

# Trade and ICT

**Import competition** and **ICT** might also threaten German jobs - and be correlated to robot installations.

- International trade with China and Eastern Europe
  - Change in German net exports vis-a-vis China and 21 Eastern European countries, normalized by the industry wage bill (UN COMTRADE)
- Information and communication technologies (ICT)
  - Change in real gross fixed capital formation volume in Euros per worker for computing and communications equipment (EUKLEMS)
- Correlations at *industry-level*: Robots & Trade (-0.09), Robots & ICT (0.04), ICT & Trade (0.05)
- *Region-level exposures* of trade and ICT: Weighted averages of industry exposures, with weights given by *initial* employment structures (analogous to robot exposure measure) Region-level exposures

# Worker-level analysis

- Long-run impact of robot exposure on worker $i$ who was employed in a manufacturing industry $j$ in 1994
- Sample construction

  Summary statistics

  - 30% random sample of all 22–44 year old workers who had a full-time job in manufacturing continuously in 1992–1994
  - Main job held on June 30 in 1994 assigns every worker to an employer and therefore to an industry
- Outcomes (over the period 1994–2014)
  - Cumulative days in employment, individual labor earnings (rel. to base year)
  - Can be decomposed into several additive parts (employment/earnings that accrued in original/different plant, industry, occupation)

$$Y_{ij} = \boldsymbol{\alpha} \cdot \mathbf{x}'_{ij} + \beta_1 \cdot \Delta\text{robots}_j + \beta_2 \cdot \Delta\text{trade}_j + \beta_3 \cdot \Delta\text{ICT}_j + \phi_{REG(i)} + \phi_{J(j)} + \epsilon_{ij}$$

- $\mathbf{x}'_{ij}$: worker-level controls (gender, foreign nationality, three skill, three tenure, two age, and six plant size categories)
- $\phi_{REG(i)}$, $\phi_{J(j)}$: Federal States dummies, four broad manuf. industries dummies

# Local labor market analysis

- Idea: Variation in local robot exposure based on the region's *initial* industry specialization
- Change in a local outcome variable (total employment, average wages, etc.) over the period 1994–2014 is regressed on the change in local robot exposure

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

  - $\mathbf{x}_r'$: demographic characteristics of the local workforces (age, gender, qualification), employment shares of nine broadly defined industry groups
  - $\Delta\text{trade}_r$, $\Delta\text{ICT}_r$: change in local trade and ICT exposure
  - $\phi_{REG(r)}$: dummies for North, South, West, East Germany

# Identification strategy

- Long-term industry- and regional trends simultaneously affecting robot installations and labor market outcomes could bias the results

1. **Fixed effects specification**
   - *Worker-level analysis*: Identification *within* broad industry groups and *within* Federal States
   - *Local labor market analysis*: Identification *conditional on* local demographic characteristics and broad industry structures, and *within* broad regions
2. **Instrumental variable estimation** (Acemoglu/Restrepo 2017)
   - Robot installations across industries in other high-income countries as an instrument for German robot exposure
     - Instrument group: Spain, France, Italy, UK, Finland, Norway, Sweden
   - Purges unobserved German-specific shocks
   - *Identifying assumption*: Pattern of robot installations in other rich countries not correlated to domestic demand/technology shocks
   - Alternative / additional instrument:
     Lagged industry share of routine-intensive occupations in 1985

# Identification strategy (cont'd)

- **Trade** and **ICT exposure** as other major economic shocks are also potentially endogenous in the estimation equation

- **Instrumental variable strategy** similar to robot exposure
    - *Trade*: Third-country trade flows of other high-income countries vis-à-vis China and Eastern Europe as an instrument for German industry-level trade exposure (Autor et al. 2013)
    - *ICT*: Industry-level investments in ICT in other high-income countries as an instrument for German ICT exposure

# Total Employment

First stage

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| **IV: Robots in other countries** | | | | | |
| | 2SLS: 100 x 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) |
| | 2SLS: First stage | | | | |
| F-Statistic on excluded instruments | 267.548 | 361.951 | 438.619 | 460.244 | 566.136 |
| 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 labour market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

- No evidence for negative employment effects from robot exposure
- Also no effects on average regional wages

# Manufacturing versus non-manufacturing

Automotive | Non-manuf. split

| | Employment | | | Average Wages | | |
|---|---|---|---|---|---|---|
| | (1) Total | (2) Manuf. | (3) Non-manuf. | (4) Total | (5) Manuf. | (6) Non-manuf. |
| **[A] Baseline**: 100 x Log-△ in employment (average wages) between 1994 and 2014 | | | | | | |
| △ robots per 1000 workers | -0.0058 | **-0.3837**** | **0.4177**** | -0.0360 | **-0.1401*** | **0.0826*** |
| | (0.120) | (0.152) | (0.206) | (0.057) | (0.073) | (0.050) |
| *N* | 402 | 402 | 402 | 7149 | 6038 | 7095 |
| **[B] Alternative employment measure**: 100 x △ in employment/population between 1994 and 2014 | | | | | | |
| △ robots per 1000 workers | -0.0190 | -0.0595** | 0.0405 | | | |
| | (0.065) | (0.027) | (0.050) | | | |
| *N* | 402 | 402 | 402 | | | |

Notes: 2SLS results including the full set of control variables. The employment estimates in columns (1) to (3) are based on one observation per region, while the unit of observation in the wage estimates in columns (4) to (6) are region x demographic cells. Standard errors clustered at the level of 50 aggregate labor market regions (employment regressions) or local labor markets (wage regressions) in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

- Effect of 1 additional robot on manufacturing jobs: -2.12 (=-0.0595/100 x 1000/0.2812)
  US: -6.2 (Acemoglu/Restrepo 2017)
- Adds up to 276,507 manufacturing jobs ≙ 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 | 0.4177** | -0.0626 | 0.1966 | 0.7497* | 0.0638 |
| | (0.206) | (0.191) | (0.236) | (0.391) | (0.122) |
| *N* | 402 | 402 | 402 | 402 | 402 |

- Business services: IT technology, cleaning, or security.
- Firms spend locally on these services
- Consistent with “freed-up labor” theory:
  workers increasingly used in other tasks as output expands

# Robustness checks

Timing | Placebo | Further robustness checks

**Timing** Split observation period in two decades: 1994-2004 and 2004-2014

**Placebo test** Regress employment/wage growth in pre-period (1984-1994) on robot exposure in 1994-2014

**Instrument countries**

- Aggregate to single instrument
- Drop direct neighbors
- Drop Eurozone countries (France, Italy, Spain, and Finland)
- Use lagged shares of routine occupations as instrument

**Industries** Construct reverse crosswalk (use robots in 2004 as weights) to classify employment data into 25 ISIC Rev.4 industries

**Regions**

- Drop East Germany
- Include Federal State fixed effects

# Worker-level - manuf. employment

First stage

| Dependent variable: Number of days employed, cumulated over full observation period following the base year | | | | | | |
|---|---|---|---|---|---|---|
| **[A] OLS, period 1994-2014** | (1) | (2) | (3) | (4) | (5) | (6) |
| Δ robots per 1000 workers | 3.3602*** | 2.1265*** | 0.7573 | 0.6399* | 0.6016 | 0.9988* |
| | (0.856) | (0.660) | (0.579) | (0.377) | (0.369) | (0.582) |
| **[B] 2SLS, period 1994-2014** | (1) | (2) | (3) | (4) | (5) | (6) |
| Δ robots per 1000 workers | 3.5591*** | 2.4035*** | 1.1025* | 0.9758*** | 0.8003** | 1.1534* |
| | (0.848) | (0.665) | (0.602) | (0.352) | (0.349) | (0.596) |
| Δ net exports / wagebill in % | | | | | 0.5644*** | 0.7051*** |
| | | | | | (0.168) | (0.169) |
| Δ ICT equipment in € per worker | | | | | 0.0279 | 0.0371 |
| | | | | | (0.031) | (0.029) |
| age, gender, nationality dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| education and tenure dummies | No | Yes | Yes | Yes | Yes | Yes |
| ln base yr earnings | No | Yes | Yes | Yes | Yes | Yes |
| plant size dummies | No | No | Yes | Yes | Yes | Yes |
| broad industry dummies | No | No | No | Yes | Yes | Yes |
| federal state dummies | No | No | No | Yes | Yes | Yes |
| drop automotive industries | No | No | No | No | No | Yes |

Notes: Based on 993,184 workers. Standard errors clustered by industry x federal state in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

- Incumbent manuf. workers in more robot-exposed industries are employed on more days in 1994–2014 than comparable workers in less exposed manuf. industries

# Individual 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. Standard errors clustered by industry x federal state in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

- Robots increase days of employment in the workers' original establishment, but some workers end up conducting different tasks than before

# (Re-)entry into manufacturing

1. Robots decrease manufacturing employment in the aggregate
2. Robots stabilize existing jobs in manufacturing firms

→ How do the two go together?

| | △ manuf. (re-)entry | | △ avg. age | |
|---|---|---|---|---|
| | (1) Entry | (2) Re-entry | (3) Manuf. | (4) Non-manuf. |
| △ robots per 1000 workers | -0.1335** | 0.0297 | 0.0244*** | -0.0290*** |
| | (0.068) | (0.079) | (0.008) | (0.010) |
| △ net exports in 1000 € per worker | 0.0797 | 0.3840*** | -0.0247 | 0.0147 |
| | (0.106) | (0.100) | (0.017) | (0.017) |
| △ ICT equipment in € per worker | -0.0185*** | -0.0143* | 0.0030*** | -0.0021*** |
| | (0.007) | (0.009) | (0.001) | (0.001) |
| $R^2$ | 0.480 | 0.417 | 0.506 | 0.802 |

Notes: $N = 402$ local labor markets. 2SLS results including the full set of control variables. Standard errors clustered at the level of 50 aggregate labour market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

- Robots induce firms to create fewer *new* manufacturing jobs for young labor market entrants. Thus, more rapid ageing of manufacturing workforce.

# Worker-level - manuf. earnings and wages

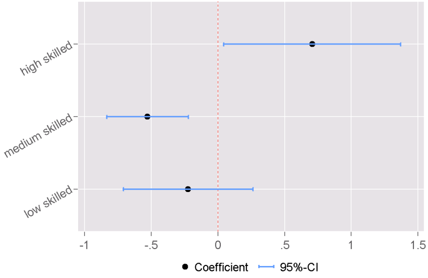
- Why do robots stabilize existing manufacturing jobs?

| | Dependent variable (1994–2014): 100 x cum. earnings / base yr earnings | 100 x ln avg. wage |
|---|---|---|
| Δ robots per 1000 workers | -0.7989*** | -0.0417*** |
| | (0.286) | (0.011) |
| Δ net exports / wagebill in % | 0.4025*** | 0.0117*** |
| | (0.106) | (0.004) |
| Δ ICT equipment in € per worker | 0.0159 | 0.0007 |
| | (0.020) | (0.001) |
| $R^2$ | 0.141 | 0.696 |

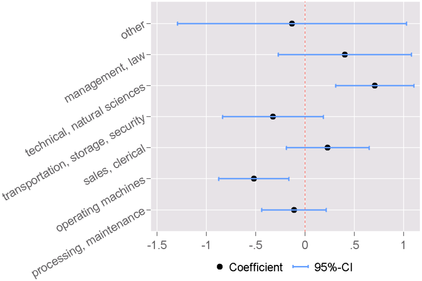
Notes: Based on 993,184 workers. Average wages are computed using (non-normalized) cumulated earnings over days employed. 2SLS results for period 1994-2014 with the full set of control variables as in the worker-level regression explaining manufacturing employment, column (5). Standard errors, clustered by industry x federal state in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

- Job stability came at the cost of lower earnings
- *Economic benchmarking:* Cumulative earnings loss of a worker at the 75th vers. 25th percentile of robot exposure (△robots per 1000 workers: 9.61 vers. 3.37) with avg. daily wage (120,70€ ): -1,266€ over twenty years

# Heterogeneous effects



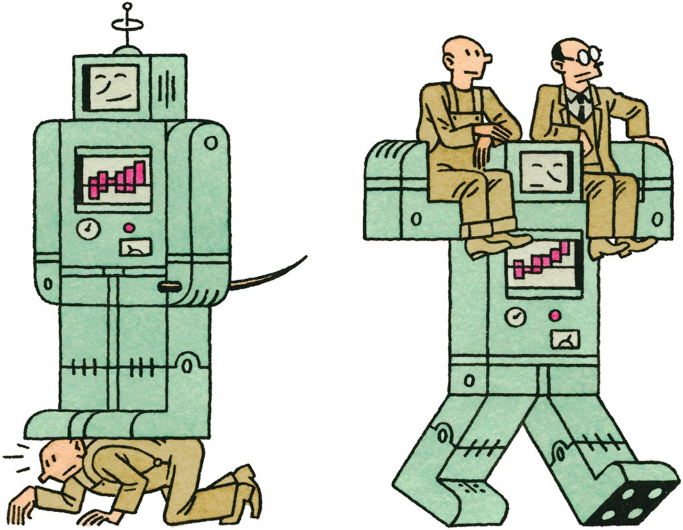

(a) by education




(b) by occupation

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

# Who Owns The Robots? Labor versus Capital



# Productivity and the Labor Share

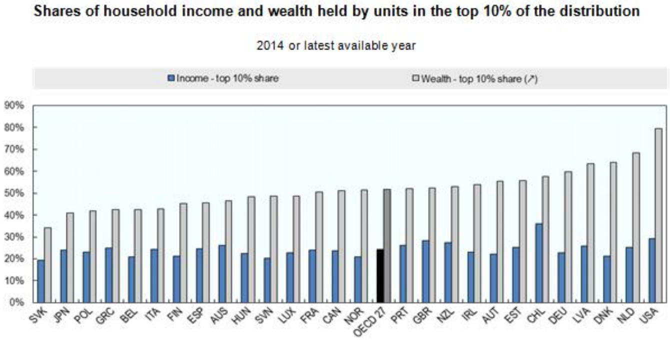
- Going back to local labor market level

| | Dependent variable: Change between 2004 and 2014 | | |
|---|---|---|---|
| | (1) Labor productivity | (2) Labor share | (3) Population |
| △ robots per 1000 workers | 0.5345** (0.268) | -0.4380** (0.192) | 0.0175 (0.190) |
| *N* | 402 | 372 | 395 |

- 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

# Falling Labour Share and the Income Distribution

# Falling Labour Share and the Income Distribution




*Source*: OECD Wealth Distribution Database, http://stats.oecd.org/Index.aspx?DataSetCode=WEALTH, and OECD Income Distribution Database, http://stats.oecd.org/Index.aspx?DataSetCode=IDD.

# Outlook: Future Work

**How do robots affect firm-level productivity and markups in Europe?**

- Productivity and markup estimation for manufacturing firms, 2004-2013, in 6 European countries (IT, FR, DE, FI, ES, SE) and 25 different industries
- Impact of robotization at different points of the industry-wide productivity distribution within a country
- Key insight: strong firms increase productivity and markups, weak (unproductive) firms lose
- Trends are stronger in more robotized industries
- Evidence that digitalization spurs the "superstar phenomenon" not only for US internet giants, but also in European manufacturing

# 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
  - Possible explanation: Strong unions and worker councils in the German labor market that have a preference for maintaining high employment levels Details
- Positive effect on labor productivity, but not on labor income
  - Contributing to the declining labor share
- Policy implications? Robot tax versus UBI versus employee asset ownership

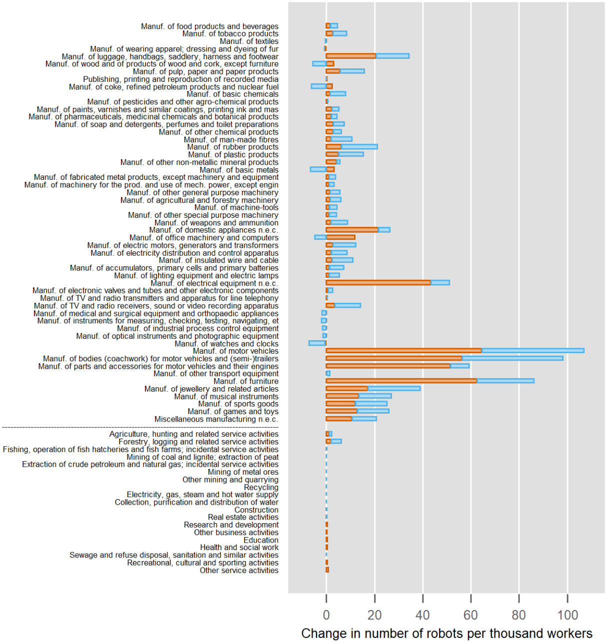

## Bottom line

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

*suedekum@dice.hhu.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

# 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** | | | | | | |
| 100 x earnings / base year earnings | 1925 | ( 1001 ) | 940 | ( 449 ) | 950 | ( 353 ) |
| days employed | 5959 | ( 2014 ) | 3015 | ( 1001 ) | 3261 | ( 802 ) |
| average daily wage | 120.7 | ( 71.6 ) | 121.7 | ( 74.4 ) | 126.8 | ( 73.9 ) |
| **[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 ) |
| dummy, 1=age $\leq$34 yrs | 0.554 | ( 0.497 ) | 0.388 | ( 0.487 ) | 0.251 | ( 0.434 ) |
| dummy, 1=age 35-44 yrs | 0.446 | ( 0.497 ) | 0.316 | ( 0.465 ) | 0.411 | ( 0.492 ) |
| dummy, 1=age $\geq$45 yrs | - | ( - ) | 0.281 | ( 0.449 ) | 0.319 | ( 0.466 ) |
| 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 ) |

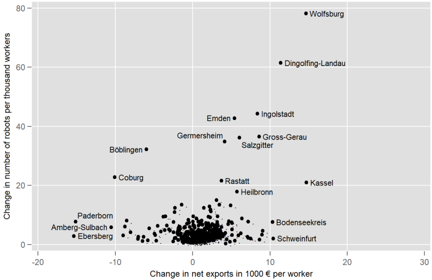
# Summary statistics, region level

back

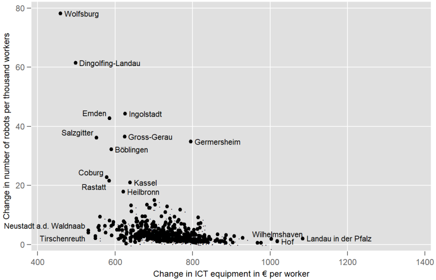
| | 1994-2014 | | 1994-2004 | | 2004-2014 | |
|---|---|---|---|---|---|---|
| observations | 993,184 | | 1,431,576 | | 1,246,414 | |
| | mean | ( sd ) | mean | ( sd ) | mean | ( sd ) |
| **[A] Outcomes (△ in logs)** | | | | | | |
| employment | -0.020 | ( 0.187 ) | -0.099 | ( 0.131 ) | 0.078 | ( 0.076 ) |
| manufacturing employment | -0.161 | ( 0.280 ) | -0.158 | ( 0.189 ) | -0.003 | ( 0.142 ) |
| manufacturing employment in automotive | 0.238 | ( 1.312 ) | 0.109 | ( 0.831 ) | 0.127 | ( 1.077 ) |
| manufacturing employment in other sectors | -0.180 | ( 0.279 ) | -0.172 | ( 0.189 ) | -0.008 | ( 0.143 ) |
| non-manufacturing employment | 0.043 | ( 0.229 ) | -0.069 | ( 0.158 ) | 0.112 | ( 0.092 ) |
| **[B] Control variables, shares in base year (in %)** | | | | | | |
| female | 34.716 | ( 4.674 ) | 34.716 | ( 4.674 ) | 34.454 | ( 5.071 ) |
| foreign | 6.981 | ( 4.781 ) | 6.981 | ( 4.781 ) | 5.565 | ( 3.842 ) |
| age $\geq$ 50 yrs | 20.101 | ( 2.366 ) | 20.101 | ( 2.366 ) | 20.903 | ( 2.347 ) |
| low skilled | 11.063 | ( 4.435 ) | 11.063 | ( 4.435 ) | 8.020 | ( 3.342 ) |
| medium skilled | 80.296 | ( 4.117 ) | 80.296 | ( 4.117 ) | 80.308 | ( 5.205 ) |
| high skilled | 7.956 | ( 3.965 ) | 7.956 | ( 3.965 ) | 11.009 | ( 4.899 ) |
| manufacturing | 31.830 | ( 12.496 ) | 31.830 | ( 12.496 ) | 29.969 | ( 11.768 ) |
| food products | 3.490 | ( 2.078 ) | 3.490 | ( 2.078 ) | 3.279 | ( 2.158 ) |
| consumer goods | 4.513 | ( 3.866 ) | 4.513 | ( 3.866 ) | 3.151 | ( 2.670 ) |
| industrial goods | 12.176 | ( 7.710 ) | 12.176 | ( 7.710 ) | 11.651 | ( 6.933 ) |
| capital goods | 11.651 | ( 9.005 ) | 11.651 | ( 9.005 ) | 11.888 | ( 8.969 ) |
| construction | 11.607 | ( 4.527 ) | 11.607 | ( 4.527 ) | 7.843 | ( 3.072 ) |
| maintenance; hotels and restaurants | 18.642 | ( 4.303 ) | 18.642 | ( 4.303 ) | 19.369 | ( 4.157 ) |
| services | 13.452 | ( 5.159 ) | 13.452 | ( 5.159 ) | 17.572 | ( 6.485 ) |
| education; social work; other organizations | 19.934 | ( 6.391 ) | 19.934 | ( 6.391 ) | 21.273 | ( 6.041 ) |
| dummy, 1=north | 0.159 | ( 0.366 ) | 0.159 | ( 0.366 ) | 0.159 | ( 0.366 ) |
| dummy, 1=south | 0.348 | ( 0.477 ) | 0.348 | ( 0.477 ) | 0.348 | ( 0.477 ) |
| dummy, 1=east | 0.192 | ( 0.394 ) | 0.192 | ( 0.394 ) | 0.192 | ( 0.394 ) |

# Region-level exposure of robots, trade, and ICT

back



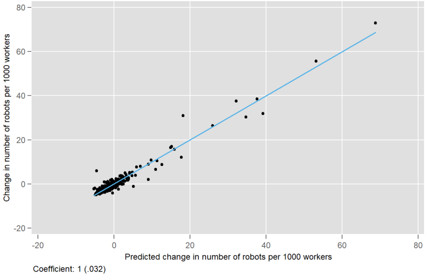

(a) Robots versus trade



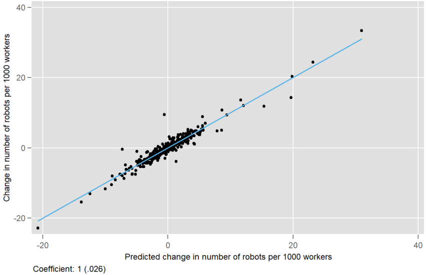

(b) Robots versus ICT

# First stage - region-level

back




(a) Region-level: Broad region dummies

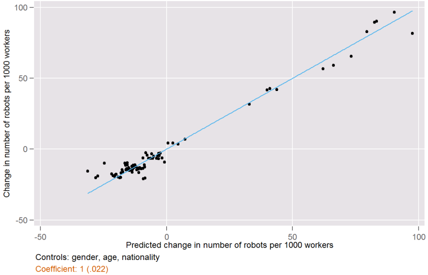



(b) Region-level: Full controls

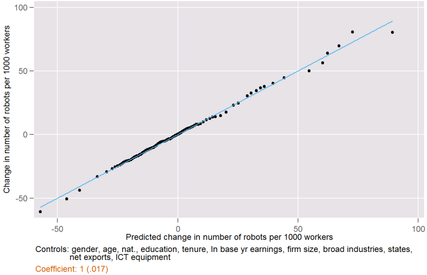
| | (a) | (b) |
|---|---|---|
| Kleibergen-Paap weak ID test | 175.4 | 20.6 |
| F-Statistic | 199.6 | 1541.1 |

# First stage - worker level

back




(a) Industry-level: only demographics




(b) Industry-level: Full controls

| | (a) | (b) |
|---|---|---|
| Kleibergen-Paap weak ID test | 393.1 | 71.8 |
| F-Statistic | 360.1 | 574.0 |

# The effects of robots in the automotive sector

back

| | (1) Manuf. | (2) Manuf. auto | (3) Manuf. other |
|---|---|---|---|
| **[A] Employment**: 100 x Log-△ in employment between 1994 and 2014 | | | |
| △ robots per 1000 workers | -0.3837** | -3.4084*** | -0.6525*** |
| | (0.152) | (1.142) | (0.210) |
| *N* | 402 | 368 | 402 |
| **[B] Average Wages**: 100 x Log-△ in average wages between 1994 and 2014 | | | |
| △ robots per 1000 workers | -0.1401* | -0.1387 | -0.3593*** |
| | (0.073) | (0.163) | (0.065) |
| *N* | 6038 | 1137 | 5990 |

Notes: 2SLS results including the full set of control variables. Columns (1) to (3) display estimates for the whole manufacturing sector, manufacturing of motor vehicles, and manufacturing except motor vehicles, respectively. The employment estimates in Panel A are based on one observation per region, while the unit of observation in the wage estimates in Panel B is region x demographic cells. Standard errors clustered at the level of 50 aggregate labor market regions (employment regressions) or local labor markets (wage regressions) in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

# Non-manufacturing employment, detailed

back

| | Dependent variable: 100 x Log-△ in employment between 1994 and 2014 | | | | |
|---|---|---|---|---|---|
| | (1) Non-Manuf. | (2) Constr. | (3) Personal serv. | (4) Business serv. | (5) Public sector |
| △ robots per 1000 workers | 0.4177** | -0.0626 | 0.1966 | 0.7497* | 0.0638 |
| | (0.206) | (0.191) | (0.236) | (0.391) | (0.122) |
| *N* | 402 | 402 | 402 | 402 | 402 |

Notes: 2SLS results including the full set of control variables. Column (1) displays estimates for the whole non-manufacturing sector. Columns (2) to (5) split the non-manufacturing sector into several subsectors, namely construction, personal services, business services, and the public sector, respectively. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

# Timing

back

| | Employment | | | Average Wages | | |
|---|---|---|---|---|---|---|
| | (1) Total | (2) Manuf. | (3) Non-Manuf. | (4) Total | (5) Manuf. | (6) Non-Manuf. |
| **[A] Stacked periods**: 100 x Log-△ in employment (1994-2004 and 2004-2014) | | | | | | |
| △ robots per 1000 workers | 0.0324 | -0.1028 | 0.3033 | -0.0078 | -0.0772 | 0.0006 |
| | (0.100) | (0.155) | (0.199) | (0.053) | (0.070) | (0.054) |
| *N* | 804 | 804 | 804 | 14333 | 12105 | 14191 |
| **[B] First period**: 100 x Log-△ in employment between 1994 and 2004 | | | | | | |
| △ robots per 1000 workers | 0.1302 | -0.0415 | 0.3121 | -0.0431 | -0.1681** | 0.0238 |
| | (0.145) | (0.318) | (0.301) | (0.064) | (0.083) | (0.072) |
| *N* | 402 | 402 | 402 | 7130 | 6023 | 7053 |
| **[C] Second period**: 100 x Log-△ in employment between 2004 and 2014 | | | | | | |
| △ robots per 1000 workers | -0.8339*** | -2.0943*** | 0.1170 | -0.1041 | -0.3509** | 0.1390 |
| | (0.230) | (0.371) | (0.321) | (0.120) | (0.165) | (0.136) |
| *N* | 402 | 402 | 402 | 7203 | 6082 | 7138 |

Notes: 2SLS results including the full set of control variables. The employment estimates in columns (1) to (3) are based on one observation per region, while the wage estimates in columns (4) to (6) exploit region x demographic cells. The regressions in Panel A additionally include region x time interaction terms. Standard errors clustered at the level of 50 aggregate labor market regions (employment regressions) or local labor markets (wage regressions) in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

# Placebo test

back

| | Employment | | | Average Wages | | |
|---|---|---|---|---|---|---|
| | (1) Total | (2) Manuf. | (3) Non-manuf. | (4) Total | (5) Manuf. | (6) Non-manuf. |
| **[C] Placebo check**: 100 × Log-$\triangle$ in employment (average wages) between 1984 and 1994 | | | | | | |
| $\triangle$ robots per 1000 workers | -0.0366 | -0.0346 | 0.0669 | 0.0412 | 0.0455 | 0.0602 |
| | (0.095) | (0.130) | (0.123) | (0.037) | (0.043) | (0.041) |
| $N$ | 326 | 326 | 326 | 5640 | 4836 | 5555 |

Notes: 2SLS results including the full set of control variables. The variable of interest is the change in robot exposure between 1994 and 2014. The employment estimates in columns (1) to (3) are based on one observation per region, while the unit of observation in the wage estimates in columns (4) to (6) are region x demographic cells. Standard errors clustered at the level of 50 aggregate labor market regions (employment regressions) or local labor markets (wage regressions) in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

# Robustness checks

back

| | Employment | | | Average Wages | | |
|---|---|---|---|---|---|---|
| | (1) Total | (2) Manuf. | (3) Non-Manuf. | (4) Total | (5) Manuf. | (6) Non-Manuf. |
| | Panel A: Just-identified IV | | | | | |
| △ robots per 1000 workers | 0.0867 | -0.1752 | 0.4655** | -0.0373 | -0.1430* | 0.0699 |
| | (0.139) | (0.192) | (0.220) | (0.058) | (0.078) | (0.052) |
| *N* | 402 | 402 | 402 | 7149 | 6038 | 7095 |
| | Panel B: IV without direct neighbors | | | | | |
| △ robots per 1000 workers | -0.0189 | -0.3999*** | 0.4088* | -0.0408 | -0.1434* | 0.0791 |
| | (0.122) | (0.148) | (0.209) | (0.057) | (0.074) | (0.050) |
| *N* | 402 | 402 | 402 | 7149 | 6038 | 7095 |
| | Panel C: IV without members of the European Monetary Union | | | | | |
| △ robots per 1000 workers | -0.0025 | -0.3423** | 0.4051* | -0.0544 | -0.1519* | 0.0652 |
| | (0.117) | (0.157) | (0.210) | (0.060) | (0.079) | (0.051) |
| *N* | 402 | 402 | 402 | 7149 | 6038 | 7095 |
| | Panel D: Cross-walk | | | | | |
| △ robots per 1000 workers | 0.0043 | -0.1601 | 0.2252 | -0.0075 | -0.0364 | 0.0535 |
| | (0.093) | (0.101) | (0.147) | (0.040) | (0.054) | (0.038) |
| *N* | 402 | 402 | 402 | 7149 | 6038 | 7095 |
| | Panel E: West Germany | | | | | |
| △ robots per 1000 workers | -0.0223 | -0.4147** | 0.4178** | -0.0551 | -0.1851*** | 0.0769 |
| | (0.123) | (0.164) | (0.199) | (0.058) | (0.072) | (0.052) |
| *N* | 325 | 325 | 325 | 5766 | 5019 | 5717 |
| | Panel F: Federal state dummies | | | | | |
| △ robots per 1000 workers | -0.0528 | -0.4166*** | 0.3625* | -0.0551 | -0.1739** | 0.0721 |
| | (0.138) | (0.153) | (0.218) | (0.056) | (0.072) | (0.049) |
| *N* | 402 | 402 | 402 | 7149 | 6038 | 7095 |

# Effect of works councils

back

Table: Effects of robot exposure and influence of unions

| **[A] Works council** | (1) employment | (2) avg. wage | (3) earnings |
|---|---|---|---|
| | at original workplace, 1995-2014 | | |
| Δ robots per 1000 workers | -23.2322*** | -8.4327*** | -0.0809 |
| | (7.586) | (2.841) | (0.049) |
| Δ robots per 1000 workers × % workers in plants with works council | 0.3924*** | 0.1331*** | 0.0007 |
| | (0.100) | (0.037) | (0.001) |
| % workers in plants with works council | 1.2404 | 1.5132 | 0.0732*** |
| | (4.107) | (1.413) | (0.012) |
| $R^2$ | 0.101 | 0.101 | 0.756 |

Notes: Based on 989,910 workers. 2SLS results for period 1994-2014. The outcome variables are cumulated days of employment (column 1), and 100 x earnings normalized by earnings in the base year (column 2) at the original workplace, cumulated over the twenty years following the base year. The outcome in column 3 is 100 x log average wages at the original workplace. The regressions are estimated by applying the 2SLS IV approach where German robot exposure, net exports to China and Eastern Europe, and ICT are instrumented with their respective counterparts in other high-income countries and include the same control variables as in column (5) of Table **??**. Standard errors clustered by industry x federal state in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Sources: IFR, COMTRADE, EUKLEMS, IAB Establishment Panel, and IEB V12.00.00 - 2015.09.15, own calculations.